

IN THE UNITED STATES PATENT AND TRADEMARK OFFICE
BEFORE THE PATENT TRIAL AND APPEAL BOARD

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CAPTION HEALTH, INC.,  
Petitioner,

vs. U.S. PATENT NO. 10,751,029  
UNIVERSITY OF BRITISH COLUMBIA,  
Patent Owner.

~~~~~  
Deposition of
MILAN SONKA, PhD

Thursday, August 6, 2026
10:00 a.m.

Taken via videoconference

Genevie Del Valle, Court Reporter

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1 MILAN SONKA, PhD, of lawful age,
2 called by the Petitioner for the purpose of
3 cross-examination, as provided by the Rules
4 of Civil Procedure, being by me first duly
5 sworn, as hereinafter certified, deposed
6 and said as follows:

7 EXAMINATION OF MILAN SONKA, PhD

8 BY MR. METZCAR:

9 Q. Good morning, Dr. Sonka. How are you?

10 A. I'm doing fine. Thank you. Thanks for asking.

11 Q. My name is Jeff Metzcar. I'm an attorney at
12 Thompson Hines and I represent the petitioner in
13 this case, Caption Health. I'm going to be
14 asking you some questions today, which you'll be
15 answering under oath.

16 Am I correct that you've had your deposition
17 taken many times before?

18 A. I have taken deposition several times, yes.

19 Q. Okay. So you're pretty familiar with this
20 process; is that -- is that fair to say?

21 A. Reasonably.

22 Q. Okay. Well, let's go over a couple ground rules
23 just so things run a little more smoothly today.

24 I think, for my purpose and the court
25 reporter's purpose, the most important thing is

1 that we try to not talk over one another. So if
2 you could try to let me finish my question before
3 you answer, that would be very helpful. And I
4 will try to let you finish your answer before I
5 move on to the next question. Okay?

6 A. Sounds good.

7 Q. And of course, even though we can see each other
8 on video, please try to make sure that you answer
9 audibly rather than with a shake of the head or a
10 nod. Okay?

11 A. Yes.

12 Q. Okay. We'll be covering a lot of ground today.
13 It is inevitable I'm going to ask a confusing
14 question. I would ask if you are confused about
15 anything that I've asked, ask for clarification.
16 Because if you do not, I will assume that you
17 understood my question. Is that fair?

18 A. That's understood.

19 Q. Okay. Today is not an endurance contest. If at
20 any point you need a break, please just let me
21 know and I will try to accommodate that as
22 quickly as possible.

23 The only thing that I ask is that we don't
24 take breaks while there's a question pending.
25 Okay?

1 A. Understood as well.

2 Q. Now, this deposition is being taken remotely. So
3 my expectation is that you are sitting there in a
4 room by yourself, not with someone else who is
5 helping you or feeding you answers.

6 Is my assumption correct?

7 A. I'm in the room alone.

8 Q. And I'd ask that you not be in running
9 communication with your counsel or anyone else
10 about your testimony or the answers that you're
11 giving.

12 Can I count on you to not do that?

13 A. Yes, that's clear.

14 Q. Are there any reasons, any medical reasons or any
15 medications that you might be on -- any reason
16 why you would not be able to give me full and
17 truthful answers today?

18 A. No, there are not.

19 Q. Great. And we already discussed that you have
20 access to the Exhibit Share folder and you can
21 see the two exhibits that I've already populated
22 there.

23 MR. METZCAR: Chris, are you able
24 to see those exhibits as well?

25 MR. MARANDO: I will be in a

1 moment, if you just give me one second.

2 Q. While you're -- while you're logging into Exhibit
3 Share, one thing I want to make sure we're clear
4 on, Dr. Sonka, is some definitions.

5 Throughout the day I'm going to be generally
6 referring to Krishnan. I assume that you
7 understand that that means Exhibit 1005 in this
8 case. It's a public patent application number
9 2005/0251013.

10 Are you familiar with that?

11 A. Yes, I understand that and I will refer to that
12 patent as Krishnan as well.

13 Q. Okay. So we'll know what we're talking about if
14 we just say Krishnan?

15 A. Yes.

16 Q. Likewise, throughout the day, I will be referring
17 to the 029 patent or the patent, and I want to
18 make sure you understand when I'm saying that,
19 I'm referring to the challenged patent in this
20 case.

21 Is that -- is that okay with you?

22 A. I understand that. It's okay with me.

23 Q. If at any point I reference a patent and you're
24 not sure which one I'm talking about, please ask
25 for clarification.

1 A. I will.

2 Q. Dr. Sonka, do you regularly serve as an expert
3 witness in cases?

4 MR. MARANDO: Objection.

5 A. As Genevie mentioned, you are coming up a little
6 muffled. Can you speak up a little bit? Or I
7 don't know.

8 Q. Do you regularly serve as an expert in patent
9 infringement cases?

10 MR. MARANDO: Objection. Form.

11 You can answer.

12 A. I don't know what "regularly" means, but I am
13 typically serving as an expert in IPR cases maybe
14 once a year or so.

15 Q. Okay. And how many of those cases have you been
16 involved in?

17 A. I don't know exactly, but I would say maybe seven
18 or eight.

19 Q. Okay. Are you -- are you registered with any
20 expert locating services?

21 A. I don't know what registered really means, but I
22 am sometimes contacted by such services.

23 Q. Which one?

24 A. Teklicon is one which comes to mind.

25 Q. Any others?

1 A. IMS, which actually may have merged with
2 Teklicon, is the other one.

3 Q. Do you know how the University of British
4 Columbia located you for this matter?

5 A. No, I do not. What I do know is that it was not
6 through one of those services.

7 Q. Okay. Thank you.

8 Did you prepare for your deposition today?

9 A. Of course I did.

10 Q. How did you prepare?

11 A. I looked at my declaration because it's been a
12 few months since I prepared it. So I carefully
13 read the entire declaration. I reviewed --
14 mostly read the Krishnan patent, the 029 patent,
15 the prior, you know, exhibits, which are
16 relevant, and looked at most relevant portions of
17 the many exhibits which are listed in my
18 declaration.

19 I have also met with the counsel and, you
20 know, prepared for the deposition in
21 collaboration discussions with him.

22 Q. Okay. And I want to be very clear, I'm not
23 asking you for any communications between you and
24 your attorney. That's privileged material and
25 I'm not asking for it, but which counsel did you

1 meet with to prepare for this deposition? Was it
2 Mr. Marando?

3 A. Mr. Marando.

4 Q. Anyone else?

5 A. Mr. -- or Ms. Moeka. Counsel can provide a last
6 name. I don't remember exactly.

7 Q. Okay. So you met with two of your attorneys?

8 A. That's correct.

9 Q. And for how long did you meet with your -- with
10 your attorneys?

11 A. For several hours in the past few days, each.

12 Q. Several hours each. So about six hours maybe?

13 A. Probably more. It was probably more like -- I
14 don't know, close to 20 hours in the past few
15 days.

16 Q. Okay.

17 A. 15 to 20.

18 Q. Do you have any documents with -- paper documents
19 with you, like your declaration?

20 A. I do not have the declaration as printed. I have
21 the patents printed as unmarked copies next to me
22 here and I have the listing of challenged claims
23 and the page from the original petition that
24 talks about the identification of the challenge
25 just for the reference. If it's okay with you as

1 the printed, otherwise, I can set it aside.

2 Q. Okay. I heard you say you have the patents with
3 you. Are you referring to the challenged patent
4 and --

5 A. I am referring to the challenged patent. I'm
6 referring to Krishnan, I'm referring to the Chen
7 reference, which is a paper, Aase patent, and the
8 Wu paper.

9 Q. Okay. Are there any markings or notes on those?

10 A. All completely -- completely clean and unmarked.

11 Q. Thank you.

12 But you do not have a paper copy of the
13 declaration with you?

14 A. I do not.

15 Q. Okay. Thank you.

16 A. It's too long.

17 Q. Saving a tree.

18 A. Exactly.

19 Q. Okay. Well, Dr. Sonka, as I understand your
20 position, you believe that the Krishnan reference
21 only uses non-neural network functions to extract
22 feature representations from images.

23 Is that a correct statement of your opinion?

24 A. My declaration states that my opinion is that for
25 feature extraction in the Krishnan patent, the

1 neural networks are not used to define the
2 features as described in the 102 module of the
3 Krishnan patent.

4 Q. And so those would be -- I refer to them as
5 non-neural network functions for feature
6 extraction. Is that a fair assessment?

7 A. Those are the non-neural network functions of the
8 Krishnan patent, yes. One of the many non-neural
9 network functions.

10 Q. And these non-neural network functions, I believe
11 your declaration refers to them as conventional
12 approaches; is that -- is that right?

13 A. My declaration refers to conventional approaches
14 in a broader sense than that, but extraction of
15 features, as described in the Krishnan patent, is
16 one of the many aspects of conventional
17 approaches as are described in my declaration.

18 Q. Let's go through -- let's go through some
19 examples.

20 What are some examples of what you would
21 consider conventional non-neural network feature
22 extraction functions?

23 MR. MARANDO: Objection. Form.

24 A. Almost everything what was done in computer
25 vision and -- I shouldn't say almost. Everything

1 that was done before the deep learning revolution
2 happened in, you know, early 2010. So after
3 2012. So that's what I consider conventional
4 approaches. Those approaches which are mostly
5 built as a pipeline of sequential steps.

6 In the context of the Krishnan patent, the
7 most important steps of such a pipeline is that
8 you get images. You hand design -- expert design
9 the features that should be derived, extracted
10 from the images. You use those features to train
11 a classifier or to use a database retrieval or
12 template matching or some other approach that
13 gets you to what you want to get and then you
14 identify a label associated with those images
15 which you entered in the beginning. Those
16 approaches -- go ahead.

17 Q. No, please, I didn't -- I thought you were done.

18 A. Those approaches have been invariably used in
19 different combinations in computer vision,
20 medical imaging, character recognition and things
21 like that.

22 So that's what I consider conventional
23 approaches, things where humans have very
24 substantial role in designing how the
25 functionality really works and what kind of

1 information is being used for potential
2 decision-making -- making in the sequential steps
3 down the road.

4 Q. Okay. I appreciate the explanation, but I did --
5 my question was specifically for examples of
6 conventional non-neural network functions for
7 feature extraction. Do you -- can you give me
8 some examples?

9 A. I can give you many --

10 MR. MARANDO: Objection. Form.

11 A. I can give you many examples from my own research
12 work. So, for example, I believe around 1996 or
13 many, many years ago, we have worked with
14 intravascular ultrasound image analysis. The
15 goal was to identify kinds of coronary disease,
16 plaque in the coronary arteries which caused the
17 heart attack.

18 From the intravascular ultrasound images, we
19 have developed a set of features, more or less in
20 a way as Krishnan is describing there in 102.
21 Then those features were calculated in the
22 intravascular ultrasound images. The calculated
23 features were entered into a classifier. The
24 classifier was trained using those features. And
25 once the classifier was trained, the images,

1 portions of the images were identified as being
2 either hard plaque or soft plaque, meaning
3 calcified plaque or lipid plaque and that was
4 provided to the physicians as a -- as a decision.
5 That's one of the examples.

6 I can give you another example, which would
7 be very similar in that. In brain imaging you
8 identify individual deep neuroanatomical
9 structures like ventricles, amygdala, caudate,
10 things like that. And those structures are
11 segmented.

12 After the segmentation, some shape properties
13 are calculated based on the expert design
14 features, what to measure on the shape. Those
15 shape indices are combined into a vector. Again,
16 extracted same as in 102, provided as a vector,
17 entered into the classifier. The classifier is
18 trained and can distinguish, for example, between
19 schizophrenic structures and normal structures in
20 the brain.

21 I can keep going because you will probably
22 find thousands of applications, examples that
23 follow more or less exactly the same pipeline.
24 That was the standard conventional typical
25 pipeline in computer vision and medical imaging.

1 Q. Okay. Again, I appreciate the explanation. I
2 think we might be missing each other a little
3 bit. I'm not necessarily looking for examples of
4 where non-neural-network feature extraction was
5 used. I was more specifically asking you about
6 some examples of non-neural network functions
7 that are used for feature extraction.

8 So let me ask it to you a different way. Are
9 you familiar with principal component analysis?

10 A. Yes, I am.

11 Q. Is that a -- is that a common feature extraction
12 function that's used on images that doesn't have
13 to be performed by neural network?

14 MR. MARANDO: Objection. Form.

15 A. Again, the decision to use a principal component
16 analysis, or PCA, is made by a human designer,
17 number one.

18 Number two, it's -- you know, it's mostly a
19 way how to decrease the dimensionality of the
20 feature space, which you start using on the input
21 of the PCA and you create more of the same
22 dimensionality feature space after the principal
23 component analysis; however, you choose some
24 smaller number of the significant meaningful
25 components that carry the most information from

1 the set.

2 So they require on the input to have those
3 human-designed calculated extracted features and
4 they provide the different representation of the
5 features, which is more compact than you started
6 with.

7 You don't need neural networks for that. I
8 agree on that. But you do need a set of already
9 extracted features to start with.

10 Q. Okay. Your position is that principal component
11 analysis requires handcrafted features; is
12 that --

13 A. No, my position is that principal component
14 analysis requires a set of features on the input
15 and generates a different set of features on the
16 output, which is a combination -- which is a
17 combination of the input features.

18 Q. Are you -- are you -- let me make sure I
19 understand.

20 Are you saying that principal component
21 analysis cannot be used directly on an image;
22 instead, it requires features that have been
23 extracted from an image?

24 MR. MARANDO: Objection. Form.

25 A. I am saying that in the context of the

1 conventional approaches, the typical way how PCA
2 was used is that you start with the set of
3 extracted features, especially in the medical
4 imaging because you want that to have the
5 understanding of what you are actually
6 determining, and then use principal component
7 analysis for that.

8 I am not saying that it's not possible to use
9 the entire image as a long vector that would be
10 input into the PCA module. I am not sure -- it
11 would be application specific. I am not sure
12 what exactly the outcome would be, but it's
13 certainly possible.

14 Q. Okay. But are you familiar with any scenarios
15 where that is done, where a principal component
16 analysis is performed on an image by taking
17 actual pixel values of the image as input to the
18 principal component analysis?

19 MR. MARANDO: Objection. Form.

20 A. I personally do not recall any work that that
21 would affect. You know, my research, it would be
22 based on -- on what you described.

23 Q. Okay. You're not familiar with that.

24 How about edge detection? Is that another
25 non-neural network feature extraction function?

1 A. It is a -- it is a non-neural network -- edge
2 detection is a non-neural network feature
3 extraction function. It is.

4 Q. And edge detection can also be performed by a
5 neural network; is that true?

6 MR. MARANDO: Objection. Form.

7 A. Edge detection in the most frequent way how you
8 do it. There are many different ways how you can
9 do edge detection. The most fundamental way how
10 to do it is a result of a convolution of an
11 interaction of the image with a kernel. And the
12 kernel traditionally was human designed for
13 determining properties that get to edges from the
14 image to be extracted. And you can have the
15 Kirsch operators, the Prewitt operators, many
16 other things, which can be used and you get an
17 edge image.

18 You can continue with that in the pipeline
19 sense, as I was describing for the conventional
20 approaches. You can use, you know, thresholding
21 of those individual edge responses to get the
22 significant edges. You can get hysteresis-based
23 thresholding in which you connect, you know,
24 different edges and so on.

25 So there are many ways, but the traditional

1 approach is start with a kernel, which is somehow
2 designed by a human, and that very probably goes
3 back to the 1970s or so.

4 Q. Understood.

5 You brought up thresholding. Is thresholding
6 another non-neural network feature extraction
7 function that was used for images?

8 MR. MARANDO: Objection. Form.

9 A. It is a function that is used for images. I
10 don't see a way how you would use it directly for
11 feature extraction without anything beyond that.

12 Q. How about statistical functions? Are there any
13 statistical functions that you're familiar with
14 that would be essentially non-neural network
15 feature extractors for images?

16 MR. MARANDO: Objection. Form.

17 A. There is a number of such approaches, and you can
18 start with very simple ones, like average
19 brightness of an image, variation of brightness
20 in the image.

21 My PhD, interestingly enough, back in, you
22 know, early 1980s, many, many years ago, was
23 dealing with texture image analysis. And so for
24 texture descriptions there is a long list of
25 statistical approaches which determine different

1 variations of pixel brightness configurations and
2 try to make sense of that and create descriptors
3 that may be useful for texture characterization.

4 Q. Okay.

5 A. Again, traditionally based on human design
6 descriptors.

7 Q. Okay. I appreciate that.

8 So now I would like to understand your
9 construction of the claim term extracted feature
10 representations and how you got them. Okay?

11 So for the record, your construction of
12 extracted feature representations is, "Feature
13 representations that are learned using a neural
14 network."

15 Is that correct?

16 A. Yes, it is correct.

17 Q. Okay. And so although we have just gone through
18 and discussed a number of non-neural network
19 feature extraction functions, your construction
20 of extracting feature representations for the
21 purpose of this patent is limited to the use of
22 neural networks; is that correct?

23 A. Let me get in my declaration in the Exhibit Share
24 to that -- to that location.

25 Q. What specifically are you looking for in your

1 declaration? I might be able to point you to it.

2 A. If you can point me to the claim construction
3 paragraph.

4 Q. Paragraph 94.

5 A. Yes, I'm there. So can you please repeat the
6 question?

7 Q. I think it was more of a summary statement, but
8 you and I have just discussed a list of examples
9 of non-neural network feature extraction
10 functions, but your claim construction is limited
11 to just features that are extracted with a neural
12 network; is that correct?

13 A. That is my claim construction, which I am
14 proposing in the paragraph 94.

15 Q. Okay. Thank you.

16 And did you review the 029 patent and its
17 prosecution history?

18 A. Yes, I have.

19 Q. Did you see anything in the 029 patent or its
20 prosecution history that disclaimed any of the
21 aforementioned conventional non-neural network
22 feature extraction approaches that you and I have
23 discussed?

24 MR. MARANDO: Objection. Form.

25 A. What I have seen in the underlying patent when I

1 was reading it in its entirety is a very clear
2 description in the specifications how the
3 features are extracted and derived. And that
4 description is very clear and it requires the
5 neural network to do that --

6 Q. Okay. Again --

7 A. -- extraction --

8 Q. I appreciate your effort to answer, Dr. Sonka.
9 I'm going to -- I'm going to ask you to please
10 listen to the questions that I'm asking and
11 answer those questions.

12 So I asked you if you saw anything in the
13 patent or its prosecution history that disclaimed
14 these other conventional non-neural network
15 feature extraction approaches?

16 MR. MARANDO: Objection. Form.

17 A. There are many things which are not disclaimed.
18 So I don't quite understand why this would be
19 relevant. But can you see the prosecution
20 history here?

21 Q. Is your answer no, you did not see anything that
22 disclaimed those?

23 A. I am not aware of any location which I can point
24 to at this moment that would specifically say
25 that other things are not allowed.

1 - - - -

2 (Thereupon, Exhibit 1001, Patent No.: US
3 10,751,029 B2, was marked for purposes of
4 identification.)

5 - - - -

6 Q. Okay. Why don't you look at the 029 patent,
7 which is Exhibit 1001. I understand you have a
8 paper copy there, but I also provided it in the
9 link on Exhibit Share.

10 A. Yes.

11 Q. And specifically I'm looking at column 6, lines
12 35 to 41.

13 A. Column 6, yes.

14 Q. Now --

15 A. What are the lines?

16 Q. For convenience, I'm going to read that into the
17 record. I'd ask you just follow along and let me
18 know if I have --

19 A. Which -- which lines are you talking about?

20 Q. 35 to 41.

21 A. Uh-huh.

22 Q. It says, "The analyzer 14 may then derive one or
23 more extracted feature representations from the
24 received set of ultrasound images. In some
25 embodiments, the analyzer 14 may implement a

1 neural network including a feature-extracting
2 neural network and the analyzer 14 may input the
3 set of ultrasound images into the
4 feature-extracting neural network in order to
5 derive the one or more extracted feature
6 representations."

7 Did I read that correctly?

8 A. I believe so. Let me make sure I am in the same
9 location. So once again, it is column?

10 Q. Column 6, line 35.

11 A. Sorry, I was someplace else. I see it now. Yes.

12 Q. Now, as I read that passage, it sounds like the
13 use of the neural network is permissive in the
14 invention, it's not required in the invention;
15 would you agree?

16 MR. MARANDO: Objection. Form.

17 A. I see that. I believe that your statement is
18 based on the word "may," am I correct?

19 Q. Correct. It says, "In some embodiments, the
20 analyzer may implement a neural network."

21 So would you agree that that's permissive?
22 It doesn't require the use of a neural network?

23 MR. MARANDO: Objection. Form.

24 A. I see the word "may." At the same time when I
25 analyze the entire patent, 029, I do not see any

1 embodiment that would not require the use of a
2 neural network.

3 Q. Okay. So just to be clear, does the 029 patent
4 mention any other embodiments in which feature
5 extraction is performed by means other than a
6 neural network?

7 MR. MARANDO: Objection. Form.

8 A. I have not -- I have not seen that. My
9 understanding is that the embodiments described
10 -- the specifications of 029 are all clearly
11 talking about neural networks being used for
12 deriving the features, both in training and in
13 extraction itself.

14 Q. Okay. I want you to -- you still got the patent
15 in front of you?

16 A. Yes, I do.

17 Q. Now I want you to turn to column 11, lines 39 to
18 42.

19 A. Column 11, lines 39 to 42, yes.

20 Q. Okay. I'm going to read that into the record.

21 "In various embodiments, alternative or
22 additional feature extracting functions and/or
23 neural networks may be used to extract features
24 of the input set of ultrasound images."

25 Did I read that correctly?

1 A. I see that sentence.

2 Q. What does that mean to you?

3 A. As I -- as I read it, my understanding is that
4 there may be other neural network ways than
5 described here that can be used to extract
6 features of the input set of ultrasound images.

7 Q. You think this is referring to exclusively neural
8 networks?

9 A. I would read it -- if I shortened it, I would
10 read it as various embodiments, alternate neural
11 networks may be used to extract features.

12 Q. But it explicitly says alternative
13 feature-extracting functions or neural networks
14 may be used, doesn't it?

15 A. It says and/or.

16 Q. Okay. Do you -- do you not understand that to be
17 referring to alternative non-neural network
18 functions can be used?

19 MR. MARANDO: Objection. Form.

20 A. I read it -- I read it alternative feature
21 extraction functions and neural networks may be
22 used is one option. And the other option, as I
23 read it, is alternative feature extraction
24 functions or neural networks may be used. And
25 the alternative functions as described in the

1 entirety of the 029 patent are always talking
2 about the neural network approaches, and there is
3 no other embodiment than that.

4 So my understanding of the sentence is that
5 all those approaches are neural network
6 approaches.

7 Q. Did you consider this passage that we just read
8 in column 11 before you provided your opinion?

9 A. I have seen this sentence before, yes.

10 Q. Okay. And am I correct that you did not quote
11 this passage or address it directly anywhere in
12 your declaration?

13 A. I do not believe this is referenced in the
14 declaration.

15 Q. Why not?

16 MR. MARANDO: Objection. Form.

17 A. I don't think I was really considering the
18 sentence when I was writing the declaration.

19 - - - -

20 (Thereupon, Exhibit 2049, Declaration of
21 Milan Sonka, was marked for purposes of
22 identification.)

23 - - - -

24 Q. Okay. Let's look at your declaration, which is
25 previously marked as Exhibit 2049. You should

1 have that as the link.

2 A. Yes, I have it.

3 Q. If you go to paragraph 99, which is on --

4 A. I'm there.

5 Q. -- the bottom of page 50.

6 A. I'm there.

7 Q. Okay. I'm going to again read this.

8 "The 02" -- excuse me.

9 "The 029 patent's figures and corresponding
10 descriptions uniformly disclose that these
11 extracted feature representations, i.e.,
12 encodings of image patterns, are learned using a
13 neural network."

14 Did I read that correctly?

15 A. Yes.

16 Q. Okay. Did you write that or did your counsel
17 write that?

18 MR. MARANDO: Objection. Form.

19 A. This is my declaration, so I am responsible for
20 it -- for the sentence.

21 Q. Okay. So even if -- well, are you saying you
22 reviewed the patent to make sure that this
23 statement was accurate?

24 A. No. I am saying that I have written substantive
25 parts of the declaration. The counsel wrote

1 substantive parts of the legal aspects of the
2 declaration and the -- you know, some of my
3 language needed to be changed to be legally
4 proper, as I am sure you know that engineers
5 write it differently.

6 And so the declaration was done in a
7 collaborative manner; however, it's my
8 declaration and I have provided the substance to
9 it.

10 Q. In paragraph 99 of your declaration, what did you
11 mean when you used the word "uniformly"?

12 A. What I meant by that is that you can say solely
13 disclose or that they consistently --
14 consistently is probably the right word.
15 Descriptions consistently disclose that these
16 extracted feature representations are learned
17 using neural networks.

18 Q. And directly after the sentence that I read,
19 paragraph 99 in your declaration goes on for
20 another seven pages, I believe, citing examples
21 in the 029 where the feature extraction is
22 performed using neural networks.

23 Was it your intention to convey to the judges
24 in this case that every time the 029 patent
25 discusses feature extraction, that feature

1 extraction is performed by a neural network?

2 A. The reason why I provided these examples were
3 that I was trying to demonstrate that
4 consistently neural networks are used in the
5 teachings of the 029 patent for feature
6 extraction and for learning the features.

7 Q. You said "consistently." But I'll ask again, was
8 it your contention to convey the idea that every
9 time the 029 patent discusses feature extraction,
10 it only does so with neural networks?

11 MR. MARANDO: Objection. Form.

12 A. I have not seen any other example than using
13 neural networks for this purpose.

14 Q. Okay. What about the passage that I read from in
15 column 11, lines 39 to 42 of the 029 patent?
16 Does that discuss using non-neural network
17 feature extraction functions?

18 A. I don't believe so because nothing else in the --
19 in the specifications or in the claims talk about
20 an embodiment which would be different from the
21 one in which neural networks are used.

22 Q. So when the 029 patent refers to alternative
23 feature extraction functions or neural networks,
24 you do not understand that to refer to any of the
25 conventional feature extracting functions?

1 MR. MARANDO: Objection. Form.

2 A. I do not because the specifications of the patent
3 and the entire flavor of the patent when read as
4 needed in the entirety is not talking about
5 conventional feature extractions.

6 The conventional feature extractions are
7 completely incompatible with the structure which
8 is shown in the 029 patent. The conventional
9 feature extraction approaches have no place to be
10 used in the -- in the architecture, which is
11 disclosed in Figure 4, I think it is, for
12 example.

13 Q. Well, we'll have to agree to disagree on that,
14 but let's -- let's move on.

15 Would you characterize the feature extraction
16 neural networks that are in the 029 patent as
17 deep neural networks?

18 A. Yes, I would.

19 Q. Would you also characterize them as deep learning
20 neural networks?

21 MR. MARANDO: Objection. Form.

22 A. I am not familiar with the term deep learning
23 neural networks. Because, you know, the deep
24 neural networks are used for learning and they
25 are used for production once they are trained.

1 So I don't know -- I am not familiar with that
2 term, how it would distinguish itself from the
3 deep neural network.

4 Q. Okay. Well, let me ask you this then: What is a
5 deep neural network, as you understand it?

6 A. As I understand, the deep neural network is a
7 neural network that has multiple hidden layers,
8 typically more than three, four, five, and many
9 more than that. And the number of hidden layers
10 specify the depths of the network.

11 Q. Okay. You say typically, I think you said three,
12 four, five.

13 Can a neural network with only one hidden
14 layer be a deep neural network, in your opinion?

15 MR. MARANDO: Objection. Form.

16 A. A three-layer neural network with one hidden
17 layer is what I would call the pre-deep learning
18 era neural network described and used, you know,
19 as a classifier, as something what you can train,
20 but does not have enough free parameters to
21 perform things which are possible to be performed
22 with deep networks.

23 Q. Is there some minimum number of hidden layers --
24 I'm talk -- by hidden layers I mean between the
25 input and the output.

1 Is there some number -- minimum number of
2 hidden layers that, in your opinion, is required
3 in order for a neural network to be called a deep
4 neural network?

5 MR. MARANDO: Objection. Form.

6 A. I am not aware of a hard number that would be
7 generally accepted. I can tell you that if the
8 network has more than six or seven -- I'd say
9 more than six hidden layers, it would be
10 considered a deep network.

11 I can think about examples where, you know,
12 three hidden layers, plus the, you know, first
13 layer and the output layer are used in the past
14 in relatively small networks, which, in my view,
15 do not satisfy the requirement of the deep
16 learning that sort of came after the AlexNet was
17 introduced.

18 So I don't think there is a crisp number as
19 you can say anything below a number is not deep
20 and above the number of hidden layers is deep. I
21 think it's associated with the entire
22 architecture and size of the network.

23 Q. Okay. Well, here's my quandary. You seem to be
24 making a distinction in your declaration between
25 early machine learning neural networks versus

1 deep neural network, and you're implying that the
2 029 patent is somehow limited to deep neural
3 networks. So I'm trying to understand from you a
4 definition of what that is.

5 MR. MARANDO: Objection. Form.

6 A. In the context of the 029 patent, the network has
7 to be deep enough and large enough to be capable
8 of deriving description features from training
9 image data. And the same network of the same
10 architecture and same size is then later used for
11 extracting those features from previously unseen
12 images. And that's what the deep learning really
13 brought to computer vision and medical imaging.

14 That functionality is what started the deep
15 learning revolution, which really changed
16 computer vision and brought us the capability of
17 self-driving cars and, you know, much better
18 character recognition and many other things.

19 Q. So let me ask you -- maybe I'll ask this a
20 different way.

21 Is a neural network considered deep, in your
22 opinion, because of its structure or because it
23 performs some other function like learning
24 features to extract?

25 MR. MARANDO: Objection. Form.

1 A. The network does not have to be able to learn
2 features to be put into the category of a deep
3 network.

4 Q. Say that again.

5 A. The network does not have to have the capability
6 or have the functionality of learning features to
7 be considered in the category of deep networks.

8 Q. Okay. Okay. I still am interested in
9 understanding, in your opinion, is a neural
10 network considered deep because of its structure
11 or because it's performing some other function
12 than non-deep neural networks?

13 MR. MARANDO: Objection. Form.

14 A. I don't think you can separate those things. You
15 know, the architecture, the structure, the size
16 enables some functionalities which are not
17 enabled by simpler neural networks.

18 I don't think we will be able to arrive --
19 and I'm not aware of any, you know, hard
20 definition which would provide a threshold of a
21 network which has less than X number of nodes or
22 X number of layers is never considered deep. I
23 don't think it exists. And if you aware of
24 something like that, please tell me.

25 Q. So again, I want to make sure I'm understanding

1 your terminology in your declaration. If you're
2 referring to a network as being a deep learning
3 network, does that mean that you believe that
4 network performs deep learning?

5 MR. MARANDO: Objection. Form.

6 A. The network performs learning. And if the
7 network structure and architecture and all the
8 associated, you know, modules that connect
9 individual layers are designed in a meaningful
10 way, it allows to learn different things. And
11 one of the different things may be to actually
12 learn optimal features with respect to the
13 objective function of the learning set. And this
14 is something which allows to use the network in
15 the end-to-end manner.

16 And here the end-to-end means that you can
17 start with inputting the raw data to the network
18 and the desired output, which may be a decision,
19 which may be label, which may be anything else
20 which is desired is generated on the output with
21 the proper training and the proper set of
22 training-truth pairs.

23 Q. Well, I'm -- your declaration emphasizes the sea
24 change that occurred with the advent of deep
25 learning, and I'm trying to understand from you a

1 definition that will allow me to look at a neural
2 network and know whether it is deep learning or
3 not. I mean, can you explain to me how I can do
4 that?

5 MR. MARANDO: Objection. Form.

6 A. You are asking me a very difficult question which
7 does not have a binary answer in my mind. My
8 opinion is that you cannot get a definition where
9 the line is between a network being deep and not
10 deep.

11 Q. Okay. At paragraph 70 of your report, it's on
12 page 35. You quote from a -- from a Medical
13 Image Analysis textbook.

14 A. Yes.

15 Q. And it says, "The term deep neural network
16 loosely refers to neural networks with three or
17 more stacked hidden layers."

18 Do you see that?

19 A. I see that and I think it's very consistent,
20 which I was trying to relay to you in the past
21 answers.

22 Q. Okay. But it's not a -- it's not a hard
23 definition; is that fair?

24 A. That's why it uses the "loosely" reference.
25 Because I don't think there is a hard definition.

1 If you are familiar with fuzzy logic, I think
2 that this is very much the fuzzy area between
3 something what is not and between something what
4 is and the area in between is gray.

5 Q. Okay. But you understand I'm trying to
6 understand how I can identify deep learning
7 neural networks since you are making a
8 distinction based on deep learning neural
9 networks. So I want to be able to understand it.
10 We'll discuss it more when we talk about your
11 claim construction.

12 So the construction that we referred to
13 earlier for extracted feature representation,
14 your construction simply refers to a neural
15 network. It does not refer to a deep neural
16 network or a deep learning neural network.

17 Is it your intention to restrict your
18 construction to deep neural networks or deep
19 learning neural networks?

20 MR. MARANDO: Objection. Form.

21 A. I have -- you know, my claim construction which
22 is here, is really following the, you know, the
23 rule -- I may not use the exact right words in
24 the legal sense, but the plain ordinary meaning
25 of that claim -- of that claim representation.

1 What I have adopted here is the construction
2 that is consistent with that used in the parallel
3 litigation, which I am not familiar with it, but
4 you probably are.

5 Q. Okay. I appreciate that, but you did not answer
6 my question.

7 Is it your intention to limit the scope of
8 your construction to deep neural networks or deep
9 learning neural networks or can any neural
10 network satisfy the construction?

11 MR. MARANDO: Objection. Form.

12 A. I already asked before, so what's your
13 distinguishing definition between deep neural
14 network and deep learning neural network?

15 Q. Well, I asked you and you didn't give me a
16 distinction. So I'm using either of them as
17 options.

18 Are you -- are you limiting your construction
19 to either of those?

20 MR. MARANDO: Objection. Form.

21 A. Deep neural network is a neural network.

22 Q. Are you saying that the only neural networks that
23 can satisfy the definition that you are providing
24 are deep neural networks?

25 MR. MARANDO: Objection. Form.

1 A. I am not stating that here. So although --
2 although in the context of my background
3 information, I certainly have an opinion that the
4 non-deep neural networks that were published,
5 presented, used prior to that, as you say, you
6 know, watershed change in 2012, were not capable
7 of learning feature representations.

8 Q. So any neural network -- it does not have to be a
9 deep neural network or a deep learning neural
10 network. Any neural network could satisfy the
11 definition that you have provided in your
12 construction; is that fair?

13 A. The construction requires the learning to be done
14 with the neural network. And the neural network
15 for that needs to have the architecture that
16 allows that.

17 Q. But it's not restricted to a deep neural network
18 that has, for example, three or more stacked
19 hidden layers?

20 MR. MARANDO: Objection. Form.

21 A. I don't think we established where the deep
22 neural network architecture starts. So I am not
23 going to agree on the statement of three or more
24 here.

25 Q. Okay. And it's not your intention to limit the

1 construction to only deep neural networks,
2 correct?

3 A. It's my intention to limit the constructions to
4 neural networks which can provide learning of the
5 feature extractions.

6 Q. Are you aware of any neural networks other than
7 deep neural networks that perform the function of
8 extracting feature representation --

9 MR. MARANDO: Objection. Form.

10 A. I am not.

11 Q. Are you aware of any neural networks other than
12 deep learning neural networks that learn on their
13 own the features that are to be extracted from
14 images --

15 MR. MARANDO: Objection. Form.

16 Q. -- other than using handcrafted features?

17 MR. MARANDO: Sorry. Just wait a
18 second. Can you -- I interrupted.

19 Can you say that again, Jeff?

20 Q. I'll repeat it.

21 Are you aware of neural networks other than
22 deep neural networks that determine on their own
23 or learn on their own which features to extract
24 from an image rather than using handcrafted
25 features?

1 MR. MARANDO: Objection. Form.

2 A. Can you please define what you mean by "on their
3 own"?

4 Q. Sure. Instead of using a handcrafted feature,
5 the neural network learns the features through
6 training.

7 A. No.

8 MR. MARANDO: Objection. Form.

9 A. No, I am not aware of that and that's why I
10 called the 2012 AlexNet being game-changing --
11 not even publication, but result on the ImageNet
12 competition at that time.

13 I think that's widely accepted that this is
14 what started the deep learning imaging
15 revolution. It took many years after 2012 before
16 it actually got accepted.

17 Q. Let me try to understand -- a better
18 understanding of your position.

19 If a neural network learned on its own the
20 features to extract from an image rather than
21 using handcrafted features, do you consider that
22 to be a deep learning neural network?

23 MR. MARANDO: Objection. Form.

24 A. I'm not aware of any scenario that would go in
25 that direction. And I don't think you can

1 specify something as being deep by functionality
2 only without considering the architecture.

3 Q. Okay. I understand that.

4 Let's look at your declaration again.

5 Paragraph 134.

6 A. I see it.

7 Q. I'm going to read a portion of that paragraph to
8 you. It's actually the paragraph -- it goes on
9 to page 87, and I'm looking four lines down on
10 page 87.

11 You say, "The shift from non-learning-based
12 feature extraction to neural network-based
13 feature learning did not occur until 2012 with
14 the introduction of AlexNet. At the time of
15 Krishnan's filing in 2005, known segmentation
16 and/or filtering methods would have been
17 understood by a person having ordinary skill in
18 the art to refer exclusively to conventional,
19 non-learning-based techniques such as edge
20 detection, thresholding, region-based methods,
21 watersheds, and dynamic programming-based
22 optimization approaches, none of which involve
23 neural networks."

24 Did I read that correctly?

25 A. You have read it correctly.

1 Q. Okay. And is that statement based on your
2 personal knowledge?

3 A. This statement is referring to the person of
4 ordinary skills understanding of what Krishnan
5 meant in the patent as known segmentation and/or
6 filtering methods.

7 Q. Well, I want to clarify that.

8 Do you understand that a person of skill in
9 the art is considering -- or is the person that
10 we use to judge, for example, obviousness of an
11 invention, that person is considered to be aware
12 of all of the prior art? Do you understand that?

13 A. It's a hypothetical person.

14 Q. And do you understand that that hypothetical
15 person is assumed to be aware of all of the prior
16 art as if it was all sitting on the desk in front
17 of them?

18 MR. MARANDO: Objection. Form.

19 A. Is that a question or is it a statement?

20 Q. I did ask you, do you understand that, that a
21 person of skill in the art is assumed to be aware
22 of all of the prior art just as if every
23 publication and every patent had been printed and
24 put on the desk in front of them?

25 MR. MARANDO: Objection. Form.

1 A. Let me go to the page 17 of my declaration here.
2 Well, I do understand that the person having
3 ordinary skill in the art would have the
4 knowledge from the teachings of the prior art,
5 including the art that is listed in my list of
6 exhibits.

7 Q. I'm sorry, did you say you do understand that the
8 person skilled in the art is assumed to be aware
9 of all the prior art?

10 A. I understand that, you know, prior art is
11 something what the -- what POSITA would be aware
12 of, yes.

13 Q. Before you submitted your declaration, including
14 the statement that I just quoted, did you do any
15 research to determine whether at the time of
16 Krishnan's filing in 2005 there were known
17 methods for extracting features from images, of
18 segmenting images using neural networks?

19 A. I didn't have to. I am well aware of techniques
20 that were used for segmenting images using neural
21 networks and for using neural networks to
22 improve, optimize parameters of handcrafted
23 features, for example.

24 Q. I'm sorry, you're saying you are aware of
25 pre-2005 neural networks that were used for image

1 segmentation?

2 A. Yes, I am.

3 Q. Okay. So can you explain to me what -- what this
4 statement in paragraph 134 means?

5 MR. MARANDO: Objection. Form.

6 A. The statement means that edge detection is not a
7 neural network approach, that thresholding is not
8 a neural network approach, the regional-based
9 methods are not a neural network approach,
10 watershed segmentation is not a neural network
11 approach, and the dynamic programming-based
12 optimization is not a neural network approach.

13 Q. Well, but at the start of the last sentence in
14 paragraph 134, you say, "At the time of
15 Krishnan's filing in 2005, known segmentation
16 and/or filtering methods would have been
17 understood by a person of ordinary skill in the
18 art...none of which involved neural networks."

19 Are you saying there that known segmentation
20 techniques as of 2005 did not involve the use of
21 neural networks?

22 A. If I look back at Krishnan and I look at examples
23 of the known segmentation and filtering methods
24 which are provided in the Krishnan patent, none
25 of them talks about neural network-based

1 approaches, and that is what this statement is
2 based on.

3 So what the statement says that known
4 segmentation and filtering methods described in
5 the Krishnan patent involved neural networks.

6 Q. Sorry. So are you trying to say -- are you
7 trying to give your opinion of how a person of
8 ordinary skill in the art would interpret
9 Krishnan?

10 Dr. Sonka appears to have frozen.

11 A. I am looking at the -- this entire section talks
12 about -- talks about prior art of Krishnan. So
13 this statement is describing the Krishnan patent.

14 Q. Are you saying that prior to Krishnan -- prior to
15 Krishnan's filing date in 2005, there were not
16 known techniques for performing image
17 segmentation using neural networks?

18 A. Can we introduce the Krishnan patent? I'll look
19 at it.

20 Q. I do have the Krishnan patent, but I'm asking you
21 from your knowledge and experience, and are you
22 saying in your declaration that before Krishnan,
23 its filing date in 2005, it was not known to use
24 neural networks for image segmentation?

25 MR. MARANDO: Objection. Form.

1 A. What I'm saying is that image segmentation -- I'm
2 not aware of image segmentation being done
3 directly with neural networks without having some
4 kind of handcrafted features in the process.

5 Q. Okay. So you're not aware of neural -- before
6 Krishnan in 2005, you're not aware of neural
7 networks being used to segment images using the
8 image directly rather than handcrafted features?

9 A. What I'm saying is that I am not aware of works
10 that would not include a handcrafted step in
11 feature definition which is used down the road by
12 neural networks.

13 Q. Are you aware of neural networks that were used
14 to perform image segmentation by taking the image
15 as input before Krishnan's filing date in 2005?

16 A. So let's -- let's make it clear what we are
17 saying. So whether I am aware of image being
18 used directly as the input into the neural
19 network? Is that a question?

20 Q. Yes.

21 A. Not without -- I'm not aware of such a
22 functionality without having a human-designed
23 feature that is required by the neural network to
24 use.

25 Q. Okay. I'm going to populate your Exhibit Share

1 folder with another exhibit.

2 MR. MARANDO: Jeff, if you want to
3 take a break at some point, I think we've
4 been going for about an hour and ten
5 minutes.

6 MR. METZCAR: Sure. That would be
7 fine. Let's take five minutes.

8 - - - -

9 (Thereupon, a recess was had.)

10 - - - -

11 (Thereupon, Exhibit 1047, Article titled,
12 "Image processing with neural networks – a
13 review", was marked for purposes of
14 identification.)

15 - - - -

16 BY MR. METZCAR:

17 Q. Dr. Sonka, we're back on the record.

18 Are you able to access Exhibit 1047 in
19 Exhibit Share?

20 A. Yes, I see it now.

21 Q. Okay. So this is a publication entitled "Image
22 processing with neural networks - a review." It
23 was published in 2002 in volume 35 of Pattern
24 Recognition, which is the journal of the Pattern
25 Recognition Society.

1 Are you familiar with the Pattern Recognition
2 journal generally?

3 A. I know it exists. That's about how far I would
4 go.

5 Q. Is it considered a reliable authority?

6 A. Yes, I would say so.

7 Q. Have you ever seen this particular publication in
8 Exhibit 1047?

9 A. It's one of the exhibits which I have listed in
10 my list, I believe.

11 Q. You think you've seen this before?

12 A. Let me make sure -- I can look or you can tell
13 me.

14 Q. I believe I'm presenting it to you for the first
15 time. I'm quite certain your counsel has not
16 cited this exhibit to me. I believe I'm bringing
17 it to your attention, but I'm asking you whether
18 you have ever seen it in any context.

19 A. I have not.

20 Q. Okay. So this is a very long review survey of
21 image processing techniques using neural
22 networks. To speed things along, I'm going to
23 direct your attention to some particular passages
24 that are relevant for our discussion. That's
25 probably going to involve me doing some reading

1 into the record. And I will direct you to
2 particular parts, and I hope that you would maybe
3 read along with me. And as before, when I get
4 done, I'll ask you if I accurately read the
5 passage and then I'll ask you some questions
6 about the passages. Okay?

7 A. Yes.

8 Q. I'm going to start with the abstract. It says --

9 MR. MARANDO: Before you get
10 started, I believe this is a new exhibit
11 you're introducing. This is in the record;
12 is that right?

13 MR. METZCAR: Correct.

14 MR. MARANDO: It's marked today?
15 I'm going to object to foundation,
16 relevance, outside scope. You can
17 continue.

18 MR. METZCAR: Well, okay. What's
19 your foundation objection?

20 MR. MARANDO: It's not of record
21 in the proceeding. You haven't -- no
22 witness has talked about it.

23 MR. METZCAR: I'm asking him about
24 it. I mean --

25 MR. MARANDO: Okay.

1 MR. METZCAR: Yeah.

2 MR. MARANDO: And my relevance
3 objection is no -- it's not in the
4 petition.

5 MR. METZCAR: Well, this is --
6 this is evidence being offered to rebut his
7 testimony and it will appear in the reply.
8 So I'm asking him about it.

9 MR. MARANDO: I understand. Just
10 stating my objections for the record.

11 MR. METZCAR: Sure. Dr. Sonka
12 made a lot of representations about what
13 was known and what was not known before
14 2012 and before 2005. We have a number of
15 documents that are directly relevant to
16 that issue. So I'm going to ask him about
17 those.

18 Q. Okay. So let's look at the abstract. It says,
19 "We review more than 200 applications of neural
20 networks in image processing and discuss the
21 present and possible future role of neural
22 networks, especially feed-forward neural
23 networks, Kohonen feature maps and Hopfield
24 neural networks. The various applications are
25 categorized into a novel two-dimensional taxonomy

1 for imaging -- for image processing algorithms.
2 One dimension specifies the type of task
3 performed by the algorithm: Preprocessing, data
4 reduction/feature extraction, segmentation,
5 object recognition, image understanding and
6 optimization. The other dimension captures the
7 abstraction level of the input data processed by
8 the algorithm: Pixel-level, local feature-level,
9 structure-level, object-level, object-set-level
10 and scene characterization."

11 Did I read that correctly?

12 A. Yes.

13 Q. Okay. And do you understand what they're talking
14 about, the extraction level of the input as being
15 either pixel-level input or feature-level input?

16 A. I believe so.

17 Q. So if you turn the page to, I believe, it's
18 marked 2280 at the top of the page. Second page.
19 I'm looking at the second column. There's a list
20 there of the various image processing
21 applications.

22 Do you see that?

23 A. I see that.

24 Q. Okay. And the second listed processing -- image
25 processing operation is data reduction/feature

1 extraction. And it's defined as, "Any operation
2 that extracts significant components from an
3 image (window). The number of extracted features
4 is generally smaller than the number of pixels in
5 the input window."

6 Then it defines segmentation. "Any operation
7 that partitions an image into regions that are
8 coherent with respect to some criterion. One
9 example is the segregation of different
10 textures."

11 Do you see that?

12 A. I do.

13 Q. Okay. Now I want you to go to the next page,
14 which is labeled 2281. And you'll see there a
15 Table 1.

16 Do you see that?

17 A. I do.

18 Q. So this is the taxonomy that they were referring
19 to. They have done a review of neural network --
20 of the use of neural network for image processing
21 and they've broken down applications that
22 perform, for example, feature extraction,
23 segmentation, or object recognition within the
24 image, and they have also broken it down by
25 whether those neural networks accept pixels as

1 the input or accept extracted features as the
2 input.

3 Do you understand that?

4 A. I do.

5 Q. Okay. And Table 1 lists at least 25 neural
6 networks in the review that extract features
7 using pixel input directly from the image.

8 Do you see that?

9 A. I do see number 25.

10 Q. Yeah, and it lists under -- in the segmentation
11 column, it lists that this review has seen 39
12 neural networks that perform image segmentation
13 directly from the pixel, pixel data, and 19 that
14 use extracted features as the input.

15 Do you see that?

16 A. I see that.

17 Q. Do you have any reason to dispute that table?

18 A. I have no opinion about this paper because I am
19 seeing it for the first time. I have not
20 provided that in my declaration. I would have to
21 study this carefully and find out what those 25
22 and 39 papers actually are before I can answer
23 your question, and that is not something that I
24 have discussed in my declaration.

25 Q. Okay. Let's -- if you turn to page 2283, second

1 column. Bottom of the second column, there's a
2 heading, 3.2.2 "Feature extraction applications."

3 Do you see that?

4 A. I do.

5 Q. It says, "Feature extraction can be seen as a
6 special kind of data reduction of which the goal
7 is to find a subset of informative variables
8 based on image data. Since image data are by
9 nature very high dimensional, feature extraction
10 is often a necessary step for segmentation or
11 object recognition to be successful. Besides
12 lowering the computational cost, feature
13 extraction is also a means for controlling the
14 so-called curse of dimensionality. When used as
15 input for a subsequent segmentation algorithm,
16 one wants to extract those features that preserve
17 the class separability well. There is a wide
18 class" -- I'm sorry. "There is a wide class of
19 ANNs that can be trained to perform mappings to a
20 lower-dimensional space, for an extensive
21 overview see reference 60. A well-known
22 feature-extraction ANN" -- and do you understand
23 ANN is artificial neural network?

24 A. Yes, I do.

25 Q. "A well-known feature-extraction ANN is Oja's

1 neural implementation of a one-dimensional
2 principal component analysis (PCA), later
3 extended to multiple dimensions."

4 Do you see that?

5 A. I do.

6 Q. It also says, "In reference 63, Baldi and Hornik
7 proved that training three-layer auto-associator
8 networks corresponds to applying PCA," or
9 principal component analysis, "directly to the
10 input data."

11 Do you -- do you have any basis to dispute
12 that any of that description is accurate?

13 MR. MARANDO: Objection. Form.
14 Foundation.

15 A. I have not provided the opinion about this. I
16 would have to look at what is reference 60, what
17 is reference 61.

18 Q. Okay.

19 A. The layer references.

20 Q. Okay. You are not personally familiar with
21 neural networks that perform feature extraction
22 before the filing date of Krishnan; is that
23 correct?

24 MR. MARANDO: Objection. Form.

25 A. I don't agree with that statement.

1 Q. Okay. So you are aware of neural networks that
2 perform feature extraction on images prior to the
3 filing date of Krishnan?

4 MR. MARANDO: Objection. Form.

5 A. Under the definition to feature extraction is
6 calculation of the features. I am aware of such
7 scenarios. I am not aware, as I already stated
8 it earlier, I'm not aware of the capabilities of
9 neural networks to design features from training
10 sets.

11 Q. Okay. I'm skipping down from where I stopped
12 reading to the next paragraph in that column. It
13 says, "Among the ANNs that have been trained to
14 perform feature extraction," and it lists a
15 number of citations there, "feed-forward ANNs
16 have been used in most of the reviewed
17 applications." And there it lists four more
18 citations.

19 SOMs -- can you tell me what a SOM means?

20 MR. MARANDO: Objection. Form.

21 Foundation.

22 A. The SO suggests self-organizing, but I don't know
23 what SOM means.

24 Q. Okay. Well, it says --

25 A. Is it defined someplace?

1 Q. It's self-organizing map. It's a type of --

2 A. Map, okay.

3 Q. "SOMs and Hopfield ANNs have also been trained to
4 perform feature extraction. Most of the ANNs
5 trained for feature extraction obtain pixel data
6 as input."

7 Do you see that?

8 A. I see it.

9 Q. Okay. Do you have any basis to dispute that
10 that's a true statement?

11 A. Again, I have not provided opinion of this paper.
12 However, we seem to be mixing things here, and we
13 are mixing use of neural networks for performing
14 a well-designed operation, handcrafted operation
15 like PCA, which has mathematical equations which
16 need to be followed, and we are mixing that with
17 designing feature extractors which are not
18 handcrafted. And once again, to be able to
19 digest it, I will require, you know, time to do
20 that and look at the references.

21 Q. Okay.

22 A. It seems to me that when you are talking about
23 pixels being used as input, at that time, most
24 likely you'd be talking about small neighborhoods
25 of pixel, not the entire images.

1 But again, I cannot provide an opinion on
2 that without going into those 200 references
3 which you are talking about and which are
4 summarized in the data.

5 Q. Yeah, I understand you can't -- you can't look at
6 those references now, but obviously you've made
7 some representations about people with skill in
8 the art not being aware of performing feature
9 extraction or image segmentation using neural
10 networks prior to Krishnan, and I'm pointing out
11 to you some documentation that discusses that and
12 asking if you have any basis to dispute what is
13 said here. I'm certain you will go back and look
14 at the references that are cited.

15 Okay. I'm going to move over to the second
16 column of the same page. I'm sorry, page 2284.
17 And in the second column there is a section
18 heading 3.3.1 "Image segmentation based on pixel
19 data."

20 Do you see that?

21 A. Yes, I do.

22 Q. So this survey in 2002 reports, "Many ANN
23 approaches have been presented that segment
24 images directly from pixel or voxel data." And
25 then it lists some 30 references. "Several

1 different types of ANNs have been trained to
2 perform pixel-based segmentation: Feed-forward
3 ANNs, SOMs, Hopfield networks, probabilistic
4 ANNs, radial basis function networks, CNNs,
5 constraint satisfaction ANNs, and RAM networks."

6 Do you see that?

7 A. I see that.

8 Q. Going down to the next column -- do you have any
9 basis as you sit here today to dispute that
10 that's an accurate characterization?

11 MR. MARANDO: Objection.

12 Foundation. Form.

13 A. That's what the paper says, yes.

14 Q. And do you agree that the paper provides
15 citations to many references to support its
16 claim?

17 MR. MARANDO: Objection to form.

18 A. It still does not show me how this is relevant to
19 what Krishnan was teaching in 102 module.

20 Q. Well, if Krishnan says that feature extraction
21 can be performed with a neural network, would
22 that have been something that a person of skill
23 in the art would have been aware of, at the very
24 least, after this publication in 2002?

25 MR. MARANDO: Objection. Form.

1 A. I have not seen that statement in Krishnan.

2 Q. If Krishnan refers to performing feature
3 extraction using known segmentation techniques
4 and states that feature extraction can be
5 implemented by a neural network, would that
6 disclose to a person in skill in the art?

7 A. I think those are two different things.

8 MR. MARANDO: Objection. Form.

9 Go ahead.

10 A. I think those are two different things. Feature
11 extraction and segmentation are two separate
12 things. Usually, traditionally, how it works is
13 that it's a sequence of operations; that you
14 segment something from the image and then you
15 calculate features from the segmented objects.
16 The segmentation itself is not giving you the
17 features which are described in 102 of Krishnan.

18 Q. I understand Krishnan -- Krishnan does, however,
19 refer to feature extraction being performed by
20 known segmentation means.

21 Do you agree with that?

22 MR. MARANDO: Objection. Form.

23 A. A POSITA would understand that segmentation
24 doesn't get you where you need to be with respect
25 to 102, and that would interpret the statement as

1 segmentation and filtering or some other
2 extraction techniques which are based on the
3 segmented portions of the image.

4 Q. So let's discuss this.

5 Do you agree that Krishnan provides
6 alternative means for analysis, including, for
7 example, the use of classifiers, which could be a
8 neural network classifier, or templates, or
9 database query methods?

10 Do you agree with that?

11 A. Can we --

12 MR. MARANDO: Objection. Form.

13 A. Can we look -- can we look at Krishnan patent?
14 We still don't have the Krishnan patent here.

15 Q. You're not familiar with that?

16 A. I would like to see the language which is exactly
17 used.

18 Q. We'll keep moving on. I'm not going to -- I'm
19 not going to waste any time going through
20 Krishnan.

21 Moving down after the passage that I quoted
22 on page 2284, second column, I'm now looking at
23 the last paragraph in that second column.

24 It says, "Hierarchical segmentation
25 approaches have been designed to combine ANNs on

1 different abstraction levels. The guiding
2 principle behind hierarchical approaches are
3 specialization and bottom-up processing: One or
4 more ANNs are dedicated to low level feature
5 extraction/segmentation, and their results are
6 combined at a higher abstraction level where
7 another neural network classifier performs the
8 final image segmentation."

9 Do you see that?

10 A. I do.

11 Q. Okay. Do you have -- as you sit here today, do
12 you have any basis to dispute that that is an
13 accurate description of things that have been
14 done?

15 MR. MARANDO: Objection.

16 A. I have not --

17 MR. MARANDO: Form.

18 Go ahead.

19 A. I have not provided an opinion in my declaration.
20 At the same time, I have no reason why not
21 understand that you can use the pipeline of these
22 processing modules, which is very consistent with
23 what I had described as traditional approaches in
24 the background in my declaration.

25 Q. If you turn to page 2285, the next page, first

1 column, you'll see at the top of the first column
2 there's a number of bulleted points there. I'm
3 reading from about the middle of the column below
4 the end of the bulleted points.

5 It says, "In most applications, ANNs were
6 trained as supervised classifiers to perform the
7 desired segmentation."

8 Did I read that correctly?

9 MR. MARANDO: Objection. Form.

10 A. Yes, you have.

11 Q. And do you have any basis to dispute that
12 statement?

13 MR. MARANDO: Objection. Form.
14 Foundation.

15 A. Can you repeat your question?

16 Q. Do you have any basis to dispute that that's an
17 accurate statement?

18 MR. MARANDO: Same objections.

19 A. Not knowing the applications which are
20 referenced, I cannot agree that in most
21 applications this was the case.

22 Q. Okay. I believe the last thing for this exhibit,
23 I'd like you to turn to page 2292. It's a full
24 page table, Table 2.

25 A. I see that table.

1 Q. Okay. So this breaks down the image processing
2 tasks -- they're listed across the top -- by the
3 type of neural network that is used to perform
4 those tasks.

5 Do you see that?

6 MR. MARANDO: Objection. Form.

7 A. I see the table. I see the matrix structure.
8 Yes, I do.

9 Q. Okay. So at the top, listed across the top in
10 the image processing tasks, included there
11 feature extraction, and then segmentation,
12 pixel-based, and then segmentation,
13 feature-based.

14 Do you see that?

15 A. I do.

16 Q. And the table lists a number of different neural
17 networks that they have -- that the authors have
18 reviewed for performing those tasks.

19 Do you see that?

20 A. I do.

21 MR. MARANDO: Objection to form.

22 Q. And do you have any -- as you sit here today, do
23 you have any basis to dispute that that's an
24 accurate -- that that table's an accurate
25 depiction of what existed in a prior art?

1 MR. MARANDO: Objection. Form.
2 Foundation.

3 A. Without knowing what we are referencing to, I do
4 not understand what they mean by segmentation
5 pixel-based. And I will repeat my comment from
6 -- which I made earlier, that this may or may not
7 be based on small neighborhoods of a specific
8 pixel, not on the entire image. I will have to
9 look at those individual citations which are, you
10 know, given in the previous paragraphs that you
11 read.

12 Q. Okay. Well, let's -- let's follow up on that.
13 The 029 patent, you agree that its feature
14 extractor is described as, at least in the
15 embodiment shown in Figure 4, a convolutional
16 neural network?

17 A. Figure 4A? Which block are you talking about?

18 Q. I'm asking you if you're aware that the 029
19 patent describes using a convolutional neural
20 network for feature extraction?

21 A. It does. It does not do that solely. It
22 combines the long short-term memory and the
23 convolutional neural network, DenseNet.

24 Q. But does a convolutional neural network operate
25 on individually parts of the image?

1 A. Not as a whole. As a whole, the input is the
2 entire image. And especially in the context of
3 029, it is the entire image. It's actually the
4 entire image sequence.

5 Q. But it's looking -- it's looking -- convolutional
6 neural network looks at the image in pieces,
7 correct?

8 The kernel progresses across the image until
9 all pixels have been evaluated, but it looks
10 individually at pieces of the image, right?

11 MR. MARANDO: Objection. Form.

12 A. Until you get to the -- you know, to later
13 layers, which may be 1x1 layers, which actually
14 consider the entire image.

15 Q. Well, you --

16 A. As a whole, the network considers the entire
17 image.

18 Q. Okay. And you expressed some confusion or you
19 don't understand whether or not these
20 segmentation applications that are listed in
21 Exhibit 1047, the ones that take pixel-based
22 input, you expressed some misunderstanding about
23 whether it was looking at the entire image or
24 only portions of the image; is that right?

25 MR. MARANDO: Objection. Form.

1 Foundation.

2 A. I would have to look at what pixel-based means.

3 Q. Okay. If you look back to page 2280, it's the
4 second page of the document.

5 A. Yep.

6 Q. So we talked about some of the image processing
7 functions at the top of column 2, but I neglected
8 to read to you farther down the abstraction level
9 of the input that is used in the author's
10 taxonomy.

11 It says about halfway down the column,
12 "Besides the actual task performed by an
13 algorithm, its processing capabilities are partly
14 determined by the abstraction level of the input
15 data. We distinguish between the following
16 abstraction levels: A. Pixel level," which is
17 defined as, "The intensities of individual pixels
18 are provided as input to the algorithm. B.
19 Local feature level. A set of derived,
20 pixel-based features constitutes the input."

21 Do you see that?

22 A. Yes.

23 Q. So, do you now understand what the table is
24 referring to when it says it located neural
25 networks that perform image segmentation using

1 pixel data, as well as neural networks that
2 perform image segmentation using feature --
3 feature-based?

4 MR. MARANDO: Objection. Form.

5 Foundation.

6 A. I am not saying I don't understand what a pixel
7 value is. What I do not understand and cannot
8 tell without reading the papers which are
9 referenced, whether the pixel-level information
10 is like a local neighborhood of a specific pixel
11 or whether it's the entire image; whether we are
12 using, you know, localized information or whether
13 somehow the entire pixel is entered into the
14 neural network.

15 I can imagine, as you just read in the
16 previous version, that there is a sequence of
17 neural network operations; that the first neural
18 network is performing individual operations on
19 some small neighborhood. The small neighborhood
20 is moving along the image, and later on, the
21 second-level neighborhood is combining those and
22 training segmentation algorithm, for example.

23 Q. And why does that matter for the question of
24 whether or not someone of skill in the art would
25 have known before Krishnan's filing date in 2005

1 whether neural networks were used to perform
2 image segmentation taking the --

3 A. Because --

4 Q. -- pixels directly?

5 MR. MARANDO: Objection. Form.

6 A. Because the -- because the neural networks simply
7 were not capable of --

8 Q. I'm sorry, I couldn't hear you. They were not
9 what?

10 A. The neural networks at that time, the
11 architecture which was used, were not capable of
12 managing images of -- especially medical images,
13 of the required size and resolution --

14 Q. Okay.

15 A. -- to be considered as the entire entity.

16 Q. So it's your position that before Krishnan in
17 2005, there weren't neural networks that were
18 capable of segmenting medical images?

19 MR. MARANDO: Objection. Form.

20 A. That's not what I said.

21 Q. Okay. Maybe you can repeat your answer.

22 MR. MARANDO: Objection. Form.

23 A. What I said that, at -- at the 2005 time, medical
24 images were not used in combination with neural
25 networks to design new features that would be

1 based on the entire images.

2 Q. Okay. Well, I think that's a different answer.
3 We're talking about designing features with the
4 neural network. We will get to that, whether or
5 not that's your -- you're limiting the claim
6 construction to that.

7 But let me ask you this: Were -- do
8 convolutional neural networks learn their own
9 features for the purpose of image analysis?

10 MR. MARANDO: Objection. Form.

11 A. Convolutional neural networks as were introduced
12 after 2012, and later than that, can learn its
13 own features, yes.

14 Q. So it's your understanding that only after 2012
15 did convolutional neural networks learn their own
16 features for image analysis?

17 MR. MARANDO: Objection. Form.

18 Q. Is that correct?

19 A. That was the introduction of the first
20 practically applicable approach that allowed
21 that. And that really brought to the community
22 the capability of learning features from
23 examples - that something that was not accepted
24 before, it was not accepted when AlexNet came, it
25 was not accepted until many years later actually.

1 At that time, the understanding was very
2 clearly done that focus must be put into hand
3 designing the features, getting the best features
4 you can think about for a particular task and
5 that those features are task-specific and that
6 you cannot have a set of uniform general features
7 or features that are designed using a general
8 algorithm that will be applicable to multiple
9 applications.

10 - - - -

11 (Thereupon, Exhibit 1048, Article titled,
12 "Segmentation of ultrasonic images with
13 neural networks", was marked for purposes of
14 identification.)

15 - - - -

16 Q. Let's look at the next exhibit. I've marked this
17 Exhibit 1048. Do you have access to it?

18 A. I see it.

19 MR. MARANDO: Objection.

20 Foundation, relevance, scope to the
21 exhibit.

22 Q. So we've been -- we've been talking about whether
23 or not it was known to perform image segmentation
24 using neural networks, including medical images.

25 This is a publication entitled "Segmentation

1 of ultrasonic images with neural networks." It
2 was published in 1991, volume 5, in the
3 International Journal of Pattern Recognition and
4 Artificial Intelligence.

5 Are you familiar with that journal?

6 A. Yes, I am.

7 Q. Okay. Is that journal considered a reliable
8 authority?

9 A. Yes, certainly.

10 Q. I'm going to direct your attention to -- well,
11 let me ask you, have you ever seen this
12 particular publication that's marked as Exhibit
13 1048?

14 A. No, I have not. I have not provided any opinion
15 on that in my declaration.

16 Q. Okay. So I'm just going to read to you the
17 abstract.

18 It says, "Neural networks differ from
19 traditional approaches to image processing in
20 terms of their ability to adapt to regularities
21 in image structure and to self-organize so as to
22 implement directed transformations. Biomedical
23 ultrasonic images are often degraded in quality
24 by noise and other factors, making enhancement
25 techniques particularly important. This paper

1 describes the use of back propagation and
2 competitive learning for enhancement and
3 segmentation of ultrasonic images of the eye. Of
4 particular interest is the extension of these
5 techniques to segmentation of three-dimensional
6 datasets, where simple thresholding and gradient
7 operation are not entirely successful."

8 Do you see that?

9 MR. MARANDO: Objection. Form.

10 Foundation.

11 A. Is the question whether you read correctly? You
12 read the abstract correctly.

13 Q. I'd like you to turn to -- turn a couple of
14 pages. The top of the page is labeled 621.

15 Under the heading "Methods," it's 1, 2, 3, 4,
16 5, 6, 7, 8 -- nine lines down. It says, "All
17 back-propagation networks described in this paper
18 accepted square input regions from the image
19 plane as input, had two hidden layers, and a
20 single output unit. During processing, the
21 network input region was scanned over the entire
22 image."

23 Did I read that correctly?

24 A. Yes.

25 MR. MARANDO: Objection. Form.

1 A. Yes, you have.

2 Q. Okay. Are you -- are you familiar at all with
3 this type of neural network for medical -- or
4 ultrasound image segmentation?

5 MR. MARANDO: Objection. Form.

6 A. I am not familiar with this paper. I am familiar
7 with this general approach described here.

8 Q. If you turn to page 625, the conclusion, it says,
9 "In the paper it is shown that neural networks
10 using either directed or undirected learning may
11 be used to segment ultrasonic images of the eye.
12 These techniques are applicable to other
13 radiological images and to processing of
14 gray-scale images in general."

15 Do you agree with that? Or do you have any
16 reason to dispute that?

17 MR. MARANDO: Objection. Form.
18 Foundation.

19 A. I cannot make an opinion because I don't know
20 what they mean by directed or undirected learning
21 here.

22 Just to comment, you know, to what you read
23 before, that's exactly what I was talking about
24 before, they were using small sub-regions of the
25 images to enter into the neural network, not the

1 images themselves.

2 - - - -

3 (Thereupon, Exhibit 1056, Article titled,
4 "Current methods in medical image
5 segmentation", was marked for purposes of
6 identification.)

7 - - - -

8 Q. Let's take a look at the next exhibit. It should
9 be labeled as -- I've labeled it as Exhibit 1056.

10 Do you see that in the Exhibit Share folder?

11 A. I don't see it. Not yet.

12 Q. Do you have it now?

13 A. No. I just see four exhibits there.

14 Q. I probably pushed the wrong button, Dr. Sonka. I
15 will fix it. Now take a look.

16 A. Yes, now I see.

17 MR. MARANDO: Objection to the
18 exhibit, foundation, relevance, scope.

19 Q. This is a publication entitled "Current methods
20 in medical image segmentation." It was published
21 in 2000 in the Annual Review of Biomedical
22 Engineering. The three named authors are all
23 from the Department of Electrical and Computer
24 Engineering at The Johns Hopkins University.

25 Are you familiar with this Annual Review of

1 Biomedical Engineering?

2 A. I am not.

3 Q. Do you consider it to be a reliable authority?

4 MR. MARANDO: Objection. Form.

5 A. I know the authors. They are very reputable
6 authors. I have no reason to believe that the
7 journal would be a bad journal.

8 Q. Okay.

9 A. So -- but I don't know the journal.

10 Q. Okay. I just want to walk you through a few
11 passages in this.

12 Starting with the abstract on the first page.
13 It says, "Image segmentation plays a crucial role
14 in many medical imaging applications, by
15 automating or facilitating the delineation of
16 anatomical structures and other regions of
17 interest. We present a critical appraisal of the
18 current status of semi-automated and automated
19 methods for the segmentation of anatomical
20 medical images."

21 Then below, in the contents of this paper,
22 you'll see it lists a variety of methods for
23 image segmentation, including thresholding,
24 region growing, classifiers, clustering, Markov
25 random field models, and artificial neural

1 networks.

2 Do you see that?

3 A. Yes.

4 Q. Okay. If we go to page 238 -- I'm sorry, 328.

5 A. Yes.

6 Q. This was published in 2000.

7 So the first full paragraph at the top of
8 page 328, "ANNs represent a paradigm for machine
9 learning and can be used in a variety of ways for
10 image segmentation. The most widely applied use
11 in medical imaging is as a classifier" -- it
12 lists some references -- "in which the weights
13 are determined by using training data and the ANN
14 is then used to segment new data. ANNs can also
15 be used in an unsupervised fashion as a
16 clustering method, as well as for deformable
17 models."

18 Do you see that?

19 A. I do.

20 Q. So if this refers to using a neural network in an
21 unsupervised fashion to perform clustering, do
22 you believe that that is using handcrafted
23 extraction features?

24 MR. MARANDO: Objection.

25 Foundation. Form.

1 A. I have not provided opinion about this paper. I
2 do not believe that --

3 Q. Would you agree with me that unsupervised
4 learning typically means that the neural network
5 is not being trained with a handcrafted feature?

6 MR. MARANDO: Objection.

7 Foundation. Form.

8 A. That would go into the category of
9 self-organizing networks, you know, for cluster
10 analysis. They are not being trained in the
11 supervised manner.

12 Q. Okay. And I believe you'll remember that in
13 Exhibit 1047 that we discussed earlier, the image
14 processing review paper, but that also listed
15 SOMs or self-organizing networks as being used
16 during the segmentation.

17 Do you recall that?

18 A. I do recall that.

19 MR. MARANDO: Objection.

20 A. But again, there is no relevance for 102 in
21 Krishnan because that requires features which are
22 associated with a specific class to be then used
23 as the input for the classifier, which is in 104,
24 105, 103. And clustering methods don't provide
25 information about a class.

1 Q. I understand that that's your position and it's
2 based on your construction, but if that
3 construction is not correct, would you agree with
4 me that before Krishnan in 2005, it was known to
5 segment medical images using neural networks that
6 take the image as input?

7 MR. MARANDO: Objection. Form.

8 A. I'm not going to provide a new opinion which is
9 not in my declaration, which is based on the
10 hypothetical of if construction is not accepted.

11 Q. All I'm asking is as a matter of fact or a matter
12 of your knowledge of what was in the prior art.

13 Would you agree with me that before
14 Krishnan -- the filing date of Krishnan in 2005,
15 it was known to segment medical images using
16 neural networks that accepted the pixel data of
17 the image as input?

18 MR. MARANDO: Objection. Form.

19 A. The neural networks at that time, the ones which
20 I'm familiar with used for image segmentation,
21 were using small subfields of images, not the
22 entire images as input into the neural network.

23 Q. Okay. So you require -- or under your
24 understanding, the 029 patent requires that the
25 entire image be received as an input rather than

1 piecewise portions of the image?

2 MR. MARANDO: Objection. Form.

3 A. My understanding is that 029 patent specifies
4 that. And the learning process described in 029
5 describes that and specifies that.

6 Q. And is it your understanding that neural networks
7 existing before Krishnan in 2005 could not accept
8 images as input because they -- computationally,
9 they could not accept that much data?

10 MR. MARANDO: Objection. Form.

11 A. You can scale anything at any time even using
12 computational hardware of that time. It would
13 not be done -- the POSITA would not do that
14 because the expectation would not be there for
15 such operation to be useful.

16 There was a reason why it didn't appear until
17 2012. There was a reason why there was a Nobel
18 Prize given in association with that, and why the
19 Nobel Prize was not given to Krishnan but
20 somebody else, because this is different.

21 Q. We discussed principal component analysis before.

22 Are you familiar with principal component
23 analysis?

24 A. Still familiar with that, yes.

25 Q. And that's a dimensionality reduction technique

1 to identify the most relevant features that will
2 best perform some later classification task; is
3 that fair?

4 A. It's an -- it's an analytical approach. It's a
5 learned approach.

6 Q. Does it identify what features from the dataset
7 that are to be used for some later task like
8 classification?

9 MR. MARANDO: Objection. Form.

10 A. PCA is useful for description of properties, not
11 for classification necessarily. So if you are
12 talking about designing features, PCA does not
13 always give you good features for classification,
14 number one. Number two, it's an analytical
15 technique. It's not a learning-based technique.

16 Q. Is principal component analysis used for feature
17 extraction from images?

18 MR. MARANDO: Objection. Form.

19 A. I would define PCA as a technique that is used
20 for feature dimensionality reduction, not for
21 feature extraction. Because you don't get any
22 new information after PCA which would not be
23 present in the original features which you are
24 feeding into the PCA module.

25 Q. Are you aware of anyone else in the field that

1 would refer to PCA, or principal component
2 analysis, as being a feature extraction function?

3 MR. MARANDO: Objection. Form.

4 A. It's very likely you can find references like
5 that. The terminology is not crisp here.

6 Q. Do you think they -- do you think if others in
7 the field do refer to PCA as being a feature
8 extraction function, do you --

9 A. You will find feature selection, feature
10 extraction, feature ordering, but that doesn't
11 change the fact that PCA gives you a combination
12 of features previously provided on the input of
13 the PCA module. They are not --

14 Q. Explain that to me. You're saying that the
15 person who's going to perform PCA has to pick the
16 features first before they perform PCA?

17 MR. MARANDO: Objection. Form.

18 A. Yes, and it depends on what you consider the
19 features. But what PCA is doing, is that you
20 have a multidimensional space. The
21 dimensionality of that space is given by the
22 number of inputs. And those inputs are
23 individual features which have been either
24 calculated or somehow acquired or associated with
25 the image, whatever they are.

1 They are features. And PCA from the
2 multidimensional space is trying to find the
3 major axes of the distributions and present --
4 represent it in a new orthogonal space
5 differently positioned. And finding the
6 dimension of that new orthogonal space which has
7 the longest eigenvector, which, therefore, is
8 identified, associated with the most important
9 descriptor of the set you are providing.

10 Q. Okay.

11 A. That, however, does not give you the most
12 important distinguishing factor, which is
13 important for classification, and that's -- if
14 you hear some thunder and lightning, I think
15 there's a thunderstorm here outside.

16 And that's the reason why PCA is a feature
17 space reduction technique and not necessarily a
18 good technique for feature finding or
19 determination in classification setting, number
20 one. Number two, it's not a learning technique.
21 It's an analytical technique.

22 Q. Are you aware of neural networks that are used to
23 perform PCA?

24 MR. MARANDO: Objection. Form.

25 A. I am not, but I can imagine that you can train

1 the neural network to approximate the analytical
2 algorithm. Approximate is the word here.

3 Q. Let me explain to you what I understand PCA to be
4 and you can explain to me why I'm wrong, or if
5 I'm wrong.

6 My understanding is that rather than
7 handcrafting or hand-picking those features that
8 an engineer or scientist believe will be the most
9 important for a classification task, instead, PCA
10 is a mathematical or computational algorithm that
11 will identify the most distinguishing feature.
12 Is that -- is that a fair assessment?

13 A. That's -- that's not true.

14 Q. Okay. Explain to me why I'm wrong.

15 A. It identifies, number one, not -- number one, it
16 only gives you the best features from the set of
17 features you use in the input. There may be
18 other features which are better and you simply
19 did not provide them in the input at all. So
20 that's number one.

21 Number two, there is a difference between --
22 you used the best distinguishing features. Not
23 true. Because the distinguishing means that you
24 are trying to distinguish between classes. PCA
25 is not doing that. PCA is giving you the best

1 description. It doesn't tell you whether the
2 description, which is most relevant, is actually
3 useful at all for the classification.

4 Q. Understood.

5 Okay. So the distinction is between
6 identifying the best features or the best
7 descriptors of the whole image rather than
8 identifying those features that will provide the
9 best classification. That's the distinction
10 you're making?

11 A. No. No, no, no. It is almost -- almost correct
12 what you said. But it's not giving you the best
13 description of the image if you want to have the
14 image on the input. It's giving you the best
15 description of the set of images -- of the entire
16 set of images from multiple classes. Not one,
17 but of the entire set of data which you are
18 subjecting to the PCA.

19 Q. Okay. Okay. So --

20 A. If you are lucky, then one class will have
21 different eigenvectors than the other class and
22 you can use it for classification. But you will
23 then use that for training the classifier down
24 the road in the pipeline -- traditional pipeline,
25 which I'm calling traditional and which I have

1 described in my background.

2 Q. Okay. But PCA is identifying features within the
3 images that can be used for later tasks?

4 A. No.

5 MR. MARANDO: Objection. Form.

6 A. No, that's not the case. PCA is reorganizing the
7 features which you are using on the input of the
8 PCA algorithm.

9 Q. Okay. Well, let's look at some -- some --

10 A. Think about it this way: You have that
11 multidimensional space. You have to fill that
12 multidimensional space somehow, and that somehow
13 is that you put your initial features there,
14 whatever they are. And they may be, you know,
15 some measurements or it may be, you know,
16 information about texture and some elongation,
17 whatever it is.

18 And then it reorganizes all those features,
19 which you have many, into a space that allows you
20 to order those features in a different way,
21 disregard the later ones and keep a smaller
22 number. And you have referenced some place in
23 some of the things that there is an issue of
24 curse of dimensionality. And that's why you do
25 it, because the more features you have, the more

1 training set data you have to have for training a
2 classifier, that being a neural network or
3 anything else.

4 So we are trying to minimize the number of
5 your features in your feature space, and PCA
6 allows you to do that. But it does not allow you
7 to create new features. It's just a combination
8 of the features which are used on the output. It
9 does not allow you to claim that you are getting
10 distinguishing features.

11 Q. Okay. I think it will be helpful for us to look
12 at another publication or two that's describing
13 PCA.

14 - - - -

15 (Thereupon, Exhibit 1051, Article titled,
16 "Unsupervised neural network learning
17 procedures for feature extraction and
18 classification", was marked for purposes of
19 identification.)

20 - - - -

21 Q. So I just sent to you what I've marked as Exhibit
22 1051. Do you have that?

23 A. I see it. I opened it.

24 Q. So this is a publication entitled "Unsupervised
25 neural network learning procedures for feature

1 extraction and classification." It was published
2 in 1996 in volume 6 of the Journal of Applied
3 Science.

4 Are you familiar with this Journal of Applied
5 Science?

6 A. I am not familiar with the journal --

7 MR. MARANDO: Objection to the
8 exhibit.

9 Hold on one second, Dr. Sonka.
10 Objection to the exhibit. Form.
11 Foundation. Relevance. Scope.

12 You can answer.

13 A. I am not familiar with the journal. I am
14 familiar with the Kluwer publisher, of course.
15 Again, this is a paper I have not seen before, I
16 have not provided my opinion on.

17 Q. I'm sorry, you said you're familiar with the
18 publisher of the paper?

19 A. By publisher, I'm familiar with Kluwer Academic
20 Publishers.

21 Q. Okay. Would you -- would you consider this to be
22 a reliable authority if it was published by
23 Kluwer?

24 A. Very likely so. Almost certainly so.

25 Q. Have you ever seen this particular publication

1 that I marked as Exhibit 1051?

2 A. As I've already said, I have not seen it. I have
3 not provided my opinion in the declaration. I am
4 not ready to provide my opinion without being
5 able to read it in full.

6 Q. Okay. Well, I want to direct your attention to a
7 couple passages and then I'll just ask you
8 whether or not you agree with them or do you have
9 a reason to dispute what they say. I understand
10 you haven't read the paper yet, but I still want
11 to ask you the question.

12 So first, let's look at the abstract.

13 It says, "In this article, we review
14 unsupervised neural network learning procedures
15 which can be applied to the task of preprocessing
16 raw data to extract useful features for
17 subsequent classification."

18 Then in the introduction, it says, "One of
19 the more difficult and important parts of the
20 classification process is the preprocessing of
21 raw data to extract useful and appropriate
22 features. The raw data are often too large or
23 complex to be used directly as input to a
24 classifier, leading to the curse of
25 dimensionality and other generalization problems

1 if insufficient training examples are available.
2 Even when this is not the case, simply reducing
3 the number of variables representing the data can
4 make learning easier in a later classifying
5 stage. In some cases, prior knowledge about the
6 problem can be used to determine heuristic
7 features such as edges in an image classification
8 problem."

9 I'm going to pause.

10 Is that -- is that the kind of thing you're
11 referring to as handcrafted features?

12 A. That's correct.

13 MR. MARANDO: Objection. Form.

14 Q. It goes on, "However, this is not possible in all
15 cases, and may not be the complete solution in
16 cases where such features are identifiable. In
17 this article, we review unsupervised neural
18 network learning procedures which can be applied
19 to this preprocessing task. In contrast to
20 either supervised or reinforcement learning
21 procedures, these unsupervised algorithms use no
22 knowledge of the eventual targets or errors of
23 the classification process. They learn their
24 eventual operation purely from observing the raw
25 input data."

1 Did I read that correctly?

2 MR. MARANDO: Objection. Form.

3 A. I see the text.

4 Q. Okay. This is from 1996, which is almost ten
5 years before Krishnan's filing date.

6 Do you have any reason to dispute that
7 someone of skill in the art would have been aware
8 of unsupervised neural network feature
9 extraction?

10 MR. MARANDO: Objection. Form.

11 A. The statement that this is needed does not give
12 me any information about how it should be done.

13 Q. Okay. Take a look -- if you turn the page to
14 page 2. Halfway down the first column is the
15 heading 2.1, "Principal component analysis and
16 subspace methods."

17 It says, "Principal component analysis (PCA)
18 is a popular dimension reduction and feature
19 extraction method."

20 Do you agree with that?

21 MR. MARANDO: Objection. Form.

22 A. I agree with the popular dimension reduction
23 technique, and we discussed that in the past.
24 Feature extraction. Extraction from what? From
25 the combined space of previous features. In that

1 sense --

2 Q. So you dispute that it's a feature extraction
3 method?

4 A. No, I don't dispute it's a feature extraction
5 method, but it's not a feature extraction method
6 that would design new features from nothing.

7 Q. Okay. If you look just below where I read,
8 there's a figure, Figure 1. And it's -- the
9 label references a three-input two-output PCA
10 network.

11 Do you see that?

12 A. I do.

13 Q. Are you familiar with neural networks for
14 performing principal component analysis?

15 A. No, I am not.

16 Q. Okay. Let's look at the next -- do you -- do you
17 -- do you dispute that the neural network that is
18 depicted in Figure 1 of that exhibit is a
19 feature-extracting neural network?

20 MR. MARANDO: Objection. Form.

21 A. As I already stated, I consider PCA to be a
22 feature space reduction technique.

23 - - - -

24 (Thereupon, Exhibit 1052, Article titled,
25 "Artificial Neural Networks for Feature

1 Extraction and Multivariate Data Projection",
2 was marked for purposes of identification.)

3 - - - -

4 Q. Okay. Let me show you the next exhibit. It's
5 marked as Exhibit 1052.

6 Do you have that in Exhibit Share?

7 Okay. So -- I'm sorry, you said you do have
8 it?

9 A. I see it, yes.

10 Q. Okay. This is a publication entitled "Artificial
11 neural networks for feature extraction and
12 multivariate data projection." It was published
13 in 1995 in volume 6 of IEEE Transactions on
14 Neural Networks' journal.

15 Are you familiar with that journal?

16 A. Yes.

17 MR. MARANDO: Objection to the
18 exhibit. Form. Foundation. Relevance.
19 Scope.

20 Q. Do you consider the journal to be a reliable
21 authority?

22 A. Yes, I do.

23 Q. I want to point out a couple of passages in this
24 -- in this publication, which again, it's
25 published in 1995. So this is about five years

1 -- or, I'm sorry, about ten years before
2 Krishnan.

3 Looking in the first column of the first
4 page, I am -- I believe the page is 296. The
5 last full para- -- or the last paragraph on the
6 page, it says, "Recently, a large number of
7 artificial neural networks and learning
8 algorithms have been proposed for feature
9 extraction and data projection," and it lists a
10 number of citations in here.

11 Do you have any reason to dispute that
12 feature extraction neural networks were proposed
13 in 1995?

14 MR. MARANDO: Objection. Form.

15 A. Isn't it interesting that, you know, we are
16 talking about 1995. The other paper was 1996.
17 The other one was shortly after that, the
18 summary. We do not have too many papers from the
19 years around 2005.

20 And my recollection, because I've been around
21 long enough, is that, you know, neural networks
22 have been coming in waves up and down. And there
23 was a lot of research, as you can see, in the mid
24 '90s, which did not really go anywhere.

25 I think that we will find a substantially

1 less number of publications from the mid 2000s
2 that are going to explore these uses. And this
3 is just a comment which I wanted to make that,
4 you know, that affects of, you know, the
5 understanding of what is taught in here, in those
6 patterns we are talking about.

7 But to answer your question --

8 Q. I'll just point out --

9 A. -- I do not -- I do not know what papers 1
10 through 5, 12 and so on are. I would have to
11 look at them and see what they consider feature
12 extraction, what they consider feature reduction,
13 and multivariate data projections before making
14 -- you know, having any opinion about this.

15 Q. Okay. And I'll just respond quickly to your
16 comment about all of these papers being too old.

17 Exhibit 1047, which we discussed, the image
18 processing with Neural Networks review, that was
19 published in 2002. And if you'll recall, it
20 showed a taxonomy, a table with over 50 neural
21 networks that had been reviewed for performing
22 feature extraction and segmentation of images.
23 So I'll just point out that that document was
24 from 2002. And we'll discuss others that are
25 more recent.

1 MR. MARANDO: Objection. Form.

2 To the extent that was a question.

3 A. If you look at it -- just to answer, you know, to
4 your comment. I'm just -- I just opened the
5 exhibit. If you look at that, it's a review. It
6 takes a while before you put together a review.

7 Interestingly enough, 1994, 1995, 1992, that
8 was -- you know, those were good years for neural
9 networks, but just to respond to what you said.

10 Q. If you turn to the second page of Exhibit 1052,
11 it's labeled page 297 at the top, you will see a
12 figure. It says Figure 1, "A taxonomy of neural
13 networks for feature extraction and data
14 projection."

15 Do you see that?

16 A. Yes, I see that.

17 Q. And it lists a variety of neural networks for
18 performing feature extraction, some of them
19 supervised, some of them unsupervised, some of
20 them linear, some of them nonlinear. They
21 include a principal component analysis network, a
22 linear -- a linear discriminant analysis network,
23 and Kohonen's map.

24 Do you see that?

25 A. I do.

1 Q. Were you aware of these networks performing
2 feature extraction?

3 MR. MARANDO: Objection. Form.

4 A. Again, the critical thing we are talking about
5 here throughout all those papers is whether you
6 used the neural networks to massage existing
7 features or whether you use them to design new
8 features not previously existed. And I do not
9 know and I'm not providing an opinion about what
10 this paper is talking about. I cannot do it on
11 the fly.

12 Q. Okay. So just to be clear, you are requiring not
13 only that the 029 patent perform feature
14 extraction with a neural network, you are
15 requiring that the 029 patent perform feature
16 extraction with a neural network that learns its
17 own features; is that correct?

18 A. Getting away from the paper we are looking at and
19 getting back to 029. The specifications of 029,
20 all the embodiments of 029 are teaching the way
21 how features are being learned from the images
22 using neural network. And the neural network is
23 described in Figure 4 and it shows that the
24 language in 029 is talking about how the training
25 of that network described in Figure 12 is being

1 used for the parameters of the 304, 306, 308
2 networks in Figure 4 of 029.

3 Q. So your understanding is -- I'm sorry.

4 Your understanding of the 029 patent and your
5 interpretation that it requires the learning of
6 extracted features is based upon the fact that
7 the neural network shown in Figure 4, you
8 interpret that to be -- to be a learning network?

9 Strike that. Strike that. We'll get back to
10 it.

11 I want to point out another passage to you in
12 Exhibit 1052. This is still on page 297. In the
13 second column there's a heading there at the
14 bottom, "Principal component analysis networks."

15 Do you see that?

16 A. Yes, I do.

17 Q. Okay. It says, "Principal component analysis,
18 also called Karhunen-Loeve transform, is a
19 well-known statistical method for feature
20 extraction, data projection, and multivariate
21 data projection and has been widely used in
22 communication, signal and image processing,
23 pattern recognition, and data analysis."

24 Do you agree with that?

25 A. With the caveat of what do we understand by

1 feature extraction. It's calculating features
2 based on the statistical approaches which are
3 hand designed. It's calculating features from
4 the set of inputs. We are saying it over and
5 over again. It's a data space reduction
6 technique.

7 Q. Let's talk a little bit about convolutional
8 neural networks, which are sometimes abbreviated
9 as CNNs.

10 Are convolutional neural networks deep
11 learning neural networks in your opinion?

12 MR. MARANDO: Objection. Form.

13 A. We talked about it. If the -- you know, the
14 convolutional neural network these days is
15 certainly understood as being the deep neural
16 network. For the network to be convolutional, I
17 don't think it has to be deep.

18 Q. Okay.

19 A. Is it going to be useful? That's a different
20 question.

21 Q. Okay. They are -- I'm sorry.

22 Convolutional neural networks, are they
23 typically used for image analysis?

24 A. These days, convolutional networks are very
25 frequently used for image analysis.

1 Q. And it's because of their architecture they're
2 able to handle large datasets like large numbers
3 of pixels; is that fair?

4 MR. MARANDO: Objection. Form.

5 A. I'd say it differently. I think that in addition
6 to what you said, they are able to identify
7 linkages across space and scale in the images
8 which may not be humanly observable and are more
9 complex than the human design features are able
10 to capture.

11 Q. Okay. So that leads me to my next question. Do
12 convolutional neural networks -- do they learn
13 the features that are -- that are to be extracted
14 through the training process rather than using
15 handcrafted features?

16 MR. MARANDO: Objection. Form.

17 A. They are capable of learning features which are
18 optimal with respect to the objective function
19 used in training for the task the network is
20 supposed to perform.

21 Q. Okay. And is AlexNet that you keep referring to,
22 is that a convolutional neural network?

23 A. It is a convolutional neural network.

24 Q. And is LeCun's LeNet, is that a convolutional
25 neural network?

1 MR. MARANDO: Objection. Form.
2 Foundation.

3 A. It is a convolutional neural network not used in
4 a way that would design new features because of
5 the complexity of that, but it's certainly a very
6 insightful neural network for the time it was
7 introduced.

8 MR. MARANDO: At what point do you
9 want to take a break?

10 MR. METZCAR: If you're asking for
11 one, I could probably go just a couple --
12 couple more minutes and then we could stop.

13 MR. MARANDO: Yeah, is that okay
14 with you, Dr. Sonka?

15 THE WITNESS: That's fine. That's
16 fine.

17 Q. In your experience, were convolutional neural
18 networks used for image analysis before
19 Krishnan's filing in 2005?

20 MR. MARANDO: Objection. Form.

21 A. It depends on the definition. Were you able to
22 see a neural network that was performing
23 convolution with some small kernels and try to
24 identify, you know, labels for individual pixels
25 in the images, perhaps for segmentation, I would

1 say yes, you could.

2 If the answer is could you use an end-to-end
3 based neural network which started with the
4 images directly, designed their own features, the
5 answer would be no.

6 Q. So maybe your -- maybe you've already answered
7 this, but were -- in your experience, were
8 convolutional neural networks being used for
9 image segmentation before Krishnan's filing date
10 in 2005?

11 MR. MARANDO: Objection. Form.

12 A. In very special, very constrained ways and
13 research settings, I would say yes, but not in a
14 way that would allow features to be learned.

15 Q. Are you saying --

16 A. The feature extractor parameters and
17 architectures could not be learned at that time.

18 Q. So are you saying those convolutional networks
19 used handcrafted features or handcrafted kernels
20 only?

21 A. They use handcrafted feature architectures and
22 may have been used for somehow improving the
23 parameters of those handcrafted features, but not
24 discover new features.

25 Q. That's based on --

1 A. It's the same difference between the traditional
2 and post-2012 scenarios.

3 Q. So only after 2012 were convolutional neural
4 networks used for image segmentation in which
5 they could learn their own features?

6 A. I think that's a --

7 MR. MARANDO: Objection. Form.

8 A. I think that's a fair statement. It happened
9 years after 2012 because there is always a long
10 delay before something this transformational is
11 -- actually bubbles through to the community and
12 the community accepts that.

13 It was certainly a vital moment for all of us
14 that features can be learned. And it has some
15 advantages and disadvantages, as I am sure you
16 know, that those features that are learned this
17 way may not make sense to humans. And that was a
18 big problem early on, and still is a big problem,
19 that, you know, interpreting those features which
20 are actually calculating -- calculated is
21 difficult or impossible.

22 And then you have a separate branch that
23 deals with the explainable artificial
24 intelligence, explainable nets, which are to make
25 sense of what is actually -- what those

1 convolutional neural networks are actually doing.

2 Q. Okay. Are you familiar with LeCun's optical
3 character recognition neural network, sometimes
4 referred to as LeNet?

5 MR. MARANDO: Objection. Form.

6 A. I believe that we are talking about the -- what
7 is it, like the 19 -- 1989 or '90 paper about a
8 postal code, a ZIP code?

9 Q. We have one that's been marked as an exhibit in
10 this case. It's Exhibit 1027 and it's addressed
11 in your declaration.

12 A. Yes, I'm familiar with that.

13 Q. Okay. So you're aware of it.

14 A. It's a great example how you do the handcrafted
15 feature as the input. You decide -- the designer
16 decides that it's going to be a 5x5 mask and then
17 the network is being used to somehow -- somehow
18 by training the network optimize the parameters
19 of the 5x5 kernel, but it cannot design kernels
20 that would not be 5x5. So there is that hand
21 design embedded in that, number one.

22 Number two, it uses the same kernel for each
23 and every location of that subimage which is
24 taken from the image of the envelope that only
25 contains that one digit.

1 So there is that handcrafted feature which
2 can be improved, optimized somehow by the
3 network, but it's not the end-to-end learning
4 which AlexNet started to teach and which made the
5 revolution.

6 Q. So I want to follow up.

7 Is it -- is it your understanding that
8 LeCun's network as described in Exhibit 1027 used
9 handcrafted features, not learned features?

10 A. Yes, hand- --

11 MR. MARANDO: Objection. Form.

12 A. It used handcrafted features to the extent that
13 it decided to use and only use a 5x5 convolution
14 kernel and nothing else. And then within that
15 constraint, and within the constraint that the
16 same kernel will be used everywhere, it uses the
17 classifier as a sort of secondary pipeline
18 element to determine the parameters of the 5x5
19 kernel.

20 But the 5x5 kernel has been decided. It may
21 not be the best one. It has not optimized that
22 kernel because there may be a better kernel which
23 is not 5x5. That's the way how it did not go
24 beyond the handcrafted feature at the beginning.

25 Q. Okay. So your understanding is that LeCun did

1 not use learned features, it used handcrafted
2 features; is that what you're saying?

3 A. I'm saying that a handcrafted --

4 MR. MARANDO: Object to form.

5 A. I'm saying that a handcrafted aspect is the start
6 of the pipeline. And in the second step of the
7 pipeline, learning, training the neural network,
8 is used to optimize those 25, plus the bias, 26
9 parameters of the kernel. But you could not go
10 to define features which are different than 5x5.
11 You could not define 5x1. You could not define
12 7x7.

13 You had a handcrafted feature in the
14 beginning, which completely and significantly
15 constrained your capability to learn the most
16 distinguishing features in the proper term of
17 that -- of the word using classification
18 techniques, learning techniques.

19 Q. Okay.

20 A. And that's what AlexNet enabled. And that's what
21 really I see as the -- as the watershed moment,
22 which made all my books, which were published
23 prior to that, overnight obsolete, and the world
24 has changed and everything is different since
25 then.

1 Q. So is it your understanding -- is your
2 construction of extracted feature representations
3 limited to feature representations that are
4 learned using a neural network just like AlexNet?

5 MR. MARANDO: Objection. Form.

6 A. As I already explained, the -- I'm using the
7 plain ordinary meaning of the term. I am
8 adopting the construction that is used in the
9 parallel proceeding. And the construction is
10 what it says. It's a -- it's a technique which
11 uses learned features which are learned using
12 neural network. I may not exactly say the
13 wording which is there, but you know what I mean.

14 MR. METZCAR: Why don't we take a
15 five-minute break and we'll come back and
16 go through some more documents.

17 - - - -

18 (Thereupon, a recess was had.)

19 - - - -

20 BY MR. METZCAR:

21 Q. All right. Dr. Sonka, we're back after a lunch
22 break. I'd like to follow up with you on a few
23 more documents.

24 - - - -

25 (Thereupon, Exhibit 1044, Article titled,

1 "Feature extraction methods for character
2 recognition - a survey", was marked for
3 purposes of identification.)

4 - - - -

5 Q. The next one I would like to show you -- I just
6 put in your Exhibit Share folder what's been
7 marked as Exhibit 1044. Do you have that?

8 A. I see it, yes.

9 Q. Okay. So this is a publication entitled "Feature
10 extraction methods for character recognition - a
11 survey." It's published in 1996 in volume 29 of
12 the Pattern Recognition Journal, which we
13 previously discussed before.

14 I assume you still consider that to be -- a
15 journal to be a reliable authority?

16 MR. MARANDO: Objection.

17 One second. Objection to the
18 exhibit. Foundation. Relevance and scope.

19 You can answer.

20 A. Having not seen this paper, I have not made an
21 opinion on this paper in the -- you know, in my
22 declaration, but the Pattern Recognition Journal
23 is certainly a reputable one.

24 Q. And you've not seen this paper specifically you
25 said?

1 A. I have not seen this paper before.

2 Q. Well, it's a 1996 survey. It discusses many
3 techniques for extracting feature representations
4 from images. Most features are to be used for
5 optical character recognition specifically.

6 One of the many techniques that is described
7 is feature extraction by neural network. And I
8 just want to point out a couple of passages for
9 you. If you turn to page 656, second column at
10 the bottom, it discusses neural network
11 classifiers.

12 Do you recall that right before our lunch
13 break we were discussing the LeCun neural network
14 for optical character recognition?

15 A. Yes.

16 Q. Okay. So the second column on page 656 under the
17 heading "Neural Network Classifiers," it says,
18 "Multi-layer feed-forward neural networks have
19 been used extensively in OCR, for example, by
20 LeCun, et al., Takahashi, and Cao, et al. These
21 networks may be viewed as a combined feature
22 extractor and classifier."

23 Do you agree that LeCun is a combined feature
24 extractor and classifier?

25 MR. MARANDO: Objection. Form.

1 A. It calculates the features in the prescribed 5x5
2 small neighborhood and then classifies
3 characters, in this case digits, accordingly.

4 Q. Okay. Did you -- before lunch, did you
5 characterize the features in LeCun as being
6 handcrafted features?

7 A. The size of the window, the portion of the
8 feature, which is critical in LeCun, has been
9 handcrafted.

10 Q. Okay. But does LeCun also learn features for
11 extraction through training?

12 MR. MARANDO: Objection. Form.

13 A. I don't know if you want to bring the LeCun's
14 paper so that we can cite it exactly, but I can
15 talk about it even if you don't.

16 LeCun states specifically that in designing
17 his features he used his prior knowledge of
18 shape, properties, which decided -- he decided to
19 be used when designing, handcrafting the 5x5
20 window. That's the handcrafted part.

21 Within that handcrafted envelope, inside of
22 that envelope starts the feature extraction. He
23 uses the neural network to train, to learn. And
24 in the end it learns the parameters of the
25 kernel, but it does not change -- the kernel

1 itself doesn't change size, doesn't change the
2 fact that it requires the kernel to be used
3 uniformly across the entire image in different
4 locations and so on. So the handcrafting
5 character of that work is, in my view,
6 undisputable.

7 Q. Okay. But it -- but it's also undisputable that
8 it does learn the parameters of the kernel?

9 MR. MARANDO: Objection. Form.

10 A. It uses that -- it uses that for classification.
11 So it's a classifier. Classifier learns, yes.

12 Q. Are the features of the -- I'm sorry, the
13 parameters of the kernel, do those not correspond
14 to features that are extracted from the image?

15 MR. MARANDO: Objection. Form.

16 A. It may be represented that way, but it really is
17 the result of the network parameter set up within
18 the constraints of the handcrafted feature.

19 So you can think about it as optimizing the
20 already-decided, man-designed feature. And that
21 was not unusual, but it does not specify that you
22 can derive, design, determine new features.

23 Q. Okay. Well, let's turn to page 67 of this
24 exhibit, 1044. I'm looking at the --

25 A. 667 or?

1 Q. 657. It's the next --

2 A. 657, yep.

3 Q. So I'm looking at column 1, the last full
4 paragraph in that column. It says, "Another
5 viewpoint can also be taken. LeCun, et al's
6 neural network" --

7 A. I don't -- I don't see that. Give me a second.
8 So the last -- the second column of 657?

9 Q. First column.

10 A. First column.

11 Q. I'm sorry, I may have misspoke. First column --

12 A. "Another viewpoint." "Another viewpoint." I see
13 it, yes.

14 Q. "Another viewpoint can also be taken. LeCun, et
15 al's neural network can be regarded as performing
16 hierarchical feature extraction."

17 And then the last sentence of that paragraph
18 says, "Note that the feature extractors are not
19 handcrafted or ad hoc selected rules, but are
20 trained on a large set of training samples."

21 I think I understand the distinction you're
22 making that it is constrained to a 5x5 pixel
23 kernel for feature extraction, but I do want to
24 understand -- or do you disagree with this
25 statement?

1 MR. MARANDO: Objection. Form.
2 Foundation.

3 A. In my mind, I draw the distinction based on the
4 differences between what 029 patent teaches, what
5 the deep learning is capable of against the
6 traditional approaches. We went over this
7 several times and I'm sure that you understand my
8 distinction, and I understand why you keep
9 asking.

10 My take is that there are two parts to the
11 feature design here. One part is handcrafted,
12 and that is based on the experience and expertise
13 of the designer -- uses that prior knowledge of
14 shape characteristics, uses the information about
15 how large the images are. Because if the images
16 would be much larger, then the kernel would have
17 to be much larger. You know, this is all
18 interconnected. This is the human intelligent
19 design.

20 After that, within the constraints of that
21 design, you are using the neural network in this
22 case to identify parameters. And in this case
23 it's those 26 parameters that are uniformly
24 applied across the entire image.

25 So I have said it before, I'm happy to say it

1 again: This is a very insightful paper. The
2 work of LeCun has been insightful many, many
3 years before it really made a difference, but it
4 does not, in my opinion, fit the definition of
5 learning features. It learns parameters of
6 hand-designed features, and that's the
7 distinction I have been making, you know, over
8 and over again.

9 Q. And is there anywhere in the 029 you can point me
10 to that discusses the learning of extracted
11 feature representation?

12 A. Let me open that 029 patent. I think I know
13 where it is.

14 So let's start with Figure 12. And Figure 12
15 describes the training process. It starts with
16 receiving sets of ultrasound images in 702. It
17 receives the desired output in 704 and 706, and
18 it trains the neural network 708. Not much
19 detail here, but the details are coming.

20 Q. Let me stop you.

21 So this is a -- this is directed to a
22 training process. You understand that there are
23 claims that are directed to neural network
24 systems and claims that are directed to methods
25 in the -- in the 029 patent?

1 A. Yes.

2 MR. MARANDO: Objection.

3 Objection. Form.

4 Q. Do you interpret those -- all of those systems
5 and methods as being restricted to just the
6 neural network training method in Figure 12?

7 MR. MARANDO: Objection. Form.

8 A. As we already established, there is one
9 embodiment that is -- or one characteristic of
10 all the embodiments in 029, that the training is
11 done using a neural network. And that's uniform
12 across the 029 patent.

13 Q. Say that again.

14 A. All the embodiments mentioned in 029 are talking
15 about using a neural network for training and for
16 feature derivation determination, as shown in
17 Figure 4.

18 Q. What about the passage that we discussed in
19 column 11 earlier that says alternative functions
20 can be used for feature extraction instead of
21 neural networks?

22 MR. MARANDO: Objection.

23 A. I already explained my understanding is that
24 those are -- say it again. Which -- which
25 portion you're looking at? Alternative

1 approaches?

2 Q. Lines 39 to 42.

3 A. In column? Which column?

4 Q. 11. It says --

5 A. I already explained my understanding -- my
6 understanding of that is that those are
7 alternative feature extraction functions and
8 neural networks; that the neural networks are
9 required throughout the pattern because that's
10 the only way how 029 is teaching that things can
11 be done in the embodiments. That's my
12 interpretation. So my opinion is that the neural
13 network is -- is there.

14 Q. Let's talk about --

15 A. Do you want me to continue explaining --
16 answering the question that you asked before
17 about how the learning is done?

18 Q. Sure. You pointed me to Figure 12. Was there
19 something else?

20 A. Right. And if you go to -- absolutely, there is.
21 If you go to column 17.

22 Q. Yes.

23 A. Line 37, it says that at block 708, which is the
24 training block, direct the trainer processor to
25 train the neural network 300 shown in Figure 4.

1 "Using each of the sets of ultrasound images
2 stored in the location 640," which was in Figure
3 11, which we did not talk about.

4 Then, at the bottom of this column,
5 additional details are given. If you look at
6 line 64 of this column 17, it says that this
7 training block, block 708, "may direct the
8 analyzer processor 100 to feed the input tensor
9 to the neural network 300, where each ultrasound
10 image first goes through an instance of the
11 commonly defined first feature-extracting neural
12 network or DenseNet feature extraction module.
13 The output tensor is commonly defined" -- skip
14 that.

15 It talks about the size of the -- of the
16 DenseNet tensors and follows by 708 and directs
17 the trainer processor 600 to flatten the output
18 tensor and -- into the 32x10 or 32x10x6000 in
19 some embodiments, for example, so that the second
20 feature-extracting neural network, the LSTM
21 module, can process it.

22 Q. And where does that -- where does that state that
23 the features that are being extracted must be
24 learned by the system as opposed to handcrafted?

25 MR. MARANDO: Objection. Form.

1 A. It's part of the training process. It's part of
2 the steps which are described in claim 12 and
3 described here in more detail, which I'll read it
4 again, that bottom of column 17, that each
5 ultrasound image goes through the instance of the
6 first feature-extracting neural network.

7 And in the training step, that's what you do.
8 Then you compare your output with the desired
9 output. As part of the training of the network,
10 you modify the weights of your network until you
11 are satisfied, until the machine is satisfied.

12 Here, if you go -- if you go to line 20 of
13 column 18. Or starting in line 18 of column 18.

14 Q. Yes.

15 A. "Block 708 may direct the trainer processor 600
16 to compare the predictions made with the quality
17 assessment value specific neural network and view
18 category specific neural network with respective
19 ground truths."

20 This is the crux of the -- of the training or
21 desired output if something else is there.

22 "In various embodiments, the predictions may
23 be compared to the quality assessment values and
24 view categories stored in the location 640 of the
25 storage memory." And the initial output may be

1 of some dimensions.

2 And so -- and then the next paragraph
3 starting in line 34 of column 18, "Block 708 may
4 direct the trainer processor 600 to determine a
5 difference between the view classification
6 predictions and the ground truth, as previously
7 provided by an expert, for example, as measured
8 by the cross-entropy loss function, which
9 produces scalar value," and so on.

10 And this is how we modify the weights. This
11 is the training process. They is how we learn
12 the features.

13 It's very clearly described here. And that's
14 what, you know, in my opinion, gives very clear
15 evidence what kind of learning process is used
16 and taught by 029.

17 Q. I'll show you a couple more documents.

18 - - - -

19 (Thereupon, Exhibit 1059, Article titled,
20 "Gradient-based learning applied to document
21 recognition", was marked for purposes of
22 identification.)

23 - - - -

24 Q. I just put in your Exhibit Share file a document
25 that's marked Exhibit 1059. Can you see that?

1 A. "Gradient-based learning applied to document
2 recognition," right?

3 Q. Yes. It's also a publication from LeCun. As you
4 said, it's entitled "Gradient-based learning
5 applied to document recognition." It was
6 published in 1998 in the journal Proceedings of
7 the IEEE.

8 Are you familiar with that journal?

9 MR. MARANDO: Objection to the
10 exhibit, foundation, relevance, and scope.
11 You can answer.

12 A. Yes, I am familiar with the Proceedings of the
13 IEEE.

14 Q. Okay. Do you consider it to be a reliable
15 authority?

16 A. Absolutely, yes.

17 Q. I'll point you to a couple passages. This is --
18 this is a lengthy publication. So we're not
19 going to talk about all of it. And it goes
20 through a description of a proposed system for
21 extracting features and doing optical character
22 recognition on checking systems -- or on checked,
23 rather.

24 But there's a couple of passages that I'm --
25 it says -- I'm looking second paragraph of the

1 introduction on page 1.

2 "The message of this paper is that better
3 pattern recognition systems can be built by
4 relying on" -- I'm sorry, "by relying more on
5 automatic learning, and less on hand-designed
6 heuristics. This is made possible by recent
7 progress in machine learning and computer
8 technology. Using character recognition as a
9 case study, we show that handcrafted feature
10 extraction can be advantageously replaced by
11 carefully designed learning machines that operate
12 directly on pixel images."

13 Did I read that correctly?

14 A. Yes, you read it correctly.

15 Q. Okay. You see at the bottom -- I don't need to
16 read this, but you see at the bottom of column 1
17 onto the top of column -- onto the top of the
18 second page -- I'm sorry. Let me correct my
19 statement.

20 The bottom of column 2 on page 1 onto the top
21 of column 1 on page 2, there is a discussion of
22 the traditional method of feature extraction and
23 classification. It shows in Figure 1 -- what it
24 says is the conventional method when you have a
25 separate feature extraction module, and then a

1 trainable classifier module.

2 Do you see that?

3 MR. MARANDO: Objection. Form.

4 A. Okay. So as always, these papers -- I have not
5 seen this paper before. I have not provided an
6 opinion in my -- in my declaration. But I do see
7 that it talks about traditional pattern
8 recognition.

9 It's nice to see that even back in '98, what
10 I was referring to as traditional approaches was
11 still considered traditional -- traditional
12 approach. This is exactly what 102 is doing, the
13 feature extraction module, getting the feature
14 vector and getting the trainable classifier
15 module, 103, 104, 105 in Krishnan. This is
16 exactly following that pipeline which I call
17 traditional and which is called traditional even
18 ten years earlier.

19 Q. I understand that's your opinion that that's what
20 it does, but I'm interested in the first full
21 paragraph underneath that figure on page 2.

22 It says, "Historically, the need for
23 appropriate feature extractors was due to the
24 fact that the learning techniques used by the
25 classifiers were limited to low-dimensional

1 spaces with easily separable classes. A
2 combination of three factors have changed this
3 vision over the last decade. First, the
4 availability of low-cost machines with fast
5 arithmetic units allows to rely more on
6 brute-force numerical methods than on algorithmic
7 refinements. Second, the availability of large
8 databases for problems with large markets and
9 wide interest, such as handwriting recognition,
10 has enabled designers to rely more on real data
11 and less on handcrafted feature extraction to
12 build recognition systems. The third and very
13 important factor is the availability of powerful
14 machine learning techniques that can handle
15 high-dimensional inputs and can generate
16 intricate decision functions when fed with these
17 large datasets."

18 Do you agree with that assessment of changes
19 that occurred over the last decade --

20 MR. MARANDO: Objection.

21 Q. -- that this paper covers?

22 MR. MARANDO: Objection to form.

23 Foundation.

24 A. Can you define what is last decade?

25 Q. Well, the paper was published in 1998; is that

1 correct?

2 A. We are talking about last decade prior to the
3 publication of the paper, not last decade prior
4 to today?

5 Q. I'm talking about changes that occurred in the
6 decade prior to 1998. Isn't that what this is
7 talking about?

8 A. It is. I wanted to be sure that that's what
9 you're asking about.

10 Q. Yes. Do you agree with that characterization of
11 changes that occurred in the decade prior to
12 1998?

13 MR. MARANDO: Objection. Form.
14 Foundation.

15 A. My view is that this is a forward-looking summary
16 of somewhat wishful thinking, number one. Number
17 two -- and the reason for that is that this
18 really did not happen for 20 more years or so.

19 Number two, you know, while we can talk about
20 the generality of the techniques which LeCun was
21 introducing in this paper and throughout, the
22 problem that they were dealing with numerical
23 digit recognition for OCR recognition is very
24 different from analyzing ultrasound medical
25 imaging in 3D.

1 I would be much more impressed if you would
2 have, you know, presented the papers that you --
3 about how neural networks are used for ultrasound
4 image analysis. At that time, I don't think that
5 that was the case.

6 So I think that as a general statement, this
7 is all good. I don't think it actually
8 materialized for many, many years after that. As
9 researchers frequently do, they are trying to
10 provide a vision and identify the direction of
11 future research.

12 Q. Okay. I've got another document I'd like to show
13 you.

14 - - - -

15 (Thereupon, Exhibit 1057, Article titled, "A
16 Shift-Invariant Neural Network for the Lung
17 Field Segmentation in Chest Radiography", was
18 marked for purposes of identification.)

19 - - - -

20 Q. Okay. This one I have marked as Exhibit 1057.
21 Let me know when you have it in your --

22 A. Hasegawa.

23 Q. Right. So this is a publication entitled, "A
24 shift-invariant neural network for the lung field
25 segmentation in chest radiography." It was

1 published in 1998 in the Journal of VLSI Signal
2 Processing, which is published by Springer.

3 Are you familiar with that journal at all?

4 MR. MARANDO: Objection.

5 Objection to the exhibit, foundation,
6 relevance -- just a second.

7 Objection to the exhibit,
8 foundation, relevance, and scope.

9 You can answer.

10 A. It's not published by Springer. It's published
11 by Kluwer.

12 Q. Oh, okay.

13 So you are familiar with it?

14 A. I am not. This is dealing with VLSI and VLSI is
15 Very Large Scale Integration dealing with
16 integrated circuits. So I don't think I've ever
17 seen this journal.

18 Q. Okay. So you don't know whether this would be
19 considered a reliable source?

20 A. I have no reason to believe it would not be a
21 reliable source. I'm just surprised that medical
22 imaging would be discussed in the VLSI Signal
23 Processing journal.

24 Q. Okay. Well, again, this is -- this is published
25 in 1998. So we're significantly before the

1 filing date of Krishnan in 2005. I want to point
2 out a couple of passages to you.

3 In the abstract, it says, "We have developed
4 a computerized method using a neural network for
5 the segmentation of lung fields in chest
6 radiography. The lung is the primary region of
7 interest in routine chest radiography diagnosis.
8 Since computer is expected to perform disease
9 pattern search automatically, it is important to
10 design appropriate algorithms to delineate the
11 region of interest. A reliable segmentation
12 method is essential to facilitate subsequent
13 searches for image patterns associated with lung
14 disease. In this study, we employed a shift
15 invariant neural network coupled with error
16 back-propagation training method to extract the
17 lung fields."

18 Did I read that correctly?

19 A. Yes, I read the same thing.

20 Q. Okay. And then if you turn the page to 242, the
21 paragraph that starts in the middle of column 1.
22 It says, "A shift-invariant neural network model
23 is a simplified version of the vision system in
24 vertebrate animals. Its signal propagation is
25 based on the discrete convolution like in the

1 traditional image processing. The most
2 significant characteristic of the shift-invariant
3 neural network is that it can automatically learn
4 and extract image features, which is necessary to
5 the assigned tasks, during its training process.
6 Because of this characteristic, manual design of
7 image processing kernel is not necessary. The
8 kernels obtained by the neural network image" --
9 I'm sorry, "by the neural network training are
10 not always understandable. However, mathematical
11 optimization of an image processing task based on
12 a neural network training system can be made much
13 more appropriate than manually designed approach.
14 Because of the optimized image processing
15 kernels, it is expected that the shift-invariant
16 neural network has the better performance than
17 methods based on manually selected kernels."

18 Did I read that correctly?

19 MR. MARANDO: Objection.

20 Foundation.

21 A. I got lost, you know, when you were reading that.
22 Can you point me once again where you were
23 reading this thing? I was thinking that you were
24 reading in 2.1, "Shift-Invariant Neural
25 Networks."

1 Q. Page 242, first column, paragraph --

2 A. 243?

3 Q. 242.

4 A. 242.

5 Q. I believe. Let me -- I'm double checking. Yes,
6 242. First column, paragraph that starts in the
7 middle of the page, "A shift-invariant neural
8 network."

9 A. Okay. Let me read it.

10 Q. Have you read that paragraph?

11 A. I have. I'm looking at the context because I
12 have not seen the paper before.

13 Q. If you could look at Figure 1, it shows receiving
14 the digitized chest radiographs and preprocessing
15 them, and then it's fed to a neural network
16 called a shift-invariant convolution neural
17 network.

18 Do you see that?

19 A. I see it.

20 Q. So do you understand this publication to be
21 describing the use of convolutional neural
22 networks to segment medical images?

23 MR. MARANDO: Objection. Form and
24 foundation.

25 A. I have not had a chance to really look into that

1 paper in detail. However, when I look at -- on
2 page 244, the bottom of the right column, it
3 shows that it starts with the handcrafted
4 features, talking about 5x5 kernels and 11x11
5 kernels, between first and second layers. And
6 this is appropriate and, you know, expected in a
7 paper published at the time.

8 So this is the same comment which I made
9 about LeCun's optical character recognition
10 paper. This starts with the human decision to
11 form the features in a --

12 Q. So you disagree with --

13 A. -- specific way. And then I envision -- I
14 couldn't tell you for sure. I didn't read the
15 paper. I envision that the neural network is
16 being used to identify the parameters of those
17 hand-designed features.

18 Q. So you disagree with the statement on 242
19 discussing the use of learned features rather
20 than handcrafted features?

21 MR. MARANDO: Objection. Form.

22 A. I think that this work was potentially exciting
23 in 1996 or whenever it was published. If you
24 look at the POSITA in 2018 when we are talking
25 about it, I don't think this would be considered

1 feature extraction without input of the human
2 designer or whatever the language exactly was
3 that you cited.

4 Q. Understood. Would it be, nevertheless,
5 considered automatic image segmentation using a
6 neural network?

7 MR. MARANDO: Objection. Form.

8 A. And so is Krishnan automatic image segmentation
9 based on hand-designed features. And this is
10 based on hand-designed features. Once you --
11 once you set it up -- once you decide that 5x5 is
12 your kernel of choice and you train the network,
13 you can do it automatically, but the feature
14 design cannot be done automatically and this
15 paper does not claim it is done automatically.

16 My quick two-minute read of the paper clearly
17 says that there are kernels of very specific
18 sizes which are hand designed and human decided
19 and not designed by the algorithm.

20 Q. Do you -- do you think that the paragraph on page
21 242, first column, starting in the middle of the
22 page that I read, do you think that provides a
23 motivation in 1998 to use convolutional neural
24 networks for medical image segmentation rather
25 than using handcrafted features?

1 MR. MARANDO: Objection. Form.
2 Relevance. Foundation.

3 MR. METZCAR: Did you run out of
4 objections?

5 A. It may give you an idea that one day it would be
6 possible, but I don't think it provides
7 motivation to do that simply because the -- you
8 know, even here, when we are talking about those
9 lung X-ray images, if you look at that, those
10 images are 2D. They are 248x2500. They are
11 immediately, you know, decreased resolution to
12 256x320 -- 312.

13 This is a great way how to publish a research
14 paper. This is not a good way how to bring this
15 to the clinical reality because you simply lose
16 so much information here. This would not
17 motivate somebody to do that because the
18 motivation means that clinicians would like to
19 accept it. They would never accept these
20 radiographs, which they fight so hard to be high
21 resolution, to be immediately decimated to, what,
22 a hundred times lower resolution than the
23 original image.

24 So it would not motivate the medical imaging
25 person to do that. They would consider that an

1 interesting, forward-looking thing.

2 Q. Okay. So you -- so you dispute that the authors
3 of this publication actually did what they said
4 they did?

5 MR. MARANDO: Objection. Form.

6 A. No.

7 Q. No?

8 A. I have not said that.

9 Q. Okay. Well, then --

10 A. I am not arguing they did not do what they did.
11 You asked whether this would motivate future
12 researchers to follow up on this.

13 Q. I see. Do you agree that the neural network that
14 is described -- I'm sorry, the convolutional
15 neural network described in this -- in this
16 publication in Exhibit 1057 is taking digitized
17 images as input?

18 MR. MARANDO: Objection. Form.

19 A. That's what the paper says.

20 Q. And do you agree that it is performing
21 segmentation of the lung region from -- directly
22 from the images?

23 MR. MARANDO: Objection. Form.

24 A. Figure 7 shows that -- it shows no neural network
25 approaches as far as I can tell.

1 Q. I'm sorry, I didn't catch that. Can you say that
2 again?

3 A. If I'm looking at Figure 6 -- and again, I
4 repeat, I did not have a chance to analyze this
5 paper in detail. But if I look at Figure 6, it
6 shows the output image of the neural network,
7 which is in panel B. This image is not a result
8 of a segmentation of the lungs.

9 To segment the lungs, it looks like Figure 7
10 is applying additional steps and filling the
11 holes and doing other things which are not done
12 by neural network, I would expect, to arrive at a
13 7B contours of the lungs.

14 Q. Okay. So this does describe doing some
15 post-processing after segmentation, but I just --
16 I want to be clear, you're disputing that this
17 describes image segmentation using a neural
18 network; is that -- am I correct?

19 MR. MARANDO: Objection. Form.
20 Foundation.

21 A. What I'm saying is that the segmentation
22 technique follows the sequence, the pipeline,
23 which I have described earlier, others described
24 earlier, as we saw, as traditional pipeline of
25 image analysis. And the segmentation, which is

1 done in neural network, needs additional steps in
2 the pipeline before they arrive and what -- what
3 would they call the segmentation boundary image
4 after that.

5 They talk about the output image, at least in
6 the Figure 6 that I see. They are not calling
7 image B, I believe, as the result of the
8 segmentation. The neural network here is used as
9 part of the pipeline, and based, as I said, on
10 the hand-designed features which decide the size
11 of the kernels and decide the substantial
12 reduction of resolution.

13 So getting back to your original image, I
14 would not see this as the direct motivation to
15 follow up with convolutional neural networks for
16 this task, for 3-dimensional image analysis,
17 simply because you did not have the overall
18 environment to do these things.

19 - - - -

20 (Thereupon, Exhibit 1058, Article titled,
21 "Toward automatic phenotyping of developing
22 embryos from videos", was marked for purposes
23 of identification.)

24 - - - -

25 Q. I'd like to show you another document. This

1 one's been labeled as Exhibit 1058.

2 Do you have it in your folder?

3 A. I'll see if it opened up.

4 Q. Do you have it?

5 A. Yes, I do.

6 Q. Okay. So this is a publication entitled "Toward
7 automatic phenotyping of developing embryos from
8 video" published in 2005 in volume 14 of IEEE
9 Transactions on Image Processing. It looks like
10 one of the authors is LeCun.

11 Are you familiar with this journal generally?

12 MR. MARANDO: Before you answer,
13 objection to the exhibit, foundation,
14 relevance, and scope.

15 You can answer.

16 A. I have not seen this particular paper. I am
17 familiar with IEEE Transactions on Image
18 Processing.

19 Q. Okay. Do you consider this journal to be a
20 reliable authority? Would you say it's
21 well-perceived or well-respected?

22 A. A well-perceived, well-respected --
23 well-respected journal.

24 Q. Okay. Thank you. I want to point out a couple
25 of passages to you and get your reaction.

1 So again, this is from 2005. It says in the
2 abstract, "We describe a trainable system for
3 analyzing videos of developing C. Elegans
4 embryos. The system automatically detects,
5 segments, and locates cells and nuclei in
6 microscopic images."

7 If you turn the page to, I believe I've
8 labeled it 13 and 14 -- or 3 of 14. Under the
9 heading "Overview of the System" -- do you see
10 that heading?

11 A. Yes, I do.

12 Q. Okay. It says, "The method proposed in this
13 paper consists in learning the entire processing
14 chain from end to end, from raw pixels to
15 ultimate object categories. The system is
16 composed of three main modules.

17 'The first module is a trainable
18 convolutional neural network, which labels each
19 pixel in a frame into one of five categories.
20 The categories are: Cell nucleus, nuclear
21 membrane, cytoplasm, cell wall, and outside
22 medium. The main advantage of convolutional nets
23 is that they can learn to map raw pixel images
24 into output labels, synthesizing appropriate
25 intermediate features along the way, and

1 eliminating the need for manually engineered
2 features. They have been widely applied to
3 detection and recognition tasks such as
4 handwriting recognition with integrated
5 segmentation, hand tracking, face recognition,
6 face detection, and generic object recognition.
7 The main advantages of convolutional neural
8 networks is that they can operate directly on raw
9 images."

10 Do you agree with that statement?

11 MR. MARANDO: Objection.

12 Foundation.

13 A. I see that. I have -- you know, I do not know
14 whether that's exactly what the -- what the paper
15 is talking about. I have not had a chance to
16 form an opinion on that.

17 Q. Do you understand this exhibit to be describing
18 the segmentation of medical imaging using
19 convolutional neural networks?

20 MR. MARANDO: Objection. Form.

21 Foundation.

22 A. I do. And at the same time, in the following
23 paragraph, I immediately see the same issue,
24 which we already discussed many times, that there
25 has been a hand-decided size of the pixel window,

1 which is in this case 40x40. So some years
2 probably passed to get from 5x5 to 40x40. But
3 that doesn't change the, you know, the
4 fundamental difference between what the 029
5 patent is teaching as being -- being learned from
6 the images and what I think based on this
7 two-minute analysis of this paper is being taught
8 by here.

9 Q. So do you understand the 029 patent to be limited
10 to the use of convolutional neural networks that
11 do not preestablish the size of the kernel
12 filter?

13 MR. MARANDO: Objection.

14 Q. Is that what you're saying?

15 A. Did I form that opinion in my declaration?

16 Q. Well, you keep making that distinction. Every
17 time I point to you another neural network that
18 accepts images and segments them, you keep
19 pointing to me this discussion about, well, yes,
20 but they handcrafted the size of the kernel. And
21 I'm trying to understand, are you saying that the
22 029 patent is limited to just the neural networks
23 that are free to select the kernel size during
24 training?

25 MR. MARANDO: Objection. Form.

1 A. My opinion is that 029 patent is teaching the way
2 how to design features without them being
3 handcrafted. I have not provided opinion that
4 this is a limited -- that 029 is limited to that
5 functionality. That opinion is not part of my
6 declaration.

7 Q. If a neural network was accused of infringing the
8 029 patent and used the convolutional neural
9 network in which the size of the kernels were
10 preselected but the features of the kernels were
11 then trained, could that neural network infringe
12 any of the claims of the 029 patent, in your
13 opinion?

14 MR. MARANDO: Objection. Form.
15 Foundation.

16 A. This is a hypothetical and I am not ready to
17 analyze that here on the spot. At the same time,
18 you know, I do recall that the petitioner has
19 agreed that 102 does not have neural network and
20 it's not neural network-based.

21 So I don't quite understand this entire line
22 of questioning because we have on the -- my
23 understanding is that there is a statement from
24 the petitioner that 102 is not a neural network.

25 Q. Respectfully, I think you have a

1 misunderstanding. The petitioner does not agree
2 that feature extraction is not performed by a
3 neural network. It certainly describes broadly
4 that other kinds of things could be included, but
5 it does not -- there's no admission that feature
6 extraction is not done by a neural network.

7 Okay. So we've been through a lot of
8 publications. I just want to follow up and
9 summarize here.

10 Based on what we've seen today and your
11 personal knowledge, was the segmentation of
12 medical images using neural networks known prior
13 to the introduction of AlexNet in 2012?

14 MR. MARANDO: Objection. Form.

15 A. I have -- go ahead. Did you have a question to
16 follow up on that?

17 Q. I was clarifying my question. I'll repeat the
18 question and then your counsel can repeat his
19 objection.

20 Was the segmentation of medical images using
21 neural networks publicly known to a person of
22 skill in the art prior to the introduction of
23 AlexNet in 2012?

24 MR. MARANDO: Objection. Form.

25 A. The distinction I was making, and I continue to

1 be making, is whether the Krishnan patent when
2 talking about image segmentation methods and
3 filtering methods in context of the 102 model
4 were done using neural networks, and I have
5 stated that it has not been done using neural
6 networks. You know, the -- Dr. Deo, I believe,
7 has stated that it is not necessarily done with
8 the neural networks. I believe that in the
9 parallel litigation the petitioner stated that
10 102 is not using neural networks.

11 And so my position is that, as I understand
12 the Krishnan patent, the 102 module is not
13 associated with a neural network.

14 Q. Okay. My question was a different question. I
15 asked you whether the segmentation of medical
16 images using neural networks was known to a
17 person of skill in the art prior to the
18 introduction of AlexNet in 2012. That was my
19 question.

20 MR. MARANDO: Objection. Form.

21 Q. Can you answer that?

22 A. The classifier at that time, any machine learning
23 method at that time, could have been used to
24 segment images based on the calculated features,
25 and in that sense, classifiers were able to be

1 used for segmentation.

2 Neural network, at that time, is a
3 classifier, same as any other classifier in
4 principle, and, therefore, it could have been
5 used for image segmentation in that way.

6 Q. Okay. Well, so was the segmentation of medical
7 images using neural network classifiers known
8 prior to the filing date of Krishnan in 2005?

9 MR. MARANDO: Objection. Form.

10 A. That segmentation was presented, demonstrated in
11 specific cases, but what was missing there
12 compared to what happened after 2012 is that all
13 the features which it used for performing the
14 classification were in one way or another using
15 steps that required human intelligent design.

16 Those features were not trained using those
17 neural networks. They were not learned using
18 neural networks. They were not learned using
19 other classifiers.

20 Q. So regardless of whether the segmentation is
21 based on learned features or handcrafted
22 features, my question is whether or not it was
23 learned before Krishnan's filing date in 2005 to
24 segment images using neural networks that accept
25 the images as input?

1 MR. MARANDO: Objection. Form.

2 A. You can say that a convolution kernel is a
3 one-layer neural network. And you can say that
4 detecting edges in the image is segmentation.
5 Because if you apply that one convolution kernel
6 to the image, you get the edges. And in that
7 absurd state and definition of your segmentation,
8 you can say that convolution neural network,
9 which is a single kernel, can be used for image
10 segmentation.

11 I don't think that a POSITA of 2005 or any
12 other time would agree with this definition of
13 segmentation because in the pipeline you need the
14 features. The features have to be somehow
15 designed. Then you have the classifier if you
16 want to use the classification pipeline. And you
17 may need some post-processing as you saw in the
18 previous cases.

19 The difference in the post-2012 is that the
20 human design of the features could have been
21 abandoned, and, therefore, new features
22 previously unavailable became available and
23 that's what helped performance to improve of not
24 only segmentation, but analysis techniques.

25 Q. Okay. So let's put aside that Krishnan

1 references segmentation or known segmentation
2 methods as being used for feature extraction.
3 Put that aside. Put segmentation aside. Let's
4 just talk about feature extraction in general.

5 Was neural network image feature extraction
6 known prior to the filing date of Krishnan in
7 2005?

8 MR. MARANDO: Objection. Form.

9 A. We need to distinguish, and that's what we are
10 talking about since we started a few hours ago,
11 that extraction means that you calculate
12 something in my definition or in my
13 understanding. Design of the features is a
14 different function of it.

15 Was it possible to extract features using
16 neural networks? It was possible to extract
17 features using any kernels, so why not a kernel
18 which is formed as a neural network?

19 Was it possible to design new feature
20 architecture, new feature -- you know, new
21 features? My opinion is that it was not.

22 Q. I want to talk about another issue. You've been
23 asking for Krishnan all day. Let's go ahead and
24 get it up.

25 A. I don't have to see it. We can skip it.

Q. I just put Exhibit 1005, what we've been referring to as Krishnan, in your marked exhibits folder.

A. I see it. I have it open.

Do you recall that we started on that conversation? You asked --

Q. Okay. And so you had asked to see Krishnan and I said I don't want to talk about it right at this point. Now we're back to it.

1 And you agree with me that those are three
2 basic embodiments that he uses, correct?

3 A. Yes, I do. Yes, I do.

4 Q. I would be -- just as a, for example, figures 2
5 -- I'm sorry, figures 4 and 5. 4 discusses the
6 templates, 5 discusses classifiers, and I believe
7 3 might be the --

8 A. It is.

9 Q. So at least in the embodiments in which Krishnan
10 is making comparisons to template, do you
11 understand that the extracted features -- well,
12 let me back up.

13 Let's talk -- let me point you directly to
14 the paragraph I'm interested in. You can keep
15 Exhibit 1005 open, but I'd also like to look at
16 your declaration, paragraph 140.

17 So paragraph 140 of your declaration you're
18 discussing, or at least you provide a cite to
19 paragraph 38 of Krishnan. Do you see that?

20 A. I see the Krishnan 38 paragraph, yes.

21 Q. So in paragraph 38 of Krishnan, it says, "For
22 example, consider the problem of identifying the
23 apical four-chamber view in echocardiography. A
24 set of typical apical four-chamber views would
25 reveal a number of features such as the presence

1 of four chambers, and a general shape of the
2 heart."

3 Then at the end it says, "These features
4 could be extracted from a test image and compared
5 to a set of features from the known view."

6 Do you see that?

7 A. I see it.

8 Q. Okay. So in paragraph 140, you quote that --
9 what I read, but you then say, "However, these
10 are features meant for computational analysis.
11 Their quantitative representation, say, a numeric
12 vector of values, would not allow a technician or
13 clinician to interpret the anatomical
14 structures."

15 Do you see that? Do you see the portion I
16 just read?

17 A. I see that.

18 Q. Okay. So I want to be clear. Are you talking
19 about the embodiment of Krishnan that would be
20 used in a neural network classifier? Are you
21 saying that the extracted features would be a
22 feature vector rather than some sort of image?

23 A. Let's make one thing clear here. If you go back
24 to your -- to figure -- let me see. Where do we
25 have it? Well, Figure 1.

1 Q. Okay.

2 A. The feature analysis is module 102 and features
3 extracted from module 102 are being used for 103,
4 104, or 105. Right?

5 And 103 is the anatomy identification, and it
6 can use any of the three basic embodiments:
7 Database, template matching, or classifiers. The
8 same way how the features are calculated are
9 being used for all three, in principle at least.

10 So can you repeat the question so that I can
11 answer that?

12 Q. Sure. What I'm trying to get at -- let's cut to
13 the chase here. I mean, the -- in paragraph 34
14 of Krishnan it talks about various features that
15 can be extracted, some of which are, for
16 example, an anatomy of interest, right? You can
17 segment an anatomy of interest?

18 It says -- it talks about a particular shape
19 from an image. And then, as we were reading in
20 paragraph 38, it says that you could extract
21 features, including a general shape of the heart.

22 And what I'm trying to understand is in the
23 -- in the various embodiments, for example,
24 template matching where you're comparing the
25 image that was received to templates to determine

1 whether or not it's a particular view or a
2 particular anatomy is there, are you saying that
3 the extracted features are always feature
4 vectors, as opposed to some portion of the image,
5 even in the template matching embodiment?

6 MR. MARANDO: Objection. Form.

7 A. I have not seen Krishnan teaching that those
8 features can be images, original images. If I am
9 missing that, can you point me where Krishnan is
10 showing that?

11 Q. So, I mean, I guess what I'm saying is, how is --
12 what is template matching? What is it?

13 A. Template matching is that you have some sample
14 data and some description of sample data. You
15 get the same description of the real data and you
16 are trying to match those together, find a match.

17 That match can be done a zillion different
18 ways. It can be done by comparing the
19 description of vectors. It can be done by
20 comparing brightness variance information here
21 and there. It -- where we are headed to, it can
22 be done by, you know, really having one image,
23 having the other image, and trying to match them.

24 Q. Right.

25 A. There are different ways.

1 Q. Right.

2 A. I have not seen -- and perhaps I missed it. I
3 have not seen information in Krishnan that would
4 be talking about template matching based on
5 images. I have always seen that this matching in
6 all those three different embodiments is based on
7 the features which are output from 102.

8 Q. Okay. But --

9 A. 102 -- and 102 features are described as the ones
10 obtained with filtering techniques and --

11 Q. Segmentations, right?

12 A. For example.

13 Q. If you segment an anatomy of interest or a
14 particular shape from the image, then -- I'm
15 trying to understand.

16 Couldn't that be -- for example, I've
17 received an ultrasound image, but I'm only
18 interested in the heart portion of the image. So
19 I segment out the heart. Now I have an image of
20 the shape of the heart and an image of the
21 chambers, whatever chambers I happened to have
22 cut through, and I compare to a template and
23 determine do I have the right view or not, a
24 template image. Is that possible?

25 A. I understand your logic. Typically, when you say

1 image segmentation, the output of image
2 segmentation is the labeled image, not the
3 image's original pixel values. Okay?

4 So if you do the segmentation of the heart
5 chamber, you would end up with either a region of
6 the heart chamber or the outline of the heart
7 chamber.

8 Q. Okay.

9 A. It doesn't really materially change what we are
10 trying to talk about here. Right?

11 And so your template -- let's say that your
12 template would be the outline and the analyzed
13 image, the features from the analyzed image would
14 be added to the outline. And then it depends on
15 your outline-to-outline matching strategy, which
16 is part of, you know, one of the embodiments of
17 how they perform that match, how they get to,
18 let's say, the probability between one and --
19 between zero and one that the match is perfect or
20 none exists.

21 Q. Okay. So looking at paragraph 34 of Krishnan at
22 the -- it's the top of the second column -- well,
23 bottom of the first column, top of the second
24 column.

25 "These features could include any kind of

1 characteristic that could be extracted from the
2 image, such as a particular shape."

3 So tell me what -- what do you understand
4 that to mean? It's extracting a particular shape
5 from the image?

6 A. Shape is an ultimately tricky thing because you
7 can describe something as circular, you can
8 describe something as oval, elliptic, straight,
9 whatever it is. You know, the description is
10 imperfect, and the human understanding of shape
11 is very difficult to quantify. And it's even
12 more difficult to find shape-to-shape
13 similarities just based on those extractions or
14 the contours or something like that.

15 So you would use the template matching. What
16 you would probably have to do is that you would
17 have to somehow align those two objects using
18 Procrustes analysis or something like that so
19 that you get the best match, and then try to
20 design, as part of the template matching process,
21 some metric which determines what is close and
22 what is not.

23 But let's talk what the patent is talking
24 about. The patent is saying you will decide it
25 somehow, doesn't matter, but you use the general

1 principle of template matching, which is applied
2 to the features resulting from 102.

3 Q. Are you familiar with the -- with the term
4 "localization" as, I'll say, compared to
5 segmentation?

6 A. If I understand what you -- what you mean, it's
7 probably what is maybe also called the detection.
8 So finding the location of some organ, finding
9 the location of the heart, finding the location
10 of something else. Say, finding the centroid of
11 that or something like that.

12 Q. Sure. So, for example, if you have --

13 A. Do we agree on that -- do we agree on that
14 definition of localization?

15 Q. Well, if you have a large image and I want to --
16 I'm only interested in a particular organ, I
17 might take out a portion of that image or segment
18 out that -- that region. So I'm not segmenting
19 out, you know, the prostate, but maybe I segment
20 out the pelvis from the entire image.

21 Do you under -- do you understand what I'm
22 talking about?

23 A. You -- you identify the region of interest for
24 the future analysis, follow-up analysis.

25 Q. Right. Right. And you probably have some

1 familiarity with this. I believe you were
2 recently in a case that involved two-step
3 segmentation.

4 A. 40 years of that, yes.

5 Q. I was -- I was -- I was surprised. Do you
6 remember Progenics Pharmaceuticals?

7 A. Uh-huh.

8 Q. Yeah, you were the expert. I was the attorney on
9 the other side in that case.

10 A. Interesting. Small world.

11 Q. So I'm familiar with this technique as well, but
12 I'm getting to the point -- what I'm trying to
13 get at is this description in Krishnan in Figure
14 34 when it talks about extracting a particular
15 shape from an image, is that -- that's not
16 limited to a particular organ.

17 It could be a region that contains an organ;
18 is that correct?

19 A. Probably wouldn't say it can be a region. I
20 think that in the -- in the context of that
21 language, features can include characteristic
22 that could be extracted from the image such as
23 particular shape.

24 You would probably try to -- talking about
25 the heart because that's what we are talking

1 about before. You would probably try to find the
2 elliptic ventricular shape. So find some object
3 that looks like an ellipse. That's how I would
4 probably interpret --

5 Q. Okay.

6 A. -- this statement.

7 Q. Okay.

8 A. And then you would try to find out how close that
9 is to an ellipse and is there a similar ellipse
10 in the template, things like that.

11 MR. METZCAR: Okay. Let me just
12 -- can we take a five-minute break? I'll
13 just go over my notes and see if there's
14 something else I want to follow up on.

15 - - - -

16 (Thereupon, a recess was had.)

17 - - - -

18 BY MR. METZCAR:

19 Q. Dr. Sonka, we're back on the record. I have a
20 few things I wanted to follow up with you on.

21 So the 029 patent refers to first
22 feature-extracting neural network, a second
23 feature-extracting neural network, and quality
24 assessment neural networks. Do you -- I think at
25 various points it refers to them as subnetworks

1 within the network that's shown in Figure 4.

2 Do you understand that those networks, those
3 subnetworks, can be trained separately?

4 A. My understanding is that this is one end-to-end
5 system.

6 Q. Okay. So according to you, it must be trained
7 end-to-end with the image input and the expect --
8 for example, the expected quality value as the
9 anticipated output?

10 A. I would not go that it must be trained that way.
11 My understanding is that the embodiment which is
12 shown here is trained that way.

13 Q. One of the embodiments that's shown in Figure 4;
14 is that what you're referring to?

15 A. That's correct.

16 Q. Could it be done differently? Can you train
17 feature extractor first and then separately train
18 classifiers based on extracted features?

19 MR. MARANDO: Objection. Form.

20 A. Everything can -- everything can always be done
21 differently. I don't -- you know, my
22 understanding is that the advantage of these
23 modern deep networks is that you don't have to do
24 it step by step. So I think that the teaching is
25 that, you know, end-to-end is giving you the

1 advantages of the overall optimality with respect
2 to the one objective function.

3 Q. Okay. I think you had printed out some of the
4 publications -- or some of the patents.

5 Do you have them in front of you? Do you
6 have the Aase reference?

7 A. Yes, I do.

8 Q. Can you remind me what exhibit number is on the
9 bottom of that?

10 A. 106.

11 Q. I'm sorry, 1006?

12 A. Yes, 1006.

13 Q. Just for the record, that's Exhibit 1006. It's
14 the Aase patent.

15 So this system -- would you agree this system
16 has a separate or a dedicated neural network for
17 image quality assessment and for view
18 identification?

19 A. Those are the modules 160 and 170, yes.

20 Q. Okay. And are those convolutional neural
21 networks, as you understand it?

22 A. Let me see if it specifically says that. Is it
23 okay for me to search for that in the document?
24 I don't -- I don't see specifically requiring
25 that to be convolutional neural network, but

1 perhaps --

2 Q. It's okay. If you don't know -- if you don't
3 know -- I mean, either the document says it is or
4 doesn't, but I believe your declaration describes
5 that those neural networks extract features
6 within their hidden layers.

7 Is that -- is that --

8 A. Yes.

9 Q. -- your understanding?

10 A. Yes. That's my -- that's my -- that's my
11 understanding of the Aase patent, yes.

12 Q. They receive images, extract features within
13 their hidden layers, and then provide view
14 quality assessment and -- I'm sorry, view
15 identification and quality assessment; is that
16 right?

17 A. Correct.

18 Q. Okay. So those neural networks are not accepting
19 extracted features; they're accepting images?

20 A. That's my understanding, yes.

21 Q. And you consider those neural networks to be the
22 types of deep learning neural networks that we've
23 been talking about where they generate their own
24 features?

25 A. That's correct. And I consider them to be

1 end-to-end neural networks which determine
2 features, design features, calculate parameters
3 of the features, and use them for classification.

4 Q. Okay. And they -- this system in Aase is
5 identifying view categories by taking a series of
6 images or short video; is that correct?

7 A. They are based on the loops, yes.

8 Q. So if these two neural networks identified as 160
9 and 170 are taking in images, extracting features
10 in their hidden layers, and outputting quality
11 assessment and a view identification, do you have
12 any thought as to how this is different at all
13 from the 029 patent?

14 MR. MARANDO: Objection. Form.

15 A. I was not asked to provide an opinion on that and
16 I have not provided an opinion on that.

17 Q. I understand you haven't provided an opinion, but
18 do you have one now? Do you have any --

19 MR. MARANDO: Objection. Form.

20 Q. -- thought about --

21 A. I have not -- I have not studied -- I have not
22 studied that from the standpoint of how similar
23 this is to 029. There are some details in the
24 Aase evidence, which -- which I would have to go
25 much deeper in -- and perhaps something's

1 missing, to be able to really do the template
2 matching between 029 and Aase.

3 Q. So you briefly discuss in your declaration this
4 concept that the 029 patent had resolved some
5 unmet need in the industry.

6 Do you recall that?

7 A. Yes, I do.

8 Q. Okay. So the Krishnan reference that we've been
9 discussing, it's a published patent application
10 and ultimately issued as a patent. It is cited
11 in many, many other subsequent patents. In fact,
12 it's cited in the 029 patent.

13 And so I guess I'd like to understand why is
14 it you think that the Krishnan application did
15 not resolve this unmet need that you've
16 identified?

17 A. Let me go a little bit back into, you know, my
18 own years of work on different problems. And
19 I'll give you a little correlative answer.

20 My first paper that dealt with intravascular
21 ultrasound is from 1996. Many, many years ago.
22 30 years ago. I don't think we, or anybody else,
23 have fully solved the problem of analyzing
24 intravascular ultrasound images to the point that
25 intravascular ultrasound has been replaced with

1 optical coherence tomography and that unmet need,
2 to some extent, disappeared because the IVUS
3 images are not taken anymore, or not that
4 frequent.

5 So I think that, you know, Krishnan may have
6 addressed the unmet need in 2005, but down the
7 road, I would expect, as with more of the
8 traditional techniques, that better performance
9 can be obtained down the -- down the road. And
10 in those 20 years post-Krishnan, some progress
11 happened and people starting to use -- and I
12 don't know who was using and how much people were
13 using Krishnan, how much -- I assume that Siemens
14 was probably using that in their -- in their
15 products, but I do not know that. And I would
16 expect that the quality and assessment, the view
17 assessment, they're not perfect. Things are
18 rarely perfect.

19 And so clinicians always ask for better
20 performance. And that's what I think is that
21 unmet need because Krishnan doesn't solve the
22 problem which they are addressing for each and
23 every image. I would not expect that 029 solves
24 that problem for each and every image or image
25 loop.

1 So that's why I think that 029 is addressing
2 the unmet need and that -- and in that sense is
3 important with respect to the secondary
4 considerations.

5 Q. Let me -- let me approach it from a different
6 direction.

7 The Krishnan reference is a -- the published
8 patent application, and it certainly states that
9 it can be used for real-time feedback of quality
10 assessments and view categorization.

11 Do you know whether it was ever actually
12 implemented in any physical device?

13 MR. MARANDO: Objection. Form.

14 A. I do not.

15 Q. You do not know?

16 A. No.

17 Q. And the 029 patent, do you know, has that patent
18 been commercialized?

19 A. I do not --

20 MR. MARANDO: Objection. Form.

21 A. I do not know that either.

22 Q. Do you know if it's been licensed to anyone?

23 A. I do not.

24 Q. Okay. Is -- I mentioned to you that Krishnan
25 reference is cited in the 029 patent.

1 Do you consider that to be an admission that
2 the Krishnan patent is a pioneering invention?

3 MR. MARANDO: Objection. Form.

4 A. If I look at the 029, which is here someplace,
5 and you look at the publications considered, it's
6 a two-column long list, right?

7 Q. Yes.

8 A. I cannot imagine proposing submitting a patent
9 application in this field without citing Krishnan
10 patent and without asking the examiner to
11 consider that and to showing the differences
12 against that. I don't know whether that itself
13 can be used to satisfy the pioneering invention
14 statement you are making.

15 Q. Okay. So the 029 patent, let's think of it a
16 different way. The 029 patent contains at least
17 two columns of cited patents, patent applications
18 and publication.

19 Do you -- do you think that the citation of
20 any of those there is an admission that they are
21 -- that all of those constitute pioneering
22 patents or publication?

23 A. That's what I think I just said. I don't think
24 that each and every one, or any for that matter,
25 should be labeled as pioneering application.

1 Q. Okay. But the mere citation of something, you
2 know, a patent application, is not an admission
3 that it's pioneering, is it?

4 A. I think that it's an admission that it's relevant
5 to the field. I think that it's an admission
6 that it's -- it's work that, at one point, has
7 been considered novel, otherwise, it would not be
8 patentable and would not get a -- get a patent
9 allowance.

10 I think that pioneering is a little too much
11 for virtually any, but important at its time, I
12 will certainly say that, and I would expect -- I
13 do not know that, but I expect that the Krishnan
14 patent was probably cited frequently in later
15 patent applications. I don't know whether it's
16 true, but I would expect that.

17 Q. Okay. You mentioned something there. Do you --
18 well, first of all, you have patents, don't you?

19 A. I do.

20 Q. Okay. So you're aware of the duty of disclosure?

21 A. Say that again. I didn't catch that.

22 Q. Duty of disclosure to disclose relevant --
23 potentially relevant material.

24 A. Yes.

25 Q. When you, as an inventor, disclose a prior art

1 reference to the patent office, do you -- are you
2 making an admission that that -- that you believe
3 that that issued patent is indeed patentable?

4 MR. MARANDO: Objection. Form.

5 A. No, that's my -- that's not my consideration and
6 it's not for me to decide, you know, regardless
7 what I think.

8 But when I do that, I am trying to state that
9 my work is different from that which was
10 previously published. That's probably primary
11 consideration. And it also means I consider that
12 work relevant, important representative of some
13 -- in some way so that the examiner could see
14 that there are some similarities that I would
15 like to -- so give it to the examiner something
16 what he or she should consider when looking at
17 the novelty of the patent.

18 So in that way it is -- it is sort of a
19 statement -- small statement that the work is
20 relevant and it was novel at one point.

21 Q. Okay. Originally you said it's not an admission
22 but it is patentable, but now you said it is an
23 admission that it's novel. You understand novel
24 to mean --

25 A. Okay. Okay. I understand what you are saying

1 and let me explain. Let me clarify that.

2 It's an admission that that work was
3 considered as novel by the -- by the patent
4 office and is considered as novel because the
5 patent still stands. And, you know, from
6 somebody who is submitting a patent that somebody
7 -- that application that somebody's not in a
8 position to argue whether the patent is or is not
9 valid or should or should not be valid.

10 So I don't think -- getting back to what I
11 will say, I don't think that including a
12 publication on the -- on the list of, you know,
13 documents to be considered has anything to do
14 about patentability or non-patentability of that.

15 Q. Understood. Okay. Thank you.

16 All right. Well, I will -- I'll turn the
17 witness over to Chris if he has any follow-up
18 questions for you.

19 MR. MARANDO: Okay. I don't have
20 any follow-ups. So Dr. Sonka will review
21 and sign the transcript, but I think we can
22 go off the record.

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(Signature not waived.)

(Deposition concluded at 3:14 p.m.)

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C E R T I F I C A T E

The State of Ohio,) SS:
County of Cuyahoga.)

I, Genevieve Del Valle, a Notary Public within and for the State of Ohio, authorized to administer oaths and to take and certify depositions, do hereby certify that the above-named witness was by me, before the giving of their deposition, first duly sworn to testify the truth, the whole truth, and nothing but the truth; that the deposition as above-set forth was reduced to writing by me by means of stenotypy, and was later transcribed into typewriting under my direction; that this is a true record of the testimony given by the witness; that said deposition was taken at the aforementioned time, date and place, pursuant to notice or stipulations of counsel; that I am not a relative or employee or attorney of any of the parties, or a relative or employee of such attorney or financially interested in this action; that I am not, nor is the court reporting firm with which I am affiliated, under a contract as defined in Civil Rule 28(D).

IN WITNESS WHEREOF, I have hereunto set my hand and seal of office, at Cleveland, Ohio, this 6th day of August 2026.

Genevieve Del Valle

Genevieve Del Valle
Notary Public, State of Ohio
My commission expires September 28, 2028

Veritext Legal Solutions
1100 Superior Ave
Suite 1820
Cleveland, Ohio 44114
Phone: 216-523-1313

August 13, 2026

To: Christopher Marando, Esq.

Case Name: Caption Health, Inc. v. University Of British Columbia

Veritext Reference Number: 8354649

Witness: Milan Sonka, PhD Deposition Date: 8/6/2026

Dear Sir/Madam:

Enclosed please find a deposition transcript. Please have the witness review the transcript and note any changes or corrections on the included errata sheet, indicating the page, line number, change, and the reason for the change. Have the witness' signature notarized and forward the completed page(s) back to us at the Production address shown above, or email to production-midwest@veritext.com.

If the errata is not returned within thirty days of your receipt of this letter, the reading and signing will be deemed waived.

Sincerely,
Production Department

NO NOTARY REQUIRED IN CA

DEPOSITION REVIEW
CERTIFICATION OF WITNESS

ASSIGNMENT REFERENCE NO: 8354649

CASE NAME: Caption Health, Inc. v. University Of British
Columbia

DATE OF DEPOSITION: 8/6/2026

WITNESS' NAME: Milan Sonka, PhD

In accordance with the Rules of Civil
Procedure, I have read the entire transcript of
my testimony or it has been read to me.

I have made no changes to the testimony
as transcribed by the court reporter.

Date Milan Sonka, PhD

Sworn to and subscribed before me, a
Notary Public in and for the State and County,
the referenced witness did personally appear
and acknowledge that:

They have read the transcript;
They signed the foregoing Sworn
Statement; and

Their execution of this Statement is of
their free act and deed.

I have affixed my name and official seal

this _____ day of _____, 20____.

Notary Public

Commission Expiration Date

DEPOSITION REVIEW
CERTIFICATION OF WITNESS

ASSIGNMENT REFERENCE NO: 8354649

CASE NAME: Caption Health, Inc. v. University Of British
Columbia

DATE OF DEPOSITION: 8/6/2026

WITNESS' NAME: Milan Sonka, PhD

In accordance with the Rules of Civil
Procedure, I have read the entire transcript of
my testimony or it has been read to me.

I have listed my changes on the attached
Errata Sheet, listing page and line numbers as
well as the reason(s) for the change(s).

I request that these changes be entered
as part of the record of my testimony.

I have executed the Errata Sheet, as well
as this Certificate, and request and authorize
that both be appended to the transcript of my
testimony and be incorporated therein.

Date

Milan Sonka, PhD

Sworn to and subscribed before me, a
Notary Public in and for the State and County,
the referenced witness did personally appear
and acknowledge that:

They have read the transcript;
They have listed all of their corrections
in the appended Errata Sheet;
They signed the foregoing Sworn
Statement; and
Their execution of this Statement is of
their free act and deed.

I have affixed my name and official seal
this _____ day of _____, 20____.

Notary Public

Commission Expiration Date

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ERRATA SHEET
VERITEXT LEGAL SOLUTIONS MIDWEST
ASSIGNMENT NO: 8354649

PAGE/LINE(S) / CHANGE /REASON

Date Milan Sonka, PhD
SUBSCRIBED AND SWORN TO BEFORE ME THIS _____
DAY OF _____, 20____ .

Notary Public

Commission Expiration Date

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Federal Rules of Civil Procedure

Rule 30

(e) Review By the Witness; Changes.

(1) Review; Statement of Changes. On request by the deponent or a party before the deposition is completed, the deponent must be allowed 30 days after being notified by the officer that the transcript or recording is available in which:

(A) to review the transcript or recording; and

(B) if there are changes in form or substance, to sign a statement listing the changes and the reasons for making them.

(2) Changes Indicated in the Officer's Certificate. The officer must note in the certificate prescribed by Rule 30(f)(1) whether a review was requested and, if so, must attach any changes the deponent makes during the 30-day period.

DISCLAIMER: THE FOREGOING FEDERAL PROCEDURE RULES ARE PROVIDED FOR INFORMATIONAL PURPOSES ONLY.

THE ABOVE RULES ARE CURRENT AS OF APRIL 1, 2019. PLEASE REFER TO THE APPLICABLE FEDERAL RULES OF CIVIL PROCEDURE FOR UP-TO-DATE INFORMATION.

VERITEXT LEGAL SOLUTIONS

COMPANY CERTIFICATE AND DISCLOSURE STATEMENT

Veritext Legal Solutions represents that the foregoing transcript is a true, correct and complete transcript of the colloquies, questions and answers as submitted by the court reporter. Veritext Legal Solutions further represents that the attached exhibits, if any, are true, correct and complete documents as submitted by the court reporter and/or attorneys in relation to this deposition and that the documents were processed in accordance with our litigation support and production standards.

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