**UNITED STATES PATENT AND TRADEMARK OFFICE**

---

**BEFORE THE PATENT TRIAL AND APPEAL BOARD**

---

NICHOLSON MANUFACTURING LTD.,

Petitioner

v.

BID GROUP TECHNOLOGIES LTD.,

Patent Owner

---

Case No. PGR2025-00081

U.S. Patent No. 12,163,947

---

# DECLARATION OF MICHAEL J. PAZZANI, PH.D. IN SUPPORT OF PETITION FOR POST-GRANT REVIEW OF U.S. PATENT NO. 12,163,947

# TABLE OF CONTENTS

I. INTRODUCTION ..... 7
A. Qualifications ..... 7
B. Materials Considered ..... 11
II. LEGAL STANDARDS ..... 12
A. Obviousness Under 35 U.S.C. § 103 ..... 13
B. Unpatentable Subject Matter Under 35 U.S.C. § 101 ..... 15
C. Indefiniteness Under 35 U.S.C. § 112 ..... 17
D. Level of Ordinary Skill in the Art ..... 17
III. SUMMARY OF GROUNDS ..... 19
IV. TECHNOLOGY BACKGROUND ..... 19
A. Debarking Machines ..... 20
B. Artificial Intelligence ..... 24
V. THE ’947 PATENT ..... 32
A. Overview of the ’947 Patent ..... 32
B. Prosecution History ..... 37
VI. BRIEF DESCRIPTION OF THE APPLIED PRIOR ART REFERENCES ..... 38
A. WO 2013/188948 (“Gagnon”) ..... 38
1. Background ..... 38
2. Disclosure ..... 39
B. CNN Based Tree Species Identification from Bark Image (“Ido”) ..... 42
C. U.S. Patent Publication No. 2019/0003829 (“Kambla”) ..... 46
1. Background ..... 46
2. Disclosure ..... 46
D. Programmable Logic Controllers (“Petruzella”) ..... 50

VII. DETAILED EXPLANATION OF THE UNPATENTABILITY GROUNDS ..... 58

A. Ground 1: Gagnon in Light of Kambla and the Knowledge of One of Ordinary Skill Renders Obvious Claims 1, 2, 3, 4, 7, 8, 9, and 10 ..... 59

1. Claim 1 Is Rendered Obvious ..... 59
2. Claim 2 Is Rendered Obvious ..... 76
3. Claim 3 Is Rendered Obvious ..... 77
4. Claim 4 Is Rendered Obvious ..... 80
5. Claim 7 Is Rendered Obvious ..... 81
6. Claim 8 Is Rendered Obvious ..... 85
7. Claim 9 Is Rendered Obvious ..... 86
8. Claim 10 Is Rendered Obvious ..... 88

B. Ground 2: Gagnon in Light of Ido and Petruzella Renders Obvious Claims 1-18 ..... 89

1. Claim 1 Is Rendered Obvious ..... 89
2. Claim 2 Is Rendered Obvious ..... 103
3. Claim 3 Is Rendered Obvious ..... 104
4. Claim 4 Is Rendered Obvious ..... 106
5. Claim 5 Is Rendered Obvious ..... 108
6. Claim 6 Is Rendered Obvious ..... 112
7. Claim 7 Is Rendered Obvious ..... 115
8. Claim 8 Is Rendered Obvious ..... 120
9. Claim 9 Is Rendered Obvious ..... 121
10. Claim 10 Is Rendered Obvious ..... 123
11. Claim 11 Is Rendered Obvious ..... 123
12. Claim 12 Is Rendered Obvious ..... 128
13. Claim 13 Is Rendered Obvious ..... 128
14. Claim 14 Is Rendered Obvious ..... 129

15. Claim 15 Is Rendered Obvious ..... 129
16. Claim 16 Is Rendered Obvious ..... 130
17. Claim 17 Is Rendered Obvious ..... 130
18. Claim 18 Is Rendered Obvious ..... 131

C. Ground 3: Gagnon in Light of Kambla and Petruzella Renders Obvious Claims 1-18 ..... 132
1. Claim 1 Is Rendered Obvious ..... 132
2. Claim 2 Is Rendered Obvious ..... 134
3. Claim 3 Is Rendered Obvious ..... 135
4. Claim 4 Is Rendered Obvious ..... 136
5. Claim 5 Is Rendered Obvious ..... 137
6. Claim 6 Is Rendered Obvious ..... 137
7. Claim 7 Is Rendered Obvious ..... 139
8. Claim 8 Is Rendered Obvious ..... 141
9. Claim 9 Is Rendered Obvious ..... 142
10. Claim 10 Is Rendered Obvious ..... 143
11. Claim 11 Is Rendered Obvious ..... 143
12. Claim 12 Is Rendered Obvious ..... 146
13. Claim 13 Is Rendered Obvious ..... 147
14. Claim 14 Is Rendered Obvious ..... 147
15. Claim 15 Is Rendered Obvious ..... 148
16. Claim 16 Is Rendered Obvious ..... 148
17. Claim 17 Is Rendered Obvious ..... 149
18. Claim 18 Is Rendered Obvious ..... 149

D. Ground 4: Claims 1-18 Are Not Patentable Under 35 U.S.C. § 101 ..... 150
1. Claims 1-18 Cover Abstract Ideas ..... 150
2. Claims 1-18 Do Not Include Additional Elements that Transform the Nature of Claim into Something

Significantly More than a Claim on the Abstract Idea ..... 157
3. Dependent Claims ..... 160
E. Ground 5: Claims 7 and 8 Are Indefinite Under 35 U.S.C. § 112 ..... 161
VIII. CONCLUSION ..... 163

I, Michael Pazzani, being over the age of 18 and competent to make the statements herein, hereby declare the following:

1. I am a citizen of the United States of America and reside in Marina del Rey, California.

2. I have been retained by counsel at Seed Intellectual Property Law Group LLP to provide my opinion on technical matters concerning the unpatentability of U.S. Patent No. 12,163,947 (the "'947 patent"). I am being compensated for my time at my normal consulting rate of $500 per hour for the first eight (8) hours of work billed per month and $400 per hour for every hour per month exceeding eight (8) hours. My compensation is not tied to the outcome of this matter or to providing any specific opinion.

3. I have no business interest in Nicholson Manufacturing Ltd. ("Nicholson"), which I understand to be the Petitioner in this case, and I have no business interest in Bid Group Technologies, Ltd. ("Bid"), which I understand to be the owner of the '947 patent.

# I. INTRODUCTION

## A. Qualifications

4. I am presently an Affiliated Scientist at the Information Sciences Institute at the University of Southern California, having retired on October 4, 2024, from a position as a Distinguished Principal Scientist. I have worked in this role since 2021. From 2019 to 2022, I was appointed as a Distinguished Scientist at the Halıcıoğlu Data Science Institute at the University of California, San Diego. From 2012 to 2019, I was a professor of Computer Science and Engineering and the Vice Chancellor for Research and Economic Development at the University of California, Riverside. From 2006 to 2012, I was a distinguished professor of Computer Science and the Vice President for Research and Economic Development at Rutgers University. From 2002 to 2006, I worked as the Division Director of Information and Intelligent Systems at the National Science Foundation ("NSF"), a federal agency that funds fundamental research at universities. This division, with an annual budget of approximately $250 million, provides funding for research on topics that included Internet Search, Natural Language Processing, Artificial Intelligence, Digital Libraries, Machine Learning, Robotics, Computer Vision, Human-Computer Interaction, and Neural Networks.

5. From 1988 to 2005, I was a professor of Information and Computer Science at the University of California, Irvine ("UC Irvine"), where I taught courses in Artificial Intelligence, Information Retrieval, Search Engines, and Machine Learning. I conducted research and supervised graduate students on projects that included Artificial Intelligence, Internet Search, Personalization and Recommendation Systems, Neural Networks, and Machine Learning. In 1999, while on leave from UC Irvine, I was CEO and co-founder of AdaptiveInfo.com ("AdaptiveInfo"), a company that personalized search and delivery of Internet news, classified ads, and restaurant listings for mobile devices such as cell phones. AdaptiveInfo was sold to Versifi Technologies in 2003.

6. My academic credentials include two degrees from the University of Connecticut: (1) a Bachelor of Science degree in Computer Engineering earned in 1980; and (2) a Master of Science degree in Computer Engineering earned in 1981. I earned a Doctor of Philosophy (Ph.D.) in Computer Science from the University of California, Los Angeles, in 1988.

7. I am an author or co-author of 52 journal articles, 85 conference papers, 14 book chapters and one book. I have also presented at approximately 32 workshops and edited an additional book.

8. I have extensive experience in the areas of search engines, machine learning, document classification and information retrieval, image classification, deep learning, and explainable artificial intelligence ("AI"), including: (a) creating and teaching a graduate course at UC Irvine entitled Information Retrieval, Filtering, and Classification (ICS 207); (b) teaching tutorials on document classification, machine learning and search at conferences put on by the International Joint Conferences on Artificial Intelligence ("IJCAI"), the Association for the Advancement of Artificial Intelligence ("AAAI"), and the Association for Computer Machinery ("ACM") (specifically, ACM's conferences on Intelligence User Interfaces ("IUI")); (c) running a company that handled news, classified, and restaurant searches for the Los Angeles Times and San Diego Union Tribune websites; (d) directing the Information and Intelligent Systems Division at the NSF, which provided funding for digital libraries, internet search, databases and machine research under my tenure; (e) receiving an AAAI Classic Paper award on personalization in web search; (f) creating a specialized search engine that classified proposals for the NSF to find reviewers for research proposals; (g) training and advising multiple PhD graduates who have worked on commercial search engines at Yahoo, Google, and Yandex; (h) serving on the Technical Advisory Board on

Internet Search for Microsoft; and (i) applying deep learning methods to medical images for the purposes of detecting diseases such as glaucoma and pneumonia.

9. I received many honors, awards, research grants and gifts. In 2014, I was awarded the AAAI Classic Paper award for a 1996 publication "for significant contributions to the field of personalizing Internet content and learning user profiles." *AAAI Classic Paper Award*, AAAI, https://aaai.org/about-aaai/aaai-awards/aaai-classic-paper-award/ (last visited Aug. 25, 2025). In 2003, I was recognized as a AAAI Fellow "for significant contributions to the development and understanding of machine learning algorithms and their relationship to human learning." *Elected AAAI Fellow*, AAAI, https://aaai.org/about-aaai/aaai-awards/the-aaai-fellows-program/elected-aaai-fellows/#2003. I have received 37 grants worth roughly $16.9 million in total. From 2019 to 2021, I served on the Defense Science Board of the U.S. Department of Defense ("DOD"), which provides the Secretary of Defense with independent advice and recommendations on scientific, technical, and other matters of special interest to the DOD.

10. From 1984 to 1988, I worked at The Aerospace Corporation, spending most of my effort working on artificial intelligence systems for detecting errors in satellite attitude control systems.

11. My full *curriculum vitae* is attached as Exhibit A to this declaration, which includes my detailed employment background, professional experience, publications, honors and awards, and other qualifications to render an expert opinion.

### B. Materials Considered

12. In forming my opinions, I reviewed the following documents, in addition to others I have cited in my declaration.

| **Document Name** |
|---|
| U.S. Patent No. 12,163,947 to Clement et al. |
| Prosecution File History of U.S. Patent Application No. 17/445,974 |
| International Patent Application No. WO 2013/188948 to Gagnon et al. ("Gagnon") |
| Junya Ido et al., *CNN-Based Tree Species Identification from Bark Image*, 10th Int'l Conf. on Graphics and Image Processing 2018 ("Ido") |
| U.S. Patent Publication No. 2019/0003829 A1 to Kambla et al. ("Kambla") |
| Frank D. Petruzella, *Programmable Logic Controllers*, chs. 1, 5, 6, 15 (5th ed. 2017) ("Petruzella") |
| Nicholson Mfg. Ltd., *A8 Manual* § 1 |
| Nicholson Mfg. Ltd., *A5B Manual* § 1 |
| Nicholson Mfg. Ltd., *A5B Brochure* |

| **Document Name** |
|---|
| Tom Fawcett, *An Introduction to ROC Analysis*, 27 Pattern Recognition Letters 861 (2006) |
| Sergey Levine et al., *Learning Hand-Eye Coordination for Robotic Grasping with Deep Learning and Large-Scale Data Collection*, 37 Int'l J. Robotics Rsch. 421 (2018) |
| *Characterization*, Merriam-Webster, https://www.merriam-webster.com/dictionary/characterization (last visited Aug. 25, 2025) |
| *Characterize*, Merriam-Webster, https://www.merriam-webster.com/dictionary/characterize (last visited Aug. 25, 2025) |
| *Sensor*, Merriam-Webster, https://www.merriam-webster.com/dictionary/sensor (last visited Aug. 25, 2025) |
| *Attribute*, Merriam-Webster, https://www.merriam-webster.com/dictionary/attribute (last visited Aug. 25, 2025) |
| Nicholson Mfg. Ltd., *A5A Brochure* (1993) |

13. In addition to the above list of references, I also considered any other references cited within the body of this declaration. I also relied on my own knowledge of and experience in the field of artificial intelligence and machine controls. I have also had a conversation with employees at Nicholson, as described below.

## II. LEGAL STANDARDS

14. In expressing my opinions and considering the subject matter of the claims of the '947 patent, I am relying on certain legal principles that have been

explained to me by counsel for Nicholson. Accordingly, I have considered the following standards in my evaluation of the technical aspects of the claims of the '947 patent.

15. I have been informed and instructed by counsel for Nicholson that for an invention claimed in a patent to be patentable, it must be, among other things, new and not obvious in light of what came before it. That which came before is generally referred to as "prior art."

16. I have been informed and instructed by counsel for Nicholson that, in this context, the burden is on the party asserting unpatentability to prove it by a preponderance of the evidence. I have been informed and instructed by counsel for Nicholson that "a preponderance of the evidence" is evidence sufficient to show that a fact is more likely than not.

### A. Obviousness Under 35 U.S.C. § 103

17. I have been informed and instructed by counsel for Nicholson that a claimed invention is not patentable if it would have been obvious to a person of ordinary skill in the field of the invention at the time the invention was made. I have been further informed and instructed by counsel for Nicholson that obviousness can be demonstrated by combining teachings from multiple prior art sources. I have also been informed and instructed by counsel for Nicholson that an

obviousness determination requires consideration of the following factors: (1) the scope and content of the prior art; (2) the differences between the prior art and the claimed subject matter; (3) the level of ordinary skill in the art; and (4) any objective evidence of obviousness or non-obviousness.

18. I have been informed and instructed by counsel for Nicholson that secondary considerations may also be considered, such as commercial success, long felt but unsolved needs, and failure of others.

19. I have been informed and instructed by counsel for Nicholson that the obviousness standard is defined in the patent statute (35 U.S.C. § 103(a) (AIA)) as follows:

> A patent for a claimed invention may not be obtained, notwithstanding that the claimed invention is not identically disclosed as set forth in section 102, if the differences between the claimed invention and the prior art are such that the claimed invention as a whole would have been obvious before the effective filing date of the claimed invention to a person having ordinary skill in the art to which the claimed invention pertains. Patentability shall not be negated by the manner in which the invention was made.

20. I have been informed and instructed by counsel for Nicholson that claimed subject matter would have been obvious to one of ordinary skill in the art if, for example, it results from (1) the combination of known elements according to known methods to yield predictable results, (2) the simple substitution of one known element for another to obtain predictable results, (3) the use of a known technique to improve similar devices in the same way, (4) applying a known technique to a known device ready for improvement to yield predictable results, or (5) pursuing known options within one's technical grasp in response to a design need or market pressure to solve a problem. I have also been informed that the analysis of obviousness incorporates the logic, judgment, and common sense of a person of ordinary skill in the art, which does not necessarily require explication in any particular reference.

### B. Unpatentable Subject Matter Under 35 U.S.C. § 101

21. I have been informed and instructed by counsel for Nicholson that laws of nature, natural phenomena, and abstract ideas are not patentable under 35 U.S.C. § 101 ("section 101"). It is my understanding that a two-step analysis is used to determine what is and what is not patent eligible. First, one must determine whether the claims at issue are directed to one of the three patent-

ineligible concepts: abstract ideas, natural laws, or natural phenomena. If so, then one must analyze whether the claims provide an inventive concept.

22. In the context of software patents, including those involving artificial intelligence, I understand that the step one inquiry usually turns on whether the claims are directed toward specific asserted improvements in computer capabilities or instead on a process or system that qualifies as an abstract idea for which computers are invoked merely as a tool. As a result, improving a user experience or providing faster applications because of using a computer is not, without more, sufficient to render the claims patent eligible at step one. I have further been informed that claims directed towards the collection and storage of information, and indicating the results of that information, all on a generic computer or using generic artificial intelligence programs operating in the normal, expected manner is also abstract.

23. I have been informed and instructed by counsel for Nicholson that step two of this analysis requires a determination of whether the claims do significantly more than simply describe the abstract method, thus transforming the idea into patentable subject matter. As part of this analysis, I understand that one must evaluate whether the claims disclose additional features that are more than well-understood, routine, conventional activity. Accordingly, I understand that

claims directed to an abstract idea implemented on a generic computer or using a generic artificial intelligence or deep learning model, without providing a specific technical solution beyond simply using these generic concepts in a conventional way, do not satisfy step two.

### C. Indefiniteness Under 35 U.S.C. § 112

24. I have been informed and instructed by counsel for Nicholson that a claim may be indefinite if the claim, read in light of the specification delineating the patent and the prosecution history, fails to inform with reasonable certainty a person of ordinary skill in the art about the scope of the invention. I have further been informed that when a claim term can refer to various different methods for determining a measurement or threshold, such term is indefinite if those methods are calculated in different ways that may yield materially different results when the claims, the specification, and the prosecution history do not indicate which method the claims cover.

### D. Level of Ordinary Skill in the Art

25. In rendering the opinions set forth in this declaration, I considered the patent claims through the eyes of "one of ordinary skill in the art." In assessing who is a person of ordinary skill in the art of the '947 patent, I considered factors such as the educational level and years of experience of the person or persons who

have developed artificial intelligence models for various industrial applications; the types of problems encountered in the art; the teachings of the prior art; and the sophistication of the technology. I have been informed and instructed by counsel for Nicholson that the person of ordinary skill in the art is not a specific real individual, but rather a hypothetical individual having the qualities reflected by the factors discussed above.

26. In my opinion, a person of ordinary skill in the art would have a Bachelor's degree in Mechanical, Electrical, Computer, or Systems engineering, plus at least two years of experience in the field of engineering programming. Alternatively, a person of ordinary skill would have a Master's degree in any of the above fields.

27. The '947 patent notes in its Abstract that the disclosed method "comprises a scanning device . . . for providing data, usually in the form of images, to a deep learning algorithm model." *See* '947 patent, Abstract. The deep learning algorithm model is "trained . . . to detect and identify, with an acceptable amount of certainty, characteristics of undebarked logs." *Id.* In addition, the "Field of the Invention" section notes that "[t]he present invention generally relates to the field of characterising an undebarked wooden log by deep learning AI [or artificial intelligence] models . . . in order to adjust, in real time, said device and obtain an

optimal debarking." *Id.*, 1:20-24. Accordingly, the '947 patent is targeted towards the use of a deep learning artificial intelligence model, further supporting my description of a person of ordinary skill.

## III. SUMMARY OF GROUNDS

| | Prior Art/Argument | Claims |
|---|---|---|
| Ground 1 | Gagnon, Kambla, knowledge of one of ordinary skill under § 103 | 1-4, 7-10 |
| Ground 2 | Gagnon, Ido, Petruzella under § 103 | 1-18 |
| Ground 3 | Gagnon, Kambla, Petruzella under § 103 | 1-18 |
| Ground 4 | Unpatentability under § 101 | 1-18 |
| Ground 5 | Indefiniteness under § 112 | 7, 8 |

## IV. TECHNOLOGY BACKGROUND

28. The disclosures in the '947 patent relate to a debarking machine in combination with and controlled by the implementation of a deep learning, artificial intelligence ("AI") algorithm. I will provide backgrounds in this section on each of those technologies.

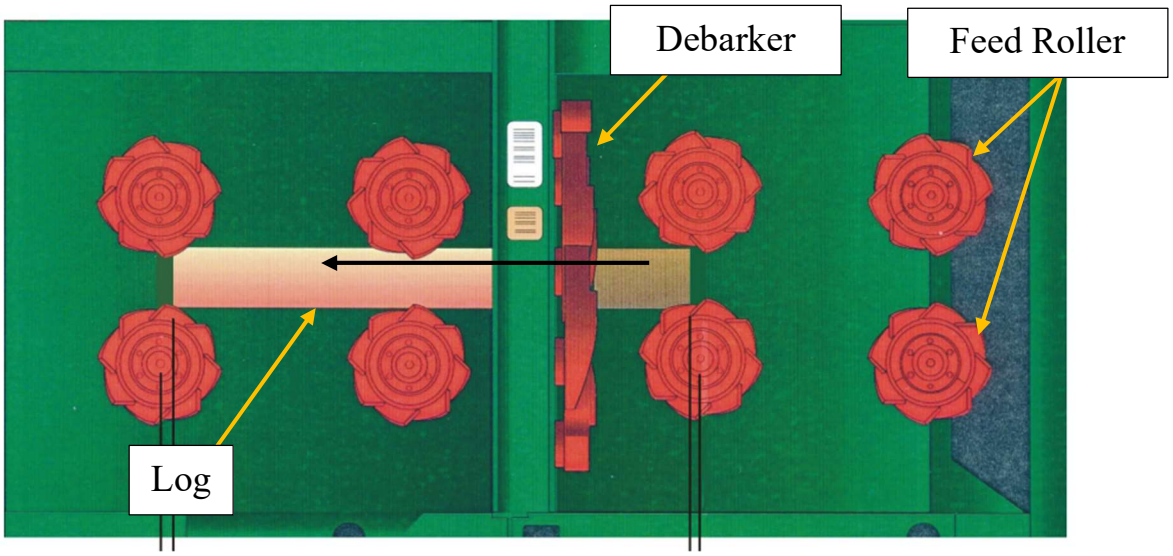
**A. Debarking Machines**

29. My understanding of debarking machines comes from conversations I have had with employees at Nicholson, namely Mike Mason and James Bowden, as well as reviewing brochures, Nicholson's and Bid's websites, and videos of debarkers in operation. My conversation with the Nicholson employees occurred on August 21, 2025. My understanding is also based on the prior art references and various industry literature that I have reviewed as part of this project, and as noted in my Materials Considered section. *See supra* § I(B).

30. A debarking machine is used to remove the outer layer of a log, in particular, the bark layer and a portion of the cambium layer. The remaining wood fiber is processed into lumber and wood chips. Typically, the industry attempts to maximize the amount of lumber that can be obtained from a debarked log, with any remaining portion of the log being turned into wood chips. My understanding is that the industry typically looks for wood chips containing less than 1% bark. Accordingly, the debarking machine should remove sufficient bark for the wood chips to be acceptable but not so much of the remaining portion of the log that it would impact the amount of lumber that could be obtained.

31. Debarking machines have been available in the United States since at least 1948. The following annotated diagram taken from a debarker manual dated

2019 illustrates a type of debarking machine that was on sale and available before the priority date of the '947 patent:




Nicholson Mfg. Ltd., *A8 Manual* § 1.4.2 (annotated). As shown in this diagram, four sets of feed rollers secure and position the log so that it can be fed through a debarker ring, going from right to left in the diagram. The feed rollers are spaced apart so that the log is secured by at least two sets of feed rollers at a time.

32. I understand that a debarking machine can have various types of debarking mechanisms; the disclosures in the '947 patent are not directed towards any particular type of mechanism. In the illustration above, the debarking machine uses a debarker ring that consists of a number of knife arms arranged radially around an opening, as shown in the following illustration:



*See* Nicholson Mfg. Ltd., *A5A Brochure*, at 4.[1]

33. As the feed rollers feed the log through the debarker ring, pressure, such as pneumatic or hydraulic pressure, is applied to the knife arms so that they engage with the outer layer of the log. In addition, a motor will cause the debarker ring to rotate around the log. As the debarker ring rotates, the knife arms remove the outer layer(s) of the log, as shown in the following illustration:

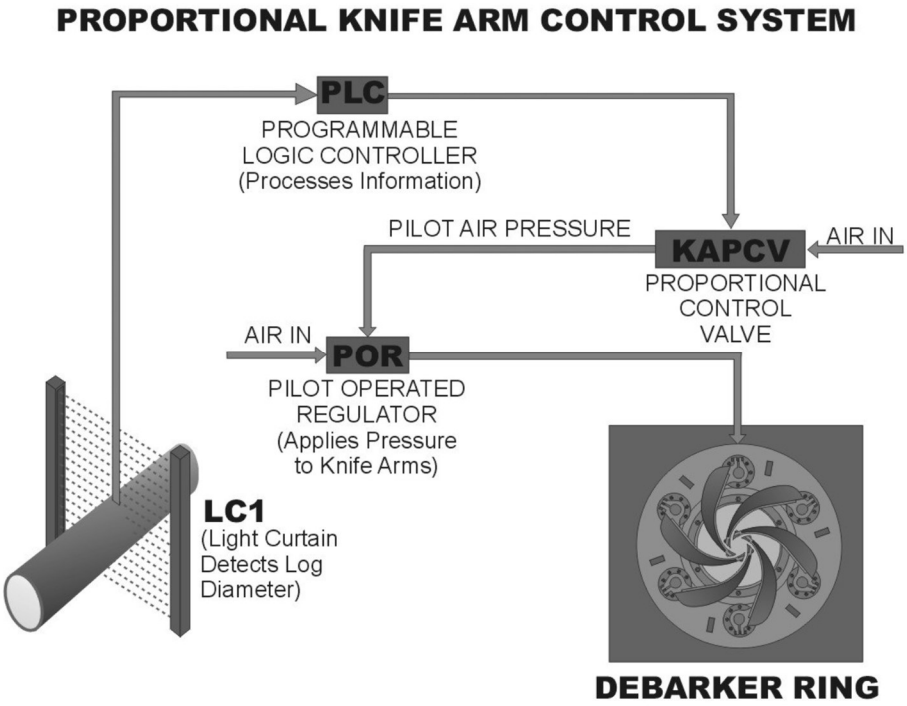
[1] Although this illustration is taken from a brochure dated 1993, I have been informed that the same type of debarker ring is used in the machine shown in *A8 Manual* § 1.4.2 from 2019.



*See* Nicholson Mfg. Ltd., *A5B Brochure*, at 2.

34. I understand that various settings on the debarking machine can be modified based on various inputs. For example, I understand that the pressure applied to the knife arms along with the angle of the knife arm tips can be modified to adapt to the type (e.g., species) and conditions of the log being debarked.

35. In addition, it has been well-known in the art that the operating parameters for a debarking machine may be modified based on the diameter of the log being input into the machine. For this reason, systems available well before the priority date of the '947 patent included a light curtain that could be used to automatically determine a log's diameter. The following illustration shows such a light curtain arrangement and how the output measurement from a light curtain could be used to set the pressure to be applied to the knife arms:




*See* Nicholson Mfg. Ltd., *A5B Manual* § 1.6.5.2.

36. The general concept for operating a debarking machine, as explained above, is consistent with those types of technologies well suited for deploying artificial intelligence. In particular, debarking machines are controlled by a set of well-known and well-understood controls, and these controls may be set based on a number of well-known inputs.

### B. Artificial Intelligence

37. Deep learning is a type of artificial intelligence known as machine learning (also known as data mining). The origins of deep learning can be traced back to the development of perceptron. *See, e.g.*, F. Rosenblatt, *The Perceptron: A*

*Probabilistic Model for Information Storage and Organization in the Brain,* 65 Psych. Rev. 386 (1958). A perceptron is the simplest form of a neural network, a single artificial neuron designed for binary classification. *See id.* at 387. The perceptron is rather simple, and receives a number of inputs, often numbers between 0 and 1. *See id.* at 389. Each input is associated with a weight that can be thought of as the importance of that input to the output. *See id.* at 389. It produces an output of 0 or 1. *See id.* at 389-90. If the sum of the weights multiplied by the inputs is greater than a threshold parameter, then the model is considered trained. *See id.* at 389, 392.

38. Learning (also known as training in the perceptron) is done by adjusting the weights. *See id.* at 391, 393. Initially, the weights are assigned randomly. *See id.* at 392. A set of training examples is presented one at time, in which the inputs and desired output is known. *See id.* at 395. If the perceptron produces the correct output, the weights are not changed. If the perceptron produces the incorrect output, a delta (i.e., difference between the correct and incorrect output) is calculated, and each weight is adjusted by adding the delta multiplying by a small number (known as the learning rate) to the weight. Iterating through the training examples and adjusting weights will converge on the optimal solution if one exists. Although groundbreaking, the perceptron's limitations

became apparent when it was proved that it could not solve a variety of problems that are not linearly separable (i.e., the solution cannot be represented as weighted sum of the inputs).

39. The field of artificial neural networks experienced a revival with the backpropagation algorithm for learning in multi-layer neural networks. *See, e.g.*, David E. Rumelhart et al., *Learning Representations by Back-Propagating Errors,* 323 Nature 533 (1986). This publication was instrumental in overcoming the limitations of perceptrons and laid the groundwork for modern deep learning. The key innovation was to use a continuous function, a sigmoid, that approximates the threshold function of the perception to compute the output as a function of the weighted inputs. *See id.* at 533. The sigmoid function allows training of multiple layers of connected neurons. *Id*. Another advantage of the sigmoid is that it produces a number between 0 and 1 that can be viewed as a probability, e.g., the probability that a patient has a particular disease. *See id.* at 535

40. A key innovation that builds upon backpropagation was the Convolutional Neural Network (CNN) in 1998. *See* Yann LeCun et al., *Gradient-Based Learning Applied to Document Recognition*, 86 Proc. IEEE 2278 (1998).

41. CNNs are specifically designed for processing image data. *Id.* at 2278-79. They use convolutional layers to automatically extract features from

images. *Id.* at 2283-84. Another breakthrough was AlexNet, which showed how the mathematics of deep learning can be efficiently implemented on graphic processing units ("GPUs") and demonstrated superior performance to older computer vision algorithms that relied on hand-crafted features. Alex Krizhevsky et al., *ImageNet Classification with Deep Convolutional Neural Networks,* Advances Neural Info. Processing Sys. 25, 1097 (2012).

42. Two additional developments occurred in 2014 and 2016 that are still in use today: VGG and ResNet. *See* Karen Simonyan & Andrew Zisserman, *Very Deep Convolutional Networks for Large-Scale Image Recognition*, arXiv, https://arxiv.org/abs/1409.1556v5 (5th version, preprint Dec. 23, 2014) (subsequent version published on April 10, 2015, in conjunction with the 3rd Annual International Conference on Learning Representations); *see also* Kaiming He et al., *Deep Residual Learning for Image Recognition*, 2016 Proc. IEEE Conf. on Comput. Vision and Pattern Recognition, 770 (2016). VGG[2] networks are known for their simplicity and depth. *See, e.g.*, Simonyan, *Very Deep Convolutional Networks* at 5, 8. They demonstrated that by stacking many small convolutional filters, a deep network could achieve state-of-the-art performance.

[2] "VGG" stands for "Visual Geometry Group," the team at the University of Oxford that developed this particular method. *Id.* at 1.

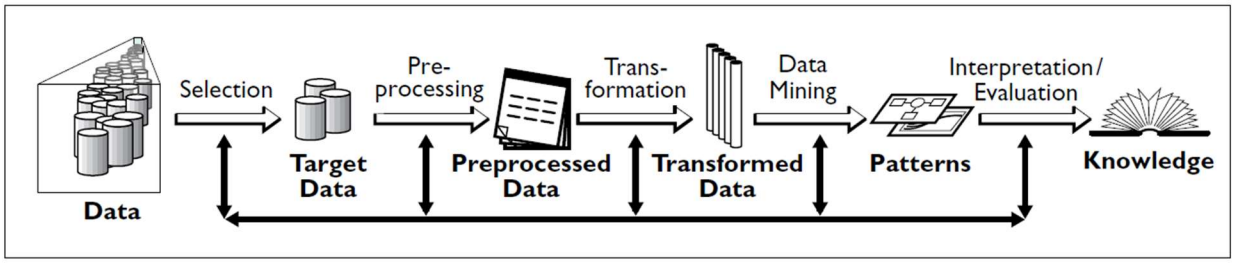
*See id.* at 2. This architecture became a benchmark and a foundation for future work. ResNet introduced residual connections that made it possible to train extremely deep networks (over 100 layers) without degradation, leading to a significant leap in performance.

43. It is important to note that VGG and ResNET are general-purpose deep learners for image classification. They require training data (images that are labeled to belong to one of several classes), and when presented with unlabeled data, produce a classification. When there are multiple classes, the CNNs can produce as an output the probability that an image belongs to each class. I have used CNNs as simple exercises for students to distinguish photos of cats from dogs, and in more complex research programs of distinguishing bird species, diagnosing COVID-19 from chest X-rays, and diagnosing glaucoma from fundus (retina) photographs.

44. Other applications use image classification technology in a wide variety of fields and have seen many commercial applications. For example, the June Oven uses image classification capabilities to classify foods placed in an oven to determine the cooking conditions (e.g., time, temperatures, mode (broiling, baking, etc.)) for the identified food. Security cameras can use image classification technology for various purposes, including to provide notification of a package

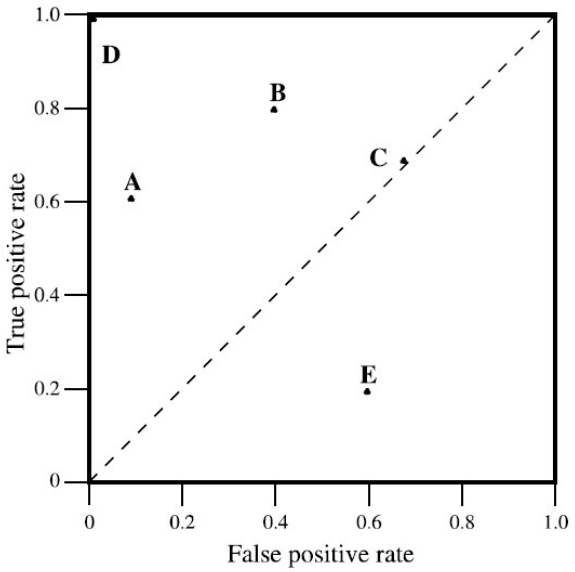
delivery or to provide threat notifications. To classify trees species, all that it requires is collecting photographs of different trees and training sufficiently on these photographs.

45. Although most technical papers focus on advances in the theory and algorithms for extracting information from data, machine learning and deep learning are typically part of a much larger process in which one collects data, represents that data, runs a machine learning algorithm, and samples the results. The figure below from Usama Fayyad et al., *The KDD Process for Extracting Useful Knowledge from Volumes of Data*, 50 Comm. ACM 27 (1996), illustrates the iterative process in which after running data mining (i.e., machine learning), the results are evaluated and we can repeat any of the prior steps, such as selecting additional data, pre-processing or transforming that data differently, or changing the data mining algorithm.




46. A variety of metrics have been used to evaluate how well a machine algorithm works. Typically, this involves a set of test examples, which have not

been used to train the machine learning system, in which the correct desired output is known for each example. Tom Fawcett, *An Introduction to ROC Analysis*, 27 Pattern Recognition Letters 861 (2006), describes several such metrics in which the desired output is compared to the actual output and a metric is computed for the set of test examples. These metrics include the accuracy (the fraction of examples correctly classified), the true positive rate (the fraction of member of a particular class that are correctly identified), and the false positive rate (the fraction of members not of a particular class that are incorrectly classified to be in that class). An ROC (receiver operating characteristic ) graph plots the true positive rate as a function of the false positive rate (see below). It can be used to compare various machine learning algorithms (or settings of a single algorithm) to decide which is the best for a particular application. Note that points below the dotted line are doing worse than chance, with points above the line performing better than chance. In a particular application, e.g., medicine, we may be willing to accept more false positives so we don't miss a true positive, even though the accuracy of doing so does not produce the optimal accuracy.




47. A confusion matrix may also be used to evaluate deep learning or machine learning algorithms in which one plots the predicted and true classification for each test example.

48. Training and evaluation of machine learning and systems relies upon having the correct or desired classifications for examples. Often, these come from human experts manually looking at the data, e.g., looking at the diagnosis performed by a doctor or the bird species identified by bird watchers. In addition, the desired classification can be determined as part of a system or by other tests without involving people examining the data used in training or evaluation. For example, Sergey Levine et al., *Learning Hand-Eye Coordination for Robotic Grasping with Deep Learning and Large-Scale Data Collection*, 37 Int'l J. Robotics Rsch. 421 (2018), describes using photos on an object in a scene to

predict whether a robot arm using a particular trajectory will be able to pick up an object. Rather than having a person make this prediction, they run the robot and sensors on the arm to determine if the robot was successful. In a medical example, photos of the fundus (back of the eye) of a patient can be used to estimate the patient's A1C level. Rather than having a person perform this task (which is difficult or impossible for people), a blood test is used to determine the A1C level. Ryan Poplin et al., *Prediction of Cardiovascular Risk Factors from Retinal Fundus Photographs via Deep Learning*, 2 Nature Biomedical Eng'g 158 (2018).

## V. THE '947 PATENT

### A. Overview of the '947 Patent

49. U.S. Patent No. 12,163,947 issued on December 10, 2024, from U.S. Application No. 17/445,974, filed on August 26, 2021. The '947 patent claims priority to U.S. Provisional Application No. 63/070,887, filed on August 27, 2020. The '947 patent is assigned to Bid Group Technologies, Ltd.

50. In general, the '947 patent discloses "[a] method for characterizing undebarked wooden logs and computing optimal debarking parameters in real time" using "a scanning device upstream of a debarker" that provides data "to a deep learning algorithm model." '947 patent, Abstract. In the "Background" section, the '947 patent describes that debarking process optimization "requires

detailed knowledge of the incoming material and knowledge of the control of the debarking devices." *Id.*, 1:57-59. Debarking parameters, such as "rotational speed and tools pressure" may depend on "environmental factors such as moisture content, species, temperature, etc." *Id.*, 1:62-65. Accordingly, "[i]t is well known in the industry that sorting wooden logs upstream of the debarker comprises operational and financial benefits." *Id.*, 1:67-2:3.

51. The specification describes the method, generally, as involving the following steps: (i) "measuring attributes of the undebarked log"; (ii) "identifying characteristics of the undebarked log based on measured attributes of the undebarked log using a trained deep learning model"; (iii) "computing operating parameters of a debarker based on the identified characteristics"; and (iv) "sending the computed operating parameters to the debarker." *Id.*, 3:11-19.

52. The following figure shows an embodiment of a system for characterizing undebarked logs consistent with the disclosures in the '947 patent:

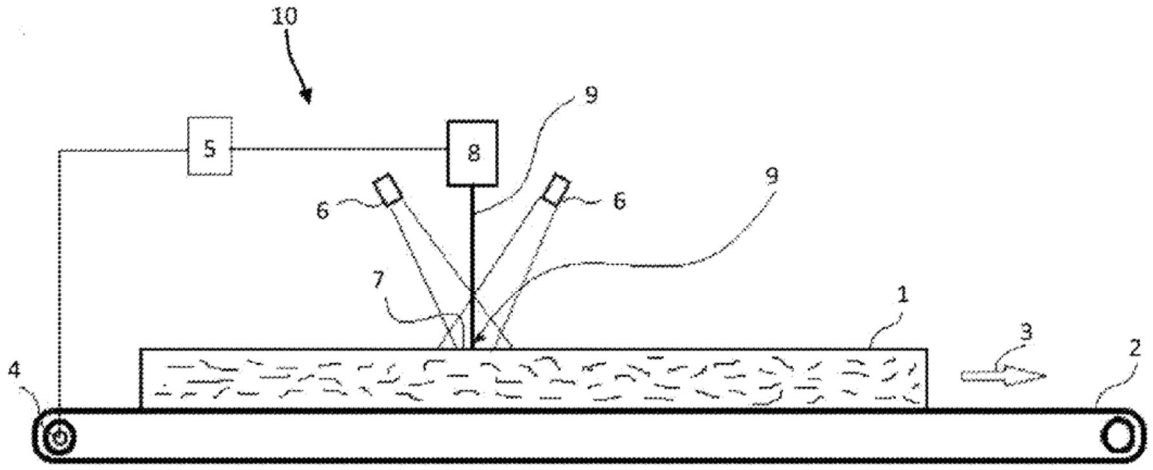



FIG. 1

*Id.*, Fig. 1.

53. In this embodiment, "[a] wooden log having bark 1 is conveyed . . . using a conveyor 2, towards direction 3." *Id.*, 4:67-5:1. The debarker further includes "lighting device [6 that] may be configured to illuminate a region/area 7 of the surface of the log with bark 1," where the light reflected from the outer surface of this region/area 7 of the log is "captured by the scanning device 8." *Id.*, 5:16-20. "[A]ny type of scanning device 8 may be used for scanning the undebarked log 1 and may be for example a line scan, an area scan camera or an infrared camera." *Id.*, 5:25-28.

54. The system also includes a "data acquisition unit 5 [that] is programmed to perform a real-time analysis of the received image data." *Id.*, 5:35-36. The data acquisition device also includes generic components (e.g., transient

memory, a CPU, a storage unit, and network unit). *See id.*, 5:5-8. According to the '947 patent, "[t]o determine characteristics of the undebarked logs 1, such as species, type, quality, freshness (moisture level), sap level, quantity of knots, and so on, the data acquisition unit 5 may be programmed to execute one or more deep learning models algorithms [*sic*] using the collected data from the scans as input." *Id.*, 5:37-42. According to the specification, "any type of deep learning algorithm may be used with the method of the present invention." *Id.*, 8:19-21.

55. The disclosed system may include "optimization software 140," as shown in Figure 3, that "is programmed to compute optimal debarking parameters 150 based on the characteristics of the log 1 identified by the log scanning software 110." *Id.*, 6:57-60. "The optimal debarking parameters 150 are inputted in the debarker control software 160," which "controls the operations of a debarker." *Id.*, 6:60-65. As disclosed in the '947 patent, some embodiments of the "optimization software 140 ha[ve] access [to] or comprise[] a table of debarking parameters . . . associated with characteristics of the log or with ranges of values of the characteristics of the log." *Id.*, 6:66-7:2. As such, "[t]he optimization software 140 may thus, in real time, adjust the debarking parameters 150 in view of the received characteristics 130 of the log to be debarked." *Id.*, 7:16-18. The '947

patent states, "[t]he optimal debarking parameters 150 may be any parameter of a debarking apparatus known in the art." *Id.*, 7:18-20.

56. In describing the technology, the '947 patent generally lists the possible operating parameters of the debarker along with a list of the possible measured characteristics but does not provide any association between the two lists. The following description is representative of the disclosures in the specification on this point:

> The operating parameters of the debarker may comprise, but are not limited to, conveying speed, rotational speed, level of pressure to be applied by the tools on the outer surface of the undebarked log, tool aperture size, etc. The measured characteristics of the undebarked logs 1 may comprise, but are not limited to, surface temperature of the log 1, species of the wood, humidity level and special features, such as knots, kink or protuberances, presence/absence of moisture or of blue stain, diameter, or shape of the log.

*Id.*, 5:46-55. At one point, the specification provides that logs of relatively higher moisture level or knot presence may require a reduced rotation speed, *id.* at 7:10-17, but the specification otherwise provides no further guidance or description

regarding the possible associations between operating parameters and log characteristics.

**B. Prosecution History**

57. The ’947 patent issued from U.S. Patent Application No. 17/445,974, filed on August 26, 2021. The ’947 patent claims priority to U.S. Provisional Patent Application No. 63/070,887, filed on August 27, 2020. I provide no opinion in this declaration as to whether U.S. Provisional Patent Application No. 63/070,887 sufficiently supports the claims in the ’947 patent.

58. In the first office action, dated April 10, 2024, the examiner rejected the pending independent claims, but noted that dependent claims 5 and 16 contained allowable subject matter if re-drafted in independent form. *See* Prosecution File History of U.S. Patent Application No. 17/445,974 (April 10, 2024, Office Action) at 15.

59. In its response, applicant amended independent claim 1 to include the limitations of claim 5, and independent claim 12 to include the limitations of claim 16. *See* Prosecution File History of U.S. Patent Application No. 17/445,974 (July 10, 2024, Office Action Response) at 1-3.

60. With these amendments along with a minor examiner’s amendment to correct two typos in the claims, the examiner allowed the pending claims. *See*

Prosecution File History of U.S. Patent Application No. 17/445,974 (August 21, 2024, Notice of Allowance) at 2-3. The '947 patent issued on December 10, 2024.

## VI. BRIEF DESCRIPTION OF THE APPLIED PRIOR ART REFERENCES

### A. WO 2013/188948 ("Gagnon")

#### 1. Background

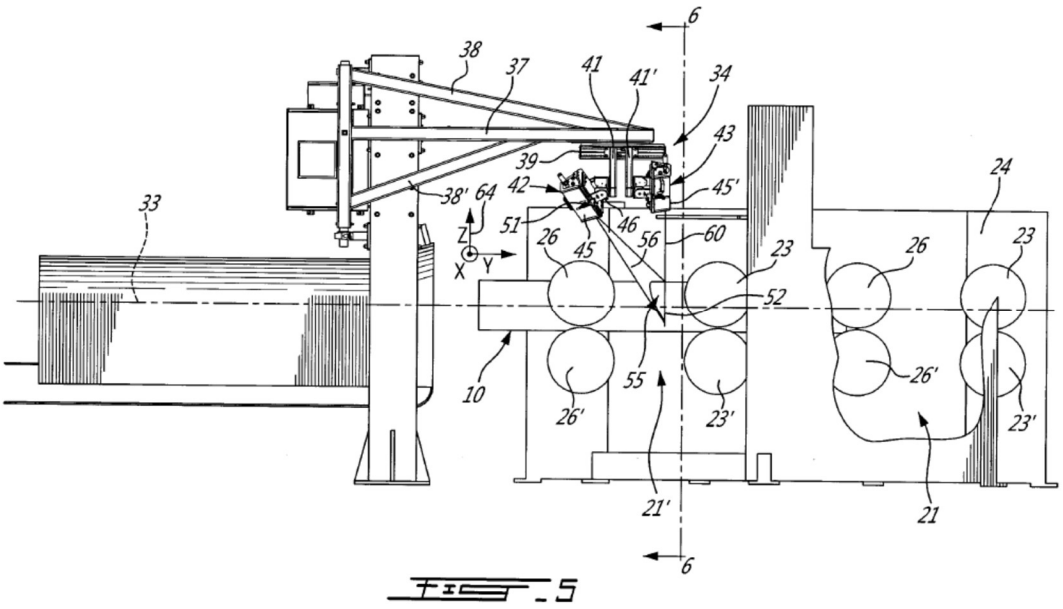
61. International Publication No. WO 2013/188948 to Gagnon et al. (hereinafter, "Gagnon") published on December 27, 2013, before the filing date of the '947 patent. My understanding is that Gagnon thus qualifies as prior art under section 102.

62. Gagnon claims priority to U.S. Patent Application No. 13/614,761 (the "'671 application"), published as U.S. Patent Publication No. 2013/0333805 on December 19, 2013, and issued as U.S. Patent No. 10,099,400 on October 16, 2018, which appears on the face of the '947 patent. *See* '947 patent, References Cited (listing both the publication and the issued patent). Although the examiner of the application that became the '947 patent characterized the disclosures in the '671 application as being "pertinent to the applicant's disclosure," the examiner did not rely upon the disclosures in Gagnon when rejecting the claims in that application. Prosecution File History of U.S. Patent Application No. 17/445,974 (August 21, 2024, NOA) at 2-3; *see* Prosecution File History of U.S. Patent

Application No. 17/445,974 (April 10, 2024, Office Action) at 2-14 (only relying on 2-14 for substantive rejections).

**2. Disclosure**

63. Gagnon discloses systems and methods "for detecting and controlling the quality of debarking at the surface of a wooden log." Gagnon, Abstract. The following illustration shows a debarking machine as disclosed in Gagnon:




*Id*., Fig. 5.

64. According to Gagnon, "wood processing involves a large variation in raw material characteristics at the input end of the sawing process in contrast with upstream processes such as drying and planning [*sic*]." *See id.* ¶ 2. "The variations of log physical properties, environmental and storage conditions, as well

as debarking operating conditions strongly influence the residual bark and fiber loss levels on the surface of debarked logs." *Id.* ¶ 3. Such log characteristics include "wood species, moisture content, freshness, mean diameter, and bark thickness." *Id.* "In particular, different wood species have their own characteristics that may affect the debarking process[;] for example black spruce is more easily debarked than balsam fir during winter." *Id.* In addition, "[a]s to the effects of environmental and storage conditions on debarking quality, air temperature . . . has an effect on wood/bark adhesion strength when the log moisture content is greater than fiber saturation point." *Id.*

65. According to Gagnon, "the performance of a rotary ring debarker depends on its main operating parameters, namely pressure applied to the cutting tools, log feed speed, ring rotational speed, and cutting tool tip overlap." *Id.* ¶ 4. Thus, "[a]t sawmill, pressure values are typically determined according to wood species, average log diameter and log surface log temperature state (frozen or non-frozen), and the radial pressure may be adjusted during debarking as the debarking log diameter is changed." *Id.*

66. Thus, according to Gagnon,

> knowing or measuring upstream the intrinsic characteristics of each log entering the debarker such as diameter and wood species, its environmentally

> influenced characteristics such as temperature and moisture content, as well as debarker tool data such as angular position of cutting tools and wear level of tools, information on fiber loss and residual bark obtained while debarking or at the output of debarker may be used to automatically perform feedback [for] the required debarker adjustments, such as magnitude of controlled pressure applied to cutting tools, ring rotational speed and log feed speed, to provide optimal performance in real time.

*Id.* ¶ 6.

67. The system disclosed in Gagnon also includes a "computer 66 that can be connected to the controller (PLC) 67 of the debarker 24 using link 70 to receive information on debarker operating parameters that could be used by the programmed computer 66 or displayed to the operator." *Id.* ¶ 49. The computer may include a control module that uses

> information on fiber loss and residual bark as measured, to provide commands enabling the controller 67 to send through link 72 feedback control signals for the required debarker adjustments providing optimal performance in real time, ***on the basis of input data related to intrinsic characteristics of each log entering the debarker*** such as wood species information, mean log diameter, taper

> shape indicator, and environmentally influenced characteristics such as log surface temperature and moisture content, coming from other sensors or data entry means through link 83.

*Id.* (emphasis added).

68. Gagnon further teaches the use of non-contact cameras, laser light curtain sensors, laser emitters, and temperature sensors for obtaining the intrinsic and environmentally influenced characteristics. *See, e.g.*, *id.* ¶¶ 49, 52.

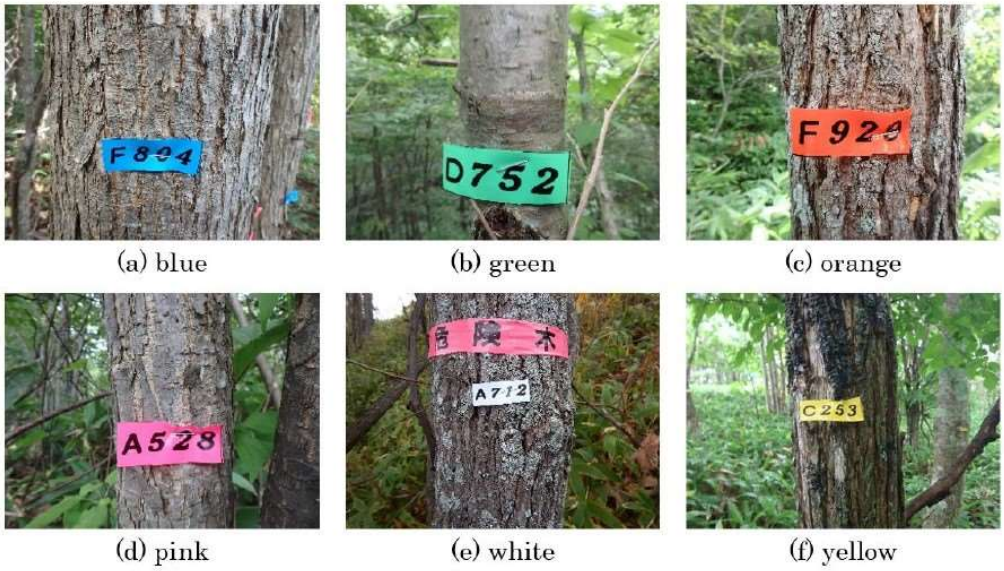
### B. CNN Based Tree Species Identification from Bark Image ("Ido")

69. The article "CNN Based Tree Species Identification from Bark Image" first published in 2019 and was included as part of the Tenth International Conference on Graphics and Image Processing (ICGIP 2018). Junya Ido et al., *CNN-Based Tree Species Identification from Bark Image*, 10th Int'l Conf. on Graphics and Image Processing 2018 ("Ido") (accessible at https://doi.org/10.1117/12.2524213 (last visited Aug. 28, 2025)). Ido published before the effective filing date of the '947 patent. In addition, I understand that the contents of Ido were made publicly available and searchable via the Digital Library for SPIE, a well-known, international professional society for optics and photonics technology. *Id*. In my opinion, a person of ordinary skill interested in artificial intelligence technology for images would be aware of SPIE and would be

motivated to search the SPIE Digital Library for relevant material as of at least 2020. Accordingly, it is my opinion that this article was reasonable accessible to a person of ordinary skill exercising reasonable diligence from at least 2020. Accordingly, it is my understanding that it qualifies as prior art under 35 U.S.C. § 102.

70. Ido discloses "a convolutional neural network (CNN)-based tree species identification method using a bark image." *See* Ido § 1. The evaluation carried out by Ido included six tree species. *Id*., Abstract. In my opinion, a person of ordinary skill would be able to take the disclosures from Ido and expand the number of tree species that could be identified by this system by including the photos of the bark from additional tree species.

71. According to Ido, the "[i]nput data for identifying the tree species of this research is a bark image," such as that shown in the following figure:




(a) blue (b) green (c) orange

(d) pink (e) white (f) yellow

*Id.* § 2.1, Fig. 1. As seen in this picture, each of the trees has a tag or tags that are placed on the trunks. *See id.* "The size of the real tag is almost the same," but because "the shooting distance [from] the tree varies depending on the individuals and photographers, the size of the tag in the image is not the same." *Id*. § 2.1.

72. According to Ido, the tag itself is not relevant to analyzing the bark area. *Id.* § 2.2. Thus, as a first step, Ido discloses that "the tag region is extracted." *Id.* Next, Ido teaches that a region of interest ("ROI") is extracted from the remaining portion of the picture. *Id.* § 2.3. As part of this process, "the ROI is extracted at a position where the tag region is the minimum." *Id.* The following pictures illustrate examples of ROIs extracted by the process described in Ido:



Figure 6. Extracted ROI images.

*Id.*, Fig. 6.

73. According to Ido, various samples of the six different tree species are collected. *Id.* § 3.1. Of the data collected, Ido "randomly selected 100 samples for each species as the test data, and the remaining samples were used as the training data." *Id.* Ido uses several different deep learning methods on this data. *Id.* § 2.4. "Recently, deep learning technologies have greatly advanced the performance of the state-of-the-art of many visual recognition tasks. In particular, CNN has been established as a powerful class of models for image recognition tasks. This paper uses four well-known CNN architectures of AlexNet [7], Inception-v3 [8], VGG-16 [9], and VGG-19 [9]." *Id.* In addition, Ido discloses that data augmentation is used to increase the number of training data to 19,995 images. *Id.* § 3.2.2. According to Ido, after training the CNN model and applying various fine-tuning techniques, it obtained an accuracy of 74.7% for identifying tree species according to images of the bark. *Id.* § 4.

### C. U.S. Patent Publication No. 2019/0003829 ("Kambla")

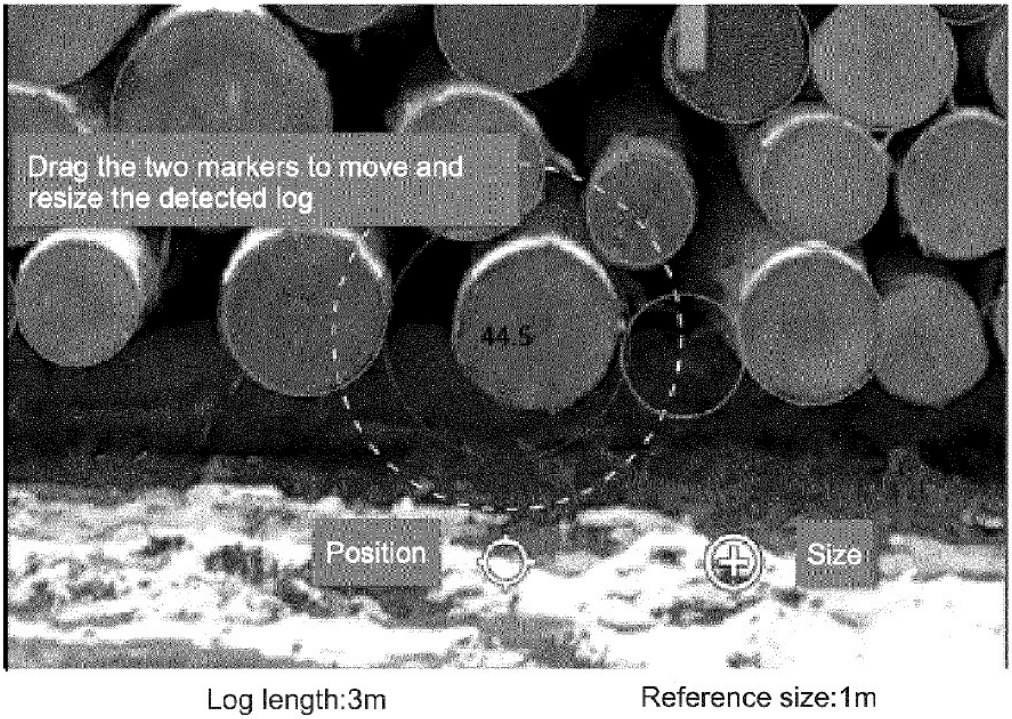
#### 1. Background

74. U.S. Patent Publication No. 2019/0003829 to Kambla et al. (hereinafter, "Kambla") published on January 3, 2019, before the priority date of the '947 patent. It is my understanding that Kambla thus qualifies as prior art under section 102.

#### 2. Disclosure

75. Kambla discloses "[a] system for determination of the volume of a stack of logs" that comprises "digital image acquisition of a stack end with a known reference dimension, image display and image recognition for determination of the total volume of timber." Kambla, Abstract. Kambla further discloses that sawmills receiving logs can use the system "to understand how much and what kind of diameter has been bought." *Id.* ¶ 19.

76. According to Kambla, the measurement process begins by using a camera "to capture a digital image of the log ends together with a known reference dimension." *Id.* ¶ 51. The following image shows the log ends of undebarked logs measured as part of the process disclosed in Kambla:

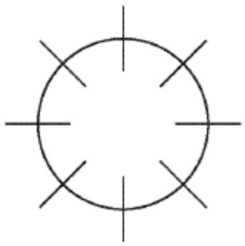



*Id.*, Fig. 9; *see* ¶ 104. According to Kambla, "[t]he detection procedure routine 18 includ[es] a cascade detector routine 20" that "employs a trained classifier, that is the output of a training process that included about 50 thousand carefully chosen and cut out images of log ends and about 10 thousand of carefully chosen images that have the context of being the background of a log, but none of them have any logs on them." *Id.* ¶ 80. "Parameters for the training process are optimized for the highest accuracy and detection rate possible." *Id.* ¶ 81.

77. Kambla further discloses that "[t]he detected log ends are returned as a list of rectangles." *Id.* ¶ 83. "A circle is then generated[,] created by taking the

center point of the rectangle and using the average of width and height of the rectangle as the diameter." *Id.* ¶ 86.

78. Kambla further describes that at this point, "[t]he system then enters the octagon routine 30 which adjusts detections to be closer to the true log." *Id.* ¶ 98. As shown in the following diagram, Kambla places eight lines along the generated circle, where the point along each line "at the highest contrast location is chosen for each of the eight lines":



*Id.*, Fig. 5; ¶ 98.

79. The system then "enters a pixelwise segmentation routine 32, which adjusts detections to be closer to the true log" by distinguishing between pixels that are in the foreground (i.e., likely the log) and pixels that are in the background. *Id.* ¶ 100; *see also id.* ¶¶ 101-03. As part of this process, the system converts the pixels to grayscale and compares the intensity of the grayscale values for each pixel to a threshold value; the system classifies those pixels having a grayscale intensity below the threshold as being background pixels. *Id.* ¶ 102.

80. Once the measurements for the logs are validated and after an optional manual process in which an operator can "fine tune" the circles, "the measurements are saved, all of [the] data is uploaded to a server," and "[a]ll measurements are stored in the smart device . . . in a digital image form wherein the circles superimposed on each of the log ends are visible." *Id.* ¶¶ 105-06. Using known log lengths, the system can determine the volume of timber in the log. *See, e.g.*, *id.* ¶ 50. According to Kambla, this process can proceed on a log-by-log basis. *Id.* ¶ 15. Further, although Kambla discloses that this process can occur on a stack of logs, Kambla does not require that a stack include any minimum number of logs. *See, e.g.*, *id.* ¶¶ 16-18. Accordingly, in my opinion, Kambla includes the situation in which a stack includes one log.

81. Finally, Kambla discloses that "a defect and tree species detector is added additionally after pixel segmentation routine 32 to determine the primary defect present of a detected log." *Id.* ¶ 89. These processes are "carried out by a trained neural network classifier (http://dl.acm.org/citation.cfm? id=2654889), that is the output of a training process that included images of logs that were of a predetermined species and had a predetermined defect or no defect." *Id.* The input to this routine includes "a subregion of the image containing the detected log" where the "subregion is centered on the log and have [*sic*] margins that are of a

predefined size relative to the log diameter in pixels." *Id.* In my opinion, the "trained neural network" is a convolution neural network commonly used in deep learning for image recognition. It can detect the presence or non-presence of a defect as well as classify images of an undebarked log into tree species.

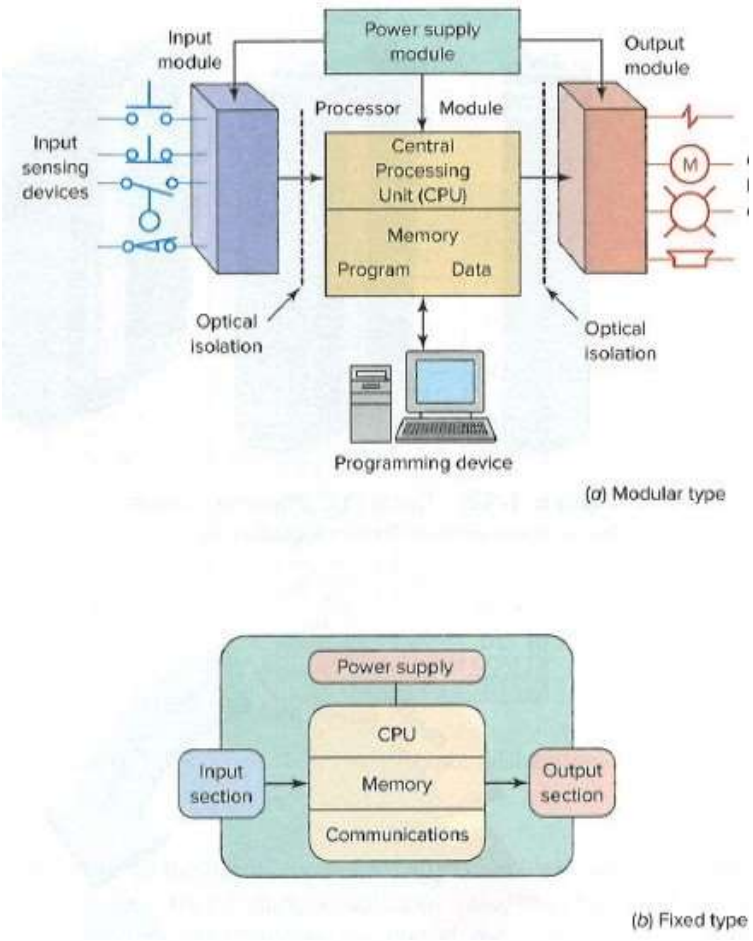
### D. Programmable Logic Controllers ("Petruzella")

82. The book Programmable Logic Controllers, 5th Edition, by Frank Petruzella ("Petruzella") has a copyright of 2017 and was published by a well-known, established educational publisher, McGraw Hill Education. I would consider McGraw Hill Education to be one of the major established publishers of educational and technical texts today and as of 2020. In addition, the fact that this is a fifth edition of a book indicates to me that the previous four editions were well received within the community. In my opinion, Petruzella was reasonably available to a person of ordinary skill using reasonable diligence in searching before the priority date of the '947 patent, and it is my understanding that Petruzella qualifies as prior art under section 102.

83. Petruzella provides a basic overview of programmable logic controllers ("PLCs"), including their components, their uses, and the manner in which they can be programmed. A PLC "is an industrial grade computer that is capable of being programmed to perform control functions." Petruzella at 2. "The

PLC is, then, basically a digital computer designed for use in machine control," but unlike a PC, the PLC "has been designed to operate in the industrial environment and is equipped with special input/output interfaces and a control programming language." *Id.* Petruzella lists a number of advantages of using PLCs over the older relay logic technology that it replaced, including that a PLC based system offers (i) increased reliability, (ii) more flexibility, (iii) lower cost, (iv) communication capabilities, (v) faster response times, (vi) easier troubleshooting capabilities, and (vii) easier field device testing capabilities. *Id.* at 2-4.

84. A PLC can be divided into different parts, as illustrated in the following diagram:

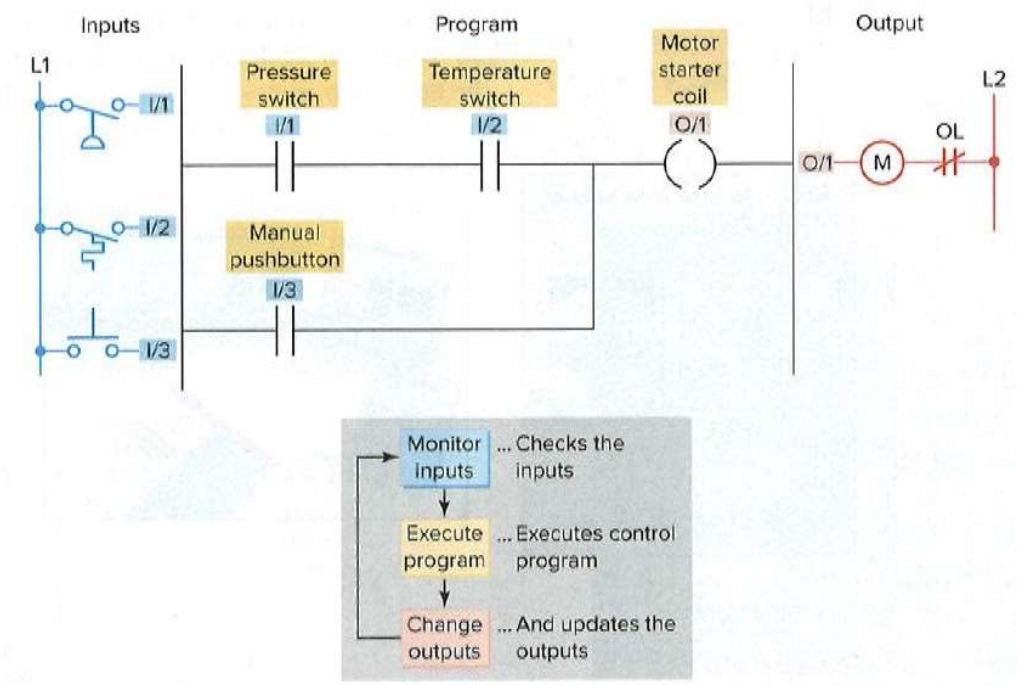



*Id.* at 5, (Fig. 1-8). "The processor (CPU) is the 'brain' of the PLC" and "usually consists of a microprocessor for implementing the logic and controlling the communications among the modules." *Id.*(emphasis removed). According to Petruzella, "[t]he processor requires memory for storing user program instructions, numerical values, and I/O devices status." *Id.*

85. The processor in the PLC executes programs. "A program is a user-developed series of instructions that directs the PLC to execute actions." *Id.* at 7 (emphasis removed). The programming language "provides rules for combining

the instructions so that they produce the desired actions." *Id.* The predominant programming language used for programming PLCs is called relay ladder logic ("RLL"), which "graphically represents rungs of contacts, coils, and special instructions blocks" and is visually based on the relay logic previously used in these industrial settings. *Id.*

86. The following diagram graphically illustrates the concept of ladder logic:




*Id.* at 9 (Fig. 1-20). As shown in the diagram, the ladder logic executes by starting on the left side rail and determining whether there is a continuous logic path from left to right across a rung given the state of the input devices. *See id.* at 10. In the above diagram, the three input devices include a pressure switch, a temperature

switch, and a manual pushbutton. *Id.* If the pressure switch and temperature switch are both closed, or if the manual pushbutton is closed, then the output device (motor starter coil) is activated. *Id.*

87. The execution of a program in a PLC follows a repeating circular path, as shown in the following diagram:

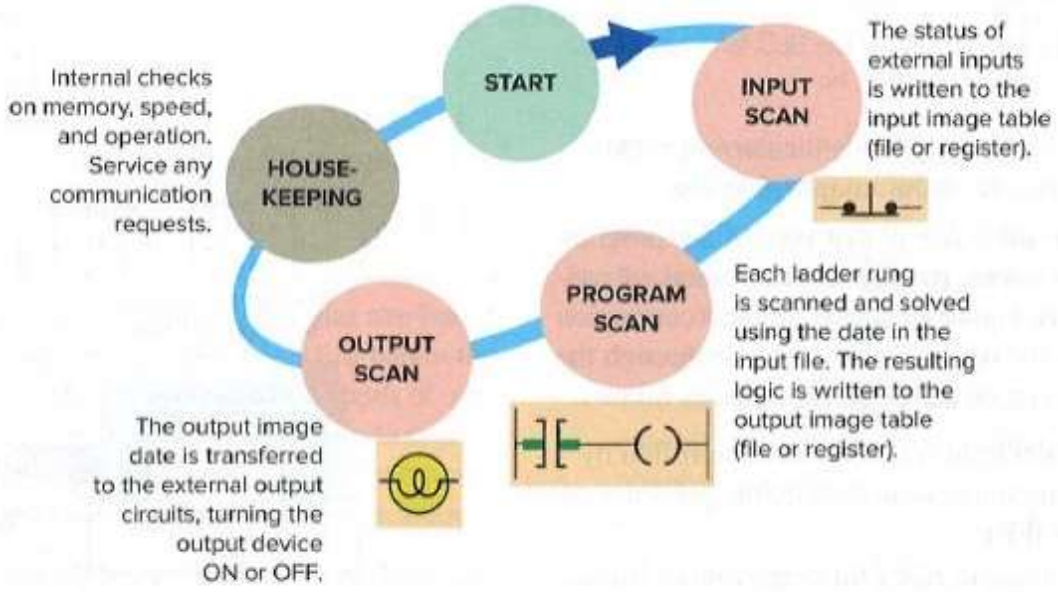
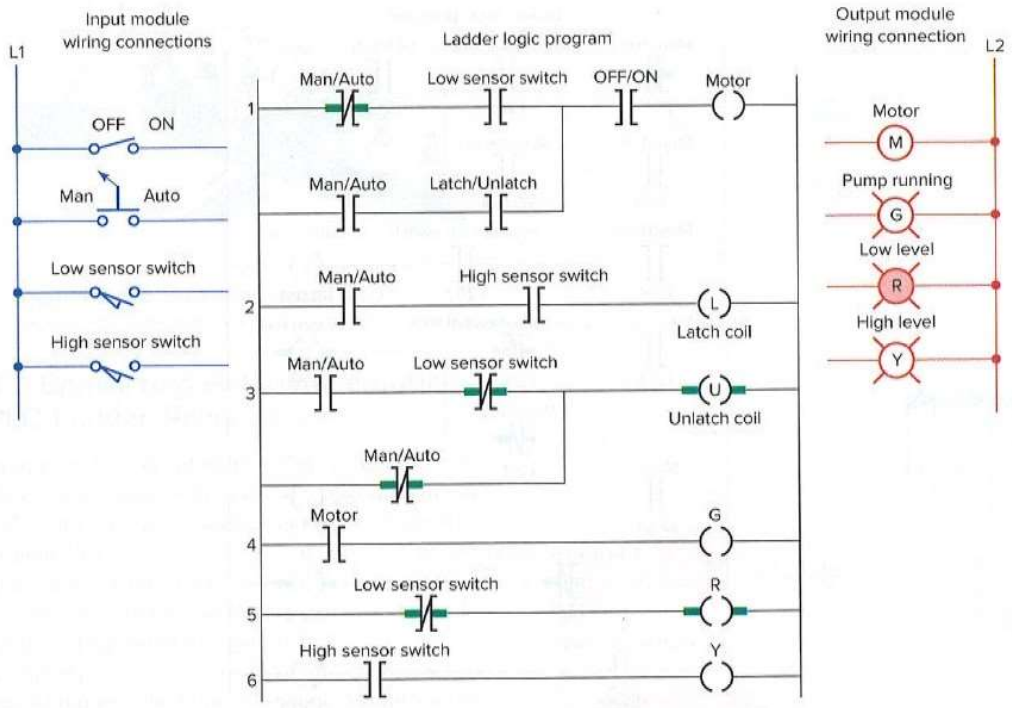



**Figure 5-8** PLC program scan cycle.

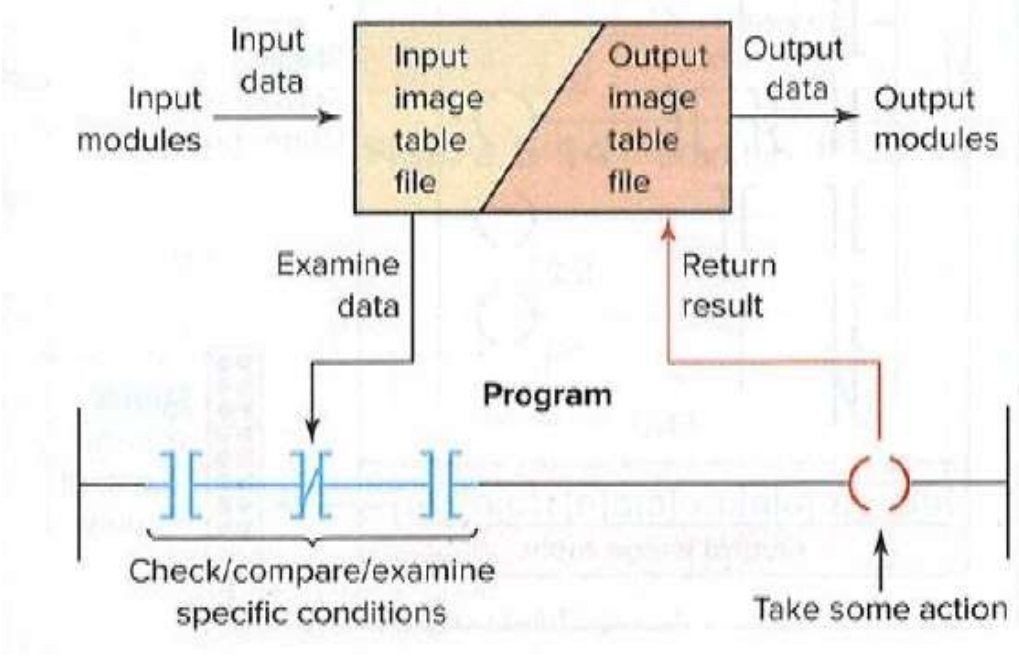
*Id.* at 78 (Fig. 5-8). According to Petruzella, "[a] typical PLC scan starts with the CPU reading the status of inputs," after which "the application program is executed." *Id.* at 6; *see also id.* at 79. After executing the program, "the status of all outputs is updated." *Id.* at 6; *see also id.* at 80.

88. It is possible for a RLL program to include multiple rungs, as shown in the following diagram:




*See id.* at 116 (Fig. 6-57). In this example, the RLL program includes six rungs. The process for executing the RLL is the same as the one-rung example discussed in paragraph 86: the status of the four inputs are monitored, the application program for each rung is executed to determine which, if any, rungs contain a continuous logical path from left to right, and the status of the output devices is determined. *See id.* at 115-16.

89. According to Petruzella, the PLC stores the values for the input devices in an "input image table file"; the values for the output devices are similarly stored in an "output image table file," as shown in the following diagram:




*Id.* at 79 (Fig. 5-9). The ladder logic program provides the association between the values for the input devices and the values for the output devices. *See id.*

90. Petruzella further discloses the use of tables, in the form of arrays, as part of the RLL program on a PLC. *See, e.g.*, *id.* at 342. The following diagram shows visual examples of one, two, and three dimensional tables that can be used in a RLL program:

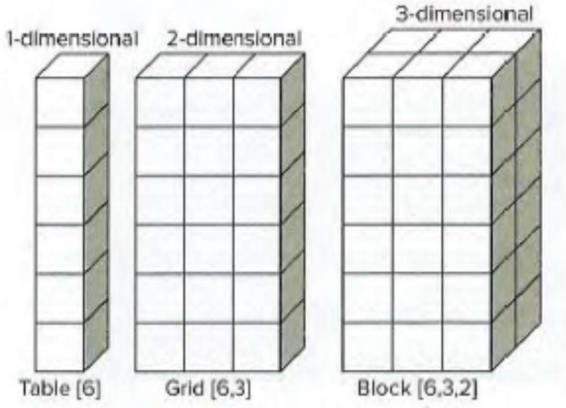



**Figure 15-24** Types of arrays.
Source: Image Courtesy of Rockwell Automation, Inc.

*Id.* (Fig. 15-24).

91. According to Petruzella, entries in a table can be indexed and accessed according to their location within the table. For example, in the table named "Temp," individual entries within the table can be accessed using the address "Temp[x]," where "x" is an integer starting from 0. *See id.* at 342-43. In the following table, for example, the temperature "180" can be accessed at Temp[2]:

**Array** - Temp
**Data Type** - INT[5]

| | |
|---|---|
| Temp[0] | 297 |
| Temp[1] | 200 |
| Temp[2] | 180 |
| Temp[3] | 120 |
| Temp[4] | 100 |

*Id.* at 343 (Fig. 15-25).

92. In my opinion, the arrays in Petruzella can be used to implement a lookup table to retrieve data based on received input values. According to Petruzella, it is advantageous to use arrays "[b]ecause arrays are numerically sequenced tags of the same data type that occupy a contiguous memory location" and for this reason, "large amounts of data can be retrieved efficiently." *Id*.

## VII. DETAILED EXPLANATION OF THE UNPATENTABILITY GROUNDS

93. I understand that petitioner raises five grounds regarding the unpatentability of each of the claims in the '947 patent, as follows:

| | Prior Art/Argument | Claims |
|---|---|---|
| Ground 1 | Gagnon, Kambla, knowledge of one of ordinary skill under § 103 | 1-4, 7-10 |
| Ground 2 | Gagnon, Ido, Petruzella under § 103 | 1-18 |
| Ground 3 | Gagnon, Kambla, Petruzella under § 103 | 1-18 |
| Ground 4 | Unpatentability under § 101 | 1-18 |
| Ground 5 | Indefiniteness under § 112 | 7, 8 |

94. I will discuss each of the grounds in the following section.

### A. Ground 1: Gagnon in Light of Kambla and the Knowledge of One of Ordinary Skill Renders Obvious Claims 1, 2, 3, 4, 7, 8, 9, and 10

95. In my opinion, claims 1, 2, 3, 4, 7, 8, 9, and 10 are unpatentable under 35 U.S.C. § 103 as obvious under Gagnon and Kambla, in light of the knowledge of a person of ordinary skill.

#### 1. Claim 1 Is Rendered Obvious

##### a. Element 1 [pre]: A computer-implemented method for characterizing an undebarked log in real time, the method comprising

96. In my opinion, the preamble of claim 1 is not limiting. Nevertheless, in my opinion, Gagnon discloses the material recited in the preamble. As disclosed in Gagnon:

> knowing or measuring upstream the intrinsic characteristics of each log entering the debarker such as diameter and wood species, its environmentally influenced characteristics such as temperature and moisture content, as well as debarker tool data such as angular position of cutting tools and wear level of tools, information on fiber loss and residual bark obtained while debarking or at the output of debarker may be used to automatically perform in feedback the required debarker adjustments . . . to provide optimal performance in real time.

Gagnon ¶ 6.

97. Gagnon further discloses that data related to the intrinsic characteristics of the log may be taken using non-contact sensors and that such sensors may be connected to a computer that receives the data from these sensors in real-time. For example, according to Gagnon, "[l]ocated adjacent the conveyor 13 is a log diameter and length measurement device 17 having its output operatively connected to the controller 67 shown in Fig. 3 for sending thereto signals indicative of the diameter and length of the log 10' as it is moved past the measuring device 17." *Id.* ¶ 49.

98. It is my understanding that the controller and associated computer in Gagnon would calculate or otherwise determine the intrinsic properties and measurements of the log based on the data received from the sensors. For example, it is a common practice for a measurement device to return raw data (e.g., an integer value) or even just an electrical signal corresponding to a detected stimulus (e.g., light) to a computer. The computer then processes this raw data or the electrical signals into a format that can be further used by the computer program and/or understood by the operator. This understanding is supported by the disclosure in Gagnon that the measurement devices send "***signals indicative*** of the diameter and length of the log" to the controller. *Id.* (emphasis added).

99. Accordingly, it is my opinion that Gagnon discloses the material recited in the preamble.

**b. Element 1[a]: performing a contactless characterization of the undebarked log;**

100. In my opinion, Gagnon and Kambla, both alone and in combination, disclose the limitation from element 1[a]. For this limitation, I am using the plain and ordinary meaning of "characterization," namely, "the act of characterizing," which itself is defined as "to describe the character or quality of." *See Characterization*, Merriam-Webster, https://www.merriam-webster.com/dictionary/characterization (last visited August 25, 2025); *see also Characterize*, Merriam-Webster, https://www.merriam-webster.com/dictionary/characterize (last visited August 25, 2025). This plain and ordinary meaning encompasses the acts of gathering data related to the characteristics of the log because this type of data is used to describe the character or quality of the log.

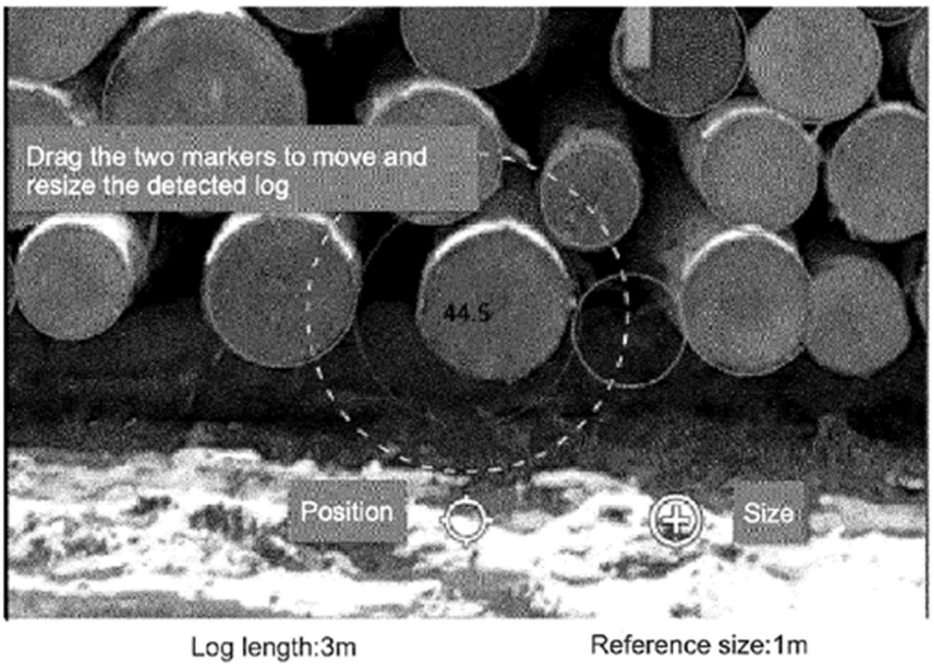
101. It is further my opinion that this interpretation is supported by the claims themselves. First, the independent claims recite "contactless characterization," which would indicate to a person of ordinary skill that the characterization process includes the processes being performed by contactless data capture devices. In addition, the dependent claims distinguish between "the

characterization" as including the capture of data, *see, e.g.*, claims 2 and 3 ("the characterization" to be done using a scanning device or sensors), and "characteristics" as being the result of some analysis, *see, e.g.,* claim 4 (listing an identification of characteristics as including tree species, moisture content, or knot presence). Finally, although the specification itself uses the term "characterization method" in the Summary of the Invention to describe the overall process to be implemented upstream of the debarking system, *see* '947 patent, 3:5-10, it does not otherwise use the term "characterization" in the detailed description. Accordingly, in my opinion, the specification includes no description that changes the interpretation I obtained from the claims.

102. Gagnon discloses that various measurements may be taken of the log based on signals obtained by contactless sensors: "[l]ocated adjacent the conveyor 13 is a log diameter and length measurement device 17 having its output operatively connected to the controller 67 shown in Fig. 3 for sending thereto signals indicative of the diameter and length of the log 10 as it is moved past the measuring device 17." *Id.* ¶ 49. Gagnon further discloses that "[a]ny appropriate ***non-contact sensor*** may be used as diameter and log length measurement device 17, such as laser light curtain sensor of type P, 600mm, supplied from ScanMeg Inc." *Id.* (emphasis added). It is my opinion that these non-contact sensors as

disclosed in Gagnon are used to capture data (diameter and length) that describe the character of the log.

103. Kambla also discloses this limitation. According to Kambla, the method employs "a hand held programmable smart device, which comprises a camera, an accelerometer and an angle sensor routine [that] is employed to assure virtual positioning of the camera parallel to the stack end" of the logs. Kambla ¶¶ 43, 50. The camera "capture[s] a digital image of the log ends together with a known reference dimension along a plane parallel to the log ends." *Id.* ¶ 44. The following figure shows that the method disclosed in Kambla is implemented on undebarked logs:



*Id*. Kambla further discloses with respect to the tree species and defect capabilities, the system captures a subregion that contains the detected log. *Id.* 89.

104. *Motivation to Combine:* It is my opinion that a person of ordinary skill would be highly motivated to incorporate Kambla's deep-learning model, along with the associated contactless image capture devices, into the debarking system disclosed by Gagnon. Gagnon discloses to a person of ordinary skill the advantages of obtaining diameter and tree species information to set the parameters in the debarking process. *See, e.g.*, Gagnon ¶ 3. Kambla provides methods for using a single hand held device to obtain diameter and tree species information. *See, e.g.*, Kambla ¶¶ 86, 89. In addition, Kamba provides a method for automating the detection of the tree species, improving upon the manual entry method described in Gagnon. *Compare id.* ¶ 89 *with* Gagnon ¶ 90. Moreover, both Kambla and Gagnon are in the same field of logging operations, and more specifically processing logs into lumber. *See, e.g.*, Kambla ¶ 1; Gagnon ¶ 1. Accordingly, in my opinion, a person of ordinary skill would look to the tree measuring and characterization features of Kambla to incorporate and improve upon the system described in Gagnon. Note that a person of ordinary skill would not necessarily incorporate the entire system from Kambla into the debarker of

Gagnon, just the specific diameter measuring and tree species identifying capabilities.

105. In my opinion, a person of ordinary skill would also expect that the deep-learning module and associated contactless image capture devices of Kambla could be successfully incorporated into the system of Gagnon. According to Kambla, the deep-learning module can be implemented on a hand held smart device. *See, e.g.*, Kambla ¶¶ 58, 80-83. Such a module would also be capable of being implemented on the quality detection and control system disclosed in Gagnon. *See, e.g.*, Gagnon ¶¶ 48-49. In addition, the system in Kambla is designed to identify and characterize individual logs that are included within a stack of many logs. *See, e.g.*, Kambla ¶¶ 83, 98. Accordingly, in my opinion, a person of ordinary skill would expect the artificial intelligence model in Kambla to function successfully when arranged at the input of a debarker system where it measures and further characterizes logs one at a time without having to distinguish logs in a pile.[3] In fact, the species identification disclosed operates on a single undebarked log. Finally, the contactless sensor disclosed in Kambla – a camera – corresponds to the same type of contactless sensor disclosed in Gagnon. *See, e.g.*,

[3] As noted above, there is nothing within Kambla indicating that the method cannot be performed on a "pile" consisting of one log.

Kambla ¶ 43; Gagnon ¶ 48. Although Gagnon discloses a camera at the output end of the debarker, Gagnon ¶ 45, in my opinion, a person of ordinary skill would be able to construct a similar setup including a camera at the input end of the debarker.

**c. Element 1[b]: identifying characteristics of the undebarked log based on the characterization of the undebarked log using a trained deep learning model;**

106. In my opinion, Kambla discloses this limitation. *See, e.g.*, Kambla ¶¶ 86, 89. As previously noted, Kambla discloses capturing images of logs using a non-contact image capture device to determine both the diameter and tree species of the log. In addition, Kambla discloses the use of a deep learning model to determine tree species information. *See id.* ¶ 89. Kambla discloses that the tree species identification feature "is carried out by a trained neural network classifier." *Id.*

107. *Motivation to Combine:* As explained above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Kambla's deep-learning model into the debarking system disclosed by Gagnon. *See supra* § VII(A)(1)(b). The same motivation to combine discussed above with respect to element 1[a] also applies here. *See id.*

**d. Element 1[c]: computing operating parameters of a debarker based on the identified characteristics; and**

108. In my opinion, the combination of Gagnon and Kambla, along with the knowledge of one of ordinary skill, discloses this limitation. As noted above, the combination of Gagnon and Kambla could identify the characteristics of a log to be processed by a debarking machine, in particular, the diameter and tree species of the log. *Supra* §VII(A)(1)(c). Gagnon further discloses using the diameter and tree species of a log to compute the operating characteristics of the debarker. *See, e.g.*, Gagnon ¶ 49. According to Gagnon, the system it discloses "may include ***a control module*** using information on fiber loss and residual bark as measured, ***to provide commands*** enabling the controller 67 to send through link 72 feedback control signals for the required debarker adjustments providing optimal performance in real time, ***on the basis of input data related to intrinsic characteristics*** of each log entering the debarker such as ***wood species information*** . . . ." *Id*. (emphasis added); *see also* ¶ 6. The following diagram shows an illustration of a debarking quality detection system 22:

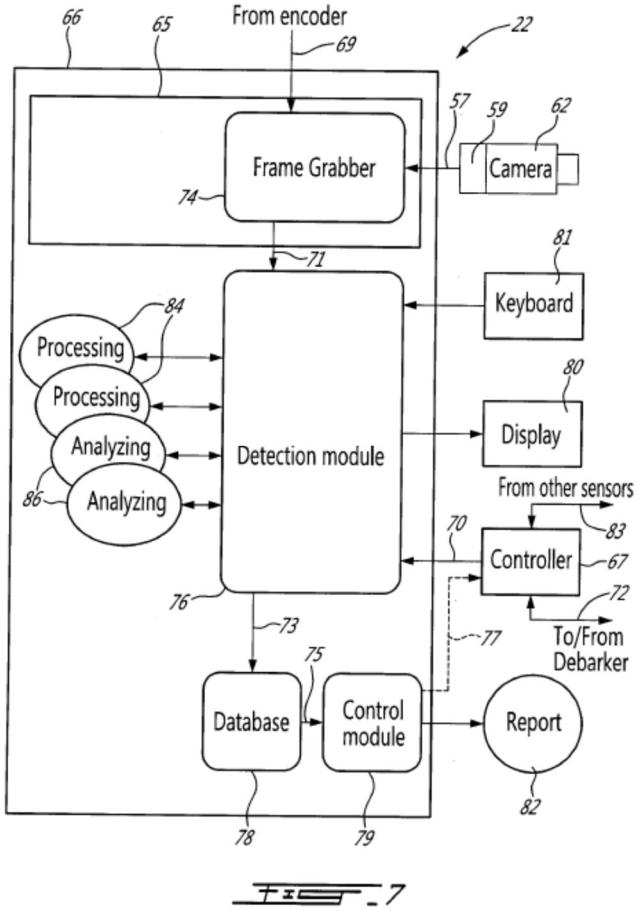



Fig. 7

*Id*., Fig. 7. In my opinion, because the control module accepts input, including tree species and diameter information, and generates a control signal for the operating parameters of the debarker, it computes those parameters based on the input data. In addition, see also the discussion, *infra* § VII(A)(1)(f), related to element 1[e], which states that "the computation of the operating parameters further comprises retrieving operating parameters . . . ." Thus, according to the claims, the computing limitation may be met by retrieving operating parameters, which Gagnon discloses.

109. Further disclosures in Gagnon support my opinion. For example, Gagnon discloses that "different wood species have their own characteristics that may affect the debarking process[;] for example black spruce is more easily debarked than balsam fir during winter." Gagnon ¶ 3. Gagnon also discloses that "an optimal debarking quality implies a compromise between fiber loss and residual bark at the debarked surface of the log, and the operating conditions at which said compromise may be reached are dependent on the characteristics of the logs fed to the debarker, such as species and dryness state (moisture content)." *Id.* ¶ 68. In my opinion, a person of ordinary skill would understand that according to these disclosures, the operating conditions and parameters for the debarker in Gagnon are based upon intrinsic information about the tree, such as tree species.

110. In addition, Gagnon discloses that "[o]ptionally, a plurality of models respectively adapted to a plurality of input parameter ranges may be built, allowing a selection of the most appropriate model according to actual measurements made on logs to be debarked." *Id.* ¶ 96. The following figure shows a schematic block diagram of a model predictive control structure as disclosed in Gagnon:

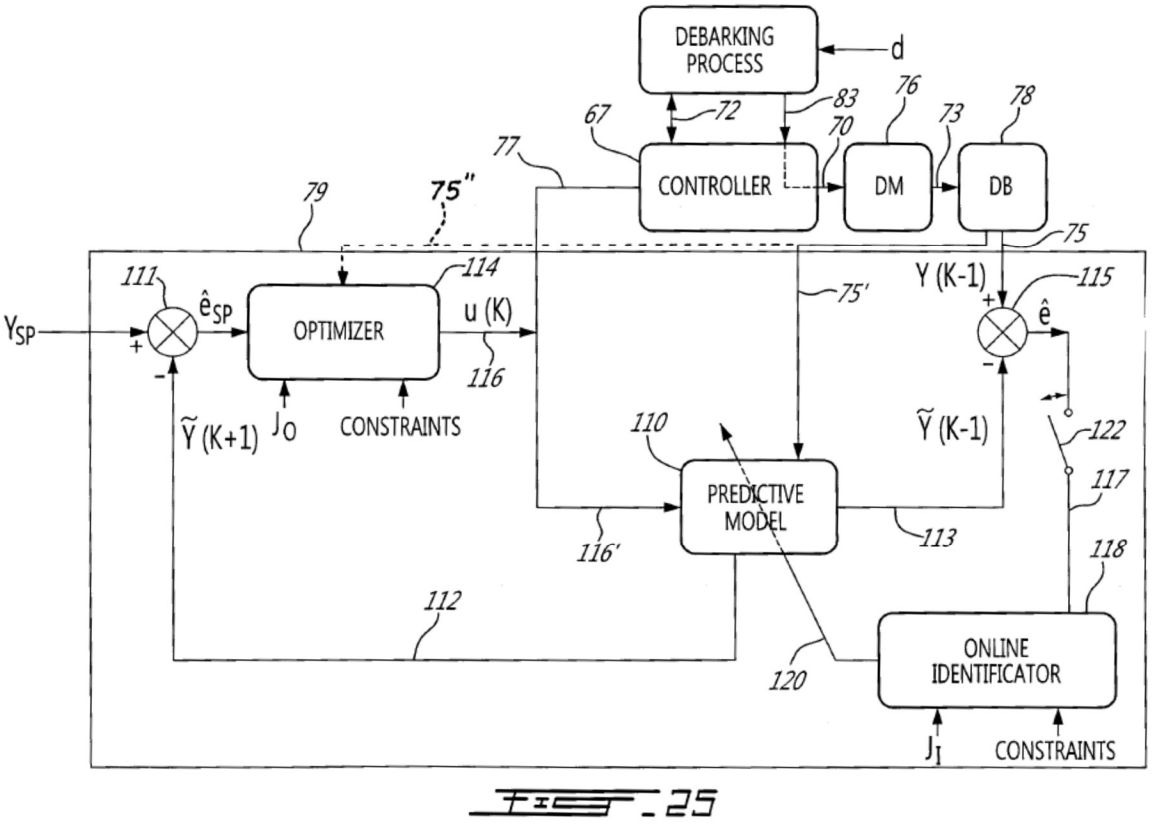



Fig. 25

*Id.*, Fig. 25. In my opinion, a person of ordinary skill would understand that such actual measurements could include tree species, especially because the disclosure in this portion of Gagnon identifies other intrinsic characteristics of the log such as diameter for making this selection.

111. Finally, it is my understanding, based on my discussion with employees at Nicholson, that determining the operating parameters of a debarker based on tree species data was well-known in the art as of the priority date of the '947 patent. To this point, I will note that the '947 patent does not associate any

particular operating parameters or values with any particular type of tree species. To the contrary, in the Background of the Invention section, the '947 patent notes that setting debarking parameters is a complicated task that may depend on variations in log characteristics such as the tree species, and that has been performed manually by debarker operators. *See* '947 patent, 1:57-66. Accordingly, this description confirms my opinion that it was within the knowledge of a person of ordinary skill to determine the control parameters for a debarker based on information related to tree species.

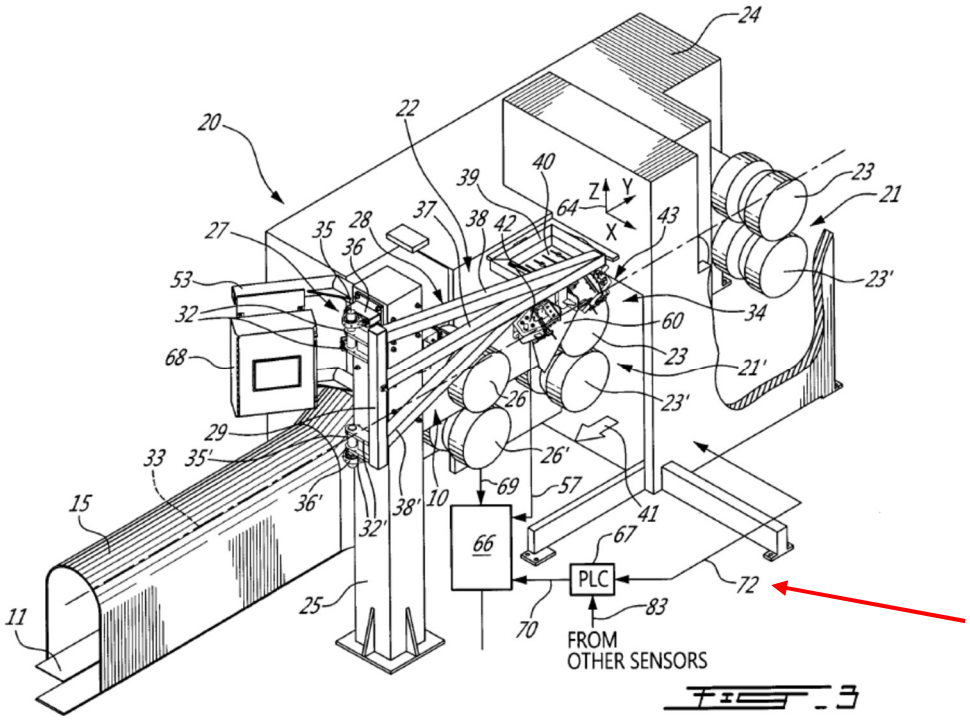
**e. Element 1[d]: sending the computed operating parameters to the debarker;**

112. Gagnon discloses this limitation. According to Gagnon, the system it discloses

> may include ***a control module*** using information on fiber loss and residual bark as measured, ***to provide commands*** enabling the controller 67 to send through link 72 feedback control signals for the required debarker adjustments providing optimal performance in real time, ***on the basis of input data related to intrinsic characteristics*** of each log entering the debarker such as ***wood species information*** . . . ."

Gagnon ¶ 49 (emphasis added); *see also* ¶ 6.

113. The following diagram illustrates the link 72 used by the system in Gagnon to allow the control module "to provide commands enabling the controller 67 to send . . . feedback control signals for the required debarker adjustments providing optimal performance in real time":




*Id.* ¶ 49; Fig. 3 (annotation added). As explained above, the feedback control signals used to make adjustments to provide optimal, real-time performance may be based, at least in part, on the tree species.

114. For the above reasons, it is my opinion that Gagnon discloses this limitation.

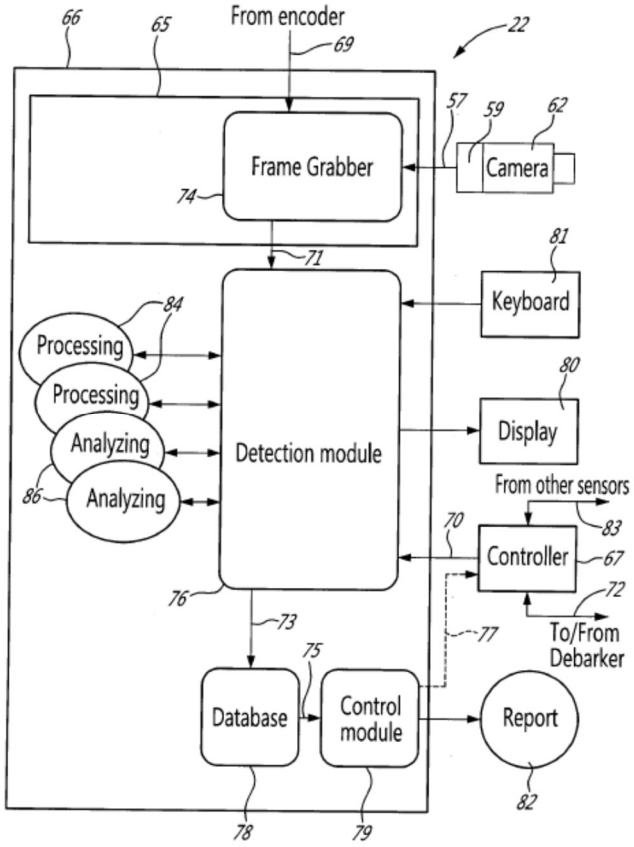
**f. Element 1[e]: wherein the computation of the operating parameters further comprises retrieving operating parameters associated with the identified characteristics.**

115. Gagnon, along with the knowledge of one of ordinary skill, discloses this limitation. For example, Gagnon discloses the use of a computer connected to a PLC "to receive information on debarker operating parameters that could be used by the programmed computer 66 or displayed to the operator." *See id.* ¶ 49. Further:

> the computer software may include a control module . . . to provide commands enabling the controller 67 to send through link 72 feedback control signals for the required debarker adjustments providing optimal performance in real time, on the basis of input data related to intrinsic characteristics of each log entering the debarker such as tree species information, mean log diameter, taper shape indicator, and environmentally influenced characteristics such as log surface temperature and moisture content, coming from other sensors or data entry means through link 83.

*Id.*

116. As seen in the following diagram, the link 83 comes into the PLC 67:




*Id.*, Fig. 7. Accordingly, it is my opinion that one of ordinary skill in the art would know that the PLC selects the debarker operating parameters based on the input data related to the intrinsic characteristics of the log (e.g., tree species). Further, as explained above, one way to implement control on a PLC is to have the PLC take an input value (e.g., tree species, as determined by the Kambla deep learning model) and retrieve the appropriate output value (e.g., debarker operating parameters) based on that input. *See supra* § VI(D). It is further my opinion that this mode of operation is within the knowledge of one of ordinary skill.

117. Gagnon also discloses that "[o]ptionally, a plurality of models respectively adapted to a plurality of input parameter ranges may be built, allowing a selection of the most appropriate model according to actual measurements made on logs to be debarked." *See* Gagnon ¶ 96. In addition, Gagnon discloses that operating parameters related to a debarked log may be obtained by the control module from an optimizer based upon the model selected from the Model Predictive Control ("MPC") structure:

> The MPC structure control module 79 further makes use of an optimizer 114 programmed for generating, at optimizer output 116, the control data represented by current control vector *u(k)* associated with the currently debarked log as designated *k*, which control data minimize predicted-setpoint error data $\hat{e}_{SP}$ in accordance with a debarking performance criterion . . . .

*Id*. ¶ 95. Thus, the selection of the model by the control module results in the control data being retrieved from the optimizer.

118. In my opinion, a person of ordinary skill would understand that such actual measurements and input parameters for selecting the appropriate model could include tree species because the disclosure in this portion of Gagnon identifies other intrinsic characteristics of the log such as diameter for making this selection. *See id*. Selecting a model based on input parameters will result in

control data in the form of a control vector being obtained by the control module, as disclosed in Gagnon. *Id*. This control data would be associated with the identification of the tree species because the model from which the control data originates would be associated with tree species. *See, e.g.*, *id.* ¶ 90. In my opinion, this process of obtaining control data from the optimizer based on the model being chosen according to tree species meets the limitation of retrieving operating parameters as recited in this claim element. Accordingly, it is my opinion that Gagnon along with the knowledge of one of ordinary skill discloses this claim limitation.

**2. Claim 2 Is Rendered Obvious**

119. As noted above, Gagnon in view of Kambla and the knowledge of one skilled in the art render obvious claim 1, from which claim 2 depends. *See supra* § VII(A)(1). In my opinion, Kambla discloses the additional limitations of claim 2, as explained below.

**a. Claim 2: The method of claim 1, the characterization of the undebarked log using a scanning device.**

120. According to the specification in the ’947 patent, the term “scanning device” may be a camera or other device that captures “color and/or grayscale images of partial or complete external surface of the undebarked wooden log.” ’947 patent, 5:25-31. It is my opinion that this use of the term is consistent with

the understanding that one of ordinary skill would have. Accordingly, I will use this plain and ordinary meaning of scanning device for this claim.

121. Kambla discloses the use of a camera to capture images of the undebarked logs. *See, e.g.,* Kambla ¶¶ 43, 50.

122. As discussed above, this characterization by Kambla may be used in the system disclosed in Gagnon for computing operating parameters. *See supra* § VII(A)(1).

**b. A Person of Ordinary Skill Would be Motivated to Combine the Scanning Device of Kambla with the Debarking System Disclosed in Gagnon**

123. As discussed above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Kambla's deep-learning model, along with the associated scanning devices, into the debarking system disclosed by Gagnon. *See supra* § VII(A)(1)(b). It is further my opinion that a person of ordinary skill would expect to successfully make such a combination for the same reasons previously discussed. *See id.*

**3. Claim 3 Is Rendered Obvious**

124. As noted above, Gagnon in view of Kambla and the knowledge of one skilled in the art render obvious claim 1, from which claim 3 depends. *See supra*

§ VII(A)(1). In my opinion, Kambla discloses the additional limitations of claim 3, as explained below.

**a. Claim 3: The method of claim 1, the characterization of the undebarked log using one or more sensors**

125. According to the ’947 patent, “the characteristics of the log 1 may be measured or calculated using different means, not shown, ***such as capturing color images using a sensor*** or camera . . .” ’947 patent, 5:55-58 (emphasis added). The ’947 patent further discloses that the system “is configured to receive data from the one or more scanning device 8 or ***sensors***, not shown, such as images of the surface of the undebarked logs 1.” *Id.*, 6:15-17 (emphasis added). Thus, in my opinion, a person of ordinary skill reading the specification of the ’947 patent would understand that a sensor could include devices capable of capturing images of the tree. Thus, although the terms “sensor” and “scanning device” may overlap, they are not synonymous because a sensor may also include other, non-scanning devices (*e.g.*, a temperature sensor).

126. This understanding is consistent with the ordinary meaning of a sensor as “a device that responds to a physical stimulus (such as heat, light, sound, pressure, magnetism, or a particular motion) and transmits a resulting impulse (as for measurement or operating a control).” *See Sensor*, Merriam-Webster, https://www.merriam-webster.com/dictionary/sensor (last visited August 25,

2025). In this case, a digital camera, such as that disclosed in Kambla, would inherently include multiple image sensors that respond to light by outputting a corresponding electrical signal. The collection of electrical signals from each of the image sensors is then used to generate an image. Based on this understanding, Kambla discloses the use of a camera that includes image sensors to capture digital images of the bark of undebarked logs. *See, e.g.*, Kambla ¶¶ 44, 51, 58. As noted above, a digital camera includes multiple image sensors. Additionally, as discussed above, this characterization by Kambla may be used in the system disclosed in Gagnon for computing operating parameters. *See supra* § VII(A)(1).

**b. A Person of Ordinary Skill Would be Motivated to Combine the Sensors of Kambla with the Debarking System Disclosed in Gagnon**

127. As discussed above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Kambla's deep-learning model, along with the associated sensors, into the debarking system disclosed by Gagnon. *See supra* § VII(A)(1)(b). It is further my opinion that a person of ordinary skill would expect to successfully make such a combination for the same reasons previously discussed. *Id*.

### 4. Claim 4 Is Rendered Obvious

128. As noted above, Gagnon in view of Kambla and the knowledge of one of ordinary skill render obvious claim 1, from which claim 4 depends. *See supra* § VII(A)(1). In my opinion, Kambla discloses the additional limitations of claim 4.

#### a. Claim 4: The method of claim 1, the identification of the characteristics of the log further comprising one or a combination of any of the followings [*sic*]: identifying the species of the log; measuring the moisture level of the log; and calculating an intensity of knot presence on the log

129. Kambla discloses this limitation, in my opinion. Kambla discloses capturing images of the bark on a tree or log using non-contact image capture devices (e.g., cameras) so that the images of the bark could be used to determine the tree species. *See, e.g.*, Kambla ¶ 89.

#### b. A Person of Ordinary Skill Would be Motivated to Combine the Tree-Species, Deep-Learning Model of Kambla with the Debarking System Disclosed in Gagnon

130. As explained above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Kambla's deep-learning model into the debarking system disclosed by Gagnon. *See supra* § VII(A)(1)(b). Indeed, Gagnon explains that information about tree species is highly relevant to determining the settings on a debarking machine. *See, e.g.*, Gagnon ¶ 3. Because

of the capabilities offered by Kambla, it is my opinion that a person of ordinary skill would be highly motivated to make this combination. *See supra* § VII(A)(1)(b). As noted above, a person of ordinary skill would expect such a combination to be successful. *Id*.

**5. Claim 7 Is Rendered Obvious**

131. As noted above, Gagnon in view of Kambla and the knowledge of one of ordinary skill render obvious claim 1, from which claim 7 depends. *See supra* § VII(A)(1). In my opinion, Kambla discloses the additional limitations of claim 7.

**a. Element 7[pre]: The method of claim 1, the trained deep learning model being trained comprising the steps of:**

132. As explained above, it is my opinion that Gagnon in combination with Kambla, in light of the knowledge of one of ordinary skill, renders obvious claim 1. *See supra* § VII(A)(1). It is further my opinion that Kambla further discloses training a deep learning model, including the steps recited in claim 7, as explained below.

**b. Element 7[a]: selecting a representative sample of a plurality of logs having identifiable characteristics;**

133. It is my opinion that Kambla discloses this limitation. Kambla discloses that the tree species and defect classifier "is the output of a training process that included images of logs that were of a predetermined species and had

a predetermined defect or no defect." *Id.* ¶ 89. Accordingly, it is my opinion that Kambla discloses training the artificial intelligence model using a representative sample of logs.

**c. Element 7[b]: scanning the plurality of logs to obtain scan data of the logs;**

134. It is my opinion that Kambla discloses this limitation. Kambla describes capturing images of logs and feeding those images into a trained log end detection model and/or a tree species and defect classifier. *Id.* ¶¶ 80, 89. Kambla further discloses that these digital images may be obtained from "a hand held programmable smart device" that includes a camera. *Id.* ¶ 50.

**d. Element 7[c]: identifying with a deep learning algorithm software of the deep learning model the identifiable characteristics of the logs based on the scan data;**

135. It is my opinion that Kambla discloses this limitation. For example, Kambla discloses the process for the identification of tree species based upon a deep learning model using the scan data. *See, e.g.*, *id.* ¶¶ 81-83, 89. Thus, in my opinion, Kambla discloses this limitation.

**e. Element 7[d]: analysing [*sic*] the identified characteristics of the logs to output an identification score; and**

136. It is my opinion that Kambla discloses this limitation. Kambla describes in detail the training process that is applied to both the log end face

classifier and the tree species identification classifier. *See, e.g.*, *id.* ¶¶ 81-83, 89. Kambla further discloses that these trained classifiers are then used to classify images of logs and log ends put into the model. *Id.* The classifiers in Kambla would be used to classify images only after the classifiers were adequately trained to accurately make the desired classifications. *See id.* ¶¶ 80-82. Thus, the accuracy score used to determine if the classifiers are adequately trained would be an identification score. *See id.* ¶ 81.

137. In addition, Kambla discloses that "[p]arameters for the training process are optimized for the highest accuracy and detection rate possible" further supporting my conclusion. *See id.*

**f. Element 7[e]: considering the deep learning model trained if the identification score is different from a predetermined value.**

138. In my opinion, Kambla discloses this limitation. As an initial matter, as noted elsewhere in my report, it is unclear what "predetermined value" means in the context of the '947 patent. *See infra* § VII(E). Indeed, this term could refer to a wide range of possible values; moreover, the values could be based on any number of various metrics (e.g., accuracy, false positive rate, false negative rate). The '947 patent provides no guidance on what this value could or should be.

139. In my opinion, however, one can infer that this limitation is met to the extent that the operator considers the model to be trained because according to the claims, the model will be considered trained if and only if the identification score differs from the predetermined value. Thus, if the identification score does not differ from the predetermined value, then the model will be considered untrained. In the case of Kambla, it is my opinion that the operator considers the model to be trained. Kambla discloses that the "trained neural network classifier" is used to determine the tree species and presence of defects. *See, e.g.*, *id.* ¶ 89. Because Kambla discloses that a trained deep learning classifier is used to classify input images, it is my opinion that these classifiers must have an identification score that is different from a "predetermined value." Otherwise, Kambla would not consider these classifiers to be trained.

**g. A Person of Ordinary Skill Would be Motivated to Combine the Scanning Device of Kambla with the Debarking System Disclosed in Gagnon**

140. As discussed above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Kambla's deep-learning models, along with the associated sensors, into the debarking system disclosed by Gagnon. *See supra* § VII(A)(1)(b). It is further my opinion that a person of ordinary skill would

expect to successfully make such a combination for the same reasons previously discussed. *See id.*

### 6. Claim 8 Is Rendered Obvious

141. As noted above, Gagnon in view of Kambla and the knowledge of one of ordinary skill render obvious claims 1 and 7, from which claim 8 eventually depends. *See supra* § VII(A)(1), (A)(5). In my opinion, Kambla discloses the additional limitations of claim 8.

#### a. Claim 8: The method of claim 7, the deep learning model being automatically trained by using the characterization of the undebarked log for the analysis of the identified characteristics of the logs to output the identification score.

142. According to the claim language, it is my opinion that a person of ordinary skill would consider a deep learning model to be automatically trained according to claim 8 if it met the conditions further specified in claim 8, in particular, that the deep learning model be trained "using the characterization of the undebarked log for the analysis of the identified characteristics of the logs to output the identification score." In my opinion, Kambla discloses these further requirements.

143. As noted in Kambla, the tree species classifier was trained using images of logs of known species, both with and without defects. *Id.* ¶ 89. In my

opinion, Kambla used the identified characterizations obtained from the pictures of the trees (e.g., log end locations and/or characterizations of the bark) during the training process to determine the characteristics of the trees (i.e., diameter and/or tree species) to arrive at an acceptable accuracy level. The disclosure of training the deep learning model in Kambla in this way results in an accuracy score that exceeds the predetermined value noted with respect to claim 7. *See supra* § VII(A)(5)(e). Accordingly, in my opinion, Kambla discloses this limitation.

**b. A Person of Ordinary Skill Would be Motivated to Combine the Automatic Training of Kambla with the Debarking System Disclosed in Gagnon**

144. In my opinion a person of ordinary skill would be motivated to combine the automatic training of the deep learning model in Kambla with the debarking system disclosed in Gagnon, for the same reasons discussed above. *See, e.g.*, *supra* § VII(A)(1)(b).

**7. Claim 9 Is Rendered Obvious**

145. As noted above, Gagnon in view of Kambla and the knowledge of one of ordinary skill render obvious claim 1, from which claim 9 depends. *See supra* § VII(A)(1). As discussed above in connection with claim limitation 7[d], Kambla also discloses the output of an identification score. *See supra* § VII(A)(5)(e). In my opinion, Kambla further discloses the additional elements of claim 9.

**a. Claim 9: The method of claim 1, the deep learning model being manually trained with training data and human validations for the analysis of the identified characteristics of the logs to output an identification score**

146. Kambla discloses the additional elements of claim 9. For example, Kambla discloses using a training process in which carefully selected images are used as part of the training process. *See* Kambla ¶ 80, 89 (discussing images with "predetermined" characteristics, like species and defect or no defect). The process of selecting the images, in my opinion, involves human validations to ensure that the correct images are chosen. In my opinion, these images are subject to human validation for the analysis of the identified characteristics, therefore meeting the additional limitations in this claim.

**b. A Person of Ordinary Skill Would be Motivated to Combine the Fine Tuning Process from Kambla with the Debarking System Disclosed in Gagnon**

147. In my opinion, a person of ordinary skill would be motivated to incorporate the disclosure in Kambla regarding training into the debarking system of Gagnon because such training would produce an accurate model given sufficient data. *See, e.g.*, Gagnon ¶ 4 (describing a need for more accurate quality control); Kambla ¶ 7 ("The aim of the present invention is to provide a system to measure timber . . . quickly, accurately and efficiently . . . ."). Moreover, a person of

ordinary skill would expect such a combination to succeed given that Kambla uses well known deep learning techniques. *See* Kambla ¶ 81. Finally, such training is well known in the art and was known as of the priority date of the '947 patent. Because such training is being used in the usual and expected manner, it is my opinion that it would be well within the capabilities of a person of ordinary skill to implement such training as part of the combined system.

**8. Claim 10 Is Rendered Obvious**

148. *Claim 10: The method of claim 1, the characterization of the undebarked log further comprising external data to the undebarked log.*

149. As noted above, Gagnon in view of Kambla and the knowledge of one of ordinary skill render obvious claim 1, from which claim 10 depends. *See supra* § VII(A)(1). As explained below, it is my opinion that Gagnon discloses the additional limitations of claim 10.

150. According to Gagnon, "environmental conditions such as log temperature state (frozen or non-frozen) have significant influence over debarking quality." Gagnon ¶ 49. Gagnon further discloses "air temperature, which influences temperature state of log surface (i.e., frozen or non-frozen), has an effect on wood/bark adhesion strength when the log moisture content is greater than fiber saturation point." *Id.* ¶ 3. Gagnon thus discloses the use of a "non-contact

temperature sensor 63 conveniently located adjacent the conveyer 13 for measuring the temperature at the surface of the next log 10' to be debarked, to send a temperature indicative signal to the controller 67 shown in Fig. 3," where "[a]ny appropriate non-contact temperature sensor . . . may be used." *See id.* ¶ 49; *see also* Figs. 4A, 4. Gagnon further discloses that the temperature sensor is located far enough upstream of the debarker to allow sufficient processing time for the computer. *Id.* ¶ 49. Accordingly, in my opinion, Gagnon discloses a non-contact temperature sensor that takes external data measurements (e.g., temperature) and uses that external data to characterize the log (e.g., frozen or unfrozen).

### B. Ground 2: Gagnon in Light of Ido and Petruzella Renders Obvious Claims 1-18

151. In my opinion, claims 1-18 are unpatentable under 35 U.S.C. § 103 as obvious under the combination of Gagnon in light of Ido and Petruzella.

#### 1. Claim 1 Is Rendered Obvious

##### a. Element 1[pre]: A computer-implemented method for characterizing an undebarked log in real time, the method comprising

152. The preamble of claim 1 is not limiting. Nevertheless, in my opinion Gagnon discloses this limitation. *See supra* § VII(A)(1).

**b. Element 1[a]: performing a contactless characterization of the undebarked log;**

153. In my opinion, Gagnon and Ido, both alone and in combination, disclose the limitation from element 1[a]. *See supra* § VII(A)(1)(b) (Gagnon).

154. Ido also discloses this limitation. Ido discloses capturing images of the bark on a tree or log using non-contact image capture devices (e.g., cameras) so that the images of the bark could be used to determine the tree species. For example, Ido discloses that "[i]nput data for identifying the tree species of this research is a bark image as shown in Fig. 1." *See* Ido § 2.1. Ido also discloses that the images may differ because of the "shooting distance" from the tree, further indicating that Ido uses a non-contact image sensor. *See id*.

155. Figure 6 also discloses exemplary images of bark that were used as part of the system:



Figure 6. Extracted ROI images.

*Id.*, Fig. 6. In my opinion, the capture of the images of trees or logs having bark also constitutes "characterizing" those trees or logs because the images describe the character of the bark on the trees and logs. *See, e.g.*, Ido § 1.

156. In my opinion, it would be clear to a person of ordinary skill that such images would be captured via a non-contact camera; otherwise, if the camera made contact with the bark, it would risk creating shadows or dark spots that would interfere with the characterizing and categorization process. Accordingly, it is also my opinion that Ido discloses this limitation.

157. *Motivation to Combine:* It is my opinion that a person of ordinary skill would be highly motivated to incorporate Ido's tree-species-identification deep-learning model, along with the associated contactless image capture devices, into the debarking system disclosed by Gagnon. Indeed, Gagnon explains that information about tree species is highly relevant to determining the settings on a debarking machine. Gagnon ¶ 3. In my opinion, one of ordinary skill in the art would understand that taking advantage of the tree-species-identification capabilities of the deep-learning model in Ido would also require that the contactless characterization disclosed in Ido – in particular, the use of cameras or other image capture devices to capture images of bark – be incorporated into the system disclosed in Gagnon. Because of the capabilities offered by Ido, *see* Ido §

4, it is my opinion that a person of ordinary skill would be highly motivated to make this combination.

158. In my opinion, a person of ordinary skill would also expect that the trained deep-learning model and associated contactless image capture devices of Ido could be successfully incorporated into the system of Gagnon, for the reasons explained immediately below.

159. First, Ido discloses that a deep learning model can be used to accurately identify tree species. *See id.* § 3.2.3 (accuracy of up to 74.7%).[4] Accordingly, based on my experience in the field, as well as my experience working with students who are first being introduced to deep-learning techniques, one would expect that Ido's trained deep-learning model would be able to accurately identify the tree species for the undebarked logs waiting to be processed by the system in Gagnon. To the extent that such tree species would be different from the six species identified in Ido, a person of ordinary skill would understand that the system in Ido could be trained to identify the tree species of interest through the ordinary training of a deep learning model using the process Ido

[4] It is my understanding in talking to employees at Nicholson that the accuracy rate for a typical human operator of a debarking machine may vary widely, where some operators may not be able to accurately identify any tree species being debarked.

describes. Moreover, a person of ordinary skill would appreciate that the accuracy of the classification system in Ido could be improved by including additional images as part of the training set of data.

160. Second, in my opinion, one of ordinary skill in the art would expect that the associated contactless image capture devices from Ido could be successfully incorporated into the system disclosed in Gagnon because these image capture devices are well-known in the art and are performing their ordinary and expected functions. Moreover, Gagnon already discloses mounting sensors on the input side of the debarking machine to capture diameter and length values, and Gagnon discloses the use of cameras to capture images on the output side of the machine. *See* Gagnon ¶¶ 45, 49; *see also* Figs. 4A, 4. Accordingly, in my opinion, a person of ordinary skill would be able to take the cameras used in Ido (or any other type of camera capable of capturing suitable images), mount those cameras to capture images on the input side of the debarking machines, and couple the output of those cameras to the controller/computer already disclosed in Gagnon, and expect such an implementation to be successful and operate correctly. In fact, such cameras would not be subject to the same variability as described in Ido, thereby removing one of the issues noted in Ido for obtaining images for the deep learning model.

161. It is my opinion that a person of ordinary skill would also be able to address the inclination issue described in Ido, *see* Ido § 2.3, by mounting the cameras in the combined system to take a picture of the log at a 90-degree angle as the log passes by on a conveyor. Note, in this respect, that Ido states that "***depending*** on the shooting condition, the tree image ***may be*** inclined." *Id.* (emphasis added). Thus, in my opinion, a person of ordinary skill would be able to arrange the combined system to resolve any inclination issue and thereby remove the one manual step described in Ido. Accordingly, in my opinion, the issue regarding inclination would not weigh against combining the tree-species identification capabilities of Ido with the debarking system described in Gagnon.

162. It would further be well within the capabilities of a person of ordinary skill to successfully deploy Ido's trained, deep-learning model and methodology on the controller/computer from Gagnon and process the captured images to identify the tree species for each of the logs to be debarked. Indeed, Ido did not identify any specific or special type of computer for deploying the deep learning program, *see generally id.*, and based on my experience, none would be needed. In addition, it is my opinion that it would be well within the capabilities of one of ordinary skill to increase the types of trees that the system could identify by using the same process identified and described in Ido for training the CNN model.

163. Accordingly, it is my opinion that a person of ordinary skill would be capable of incorporating the deep-learning algorithm from Ido, along with the necessary hardware, into the debarking machine disclosed in Gagnon; that a person of ordinary skill would be highly motivated to make this combination; and that a person of ordinary skill would expect that such a combination would succeed, for the reasons explained above.

**c. Element 1[b]: identifying characteristics of the undebarked log based on the characterization of the undebarked log using a trained deep learning model**

164. In my opinion, Ido discloses this limitation. As noted above, Ido discloses capturing images of the bark on a tree using non-contact image capture devices (e.g., cameras) so that the images of the bark could be used to determine the tree species.[5] *See supra* § VII(B)(1)(b). For example, Ido discloses as one objective of the project "to extract a bark region of interest (ROI) from the tree image" and then show "an optimal condition to obtain high recognition accuracy." Ido § 1.

[5] It is my understanding from talking to employees at Nicholson that the type of bark-based identification performed on standing trees in Ido would work on logs because the characteristics of the bark would not change appreciably once the tree is cut and the log transported to the sawmill.

165. In addition, Ido discloses a trained deep learning model. As disclosed in Ido, the CNN model it implements "is a deep artificial neural network that is used primarily to classify images." *Id*. Ido further discloses that after data augmentation, "the number of training data is 19,995" images. *See* Ido § 3.2.2. Using this dataset, the trained deep learning model was able to correctly identify the tree species with an accuracy rate of up to 74.7% based on the images of the bark captured by a non-contact image capture device. *Id*. Accordingly, it is my opinion that Ido discloses this limitation.

166. *Motivation to Combine:* As explained above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Ido's tree-species-identification deep-learning model into the debarking system disclosed by Gagnon. *See supra* § VII(B)(1)(b). Indeed, Gagnon explains that information about tree species is highly relevant to determining the settings on a debarking machine. *See* Gagnon ¶ 3. Because of the capabilities offered by Ido, it is my opinion that a person of ordinary skill would be highly motivated to make this combination.

167. In my opinion, a person of ordinary skill would also expect that the trained deep-learning model of Ido could be successfully incorporated into the system of Gagnon, for the reasons explained above. *See supra* § VII(B)(1)(b).

**d. Element 1[c]: computing operating parameters of a debarker based on the identified characteristics; and**

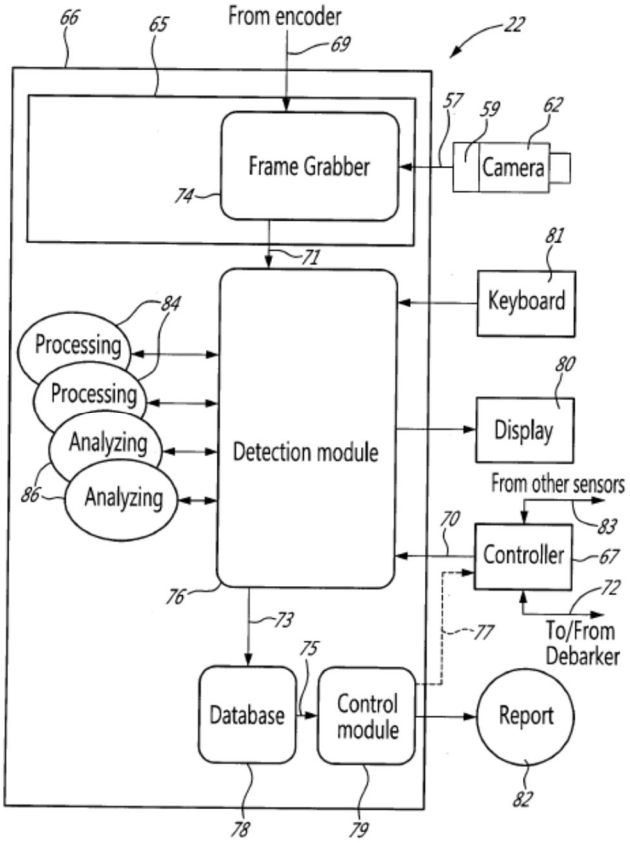
168. In my opinion, Gagnon in combination with Ido and Petruzella discloses this limitation.

169. As noted above, the combination of Gagnon and Ido could identify the characteristics of a log to be processed by a debarking machine, in particular, the tree species of the log. *See supra* § VII(B)(1)(c). Gagnon further discloses using the tree species of a log to compute the operating characteristics of the debarker. *See, e.g.*, Gagnon ¶ 49.

170. According to Gagnon, the system it discloses:

> may include ***a control module*** using information on fiber loss and residual bark as measured, ***to provide commands*** enabling the controller 67 to send through link 72 feedback control signals for the required debarker adjustments providing optimal performance in real time, ***on the basis of input data related to intrinsic characteristics*** of each log entering the debarker such as ***wood species information*** . . . ."

*Id*. (emphasis added); *see also id.* ¶ 6. The following diagram shows an illustration of a debarking quality detection system 22:




Gagnon, Fig. 7.

171. As shown in Figure 7 of Gagnon, the input for the wood species information would be obtained by controller 67, which Gagnon discloses as being a PLC. *Id.*; *see id.* ¶ 49. According to Petruzella, a PLC includes a central processing unit that "consists of a microprocessor for implementing the logic and controlling the communications among the modules." Petruzella at 5, Fig. 1-8. The PLC also includes a memory component "for storing user program instructions, numerical values, and I/O devices status." *Id.* at 5. Accordingly, Petruzella discloses to a person of ordinary skill that the PLC disclosed in Gagnon

could receive the input values related to tree species, perform any necessary calculations regarding the output parameters using the PLC's processor component, and output those values to the debarker.

172. In addition, as discussed below, Petruzella discloses to one of ordinary skill that the PLC will retrieve the operating parameters of the debarker machine based on the input characteristics of the tree. *See infra* § VII(B)(1)(f). As noted in my discussion above, retrieving the operating parameters also satisfies the "computing" claim limitation. *See supra* § VII(A)(1)(d).

173. *Motivation to Combine:* It is my opinion that a person of ordinary skill would be motivated to combine the teachings from Petruzella related to PLC operation with the system disclosed in Gagnon because Gagnon explicitly identifies a PLC for receiving input and determining values for the debarker. Gagnon ¶ 49. In addition, Petruzella notes numerous advantages of using PLCs over prior systems, including that PLCs have a faster response time, are easier to troubleshoot, and provide increased flexibility along with better reliability. *See* Petruzella at 2-3. In addition, PLCs were well known as of the priority date of the '947 patent, and the manner in which the PLC from Petruzella is being incorporated into the system of Gagnon uses the PLC in its ordinary and expected

manner; accordingly a person of ordinary skill would expect this combination to succeed without undue experimentation.

**e. Element 1[d]: sending the computed operating parameters to the debarker;**

174. As noted above, it is my opinion that Gagnon discloses this limitation. *See supra* § VII(A)(1)(e).

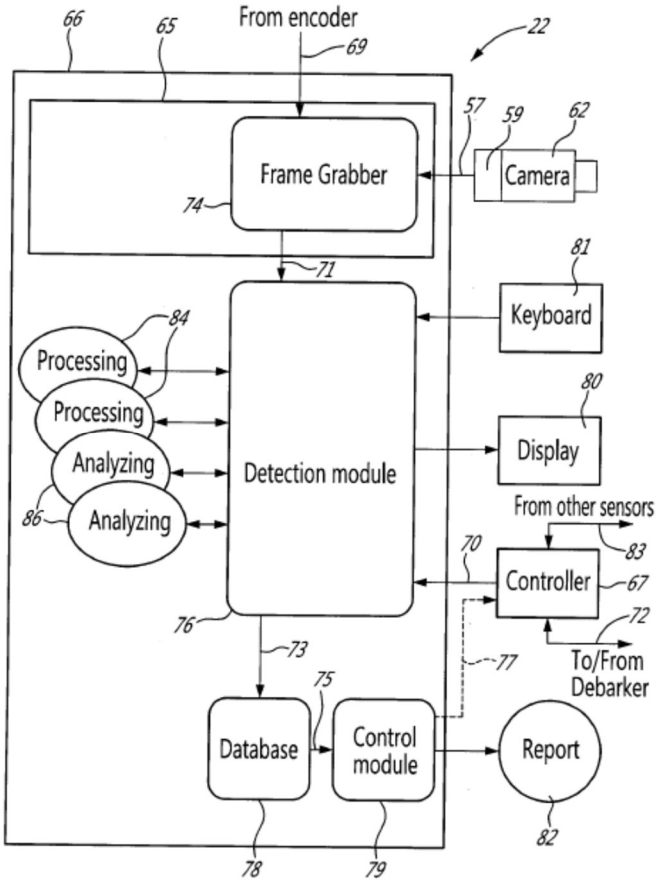
**f. Element 1[e]: wherein the computation of the operating parameters further comprises retrieving operating parameters associated with the identified characteristics.**

175. In my opinion, Gagnon in light of Petruzella discloses this limitation. For example, Gagnon discloses that

> the computer software may include a control module . . . to provide commands enabling the controller 67 to send through link 72 feedback control signals for the required debarker adjustments providing optimal performance in real time, on the basis of input data related to intrinsic characteristics of each log entering the debarker such as tree species information, mean log diameter, taper shape indicator, and environmentally influenced characteristics such as log surface temperature and moisture content, coming from other sensors or data entry means through link 83."

Gagnon ¶ 49.

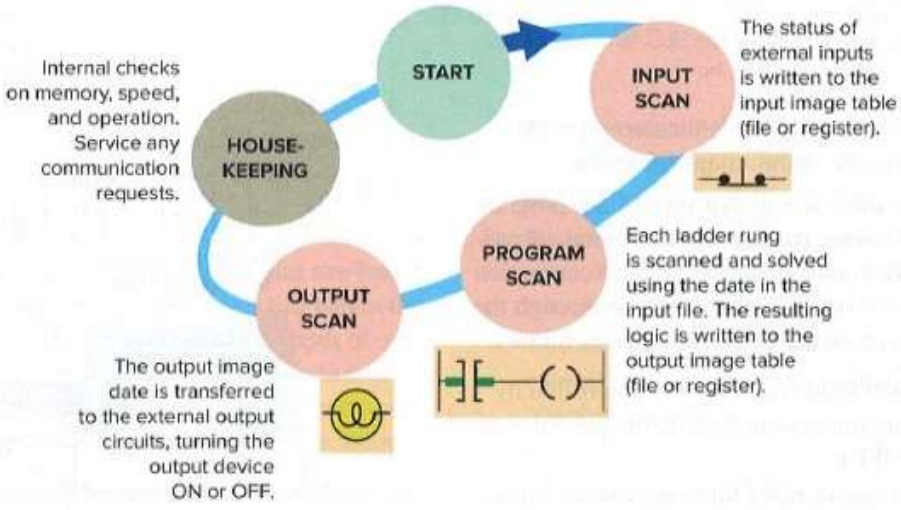
176. As seen in the following diagram, link 83 comes into the PLC 67:




*Id.*, Fig. 7. As noted above, Gagnon discloses the use of a PLC for receiving the input of wood species and determining the operating parameters for the debarker based on that input. *Id.* ¶ 49.

177. Petruzella discloses the components of a PLC, which include both a processor and a memory component. Petruzella at 5. Under an elemental understanding of computer operation, operating values calculated by the PLC as a result of limitation 1[c] will be stored in the memory of the PLC at a memory

address. *See id*. at 5-6. The processor in the PLC will then retrieve these values so that they can be transmitted to the debarker via the communication port. *See, e.g.*, *id.* at 12, 75, 78. Such a process is shown in the following figure, in which each ladder rung of a PLC program "is scanned and solved using the dat[a] in the input files," where "[t]he resulting logic is written to the output image table":




*Id.* at 78 (Fig. 5-8). Once each rung is scanned and solved, "[t]he output image dat[a] is transferred to the external output circuits, turning the output device ON or OFF." *Id.*

178. In the combined system, the values of the input file would correspond to tree species and the values of the output file would correspond to debarker operating parameters. Because the logic ladder is solved rung by rung, the input values on a specific rung related to a specific tree species are associated with the operating parameters contained on that same rung.

179. Thus, in short, the program in Petruzella updates the data in the output file based on the values contained in the input file, and then once the output file is updated, the processor retrieves the new values from the output file to transfer them to the output device (i.e., components of the debarker in the case of the combined system). *Id*. In my opinion, this description of the normal way that a PLC functions meets this limitation of claim 1. *See supra* § VII(B)(1)(d).

180. *Motivation to Combine:* In my opinion, the motivation to combine discussed above with respect to limitation 1[c] also applies here. *Id.*

**2. Claim 2 Is Rendered Obvious**

181. *Claim 2: The method of claim 1, the characterization of the undebarked log using a scanning device*.

182. As noted above, Gagnon in view of Ido and Petruzella renders obvious claim 1, from which claim 2 depends. *See supra* § VII(B)(1). In my opinion, Ido discloses the additional elements of claim 2.

183. Ido discloses the use of a camera to capture images of the bark of undebarked logs. *See supra* § VII(B)(1)(b). For example, Ido discloses that it uses a data set that includes "training data" of "19,995" images and notes that such training data was captured from photographers. Ido § 3.2.2. In addition, in discussing testing, Ido discloses that one or more images of undebarked trees are

used in determining a tree species. *See, e.g.*, Ido § 2.3; Fig. 6 (showing regions of interest of bark from trees and/or logs). Based on the understanding of this term set forth above, the cameras used in Ido to capture images of bark constitute "scanning devices." *See supra* § VII(A)(2). Accordingly, it is my opinion that Ido discloses this limitation.

184. As discussed above, this characterization by Ido may be used in the system disclosed in Gagnon for computing operating parameters. *See supra* § VII(B)(1)(d).

185. *Motivation to Combine:* As discussed above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Ido's tree-species-identification deep-learning model, along with the associated scanning devices, into the debarking system disclosed by Gagnon. *See supra* § VII(B)(1)(b). It is further my opinion that a person of ordinary skill would expect to successfully make such a combination for the same reasons previously discussed. *See id*.

**3. Claim 3 Is Rendered Obvious**

186. *Claim 3: The method of claim 1, the characterization of the undebarked log using one or more sensors*.

187. As noted above, Gagnon in view of Ido and Petruzella render obvious claim 1, from which claim 3 depends. *See supra* § VII(B)(1). In my opinion, Ido discloses the additional elements of claim 3.

188. As noted above, a sensor may include a camera. *See supra* § VII(A)(3)(a).

189. Based on this understanding, Ido discloses the use of a digital camera that includes image sensors to capture images of the bark of undebarked logs. *See supra* § VII(B)(1)(b). For example, Ido discloses that it uses a data set that includes "training data" of 19,995 images and notes that such training data was captured from photographers. Ido §§ 2.1, 3.2.2. In addition, Ido discloses that the images are comprised of pixels, *see, e.g.*, *id.* §§ 2.3, 3.1 (listing various image sizes in terms of pixels), indicating that the pictures were obtained using a digital camera comprised of multiple image sensors, where each image sensor is associated with a pixel. Accordingly, in my opinion, Ido discloses the use of one or more sensors in the characterization of the undebarked log.

190. As discussed above, this characterization by Ido may be used in the system disclosed in Gagnon for computing operating parameters. *See supra* § VII(B)(1)(d).

191. *Motivation to Combine:* As discussed above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Ido's tree-species-identification deep-learning model, along with the associated sensors, into the debarking system disclosed by Gagnon. *See supra* § VII(B)(1)(b). It is further my opinion that a person of ordinary skill would expect to successfully make such a combination for the same reasons previously discussed. *See id*.

**4. Claim 4 Is Rendered Obvious**

192. *Claim 4: The method of claim 1, the identification of the characteristics of the log further comprising one or a combination of any of the followings [*sic*]: identifying the species of the log; measuring the moisture level of the log; and calculating an intensity of knot presence on the log*.

193. As explained above, it is my opinion that Gagnon in view of Ido and Petruzella teaches, and therefore renders obvious, the limitations of claim 1, from which claim 4 depends. *See supra* § VII(B)(1). It is further my opinion that Ido discloses the additional elements of claim 4.

194. Ido discloses capturing images of the bark on a tree or log using non-contact image capture devices (e.g., cameras) so that the images of the bark could be used to determine the tree species. *See supra* § VII(B)(1)(b). For example, Ido discloses "a convolutional neural network (CNN)-based tree species identification

method using a bark image." Ido § 1. Further, Ido discloses the ability to identify up to 6 different types of tree species. *Id.* § 1; *see id.*, Table 2. It is further my opinion that it would be well within the capabilities of one of ordinary skill to expand the number of trees that the system in Ido could identify by following the instructions and descriptions in Ido.

195. In addition, Ido discloses a trained deep learning model. As disclosed in Ido, the CNN model it implements "is a deep artificial neural network that is used primarily to classify images." Ido § 1. Ido further discloses that after data augmentation, "the number of training data is 19,995." Ido § 3.2.2. Using this dataset, the trained deep learning model was able to correctly identify the tree species with an accuracy rate of up to 74.7% based on the images of the bark captured by a non-contact image capture device. *Id.* §§ 2.1, 3.2.2. Accordingly, it is my opinion that Ido discloses this limitation.

196. *Motivation to Combine:* As explained above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Ido's tree-species-identification deep-learning model into the debarking system disclosed by Gagnon. *See supra* § VII(B)(1)(b). Indeed, Gagnon explains that information about tree species is highly relevant to determining the settings on a debarking machine. *See* Gagnon ¶ 3. Because of the capabilities offered by Ido, it is my

opinion that a person of ordinary skill would be highly motivated to make this combination.

197. In my opinion, a person of ordinary skill would also expect that the trained deep-learning model from Ido could be successfully incorporated into the system of Gagnon, for the reasons discussed above. *See supra* § VII(B)(1)(b).

### 5. Claim 5 Is Rendered Obvious

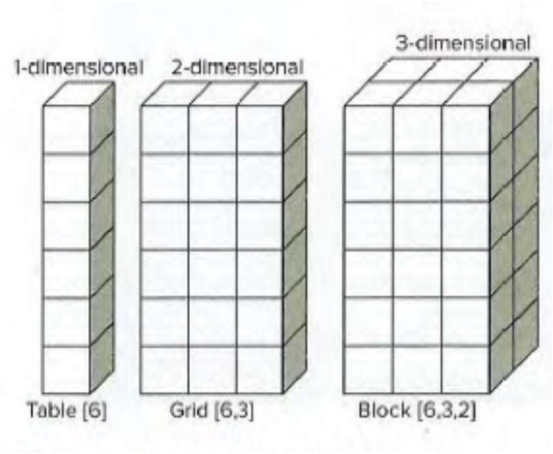
198. As noted above, Gagnon in view of Ido and Petruzella renders obvious claim 1, from which claim 5 depends. *See supra* § VII(B)(1). In my opinion, Petruzella and/or Petruzella in light of Ido discloses the additional limitations of claim 5.

#### a. Claim 5: The method of claim 1, the operating parameters being indexed in a table having operating parameters associated with one or more log characteristics

199. Petruzella discloses the components of a PLC, which include both a processor and a memory component. *See* Petruzella at 5-6. As described by Petruzella, the ladder logic implementation of PLCs results in each ladder rung of a PLC program being "scanned and solved using the dat[a] in the input files," where "[t]he resulting logic is written to the output image table." *Id.* at 78 (Fig. 5-8). Once each rung is scanned and solved, "[t]he output image dat[a] is transferred" from the output image table "to the external output circuits, turning the output

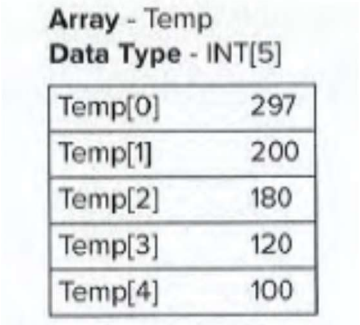
device ON or OFF." *Id.* Because the logic ladder is solved rung by rung, the input values on a specific rung related to a specific tree species are associated with the operating parameters for the debarker contained on that same rung and stored in the output image file. *See id*. In my opinion, this logic ladder constitutes an indexed table.

200. As a second example, Petruzella also discloses the use of single and multiple dimension arrays for storing data values, as shown in the following illustration:




Petruzella at 342 (Fig. 15-24). According to Petruzella, "an array is a tag type that contains a block of multiple pieces of data" where the "array occupies a contiguous block of values." *Id.* Further, the elements in an array "may be a basic data type or a structure." *Id.*

201. Petruzella also discloses how each element in an array can be accessed, as shown in the following diagram:




*See id.* at 343 (Fig. 15-25).

202. In my opinion, a person of ordinary skill could take the teachings from Petruzella to construct an array of elements containing operating parameters in which each element could be accessed based on the tree species. In this example, the array "Temp" shown in Figure 15-25 would be renamed "Parameters," and each number in brackets would correspond to a specific type of tree, such as the trees identified by Ido's artificial intelligence program.

203. In fact, Ido includes a chart in which each tree is associated with a number that could be easily incorporated into the PLC array example provided by Petruzella:

Table 1. Six species and number of samples.

| No. | Scientific name | Number of samples |
|---|---|---|
| 1 | Ulmus | 241 |
| 2 | Quercus | 630 |
| 3 | Salix | 216 |
| 4 | Betula | 223 |
| 5 | Itaya amicorum | 305 |
| 6 | Alnus japonica | 318 |

Ido, Table 1. Accordingly, under this simple example, the operating parameters associated with *Ulmus* could be found in the Parameters array at Parameters[1], for example.

204. Accordingly, in my opinion, Petruzella and/or Petruzella combined with Ido disclose the further limitations of claim 5.

**b. A Person of Ordinary Skill Would be Motivated to Combine the Array Features from Petruzella with the Debarking System Disclosed in Gagnon**

205. In my opinion, a person of ordinary skill would be motivated to incorporate the disclosure in Petruzella regarding the use of an array into the debarking system of Gagnon because such a combination would result in a more efficient and faster control system. According to Petruzella, "[t]he use of arrayed data types offers the fastest data throughput (output) from a ControlLogix processor." Petruzella at 343. I understand from my conversation with Nicholson that ControlLogix controllers are widely used in their debarker systems and within

the industry. "Because arrays are numerically sequenced tags of the same data type that occupy a contiguous memory location, large amounts of data can be retrieved efficiently." *Id.* This characteristic would be especially useful when multiple operating parameters are stored in each element of an array as part of a structure. Because the array offers faster throughput, in my opinion, a person of ordinary skill would be motivated to combine this functionality with the debarker system disclosed in Gagnon to achieve faster throughput of debarked logs.

#### 6. Claim 6 Is Rendered Obvious

206. As noted above, Gagnon in view of Ido and Petruzella renders obvious claims 1 and 5, from which claim 6 depends. *See supra* §§ VII(B)(1), (5). In my opinion, Ido in light of Petruzella discloses the additional limitations of claim 6.

##### a. Claim 6: The method of claim 5, the indexation of the log operating parameters taking into account the intensity level of the one or more log characteristics

207. As noted above, Ido discloses the use of an array of image sensors in a digital camera to capture images of the bark on a tree or log. *See supra* § VII(B)(3). As part of the process of capturing images, the image sensors will capture various ranges of light intensities. For example, an image sensor that captures a higher intensity of light will appear lighter as compared to a

corresponding image sensor that captured comparatively less light, which will appear relatively darker. Thus, each image sensor in the picture below captured a certain range of light intensity:



Ido, Fig. 6. The collection of intensities captured by the array of image sensors together are used to identify the characteristics of the log (e.g., the tree species) in the artificial intelligence system of Ido. *See, e.g.*, Ido § 3.2.2. Then the characteristic of the log is associated with, and used to index, the operating parameters stored in an array such as that disclosed in Petruzella as explained in connection with claim 5.

208. Ido discloses a second type of intensity level, as well. In particular, Ido discloses the use of various deep-learning CNN models that return probability values based on the different categories that an item is to be sorted into. *Id*. In the scenario described by Ido, the four CNN models listed in Table 3 will return a set

of six probabilities each time a picture of a tree or log is to be categorized. *See id.*, Table 3. These six probabilities will correspond to the six tree species each model has been trained to learn. *See id.* § 4. These probabilities correspond to the intensity levels recited in claim 6. Further, these intensity levels will be used when indexing the table because the deep-learning model will categorize the picture of the tree according to the highest probability across the six tree species. Thus, in this situation, the tree species with the highest probability will be used to index the table.

209. Accordingly, it is my opinion that Ido discloses the intensity levels of the log characteristics being used to index the operating parameters as stored in a table such as shown in Petruzella.

**b. A Person of Ordinary Skill Would be Motivated to Combine the Tree Identification Features from Ido and the Array Functionality Disclosed in Petruzella with the Debarker System Disclosed in Gagnon**

210. As noted in the preceding section, the use of intensity levels in Ido are used as part of the artificial intelligence process for determining the characteristics of a log. In addition, as noted earlier, a person of ordinary skill would be motivated to incorporate this artificial intelligence functionality into the debarker system disclosed in Gagnon. *See supra* § VII(B)(1)(b).

211. In addition, as noted earlier, a person of ordinary skill would be motivated to incorporate the array disclosed in Petruzella into the debarker system disclosed in Gagnon. *See supra* § VII(B)(5)(b).

212. Finally, in my opinion, a person of ordinary skill would expect to successfully combine the artificial intelligence features of Ido and the array functionality of Petruzella with the debarker system of Gagnon because each of these components (i.e., Ido's artificial intelligence features and Petruzella's array functionality) is operating in its normal and expected manner.

### 7. Claim 7 Is Rendered Obvious

213. As noted above, Gagnon in view of Ido and Petruzella renders obvious claim 1, from which claim 7 depends. *See supra* § VII(B)(1). In my opinion, Ido discloses the additional limitations of claim 7.

#### a. Element 7 [pre]: The method of claim 1, the trained deep learning model being trained comprising the steps of:

214. As explained above, it is my opinion that Gagnon in combination with Ido and Petruzella renders obvious claim 1. *See supra* § VII(B)(1). It is further my opinion that Ido further discloses training a deep learning model, including the steps recited in claim 7, as explained below.

**b. Element 7[a]: selecting a representative sample of a plurality of logs having identifiable characteristics;**

215. It is my opinion that Ido discloses this limitation. For example, Ido describes "a convolutional neural network (CNN)-based tree species identification method using a bark image." Ido § 1. Ido further discloses that "[w]e randomly selected 100 samples for each species as the test data, and the remaining samples were used as the training data." *Id.* § 3.1. Accordingly, it is my opinion that Ido discloses training the artificial intelligence model using a representative sample of trees, each the subject of one of its tree images. It is further my opinion that a person of ordinary skill would understand that the same training could be performed on trees that have been cut down (i.e., logs) as well as trees still standing.

**c. Element 7[b]: scanning the plurality of logs to obtain scan data of the logs;**

216. It is my opinion that Ido discloses this limitation. Ido describes that "shooting distance of tree varies depending on individuals and photographers." *Id.* § 2.1. Ido further discloses that the "[c]ollecting task is cooperated by several company workers," and that "there are five types of tree image size: 1280x960 [pixels] 1440x1920 [pixels], 1600x1200 [pixels], 1920x1440 [pixels], 2048x1536 [pixels]." *Id.* § 3.1.

**d. Element 7[c]: identifying with a deep learning algorithm software of the deep learning model the identifiable characteristics of the logs based on the scan data;**

217. It is my opinion that Ido discloses this limitation. Ido for example discloses that "[w]e evaluated the proposed method with six tree species" and "carried out the evaluation experiment with various conditions," obtaining "the highest recognition accuracy of 74.7%." *Id.* § 4. In addition, Ido discloses examples of the extracted regions of interest (ROIs) that would be used to identify the tree species. *Id.*, Fig. 6. The following pictures provide illustrations of exemplary ROIs:





218. It is my opinion that a person of ordinary skill in the art would understand that the deep-learning model described in Ido would identify the tree species based on characteristics identifiable in the captured image data.

**e. Element 7[d]: analysing [*sic*] the identified characteristics of the logs to output an identification score; and**

219. It is my opinion that Ido discloses this limitation. For example, Ido discloses various accuracy measures for different types of analyses. *See, e.g., id.*, Table 3. As disclosed in Ido, the highest recognition accuracy achieved was 74.7%. *Id.* § 4. In my opinion, a person of ordinary skill would understand that the recognition accuracy score is a type of identification score.

**f. Element 7[e]: considering the deep learning model trained if the identification score is different from a predetermined value.**

220. In my opinion, Ido discloses this limitation. As an initial matter, as noted elsewhere in my report, it is unclear what "predetermined value" means in the context of the '947 patent. *Infra* § VII(E); *see also supra* § VII(A)(5)(f). Indeed, this term could refer to a wide range of possible values; moreover, the values could be based on any number of various metrics (e.g., accuracy, true positive, false positive). The '947 patent provides no guidance on what this value could or should be.

221. As noted before, one can infer that this limitation is met to the extent that the operator considers the model to be trained because according to the claims, the model will be considered trained if and only if the identification score differs

from the predetermined value. *Supra* § VII(A)(5)(f). In the case of Ido, it is my opinion that the operator does consider the model to be trained. For example, Ido discloses a successful accuracy score of 74.7%. Ido § 3.2.2. Moreover, Ido characterizes the research done as resulting in "an optimal condition to obtain high recognition accuracy for our problem." *Id.* § 1.

222. In addition, it is my opinion that, at least in some cases, a person of ordinary skill would consider the model to be trained if its accuracy score exceeds the score that would be obtained by randomly guessing the tree species. Here, that value would be about 16.7% with six tree species, whereas Ido discloses a successful accuracy score of 74.7%. *See id.* § 4. In this case, a person of ordinary skill would consider the deep learning system in Ido trained because the 74.7% accuracy rate exceeds the 16.7% random rate.

**g. Motivation to Combine**

223. As discussed above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Ido's tree-species-identification deep-learning model, along with the associated sensors, into the debarking system disclosed by Gagnon. *See supra* § VII(B)(1)(b). It is further my opinion that a person of ordinary skill would expect to successfully make such a combination for the same reasons previously discussed. *See id*.

### 8. Claim 8 Is Rendered Obvious

224. *Claim 8: The method of claim 7, the deep learning model being automatically trained by using the characterization of the undebarked log for the analysis of the identified characteristics of the logs to output the identification score*.

225. As explained above, it is my opinion that Gagnon in view of Ido and Petruzella teaches, and therefore renders obvious, the limitations of claim 1 and claim 7, from which claim 8 depends. *See supra* §§ VII(B)(1), (7). It is further my opinion that Ido discloses the additional elements of claim 8.

226. As noted above, according to the claim language, it is my opinion that a person of ordinary skill would consider a deep learning model to be automatically trained according to claim 8 if it met the conditions further specified in claim 8. *See supra* § VII(A)(6).

227. As noted in Ido, it applied training data of 19,995 images for the various CNN models. Ido § 3.2.2. In this approach, Ido further applied fine-tuning techniques to the CNN models, both with and without data augmentation. *Id.* The highest accuracy value achieved during this process was 74.7%. *Id.* In my opinion, Ido used the identified characterizations obtained from the pictures of the trees (e.g., characterizations of the bark) during the training process to determine

the characteristics of the trees (i.e., tree species) to arrive at the accuracy value of 74.7%. The disclosure of training the deep learning model in Ido in this way results in an accuracy score that differs from the predetermined value noted with respect to claim 7. Accordingly, in my opinion, Ido discloses this limitation.

228. *Motivation to Combine:* In my opinion, a person of ordinary skill would be motivated to combine the automatic training of the deep learning model in Ido with the debarking system disclosed in Gagnon, for the same reasons discussed above. *See, e.g.*, *supra* § VII(B)(1)(b).

229. In addition, because the automatically trained model results in accuracy scores that exceed the "predetermined values" of claim 7, a person of ordinary skill would expect that the automatically trained CNN model of Ido could be successfully incorporated into the debarker system of Gagnon.

**9. Claim 9 Is Rendered Obvious**

230. *Claim 9: The method of claim 1, the deep learning model being manually trained with training data and human validations for the analysis of the identified characteristics of the logs to output an identification score.*

231. As noted above, Gagnon in view of Ido and Petruzella renders obvious claim 1, from which claim 9 depends. *See supra* § VII(B)(1). As discussed above in connection with claim limitation 7[d], Ido also discloses the

output of an identification score. *See supra* § VII(B)(7)(e). In my opinion, Ido further discloses the additional elements of claim 9.

232. For example, Ido discloses that once the ROI is captured, it can be fed into the deep learning model for training purposes using a technique known as transfer learning. Ido § 3.2.2. As part of the fine-tuning process, Ido "start[s] training a CNN to learn features for a broad domain with a classification function targeted at minimizing error in that domain." *Id.* Then, Ido "replace[s] the classification function and optimize[s] the network again to minimize error in another, more specific domain" by "transferring the features and the parameters of the network from the broad domain to the specific one." *Id.* In my opinion, a person of ordinary skill would understand that transferring the features and parameters would constitute manually training the deep learning model by using human validation.

233. *Motivation to Combine:* In my opinion, a person of ordinary skill would be motivated to incorporate the disclosure in Ido regarding training into the debarking system of Gagnon because such training would produce an accurate model given sufficient data. *See supra* § VII(B)(1)(b). Moreover, a person of ordinary skill would expect such a combination to succeed given the high accuracy score achieved by the training process in Ido. *See id*. Finally, such training is well

known in the art, and was known as of the priority date of the '947 patent. Because such training is being used in the usual and expected manner, it is my opinion that it would be well within the capabilities of a person of ordinary skill to successfully implement such training as part of the combined system.

### 10. Claim 10 Is Rendered Obvious

234. *Claim 10: The method of claim 1, the characterization of the undebarked log further comprising external data to the undebarked log.*

235. As noted above, Gagnon in view of Ido and Petruzella render obvious claim 1, from which claim 10 depends. *See supra* § VII(B)(1). It is further my opinion that Gagnon discloses the additional limitations of claim 10. *See supra* § VII(A)(8).

### 11. Claim 11 Is Rendered Obvious

#### a. Element 11[pre]: A system for characterizing an undebarked log in real time, the system comprising:

236. The preamble of claim 11 is not limiting. Nevertheless, in my opinion, Gagnon discloses the material recited in the preamble. *See supra* § VII(A)(1)(a).

#### b. Element 11[a]: a contactless log characterization sensor for identifying attributes of the undebarked log;

237. In my opinion, Gagnon and Ido, both alone and in combination, disclose the limitation from element 11[a]. *See supra* § VII(A)(1)(b) (Gagnon);

§§ VII(B)(1)(b), (3) (Ido). In my opinion, a person of ordinary skill in the art would interpret the term "attributes" to mean "a quality, character, or characteristic ascribed to someone or something." *See Attribute*, Merriam-Webster, https://www.merriam-webster.com/dictionary/attribute (last visited August 25, 2025). This definition is consistent with the usage of the term within the specification of the '947 patent. *See, e.g.*, '947 patent, 3:54-62. Under this interpretation, the "attributes" of claim 11 would correspond to the images of bark described with respect to claim limitation 1[a]. *See supra* § VII(B)(1)(b).

**c. Element 11[b]: a characterizing unit in communication with the contactless log characterization sensor, the characterizing unit comprising:**

238. In my opinion, Ido discloses this limitation. *See supra* § VII(B)(1)(c). The components of the characterizing unit as disclosed in Ido are discussed in the sections immediately below.

**(1) Element 11[b][i]: a deep learning model; and**

239. In my opinion, Ido discloses this limitation. *See supra* § VII(B)(1)(c)

**(2) Element 11[b][ii]: a computerized device configured to identify characteristics of the undebarked log based on measured attributes of the undebarked log using the deep learning model;**

240. In my opinion, Ido discloses this limitation. *See supra* § VII(B)(1)(c). Ido's tree-species identification functionality is a deep learning model and would be implemented on a computerized device, such as the hand held device that captures the log images, which along with the deep learning model would be the characterizing unit. *See id*.

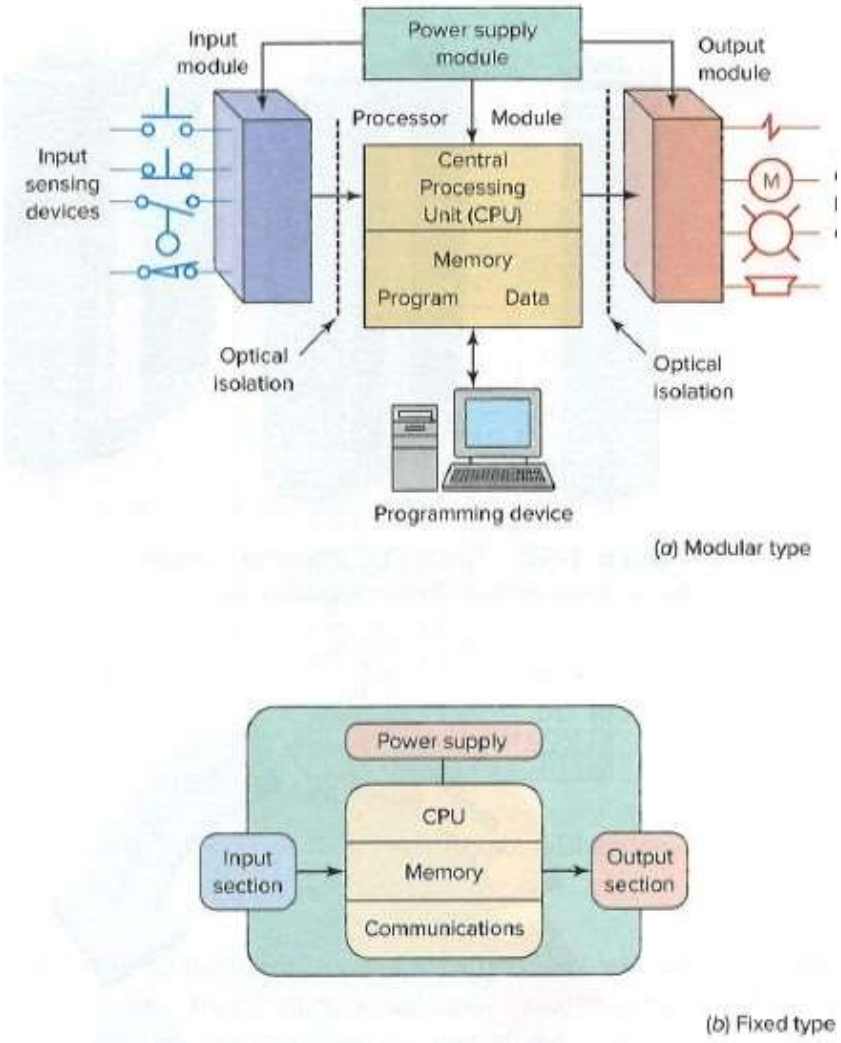
**d. Element 11[c]: a debarker optimizer in communication with the characterizing unit, the debarker optimizer being configured to compute operating parameters of a debarker based the [*sic*] characteristics identified by the characterizing unit; and**

241. In my opinion, the combination of Gagnon and Ido, along with Petruzella, discloses this limitation. *See supra* § VII(B)(1)(c), (d). In my opinion, the processor component of the PLC disclosed in Gagnon and further explained in Petruzella corresponds to the debarker optimizer. *See, e.g.*, Gagnon ¶ 49, Fig. 7; *see also* Petruzella at 5-7, Fig. 1-8. The processor component of the PLC disclosed in Gagnon (i.e., the "debarker optimizer") would communicate with the computerized device that captures log images of Ido (i.e., the "characterizing unit")

via the link 72 of Gagnon. *See, e.g.*, Gagnon ¶ 49, Fig. 7; *see also* Petruzella at 5-7 (Fig. 1.8); *see also supra* § VII(B)(11)(c).

**e. Element 11[d]: a debarker controller in communication with the debarker optimizer and the debarker, the debarker controller being configured to control the debarker using the computed operating parameters from the debarker optimizer,**

242. In my opinion, Gagnon and Petruzella disclose this limitation. As noted above, Gagnon discloses sending the computed operating parameters to control the debarker. *See supra* § VII(B)(1)(e). Further, Petruzella discloses a communication unit that operates to provide communications with the output components (i.e., the components of the debarker), as shown in the following diagram:




Petruzella, Fig. 1-8; *see id*. at 6-7.

243. According to Petruzella, "[t]he I/O system forms the interface by which field devices are connected to the controller" and thereby "condition the various signals received from or sent to external field devices." *Id*. at 6. In my opinion, the I/O system and communications component in Petruzella serve as the

debarker controller. The I/O system and communications component are also in communication with the processor component of the PLC. *See, e.g.*, *id.* at 5.

**f. Element 11[e]: wherein the characteristics identified by the characterizing unit are indexed in a table comprising operating parameters associated with one or more identifiable log characteristics.**

244. In my opinion, Petruzella and/or Petruzella in light of Ido discloses the limitations of claim element 11[e]. *See supra* § VII(B)(5).

### 12. Claim 12 Is Rendered Obvious

245. *Claim 12: The system of claim 11, the deep learning model being trainable*.

246. As noted above, Gagnon in view of Ido and Petruzella render obvious claim 11, from which claim 12 depends. *See supra* § VII(B)(11). In my opinion, Ido discloses the additional elements of claim 12. *See supra* §§ VII(B)(7)-(9).

### 13. Claim 13 Is Rendered Obvious

247. *Claim 13: The system of claim 12, the deep learning model being automatically trainable with the measured attributes of the undebarked log*.

248. As noted above, Gagnon in view of Ido and Petruzella render obvious claims 11 and 12, from which claim 13 depends. *See supra* § VII(B)(11). In my opinion, Ido discloses the additional elements of claim 13. *See supra* §§ VII(B)(8)-(9).

### 14. Claim 14 Is Rendered Obvious

249. *Claim 14: The system of claim 12, the deep learning model being manually trainable with sample logs having identifiable characteristics and with human intervention*.

250. As noted above, Gagnon in view of Ido and Petruzella render obvious claims 11 and 12, from which claim 14 depends. *See supra* §§ VII(B)(11), (12). In my opinion, Ido discloses the additional elements of claim 14. *See supra* §§ VII(B)(8)-(9). In this respect, the "human intervention" limitation recited in claim 14 is met for the same reasons that the "human validations" limitation in claim 9 is met. *See supra* § VII(B)(9).

### 15. Claim 15 Is Rendered Obvious

251. *Claim 15: The method* [sic] *of claim 11, the characterizing unit taking into account the intensity levels of the identified log characteristics when indexing the characteristics in the table*.

252. As noted above, Gagnon in view of Ido and Petruzella render obvious claim 11, from which claim 15 depends. *See supra* § VII(B)(11). In my opinion, Ido in light of Petruzella discloses the additional limitations of claim 15. *See supra* § VII(B)(6).

### 16. Claim 16 Is Rendered Obvious

253. *Claim 16: The system of claim 11, the system further comprising one or more light sources for illuminating the undebarked log when identified by the log measurement device*.

254. As noted above, Gagnon in view of Ido and Petruzella render obvious claim 11, from which claim 16 depends. *See supra* § VII(B)(11). In my opinion, Gagnon in light of Ido discloses the additional limitations of claim 16. Gagnon discloses the use of a light source at the output of the debarker to assist in obtaining intensity image data for logs that have been debarked. *See, e.g.*, Gagnon ¶¶ 44, 48. In my opinion, for the same reasons, a person of ordinary skill would be motivated to include a light source on the input side of the debarker machine where the sensors and scanning devices for Ido would be located for obtaining images for the deep learning, tree identification model.

### 17. Claim 17 Is Rendered Obvious

255. *Claim 17: The system of claim 11, the system further comprising external sensors identifying attributes external to the undebarked log, the attributes external to the undebarked log being used by the debarker optimizer*.

256. As noted above, Gagnon in view of Ido and Petruzella renders obvious claim 11, from which claim 17 depends. *See supra* § VII(B)(11). In my

opinion, Gagnon discloses the additional limitations of claim 17. *See supra* § VII(B)(8). In addition, Gagnon discloses the signals from the external sensors being input into the PLC component to be used by the processor component (i.e., the debarker optimizer) in the debarking process. *See, e.g.*, Gagnon ¶ 49, Fig. 7.

### 18. Claim 18 Is Rendered Obvious

257. *Claim 18: The system of claim 11, the log measurement device being any one or a combination of a line scanner, an area scan camera or an infrared camera*.

258. As noted above, Gagnon in view of Ido and Petruzella render obvious claim 11, from which claim 18 depends. *See supra* § VII(B)(11). Further, it is unclear what the limitation "the log measurement device" references because that term is not used in claim 11. In any event, Ido discloses the use of an area scan camera to obtain images of the undebarked trees and logs. *See* Ido, Fig. 1. In addition, Gagnon discloses the use of a line scanner as part of a "diameter and log length measurement device." *See, e.g.*, Gagnon ¶¶ 46, 49. Accordingly, to the extent this claim limitation can be understood, it is disclosed in both Ido and Gagnon.

### C. Ground 3: Gagnon in Light of Kambla and Petruzella Renders Obvious Claims 1-18

259. In my opinion, claims 1-18 are unpatentable under 35 U.S.C. § 103 as obvious under Gagnon in light of Kambla and Petruzella.

#### 1. Claim 1 Is Rendered Obvious

##### a. Element 1[pre]: A computer-implemented method for characterizing an undebarked log in real time, the method comprising

260. The preamble of claim 1 is not limiting. Nevertheless, in my opinion Gagnon discloses this limitation. *See supra* § VII(A)(1)(a).

##### b. Element 1[a]: performing a contactless characterization of the undebarked log;

261. In my opinion, Gagnon and Kambla, both alone and in combination, disclose the limitation from element 1[a]. *See supra* § VII(A)(1)(b).

262. *Motivation to Combine:* It is my opinion that a person of ordinary skill would be highly motivated to incorporate Kambla's deep-learning model, along with the associated contactless image capture devices, into the debarking system disclosed by Gagnon for the reasons described above. *See id.*

##### c. Element 1[b]: identifying characteristics of the undebarked log based on the characterization of the undebarked log using a trained deep learning model

263. In my opinion, Kambla discloses this limitation. *See supra* § VII(A)(1)(c).

264. *Motivation to Combine:* As explained above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Kambla's deep-model, along with the associated contactless image capture devices, into the debarking system disclosed by Gagnon. *See supra* § VII(A)(1)(b). The same motivation to combine discussed above with respect to element 1[a] also applies here. *See id.*

**d. Element 1[c]: computing operating parameters of a debarker based on the identified characteristics; and**

265. In my opinion, Gagnon in view of Kambla and Petruzella renders obvious this limitation.

266. As noted above, the combination of Gagnon and Kambla could identify the characteristics of a log to be processed by a debarking machine, in particular, the diameter and tree species of the log. *See supra* § VII(A)(1)(d). Gagnon further discloses using the diameter and tree species of a log to compute the operating characteristics of the debarker. *See, e.g.*, Gagnon ¶ 48.

267. As shown in Figure 7 of Gagnon, the input for the wood species and diameter information would be obtained by controller 67, which Gagnon discloses as being a PLC. *Id.* ¶ 49, Fig. 7. According to Petruzella, a PLC includes both a central processing unit that "consists of a microprocessor for implementing the logic and controlling the communications among the modules." Petruzella at 5

(Fig. 1-8). The PLC also includes a memory component "for storing user program instructions, numerical values, and I/O devices status." *Id.* Accordingly, Petruzella discloses to a person of ordinary skill that the PLC disclosed in Gagnon could receive the input values related to tree species and diameter, perform any necessary calculations regarding the output parameters using the PLC's processor component, and output those values to the debarker.

268. *Motivation to Combine:* I previously explained the motivation to incorporate the teachings of the PLC from Petruzella into the debarker system disclosed in Gagnon. *See supra* § VII(B)(1)(d).

**e. Element 1[d]: sending the computed operating parameters to the debarker;**

269. As noted above, it is my opinion that Gagnon discloses this limitation. *See supra* § VII(A)(1)(e).

**f. Element 1[e]: wherein the computation of the operating parameters further comprises retrieving operating parameters associated with the identified characteristics.**

270. As noted above, it is my opinion that Gagnon in light of Petruzella discloses this limitation. *See supra* § VII(B)(1)(f).

### 2. Claim 2 Is Rendered Obvious

271. *Claim 2: The method of claim 1, the characterization of the undebarked log using a scanning device*.

272. As noted above, Gagnon in view of Kambla and Petruzella render obvious claim 1, from which claim 2 depends. *See supra* § VII(C)(1). In my opinion, Kambla discloses the additional elements of claim 2. *See supra* § VII(A)(2).

273. *Motivation to Combine:* As discussed above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Kambla's deep-learning model, along with the associated scanning devices, into the debarking system disclosed by Gagnon. *See supra* § VII(A)(1)(b). It is further my opinion that a person of ordinary skill would expect to successfully make such a combination for the same reasons previously discussed. *Id.*

**3. Claim 3 Is Rendered Obvious**

274. *Claim 3: The method of claim 1, the characterization of the undebarked log using one or more sensors*.

275. As noted above, Gagnon in view of Kambla and Petruzella renders obvious claim 1, from which claim 3 depends. *See supra* § VII(C)(1). In my opinion, Kambla discloses the additional elements of claim 3. *See supra* § VII(A)(3).

276. *Motivation to Combine:* As discussed above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Kambla's deep-

learning model, along with the associated sensors, into the debarking system disclosed by Gagnon. *See supra* § VII(A)(1)(b). It is further my opinion that a person of ordinary skill would expect to successfully make such a combination for the same reasons previously discussed. *Id.*

#### 4. Claim 4 Is Rendered Obvious

277. *Claim 4: The method of claim 1, the identification of the characteristics of the log further comprising one or a combination of any of the followings [*sic*]: identifying the species of the log; measuring the moisture level of the log; and calculating an intensity of knot presence on the log*.

278. As explained above, it is my opinion that Gagnon in view of Kambla and Petruzella teaches, and therefore renders obvious, the limitations of claim 1, from which claim 4 depends. *See supra* § VII(C)(1). It is further my opinion that Kambla discloses the additional elements of claim 4. In particular, Kambla discloses identifying the species of the log. *See* Kambla ¶ 89.

279. *Motivation to Combine:* As explained above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Kambla's deep-learning model into the debarking system disclosed by Gagnon. *See supra* § VII(A)(1)(b).

### 5. Claim 5 Is Rendered Obvious

280. *Claim 5: The method of claim 1, the operating parameters being indexed in a table having operating parameters associated with one or more log characteristics.*

281. As noted above, Gagnon in view of Kambla and Petruzella render obvious claim 1, from which claim 5 depends. *See supra* § VII(C)(1). In my opinion, Petruzella discloses the additional limitations of claim 5. *See supra* § VII(B)(5).

### 6. Claim 6 Is Rendered Obvious

282. As noted above, Gagnon in view of Kambla and Petruzella render obvious claim 1, from which claim 6 eventually depends. *See supra* § VII(C)(1). In my opinion, Kambla in light of Petruzella discloses the additional limitations of claim 6.

#### a. Claim 6: The method of claim 5, the indexation of the log operating parameters taking into account the intensity level of the one or more log characteristics

283. As noted above, Kambla discloses the use of an array of image sensors to capture images of the bark on a tree or log. *See supra* § VII(A)(3). As part of the process of capturing images, the image sensors will capture various intensities of light. For example, an image sensor that captures a higher intensity of light will appear lighter as compared to a corresponding image sensor that

captured comparatively less light, which will appear relatively darker. The collection of intensities captured by the array of image sensors together are used to identify the characteristics of the log (e.g., the tree species) in the artificial intelligence system of Kambla. *See, e.g.*, Kambla ¶ 89. The identified characteristics of the log are associated with, and used to index, the operating parameters stored in an array such as that disclosed in Petruzella as explained in connection with claim 5. *See supra* § VII(B)(5).

284. As another example of intensity levels, a neural network classifier, like that of Kambla, is able to output probability values based on the different categories that an item is to be sorted into. *See, e.g.*, *id.* ¶ 89; *see also supra* §§ IV(B), VII(B)(6)(a). These probabilities would correspond to the tree species of an undebarked log and the intensity levels recited in claim 6. These intensity levels will be used when indexing the table because the neural network classifier will categorize the picture of the tree according to the highest probability across the six tree species. Thus, in this situation, the tree species with the highest probability will be used to index the table.

285. Accordingly, it is my opinion that Kambla discloses the intensity levels of the log characteristics being used to index the operating parameters as stored in a table such as shown in Petruzella.

**b. A Person of Ordinary Skill Would be Motivated to Combine the Deep Learning Features from Kambla and the Array Functionality Disclosed in Petruzella with the Debarker System Disclosed in Gagnon**

286. As noted in the preceding section, the use of intensity levels in Kambla are used as part of the artificial intelligence process for determining the characteristics of a log. In addition, as noted earlier, a person of ordinary skill would be motivated to incorporate this artificial intelligence functionality into the debarker system disclosed in Gagnon. *See supra* § VII(A)(1)(b).

287. In addition, as noted earlier, a person of ordinary skill would be motivated to incorporate the array disclosed in Petruzella into the debarker system disclosed in Gagnon. *See supra* § VII(B)(5)(b).

288. Finally, in my opinion, a person of ordinary skill would expect to successfully combine the artificial intelligence features of Kambla and the array functionality of Petruzella with the debarker system of Gagnon because each of these components (i.e., Kambla's artificial intelligence features and Petruzella's array functionality) is operating in its normal and expected manner.

**7. Claim 7 Is Rendered Obvious**

289. As noted above, Gagnon in view of Kambla and Petruzella render obvious claim 1, from which claim 7 depends. *See supra* § VII(C)(1). In my opinion, Kambla discloses the additional limitations of claim 7.

**a. Element 7[pre]: The method of claim 1, the trained deep learning model being trained comprising the steps of:**

290. As explained above, it is my opinion that Gagnon in combination with Kambla and Petruzella render obvious claim 1. *See supra* § VII(C)(1). It is further my opinion that Kambla further discloses training a deep learning model, including the steps recited in claim 7, as explained below.

**b. Element 7[a]: selecting a representative sample of a plurality of logs having identifiable characteristics;**

291. It is my opinion that Kambla discloses this limitation. *See supra* § VII(A)(5)(b).

**c. Element 7[b]: scanning the plurality of logs to obtain scan data of the logs;**

292. It is my opinion that Kambla discloses this limitation. *See supra* § VII(A)(5)(c).

**d. Element 7[c]: identifying with a deep learning algorithm software of the deep learning model the identifiable characteristics of the logs based on the scan data;**

293. It is my opinion that Kambla discloses this limitation. *See supra* § VII(A)(5)(d).

**e. Element 7[d]: analysing [*sic*] the identified characteristics of the logs to output an identification score; and**

294. It is my opinion that Kambla discloses this limitation. *See supra* § VII(A)(5)(e).

**f. Element 7[e]: considering the deep learning model trained if the identification score is different from a predetermined value.**

295. In my opinion, Kambla discloses this limitation. *See supra* § VII(A)(5)(f).

**g. A Person of Ordinary Skill Would be Motivated to Combine the Scanning Device of Ido with the Debarking System Disclosed in Gagnon**

296. As discussed above, it is my opinion that a person of ordinary skill would be highly motivated to incorporate Kambla's deep-learning models, along with the associated sensors, into the debarking system disclosed by Gagnon. *See supra* § VII(A)(1)(b). It is further my opinion that a person of ordinary skill would expect to successfully make such a combination for the same reasons previously discussed. *See id*.

**8. Claim 8 Is Rendered Obvious**

297. *Claim 8: The method of claim 7, the deep learning model being automatically trained by using the characterization of the undebarked log for the*

*analysis of the identified characteristics of the logs to output the identification score.*

298. As noted above, Gagnon in view of Kambla and Petruzella render obvious claims 1 and 7, from which claim 8 depends. *See supra* §§ VII(C)(1), (7). In my opinion, Kambla discloses the additional limitations of claim 8. *See supra* § VII(A)(6).

299. *Motivation to Combine:* In my opinion a person of ordinary skill would be motivated to combine the automatic training of the deep learning model in Kambla with the debarking system disclosed in Gagnon, for the same reasons discussed above. *See supra* § VII(A)(1)(b).

**9. Claim 9 Is Rendered Obvious**

300. *Claim 9: The method of claim 1, the deep learning model being manually trained with training data and human validations for the analysis of the identified characteristics of the logs to output an identification score.*

301. As noted above, Gagnon in view of Kambla and Petruzella render obvious claim 1, from which claim 9 depends. *See supra* § VII(C)(1). As discussed above in connection with claim limitation 7[d], Kambla also discloses the output of an identification score. *See supra* § VII(A)(5)(e). In my opinion,

Kambla further discloses the additional elements of claim 9. *See supra* § VII(A)(7).

302. *Motivation to Combine:* In my opinion, a person of ordinary skill would be motivated to incorporate the disclosure in Kambla regarding training into the debarking system of Gagnon for the reasons discussed above. *See supra* § VII(A)(7)(b).

**10. Claim 10 Is Rendered Obvious**

303. *Claim 10: The method of claim 1, the characterization of the undebarked log further comprising external data to the undebarked log.*

304. As noted above, Gagnon in view of Kambla and Petruzella render obvious claim 1, from which claim 10 depends. *See supra* § VII(C)(1). It is further my opinion that Gagnon discloses the additional limitations of claim 10. *See supra* § VII(A)(8).

**11. Claim 11 Is Rendered Obvious**

**a. Element 11[pre]: A system for characterizing an undebarked log in real time, the system comprising:**

305. The preamble of claim 11 is not limiting. Nevertheless, in my opinion, Gagnon discloses the material recited in the preamble. *See supra* § VII(A)(1)(a).

**b. Element 11[a]: a contactless log characterization sensor for identifying attributes of the undebarked log;**

306. In my opinion, Gagnon and Kambla, both alone and in combination, disclose the limitation from element 11[a]. *See supra* §§ VII(A)(1)(b), (C)(3). In my opinion, a person of ordinary skill in the art would interpret the term "attributes" to mean "a quality, character, or characteristic ascribed to someone or something." *See supra* § VII(B)(11)(b); *see also Attribute*, Merriam-Webster, https://www.merriam-webster.com/dictionary/attribute (last visited August 25, 2025). This definition is consistent with the usage of the term within the specification of the '947 patent. *See, e.g.*, '947 patent, 3:54-62. Under this interpretation, the "attributes" of claim 11 would correspond to the images of bark and/or log ends described with respect to claim limitation 1[a]. *See supra* § VII(A)(1)(b).

**c. Element 11[b]: a characterizing unit in communication with the contactless log characterization sensor, the characterizing unit comprising:**

307. In my opinion, Kambla discloses this limitation. *See supra* § VII(A)(1)(c). The components of the characterizing unit as disclosed in Kambla are discussed in the sections immediately below.

**(1) Element 11[b][i]: a deep learning model; and**

308. In my opinion, Kambla discloses this limitation. *See supra* § VII(A)(1)(c).

**(2) Element 11[b][ii]: a computerized device configured to identify characteristics of the undebarked log based on measured attributes of the undebarked log using the dep learning model;**

309. In my opinion, Kambla discloses this limitation. *See supra* § VII(A)(1)(c). Kambla's tree-species identification functionality is a deep learning model and would be implemented on a computerized device, such as the hand held device of Kambla, which together with the deep learning model would be the characterizing unit. *See id.*; Kambla ¶¶ 86, 89.

**d. Element 11[c]: a debarker optimizer in communication with the characterizing unit, the debarker optimizer being configured to compute operating parameters of a debarker based the characteristics identified by the characterizing unit; and**

310. In my opinion, the combination of Gagnon and Kambla, along Petruzella, discloses this limitation. *See supra* § VII(C)(1)(d). In my opinion, the processor component of the PLC disclosed in Gagnon and further explained in Petruzella corresponds to the debarker optimizer. *See, e.g.*, Gagnon ¶ 49, Fig. 79; *see also* Petruzella at 5-7 (Fig. 1-8). The processor component of the PLC

disclosed in Gagnon (i.e., the "debarker optimizer") would communicate with the computerized device that captures log images of Kambla (i.e., the "characterizing unit") via the link 72 of Gagnon. *See, e.g.*, Gagnon ¶ 49, Fig. 7; *see also* Petruzella at 5-7 (Fig. 1.8); *see also supra* § VII(B)(11)(j).

**e. Element 11[d]: a debarker controller in communication with the debarker optimizer and the debarker, the debarker controller being configured to control the debarker using the computed operating parameters from the debarker optimizer,**

311. In my opinion, the combination of Gagnon and Petruzella discloses this limitation. *See supra* § VII(B)(11)(e).

**f. Element 11[e]: wherein the characteristics identified by the characterizing unit are indexed in a table comprising operating parameters associated with one or more identifiable log characteristics.**

312. In my opinion, Petruzella discloses the limitations of claim element 11[e]. *See supra* § VII(B)(5).

### 12. Claim 12 Is Rendered Obvious

313. *Claim 12: The system of claim 11, the deep learning model being trainable*.

314. As noted above, Gagnon in view of Kambla and Petruzella render obvious claim 11, from which claim 12 depends. *See supra* § VII(C)(11). In my

opinion, Kambla discloses the additional elements of claim 12. *See supra* §§ VII(A)(5)-(7), (C)(7)-(9).

**13. Claim 13 Is Rendered Obvious**

315. *Claim 13: The system of claim 12, the deep learning model being automatically trainable with the measured attributes of the undebarked log*.

316. As noted above, Gagnon in view of Kambla and Petruzella render obvious claims 11 and 12, from which claim 13 depends. *See supra* §§ VII(C)(11)-(12). In my opinion, Kambla discloses the additional elements of claim 13. *See supra* §§ VII(A)(6), (C)(8).

**14. Claim 14 Is Rendered Obvious**

317. *Claim 14: The system of claim 12, the deep learning model being manually trainable with sample logs having identifiable characteristics and with human intervention*.

318. As noted above, Gagnon in view of Kambla and Petruzella render obvious claims 11 and 12, from which claim 14 depends. *See supra* §§ VII(C)(11)-(12). In my opinion, Kambla discloses the additional elements of claim 14. *See supra* §§ VII(A)(7), (C)(9). In this respect, the "human intervention" limitation recited in claim 14 is met for the same reasons that the "human validations" limitation in claim 9 is met. *See id.*

### 15. Claim 15 Is Rendered Obvious

319. *Claim 15: The method [*sic*] of claim 11, the characterizing unit taking into account the intensity levels of the identified log characteristics when indexing the characteristics in the table*.

320. As noted above, Gagnon in view of Kambla and Petruzella render obvious claim 11, from which claim 15 depends. *See supra* § VII(C)(11). In my opinion, Kambla in light of Petruzella discloses the additional limitations of claim 15. *See supra* §§ VII(B)(5), (C)(6).

### 16. Claim 16 Is Rendered Obvious

321. *Claim 16: The system of claim 11, the system further comprising one or more light sources for illuminating the undebarked log when identified by the log measurement device*.

322. As noted above, Gagnon in view of Kambla and Petruzella renders obvious claim 11, from which claim 15 depends. *See supra* § VII(C)(11). In my opinion, Gagnon in light of Kambla discloses the additional limitations of claim 16. Gagnon discloses the use of a light source at the output of the debarker to assist in obtaining intensity image data for logs that have been debarked. *See, e.g.*, Gagnon ¶ 48. In my opinion, for the same reasons, a person of ordinary skill would be motivated to include a light source on the input side of the debarker

machine where the sensors and scanning devices for Kambla would be located when incorporated into the system disclosed by Gagnon for obtaining images for the deep learning, tree identification model.

### 17. Claim 17 Is Rendered Obvious

323. *Claim 17: The system of claim 11, the system further comprising external sensors identifying attributes external to the undebarked log, the attributes external to the undebarked log being used by the debarker optimizer*.

324. As noted above, Gagnon in view of Kambla and Petruzella renders obvious claim 11, from which claim 17 depends. *See supra* § VII(C)(11). In my opinion, Gagnon discloses the additional limitations of claim 17. *See supra* § VII(A)(8). In addition, Gagnon discloses the signals from the external sensors being input into the PLC component to be used by the processor (i.e., the debarker optimizer) in the debarking process. *See, e.g.*, Gagnon ¶ 49, Fig. 7.

### 18. Claim 18 Is Rendered Obvious

325. *Claim 18: The system of claim 11, the log measurement device being any one or a combination of a line scanner, an area scan camera or an infrared camera*.

326. As noted above, Gagnon in view of Kambla and Petruzella render obvious claim 11, from which claim 18 depends. *See supra* § VII(C)(11). Further,

it is unclear what the limitation "the log measurement device" references because that term is not used in claim 11. In any event, Kambla discloses the use of an area scan camera to obtain images of the undebarked trees and logs. *See* Kambla ¶¶ 43, 50. In addition, Gagnon discloses the use of line scanner as part of a "diameter and log length measurement device." *See, e.g.*, Gagnon ¶¶ 46, 49. Accordingly, to the extent this claim limitation can be understood, it is disclosed in both Kambla and Gagnon.

### D. Ground 4: Claims 1-18 Are Not Patentable Under 35 U.S.C. § 101

327. In my opinion, the claims of the '947 patent cover an abstract idea and do not include any additional elements that transform the nature of the claim into something significantly more than a claim on that abstract idea.

#### 1. Claims 1-18 Cover Abstract Ideas

328. In my opinion, claims 1-18 cover the abstract idea of incorporating artificial intelligence capabilities into the existing, well-known process of debarking. As discussed below, the '947 patent does not change the nature of either artificial intelligence or the debarking process. Instead, the '947 patent merely applies a generic implementation of artificial intelligence to the field of debarking, in effect, using artificial intelligence to automate the process that

debarking operators had previously employed in obtaining characteristics of a log and using those characteristics to set the operating parameters for the debarker.

329. The '947 patent does not improve upon the artificial intelligence, deep-learning process, in my opinion. To the contrary, the specification notes "that any type of deep learning algorithm may be used with the method of the present invention and is not limited to one type only." *See* '947 patent, 8:19-22. In certain circumstances, the specification even relates that "more than one model of deep learning algorithms may be used" and "may be determined based on the received data from the scanning device." *Id.*, 8:22-25. The specification, though, leaves it to the practitioner to decide in what circumstances it would be preferable to use one deep learning model over another based on the received data. *See, e.g., id.*, 8:25-28.

330. Moreover, in my opinion, the description and claims related to training the deep learning model merely describe processes that are incidental to building a deep learning model in the first place. In fact, as noted in my background section, deep learning models are developed by training the models in various ways. *See supra* § IV(B). The '947 patent merely describes, at a very high level, various well-known ways for training a deep learning model. *See, e.g.*, *id.*, 3:35-53, 6:35-40. Thus, in my opinion, the '947 patent does not purport to

improve upon the training processes or procedures used to train a deep learning model. In fact, at one location, the specification discloses that the training process it describes "may both provide unexpectedly good ***or bad*** results." '947 patent, 7:58-60 (emphasis added).

331. According to the claims and the specification of the '947 patent, the deep learning component of the system is used by the data acquisition unit to "determine characteristics of the undebarked logs 1." *See, e.g.*, *id.*, 5:37-42. The "Field of the Invention" section further states that "[t]he present invention generally relates to the field of characterising an undebarked wooden log by deep learning AI [or artificial intelligence] models." *Id.*, 1:20-22.

332. This description of deep learning to determine characteristics of the undebarked logs is consistent with the disclosures elsewhere in the specification of the '947 patent. *See, e.g.*, *id.*, 3:35-53 (training deep learning model to detect characteristics of log); 6:23-31 (noting that "[t]he log scanning and deep learning model application software 110 is programmed to identify the characteristics of the conveyed log 1"). The claims are also consistent with this description in the specification, notably, limiting the use of artificial intelligence/deep learning to determine the characteristics of the log. *See, e.g.*, claims 1, 11. Accordingly, the specification applies a generic artificial intelligence/deep learning model to classify

logs to be processed by a debarker. Thus, in my opinion, the disclosures in the specification are not directed towards improving the operation of an artificial intelligence model.

333. The '947 patent does not improve upon the debarking process but instead, merely automates it. Throughout the specification, the '947 patent provides no more description than that certain characteristics of a log may have an impact on the operating parameters for the debarking process. For example, according to the '947 patent, optimizing the debarking process "requires detailed knowledge of the incoming material and knowledge of the control of the debarking devices in order to decrease fiber loss and remaining bark quantity." *Id.*, 1:57-60. The specification further describes that "[t]raditionally, human judgement was the only way to adjust the settings of debarkers." *Id.*, 2:47-48. Far from teaching a new or unexpected setting for debarkers, the alleged improvement described in the '947 patent is focused on "providing ***an efficient log characterization method*** upstream from the debarking system ***that may allow automatic adjustment*** of the debarker." *See id.*, 3:7-10 (emphasis added). Notably, the '947 patent discloses that "[t]he optimal debarking parameters 150 may be ***any parameters*** of a debarking apparatus ***known in the art*** . . . ." *See id.*, 7:18-20 (emphasis added).

Accordingly, in my opinion, nowhere does the '947 patent describe anything other than using a debarking machine in the ordinary and expected manner.

334. Similarly, the '947 patent does not describe any improvement to the general operation of a computer used in the disclosed system. In fact, the detailed description makes only one mention of a computer, noting that "[t]he system further comprises a data acquisition unit 5, typically embodied as a computerized device 5" that may include a CPU, and storage and network units. *Id.*, 5:4-8. Moreover, in the system claims, the "computerized device" merely functions to identify characteristics of the undebarked log based on measured attributes. *Id.*, claim 11. Further, the "debarker optimizer" also merely functions to compute operating parameters for the debarker based on the identified characteristics of the log. *Id.* Thus, the claims do not recite and are not directed towards any specific improvement in the operation of the computerized device or the debarker optimizer. Instead, in my opinion, the computerized device and debarker optimizer, as recited in the claims, function as any normal computerized device would function.

335. Furthermore, the use of a table recited in independent claim 11 merely describes an abstract process of storing and organizing data. Claim 11 includes the limitation of "wherein the characteristics identified by the characterizing unit are

indexed in a table comprising operating parameters associated with one or more identifiable log characteristics." *Id.*, claim 11. This claim, however, fails to specify any particular structure for such a table, and the specification does not elaborate. *Id.*; *see, e.g.*, *id.*, 3:30-32, 4:9-14, 5:43-46, 6:66-7:2. Even if it did, such structure would specify nothing more than a way for storing data. In fact, this type of structure would not change the character of the information stored in the table. Instead, the character of the input data (i.e., characteristics of the log) and the output data (i.e., operating parameters) would remain the same in the table described in the '947 patent. *See, e.g.*, *id.*, 3:30-32, 4:9-14, 5:43-46, 6:66-7:2.

336. In addition, the '947 patent specification and/or claims do not specify any type of relationship or association between the input data and the output data as part of the table. Instead, the specification merely provides the following description on this point:

> The system **10** may further comprise a parameter index or table. Such table generally comprises specific operating parameters of the debarker associated with a range of characteristics of the log. The operating parameters of the debarker may comprise, but are not limited to, conveying speed, rotational speed, level of pressure to be applied by the tools on the outer surface of the undebarked log, tool aperture size, etc. The measured

> characteristics of the undebarked logs **1** may comprise, but are not limited to, surface temperature of the log **1**, species of the wood, humidity level and special features, such as knots, kink or protuberances, presence/absence of moisture or of blue stain, diameter or shape of the log.

*Id.*, 5:43-55. All this description does is provide a non-exhaustive list of operating parameters in one sentence and a non-exhaustive list of log characteristics in the next without specifying any relationship or association between any specific operating parameter and any particular characteristic. Accordingly, in my opinion, any relationships or associations specified in the table would be based on known relationships in the debarking process.

337. The ’947 patent, in effect, discloses the uses of an already available technology in deep-learning, with its already available basic functions, as a tool in implementing the debarking process. The ’947 patent and its claims do not improve on this process. Instead, the ’947 patent merely seeks to automate a process using artificial intelligence that humans previously performed. For this reason, it is my opinion that the claims of the ’947 patent are directed towards an abstract idea.

### 2. Claims 1-18 Do Not Include Additional Elements that Transform the Nature of Claim into Something Significantly More than a Claim on the Abstract Idea

338. In my opinion, none of the claims in the ’947 patent include any additional element or collection of elements that transforms the claim into something significantly more than a claim covering the abstract idea, as discussed below.

339. Claim 1 recites a method that includes the steps of (i) performing a characterization of an undebarked log; (ii) using a deep learning model to identify characteristics of that log; (iii) computing operating parameters for a debarker; and (iv) sending those parameters to the debarker. *See id.*, claim 1. Nothing within this claim, either individually or in combination, takes it out of the abstract idea of obtaining characteristics of a log that are used to set the operating parameters for a debarker.

340. The claim also recites the limitation of “the computation of operating parameters further comprises retrieving operating parameters associated with the identified characteristics.” *Id.* In my opinion, however, this limitation merely recites a basic characteristic and functionality of a computer. Indeed, regardless of how the operating parameters are determined – whether they are calculated through an equation or obtained from a look-up table – the computer device will at some

point need to ***retrieve*** those parameters from a memory location before sending them to the debarker. In the calculation scenario, for example, once the operating parameters are determined, any computer system will store those determined parameters in a memory location, where they will then be retrieved by the computer system before sending those parameters to the debarker. Accordingly, in my opinion, there will always be a "retrieval" step of the operating parameters from computer memory before the computer sends those parameters to the debarker as part of the normal operation of a computer. Because this claim limitation recites no more than the inherent functionality of a computer, in my opinion, it does not serve to transform the claim into something significantly more.

341. Claim 11, likewise, fails to recite something significantly more to transform the nature of the claim. Claim 11 recites a system that includes (i) a contactless sensor; (ii) a characterizing unit that includes "a deep learning model" and a computerized device "configured to identify characteristics of the undebarked log"; (iii) a debarker optimizer "configured to compute operating parameters of a debarker based" on the identified characteristics; and (iv) a debarker controller configured to "control the debarker using the computed operating parameters." *See id.*, claim 11. Stripped of its debarker-centric terminology, however, this claim recites no more than a system that includes

generic sensors that feed data into a generic deep learning module implemented on a generic computer to discern characteristics of a log, those characteristics then being used by the computer to determine operating parameters that are sent to control the debarker. In my opinion, none of these elements takes the claim outside the realm of covering the abstract idea.

342. The last limitation of claim 11 recites that "the characteristics identified by the characterizing unit are indexed in a table comprising operating parameters associated with one or more identifiable log characteristics." *See id.* However, using a table to make associations between input values and output values is nothing new. *See, e.g.*, Petruzella at 343, Fig. 15-25. This concept is nothing different than the ubiquitous "Popcorn" functionality on microwave ovens that receives as input from a sensor that a bag of popcorn was in the microwave and then looks-up, likely from a table, the operating parameter specifying the amount of time to run the microwave. Similarly, in the case of claim 11, the debarker receives as input some characteristic regarding the log (e.g., diameter) and then looks up from the table some operating parameter for the debarker (e.g., pressure for the knife arms). Indeed, this limitation does not even specify the type of association between the operating parameters and log characteristics. *See* '947 patent, claim 11. Although the requirement of using the table may restrict the type

of technology the claim covers, in my opinion, this process does not take it outside the realm of claiming an abstract idea.

### 3. Dependent Claims

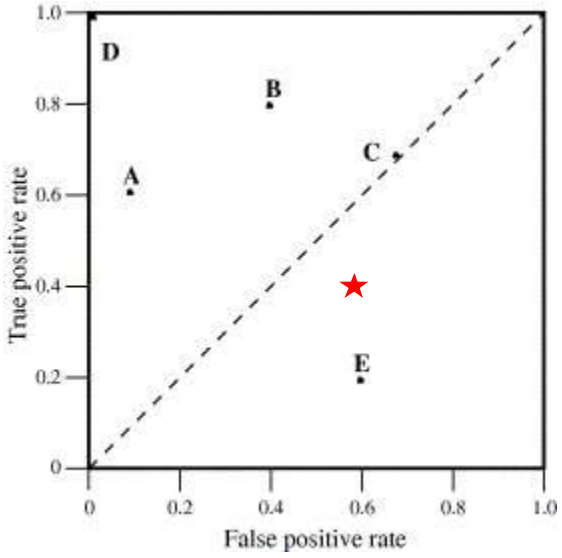
343. In my opinion, the dependent claims do not rescue the claims from reciting abstract ideas. For example, dependent claims 7, 8, 9, 12, 13, and 14 merely recite common methodologies for developing a deep learning model through training. However, training is an inherent part of developing a deep learning model, and reciting well-known techniques in a normal and expected way does not make the claims less abstract. Dependent claims 2, 3, 16, and 18 recite generic types of sensors or light sources to be used when capturing data in the normal and expected way. However, the recitation of generic types of sensors or light sources does not make the claims less abstract. Dependent claims 4, 5, 6, 10, 15, and 17 are directed towards the use of additional sensors or limit the types of data to be input into the claimed system. However, specifying the type of data captured by the system or the sensors used to capture the data is simply pre-solution activity that does not make the claims less abstract. None of these claim limitations, though, take the claims outside the realm of covering an abstract idea nor do they provide the "something significantly more" that is needed to transform these claim.

### E. Ground 5: Claims 7 and 8 Are Indefinite Under 35 U.S.C. § 112

344. It is my opinion that claims 7 and 8 do not reasonably inform a person of ordinary skill regarding the scope of these claims. In particular, claim 7 recites the term "predetermined value" but provides no guidance on what that predetermined value should be. *See* '947 patent, claim 7. Moreover, the specification fails to provide any guidance on what the predetermined value should be to consider a model to be trained. In fact, the extent of the disclosure in the specification regarding predetermined value is that the model is "created" if "the performances are equal or above a predetermined level," whereas the model is trained with "different parameters" if the "performances are under the predetermined level." *Id.*, 7:34-40; *see* 3:43-45. Notably, the specification differs from the claim in that the specification discloses that the performance be equal to or above the predetermined level for the system to be considered trained, *see id.*, 7:34-40, whereas claim 7 recites that the identification score must be "different" from the predetermined value.

345. As noted in my background section, a person of ordinary skill could use different metrics to determine if a deep learning model is sufficiently trained. *See supra* § IV(B). For example, a person of ordinary skill could use metrics related to accuracy, to true positive rates, and/or to false positive rates, or a

combination of any two or more of these metrics, to judge whether the model is sufficiently trained. Moreover, each of these metrics can arrive at different results as to whether they are met, as shown by the following diagram:




Fawcett, *supra* ¶ 46, at 862 (Fig. 2). As seen in the above diagram, a user employing an accuracy metric at point E may consider model results depicted by the star to be satisfactory but a user employing a metric at point A may not. In this scenario, the user employing the point E metric may infringe whereas the user employing the point A metric may not, even though they implemented and trained the same deep learning model. Accordingly, the lack of guidance in the '947 patent regarding the metric to use may result in different infringement results for users of the same system based on the user's subjective determination of what an acceptable "predetermined value" may be.

346. Because a practitioner can use different metrics to determine if a model is adequately trained, because the use of different metrics may result in different results regarding whether claim 7 is satisfied, and because the claims and the specification provide no guidance on the correct metric to use, it is my opinion that claim 7 fails to inform with reasonable certainty a person of ordinary skill in the art about the scope of the invention.

347. Moreover, it is my opinion that claim 8 also fails to inform with reasonable certainty a person of ordinary skill in the art about the scope of the invention because it depends from claim 7.

## VIII. CONCLUSION

348. For the reasons set forth above, I believe that Claims 1-18 of the '947 Patent are unpatentable.

349. I reserve the right to supplement my opinions in the future to respond to any arguments the Patent Owner raises and to take into account new information as it becomes available to me.

//

I declare under penalty of perjury under the laws of the United States of America that the foregoing is true and correct.

Dated August 29, 2025.

Respectfully submitted,



Michael J. Pazzani, Ph.D.

# EXHIBIT A

# Michael J. Pazzani

21 Voyage St., Unit B, Marina Del Rey, CA 90292• 703-798-9797 • pazzani@gmail.com

## Career Summary

Recognized leader in artificial intelligence, machine learning and recommendation systems technology with accomplishments in academic, commercial and government R&D.

Department Head of Information and Computer Science leading growth in education and research programs.

Senior Research Official overseeing development of research collaborations, federal funding, corporate relations and technology commercialization.

Innovator who led a personalization company for mobile devices from initial concept to revenue.

Expert witness for plaintiff or defendant on validity and infringement on patents involve machine learning, personalization, recommendation systems, artificial intelligence, neural nets & deep learning.

## Education

| | |
|---|---|
| University of California, Los Angeles. **Ph.D. Computer Science** | 1988 |
| University of Connecticut. **M.S. Computer Engineering** | 1981 |
| University of Connecticut. **B.S. Computer Engineering** | 1980 |

## Experience

- Information Sciences Institute, University of Southern California, Los Angeles CA Research Scientist (2021-2024) Affiliated Scientist (2024-Present)
- Halıcıoğlu Data Science Institute, University of California, San Diego, CA
  Distinguished Scientist (2019-2022)
- University of California, Riverside, Riverside, CA 2012-2019
  Vice Chancellor for Research and Economic Development and Professor of Computer Science and Engineering, Statistics & Psychology (2012-2019) Emeritus Professor (2019-Present)
  - Oversight of research and technology commercialization
  - Increased new federal grants from $68M to $131M
  - Conduct research on Deep Learning and Explainable Artificial Intelligence
- Rutgers, The State University of New Jersey, New Brunswick, NJ 2005-2012
  Vice President of Research and Economic Development & Distinguished Professor of Computer Science (2006-2012)
  - Oversight of research and technology commercialization
  - Increased federal grants from $129M to $271M
  - Managed Technology Commercialization Office, increasing royalties by 80%
  - Conducted research on transfer learning and computational advertising
- National Science Foundation, Arlington, VA2002-2006
  Director, Information and Intelligent Systems
  - Managed budget of approximately $250M to support basic research in artificial intelligence, data science, machine learning, robotics, internet search, computer vision, and human-computer interaction
  - Coordinated research program with Library of Congress and National Institutes of Health
- AdaptiveInfo, Irvine, CA 2000-2001
  CEO and co-founder
  - Innovated personalization methods for wireless web. Customers included Los Angeles Times, Sprint and San Diego Union Tribune. Sold to Versifi in 2001.



Nicholson Manufacturing Ltd.
EX-1002, Page 166

- University of California, Irvine, Irvine, CA 1988-2005
  Chair, Information and Computer Science 1995-2000
  Professor, Information and Computer Science 1988-2005
  - Conducted research on machine learning, personalization, internet search, recommendation systems, time series analysis, cognitive science, mobile devices and usability, medical informatics
  - Increased Corporate Support from $0.6M to $6M and federal funds from $2M to $6M
- Aerospace Corporation, El Segundo, CA 1984-1988
  Member of the Technical Staff
  - Developed artificial intelligence systems to diagnose satellite anomalies
- Mitre Corporation, Bedford, M A 1980-1984
  Member of the Technical Staff 1980-1983 & Artificial Intelligence, Group Leader 1983-1984
  - Developed artificial intelligence and natural language processing systems

## Honors

AAAI Classic Paper Award recognized in 2014 for paper published in 1996 "*for significant contributions to the field of personalizing Internet content and learning user profiles".*

Fellow of Association for the Advancement of Artificial Intelligence in 2003 *"for significant contributions to the development and understanding of machine learning algorithms and their relationship to human learning".*

## Board and Community Service

- Defense Science Board 2019-2021
  Member: Provide the Secretary of Defense, with, independent advice and recommendations on scientific, technical, manufacturing, acquisition process, and other matters of special interest to the Department of Defense.
- Corporation for Education Network Initiatives in California (CENIC)2013-2019
  Member, Board of Directors: CENIC advances education and research statewide by providing a world-class network essential for innovation.
- Science, Technology, and Research Board, California Technology Council 2016-2019
  Board Member. commercialization and to building scalable industry partnerships,
- Riverside ExCITE, Riverside, CA 2014-2016
  Member, Board of Directors An incubator in partnership with business, government and UCR.
- Council on Competitiveness: Technology Leadership & Strategy Initiative 2014-2019
  Member
- ACM International Conference on Intelligent User Interfaces, Palo Alto, CA 2011
  Co-Chair
- New Jersey Research & Education Network (NJEDGE) 2010-2012
  Member, Board of Directors
- NJEDGE provides collaborative resources and networked services in support of education and research.
- Commercialization Center for Innovative Technologies (CCIT) 2008-2012
  Member, Board of Directors life science and technology incubator for NJ entrepreneurs.
- National Library of Medicine, Bethesda, MD 2003-2005
  Board of Regents
- CombiChem, Inc, (NASDAQ: CCHM), San Diego, CA 1998-1999
  Member, Board of Directors. CombiChem was a leader in computational drug design that was purchased by Dupont in 1999.



Nicholson Manufacturing Ltd.
EX-1002, Page 167

## Expert Witness Experience

- Tucker v. Apple. (3:25-cv-05197)
- FRIENDLIAI INC., v HUGGING FACE, INC., (C.A. No. 23-816-MN )
- Open Text Corporation et al v. Hyland Software, Inc. (8:2022cv01638)
- Masterobjects Inc. v. Facebook Inc. (6:20-cv-00087)
- Masterobjects Inc. v. Amazon Com Inc. (1:20-cv-03478)
- Sisvel International S.A., through Italian subsidiary S.I.Sv.El. Societa' Italiana Per Lo Sviluppo Dell'Elettronica S.p.A. (Sisvel Italy), vs Rakuten (Rakuten Kobo) (1:18-cv-00068), Rhapsody (1:18-cv-00069), and Spotify (1:18-cv-00070
- LOOKSMART GROUP, INC v. MICROSOFT CORP. C.A. NO. 17-cv-04709-JST
- Space Data Corporation v. Alphabet Inc., Google LLC, and Loon LLC, 5:16-cv-03260
- ROVI SOLUTIONS CORPORATION & UNITED VIDEO PROPERTIES, INC. vs. VIRGIN MEDIA LIMITED ,VIRGIN MEDIA PAYMENTS LIMITED & TiVo. Claim No. HC12 D01783
- PERSONALIZED USER MODEL, LLP.,v. GOOGLE, INC.,C.A. No. 09-525 (JJF)
- IBM v Amazon No. 6:06-cv-452:
- Pinpoint v. Amazon (N.D. Ill. December 6, 2004) (No. 03 C 4954)

Nicholson Manufacturing Ltd.
EX-1002, Page 169

## Most Important Publications (h-index 70- 43,000 citations)

Fan, R., Alipour, K., Bowd, C., Christopher, M., Brye, N., Proudfoot, J.A., Goldbaum, M.H., Belghith, A., Girkin, C.A., Fazio, M.A., Liebmann, J.M., . Weinreb, R., Pazzani, M., Kriegman, D., and Zangwill, L. (2023). Detecting Glaucoma from Fundus Photographs Using Deep Learning without Convolutions: Transformer for Improved Generalization. Ophthalmology Science, 3(1), p.100233.

Pazzani, M., Soltani, S, Kauffman, R., Qian, S. Hsiao, A. (2022) Expert-Informed, User-Centric Explanations for Machine Learning, Proceedings of the AAAI Conference on Artificial Intelligence.

Daniel Billsus, and Michael J. Pazzani (2007). Adaptive News Access, in "The Adaptive Web: Methods and Strategies of Web Personalization" (Springer, LNCS #4321), February 2007

Michael J. Pazzani and Daniel Billsus, (2007).Content-based Recommendation Systems,. in "The Adaptive Web: Methods and Strategies of Web Personalization" (Springer, LNCS #4321), February, 2007

Hettich, S & Pazzani M (2006). Mining for Proposal Reviewers: Lessons Learned at the National Science Foundation. The Twelfth Annual SIGKDD International Conference on Knowledge Discovery and Data Mining. Philadelphia.

Keogh, E., Chakrabarti, K., Pazzani, M. & Mehrotra (2001). Locally adaptive dimensionality reduction for indexing large time series databases. SIGMOD 2001. Best paper award.

Bay, S.D., Pazzani, M.J. Detecting Group Differences: Mining Contrast Sets. Data Mining and Knowledge Discovery 5, 213–246 (2001). https://doi.org/10.1023/A:1011429418057

Pazzani, M. (2000). Knowledge discovery from data? IEEE Intelligent Systems 15(2): 10-13 (2000)

Pazzani, M. (1999). A Framework for Collaborative, Content-Based and Demographic Filtering. Artificial Intelligence Review. 13(5-6): 393-408

Domingos, P. & Pazzani, M. (1997). Beyond Independence: Conditions for the Optimality of the Simple Bayesian Classifier. Machine Learning. 29, 103-130.

Pazzani M. & Billsus, D. (1997). Learning and Revising User Profiles: The identification of interesting web sites. Machine Learning 27, 313-331.

Pazzani, M., Muramatsu J. & Billsus, D. (1996). Syskill & Webert: Identifying interesting web sites. Proceedings of the National Conference on Artificial Intelligence, Portland, OR.

Murphy, P. & Pazzani, M. (1994). Exploring the decision forest: An empirical investigation of OCCAM's razor in decision tree induction. Journal of Artificial Intelligence, 1, 257-275.

Pazzani, M. & Kibler, D. (1992). The role of prior knowledge in inductive learning. Machine Learning, 9, 54-97.

Pazzani, M. (1991). The influence of prior knowledge on concept acquisition: Experimental and computational results. Journal of Experimental Psychology: Learning, Memory & Cognition, 17, 3, 416-432.



Nicholson Manufacturing Ltd.
EX-1002, Page 170

Pazzani, M. (1991). A computational theory of learning causal relationships. Cognitive Science, 15, 401-424.



Nicholson Manufacturing Ltd.
EX-1002, Page 171

## Grants

Research Initiation: Induction of Causal Theories. National Science Foundation. July 15, 1989 - December 31, 1991. $69,981.

*Using Domain Knowledge to Influence Similarity Judgments*. Science Applications International Corporation, McLean, VA 22102. April 1, 1990 - Sept 30, 1993. $154,000.

*Machine Learning Techniques for Modification and Maintenance of Expert System Knowledge Bases.* NYNEX: 8/92 - 7/94. $50,000.

Long and Medium-Term Research: Information-based Approaches to Learning Relational Concepts. National Science Foundation, 9/92 - 11/93. $9550.

A Combined Analytic and Inductive Approach to Learning in Knowledge-Based Systems. AFOSR and ARPA, 9/30/92- 9/29/95. $378,468.

*Research in Machine Learning:* Nippon Telephone and Telegraph. 6/93 - 7/94. $22,500.

*Minimizing misclassification costs:* NYNEX 8/93 - 7/94. $25,000.

Issues in Scaling up Machine Learning. AFOSR, 9/93 - 8/96. $129,863

Learning Probabilistic Relational Concepts. National Science Foundation, 1994-1997. $185,000.

*Knowledge discovery in economic and political databases*: Evidence Based Research, Arlington, VA 1994 - 1995. $75,000.

Approximate Methods for Inference and Learning in Belief Networks. 1996 - 1997. AFOSR. $138,454.

A Distributed Biomedical Computing Laboratory, National Science Foundation, 1997-1998. $149,917 (PI: Lubimor Bic).

Graduate Fellowships in Biomedical Computing, Department of Education, 1997-2000. $731,790 (PI: Lubimor Bic)

Knowledge Discovery in Problem Reports, TouchStone, 1997-1998. $21,905.

From Computer Data to Human Knowledge: A Cognitive Approach to Knowledge Discovery and Data Mining, National Science Foundation, 1998-2001. $240,000.

Graduate Assistance in Areas of National Need - UCI - ICS, Department of Education, 1998-2001. $734,365.

An Online Repository of Large Data Sets for Data Mining Research and Experimentation, National Science Foundation, 1998-2000. $99,737. (PI: Padhraic Smyth)

Adaptive Navigation in Information Space, Daimler Chrysler, 1998-1999. $31,069.

Adaptive Navigation in Information Space, Daimler Chrysler, 1999-2000. $26,000.

Organization and Navigation of Digital Documents, FileNET, 1999-2000. $119,176



Nicholson Manufacturing Ltd.
EX-1002, Page 172

*Intelligent Agents:* Mitsubishi Electronics Corp. $40,000 (1999)

*Machine Learning*: Hughes Research Laboratory. $10,000 (1999)

*Mobile Personalization*, Qualcomm, equipment donation (1999).

*Text Classification*: Websense. 20,000 (2000).

*E-commerce:* The Irvine Company, $10,000 (2000).

Transfer Learning, DARPA, $225,000. 2006-2009

NJ-NANO: New Jersey Commission on Science and Technology: $500K: 2006-2007

"Partnerships for Innovation" program to explore the use of agricultural materials in medical devices, food packaging, and fragrance delivery. NSF, $600K (PI: K. Kohn): 2007-2009

Technology Commercialization Fund: New Jersey Commission on Science and Technology: $500K: 2007-2008

NSF: Institutionalizing the IGERT Innovations at Rutgers, 2009-4014 $1.25M (PI: P Furmanski)

Johnson & Johnson: Life Sciences Technology Commercialization $350,000 (2008-10)

CC*IIE Networking Infrastructure: University of California Riverside's Science DMZ. National Science Foundation. $500,000. 2014-2015

Citrus Partnership. Eurosemillas, $1.25M. 2015-2020.

Citrus Research Equipment at the University of California, Riverside, Economic Development Administration $500,000 2017-18

Explainable Learning, DARPA via NAVAL RESEARCH LABORATORY $720,000 2017-2021

Mobility Hub and Central Campus Neighborhood Improvements. Federal Transit Administration $4.4M 2017-2020

Life Science Incubator for University of California, Riverside. Economic Development Administration $2.5M 2019-2021

*RAPID: Explainable Machine Learning for Analysis of COVID-19 Chest CT* NATIONAL SCIENCE FOUNDATION, $ 120,243.00, 2020-2021



Nicholson Manufacturing Ltd.
EX-1002, Page 173

# Complete Publication List

**Books**

1. Pazzani, M. (1990). Creating a memory of causal relationships: An integration of empirical and explanation-based learning methods. Hillsdale, NJ: Lawrence Erlbaum Associates.

**Edited Books**

1. Fisher, D., Pazzani, M. & Langley, P. (1991). Concept formation: Knowledge and experience in unsupervised learning. San Mateo, CA: Morgan Kaufmann.

**Journal Articles**

1. Cullingford, R. & Pazzani, M. (1984). Word-meaning selection in multiprocess language understanding programs. IEEE Transactions on Pattern Analysis and Machine Intelligence, 6,4, 493-509.

2. Pazzani, M. (1987). Explanation-based learning for knowledge-based systems. International Journal of Man-Machine Studies, 26, 413-433.

3. Pazzani, M. (1987). Failure-driven learning of fault diagnosis heuristics. IEEE Transactions on Systems, Man and Cybernetics: Special issue on Causal and Strategic Aspects of Diagnostic Reasoning, 17, 3, 380-394.

4. Pazzani, M. (1990). Learning in order to avoid search in logic programming. Computers and Mathematics with Applications, 2, 10, 101-110.

5. Pazzani M. & Dyer, M. (1990). Memory organization and explanation-based learning. International Journal of Expert Systems, 2, 3, 331-358.

6. Pazzani, M. (1991). A computational theory of learning causal relationships. Cognitive Science, 15, 401-424.

7. Pazzani, M. (1991). Learning to predict and explain: An integration of similarity-based, theory-driven and explanation-based learning. Journal of the Learning Sciences, 1, 2, 153-199.

8. Pazzani, M. (1991). The influence of prior knowledge on concept acquisition: Experimental and computational results. Journal of Experimental Psychology: Learning, Memory & Cognition, 17, 3, 416-432.

9. Pazzani, M. & Brunk, C. (1991). Detecting and correcting errors in rule-based expert systems: an integration of empirical and explanation-based learning. Knowledge Acquisition, 3, 157-173.

10. Pazzani, M. & Kibler, D. (1992). The role of prior knowledge in inductive learning. Machine Learning, 9, 54-97.

11. Pazzani, M. & Sarrett, W. (1992). A framework for average case analysis of conjunctive learning algorithms. Machine Learning, 9, 349-372.

12. Pazzani, M. (1993). Learning causal patterns: Making a transition from data-driven to theory-driven learning. Machine Learning, 11, 173-194.



Nicholson Manufacturing Ltd.
EX-1002, Page 174

13. Murphy, P. & Pazzani, M. (1994). Exploring the decision forest: An empirical investigation of OCCAM's razor in decision tree induction. Journal of Artificial Intelligence, 1, 257-275.

14. Ali K. & Pazzani M. (1995). HYDRA-MM: Learning Multiple Descriptions to Improve Classification Accuracy. International Journal on Artificial Intelligence Tools, 4.

15. Ali K. & Pazzani M. (1996). Error Reduction through Learning Multiple Descriptions Machine Learning, 24:3.

16. Merz, C. Pazzani, M & Danyluk, A. (1996). Tuning Numeric Parameters to troubleshoot a telephone network. IEEE Expert, Feb 1996, pg. 44-49.

17. Shankle, W.R., Datta, P., Dillencourt, M. & Pazzani, M. (1996). Improving Dementia Screening Tests with Machine Learning Methods. Alzheimer's Research. 2(3).

18. Pazzani, M., See, D., Shroeder, E. & Tilles, J. (1997). Application of an Expert System in the Management of HIV-infected patients. Journal of AIDS and Human Retrovirology. 15:356-362.

19. Pazzani M. & Billsus, D. (1997). Learning and Revising User Profiles: The identification of interesting web sites. Machine Learning 27, 313-331.

20. Domingos, P. & Pazzani, M. (1997). Beyond Independence: Conditions for the Optimality of the Simple Bayesian Classifier. Machine Learning. 29, 103-130.

21. Mani, S., Shankle, R., Dick, M & Pazzani, M. (1999). Two-Stage Machine Learning Model for Guideline Development. Artificial Intelligence in Medicine. 16, 51-80.

22. Merz, C. & Pazzani, M. (1999). A Principal Components Approach to Combining Regression Estimates Machine Learning. 36, 9-32.

23. Lathrop, R. & Pazzani, M. (1999). Combinatorial Optimization in Rapidly Mutating Drug-Resistant Viruses. Journal of Combinatorial Optimization. 3, 301-320.

24. Keogh, E., Chakrabarti, K., Pazzani, M. & Mehrotra, S (2000) Dimensionality Reduction for Fast Similarity Search in Large Time Series Databases. Knowledge and Information Systems 3(3): 263-286.

25. Pazzani, M. (1999). A Framework for Collaborative, Content-Based and Demographic Filtering. Artificial Intelligence Review. 13(5-6): 393-408

26. Pazzani, M. (2000). Learning with Globally Predictive Tests. New Generation Computing 18(1): 28-38

27. Pazzani, M. (2000). Knowledge discovery from data? IEEE Intelligent Systems 15(2): 10-13 (2000)

28. Billsus, D. & Pazzani, M. (2000). User Modeling for Adaptive News Access. User Modeling and User-Adapted Interaction. 10:2/3. 147-180

29. M. J. Pazzani, S. Mani, W. R. Shankle (2001). Acceptance of Rules Generated by Machine Learning among Medical Experts. Methods of Information in Medicine; 40: 380-385.



Nicholson Manufacturing Ltd.
EX-1002, Page 175

30. G. Webb, Michael J. Pazzani, Daniel Billsus, (2001).Machine learning for user modeling. User Modeling and User-Adapted Interaction 11: 19-20, 2001

31. Bay, S. D. & Pazzani, M. J. (2001). Detecting Group Differences: Mining Contrast Sets. Data Mining and Knowledge Discovery.

32. Daniel Billsus, Clifford A. Brunk, Craig Evans, Brian Gladish & Michael Pazzani (2002) Adaptive Interfaces for Ubiquitous Web Access, CACM p 34-38.

33. Pazzani, M. & Billsus, D. (2002). Adaptive Web Site Agents. Journal of Agents and Multiagent systems,5(2) 205-218

34. Keogh, E., Chakrabarti, K., Mehrotra S. & Pazzani, M (2002). Locally adaptive dimensionality reduction for indexing large time series databases. ACM Transactions on Database Systems, June 2002

35. Keogh, E. & Pazzani, M. (2002). Learning the Structure of Augmented Bayesian Classifiers. Vol. 11, No. 4 (2002) 587-601

36. Miyahara, K. & Pazzani, M. J. (2002). Improvement of Collaborative Filtering with the Simple Bayesian Classifier. IPSJ Journal, Vol.43, No.11, Information Processing Society of Japan, November, 2002

37. Rawassizadeh R; Tomitsch M; Nourizadeh M; Momeni, E; Peery, A Ulanova, L. & Pazzani, M (2015). Energy-Efficient Integration of Continuous Context Sensing and Prediction into Smartwatches. . *Sensors*, 22616-22645.

38. Rawassizadeh, R., Momeni, E., Dobbins, C., Gharibshah, J. Pazzani, M. (2016) Scalable Mining of Daily Behavioral Patterns from Multivariate Temporal Data. In IEEE Transactions on Knowledge and Data Engineering. 28(11), 3098-3112.

39. Rawassizadeh, R., Sen, T., Kim, S.J. Meurisch, C. Keshavarz,H. Mühlhäuser, M. & Pazzani, M.. Manifestation of virtual assistants and robots into daily life: Vision and challenges. CCF Trans. Pervasive Comp. Interact. (2019) 1: 163-174.

40. Rawassizadeh, R., Dobbins, C., Akbari, M., & Pazzani, M. (2019). Indexing Multivariate Mobile Data through Spatio-Temporal Event Detection and Clustering. *Sensors,19*(3), 448.

41. Rawassizadeh, R., Keshavarz, H., & Pazzani, M. (2019). Ghost Imputation: Accurately Reconstructing Missing Data of the Off Period. IEEE Transactions on Knowledge and Data Engineering.

42. Rawassizadeh, R., Sen, T., Kim, S. J., Meurisch, C., Keshavarz, H., Mühlhäuser, M., & Pazzani, M. (2019). Manifestation of virtual assistants and robots into daily life: Vision and challenges. CCF Transactions on Pervasive Computing and Interaction, 1(3), 163-174.

43. Ivaturi, P., Gadaleta, M., Pandey, A. C., Pazzani, M., Steinhubl, S. R., & Quer, G. (2020). Explaining the Deep Learning Black Box by Identifying Segments of the Single-Lead ECG Signal Used for Detection of Atrial Fibrillation. Circulation, 142(Suppl_3), A17189-A17189.

44. P. Ivaturi, M. Gadaleta, A. C. Pandey, M. Pazzani, S. R. Steinhubl and G. Quer, (2021) A Comprehensive Explanation Framework for Biomedical Time Series Classification, in IEEE Journal of Biomedical and Health Informatics, doi: 10.1109/JBHI.2021.3060997.



Nicholson Manufacturing Ltd.
EX-1002, Page 176

45 Huynh, J., Masoudi, S., Noorbakhsh, A., Mahmoodi, A., Kligerman, S., Yen, A., Jacobs, K., Hahn, L., Hasenstab, K., Pazzani, M. and Hsiao, A., 2022. Deep Learning Radiographic Assessment of Pulmonary Edema: Optimizing Clinical Performance, Training With Serum Biomarkers. IEEE Access, 10, pp.48577-48588.

46 Pazzani, M. Soltani, S., Kumar, K.. Alipour, A and Ahamed, A. (2022). Improving Explanations of Image Classifiers: Ensembles and Multitask Learning. International Journal of Artificial Intelligence and Applications (IJAIA) 13.

47. Fan, R., Alipour, K., Bowd, C., Christopher, M., Brye, N., Proudfoot, J.A., Goldbaum, M.H., Belghith, A., Girkin, C.A., Fazio, M.A., Liebmann, J.M., . Weinreb, R., Pazzani, M., Kriegman, D., and Zangwill, L. (2023). Detecting Glaucoma from Fundus Photographs Using Deep Learning without Convolutions: Transformer for Improved Generalization. Ophthalmology Science, 3(1), p.100233.

48. K. A. Hasenstab, J. Huynh, S. Masoudi, G. M. Cunha, M. Pazzani and A. Hsiao, "Feature Interpretation Using Generative Adversarial Networks (FIGAN): A Framework for Visualizing a CNN's Learned Features," in IEEE Access, vol. 11, pp. 5144-5160, 2023, doi: 10.1109/ACCESS.2023.3236575.

49. Rasheed, H., Iyengar, S., Nguyen, V., Li, Z., Kumar, A., Lee, A., Pazzani, M. & Xu, B. Y. (2024). Development and Validation of a Deep Learning Algorithm to Automate Detection of Referable Glaucoma in a Safety Net Teleretinal Program. *Investigative Ophthalmology & Visual Science*, *65*(7)

50. Nguyen, V., Iyengar, S., Rasheed, H., Apolo, G., Li, Z., Kumar, A., Pazzani, M. & Xu, B. Y. (2025). Comparison of Deep Learning and Clinician Performance for Detecting Referable Glaucoma from Fundus Photographs in a Safety Net Population. *Ophthalmology Science*, *5*(4).

51. Yu, K., Li, Z., Munimadugu, S., Kesselman, C., Shean, R.S., Hong, A.T., Frediani, T., Tang, A., Dea, N., Ambite, J.L. and Pazzani, M., 2025. Testing Computable Phenotypes of Moderate to Severe Glaucoma Based on Standardized Data Concepts. *Investigative Ophthalmology & Visual Science*, *66*(8).

52. Bolo, K., Munimadugu, S., Li, Z., Nguyen, T.H., Nguyen, V., Do, J., Wong, B., Daskivich, L., Pazzani, M., Ambite, J.L. and Kesselman, C., 2025. A comparison of foundation and supervised learning models for automated detection of referable glaucoma from fundus photographs. *Investigative Ophthalmology & Visual Science*, *66*(8).

**Book Chapters**

1. Pazzani, M. (1988). Explanation-based learning for knowledge-based systems. In B. Gaines & J. Boose (Eds.), Knowledge acquisition for knowledge-based systems. (pp. 215-238). London: Academic Press.

2. Pazzani, M. (1989). Creating high-level knowledge structures from simple elements. In K. Morik (Ed.), Knowledge representation and organization in machine learning. Lecture notes in Artificial Intelligence, No 347. New York: Springer-Verlag.

3. Pazzani, M. & Flowers, M. (1990). Scientific discovery in the layperson. In J. Shrager & P. Langley (Eds.), Computational models of scientific discovery and theory formation. San Mateo, CA: Morgan Kaufmann.

4. Fisher, D. & Pazzani, M. (1991). Theory-guided concept formation. In D. Fisher, M. Pazzani & P. Langley (Eds.), Concept formation: Knowledge and experience in unsupervised learning. San Mateo, CA: Morgan Kaufmann.



Nicholson Manufacturing Ltd.
EX-1002, Page 177

5. Fisher, D. & Pazzani, M. (1991). Concept formation in context. In D. Fisher, M. Pazzani & P. Langley (Eds.), Concept formation: Knowledge and experience in unsupervised learning. San Mateo, CA: Morgan Kaufmann.

6. Pazzani, M. (1989). Learning fault diagnosis heuristics from device descriptions. In Y. Kodratoff & R. Michalski (Eds.), Machine Learning: An artificial intelligence approach (Vol. III). San Mateo, CA: Morgan Kaufmann

7. Pazzani, M., Brunk, C. & Silverstein, G. (1992). A information-based approach to combining empirical and explanation-based learning. In S. Muggleton (Ed.). Inductive Logic Programming (pp 373-394), London: Academic Press.

8. Pazzani, M. (1994). Learning causal patterns: Making a transition from data-driven to theory-driven learning. In Ryszard Michalski & Georghe Tecuci (Eds.) Machine Learning (Vol. IV): A Multi-Strategy Approach. San Mateo, CA: Morgan Kaufmann. (Extended version of Journal paper 4.12).

9. Hirschberg, D., Pazzani. M. & Ali, K. (1995). Average case analysis of k-CNF and k-DNF learning algorithms. In S. Hanson, M. Kearns, T. Petsche and R. Rivest Computational Learning Theory and Natural Learning Systems: Constraints Prospects. Cambridge, MA: MIT Press.

10. Yamazaki, T., Pazzani, M. & Merz, C. (1996). Acquiring and updating hierarchical knowledge for machine translation based on a clustering technique. In Wermter, Riloff & Scheler (Eds.) Connectionist, Statistical, and Symbolic Approaches to Learning for Natural Language Processing.

11. Pazzani, M. (1997). Searching for dependencies in Bayesian classifiers. Artificial Intelligence and Statistics IV, Lecture Notes in Statistics, Springer-Verlag: New York.

12. W. R. Shankle, Subramani Mani, Michael J. Pazzani & Padhraic Smyth. (1997). Detecting very early stages of dementia from normal aging with machine learning methods. In Keravnou, E., Garbay, C., Baud, R. & Wyatt, editors, Lecture Notes in Artificial Intelligence: Artificial Intelligence in Medicine, AIME97, volume 1211, pages 73-85, Springer.

13. Daniel Billsus, and Michael J. Pazzani (2007). Adaptive News Access , In "The Adaptive Web: Methods and Strategies of Web Personalization" (Springer, LNCS #4321), February 1, 2007

14. Michael J. Pazzani and Daniel Billsus, (2007).Content-based Recommendation Systems. In "The Adaptive Web: Methods and Strategies of Web Personalization" (Springer, LNCS #4321), February 1, 2007

**Workshops**

1. Pazzani, M. (1987). Inducing causal and social theories: a prerequisite for explanation-based learning. Proceedings of the Fourth International Workshop on Machine Learning (pp. 230-241). Irvine, CA: Morgan Kaufmann.

2. Pazzani, M. (1987). Creating high-level knowledge structures from primitive elements. Knowledge Representation and Knowledge Organization in Machine Learning Workshop. Geseke, Germany.

3. Pazzani, M. (1988). Selecting the best explanation for explanation-based learning. AAAI Symposium on Explanation-Based Learning (pp. 156-170). Stanford University.



Nicholson Manufacturing Ltd.
EX-1002, Page 178

4. Pazzani, M. (1988). Learning during plan recognition. AAAI Workshop on Plan Recognition. (pp. 1-5). St. Paul, MN.

5. Pazzani, M. (1989). Indexing strategies for goal specific retrieval of cases. Proceedings of the Case-Based Reasoning Workshop (pp. 31-35). Pensacola Beach, FL: Morgan Kaufmann.

6. Pazzani, M. (1989). Explanation-based learning with weak domain theories. Proceedings of the Sixth International Workshop on Machine Learning (pp. 72-74). Ithaca, NY: Morgan Kaufmann.

7. Sarrett, W. & Pazzani, M. (1989). One-sided algorithms for integrating empirical and explanation-based learning. Proceedings of the Sixth International Workshop on Machine Learning (pp. 26-28). Ithaca, NY: Morgan Kaufmann.

8. Schulenburg, D. & Pazzani, M. (1989). Explanation-based learning of indirect speech act interpretation rules. Proceedings of the First International Lexical Acquisition Workshop. Detroit, MI.

9. Pazzani, M. J. & Brunk, C. A. (1990). Detecting and correcting errors in rule-based expert systems: an integration of empirical and explanation-based learning. Knowledge Acquisition for Knowledge-Based Systems Workshop.

10. Pazzani, M., Brunk, C. & Silverstein, G. (1991). A knowledge-intensive approach to learning relational concepts. Proceedings of the Eighth International Workshop on Machine Learning (pp. 432-436). Evanston, IL: Morgan Kaufmann.

11. Silverstein, G. & Pazzani, M. (1991). Relational clichés: Constraining constructive induction during relational learning. Proceedings of the Eighth International Workshop on Machine Learning (pp. 203-207). Evanston, IL: Morgan Kaufmann.

12. Cain, T., Pazzani, M. & Silverstein, G. (1991). Using domain knowledge to influence similarity judgments. Proceedings of the Case-Based Reasoning Workshop. Washington, DC: Morgan Kaufmann.

13. Brunk, C. & Pazzani, M. (1991). An investigation of noise tolerant relational learning algorithms. Proceedings of the Eighth International Workshop on Machine Learning (pp. 389-391). Evanston, IL: Morgan Kaufmann.

14. Murphy, P. & Pazzani, M. (1991). ID2-of-3: Constructive induction of m-of-n discriminators for decision trees. Proceedings of the Eighth International Workshop on Machine Learning (pp. 183-187). Evanston, IL: Morgan Kaufmann.

15. Hirschberg, D., Pazzani, M. & Ali, K. (1991). Average case analysis of k-CNF and k-DNF learning algorithms. Second International Workshop on Computational Learning Theory and Natural Learning Systems: Constraints and Prospects. Berkeley, CA.

16. Pazzani, M. (1992). When Prior Knowledge Hinders Learning. AAAI Workshop on Constraining learning with Prior Knowledge. San Jose, CA.

17. Murphy, P & Pazzani, M. (1993). Exploring the decision forest. Computational Learning and Natural Learning, Provincetown, MA.



Nicholson Manufacturing Ltd.
EX-1002, Page 179

18. Pazzani, M., Murphy, P., Ali, K. & Schulenburg, D. (1994). Trading off coverage for accuracy in forecasts: Applications to clinical data analysis. AAAI Symposium on AI in Medicine (pp. 106-110). Stanford, CA.

19. Ali K., Brunk C. & Pazzani M. (1995). Learning Multiple Relational Rule-based Models. In Preliminary Papers of the 5th International Workshop on Artificial Intelligence and Statistics. Fort Lauderdale, FL.

20. Pazzani, M. (1995). Searching for dependencies in Bayesian classifiers. In Preliminary Papers of the 5th International Workshop on Artificial Intelligence and Statistics. Fort Lauderdale, FL.

21. Pazzani, M., Muramatsu J. & Billsus, D. (1996). Syskill & Webert: Identifying interesting web sites. AAAI Spring Symposium. Stanford, CA.

22. Starr, B. Ackerman, M. & Pazzani, M. (1996). Do I Care? -- Tell Me What's Changed on the Web. AAAI Spring Symposium. Stanford, CA.

23. R. Shankle, P. Datta & Pazzani, M. (1996). Applying machine learning to an Alzheimer's database, AAAI-96 Spring Symposium AI in Medicine: Applications of Current Technologies. Stanford, CA.

24. Merz, C. & Pazzani, M. (1997). Handling redundancy in ensembles of learned models using principal components. AAAI Workshop on Integrating Multiple Models.

25. Merz, C. & Pazzani M. (1997). Combining neural network regression estimates using principal components. Preliminary Papers of the 6th International Workshop on Artificial Intelligence and Statistics.

26. Mani, M., McDermott, S. & Pazzani, M. (1997). Generating models of mental retardation from data with machine learning Proceedings IEEE Knowledge and Data Engineering Exchange Workshop (KDEX-97), p. 114-119, IEEE Computer Society.

27. Keogh, E. & Pazzani, M. (1998). An enhanced representation of time series which allows fast and accurate classification, clustering and relevance feedback. AAAI Workshop on Predicting the Future: AI Approaches to Time-Series Analysis. Madison, Wisc.

28. Pazzani, M. & Billsus, D. (1999). Evaluating Adaptive Web site Agents. Workshop on Recommender Systems Algorithms and Evaluation, 22nd International Conference on Research and Development in Information Retrieval.

29. Bay, S. D. & Pazzani, M. J. (2000). Characterizing Model Performance in the Feature Space. In ICML 2000 Workshop on What Works Well Where.

30. Keogh, E., S. Chu & Pazzani, M. (2001). Using ensembles of representations for indexing large databases. International Workshop on Mining Spatial and Temporal data. In conjunction with the Fifth Pacific-Asia Conference on Knowledge Discovery and Data Mining (PAKDD-01).

31. Pazzani, M. (2005). Beyond Idiot Savants: Recommendations and Common Sense Workshop on Beyond personalization: the next stage of recommender systems research. Intelligent User Interfaces Conference, San Diego, CA



Nicholson Manufacturing Ltd.
EX-1002, Page 180

32. Michael Pazzani, Amir Feghahati, Christian Shelton, and Aaron Seitz. (2018) Explaining contrasting categories. In Workshop on Explainable Smart Systems (EXSS), ACM Intelligent User Interface Conference, Toyko, Japan.

**Conference papers**

1. Pazzani, M. (1983). Interactive script instantiation. Proceedings of the National Conference on Artificial Intelligence (pp. 320-326). Washington DC: Morgan Kaufmann.

2. Pazzani, M. (1984). Conceptual analysis of garden-path sentences. Proceedings of the Tenth International Conference on Computational Linguistics (pp. 486-490). Stanford, CA.

3. Pazzani, M. (1985). Explanation and generalization-based memory. Proceedings of the Seventh Annual Conference of the Cognitive Society Conference (pp. 323-328). Irvine, CA: Lawrence Erlbaum.

4. Pazzani, M. & Brindle. A. (1986). Automated diagnosis of attitude control anomalies. Proceedings of the Annual AAS Guidance and Control Conference. Keystone, CO: American Astronautical Society.

5. Pazzani, M. (1986). Refining the knowledge base of a diagnostic expert system: An application of failure-driven learning. Proceedings of the Fifth National Conference on Artificial Intelligence (pp. 1029-1035). Philadelphia, PA: Morgan Kaufmann.

6. Pazzani, M., Dyer, M. & Flowers, M. (1986). The role of prior causal theories in generalization. Proceedings of the Fifth National Conference on Artificial Intelligence (pp. 545-550). Philadelphia, PA: Morgan Kaufmann.

7. Pazzani, M., Dyer, M. & Flowers, M. (1987). Using prior learning to facilitate the learning of new causal theories. Proceedings of the Tenth International Joint Conference on Artificial Intelligence (pp. 277-279). Milan, Italy: Morgan Kaufmann.

8. Pazzani, M. & Dyer, M. (1987). A comparison of concept identification in human learning and network learning with the generalized delta rule. Proceedings of the Tenth International Joint Conference on Artificial Intelligence (pp. 147-151). Milan, Italy: Morgan Kaufmann.

9. Pazzani, M. (1988). Integrated learning with incorrect and incomplete theories. Proceedings of the Fifth International Conference on Machine Learning (pp. 291-298). Ann Arbor, MI: Morgan Kaufmann.

10. Pazzani, M. (1988). Integrating empirical and explanation-based learning methods in OCCAM. Proceedings of the Third European Working Session on Learning (pp. 147-166). Glasgow, Scotland: Pitman.

11. Pazzani, M. (1989). Learning from historical precedent. Artificial Intelligence Systems in Government Conference (pp. 150-156). Washington, DC.

12. Pazzani, M. (1989). Explanation-based learning of diagnostic heuristics: A comparison of learning from success and failure. Artificial Intelligence Systems in Government Conference (pp. 164-169). Washington DC.

13. Pazzani, M. & Schulenburg, D. (1989). The influence of prior theories on the ease of concept acquisition. Proceedings of the Eleventh Annual Conference of the Cognitive Science Society (pp. 812-819). Ann Arbor, MI: Lawrence Erlbaum.



Nicholson Manufacturing Ltd.
EX-1002, Page 181

14. Pazzani, M. (1989). Detecting and correcting errors of omission after explanation-based learning. Proceedings of the Eleventh International Joint Conference on Artificial Intelligence (pp. 713-718). Detroit, MI: Morgan Kaufmann.

15. Pazzani, M. & Sarrett, W. (1989). Average case analysis of conjunctive learning algorithms. Proceedings of the Seventh International Conference on Machine Learning (pp. 339-347). Austin, TX: Morgan Kaufmann.

16. Pazzani, M. & Silverstein, G. (1990). Feature selection and hypothesis selection: Models of induction. Proceedings of the Twelfth Annual Conference of the Cognitive Science Society (pp. 221-228). Cambridge, MA: Lawrence Erlbaum.

17. Billman, D., Fisher, D., Gluck, M., Langley, P., Pazzani, M. (1990). Computational models of category learning. Proceedings of the Twelfth Annual Conference of the Cognitive Science Society (pp. 989-996). Cambridge, MA: Lawrence Erlbaum.

18. Hirschberg, D. & Pazzani, M. (1992). Average case analysis of k-CNF learning algorithms. Proceedings of the Tenth International Conference on Machine Learning (pp. 206-211). Aberdeen, Scotland: Morgan Kaufmann

19. Pazzani, M. & Brunk, C. (1993). Finding Accurate Frontiers: A Knowledge-Intensive Approach to Relational Learning. The National Conference on Artificial Intelligence (pp. 328-334). Washington, D.C: AAAI Press

20. Ali, K. & Pazzani, M. (1993). HYDRA: A noise-tolerant relational concept learning algorithm. The International Joint Conference on Artificial Intelligence, Chambery, France.

21. Wogulis, J. & Pazzani, M. (1993). A methodology for evaluating theory revision systems: Results with AUDREY II. The International Joint Conference on Artificial Intelligence, Chambery, France.

22. Murphy, P. & Pazzani, M. (1994). Revision of production system rule-bases. Proceedings of the 11th International Conference of Machine Learning, New Brunswick. Morgan Kaufmann, 199-200.

23. Pazzani, M., Merz, C., Murphy, P., Ali, K., Hume, T. & Brunk, C. (1994). Reducing Misclassification Costs. Proceedings of the 11th International Conference of Machine Learning, New Brunswick. Morgan Kaufmann, 217-225.

24. Ali K., Brunk C. & Pazzani M. (1994). On Learning Multiple Descriptions of a Concept. In Proceedings of the Sixth International Conference on Tools with Artificial Intelligence. New Orleans, LA: IEEE Press.

25. Merz, C. & Pazzani M. (1994). Parameter Tuning for the MAX Expert System, In Proceedings of the Sixth International Conference on Tools with Artificial Intelligence. New Orleans, LA: IEEE Press. pp. 632-639.

26. Yamazaki, T., Pazzani, M & Merz, C. (1995). Learning Hierarchies from Ambiguous Natural Language Data, Proceedings of the 12th International Conference of Machine Learning.

27. Brunk, C. & Pazzani, M. (1995). A Linguistically-Based Semantic Bias for Theory Revision Proceedings of the 12th International Conference of Machine Learning.



Nicholson Manufacturing Ltd.
EX-1002, Page 182

28. Hume, T. & Pazzani, M. (1995). Learning Sets of Related Concepts: A Shared Task Model. Proceedings of the Sixteen Annual Conference of the Cognitive Science Society. Pittsburgh, PA: Lawrence Erlbaum.

29. Pazzani, M. (1995). An iterative-improvement approach for the discretization of numeric attributes in Bayesian classifiers. Proceedings of the First International Conference on Knowledge Discovery and Data Mining. Montreal: AAAI Press

30. Pazzani, M., Nguyen, L. & Mantik, S. (1995). Learning from hotlists and coldlists: Towards a WWW information filtering and seeking agent. In Proceedings of the Seventh International Conference on Tools with Artificial Intelligence

31. Domingos, P. & Pazzani, M. (1996). Beyond Independence: Conditions for the Optimality of the Simple Bayesian Classifier. Proceedings of the International Conference on Machine Learning.

32. Pazzani, M., Muramatsu J. & Billsus, D. (1996). Syskill & Webert: Identifying interesting web sites. Proceedings of the National Conference on Artificial Intelligence, Portland, OR.

33. Billsus, D. & Pazzani, M (1996). Revising user profiles: The search for interesting Web sites. International Multi-Strategy Learning Conference. Harpers Ferry, Va.

34. Pazzani, M. (1996). Constructive Induction of Cartesian Product Attributes. Information, Statistics and Induction in Science. Melbourne, Australia.

35. Starr, B., Ackerman, M. & Pazzani, M. (1996). Do-I-Care: A Collaborative Web Agent. Proceedings of the ACM Conference on Human Factors in Computing Systems (CHI'96), April, 1996, pp 273-274.

36. Merz, C. & Pazzani, M. (1996). Combining neural network regression estimates with regularized linear weights. Advances in Neural Information Processing Systems 9, Proceedings of the 1996 Conference. MIT Press, 564-570.

37. Pazzani, M., Mani, S. & Shankle, W. R. (1997). Beyond concise and colorful: learning intelligible rules. Proceedings of the Third International Conference on Knowledge Discovery and Data Mining, Newport Beach, CA. AAAI Press, 235-238.

38. Pazzani, M., Mani, S. & Shankle, W. R. (1997). Comprehensible knowledge-discovery in databases. In M. G. Shafto & P. Langley (Ed.), Proceedings of the Nineteenth Annual Conference of the Cognitive Science Society, pp. 596-601. Mahwah, NJ:Lawrence Erlbaum.

39. Pazzani, M., Iyer, R., See, D., Shroeder, E. & Tilles, J. (1997). CTSHIV: A Knowledge-based System in the Management of HIV-infected patients. Proceedings of the International Conference on Intelligent Information Systems.

40. Shankle, W.R., Mani, S., Pazzani, M. J. & Smyth, P. (1997). Use of a Computerized Patient Record Database of Normal Aging and Very Mildly Demented Subjects to Compare Classification Accuracies Obtained with Machine Learning Methods and Logistic Regression. Computing Science and Statistics, 29: 201-209.

41. Billsus, D. & Pazzani, M. (1998). Learning Collaborative Information Filters. Proceedings of the International Conference on Machine Learning. Morgan Kaufmann Publishers. Madison, Wisc.



Nicholson Manufacturing Ltd.
EX-1002, Page 183

42. Webb, G. & Pazzani, M. (1998). Adjusted Probability Naive Bayesian Induction. 11th Australian Joint Conference on Artificial Intelligence. Brisbane, QLD. Australia.

43. Pazzani, M. (1998). Learning with Globally Predictive Tests. The First International Conference on Discovery Science Fukuoka, Japan.

44. Mani, S. & Pazzani, M. (1998). Guideline Generation from Data by Induction of Decision Tables Using a Bayesian Network Framework JAMIA supplement p. 518-522.

45. Shankle, R., Mani, S., Dick, M & Pazzani, M. (1998). Simple Models for Estimating Dementia Severity Using Machine Learning MedInfo'98: 9th World Congress on Medical Informatics, Seoul, Korea, 1998.

46. Lathrop, R., Steffen, N., Raphael, M., Deeds-Rubin, S., Pazzani, M., Cimoch, P., See, D., Tilles, J. (1998). Knowledge-based Avoidance of Drug-Resistant HIV Mutants Proceedings of the 10th Conference on Innovative Applications of Artificial Intelligence, Madison, Wisc.

47. Keogh, E. & Pazzani, M. (1998). An enhanced representation of time series which allows fast and accurate classification, clustering and relevance feedback. Proceedings of the Fourth International Conference of Knowledge Discovery and Data Mining. pp 239-241, AAAI Press.

48. Cimoch, P.J., See, D.M., Pazzani, M.J., Reiter, W.M., Lathrop, R.H., Fasone, W.A, Tilles, J.G.; (1998). Application of a genotypic driven rule-based expert artificial intelligence computer system in treatment experienced HIV-infected patients. Immunologic and virologic response. Proc. of the 12th World AIDS Conf., Geneva, Switzerland, extended abstract #32297

49. Keogh, E. & Pazzani. M. (1999). Learning augmented Bayesian classifiers: A comparison of distribution-based and classification-based approaches. Uncertainty 99 AI and Statistics, Ft. Lauderdale, Florida, 225-230.

50. Billsus, D. & Pazzani, M. (1999). A Hybrid User Model for News Story Classification, Proceedings of the Seventh International Conference on User Modeling (UM '99), Banff, Canada.

51. Billsus, D. & Pazzani, M. (1999). A Personal News Agent that Talks, Learns and Explains, Proceedings of the Third International Conference on Autonomous Agents (Agents '99), Seattle, Washington.

52. Bay, S. D. & Pazzani, M. J. (1999). Detecting Change in Categorical Data: Mining Contrast Sets. In Proceedings of the Fifth International Conference on Knowledge Discovery and Data Mining.

53. Pazzani, M. J. & Bay, S. D. (1999). The Independent Sign Bias: Gaining Insight from Multiple Linear Regression. In Proceedings of the Twenty-First Annual Meeting of the Cognitive Science Society.

54. Pazzani, M.& Billsus, D. (1999). Adaptive Web Site Agents. Proceedings of the Third International Conference on Autonomous Agents (Agents '99), Seattle, Washington.

55. Keogh, E. & Pazzani, M. (1999). Relevance Feedback Retrieval of Time Series Data The Twenty-Second Annual International ACM-SIGIR Conference on Research and Development in Information Retrieval.

56. Eamonn J. Keogh, Michael J. Pazzani: (1999). Scaling up Dynamic Time Warping to Massive Datasets. Principles and Practice of Knowledge Discovery in Databases, Prague, Czech Republic.



Nicholson Manufacturing Ltd.
EX-1002, Page 184

57. Eamonn J. Keogh, Michael J. Pazzani: (1999). An indexing scheme for similarity search in large time series databases. The 11th International Conference on Scientific and Statistical Database Management. Cleveland, Ohio.

58. S. Mani, M.B. Dick, M.J. Pazzani, E.L. Teng, D. Kempler, I.M. Taussig (1999). Refinement of Neuro-Psychological Tests for Dementia Screening in a Cross Cultural Population Using Machine Learning. Joint European Conference on Artificial Intelligence in Medicine and Medical Decision Making Aalborg, Denmark.

59. Bay, S. D. & Pazzani, M. J. (2000). Discovering and Describing Category Differences: What makes a discovered difference insightful?. Proceedings of the 22nd Annual Meeting of the Cognitive Science Society.

60. Bay, S. D. & Pazzani, M. J. (2000). Characterizing Model Errors and Differences. In Proceedings of the Seventeenth International Conference on Machine Learning.

61. Keogh, E. & Pazzani, M. (2000) Scaling up Dynamic Time Warping for Data Mining Applications. In 6th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Boston, 2000.

62. Keogh, E. & Pazzani, M. (2000) A simple dimensionality reduction technique for fast similarity search in large time series databases. In the Fourth Pacific- Asia Conference on Knowledge Discovery and Data Mining. Kyoto, Japan..

63. Michael J. Pazzani: (2000) Representation of electronic mail filtering profiles: a user study. Intelligent User Interfaces 2000: 202-206

64. Daniel Billsus, Michael J. Pazzani, James Chen: (2000) A learning agent for wireless news access. Intelligent User Interfaces 2000: 33-36

65. Koji Miyahara, Michael J. Pazzani: (2000) Collaborative Filtering with the Simple Bayesian Classifier. PRICAI 2000: 679-689

66. Keogh, E., Chu, S., Hart, D. & Pazzani, M. (2001). An Online Algorithm for Segmenting Time Series. IEEE International Conference on Data Mining.

67. Keogh, E., Chu, S. & Pazzani, M. (2001). Ensemble-Index: A New Approach to Indexing Large Databases. In 7th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco.

68. Keogh, E., Chakrabarti, K., Pazzani, M. & Mehrotra (2001). Locally adaptive dimensionality reduction for indexing large time series databases. SIGMOD 2001. Best paper award.

69. Keogh, E. & Pazzani, M. (2001). Derivative Dynamic Time Warping. In First SIAM International Conference on Data Mining (SDM'2001), Chicago, USA.

70. George Buchanan, Sarah Farrant, Matt Jones, Harold W. Thimbleby, Gary Marsden, Michael J. Pazzani: (2001) Improving mobile internet usability. WWW 10: 673-680.

71. Chu, S., Keogh, E., Hart, D. & Pazzani, M. (2002). Iterative Deepening Dynamic Time Warping for Time Series. The Second Siam International Conference on Data Mining.



Nicholson Manufacturing Ltd.
EX-1002, Page 185

72. Pazzani, M. (2002). Commercial Applications of Machine Learning for personalized wireless portals. Pacific Rim Conference on Artificial Intelligence, Springer. Pp 1-5.

73. Billsus, D., Klefstad, R & Pazzani, M.(2005). Adaptive Personalization of Mobile Content Delivery. Human Computer Interaction, Las Vegas.

74. Pazzani, M. & Brunk, C. (2005). An Improved Representation for Content-Based Television Personalization. Human Computer Interaction, Las Vegas.

75. Hettich, S & Pazzani M (2006). Mining for Proposal Reviewers: Lessons Learned at the National Science Foundation. The Twelfth Annual SIGKDD International Conference on Knowledge Discovery and Data Mining. Philadelphia.

76. Yong Ge, Hui Xiong, Alexander Tuzhilin, Keli Xiao, Marco Gruteser, Michael J. Pazzani: (2010) An energy-efficient mobile recommender system. KDD 2010: 899-908

77. Mesterharm, C, Pazzani, M. (2011) Active learning using on-line algorithms. KDD 2011: 850-858.

78. Rawassizadeh, Reza & Dobbins, Chelsea & Nourizadeh, Manouchehr & Ghamchili, Zahra & Pazzani, Michael. (2017). A Natural Language Query Interface for Searching Personal Information on Smartwatches.. 10.1109/PERCOMW.2017.7917645.

79. Feghahati, A., Shelton, C. Pazzani, M., And Tang, K. (2020). CDeepEx: Contrastive Deep Explanations. European Conference on Artificial Intelligence.

80. Soltani, S., Kaufman, R. A., & Pazzani, M. J. (2022). User-Centric Enhancements to Explainable AI Algorithms *for Image Classification. In Proceedings of the Annual Meeting of the Cognitive Science Society (Vol. 44, No. 44).*

81. Pazzani, M., Soltani, S, Kauffman, R., Qian, S. Hsiao, A. (2022) Expert-Informed, User-Centric Explanations for Machine Learning, Proceedings of the AAAI Conference on Artificial Intelligence.

82. Ahamed, A . Alipour, A Kumar, K.. Soltani, S., and. Pazzani, M (2022). Improving Explanations of Image Classification with Ensembles of Learner. 8th International Conference of Artificial Intelligence and Applications. Vienna, Austria

83. Nguyen, H., Nguyen, H., Chang, M., Pham, H., Narayanan, S., & Pazzani, M. (2024). ConPro: Learning Severity Representation for Medical Images using Contrastive Learning and Preference Optimization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 5105-5112).

84. Nguyen, H., Nguyen, H., Chang, M., Pham, H., Narayanan, S. and Pazzani, M., 2024. ConPro: Learning Severity Representation for Medical Images using Contrastive Learning and Preference Optimization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 5105-5112).

85. Li, Z., Kesselman, C., D'Arcy, M., Pazzani, M. and Xu, B.Y., 2024, September. Deriva-ML: A Continuous FAIRness Approach to Reproducible Machine Learning Models. In *2024 IEEE 20th International Conference on e-Science (e-Science)* (pp. 1-10). IEEE.



Nicholson Manufacturing Ltd.
EX-1002, Page 186