Convolutional Neural Networks in Orbital Abscess Detection

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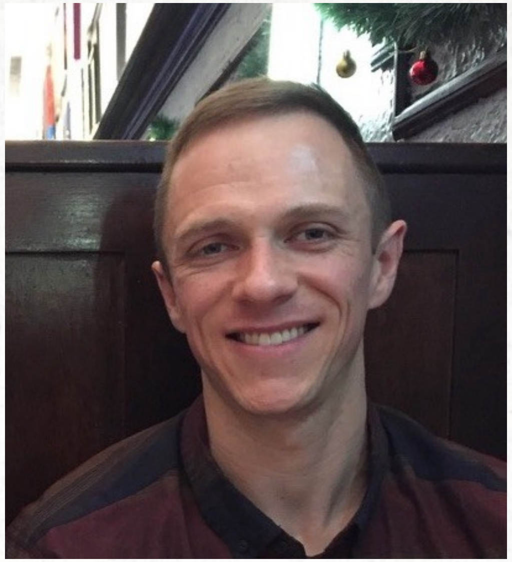
OUR TEAM

Bill Steel



Ryan Summers

Agenda

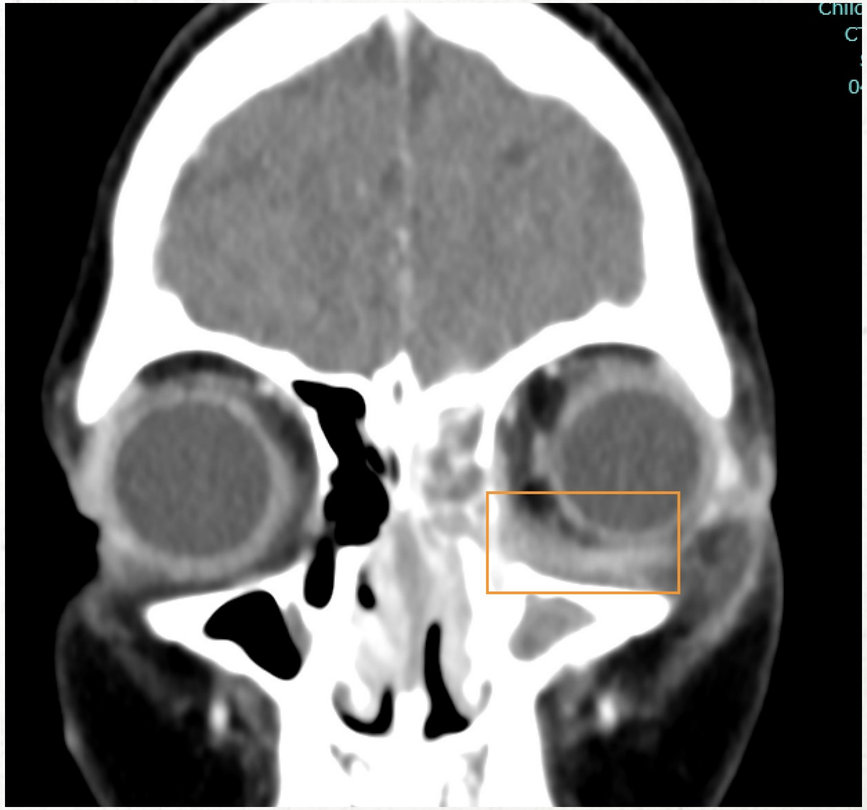
- ***Introduction/Background***
- Executive Summary
- About our Data
- Data Preparation
- Modeling
- Results
- Conclusions and Next Steps

Introduction

Orbital cellulitis is a complex diagnosis that involves an ophthalmologist. Our model is intended to assist a primary care physician/regular eye doctor in rapidly identifying the condition as it's time sensitive.

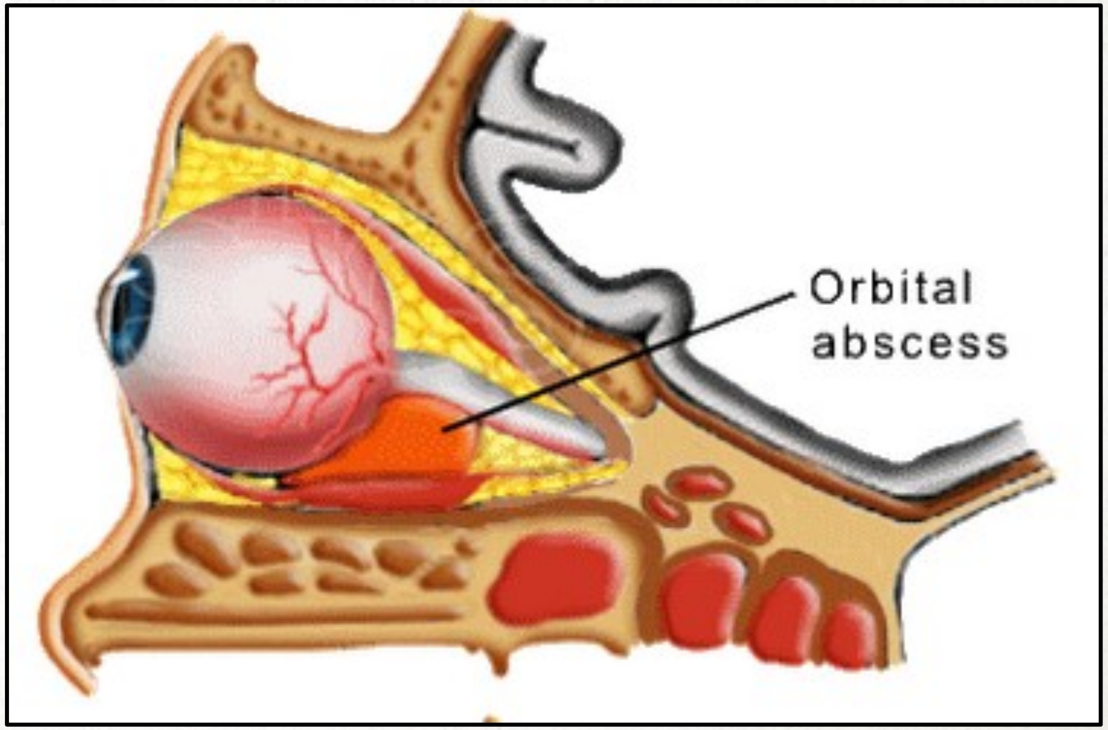
- Orbital cellulitis (OC) is a prevalent cause of pediatric ophthalmic admissions in the US.
- OC is a very rare infectious disease, often accompanied by complications such as orbital abscesses.
- Accurate identification of abscess characteristics is crucial.

Left Inferior (Bottom of left eye)



Background

- An accumulation of pus within the orbit, typically occurring behind the eyelids in the orbit.
- Can cause vision loss, meningitis, blood clots in the sinuses, and potentially life-threatening.
- Objective is to develop a deep Convolutional Neural Network (CNN) model to classify the presence of an orbital abscess based on Computed Tomography (CT) imaging.



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Executive Summary

Ultimately, we achieved a model accuracy of 85% on our test data given some difficult challenges.

- Transfer learning starting with the VGG16 (CNN model used for image recognition) was most effective.
- Overfitting was a challenge, but additional dense layers and dropout reduced overfitting and improved model robustness resulting in improved accuracy/low loss.
- Augmentation techniques like pixel normalization and shearing improved performance.
- Clearly, CNNs offer promise for abscess identification addressing limitations of traditional methods.
- Future focus: obtain more images and further develop image augmentation methods to improve accuracy and model robustness.

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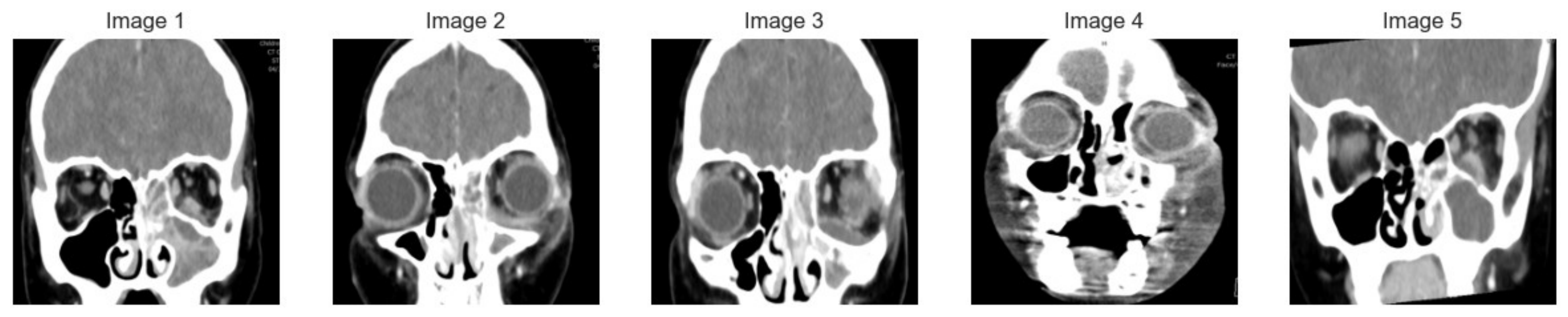
About Our Data

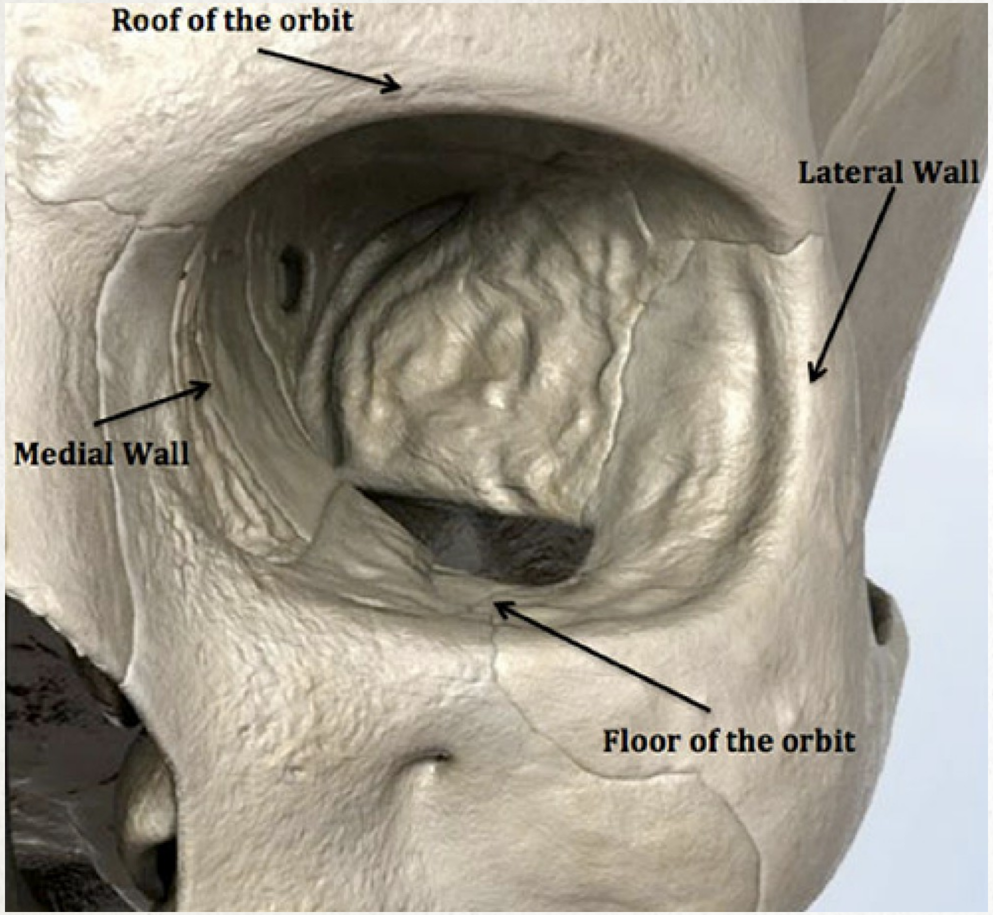
- Imaging provided by the University of Colorado Anschutz Ophthalmology Department.

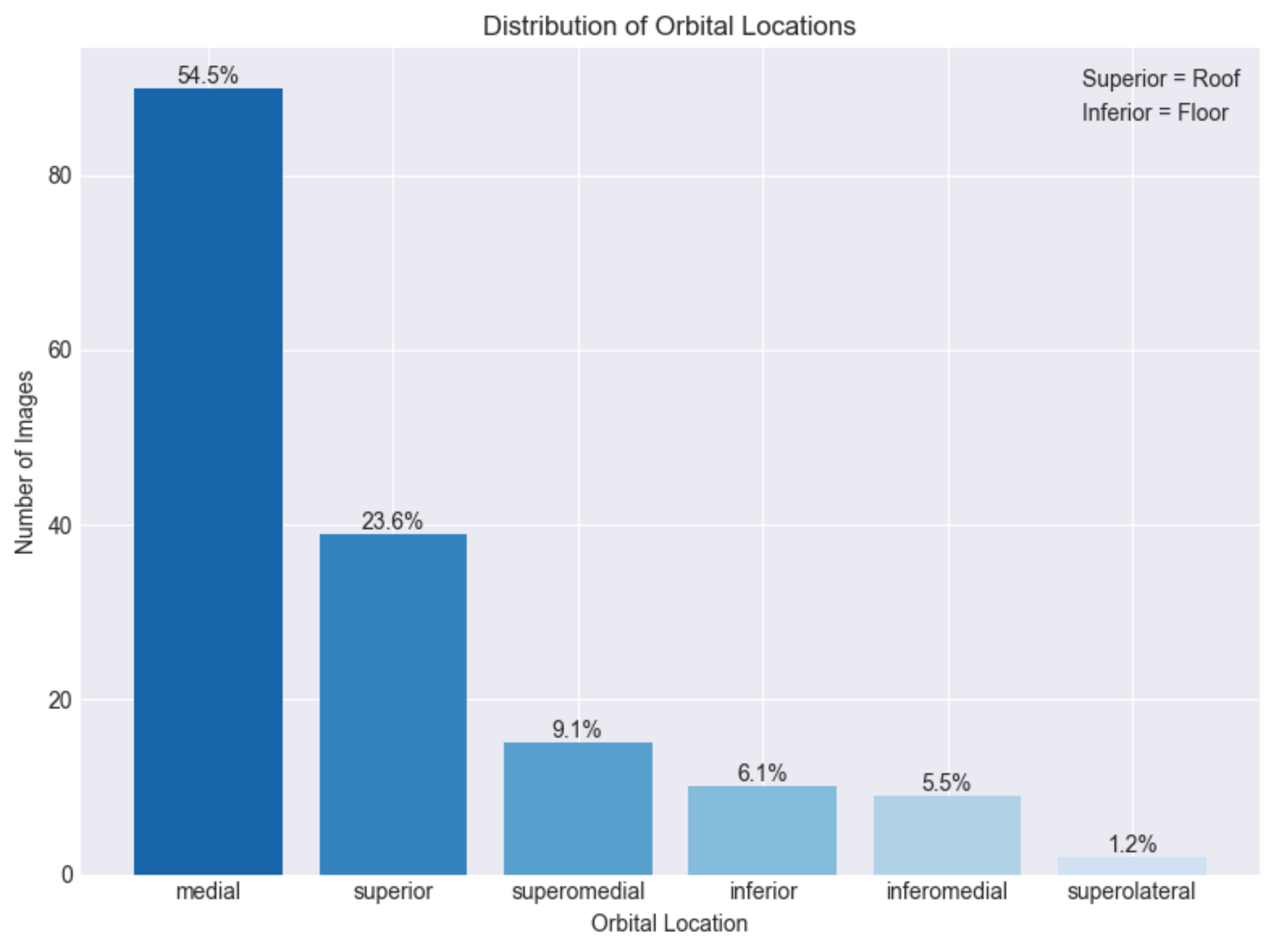
- 165 coronal cuts of orbital Computed Tomography (CT) scans.

- Children (<18yrs) admitted to CU Anschutz hospital between 2018 and 2022.
  - White: **82.7%**
  - Black: **11.9%**
  - Asian: **5.4%**
  - Hispanic (regardless of race): **20%**



Orbital Abscess Locations





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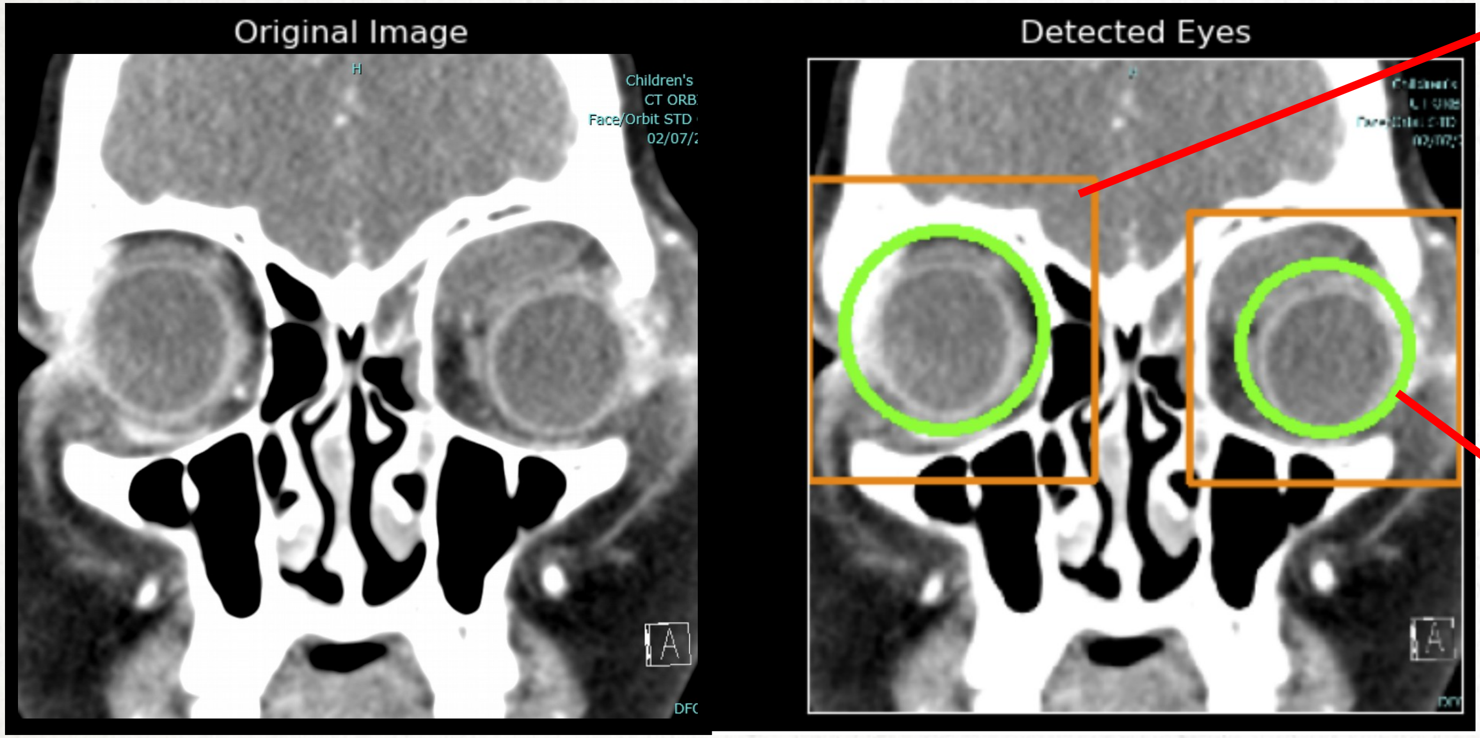
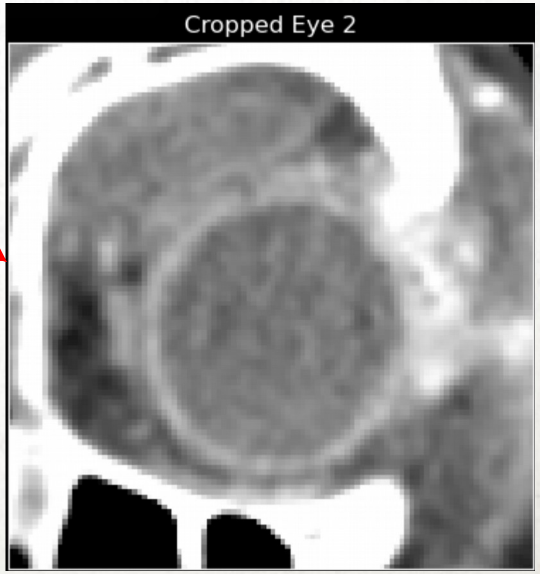
Eye Detection & Cropping

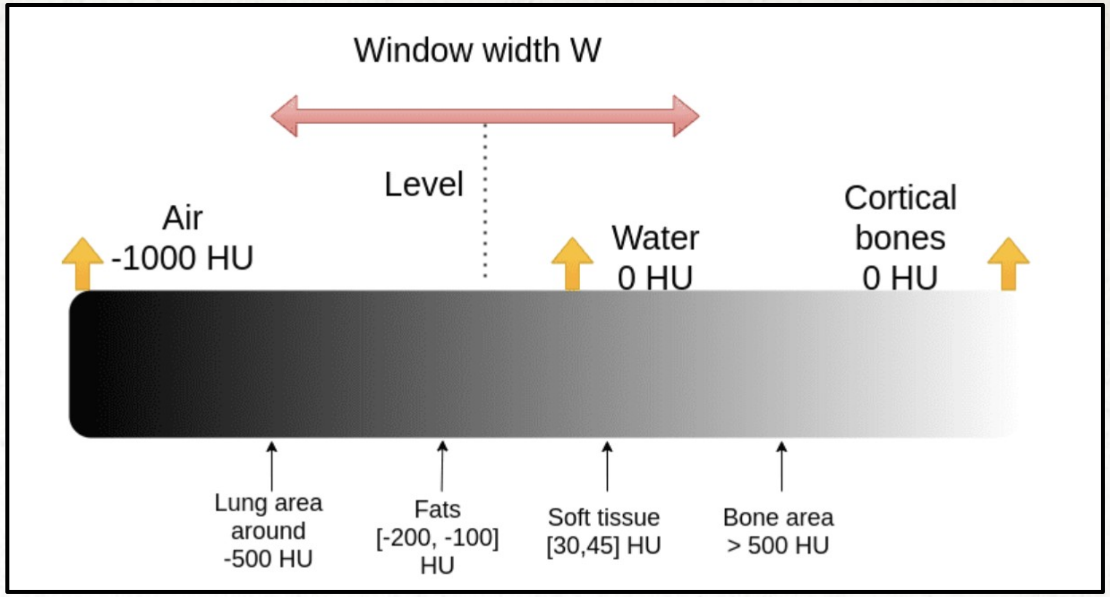
- Each CT Scan was cropped into two classes:
  - “Healthy” and “Infected”





Augmentation Methods

- Hounsfield Unit – Radio Densities
    - Abscesses: ~0-46 HU
- Five density levels mapped to each eye
- Shearing, rotated, flipped vertically/horizontally, and normalized pixels to range of [0,1]



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Modeling Approach

Our approach leveraged an existing medical imaging model with added layers to create a robust model for accurately classifying our specific eye images.

1. Transfer Learning: We used a pre-trained model called VGG16, which has already learned to recognize general patterns in images.

- Initial Freezing: We initially kept all the layers of VGG16 unchanged to utilize its existing knowledge.
- Selective Unfreezing: We later allowed the last few layers of VGG16 to be updated so the model could better adapt to our specific medical images.

2. Custom Enhancements: We added extra layers on top of VGG16 to improve its ability to extract relevant features from the images.

3. Classification Layers:

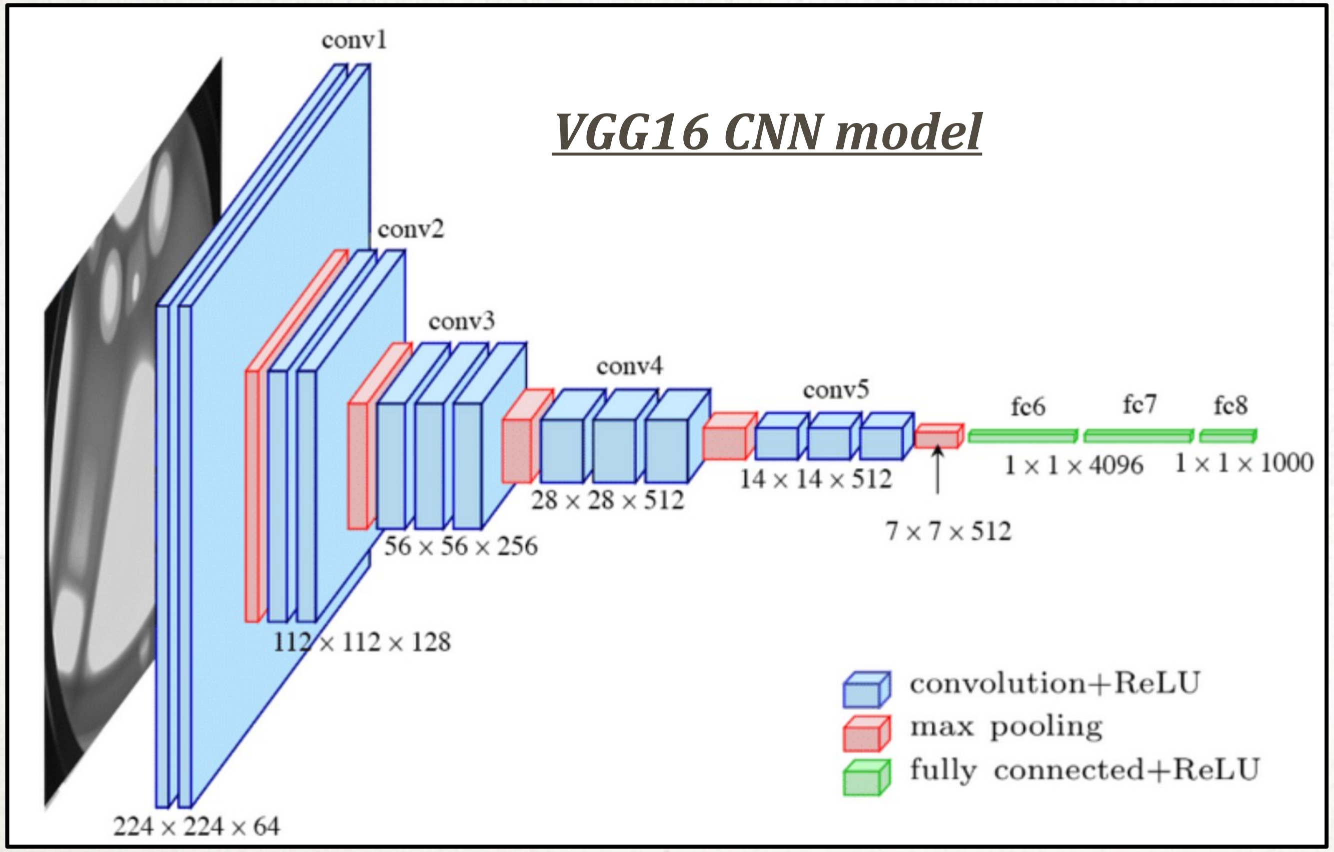
- We transformed the output from the enhanced layers into a format suitable for decision making.
- We included several layers to refine this output and prevent overfitting (where the model performs well on training data but not on new data).
- We used a final layer to make a yes/no decision for each eye image.

4. Model Optimization:

- We adjusted the model to learn effectively from our data.
- We measured performance using metrics like accuracy, precision, and recall to ensure the model is reliable and effective.

Modeling

As previously discussed, we used the "transfer learning" approach given our data limitations. The VGG16 model was our starting point.

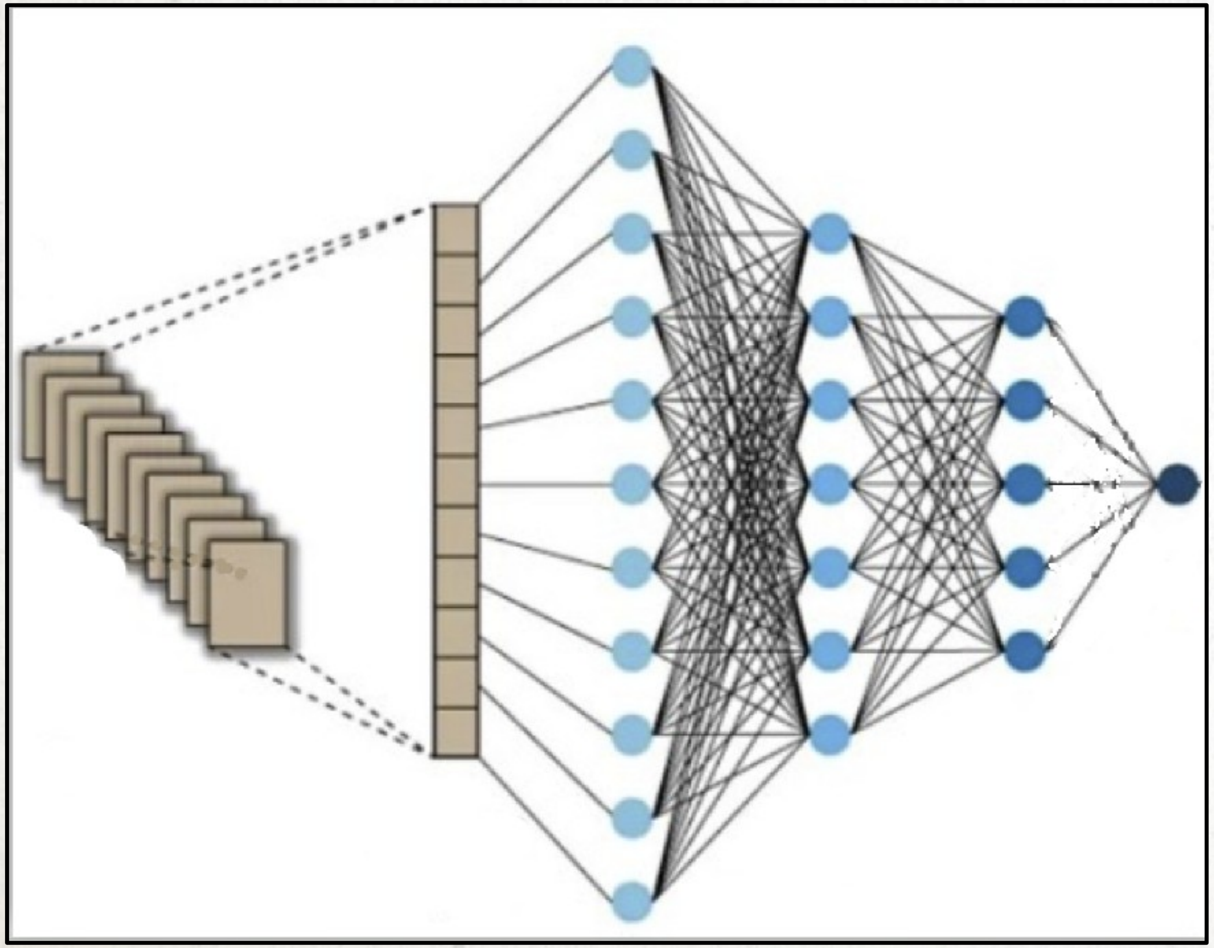


- VGG16 is a pre-trained model on the ImageNet dataset. We loaded it with its custom weights, excluding the top 4 layers of the VGG16 model, and set the input shape to our desired image size with 3 color channels (RGB).

- Conv2D and MaxPooling2D layers: VGG16 consists of a series of convolutional layers (Conv2D) followed by max-pooling layers (MaxPooling2D). These layers extract features from the input images.

Modeling

We added several layers to train the model with respect to our eye images aimed at preventing overfitting for a more robust model.



Flatten Layer: Converts the 3D output from the convolutional layers into a 1D vector.

Dense Layers: Added fully connected layers:

- Layer 1: 256 units, ReLU activation, and L2 regularization with a factor of 0.001.
- Layer 2: 128 units, ReLU activation, and L2 regularization.
- Layer 3: 64 units, ReLU activation, and L2 regularization.

Dropout Layer:

- Adds a dropout layer with a 50% dropout rate to prevent overfitting by temporarily disconnecting 50% of the neurons during training.

Output Layer:

- Adds a single-unit dense layer with sigmoid activation for binary classification, with L2 regularization.

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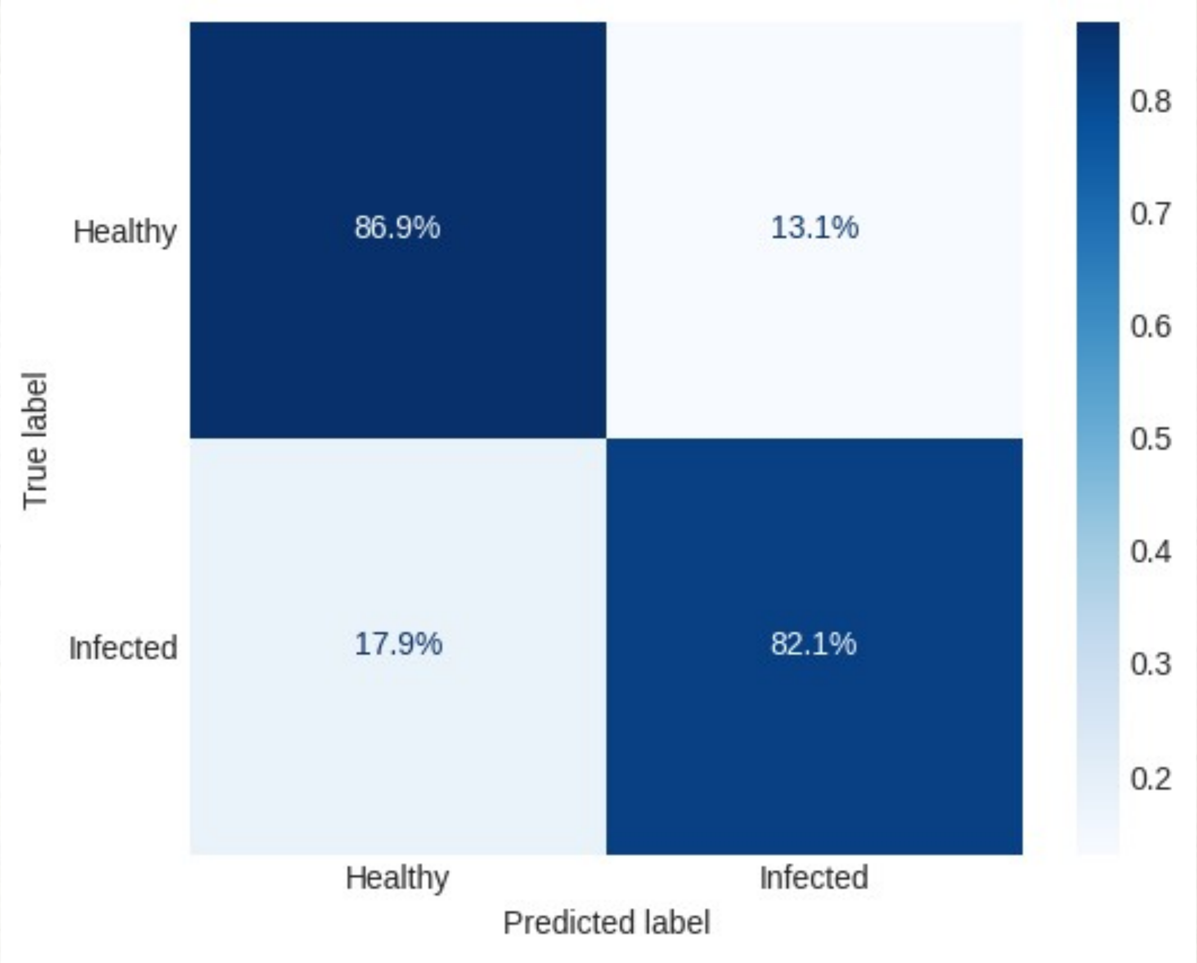
Training & Validation Results

- A noticeable zig-zag pattern was noted over each epoch.
- This indicates the model has varying degrees of model generalization across epochs
- This raises concerns of:
  - Overfitting
  - Model complexity
  - Regularization rate
  - Learning rate (LR) fluctuations (reduced LR when validation loss stops improving)

Model Evaluation Results

- Test Loss: 1.0897
- Test Accuracy: 84.57%
- F1-Score: 84.55%
- Precision: 84.59%
- Recall (Sensitivity): 84.57%
- Specificity: 86.9%

	precision	recall	f1-score	support
0	0.8391	0.8690	0.8538	84
1	0.8533	0.8205	0.8366	78
accuracy			0.8457	162
macro avg	0.8462	0.8448	0.8452	162
weighted avg	0.8459	0.8457	0.8455	162



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Conclusions

- Freezing the base layers and unfreezing the top four layers of the VGG16 model proved to be the most effective strategy compared to other combinations of freezing/unfreezing layers. Additionally, the incorporation of three additional dense layers and a dropout layer to mitigate overfitting enhanced the model's performance.
  - L2 regularization was applied to the three dense layers to further address overfitting concerns.
  - However, despite these optimizations, the model still exhibited signs of overfitting, with training accuracy often reaching 100% while validation and test accuracies ranged from 50% to 85%.

- Augmentation techniques played a crucial role in improving model performance, with methods such as image flipping, intensity adjustments, shear, and rotation proving to be effective. Notably, normalizing pixel values to the range of [0, 1], combined with shearing techniques and variations in density levels, yielded superior results compared to other augmentation methods. Conversely, vertical/horizontal flipping, image rotation, and zooming did not contribute significantly to performance improvement.

- The diverse nature of abscesses, characterized by variations in shape, size, appearance, and location, poses challenges for accurate prognosis. Traditional methods reliant on physician specialists suffer from drawbacks such as high costs, physician fatigue, and limited availability within healthcare systems. The integration of deep learning techniques, particularly convolutional neural networks (CNNs), offers a promising solution by extracting essential features from imaging data to aid in diagnosis and prognosis.
  - However, CNNs are not without limitations, notably the "black box" issue, where the rationale behind a model's feature selection remains opaque. Ongoing research efforts aim to address this issue by unraveling the network's perception at both output and intermediate layers, providing physicians with valuable insights into feature importance.

Next Steps

These advancements hold the potential to significantly enhance diagnostic capabilities and improve patient outcomes in the field of orbital abscess identification.

- Moving forward, efforts will focus on further mitigating overfitting and refining the model's ability to identify the location and size of abscesses.
- Collecting more data an introducing it into the model. These images are difficult to come by.
- Look at other methods data augmentation and refinement.