<u>Video by Dr. Karlin - AI and plastic eye surgery</u>

All right, everybody, I would like to introduce to you Professor Dr. Justin Carlin, who is a professor of ophthalmology it in the Julesz time I clinic. And he specializes in plastic and reconstructive surgery, board certified American Board of ophthalmology and has completed the prestigious fellowship at UCLA and Danthine Center for eye ophthalmology. And what I wanted to you can see all his training here. But what I wanted to mention is that Dr. Carlin as a client has really, really impressed me 2D out the time that I have worked with him for the last couple of years. He has worked with multiple teams from your groups from 141 ASL. And his knowledge is not to be elaborated because the top institutions he graduated from all speaks for himself. But what he has amazed and impressed me about is his patients and his carrying attitude in explaining medical concepts to the students and using technology that they can follow. And you know, I mean, just so kind so wonderful, so patient and all that. And you're going to laugh at this one. But as a statistician, I always like data. So this morning when I was looking at his profile on the internet trying to find information, I read his patient ratings. So here you go. Dr. Carlin is a very, uh, oh, I had a very innovative, very painful eye infection I got from a water park. Dude was super chill. We have actually spent a lot of time at a water park as a kid and figured out high caught it. So this is exactly what I'm talking about here, relates to people he called him was extremely caring, professional, personable and attentive, grabbed off and procedures in plain English. This is what I was saying. Very respectful of senior doctor, a medical intern, spoke up with observations and suggestion, exceptional bedside manner and sense of humor under stressful situations. I had a terrible I'm very painful eye injury and I was a very difficult fish and Dr. Carlin had the patient than bedside manner of a saint. I will be referring to him and uses services indefinitely. Is definitely above and beyond most doctors. It was very helpful for me. Very caring and kind goes the extra mile to help you. He explained thoroughly, never rushed. So the ratings speak for how it has been to the 141 students as a client. I keep on saying consultant as a client. And honestly, I cannot think I cannot thank you. Thank him enough for taking time out of his busy schedule patient care to come out and talk to you. So now you understand that all my observations are valid because they correlate directly to what the patients are saying. So that's my introduction of Dr. Carlin. And thank you very much. And you now can have the board. And may learn to kind to me you're really too kind. I will. It still I validated miles. That's how we might my kids say they say mom can never you cannot get accompaniment from my mother unless you work hard on it. So you deserve I'm just really honored to be here and to have such mentors and colleagues like you and I hope that this talk will be valuable and maybe we'll pick some interests in for some of you in the project that we're working on? I work in the space That's the combination of both reconstructive surgery of the eye and surrounding. And I also work in sort of some, in some capacity in aesthetic surgery and cosmetic surgery. So patients who are looking to rejuvenate or improve their appearance in some way. So I'm I while I see many patients with severe deformities and medical problems and traumas and so forth. I also see patients who are looking for some measure of either rejuvenation, that is to look younger or some measure of enhancement. So this project kind of gets more at how we, as practitioners see and evaluate age when we look at the face. And there have been many papers written on this about what are the structural and the, the features of the face that sort of determine what the aging face looks like versus the young face. And so I wanted to get at that a little bit more instead of sort of talking from the standpoint of art or history. And I wanted to sort of turn the tools of computer science if we can, to try to get a more objective measure of what, what age is and whether or not surgery on the eyes and eyelids can affect the perception of age. Okay. So I want to tell you a little bit about a study that we've been working on. I'll give you our reasons for the study. I'll talk about some of the central questions.

We'll talk about our hypotheses that we've examined so far, some methods and addressing that and the results we've accumulated and then we'll discuss together and hopefully I can open and first inspire, then open the floor to some questions if anybody's interested. So here patients who are the typical look of some patients that come into our clinic. And they, they tend to have either droopy upper eyelids or puffy lower eyelids or some combination of both. So you take a look and after surgery there's certainly some kind of improvement there, the overall look, but it's often hard to quantify what it is. The patient's right look younger, they might look more refreshed. So what is it exactly here that makes them look younger? And then what can we put a number on? That is the real question. So can we develop and validate a tool to quantify perceived age? And what would we, how would we determine the reliability? And I guess, along with accuracy, how return the validity of such a measurement tool. And once we find that tool, how can we optimize the conditions to make sure that the measurements that the two are giving us our R. You know, something we can use in, let's say, clinical practice or something that's sort of a useful and measure and something that will give us more information than just what our IC. So one tool that I thought would be great to incorporate here is artificial intelligence and deep learning. So these tools, I don't wanna get too much into the details. I'm sure some of the students in this class have more than a hobbyist interests and have probably have more knowledge than I do on the specifics of this computer science technique. But the basic idea is, you can train a computer to look for certain features that interests you by feeding it many different photographs or photographs or words or paragraphs, along with a set of labels with those photographs. And and then you can show photographs that it's never seen before. And it can make a prediction about whether or not that represents a certain label that you're looking for there in the medical world, the examples are, of course, chest x-rays and breast cancer. And one of the more famous examples has been skin lesions. So there has been tremendous amount of tension placed upon tools where you can snap a photo of the skin and then it'll tell you whether it's cancer or not. Okay. Now, again, for those who have more computer science background and I do I don't I don't claim to be computer scientists in any capacity, but, you know, I have sort of just a dilettante understanding of how neural networks work. And enough that these days the technology has advanced so much. And even somebody like me who doesn't have a whole lot of technical knowledge, can still train a model and deploy it. So here's the classic example that I'm showing in this photograph is taking written text, let's say of a number of the number 0, digits 0 through nine. And being able to train a computer to recognize what number that is. Okay? So the hypothesis here is that we can make an AI model it's sufficiently reliable to detect patient age. And then we can use this tool to show that maybe we can either deceive the, the AI model is showing that patients actually look younger after eyelid surgery. And then the next corollary is how much younger they look after eyelid surgery. And that might be dependent on a variety of factors. One of which, for example, which is a sort of grades that part out. But is there a certain type of surgery that makes patients look younger than another one is upper eyelid surgery better than lower? Is having upper and lower done better than having each one alone? These are my C better, meaning each one of those surgeries make patients look younger than some other one. Okay. So what I did is I started again from sort of the hobbyist side and I trained and validated in AI model using 10 thousand front-facing photographs from our database. These are patients who are between the ages of 278 years old. And then from that just training of the model using the validation set, which is a held-out set of about 10 percent or so of those photographs. We, you know, we can check the accuracy. So we compare the predicted and the actual age, and then we can check the reliability. So on a separate test set, okay, of, of patients I have there are certain patients that are in this test set and have multiple photos taken on different dates. And the question is whether or not we can get a reliable measure by giving the AI these pictures of the same patients. And I'll show you some examples of that. And to show whether that would give a reliable and predictable measure even though it's the same patient but on different dates, maybe slightly different photographic conditions. So here's just the results of the training and validation. You can see. Here on the left is small photograph of just a matrix of many, many different photos that were fed in there. And then of course, the on the right you see a confusion matrix and that shows it's generally follow sort of a linear trend on one axis, on the y-axis, of course is the predicted a, or the actual age. And on the X-axis is the predicted age. And just looking at the data from the 30000 foot view, you can see there's sort of a general correlation between the two. And this is sort of the internal control to show that the model is working. Okay. Now, then what we did is we took a separate dataset, sort of none of the patients in a separate dataset. We're in the training or validation sets and we decided to look at these. Now these patients are special and obeyed hat. We have pictures of them before they've had eyelid surgery and after so it's a 103 patients and a total of about 300 and two photographs and you might be thinking, okay, so you've got a 103 patients in every single one of them has a before and after surgery. So that's a total of 206 photographs. The remaining photographs are sort of additional photographs that were taken on different dates of these patients, either before or after surgery. Okay. So there'll be more on that in just a moment. But what you can see here is if you take those photographs, those 300 and two photographs and you put them you put them all into the weather there before surgery or after surgery, obviously being post before surgery being pre. You put them all through that model and you say, well, what is the model that I trained on the 10 thousand photos? If I take these new photos and put them in, what does it actually, what does it show? What does it predict at? It turns out that in general, overall the model tends to be the mean. The average tends to be pretty close to what? The pretty close to what in terms of accuracy, fairly close to the actual way. So definitely predicted and actual is about an average of about a year. And it tends to it. You see the negative number here next to all in that table. And that shows that the model tends to predict slightly younger on average for all patients. Now there are some that predicts older, some little predict younger, but in general tends to predict slightly younger. And that's more true for the patients after surgery than it is for those before. So this is just an exploratory data analysis of our data set. Okay. Now here's an example of a patient who both of these photographs are of the patient before surgery. Okay. But what you'll notice is that they're taken on two different dates under two different lighting conditions. And the question is, in order to answer the question of whether the model that I've trained overall is reliable. We can feed it these two photographs, which of course are the same patient. And we can ask the question of whether or not we get a correlation and to what degree are they correlated between the age that's predicted for each of these two photographs that make sense. So far am I doing okay? Does that make sense? If two photographs of the same patient before surgery, and we want to know if the model predicts the same age. So far so good. So here's sort of our first check of the reliability here. And I just want to focus your attention on the left sided table on the top left corner. So what you see here is if you compare the predicted and the actual ages of patients. These are patients all before surgery. Nobody has had surgery in the intervening time between the first second photograph. That's so pre-surgery one and pre-surgery to photograph, there is a correlation coefficient of about 0.17. Okay. And that's for 57 patients. Each of them has two photographs of 57 times two of course is 114, that's the sample size. And so what you see here that there's a correlation coefficient That's probably would be considered to be pretty good. Am I right, professor? Is that yes, absolutely right. But I think that yeah. The sample size, that's a 114. I think it's only 57 APA 114 that have that correlation. Well, no, it's it's 57 patients but because they have two photographs. So it's all okay. When you batch then you do the correlation, you still have 57 pairs of observations. That's exactly right. Yeah, So now the last edges and still 57. Yeah. The last group had astutely notice the group that worked on this for this project with us had astutely noticed that part millionaires move this slightly move the ones. They had astutely noticed that photographs that were taken closer to each other in time. So if a patient had a photograph taken in January and then another one in March tended to be closer in age prediction and those that were taken further apart. And so they looked at of those photographs, they found 41 patients who had photographs that were taken within six months of each other. That's the less than 0.5 absolute value year column there. And you see that that was about 41 patients, so 82 photos total and then the correlation coefficient, of course one up to 0.87. So this model tends to be more reliable for pre-surgery patients when the photographs are taken. A short period of time of each other, which sort of makes sense because nothing would have changed your happened in the intervening time period. So it's more so for photos taken in a half a year period than it is for photos taken one-year period than in this for photographs that are all the photographs, all commerce. That's kind of the one interesting observation there. Now, I won't bore you, but we did a similar a similar analysis with the post surgery photos and it turns out we found the same thing that it tends to be about. A little bit better correlated when the photographs are taken within a short period of time. But it was a much smaller number of observations, so I won't show here. So then the next part of our, our, our sort of statistical journey here is looking at what Lee, how we can deal with some of these outliers. Because some patients, for example, we would have had one photograph will predict that there are 35 and then photograph that was taken six months later. They haven't even had surgery intervening period well predicted their 57 years old. So I mean, something is not quite right with those particular outlier. So we decide either we can say, well, there's so far outside of the range prediction of what you would expect and compared to most of the other observations that maybe we can make, take statistical criteria to show that, that maybe they're skewing our observation so much and our correlation covariance so much that they can be thrown out based on a statistical cutoff. Or we could look at clinical criteria and what the clinical criteria mean. And this is a picture of me, as you can probably tell, is for all of these photos that we have, can we find some measurements? Let's say of the eyelid or the Brower are some lower eyelid. I won't bore you with the details of the measurements. So let's say there's some measurements here that are anthropometric measurements, eyelid and brown measurements. And if you have a patient that's taken in January, a photo of a patient is taken in January and another one It's taking, let's say in April, you'd expect if nothing has changed in that intervening time, that all those measurements should be about the same, right? Nothing shape. But let's say you say, you'll notice, okay, we do all the measurements and there are some patients that had a big change in, let's say those, those measurements, maybe we can use clinical criteria to see if those are removing. Those would also improve our accuracy is because reliability would ostensibly go down. If you have one patient that has some degree of asymmetry in one photograph, but in the next photograph that, that those measurements are all, all normal, right, so statistical criteria, we kind of use the cutoff here and you'll have to forgive me for not understanding all of the details. But here we found which, which outliers in this, in this plot here where we're skewing, we're reducing the correlation coefficient the most. And after removing those, you can see the correlation coefficient changes from 0.779. It goes up by about 0.06 to 0.839. And that's with only removal of two values. So you can see that improve the correlation coefficient considerably with only removing two values, okay? Now with statistical criteria, okay? If we were to look at two photos that were taken, one in January, one in April. And you were to say, okay, if we remove all the ones that have a difference of X amount, either the eyebrow is much higher in April than it is in January, or the eye lid on one picture is lower and we have cutoffs, for example, of like the, the upper eyelids in both pictures needs to be within a certain range of each other. They can't have changed too much or the lower eyelids can't have changed too much from one. Does that improve if we if we throw out all the pictures, all the patients that had too much of a change. Does that change our our correlation? It turns out it doesn't. So we use our clinical criteria to find photographs that were the most consistent in eyelid measurement. But it turns out that, that actually slightly worse and the correlation coefficient. And if I direct your attention all the way to the right of the screen where it says, all you can see are starting correlation coefficient, which is 0.779. But once we remove its patients or remove outliers from the clinical criteria, the correlation coefficient actually went down to 0.6258, etc. So the conclusion from this is that the clinical criteria are not necessarily helpful in driving the reliability of this model. Okay. So in summary, overall, just an exploratory look at the model that we have so far is that it tends to predict patients being slightly younger than their actual age on average. Now, notably, post-surgery patients are predicted even, even younger than they are pre-surgery. Which is, gives us sort of an enticing result to think to ourselves, Well, wait a second, maybe. After surgery we tend to trick the model even more of a greater proportion of patients would be considered to be younger. But we haven't looked at the statistical significance of that quite yet. So that's, that's sort of an enticing results that let me go back to that slide just to remind you, you can see here that when you look at post and pre, the preoperative patients are on predicted on average about a year younger. And the post alveolar if patients are printed on average about two years younger than their actual age. So this is sort of enticing, but we haven't gone further than this to look at the the statistical significance of that. One other thing that we learned after we had we had the clinical criteria that we looked at for whether to remove outliers and the statistical criteria. And it turned out that using statistical criteria was better to improve the reliability of the model than using using a clinical criteria. So, so we can conclude from this part of the study that the clinical criteria, really not, at least in the thresholds and the, the, the measurements that we took were not useful in improving the reliability. So some future directions here. So we sort of establish the reliability of this model with this particular data set. An important question going forward for an enterprising student might be whether or not our model that I trained, the one that has a hobbyists that I train, is it compares to any of the commercially available models for measuring age. So there are models out there through Microsoft or I'm sure you can find them on Google and so forth. To measure. Age from a photograph doesn't seem that, that tough, right? So future states could compare the model and I trained with the commercially available models. Or likewise, we could train even more robust models using more photographs, for example, and compare the reliability of various models on our dataset to find the most reliable. And then furthermore, future studies could look at whether or not the model is more reliable for patients of a given gender or a given age or a given skin type are given ethnicity. We can also look at whether or not the photograph quality plays a role. Here is a more reliable for photos that are a certain exposure or taken under certain camera condition. So these are all sort of open questions. And I don't want to discount how important it is to look at these sources of bias in the model because this is a sort of a hot topic in AI right now, it's very important to recognize that an AI model that's trained, let's say on faces that are all East Asian configuration of the face might be much less reliable on somebody who's, let's say from a Middle Eastern type of facial background. So there are a lot of sort of sticky questions in here about, about bias with an AI models. And certainly there's, there, there's, there are many questions to explore in that realm as well, so I don't want to discount that. Now also, one of the, one important thing that the students had pointed out is that we, we should. And then sort of the enticing result was that the postoperative photos sort of looked at the changes between the excuse me, the exploratory data analysis looked at the difference between predicted and actual age, right? And so it would be nice in a future iteration is study to look at whether or not this model shows a stigma, is statistically significant. Change in the direction of prediction, like predicting younger for postoperative compared to pre-operative. Okay, I might've mentioned that already. And then like, like I said before, future models, we'll use larger number of photos and maybe we'll include photos from different datasets now and remember all the photos that I used for training this model more front-facing. Maybe we'll be able to improve the accuracy and the reliability of the model. If we train the model using photos from different angles, facial angles, and also from different cameras in different datasets. All right, and I'll leave the discussion of the implications in a summary for all of us. And if anybody has any questions or would like to, we'd like to give us criticisms and critiques and ideas. I'm happy to open the floor to you. I think that I just had a comment and I don't know whether it even makes sense. I think probably like maybe you said the clinical criteria was not as effective as the statistical criteria. I think that for example, if you in medicine, now you answer my question. I'm not sure if I what I mean when I'm saying makes sense. If you look, for example, at the relationship, let's say between H and hypertension and blood pressure for example, that diabetic type 2, that's something we've been working on. For thousands and thousands of people, it follows the same pattern. And so you could probably have a threshold there. That would make sense. Let's say if you kept the age here, for example, your model becomes less or more valid or reliable or whatnot. But for the eye, I think it is so individual, you have so much with inpatient variability that this statistical criteria might make more sense than the medical because it will be pretty hard to say where are you going to cut this? Because especially given the age, given the ethnicity, given gender, given all of the stuff you talked about, all those distances of PDB and pupil to brow and, you know, MRD. All of those could be very different from each other. So that's always the wise sage added on a criteria is not going to make sense Unless you will make a lot of other stuff constant, you know, absolutely, you're absolutely right. There's micro variations here and there's plenty of variability in his measurements that's using them in any kind of meaningful sense, has to take all of those factors into account. Your zygotes taken agender, the city and so forth. And so you are, you can't be more right? We're about ready to assign R groups by probably Friday or this Friday. So we will have, actually, we have plants. So that will be one more week ahead this quarter for the students to work on the projects. So they're going to have week five to week 10, which means six full weeks to work on it. So I think that if you think that I don't know whether that's an important variable or not. But if you think that, for example, photos that are taken from another angle rather than front face is something that interests you. And then if you train your AI model using some of that data and providing us with that, then we could look at that separately. What I mean, I have a team of nine to ten people, nine people, eight people. Maybe half of the team could look at the photos that have been taken like from a different angle. What I what I was thinking for them, if we were to train a model that had a lot more photographs are from different angles. What we could do is we can compare the reliability of this model with that other model route. Then once we determine which one is potentially more reliable and more accurate, then we can go forward with the next step. So I think as we were likewise, you could also, you know, I would be. For the right group of students we can consider even had given them access enough to the photos so that they could they could test it on commercially available age detail. I particularly liked that idea and I, I just think that that is something that and needs its own, you know, research, its own team of people to look at. So I think that, that's pretty interesting. Well, I made my two comments and I'm very excited. And on Wednesday we'll talk further so we will have more clear questions that you want the team to work on. But yeah, this is pretty fascinating study.

And especially, yeah, I would like to leave they leave their time open for for students and Sam to ask questions. Thank you so much. Yeah. Dr. I'll kick it off with a brief question. When it comes to Image Recognition. My general understanding is that kind of breaks it down by pixel and color and shading and whatnot. Is there a way in your model? Kinda within the neural network to pinpoint certain areas of the eye that are better at predicting age than others. Like for example, maybe excluding eyebrows because the eyebrow wouldn't help that much. But focusing on the bags underneath or different aspects of the retina itself. And retinal scanners are more for medical purposes, glaucoma, macular degeneration. But could it, could that be used to help predict age instead of a disease? Or what are the best areas to look at if that's possible. That's an excellent question. So really, that shows that you're really thinking sets. First of all, I want to share with you something very interesting. So there was a study that was done of retinal scans. Now the retina is inside the eye. It's not a person's face, it's inside the eye. You can go into Google and just search retinal images. You'll see what it looks like. It looks like the back of somebody's either some blood vessels back there's kind of an orange color and see the optic nerve. They fed this model, the pictures, the back with somebody's eye and their age, and that was it. And they did hundreds of thousands of photos. And you know what? Based on that, they were able to predict a person's age within about two years. Just from looking at the back of the eye, they were able to predict their blood pressure, which is something that no doctor can do. No doctor can tell the age by looking at the back of the I know Dr. Can tell the blood pressure by looking at the back of the eye. It we're able to predict a person's gender or their biological sex by looking at the back, just a picture of the back of the eye given to the AR model was highly accurate at that. And so what you're getting at is sort of one of the most important things about these neural networks is can they find the critical features that we use to make our decisions? And one way you can do that is exactly right. You can exclude certain parts of a photograph and see whether or not it changes the model's efficiency or are reliability and accuracy. So that's really your spot on. That's exactly the right question, the question to be asked. Now, there is a way with the model that I've trained to be able to do what's called a heatmap. What's a heat map? It shows you the pixels that the computer is using to make its decision. Okay. Problem with the heatmaps is sometimes it can tell you what you want to know and you confirm what you look at. But if it doesn't show you any useful data, like for example, if it made exactly the right prediction. But the pixels that use we're kind of in the corner of the image and highlighting the person's hair doesn't mean anything. So you tend to ignore you can't ignore it, right? So the point being is, yes, you're getting it really the philosophical crux of using these models can tell us something that we don't know already. You can find things in the data that we don't see. And then you sort of touched upon maybe potential methodologies to do that. But I encourage you to think about that more. Is the field of AI is huge. This is what they're asking for in the job market for you guys coming out and those you're going to go into masters and PhD. This is the hot topic within FinTech and within medical science. And with it within you go to Google and, and, and, and Tesla. It's all about knowing our deep learning works and being able to apply it. So you're thinking the exact right way eight. And I really appreciate that. Bravo. Good question. Dr. Curlin. I had a question. Yeah. Thank you so much for your talk first of all. But I want to ask, have you considered using something like transfer learning to use the information from a model that's more generally trained on leg bigger datasets. Because I've heard in general that they're better at identifying features in images. And like, you can use those general models to fine tune to your particular dataset. So considering that, like you have like 57 images, like data scarcity could be like, you know, like handled a little bit easier with using, using the general purpose model. So the, I use the fast AI system, which again is for hobbyists. For those of you who are a lot more, a lot more versed in this than I am, that the fast AI is probably something that's very rudimentary, but they actually implement transfer learning as far as I know, using the ImageNet. So it starts on ImageNet and then you can train your model on top of that and reinvent it normalizes based on the ImageNet statistics. So again, I'm coming from a place of, I'm not an ultra rapid area and I'm not a person who speaks outside his area of expertise. I know about eyes and I know about the face. Beyond that. When it comes to computer science, I defer to people who know more than me. So that's a that's a really good question. I appreciate that suggestion. That's great. Thank you. Have a minor in computer science. What's that? I saw anybody in the crowd with a minor in Computer Science. I'm OK. So that's that unfortunately isn't a minor in Computer Science at UCLA or somebody who came from the major two statistics. I don't know. Generally they transfer, it goes the other way. Not many people coming into statistics. From computer science? Yeah. Correct. Okay. Other questions. Hi, Dr. So my question is more about you mentioned how there could have been accomplished with, let's say like lighting and other things with the exclosure with the pictures. So my question is more about if there was any industry specific conflict, select, Let's see darkness under the eyes. That may be a common indicator of age and that could go to a photo, the photo was taken. So any examples of that? Got really good question and that's it. That's what I was thinking about going forward in the same way that we use clinical criteria. We can also use photographic criteria to determine the reliability. For example, if there's a certain range and there's ways to get that data actually in bulk from a list of photographs. So you can, there's a file that's called EXIF that every photograph as sort of a data file that comes with a digital photograph. So it would be possible to, for each of the photographs that we've taken to have that is again, something that could be looked at as a covariate. So that's sort of what I'm planning to add to the data set is just each, each photograph will have like what was the aperture size and the f-stop and exposure and so forth. And then we can look at that is whether or not you're exactly right. Like does, does that affect the appearance of dark circles under the eyes? And that's, you know, this is sort of creeping into another project which I don't know if they've heard about from Dr. root men, which is looking into whether exposure photographs makes us look more or less attractive to outside observers. Did you guys hear about that projects? I already went ahead about it on Wednesday. Okay. I was wondering actually with it, Is there any way to combine the two projects, like your AI, which is external exposure study. I've thought about whether or not we can use some of these photographs to give them to experts, to sort of guess, guess the age, and compare whether or not the human is more reliable, you know, kind of a man versus machine type of thing. That I don't know what the necessary the value that I've only thought about that in passing. Because I saw that in your speech. You are talking about the effect of exposure on how AI predicts the age. So right here, root lenses study, you've got six exposures, right? Of five or six exposures. And we're trying to find out whether the perception of beauty depends on those five or six exposures. But the limitation is that you only have 10 people taking photos under 10105 or six exposures. If you want the eye to train your model, you're going to need a lot more photos, I assume. Well, it wouldn't be for the training, but you could use those same photos for testing. Maybe what I could do is I could put the photographs of different exposures, known exposures into the AI model and see if there's sort of a systematic weather. They tend to predict younger, different the exposure data. I'm surprised we didn't think of that before that year. That's a really good ideas. I guess you could, because if there is any way that you could connect that study into the AI study, that would be pretty interesting and we could probably do an exploration of it, maybe the squashed it or are absolutely. Okay, I will let them know that's a fantastic idea. Acquire the look that I like, I can move. I didn't think of that. Now. Now that you said, you make it look so easy to think that ideas with, That's great. Other questions, Yes, You guys still have about seven minutes for questions. If you have Pam till trivia here. I do airtime into three depends on the doc there. Yeah. Well, I think somebody had a question. Sorry. Yeah. Sorry. Yeah. This is the switchers is super interesting. It makes sense considering your work and reconstructive surgery, but beyond its use in my anti-aging procedures, what do you imagine could be the use of these images? Like Have you thought about, like trying to predict signs of exhaustion or depression? Just like I know sometimes that can show in a person's face. That's also fantastic idea with a big enough data set and the right labels. That's, I think that that's, that would be a beautiful project to do. And then that's another thing is maybe the quantification of whether or not a patient improves after eyelid surgery is not just their age, but also maybe they look happier or they look less depressed or, you know, these are all kind of the the all the meetings that I go to. The meetings you guys go to, you go and you see, you'll see statistics and you see numbers and say, Wow, what a beautiful proof. And that looks right. When I go up to the meetings, we have people showing pictures of their before and afters. That's it. And everybody goes, oh, wow. She's such a great surgeon. She's amazing. And then they show their pictures. And so duh, but there's no objective quantification. So using age is perhaps one of them or whether they look younger, but I love that idea, whether they look less depressed or less sad or less, look more happy, more refreshed, less tired. So that's, that's certainly is a, another semi-quantitative measure that could be, that could be added to this. After I add them up, I was like, What Octave Rule time does that crowdsource people going in and saying they're more attractive or tire. And rating the beauty, perception of beauty at giving that kept a whole bunch of stuff constant. But Emily Moore, more to your question, I think that would be brilliant and certainly a next step that you could use that as a diagnostic tool, as a screening tool. You take a picture of somebody like, hey, you know, this person. We looked at their photos and they may be depressed and they don't even know it or their family members don't know it. But maybe this is associated with depression. Depression is one of those things that's, can be really tough to diagnose for this mission is angry all that. Yeah, exactly. I'm not per se what everybody's thinking. Well, you know, there's certain faces and resting phases that can make people look angry or so. That could be, you could train an AI model to find all kinds of things. Yeah, exactly. It looks like you're on a town, has something that he said, Yeah, exactly like a pre-screen, somebody comes in and that's, that's sort of and that's something that you can use to follow a person's treatment over time. Maybe it could even independent of their expression. So a lot of very interesting ideas here. Remember the Rorschach test when we have to draw that way, either way. Certainly these liking some of the questions from the group, this has got a lot of thinkers in this group. I thought it was really interesting that the statistical features were more significant than the clinical features. I mean, what do you think of it as like someone who has domain expertise in ophthalmology. You know, the students complain to me and rightly so that they didn't get access to the photographs when they were looking at this, as you said, they couldn't tell if there was a big difference between the angle of the fault to photographs that were the statistics show that one difference between predicted and actual was small and one difference was very large. So there was two very different predicted ages for the same patient, for two different photos. So I think that probably there's something to those photos, whether it's exposure or whether it's like changes in angle or maybe slight changes in expression. You're asking a really good question about whether or not, you know what it exactly was about those that led to such a statistical anomaly for them being predicted. It's such wildly different ages. I don't have an answer to that yet, but that's sort of what the next but you're, you're, you're thinking the right way. That's, that's the next thing you want to look at what it is about those photos that caused him to be such a statistical anomaly as Emily is pointing out, maybe when they come out on one day, they're happier than when they come up and another day. Or even your 25. And you can look at your picture in the day when you're in a party and you're not feeling so good or something and you say, Oh my God, that looks so terrible. And you are in another party and you're happy. That looks pretty good that so your problem that maybe you need them, you need to give them a depression test before you know, but these are designers. And see how there is a question about the person's mood. You know, you don't need to give them a very long cellularly or something. The most important, at least as far as I know from medicine and medical school, the most important screening question for whether somebody is depressed, if you ask them, are you depressed? Yeah. Or something or just a single question, what do you think? How do you see life today or whatever, you know? And maybe that would be actually something interesting to ask. Okay. Sam, you have any comments you're going to be working with students digest at the core there. So what are your thoughts? Thanks for the presentation. It was really good. It's really interesting and there's been a lot of a lot of good ideas going around, so yeah, thanks for the talk. Thank you, Sam. Thanks for being here. Okay. Other questions? Okay. So I know Dr. Cortland is a busy in the afternoons with his clinic, so we want to take more of your time. But if by Thursday but by Wednesday when we meet at four o'clock, if you know, it was good that we were able to discuss this a little bit. So hopefully maybe between now and then you get some for their time to discuss this with your colleague, Dr. Drew plan. And that would give more direction into where we're going with what you're doing, discourse and what you could potentially doing their quarters to come. Yeah. I cannot. Thank you enough. Dr. Calling so much. Thank you very, very much. Really appreciate it. And thank you. And thank you for all the kind words and giving me a platform talking and thank you to all the students for being here and for asking questions and for even thinking and listening to my presentation. So I really appreciate it. Thank you very much. I'm so honored to be here. Thank you very much. Okay. So Wednesday, I'm going to be actually talking about repeated measures and bringing in some of the projects from Julie Stein to talk about. And then hopefully by next Monday, everybody will have their group on their clients. We're still working on it. But we tried very hard to get earlier, to get ready earlier this quarter on. I think they're pretty successful at that because prior quarters we've already about week four. But I think that we should be getting the five. Of course you will have one more speaker next week, but hopefully by Monday, I don't know if the speaker is here on Monday, then we'll talk convinced Dave, he's here on Wednesday. We'll talk Monday regarding project. Okay. Thank you so much for coming. And I really enjoyed the stock and I hope you guys the tools. Okay. Thanks, Amelia. Take care of yourself. Buh-bye. Thank you, Sam. Can v Let me stop this screen. Yeah.