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

MICROSOFT CORPORATION,)Volume 2
)
 Petitioner,)
)
 vs.)Case No. IPR2023-01046
)
REALD SPARK, LLC,)
)
 Patent Owner.)
)

CONTINUED REMOTE DEPOSITION
OF
ELI SABER, Ph.D.
Friday, June 7, 2024
Webster, New York

Reported by:
B. Suzanne Hull, CSR No. 13495
JOB No. 6745758

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EXAMINATION BY

PAGE

MR. STEIN

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** NO EXHIBITS WERE MARKED **

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Webster, New York

Friday, June 7, 2024; 12:32 p.m.

THE REPORTER: Raise your right hand,
please, sir.

Do you solemnly swear or affirm that the
testimony you shall give shall be the truth, the
whole truth, and nothing but the truth.

THE WITNESS: I do.

ELI SABER, Ph.D.,
called as an expert witness by counsel for
Petitioner, being first duly sworn, testified as
follows:

THE REPORTER: Thank you.

Mr. Stein.

MR. STEIN: Thank you.

EXAMINATION

BY MR. STEIN:

Q. Well, hello again, Dr. Saber.

I'm glad your power has been restored.

MR. STEIN: So we are continuing the
deposition from June 5th, now that Dr. Saber has his

1 power back.

2 BY MR. STEIN:

3 Q. Dr. Saber, just to start, could you let me
4 know what materials you have to reference on your
5 computer based on the deposition from June 5th?

6 A. Yes.

7 I have Exhibit 2008, supplemental
8 declaration. I have Exhibit 1001, the '985 patent.
9 I have Exhibit 1006, Ganin. I have Exhibit 1005,
10 Chalom. I have Exhibit 1007, Aslan. I have
11 Exhibit 1059, and I have Exhibit 1065. Those are all
12 the exhibits that were e-mailed to me at the last
13 session.

14 Q. Sorry for my silence. I am just connecting
15 to the realtime.

16 (Short recess taken from
17 12:33 p.m. to 12:35 p.m.)

18 BY MR. STEIN:

19 Q. Okay. All right. Dr. Saber, so I don't --
20 I don't want to have to repeat, sort of, the rules of
21 the deposition.

22 So could you just confirm for me that, sort
23 of, the rules we went over last time are going to
24 apply here as well?

25 A. Confirmed.

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1 Q. Okay. All right. So at the end of the
2 deposition last time do you recall we were talking
3 about the Aslan reference, Exhibit 1007?

4 A. I do.

5 Q. And we were discussing parallel and serial
6 training with reference to the Aslan reference,
7 Exhibit 1007, at paragraph five.

8 Do you remember that?

9 A. I don't, but I'm glad you reminded me.

10 Q. Okay. Well, if you could just pull up
11 Exhibit 1007, the Aslan reference, and take a look at
12 paragraph five for me and let me know when you get
13 there.

14 (Reporter interruption.)

15 BY MR. STEIN:

16 Q. Okay. Dr. Saber, referring to paragraph
17 five here, do you see the second sentence of
18 paragraph five refers to parallel training and it
19 also refers to sequential training, both of which
20 Aslan has included in quotations there in that
21 paragraph?

22 A. Yes.

23 I do see that.

24 Q. And what does sequential training --
25 training mean to a POSITA in this -- this time

1 period, pre 2017?

2 A. Well, he described -- Aslan describes it in
3 a very nice sentence. Aslan says:

4 "In sequential training" --

5 I am looking at paragraph five, roughly the
6 sixth line down or so:

7 "In sequential training, the first
8 machine-learning algorithm is fully trained
9 prior to initiating the training of a second
10 machine-learning algorithm."

11 Q. So when you are doing sequential training,
12 you are -- you have at least two machine-learning
13 algorithms in this pre 2017 time frame?

14 MS. MAURI: Objection. Form.

15 THE WITNESS: Yeah.

16 I mean, essentially, what he is doing here
17 is he is saying in sequential training you have
18 a first machine-learning al- -- model in this case
19 that is fully trained prior to initiating the
20 training of a second machine-learning model. You
21 train the first one, and then you train the second
22 one.

23 BY MR. STEIN:

24 Q. And do you know if Aslan provides examples
25 of the types of machine-learning algorithms that

1 might be trained in parallel or sequentially?

2 A. I'm -- I'm not sure what you mean. I mean,
3 Aslan talks about training -- joint model training
4 where he is training, you know, two machine-learning
5 algorithms.

6 Q. Are you familiar with the Aslan reference?

7 A. Oh, yes. Absolutely.

8 Q. So you are -- you are an expert in the Aslan
9 reference; right?

10 MS. MAURI: Objection. Form.

11 THE WITNESS: I -- I am familiar with the
12 Aslan reference, yes.

13 BY MR. STEIN:

14 Q. But you can't tell me whether Aslan provides
15 examples of the types of machine-learning algorithms
16 that can be trained in parallel or sequentially?

17 MS. MAURI: Objection. Form.

18 THE WITNESS: So, for instance, as you look
19 at the Aslan figures, like you look at figure one,
20 you have a picture student model as an example. You
21 look at figure three -- or sorry. Figure -- figure
22 three, you have a teacher and then a student and then
23 another student model and then another -- dot, dot,
24 dot -- student model; so you have a teacher with --
25 multiple student models are connected.

1 Figure five has a training database that is
2 feeding multiple teacher models and then which all
3 feed the student model; so he has got different
4 architectural configurations.

5 BY MR. STEIN:

6 Q. Okay. You referred me to figure one of
7 Aslan Exhibit 1007.

8 In figure one, what is the reference numeral
9 for teacher ML model and what is the reference
10 numeral for student ML model?

11 A. So in reference one, the teacher model is
12 referenced 100 and the student model is referenced
13 102.

14 Q. Okay. Let's take a look at paragraph
15 twenty-two of the Aslan reference, Exhibit 1007.

16 Do -- those reference numerals you just
17 identified for me, 100 and 102, do they appear in
18 paragraph twenty-two?

19 A. Yes.

20 The first sentence of paragraph twenty-two
21 shows -- states the machine-learning model is 100 and
22 102, et cetera.

23 Q. And then it goes on in paragraph twenty-two
24 to say:

25 "Any of the machine-learning models

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1 discussed herein can be implemented as any
2 type of machine-learning model."

3 So are you familiar with what a type of
4 machine-learning model is in the pre 2017 time frame?

5 A. Yes.

6 Q. So what is a type of a machine-learning
7 model in the pre 2017 time frame?

8 MS. MAURI: Objection. Form.

9 THE WITNESS: Well, if you continue reading
10 that paragraph twenty-two, Aslan states with context:

11 "The machine-learning model is 100 and
12 102 and any of the machine-learning models
13 discussed herein can be implemented as any
14 type of machine-learning model."

15 And then he continues on to say:

16 "For example, suitable machine-learning
17 models for use with the techniques and
18 systems described herein include, without
19 limitation, freebased models, support vector
20 machines, neural methods, neural nets, random
21 forests, et cetera, et cetera.

22 BY MR. STEIN:

23 Q. And so these types of machine-learning
24 models that Aslan lists in paragraph twenty-two,
25 those were known elements to a POSITA in the pre 2017

1 time frame?

2 A. Yes.

3 They would be known to a POSITA.

4 Q. And if we are looking back at figure one, in
5 terms of examples of the types of the teacher ML
6 model 100, any of these listed in paragraph
7 twenty-two could be the teacher model in figure one
8 of Aslan?

9 A. Well, it depends, obviously, on the
10 application. It depends on what you are trying to
11 achieve. It depends on what you are trying to
12 accomplish; so, hypothetically speaking, you would
13 want -- you would select the appropriate
14 machine-learning algorithm for the application that
15 you are, you know, doing.

16 Q. So what is in Aslan -- let's go to paragraph
17 two, please, of Exhibit 1007.

18 In that last sentence of paragraph two of
19 Exhibit 1007, does Aslan provide an example of a task
20 that can be performed with the system that Aslan
21 describes?

22 MS. MAURI: Objection. Form.

23 THE WITNESS: So are you referring to
24 paragraph two, the sentence that starts, "For
25 example, a trained machine-learning model can

1 comprise a classifier"?

2 BY MR. STEIN:

3 Q. Yes, I am.

4 A. Yeah.

5 So Aslan states:

6 "For example, a trained machine-learning
7 model can comprise a classifier that is
8 tasked with classifying a known input as one
9 of multiple class labels, e.g., labeling the
10 image of a cat or a dog."

11 Q. Does Aslan describe the use of an objective
12 function in its joint training, as described in
13 Exhibit 1007?

14 A. Yes, it does.

15 Q. And does Aslan indicate whether one
16 objective function can be used to train multiple
17 machine-learning models?

18 A. Well, so if you look at paragraph
19 thirty-five of Aslan and equation two that follows
20 that paragraph, Aslan describes the objective
21 function for joint training of the first and second
22 models.

23 Q. So it says:

24 "The objective function for joint
25 training of the first and second models."

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1 So does that mean multiple objective
2 functions are used for each of these models or does
3 it mean one objective function is used for both of
4 the models?

5 A. What he pro- --

6 MS. MAURI: Objection. Form.

7 THE WITNESS: What he is proposing here is
8 one objective function to be used for the joint
9 training.

10 BY MR. STEIN:

11 Q. Let's look at paragraph seven. Paragraph
12 seven of Aslan, Exhibit 1007, also refers to an
13 objective function.

14 Do you see that in the first sentence?

15 A. Paragraph seven? Generating an objective
16 function, yes. I see that on the second line of
17 paragraph seven.

18 Q. And then it says:

19 "An objective function that is to be
20 used for jointly training a set of
21 machine-learning models."

22 So what is a set of machine-learning models
23 to a POSITA in the pre 2017 time frame?

24 A. More than one machine-learning model.

25 Q. I want to go back to paragraph twenty-two of

1 Aslan, Exhibit 1007. And I was asking you earlier
2 for examples of what these machine-learning models
3 100 and 102 might be.

4 A. Yes.

5 Q. Yeah.

6 So one of the listed examples is a kernel
7 method; so in the pre 2017 time frame, are you
8 familiar with what a kernel method would have been?

9 A. Yes.

10 Q. So could a kernel method have been one of
11 the machine-learning models 100?

12 A. Yes.

13 Q. What about a Kal- -- a Kalman -- am
14 I pronouncing that right? A Kalman filter.

15 Could that have been one of -- Kalman, could
16 that have been the machine-learning model 102?

17 A. Well, it depends, obviously, on the
18 applications a little bit. A Kalman filter is
19 usually used in temporal-type applications; so it is
20 not -- it is not generally used for classification
21 and imagery. It is -- it is a -- it is
22 a temporal-type filter.

23 Q. And it all -- we also have listed here as an
24 example a neural network.

25 Could a neural network have been the

1 machine-learning model 100, consistent with the Aslan
2 reference?

3 A. That is what it states.

4 Q. And what about the machine-learning model
5 102? Could that have been a random forest consistent
6 with the Aslan reference?

7 A. Again, that is what it states, but the --
8 but the devil is usually in the details and what the
9 application is about how it is done; so on the
10 surface that is what it states. But the devil is
11 usually in the details of how things are
12 accomplished.

13 Q. Sure.

14 So with respect to what it states in
15 paragraph twenty-two of the Aslan reference,
16 Exhibit 1007, a POSITA would have known the
17 machine-learning model 100 could have been a neural
18 network and machine-learning model 102 could have
19 been a random forest; correct?

20 MS. MAURI: Objection. Form.

21 THE WITNESS: Again, generally speaking,
22 yes. But it depends, obviously, on the specific
23 application that is being done, what is being done,
24 how it is being done, what is the purpose of the --
25 of the machine-learning model; so it is not just, you

1 know, randomly putting things together, but yes.
2 Generally speaking, you could have -- you know, Aslan
3 does state that.

4 BY MR. STEIN:

5 Q. Now, I'm wondering about your understanding
6 of the ordinary function of a neural network in the
7 pre 2017 time frame to a POSITA.

8 Would you be able to tell me what the
9 ordinary function of a neural network was in that
10 time frame?

11 MS. MAURI: Objection. Form.

12 THE WITNESS: You are asking a very big
13 question. There are chapters in books on that.

14 So what exactly do you want to know?

15 BY MR. STEIN:

16 Q. Do you understand what the word ordinary
17 means?

18 A. Yes.

19 MS. MAURI: Objection. Form.

20 BY MR. STEIN:

21 Q. Do you understand what the word function
22 means?

23 MS. MAURI: Objection. Form.

24 THE WITNESS: Yes.

25 ///

1 BY MR. STEIN:

2 Q. And do you understand what the words
3 ordinary and function mean when they are used
4 together?

5 MS. MAURI: Objection. Form.

6 THE WITNESS: Again, you would have to show
7 me what are you doing, you know? Show me the
8 equation. Show me what you are doing. Just stating
9 it doesn't really indicate to me what you are talking
10 about exactly; so the English meaning of the words is
11 not the same thing as the technical meaning of the
12 words in a given application.

13 BY MR. STEIN:

14 Q. Okay. So let's start with -- so what is the
15 technical meaning of the phrase ordinary function?

16 A. An ordinary function. Okay. A logarithm.
17 An LN of X and F of X equals two LN of X plus three
18 is an ordinary function -- a function.

19 Q. And what would be the ordinary function of
20 a neural network in the pre 2017 time frame to
21 a POSITA?

22 A. Well, it -- you know, generally speaking,
23 you would have a series of input nodes that are
24 connected -- fully connected through a series of
25 layers. Let me just say for illustration purposes we

1 have five layers; so I have an input layer. I have
2 four, let's say, hidden layers, and then we have an
3 output layer. And each layer has a series of nodes,
4 and those nodes are interconnected by connections
5 that have weights on them. And they have biases and
6 they have activation functions. I mean, that is just
7 a generic -- you know, one type of neural net.

8 Q. And specifically in the context of image
9 classification, what would be the ordinary function
10 of a neural network in the pre 2017 time frame?

11 A. Well, you would have to tell me what type of
12 image classification are you doing so we can be more
13 specific. I mean --

14 Q. I'm referring --

15 A. Go ahead.

16 Q. Okay. Paragraph two of Aslan can hopefully
17 help provide the context; so that -- that last
18 sentence of paragraph two talks about an image
19 classification text.

20 So would it be appropriate to use that as an
21 example to allow you to answer the question about
22 what an ordinary function of a neural network was in
23 the pre 2017 time frame?

24 MS. MAURI: Objection. Form.

25 THE WITNESS: So if you are talking about

1 the sentence that essentially says classifying
2 unknown objects, labeling the image of a cat -- as
3 a cat or a dog; so if you are talking about that,
4 that is -- obviously, it would be an image
5 classification task, and you probably would, you
6 know, be using, like, a convolution of neural net to
7 start and then to fully connect that together with
8 a fully connected architecture; so your overall
9 architecture would probably have the CNN at the start
10 connected with the fully connected architecture due
11 to the classification with two outputs. You want
12 output that is on when it is a cat, the other output
13 that is on when it is a dog.

14 BY MR. STEIN:

15 Q. Now, when we were talking about that you
16 might have different examples of what type of
17 machine-learning algorithm is used as the teacher ML
18 model 100 and the student ML model 102, we were
19 looking at paragraph twenty-two.

20 And one example I would like to ask about is
21 if the teacher ML model is a neural network and the
22 student ML model is a support vector machine, would
23 that system be able to perform the image
24 classification task -- task described in paragraph
25 two of Aslan?

1 MS. MAURI: Objection. Form.

2 THE WITNESS: Well, it depends on how you
3 are designing the neural networks. I mean, it
4 requires -- it is -- it is a -- you have a very
5 generic and very hypothetical question; so I would
6 have to see what is the architecture that you are
7 designing specifically, and I would be happy to
8 answer that.

9 But, generally speaking, as I mentioned to
10 you, if I have an image of a cat, I can have
11 a convolution of neural net layers to process the
12 image followed by fully connected layers to do the
13 classification and then give you an output that is
14 a cat or a dog.

15 BY MR. STEIN:

16 Q. In paragraph twenty-two, do you see in --
17 I don't know -- seven, eight lines up from the bottom
18 of paragraph twenty-two there is the word "and" and
19 the word "ensemble" is in quotations.

20 Do you see that in Aslan?

21 A. Yes. Yes.

22 Q. Okay. So what is an ensemble to a POSITA in
23 this pre 2017 time frame?

24 A. Well, Aslan describes it very well. An
25 ensemble can comprise a collection of models whose

1 outputs predictions are combined, such as by -- such
2 as by using weighted averaging or voting.

3 Q. And so could -- a random forest classifier,
4 could that be an ensemble in the pre 2017 time frame?

5 A. Generally speaking, yes. I mean, obviously
6 I would have to see what the architecture looked
7 like. But generally speaking, yes. You could have
8 that as part of an ensemble.

9 Q. And if we turn to paragraph three of Aslan,
10 Exhibit 1007, do you think -- do you see that
11 paragraph three, sort of, identifies an issue with
12 ensembles?

13 It says:

14 "For example, because ensembles
15 typically require a relatively large
16 footprint and powerful processing resources
17 to execute at runtime."

18 Do you see that in paragraph three?

19 A. Yes.

20 Q. So why -- why do ensembles typically require
21 a typically large storage footprint and powerful
22 resources to execute at runtime?

23 A. Well, if you have two different
24 machine-learning architectures, each of them have 100
25 layers and each layer has a hundred neurons, that is

1 a pretty big -- I mean, that is a large architecture
2 that you have to train all of that. And to train all
3 of that requires a lot of time and resources.

4 Q. I want to go back. You recall we were
5 talking about the phrase ordinary function, and
6 I want to recalibrate on -- to make sure we are
7 talking about the same meaning of the term function.

8 So you told me you understand what the word
9 function means; right?

10 A. Yes.

11 Q. So I -- I want to use the term less in its
12 mathematical sense and more in its more common
13 parlance of, sort of, the purpose of something.

14 Do you understand how function could have
15 that meaning rather than, sort of, its mathematical
16 definition?

17 MS. MAURI: Objection. Form.

18 THE WITNESS: Well, again, you would have to
19 show me the context of what you are talking about; so
20 you are just throwing a random word in the air, and
21 that is not helpful. You have to show me what is the
22 context that you are talking about. Then we can
23 discuss the details.

24 BY MR. STEIN:

25 Q. So what -- what is your understanding of the

1 different meanings that the word function might have?

2 A. Well, I gave you an example. You know,
3 a mathematical function, F of X. F of X equals 2X.
4 When X is one, F of X is two; so that -- that is
5 a function.

6 Q. Any other examples that come to mind for you
7 for other meanings that the word function may have?

8 A. I am attending a function at 6:00 o'clock at
9 the local -- at the local club here. That is
10 a function; so it depends on the context of what we
11 are talking about, I mean.

12 Q. What about --

13 A. Yeah.

14 Go ahead.

15 Q. What about the function of my car is to
16 drive me to work without falling apart.

17 Is that an understanding of function that
18 you are familiar with?

19 A. Yes.

20 MS. MAURI: Objection. Form.

21 THE WITNESS: It depends on the context; so
22 you put that in a context, and then that obviously
23 has a meaning. It depends on the context.

24 BY MR. STEIN:

25 Q. And what about if I said the function of

1 this neural network that I have trained is to
2 classify images as dogs or cats? Would that be an
3 understanding of function that you would recognize?

4 A. Again, yes.

5 Once you understand the context, it makes
6 sense.

7 Q. Okay. So in the context I have just
8 provided, what does the word function mean?

9 MS. MAURI: Objection. Form.

10 THE WITNESS: Which one of those contexts
11 are you talking about? You provided three of them.
12 BY MR. STEIN:

13 Q. The most recent one; so I'll read it again.

14 What if I said the function of this neural
15 network that I have trained is to classify images as
16 dogs or cats? So that is the context.

17 A. The purpose. The operation. The objective,
18 in a sense.

19 Q. So with -- with that understanding, what
20 would be the ordinary function of a random forest
21 classifier in the pre 2017 time frame?

22 MS. MAURI: Objection. Form.

23 THE WITNESS: The function of a random
24 forest classifier is to perform classification,
25 looking -- looking at various features that -- you

1 have the -- you know, the -- you know, the term and
2 the image, you perform a classification.

3 I mean, if you look at the -- for instance,
4 Chalom -- figure three of Chalom, you can see
5 a random forest classifier labeled 306 who takes in
6 as input the feature sets from the previous block,
7 303, and performs a classification and provides
8 a motion vector field.

9 BY MR. STEIN:

10 Q. So that is -- that is the ordinary function
11 of a random classifier in the pre 2017 time frame?

12 MS. MAURI: Objection. Form.

13 THE WITNESS: I think you said the random
14 classifier, but that is the function of a random
15 forest classifier. You have to be careful with your
16 words, sir.

17 BY MR. STEIN:

18 Q. You got me again.

19 A. I'm listening -- I'm listening very
20 carefully to every word you say.

21 Q. I appreciate that, yes.

22 So I did mean random forest classifier.

23 So what you provided to me with reference to
24 Chalom, is that the ordinary function of a random
25 forest classifier in the pre 2017 time frame?

1 A. Generally speaking, yes. That is the
2 common -- that is what would -- a random forest
3 classifier would be designed to do.

4 Q. And if I -- if I used that random forest
5 classifier that we are referring to from Chalom in
6 the context of its Aslan -- in the context of this
7 Aslan reference, would it be performing that ordinary
8 function?

9 MS. MAURI: Objection. Form.

10 THE WITNESS: Again, I would have to see
11 what exactly are you doing. Does it make sense to
12 have -- to have the other random forest or not? So
13 it depends on what you are doing, what the
14 application is, what the architecture is. You
15 can't -- I mean, you can't put a square peg in
16 a round hole. It depends on what is the architecture
17 you are doing. What are you planning to do? What
18 was the objective? Then you design the right
19 classifier.

20 Putting a random forest classifier on the
21 start of a neural network instead of a -- instead of
22 a CNN to do -- to deal with images would not -- would
23 not make a lot of sense.

24 BY MR. STEIN:

25 Q. Let 's turn to para- -- paragraph forty-five

1 of Aslan, Exhibit 1007.

2 Do you see in that paragraph it says --

3 A. I'm not there, sir. Just one second.

4 Paragraph forty-seven?

5 Q. Forty-five.

6 A. Forty-five. Sorry.

7 What is your question?

8 Q. So in paragraph forty-five -- it says early
9 on in the paragraph:

10 "One type of machine-learning model can
11 be transformed," in quotes, "into another
12 type of machine-learning model."

13 So do you have an understanding of what that
14 means to a POSITA in the pre 2017 time frame?

15 A. Yes.

16 That is very, very generic, but yes. Again,
17 it depends on the application you are doing, but yes.

18 Q. So what does it mean to transform one type
19 of machine-learning model into another type of
20 machine-learning model?

21 A. Just what it says. You transform it from
22 one type to another type. I have a perceptron, and
23 I'm going to transform it into a support vector
24 machine; so it depends on -- again, it depends on the
25 application. You are asking hypothetical questions

1 that really are very hypothetical and very generic,
2 very open. And the devil is usually in the details,
3 and you have to see the details in the technical
4 application to be able to provide good answers to
5 these questions.

6 Q. And at the end of paragraph forty-five it
7 says:

8 "The architecture can be optimized in at
9 least one of the models for deployment
10 purposes."

11 Do you understand what that phrase means to
12 a POSITA in the pre 2017 time frame?

13 A. Yes.

14 Q. And what does that phrase mean to a POSITA
15 in the pre 2017 time frame?

16 A. Just what it says. The architecture can be
17 optimized; so you are going to make it -- you are
18 going to optimize it. You are going to improve it in
19 at least one of the models for deployment purposes.
20 And you want to deploy your model on a mobile phone
21 where you have limited, perhaps, resources; so you
22 have -- you are going to optimize it.

23 Q. So I could optimize a random forest
24 classifier for deployment on a mobile phone in the
25 pre 2017 time frame?

1 MS. MAURI: Objection. Form.

2 THE WITNESS: Again, yeah.

3 Generically speaking, yes. It depends on
4 the application. It depends on how you designed it.
5 It depends on the features you selected. It depends
6 how you are going to do the optimization. There is
7 a lot of open questions here.

8 BY MR. STEIN:

9 Q. Turning to paragraph twenty of the Aslan
10 reference, Exhibit 1007.

11 A. Paragraph twenty, you said, sir; right?

12 Q. Yeah. Two, zero.

13 A. I am there.

14 Q. Okay. So you see the second -- the third
15 sentence:

16 "Although many examples provided herein
17 are discussed in terms of using joint
18 training for model compression."

19 So....

20 A. I don't see it yet. Give me one second.

21 Yeah. Third. Okay. Although -- go ahead.

22 Q. "Although many examples provided herein are
23 discussed in terms of using joint training
24 for model compression."

25 A. Yes.

1 Q. Do you have an understanding of what model
2 compression would mean to a POSITA in the pre 2017
3 time frame?

4 A. Yes.

5 Q. And is Aslan suggesting a technique that can
6 be used for model compression in this reference?

7 MS. MAURI: Objection. Form.

8 THE WITNESS: In gen- -- in very general
9 terms. It doesn't provide any details. It is just
10 saying yes. You can do model compression in that
11 sentence. That sentence essentially says, yeah. You
12 can do model compression. It is -- it is the
13 details, sir, that really make all the difference.
14 You know, sentences like this are a high overview.
15 Anybody can make these disclosures. It is the
16 details that make all the difference.

17 BY MR. STEIN:

18 Q. Sure.

19 But in the pre 2017 time frame then, Aslan
20 is teaching to a POSITA one technique for model
21 compression.

22 Is that accurate?

23 MS. MAURI: Objection. Form.

24 THE WITNESS: As Aslan is disclosing. It is
25 not teaching because there is no equations here.

1 There is no details of how you would do it. It is
2 just saying you can do this; so it is disclosing that
3 you can do this. It doesn't provide any details of
4 how you can do it.

5 BY MR. STEIN:

6 Q. Okay. So in the pre 2017 time frame is
7 Aslan disclosing to a POSITA a technique for model
8 compression?

9 MS. MAURI: Objection. Form.

10 THE WITNESS: Well, Aslan is stating --
11 right? -- that the -- so let's read Aslan exactly so
12 it is -- it is clear for the record.

13 Aslan states:

14 "Although many examples provided herein
15 are discussed in terms of using joint
16 training for model compression, i.e.,
17 training relatively compact model in terms of
18 storage footprint in parallel with a large,
19 more complex model to approximate the
20 function learned by the complex model, the
21 techniques and systems described herein are
22 not limited to model compression."

23 So he is basically stating -- making
24 a statement that although, you know, their examples
25 are used here for model compression, they are not

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1 limited to that. It doesn't teach how to do model
2 compression, just stating that.

3 BY MR. STEIN:

4 Q. Okay. So in the pre 2017 time frame, is
5 Aslan stating to a POSITA that he is disclosing
6 a technique for model compression?

7 MS. MAURI: Objection. Form.

8 THE WITNESS: He is not disclosing
9 a technique for model compression. He is just
10 disclosing that model compression is possible. There
11 is no technique here. If I were to give this to one
12 of my students and say, go implement it, just by
13 reading that sentence they wouldn't -- they would --
14 they would look at me and say, what do you want --
15 what do you want me to implement? There are no
16 equations here. It is just a statement.

17 BY MR. STEIN:

18 Q. In that same paragraph, paragraph twenty, in
19 the clause we have been discussing he says:

20 "i.e.," comma, "training a relatively
21 compact model in terms of storage footprint."

22 So do you understand what it means to train
23 a relatively compact model in terms of storage
24 footprint to a POSITA in the pre 2017 time frame?

25 A. Yes.

1 Q. And let's look at paragraph forty-four as
2 well.

3 So paragraph forty-four --

4 A. One second, sir. I am getting there.

5 Q. Okay.

6 A. You are quicker on paper, I think.

7 Yeah. Please go ahead.

8 Q. So paragraph forty-four of Aslan,
9 Exhibit 1007, reads:

10 "The joint training techniques described
11 herein can be used for various applications.
12 One example application is model
13 compression."

14 Do you see that?

15 A. Yes.

16 Q. So is Aslan telling a POSITA in the pre 2017
17 time frame that its joint training techniques can be
18 used for model compression?

19 MS. MAURI: Objection. Form.

20 THE WITNESS: Yes.

21 He is making that statement, as well as
22 stating one example application is model compression.

23 BY MR. STEIN:

24 Q. Okay. Let's turn to your declaration,
25 Exhibit 2008, which you indicated to me that you have

1 in front of you.

2 A. I do, and -- yes.

3 Q. Actually -- okay. Okay. So on page
4 forty-nine, Paragraph 108 of your declaration,
5 Exhibit 2008 -- and I'll wait until you get there.

6 A. Paragraph 108.

7 Okay. I am there.

8 Q. Paragraph 108, in the second sentence you
9 say:

10 "If Chalom's machine-learning algorithm
11 is inaccurate, a POSITA would look to the
12 training data in resolution of the
13 classifier."

14 Do you see that sentence?

15 A. Yes. Yes, I do.

16 Q. Is there anything else that a POSITA might
17 look to, besides the training data and resolution of
18 the classifier?

19 MS. MAURI: Objection. Form.

20 THE WITNESS: So you see if you continue
21 reading that whole section and when you get to
22 Paragraph 111 -- so -- a POSITA looking at Chalom's
23 algorithm and wants to improve the accuracy of
24 Chalom's system; so if you look at my Paragraph 111.

25 So it states:

1 "A POSITA looking to improve the
2 accuracy of Chalom's system would consider
3 other simpler and well-known choices."

4 And the listing of the choices isn't --
5 doesn't mean that is the order of them. It is just
6 they are saying I am listing them there; so the
7 first -- one of the first things you would look at is
8 the size of your training dataset; so if I only have
9 fifty pages -- fifty faces in my dataset and I -- you
10 know, it is probably too small; so you want a large
11 enough dataset.

12 The next step you would look at is the
13 diversity of your dataset. Does it have all the type
14 of faces and colors of skin that I might -- might
15 want to have in my data -- in my training dataset?

16 So those are two primary colors. You want
17 to make sure your dataset represents the entire space
18 that you are trying to classify or -- for your
19 application.

20 You would look at the random forest
21 classifier, you know. Do you -- do you have
22 enough -- the proper features, finer features? Do
23 you want a finer resolution on some of the features?
24 Maybe changing the structure of your objective
25 function or the structure of the machine-learning

1 algorithm that you have. I have got ten layers.
2 Maybe I should add two more. Maybe I should put more
3 nodes in a given layer; so those are all some of the
4 things you would start by doing.

5 And then you would obviously look at
6 ablation studies. You would look at K-fold type
7 studies. You would look at constructing in the
8 training datasets, validation datasets, test
9 datasets; so there is a lot of things that you would
10 do as a POSITA to improve the accuracy of Chalom's
11 algorithm.

12 But having a second algorithm -- a second
13 machine-learning on the end of that would not be what
14 a POSITA would be doing.

15 BY MR. STEIN:

16 Q. That's -- it is going to take us a lot
17 longer if you don't just answer the question; so you
18 can keep -- if you want those long answers, it is
19 just going to take a little longer here because we
20 are pretty close to wrapping up.

21 MS. MAURI: Objection. Argumentative.

22 MR. STEIN: That -- and I will object to
23 that last answer as being entirely wholly
24 nonresponsive.

25 ///

1 BY MR. STEIN:

2 Q. So let's turn to Paragraph 110 on page fifty
3 of your declaration.

4 A. Yes, sir.

5 Q. So here do you see the last sentence you
6 say, "The natural consequences of these issues"?

7 So yes or no, do you see that clause, "The
8 natural consequences to address these issues"?

9 A. The sentence says:

10 "Therefore, the natural consequence to
11 address these issues."

12 There is no S on the consequence.

13 Okay?

14 I see it.

15 Q. And then in Paragraph 111, right below that
16 on page fifty, do you see where you say, "A POSITA
17 looking to improve the accuracy of Chalom's system
18 would consider other simpler and well-known technical
19 choices"? Do you see that?

20 A. Yes.

21 That is the one I was talking to you about
22 in the previous answer.

23 Q. Yeah. Understood.

24 So those options that you list, are those
25 the best options to try for a POSITA in this time

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1 frame?

2 A. Well, those are some of the options. There
3 are obviously -- like I just said to you, there are
4 other options you would also try, like, you know,
5 taking -- assuming you have the training data --
6 a large database, you would randomly pick, let's say,
7 80 percent of your database as your training dataset.
8 You would pick 10 percent of that database randomly
9 as your validation dataset, and you would pick
10 10 percent as your test dataset. You would use the
11 training dataset to do the training and use the
12 validation dataset to -- to -- to optimize the
13 hyperparameters of the algorithm. And then you would
14 use the test dataset to determine the accuracy of the
15 algorithm and see how well it would -- it generalizes
16 to a dataset that it hasn't seen.

17 Now, there is what we call ablation studies
18 that you would have -- you would have to do to
19 determine which features are more effective,
20 et cetera. And there is also great, what we call,
21 K-fold cross-validations where you would use
22 a different look into the database. You would pick
23 different random samples.

24 There are a lot of other things you would do
25 to essentially improve the accuracy of your algorithm

1 of, you know, whatever the algorithm -- like -- like,
2 the Chalom algorithm, for example -- the application
3 of what Chalom is doing. What you would not do is
4 add a second machine-learning algorithm. That --
5 that -- that would not be what a POSITA would do.

6 Q. Okay. Again, these -- you can just give me
7 a simple yes or no and then we can -- because my
8 question was just the options that you list, are
9 those the best options for a POSITA in this time
10 frame to try?

11 And then you went on for about four minutes
12 with a nonresponsive answer; so if you want to try
13 and end this early, I would try to just answer the
14 question.

15 MS. MAURI: Objection. Argumentative.

16 BY MR. STEIN:

17 Q. The next question here, if we go to
18 Paragraph 112 of your declaration on page fifty-one.

19 A. Yes.

20 Q. Do you see on page fifty-one, in the middle
21 lower part of the paragraph in a sentence beginning
22 with the word hence, h-e-n-c-e?

23 A. I'm looking for it. Just give me one
24 moment.

25 Yes. I see -- I see the word hence roughly

1 seven or eight lines down in the paragraph.

2 Q. And when -- in your discussion here of the
3 other options that a -- in your opinion, a POSITA
4 might try to improve accuracy in Chalom's
5 classifiers, it is your understanding that the POSITA
6 needs to find the best technical solution.

7 Is that your understanding?

8 MS. MAURI: Objection. Form.

9 THE WITNESS: Well, the POSITA is looking to
10 improve the accuracy of the classifier overall,
11 however you measure it; so to improve the accuracy of
12 your classifier means you want more and more accurate
13 results.

14 So instead of classifying, you know,
15 a thousand faces and having ten errors, I want to
16 classify a thousand faces with two errors; so I'm
17 trying to improve the accuracy of my classifier, you
18 know.

19 A POSITA -- these are some of the things
20 a POSITA would do looking -- if I am looking at
21 Chalom's algorithm -- and what I described to you
22 earlier is essentially what we call peeling the
23 onion. You look at every piece of the algorithm and
24 still go through every piece starting at the
25 beginning with the training dataset and working your

1 way piece by piece and looking at the features,
2 looking at ablation studies, which features are more
3 important. And you would work your way throughout
4 the whole algorithm, including the random forest
5 classifier, to essentially improve the accuracy of
6 the overall algorithm. That is typically what
7 a POSITA would do.

8 BY MR. STEIN:

9 Q. Okay. In Paragraph 115 on page fifty-three
10 of your declaration --

11 A. Yes.

12 Q. -- in the first sentence you state:

13 "The properly designed RFC, as taught by
14 Chalom, would serve POSITA's purposes without
15 the need for adding another machine-learning
16 algorithm."

17 So when would you have a need for another
18 machine-learning algorithm?

19 A. Well, certainly not in Chalom's application.

20 Q. You've got to try and answer the question or
21 we are just never going to get out of here. I mean,
22 just -- just answer the question.

23 I said the first sentence you reference --

24 A. Yes.

25 Q. -- and then I asked you when would a POSITA

1 need another machine-learning algorithm?

2 MS. MAURI: Objection. Argumentative.
3 Form.

4 THE WITNESS: I get it. It depends on the
5 application you are doing. If I am doing -- I want
6 to take images and do segmentation on them and I want
7 to take images and -- and classify skin colors,
8 I probably would use two different algorithms. But
9 this is not the case in Chalom.

10 BY MR. STEIN:

11 Q. Okay. I am doing -- I am doing what Chalom
12 is doing; right?

13 So Chalom's title, Exhibit 1005, eye contact
14 correct in realtime using machine-learning; so I am
15 doing what Chalom is doing.

16 A. Correct.

17 Q. When might I want to use a second
18 machine-learning algorithm to accomplish that?

19 A. You would --

20 MS. MAURI: Objection. Form.

21 THE WITNESS: You would not. A POSITA
22 looking -- a POSITA looking -- reading through Chalom
23 and looking at Chalom's techniques and what Chalom is
24 describing would do what I describe in all those
25 paragraphs because this is one application. You are

1 taking an input image and you are correcting its
2 gaze. There would be no need to do -- to add
3 a second machine-learning algorithm.

4 BY MR. STEIN:

5 Q. So what you describe as the best option for
6 improving Chalom if it has accuracy or efficiency
7 issues.

8 Is that your testimony?

9 MS. MAURI: Objection. Form.

10 THE WITNESS: Well, what I have described to
11 you here are options to improve accuracy or
12 efficiency. You would have to, obviously, test those
13 different options for the algorithm once you have it
14 implemented to determine which ones of them are
15 more -- more effective or not. You know, how much is
16 this option effective? How much is that option
17 effective?

18 I would have to look at Chalom's training
19 database to see what it looks like. Does it have all
20 the possible angles of gaze that you would need?
21 Does it address -- does it have all the proper faces
22 and colors of faces? Does it have white skin? dark
23 skin? You know, you have to look at all of the
24 details. The devil is in the details.

25 ///

1 BY MR. STEIN:

2 Q. You mentioned needing to do testing.

3 Did you perform any testing to inform the
4 opinions that you offer in Exhibit 2008?

5 MS. MAURI: Objection. Form.

6 THE WITNESS: No.

7 I did not perform any testing, but I have,
8 obviously, been working in this area for thirty-plus
9 years; so I am very familiar with machine-learning
10 algorithms and pattern recognition algorithms.

11 I have designed, developed, coded many of them.

12 BY MR. STEIN:

13 Q. Now in Paragraph 119 on paragraph fifty-five
14 of your declaration, Exhibit 2008, you mention in the
15 second sentence, beginning with "In other words."
16 Just let me know when you are there.

17 A. Yes.

18 I am there.

19 Q. Okay. You mention:

20 "These motion vectors are intended to
21 provide the appropriate amount of
22 displacement in the X and Y directions for
23 the pixel located at I," comma, "J."

24 Do you see that?

25 A. Yes.

1 As an example, obviously, yes.

2 Q. Okay. And then you continue:

3 "In addition, motion vectors are
4 typically expressed by decimal numbers."

5 Are there other ways to express motion
6 vectors besides decimal numbers?

7 MS. MAURI: Objection. Form.

8 THE WITNESS: Well, if you are not -- if you
9 are not worried as much about the accuracy, you might
10 express some with integers. You might say, okay.

11 I am not going to have a 12.5. I am just going to
12 have a twelve or thirteen because that will stick to
13 the pixel grid, and that will do any interpolation,
14 in a sense, or not have subpixel accuracy.

15 BY MR. STEIN:

16 Q. So you could -- you could express motion
17 vectors as integers and not use interpolation.

18 Is that what you just told me?

19 A. You could do that --

20 MS. MAURI: Objection. Form.

21 THE WITNESS: Obviously, you could do that,
22 but that would obviously not be as accurate. And
23 because you are -- you know, you start to accumulate
24 error when you do that.

25 MR. STEIN: Okay. Why don't we take a --

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1 just give me five minutes just to look through notes,
2 and I think that is the end of my questioning.

3 THE WITNESS: Oh, very good.

4 MS. MAURI: So be back at 1:30 Pacific Time?

5 MR. STEIN: Yes.

6 THE WITNESS: I'll be on my desk at 4:30
7 Eastern.

8 (Short recess taken from
9 1:25 p.m. to 1:32 p.m.)

10 MR. STEIN: All right. So thank you,
11 Dr. Saber, for your testimony.

12 I have no further questions.

13 THE WITNESS: You are very welcome. And it
14 has been my absolute pleasure to meet you in person
15 on Zoom. My apologies for having the power go out on
16 Wednesday.

17 MR. STEIN: No problem. Nothing you could
18 do about it. And thank you.

19 MS. MAURI: I have no questions.

20 MR. STEIN: Okay.

21 THE REPORTER: Ms. Mauri, would you like
22 a copy?

23 MS. MAURI: Yes, please.

24 THE REPORTER: Would either of you like
25 a rough?

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MS. MAURI: No.

MR. STEIN: We would like -- we would like
the rough, but we also need the -- actually, I would
rather just -- we'll -- tonight. No rough, just the
final first thing Saturday morning.

MS. MAURI: I'll do the same.

(1:32 p.m.)

--00000--

STATE OF CALIFORNIA)
) ss.

COUNTY OF KERN)

I, ELI SABER, Ph.D., do hereby certify:
That I have read the foregoing
deposition;

That I have made such changes in form and/or substance to the within deposition, as might be necessary to render the same true and correct;

That having made such changes thereon, I
hereby subscribe my name to the deposition.

I declare, under penalty of perjury, that the foregoing is true and correct.

Executed this _____ day of _____,
2024, at _____, California.

ELI SABER, Ph.D.

1 STATE OF CALIFORNIA)
) ss.
2 COUNTY OF KERN)

5 I, B. Suzanne Hull, a Certified Shorthand
6 Reporter in the State of California, holding
7 Certificate Number 13495, do hereby certify that
8 ELI SABER, Ph.D., the witness named in the foregoing
9 deposition, was by me duly sworn; that said
10 deposition, was taken Friday, June 7, 2024, at the
11 time and place set forth on the first page hereof.

12 That upon the taking of the deposition, the
13 words of the witness were written down by me in
14 stenotypy and thereafter transcribed by computer
15 under my supervision; that the foregoing is a true
16 and correct transcript of the testimony given by the
17 witness.

18 Pursuant to Federal Rule 30(e), transcript
19 review was requested.

20 I further certify that I am neither counsel
21 for nor in any way related to any party to said
22 action, nor in any way interested in the result or
23 outcome thereof.

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1 Dated this 7th day of June, 2024, at
2 Bakersfield, California.

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7 B. Suzanne Hull, CSR No. 13495
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