



DIABETIC RETINOPATHY GRADE DETECTION

Ophthalmology Application

Third Capstone Project Presentation

Springboard DSCT Bootcamp

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PROBLEM IDENTIFICATION

STATEMENT

Diabetes has reached impressive numbers by 2017, having almost 425 million people facing the disease and estimating almost 629 million by 2045. According The American Society of Retina Specialists, half of the patients with diabetes suffer from retinopathy and is the number one cause of irreversible blindness in working-age people.

Recent works on Deep Learning in ophthalmology showcase its potential to at least partially replace human graders, while providing a similar level of accuracy. Nonetheless, being more adopted as a medical-aid systems than a replacement itself.

STAKEHOLDERS TO PROVIDE KEY INSIGHTS

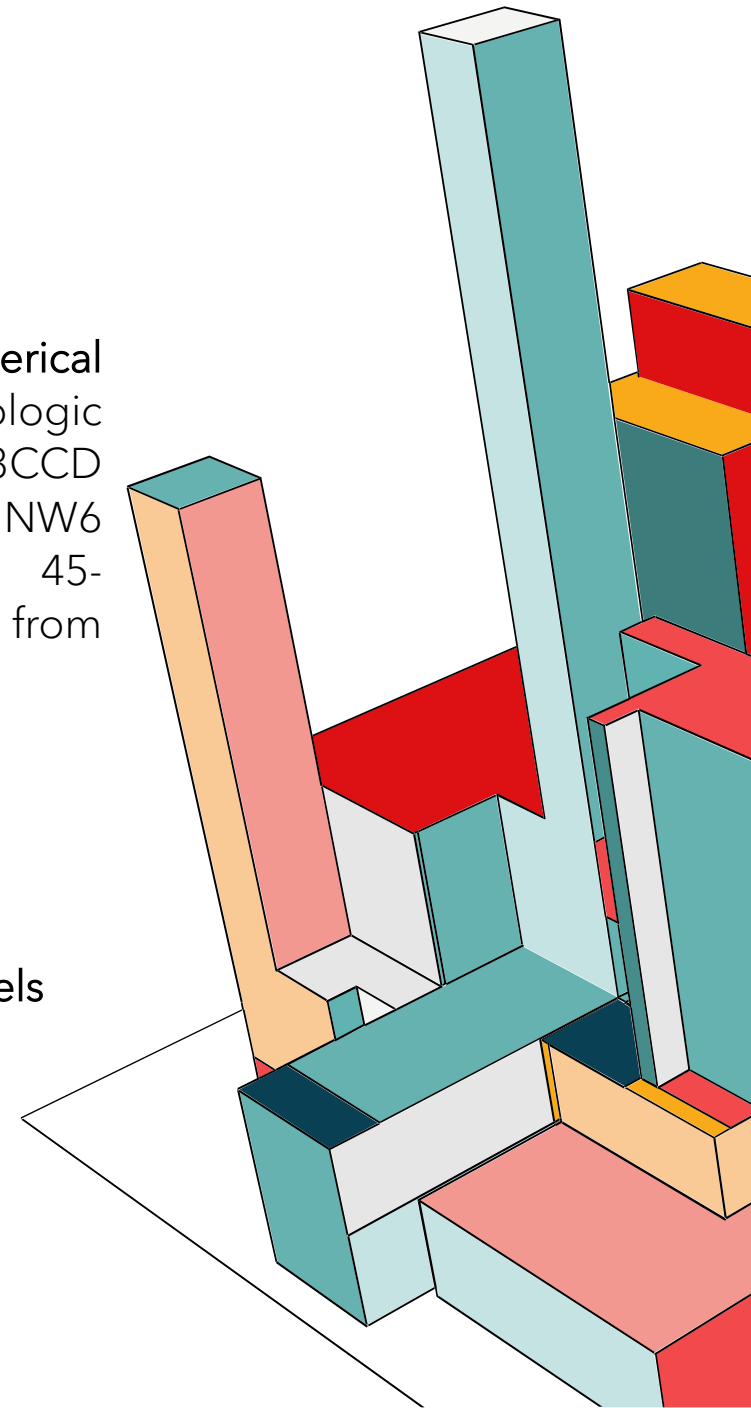
- Diabetic Retinopathy / Ophthalmology Institutes or Universities
- Microscope or Ophthalmology Companies
- Springboard Mentor

SCOPE OF SOLUTION SPACE

Dataset: 1200 eye fundus color numerical images acquired by 3 ophthalmologic departments using a color video 3CCD camera mounted on a Topcon TRC NW6 non-mydratic retinography with a 45-degree field of view and downloaded from the [Messidor Database](#).

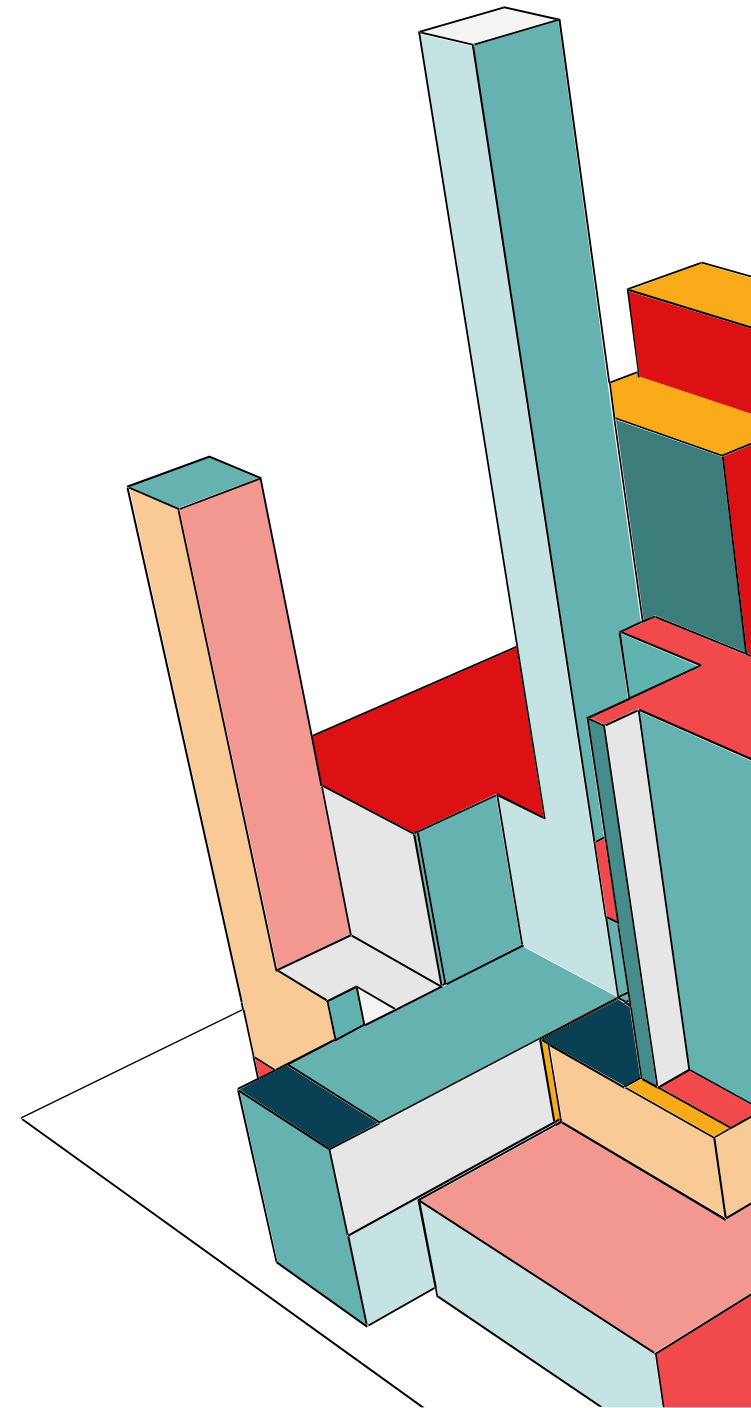
KEY DATA SOURCES

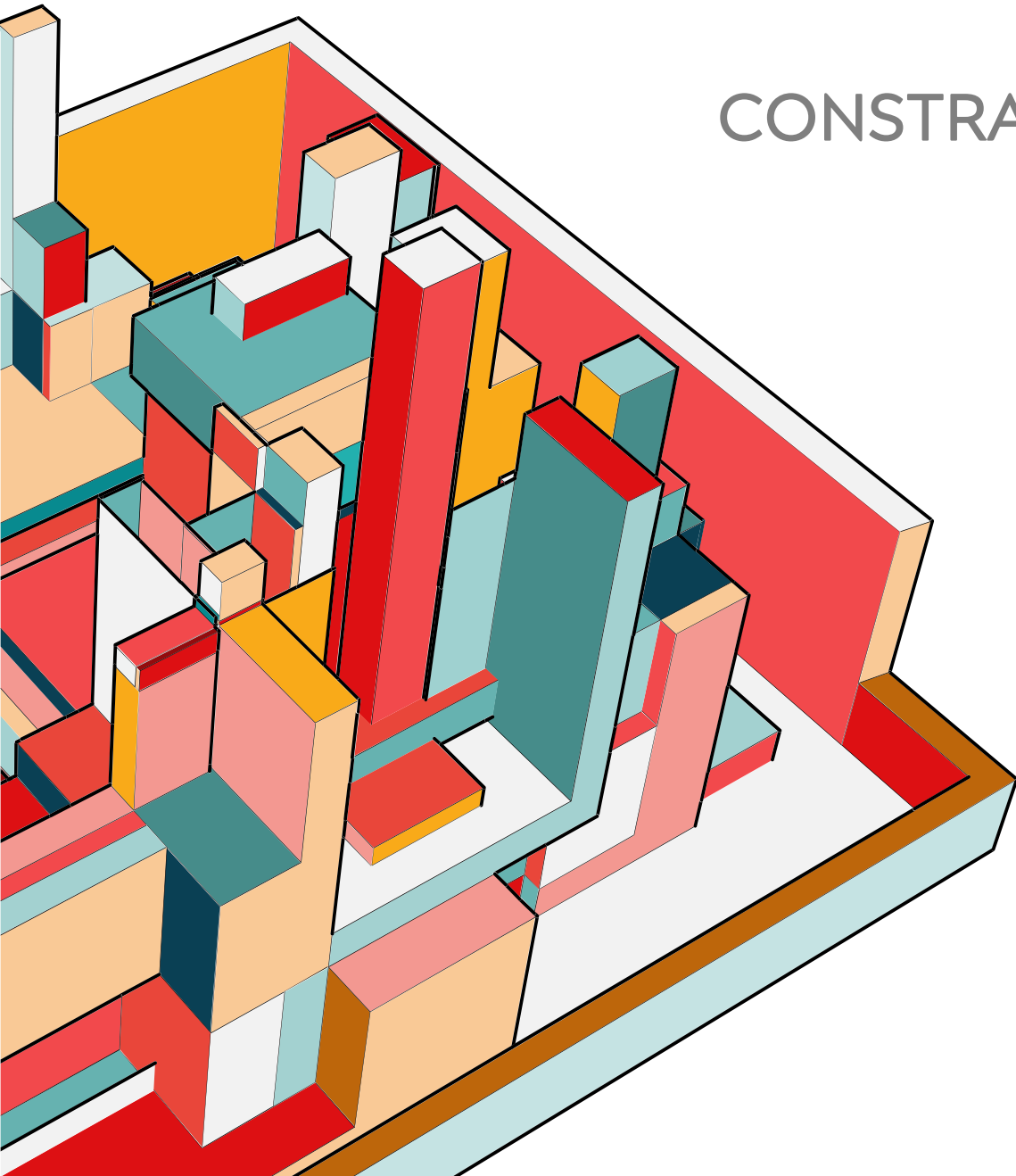
- 1200 images in .tif file format
- Tabular data containing image labels



CRITERIA FOR SUCCESS

- Implement a **Deep Learning algorithm** **able to detect at least 80%** of the Retinopathy Grade in .tif images
- Implementing a **Risk of Macular Edema Classifier**
- Having a deployable pipeline for **DR grade detector in a clinical** setting





CONSTRAINS WITHIN SOLUTION SPACE

- Not getting enough **computational power** to analyze all file images.
- **Image format** not being the correct one for proper analysis or implementation
- **Class imbalance** for the binary class or multi class project
- Deep learning model lacking **interpretability**

KEY FINDINGS AND INSIGHTS

Multiclass classification project
(Class 0-Normal, Class 1, Class 2 and Class 3: grade of DR)
1309 images after manual data augmentation

Architectures Tried

CNN with data transformation

CNN without data transformation

ResNet18 NN Architecture

Constraints faced

Not enough information for a second label. Dataset only enough for a DR grade classification

CPU power made the ResNet18 training a very long process

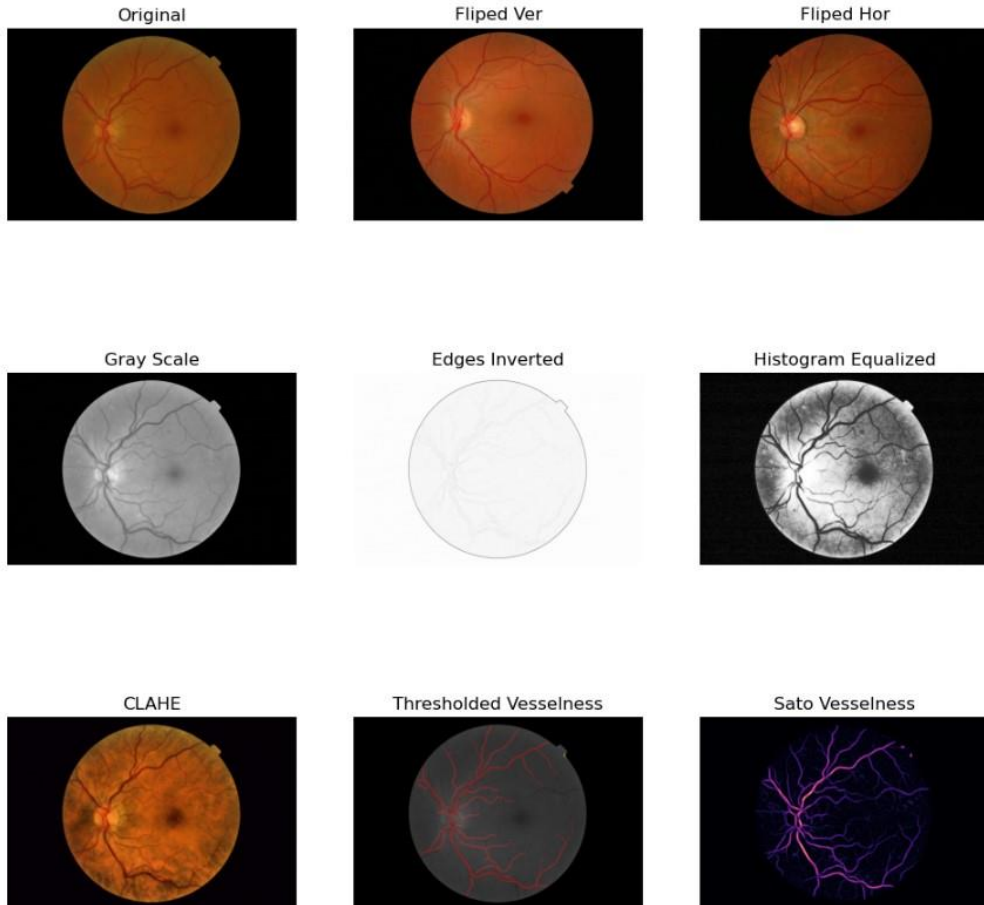
Key Insights

Correct image processing is critical for model performance

Simple CNNs are fast but could lack performance in terms of accuracy

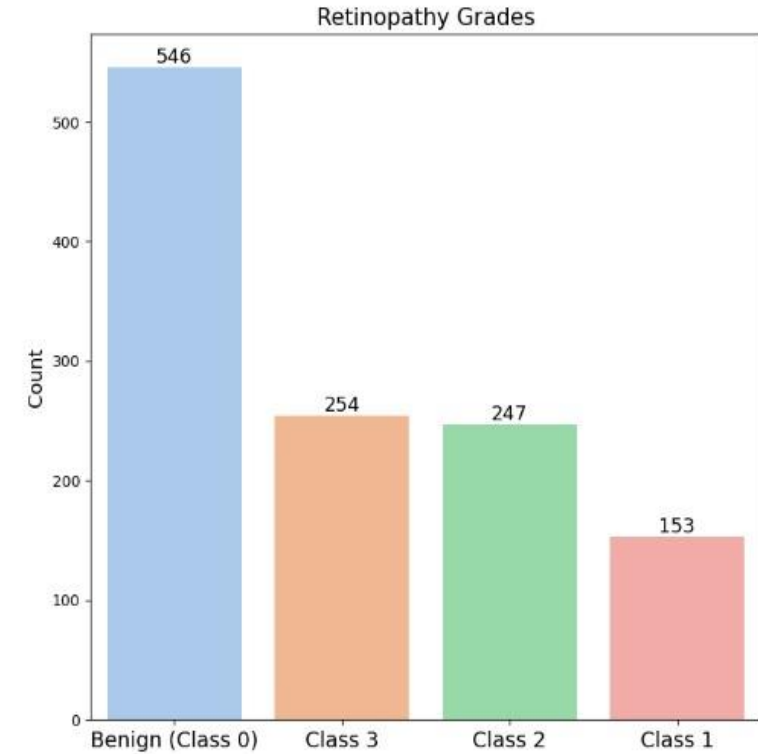
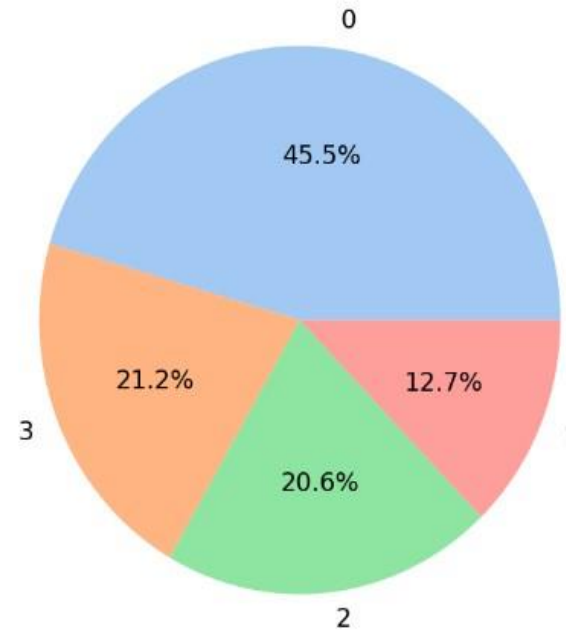
Transfer Learning is proven to be very effective for computer vision problems like this one

TYPES OF IMAGE PROCESSING



CLASS BALANCE

Retinopathy Classes: Benign (Lvl 0), Lvl 1, Lvl 2, Lvl 3



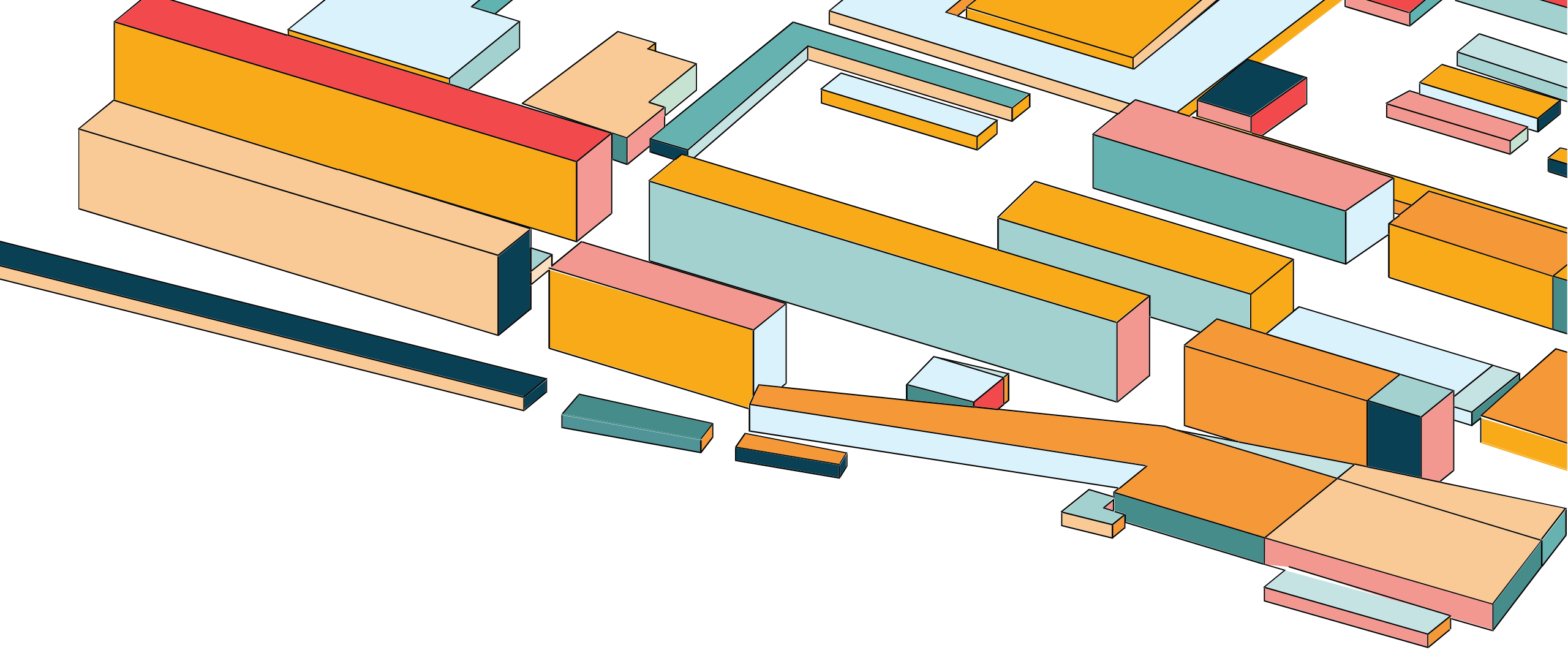
For this project we only used:

Normalization

Resizing to 224x224x3

$$\mu = \frac{\text{sums}}{(N)}$$

$$\sigma = \sqrt{\frac{\text{sumssquared}}{N} - \mu^2}$$



MODEL RESULTS AND ANALYSIS

MODELS AND METRICS USED

DATA PREPROCESSING PIPELINE

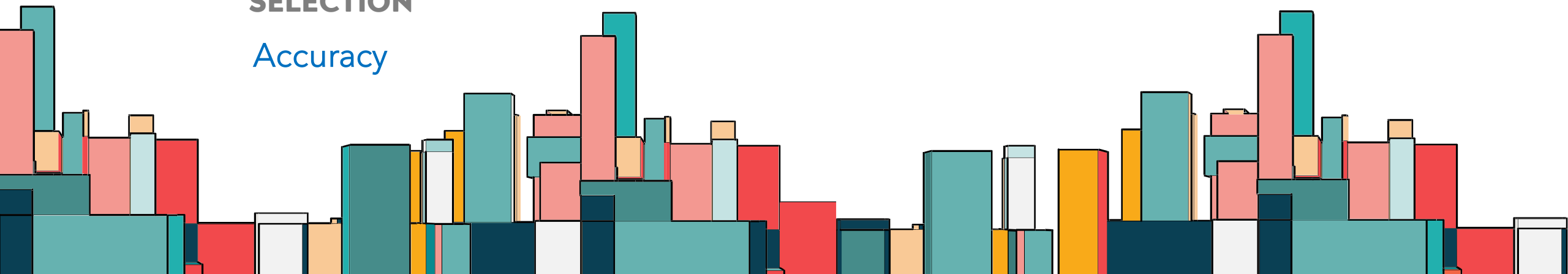
- Data Preprocessing Pipeline
- 1.- Image to tensor
 - 2.- Normalize
 - 3.- Random affine images (train)
 - 4.- Save as numpy arrays
 - 5.- Loaders: batch sizes of 10

MODEL RESULTS

Network Architecture	Accuracy	Computation Time (on CPU)
CNN with Random Affine Transformation	42.3%	309 seconds
CNN without RA	57.9%	302 seconds
RessNet18	80.3%	2.5 hours

METRICS PRIORITIZED FOR MODEL SELECTION

Accuracy



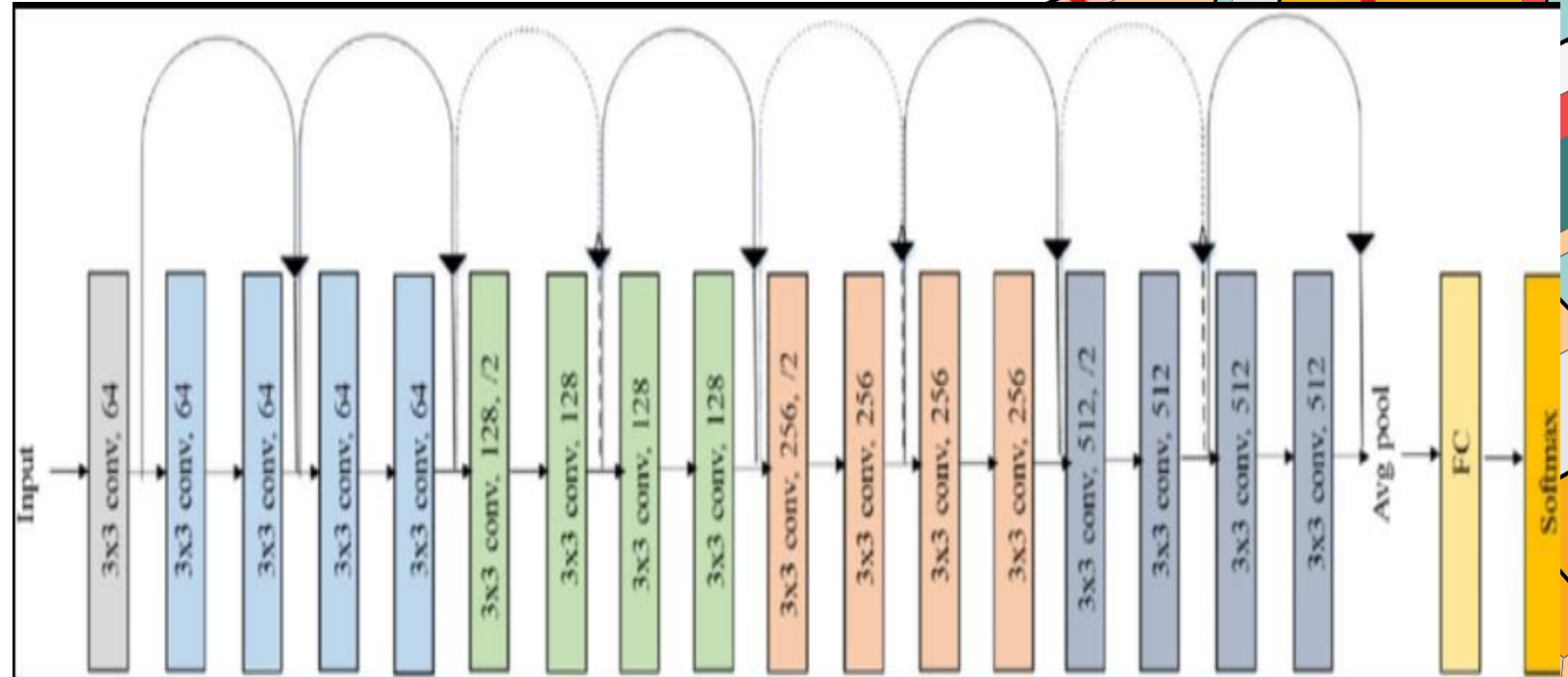
MODEL SELECTION RESULTS

The model selected was:

ResNet18 Architecture

Considerations:

- Accuracy
- Transfer learning
- Accessibility



| Accuracy | 0.803 |

SUMMARY & FUTURE WORK

KEY TAKEAWAYS

1. Key importance in using robust architectures and transfer learning
2. Importance of correct image preprocessing
3. Effectiveness for DR Grade classification by using DL techniques

FUTURE WORK

1. Trying different processing tools in images
2. Gather more data from different locations (demographics) to check if the model is generalizable.
3. Training the ResNet18 using GPU resources.
4. Complementing the project to include a "risk of macular edema" classifier

THANK YOU

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