Ocular Disease Detection Through Machine Learning

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Fnu Vishal, Jose M Teodosio-Meza, Solomon Lemma, Irina Chernyavsky and Katie Lamberto

Outline of Presentation

- Overview and Problem Statement
- Background: Eye Disease Prevalence
- Image Collection and Processing
- Modeling
- Flask App
- Conclusions

Problem Statement

Develop a machine learning model to accurately categorize fundus images of eyes as having glaucoma, cataracts, diabetic retinopathy, or no abnormal condition.

Normal Fundus Image of Eye

Facts of Common Eye Disorders in US

- **93 million adults** are at high risk for serious vision loss
  - **half** of the number don't **visit an eye doctor in a year**.
- About 3.66% of the total population over the age of 40 have vision impairment
- The prevalence of visual impairments increase with age
  - 15% of people 45-64
  - 17% of people 65-74
  - 26% of people 75 and older
- It impacted the country economy more than $145 billion annually

Sources: https://www.cdc.gov, American Academy of Opthamology (http://www.aao.org/), and National Eye Institute (http://www.nei.nih.gov)

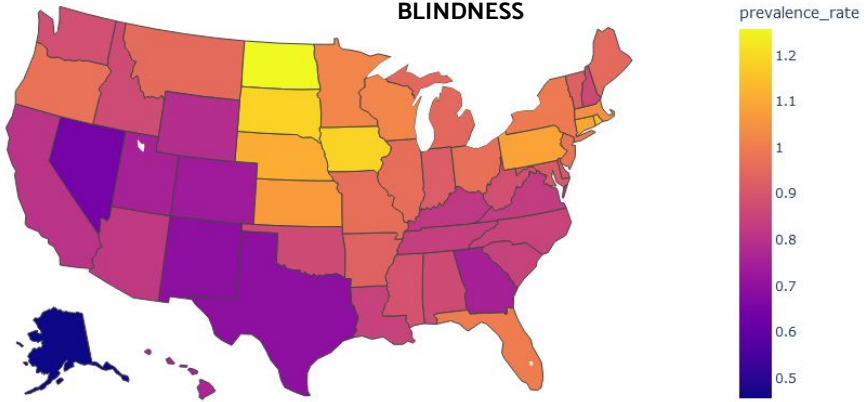
Data on Vision Problems

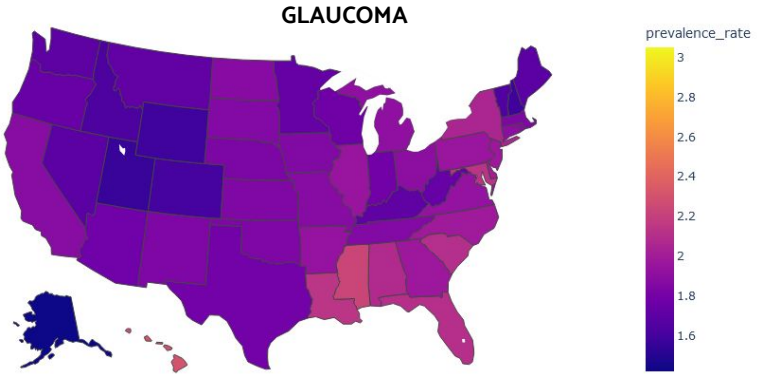
- It contains > 52,000 observation of vision problems including:
  - Non-modifiable features (race, sex and age)
  - Modifiable features (vision problems, case number, population, location..)

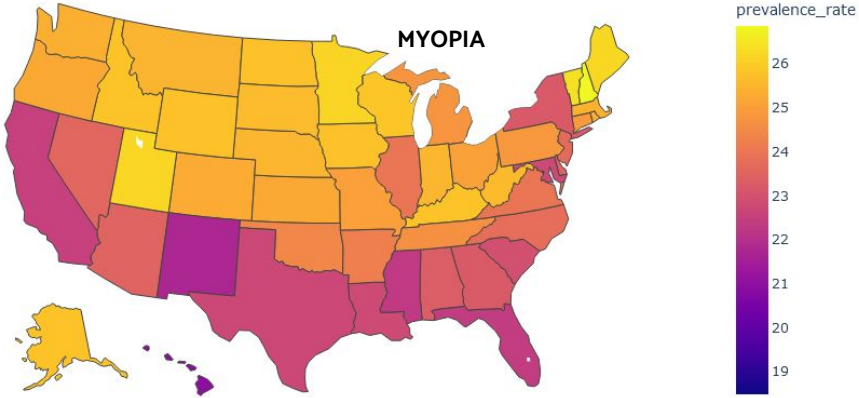
- The cleaned data were used for:
  - Features engineering
  - EDA
  - Model building

Data Exploration

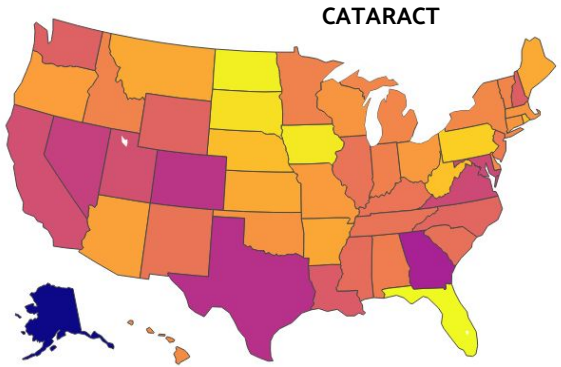
- Prevalence of the diseases

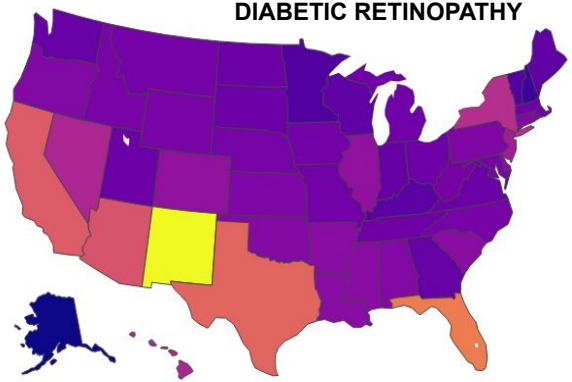


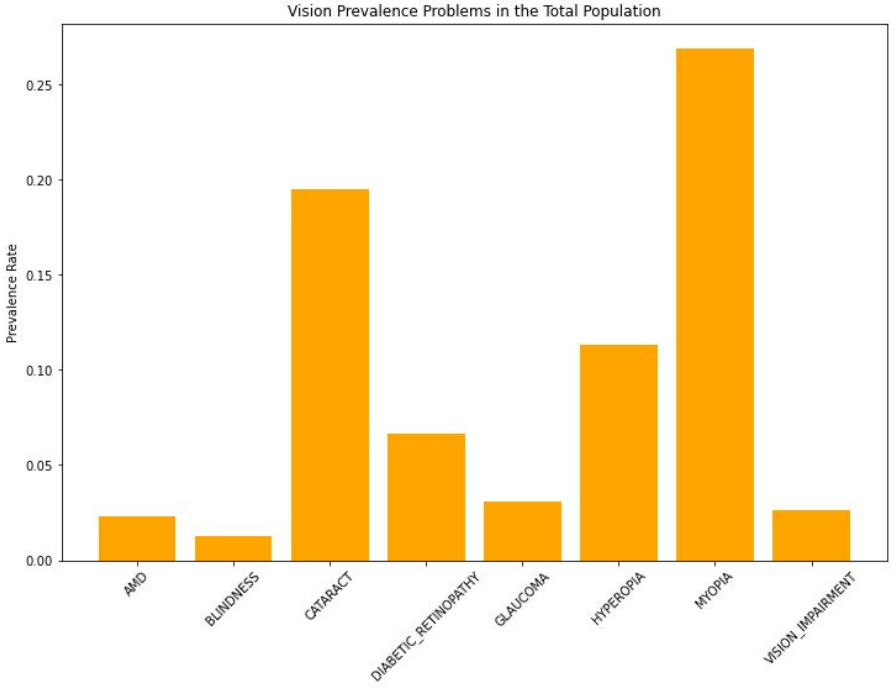




Data Exploration







- The map clearly shows the northern states has higher eye diseases prevalence rate except caused by high blood sugar(Diabetic Retinopathy).

Image Collection and Processing

Data Collection

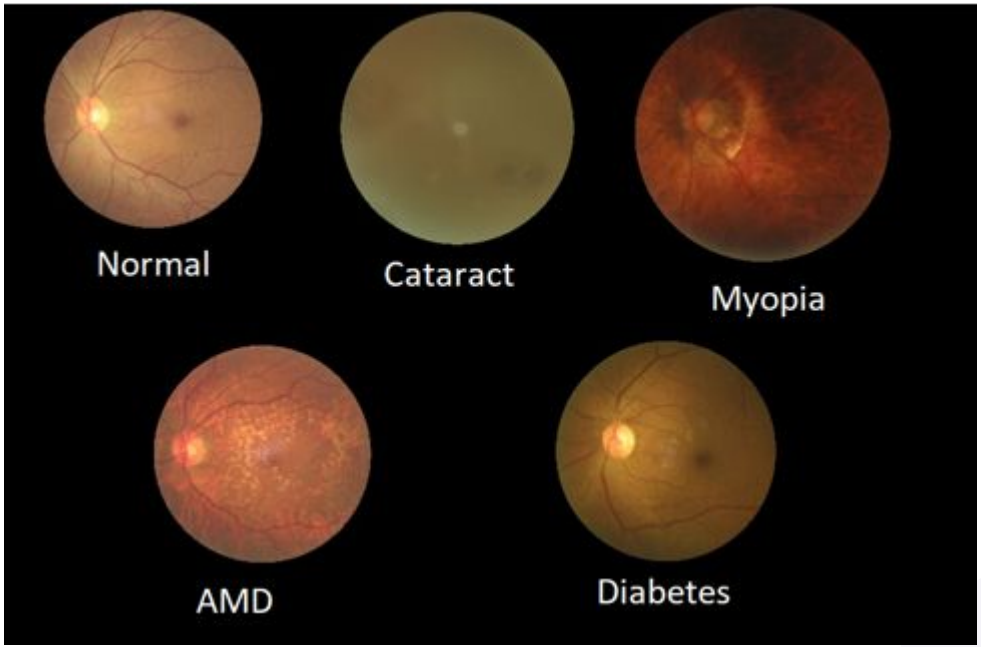
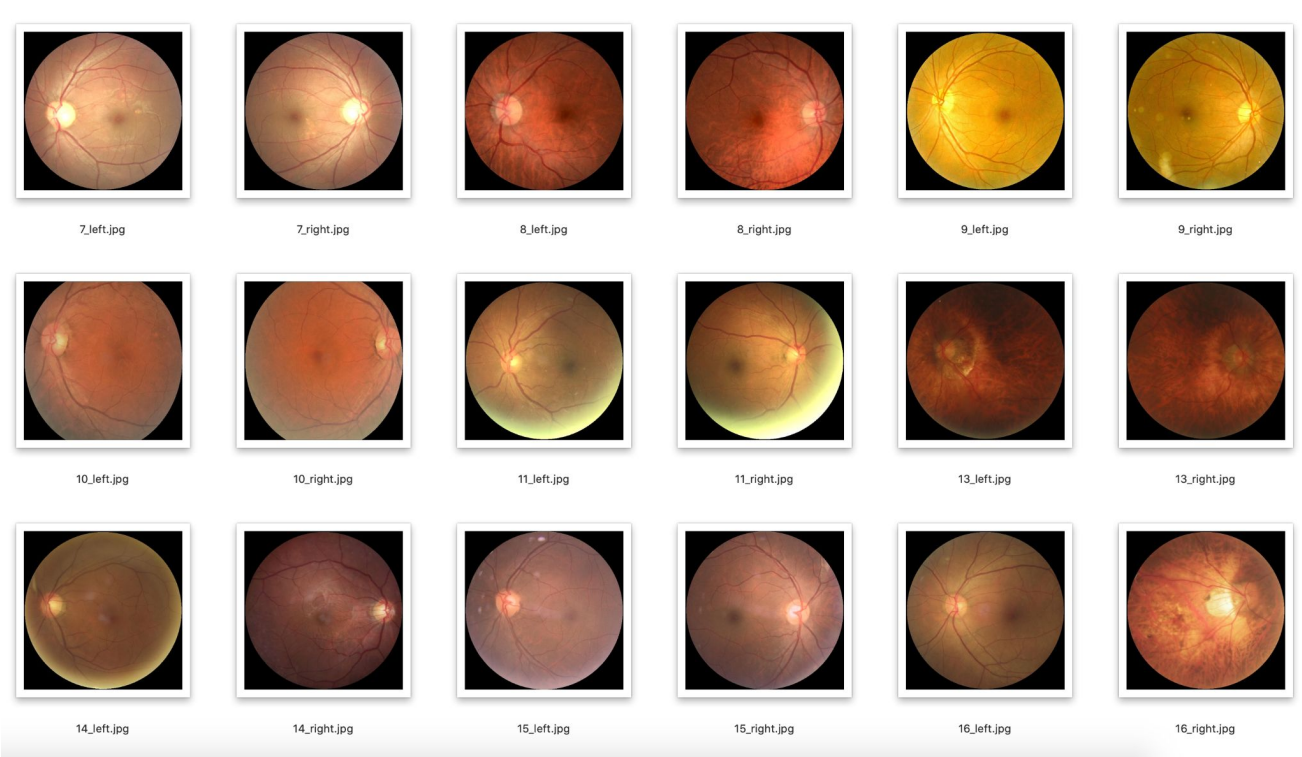
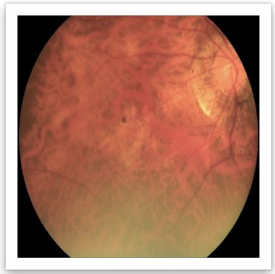


Image Processing

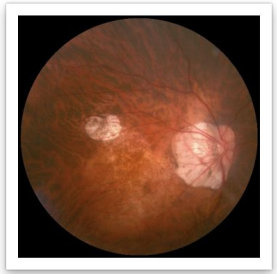


Final Sorting

16_right.jpg



18_right.jpg

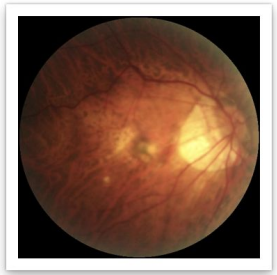


46_right.jpg

54_right.jpg

106_right.jpg

145_right.jpg



214_right.jpg

233_right.jpg

Image Preparation

- Resize to 512 x 512 pixels

- Organize by eye condition:
  - 300 normal eye images
  - 404 with glaucoma
  - 468 with cataracts
  - 468 with diabetic retinopathy

Normal Fundus Image of Eye

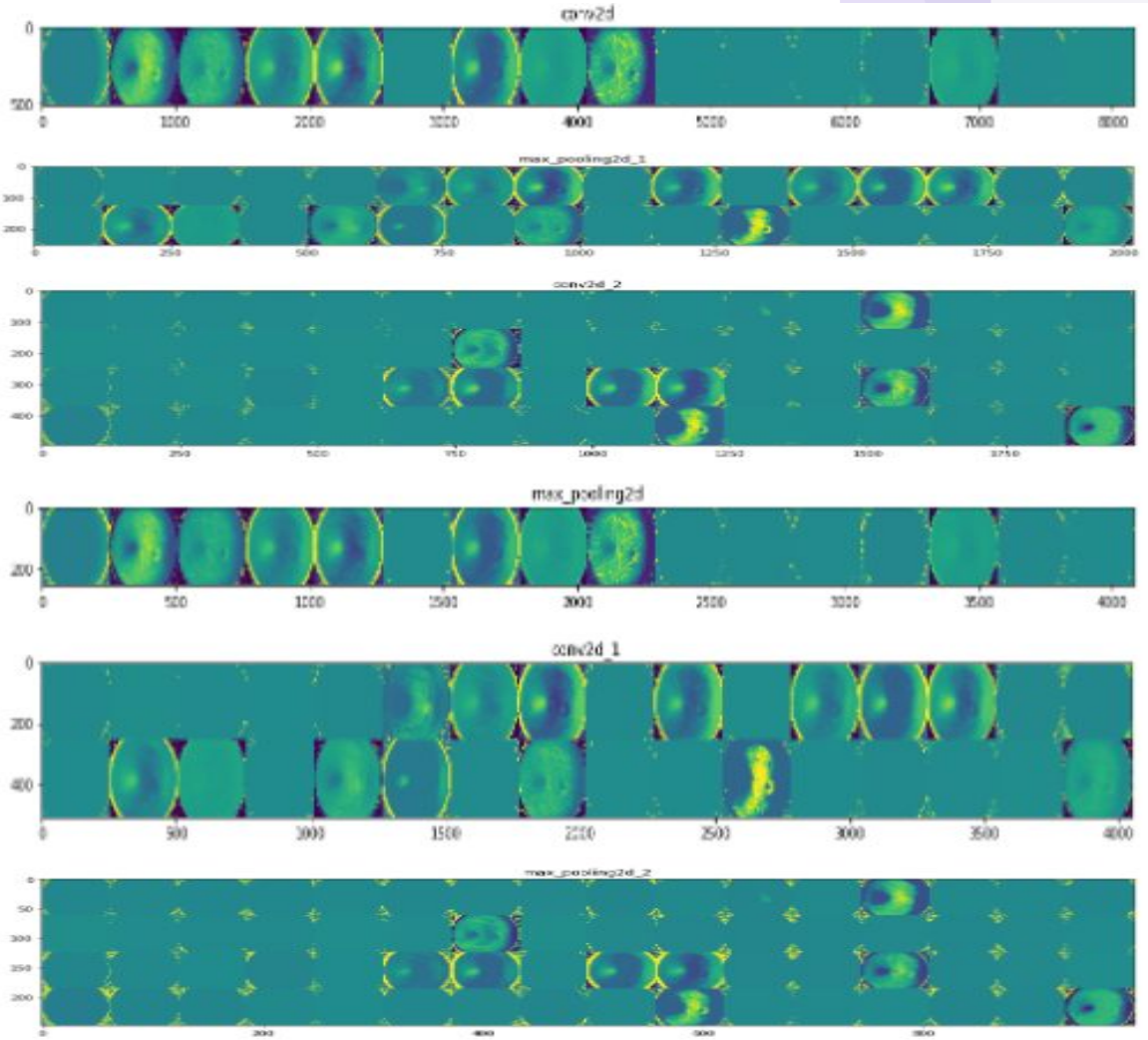
- Very Small Dataset → Image Augmentation
  - Randomized rotation, horizontal flip, and brightness

Convolutional Neural Network (CNN) Model

- **Input shape: 512x512 pixels with 3 channels** (RGB)
- **Convolutional 2D layer** to create 16 3x3 filters for feature detection
- **MaxPooling layer** to take the maximum value in every 2x2 grid
- **3 more Convolutional 2D layers with MaxPooling layers**
  - 32, 32, and 64 nodes, all with 3x3 filters
- **Flatten layer** to bridge between Convolutional and Dense layers
- **2 Dense layers** with 256 nodes each to analyze the features
- **Output layer** with sigmoid activation for binary output

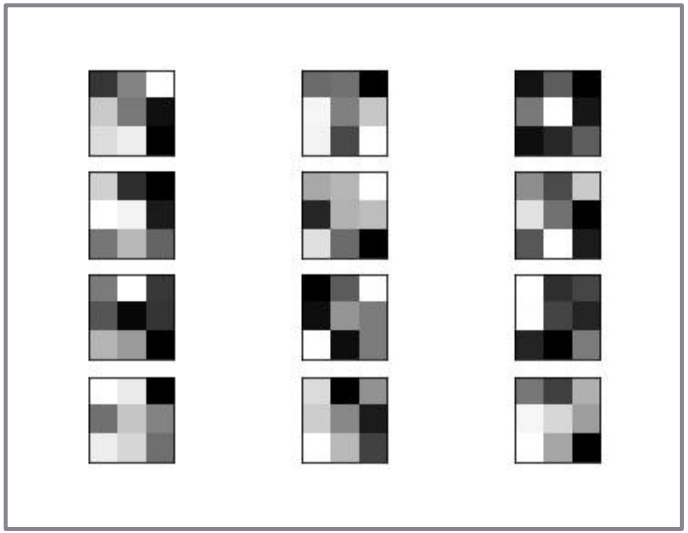
Feature Maps

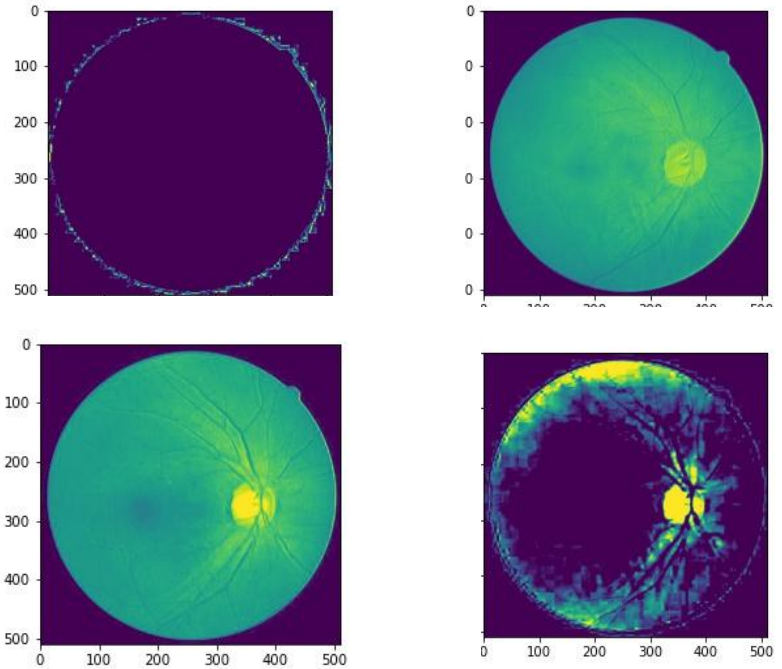
- Here every horizontal strip represents corresponding layers in our CNN model.
- It is used to visualize the output of filter at each layer.
- It is used to get better understanding on how the image is processed and feature extraction done at every layer.



Visualizing Filters and Feature Maps

- 3x3 filters





CNN Model Fitting

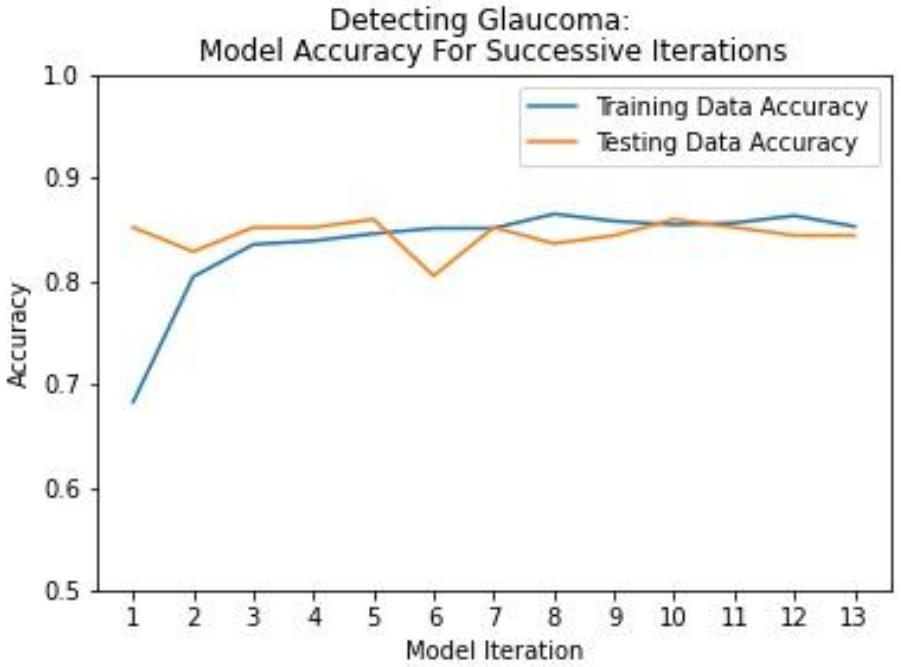
- Use binary classification: Each disease vs. normal eyes
  - Glaucoma, Cataracts, and Diabetic Retinopathy
- Run through variations of the training data up to 30 times
  - Stop early when performance levels out
- During each run, process and learn from batches of 32 images at a time

Glaucoma CNN Model Results

Baseline Accuracy: 57.4%

Model Training Accuracy: **85.2%**

Model Testing Accuracy: **84.4%**

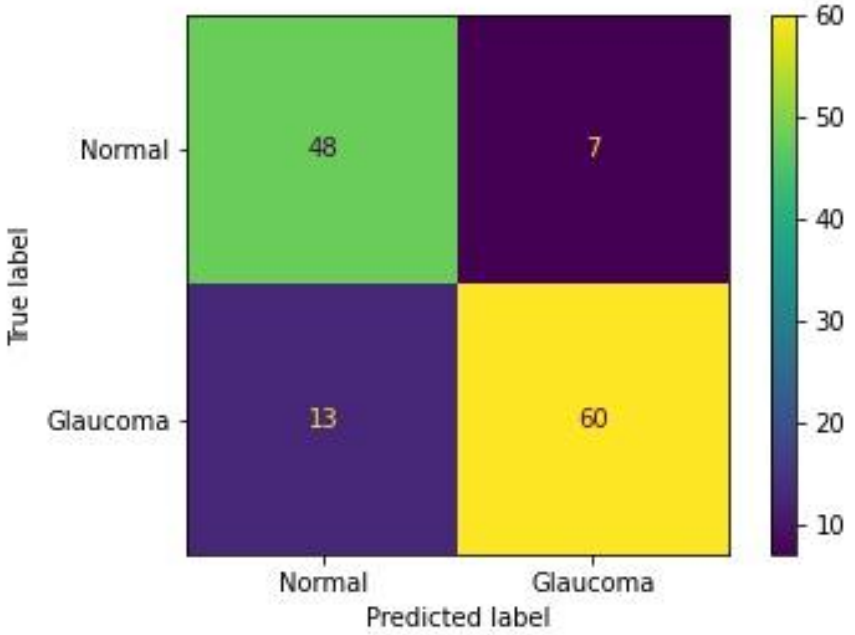


Glaucoma CNN Model Results

Test Results:

82% Sensitivity

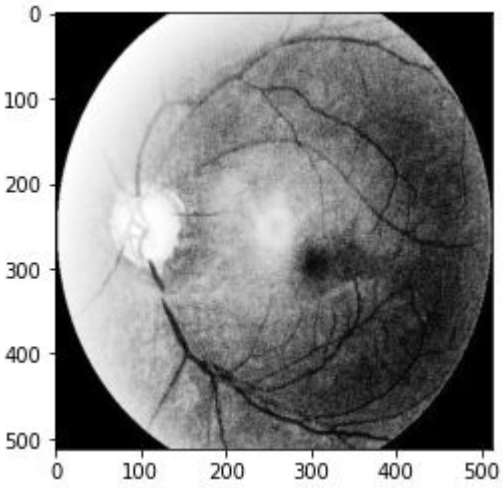
87% Specificity



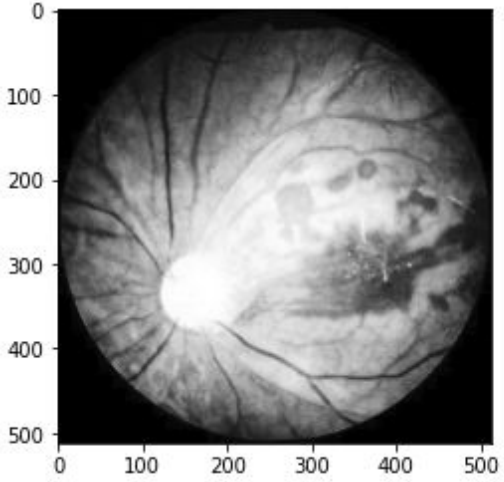
SVM and KNN Modeling

Image Processing- flattening

- Images converted to greyscale, flattened and turned into 2-D arrays



Retinopathic eye



Normal eye

Image Processing - Wavelet transform

- Each image can be represented with a linear combination of sine-waves
- Image filtering is an important aspect of processing because without it we train our models to learn noise
- Wavelet-transform was applied which is a transformation that allows changes in the time extension, but not shape
- It produces as many coefficients as there are pixels in the image
- It has many family functions, among which is Haar family that was used in the project

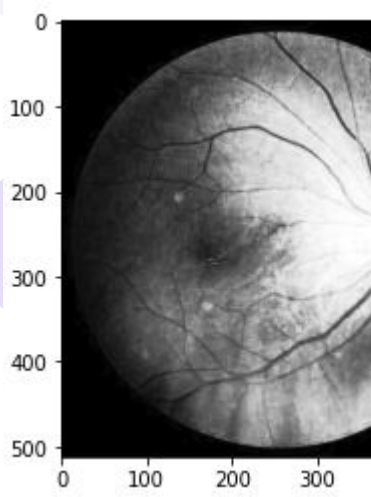
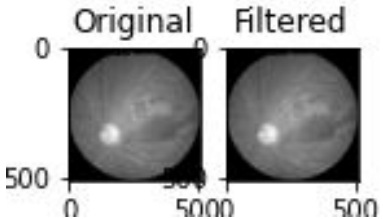


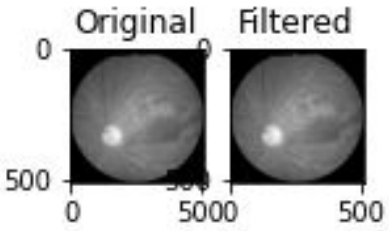
Image Processing - applying filters

- There are many types of filters, each with a different purpose:

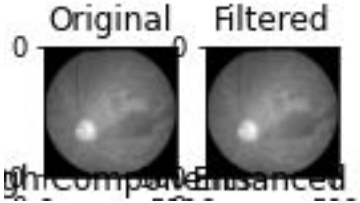
Mean filter - low-pass, computes average intensities of pixels



Median filter - replaces each pixel in a neighborhood with the median intensity



Gaussian filter - modified mean filter, but uses weights



Sobel-edge filter - sums horizontal and vertical gradients at the two points

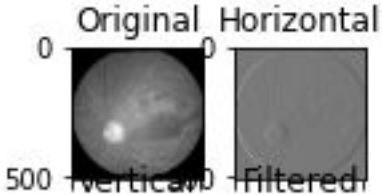


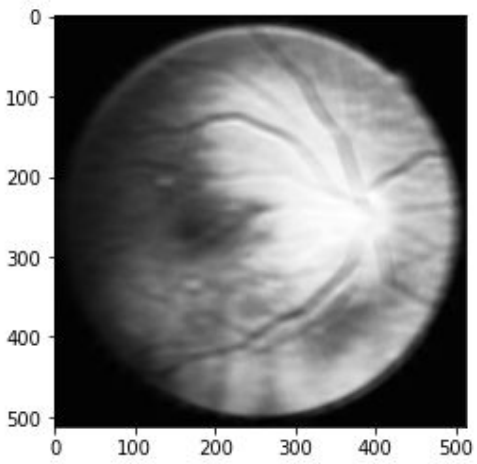
Image Processing - filters summary

Filter	Use
Mean Filter	Reduce Gaussian Noise smooth the image after upsampling.
Median Filter	Reduce salt and pepper noise.
Sobel Filter	Detect edges in an image.
Gaussian Filter	Reduce noise in an image.
Canny Filter	Detect edges in an image.
Weiner Filter	Reduce additive noise and blurring.

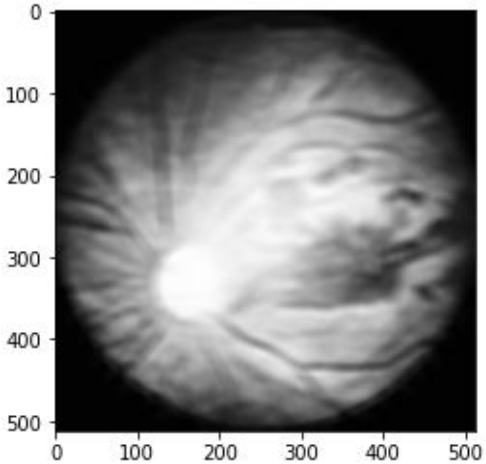
Gaussian filter was applied for image processing

Image Processing - image convolutions

- Images were processed with image convolutions with the Gaussian filter as a kernel



Retinopathic image



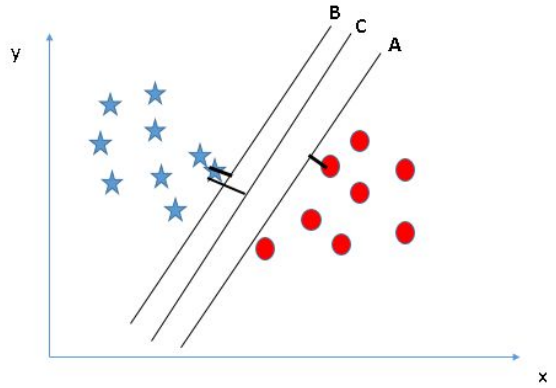
Normal image

Image - modeling

- SVM

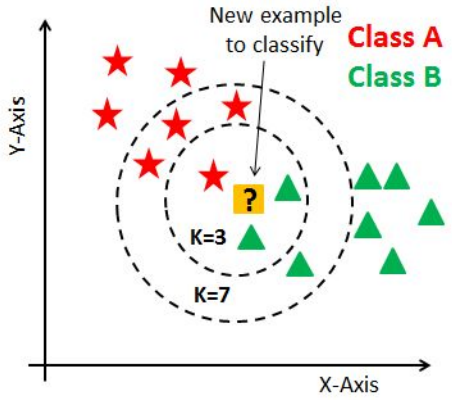
Models were optimized with Grid Search parameters

77% accuracy score



- KNN

70% accuracy score



Flask Application

Built with:

Python

Java

React

Bootstrap

CSS

HTML

Thank You!