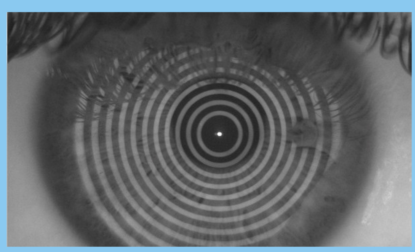

DETECTING KERATOCONUS AND ASTIGMATISM WITH DEEP LEARNING

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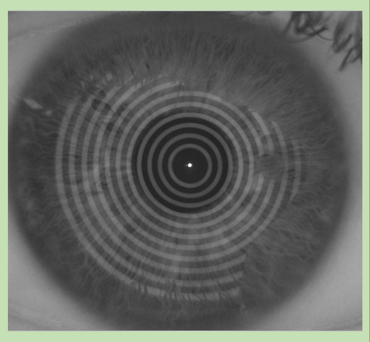
Motivation - Keratoconus and Astigmatism Corneal Disorders

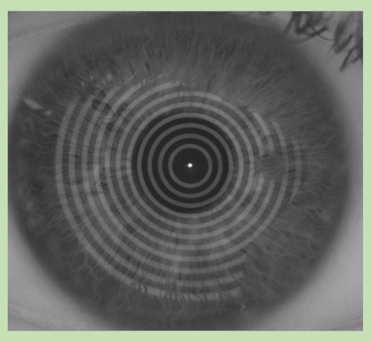
Placido Disks Corneal Images



Measures The Corneal symmetry by projecting a series of concentric light rings on the cornea and examining the reflections. On a normal cornea the rings will reflect in a symmetric manner while on an irregular cornea they will reflect in a skewed manner.

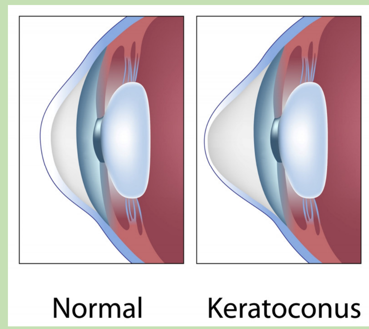
Corneal Images Data Set

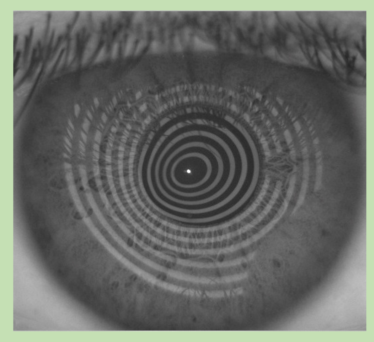
Healthy 103 images



Round Cornea with normal thickness.

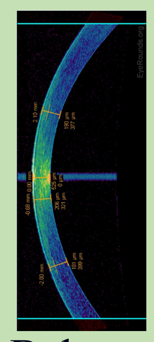
Keratoconus Disease (KC) 86 images

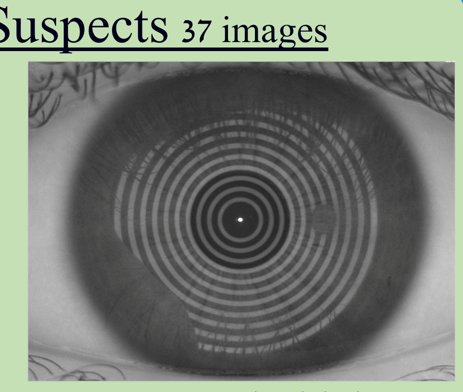




Progressive thinning and weakening of the cornea causes it to bulge outward, which results in significant visual deterioration.

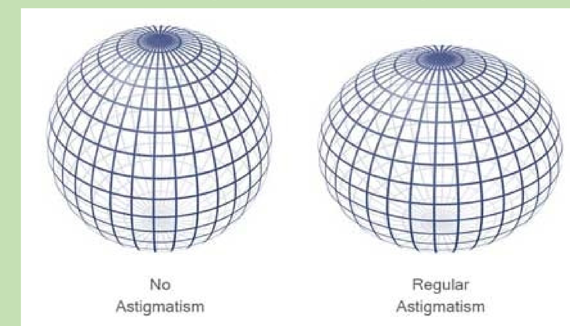
KC Suspects 37 images

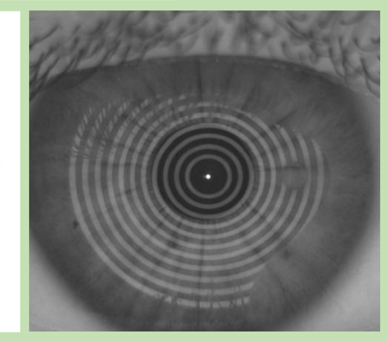




Below average corneal thickness or mild curvature irregularities. No significant visual deterioration.

Regular Astigmatism 31 images





A 'squashed' cornea that resembles a Football more than a Soccer ball.

Goal

Implement a robust and flexible system that could be extended to different disorders and adapted to different types of input data. It is more than possible that corneal imaging techniques other than Placido disks would be employed in the future.

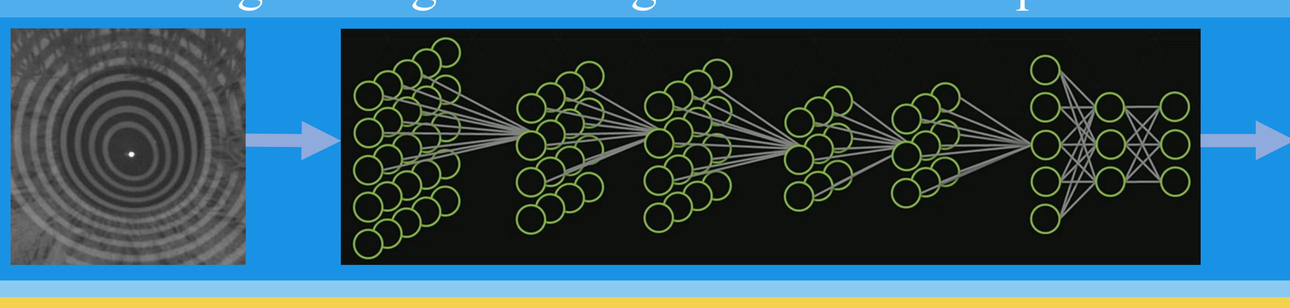
Previous projects that were conducted under the supervision of Dr. Yekutieli used 'Conventional' machine learning algorithms to approach the subject. These 'shallow-structure' algorithms cannot, generally, handle the complexity of visual data. Therefore, they require excessive preprocessing procedures, known as **feature engineering**, in order to make the data simple enough to learn. **Feature engineering** is a research and labor intensive task. Moreover, it might be input-specific, meaning that experimenting with different types of images would require repeating the procedure. For that reason, the system should be able to classify images without any form of feature engineering that could tie it to a specific type of input.

Approach - Deep Learning with Convolutional Neural Networks (CNN)

CNNs bypass feature engineering requirements by learning prominent features automatically from large amounts of raw visual data.

Deep Learning Revolution

No feature engineering – Feeding the net with raw pixels without preprocessing



Classification Output

Challenges Posed by Deep Learning:

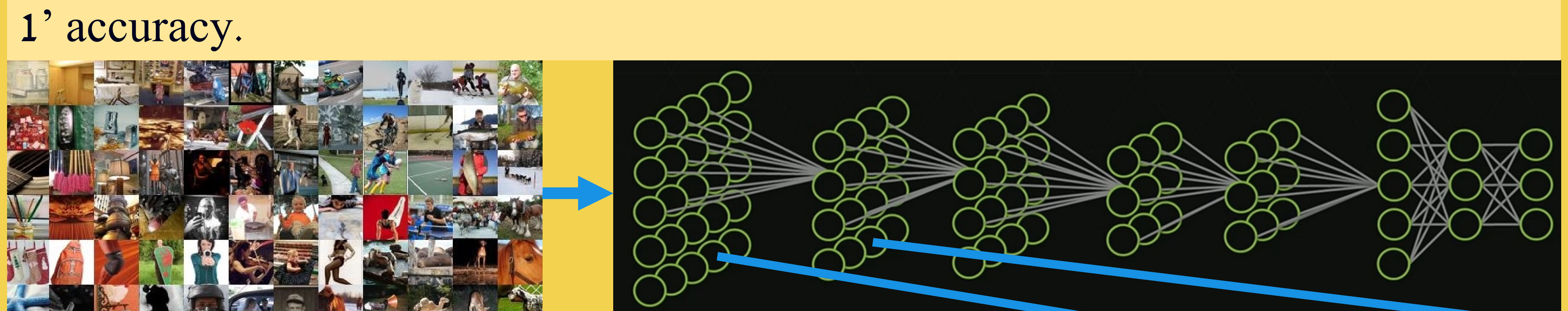
- Requires massive amounts of training data ('Big Data'). We have 257 images, which is considered an extremely small amount of data.
- Requires large computational power - training a CNN from scratch can take days on expensive, dedicated hardware.

Solution to Deep Learning Challenges - Transfer Learning

1. Take a Pre-Trained Network

CNNs trained on large numbers of images learn generic, low-level visual features like edges and color blobs. We can take a pre-trained net and use its knowledge for our problem.

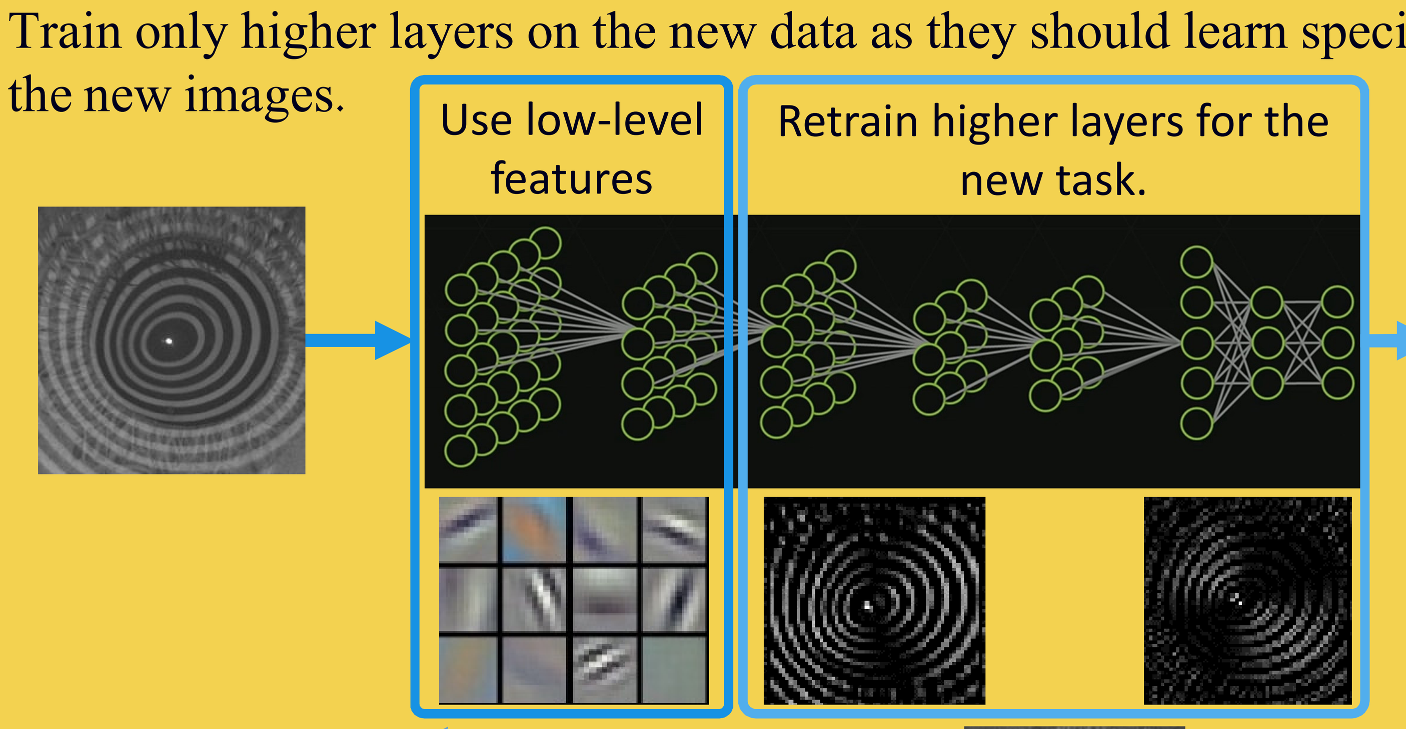
The pre-trained net we chose is 'caffenet' CNN, which has 60 million weights (parameters) and was trained on 1.2 million images, from a 1000 categories. It is based on AlexNet who won the 2012 ILSVRC (ImageNet Large Scale Visual Recognition Challenge) where it achieved 80.4% 'top-5' accuracy and 57.4% 'top-1' accuracy.



* **Weights** – The parameters optimized during training.
* **'top-k' accuracy** – The correct label is among the net's top-k guesses. Measuring top-5 accuracy makes sense when considering how ILSVRC images are labeled.

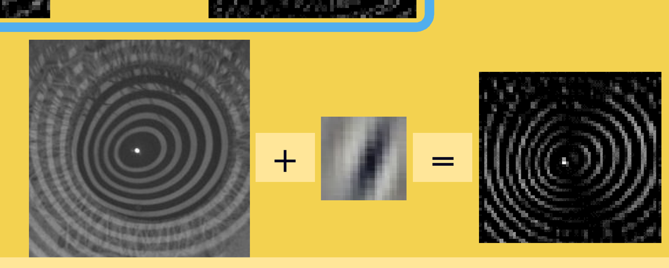
2. Fine-Tune the Net to Classify Our Images

Train only higher layers on the new data as they should learn specific features of the new images.



Classification Output

Convolution filters, learned from a million images, contain low-level visual features.



Previously learned filters can immediately be used to extract features from new data.

Results

Confusion Matrix shows the net's predictions by classes. The diagonal shows correct predictions, i.e., instance of class A was classified as A, while every cell outside the diagonal shows wrong predictions, i.e., class A was classified as some class B.

	Predicted Labels				
	Label	Healthy	KC	AST	Total
True Labels	Healthy	95.14% N=98	1.94% N=2	2.92% N=3	103
	KC	1.16% N=1	95.34% N=82	3.48% N=3	86
	AST	9.67% N=3	6.45% N=2	83.88% N=26	31
Average accuracy – 93.6%					220

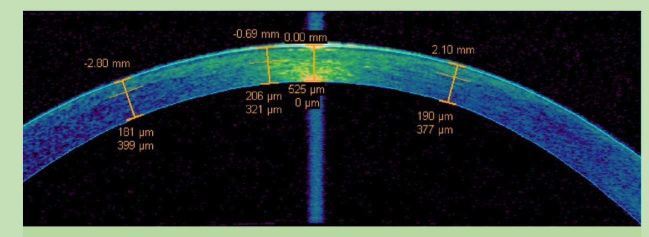
The net achieved **93%** accuracy on the healthy, KC, and regular astigmatism data sets. 1% of KC images and 9.6% of astigmatism classes were classified as healthy.
Taking into account that the Astigmatism set is the smallest set, the results are very good.
The results are from cross-validation, where in each round training spanned over 50 epochs (the net 'saw' each image 50 times) and took 5 minutes.

	Predicted Labels					
	Label	Healthy	KC	KC Suspects	AST	Total
True Labels	Healthy	87.38% N=90	0.97% N=1	11.65% N=12	0% N=0	103
	KC	1.16% N=1	91.86% N=79	2.32% N=2	4.65% N=4	86
	KC Suspects	45.94% N=17	18.92% N=7	32.43% N=12	2.7% N=1	37
	AST	12.9% N=4	9.67% N=3	3.22% N=1	74.2% N=23	31
Average accuracy – 79.3%						257

Classifying the KC suspects class proved to be hard. Only 32.4% of the Suspects were correctly classified, while 45.9% of the suspects were classified as healthy. 51% of the suspects were classified as either KC suspects or KC. Introducing the KC suspects also brought down the classification accuracy of the healthy class, probably since a large number of suspect images resemble healthy images.

Conclusions

- Transfer Learning showed very good results on the healthy, KC, and Astigmatism sets.
  The method achieved high accuracy in short training time despite learning from extremely small and imbalance data sets.
- It is most likely that Placido images do not hold any data about the corneal thickness.
  Therefore, it might be impossible to correctly classify KC suspects that have thin corneas with no surficial distortions.
  Classifying the KC suspects might require a new imaging technique that could extract data about corneal thickness.



More advanced corneal imaging techniques can be used to measure corneal thickness.