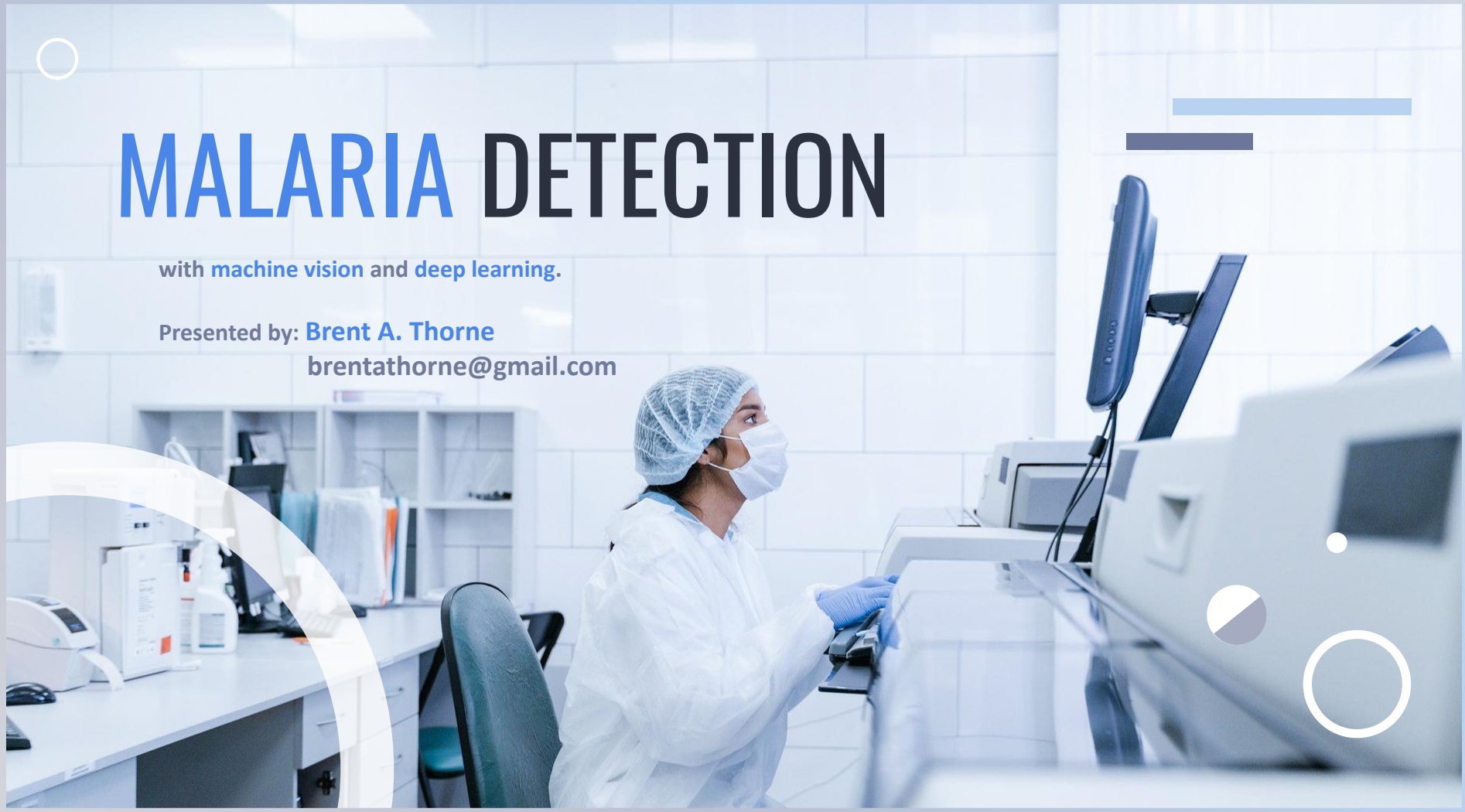
MALARIA DETECTION

with machine vision and deep learning.

Presented by: Brent A. Thorne
brentathorne@gmail.com



MALARIA DETECTION

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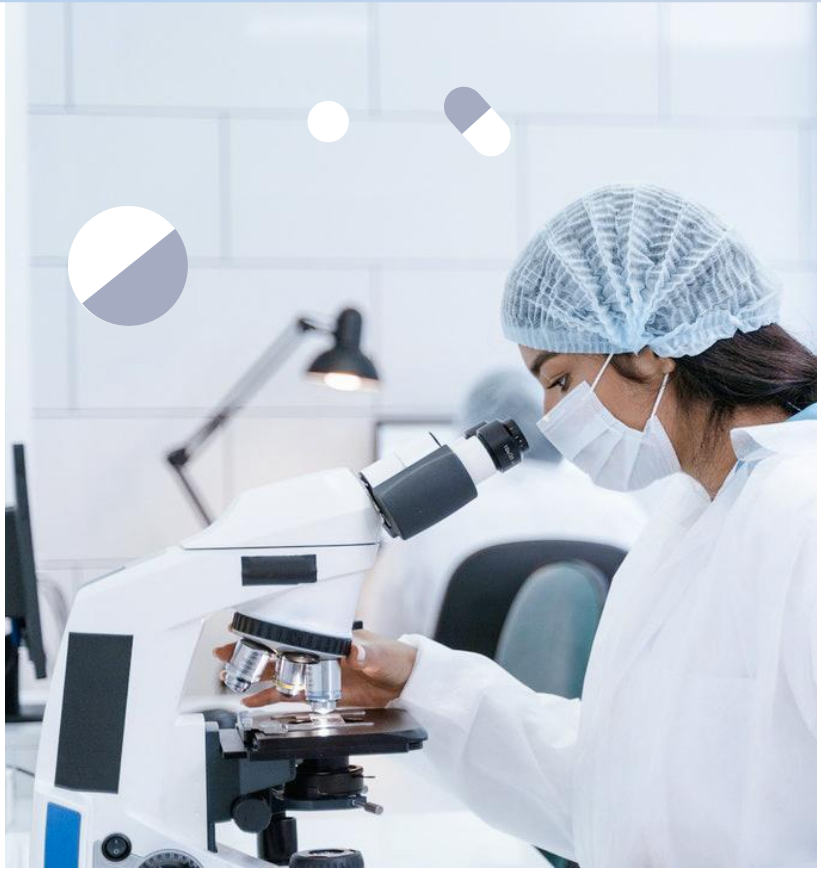
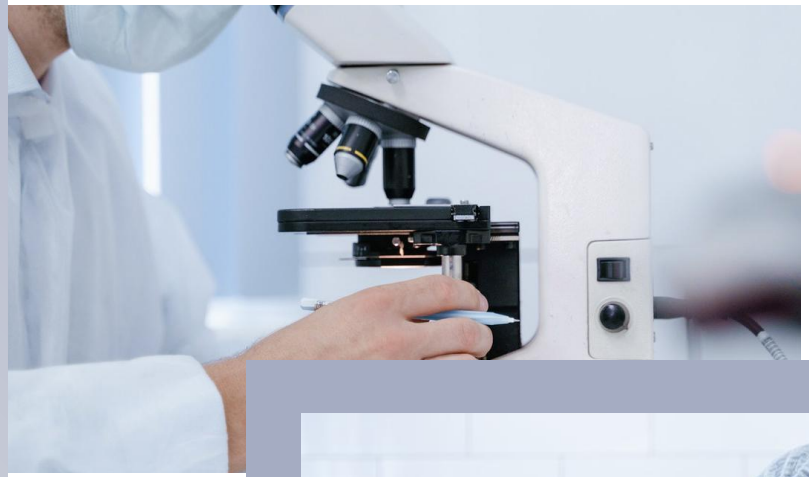




MALARIA DETECTION

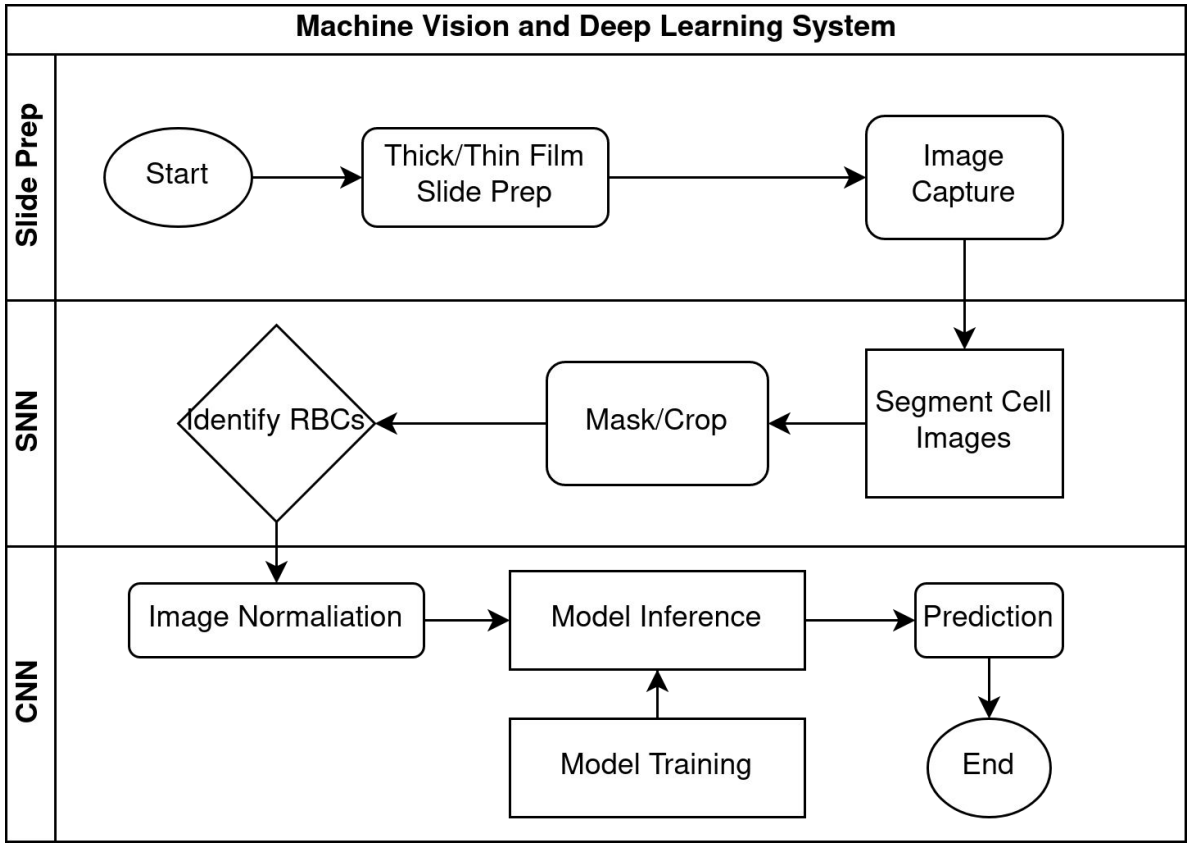
TECHNOLOGY

With the advent of inexpensive and high quality imaging hardware there exists an opportunity to improve the detection rate of Malaria through the use machine vision and deep learning algorithms.

MISSION OBJECTIVE

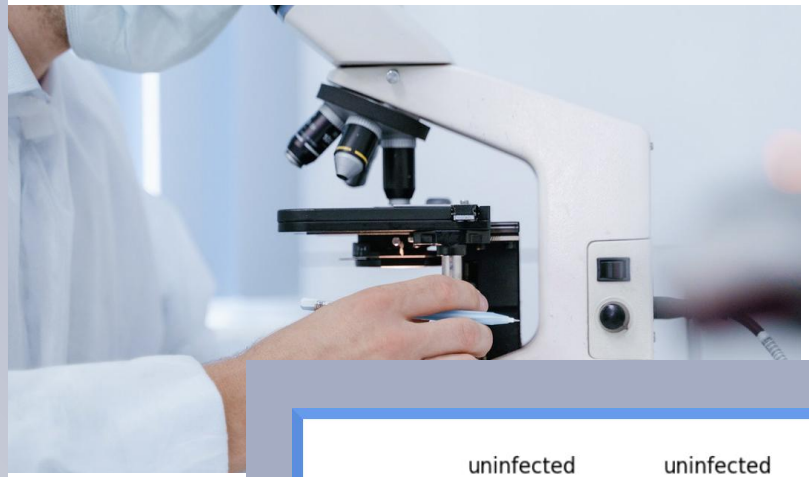
Build an accurate and efficient machine vision model that can improve the detection rate of the laboratory technician.

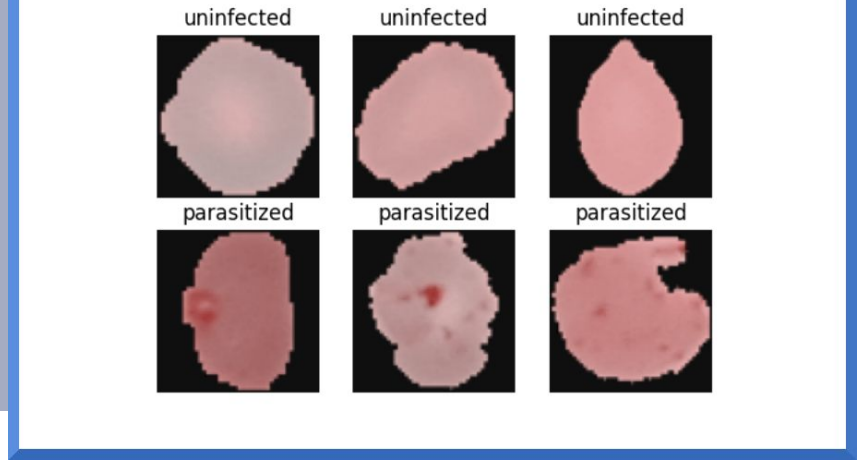
DRIVING COMPONENTS



SOLUTION SUMMARY

- A CNN model chosen based on the nature of the dataset--color images.
- We utilize transfer learning to save and compare model architectures.
- Consider model complexity, execution time, memory allocation and file accesses.
- We evaluate model performance based on precision, recall, and f1-score.
- We minimize false-negatives (Misclassified infected cells).





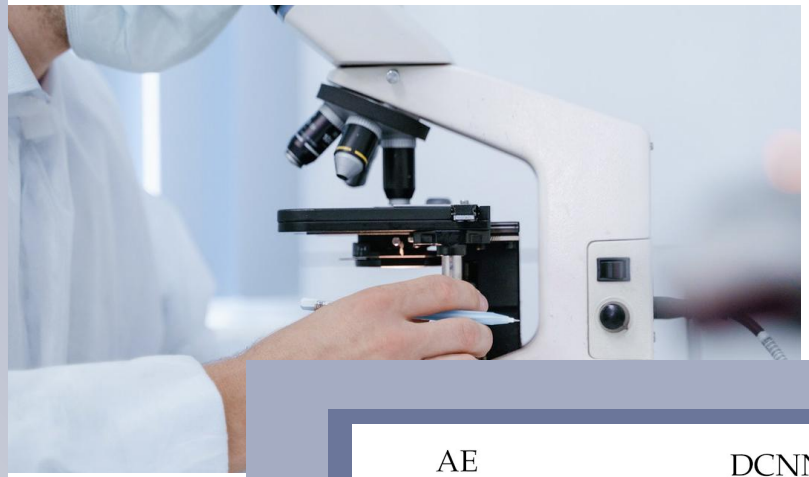
MALARIA DETECTION

IMAGE PROCESSING

We minimize image processing to assure hidden features are available for hypertuning. Images are resized to reduce model complexity and a border added to improve data augmentation.

EXECUTIVE SUMMARY

- Several models of varying layer complexity were compared.
- We found that model performance wasn’t necessarily a function of complexity.
- We also discovered that we could extract certain layers with image processing.
- This removed latent variables that might have been made available to the model.



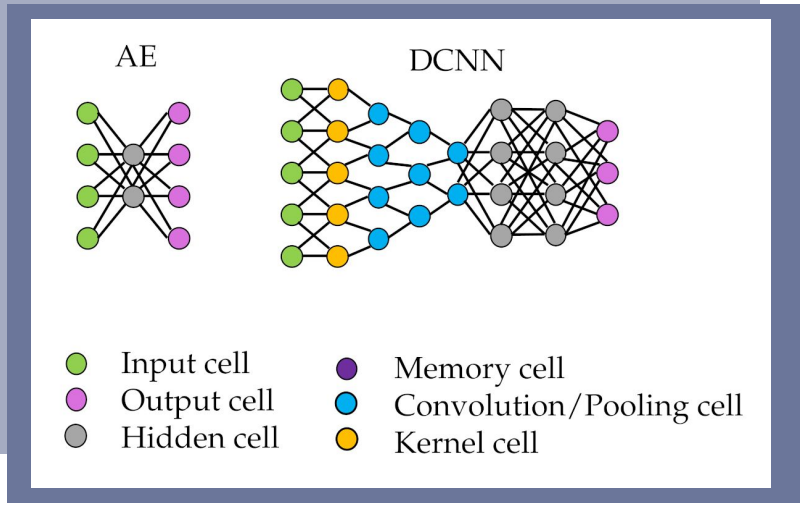


Figure adapted from Brunton/Kutz[6], Figure 6.18.

MALARIA DETECTION

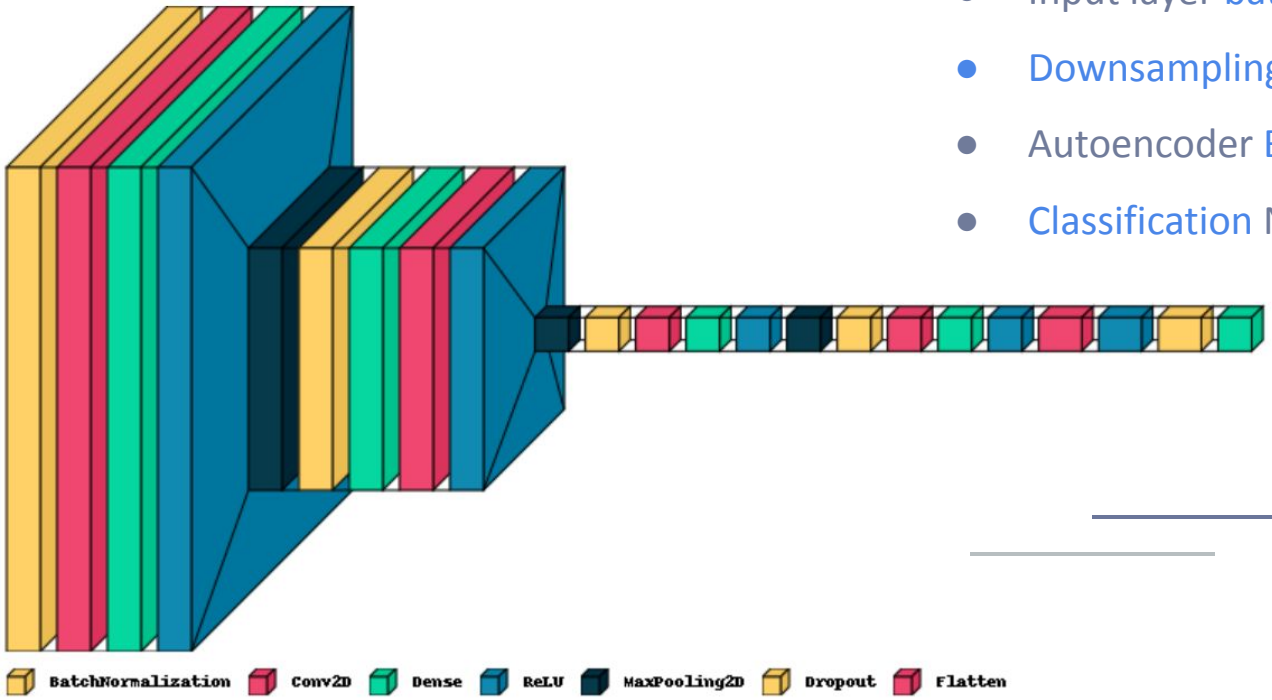
PROPOSED MODEL

Maximized accuracy with a balance complexity, memory usage, and execution time.

RESULTING MODEL

Deep Convolutional Neural Network

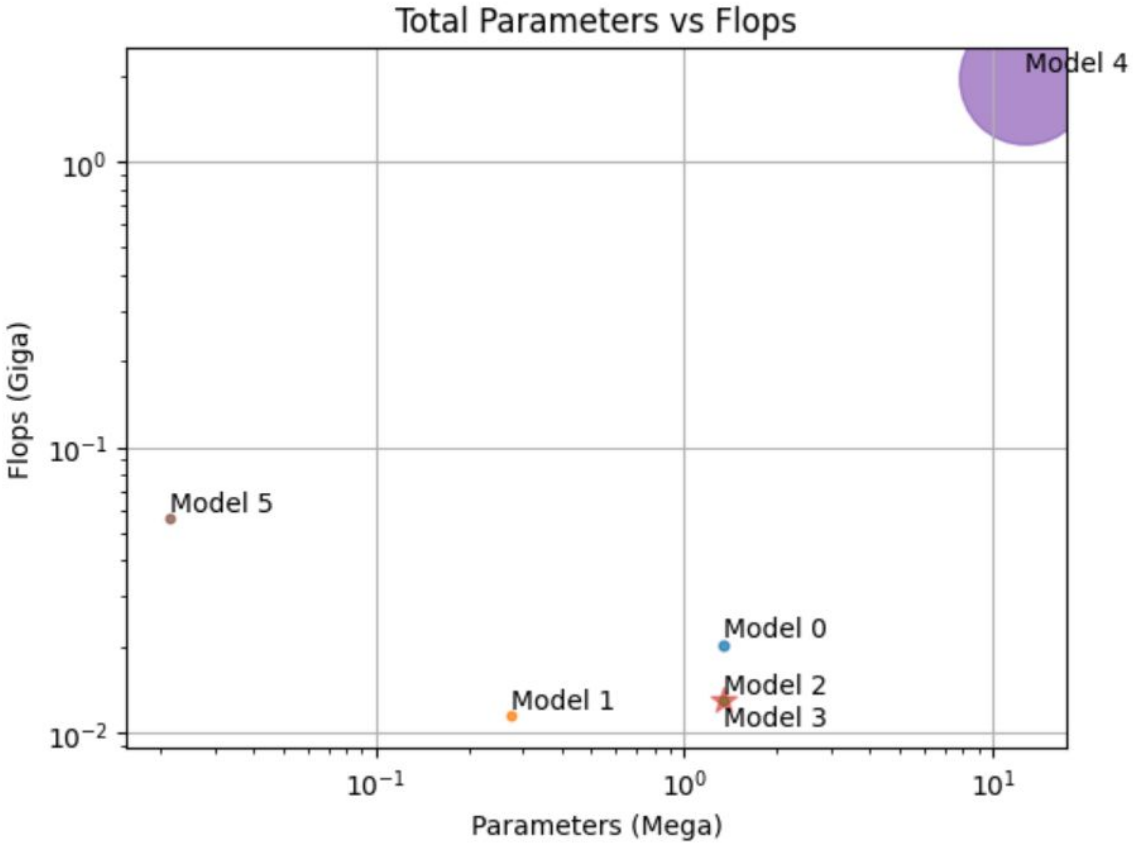
- Input layer batch-normalization
- Downsampling
- Autoencoder Bottleneck Feature
- Classification Network



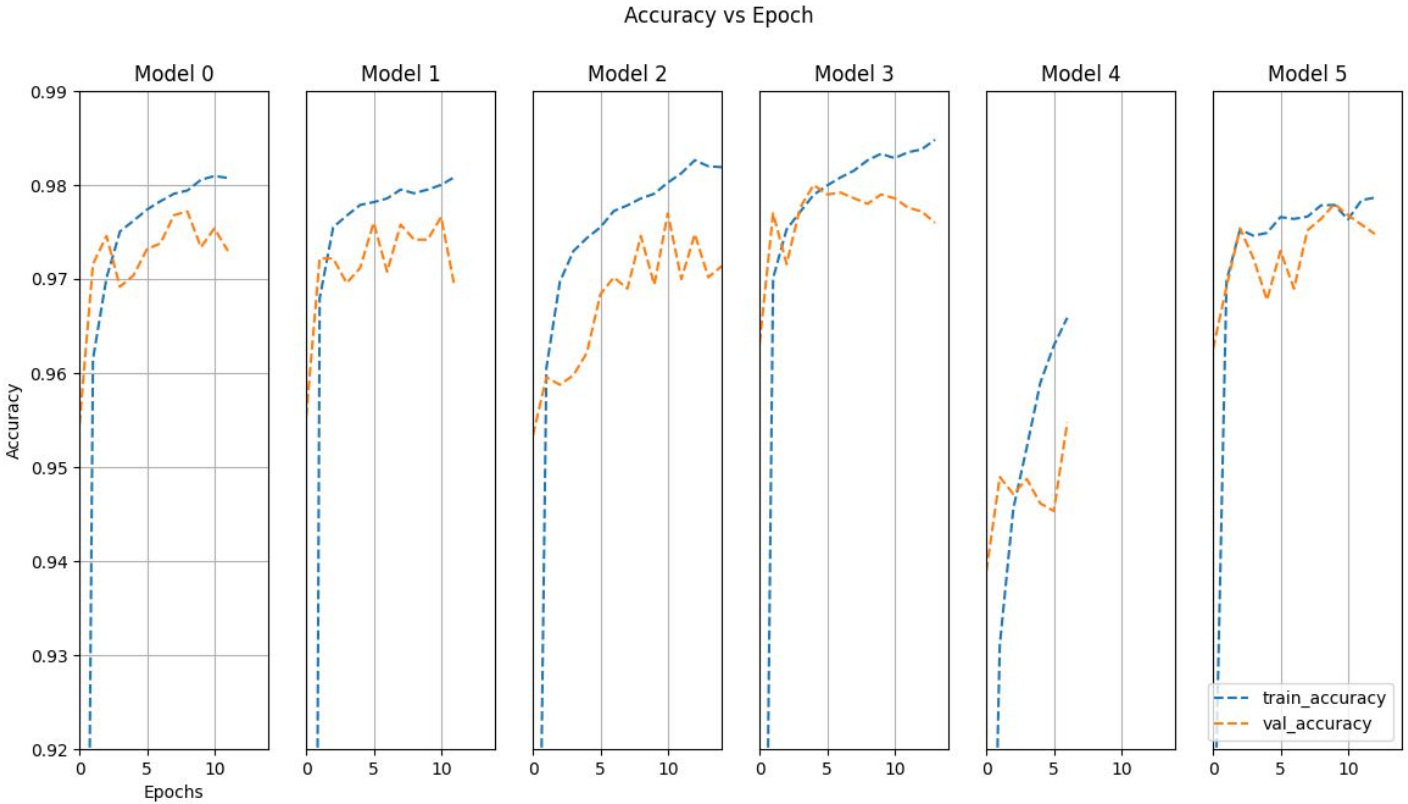
TESTED MODEL ARCHITECTURES

- Model 0: Three Convolution Layers with Dropout
- Model 1: Four Convolution Layers with Dropout
- Model 2: Three Convolution Layers with Dropout and first-layer batch normalization
- Model 3: Three Convolution Layers with Dropout and first-layer batch normalization (w/Augmented Data)
- Model 4: VGG16 Transferred at block3_pool Layer with two dense layers
- Model 5: Autoencoder

MODEL COMPLEXITY



MODEL TRAINING

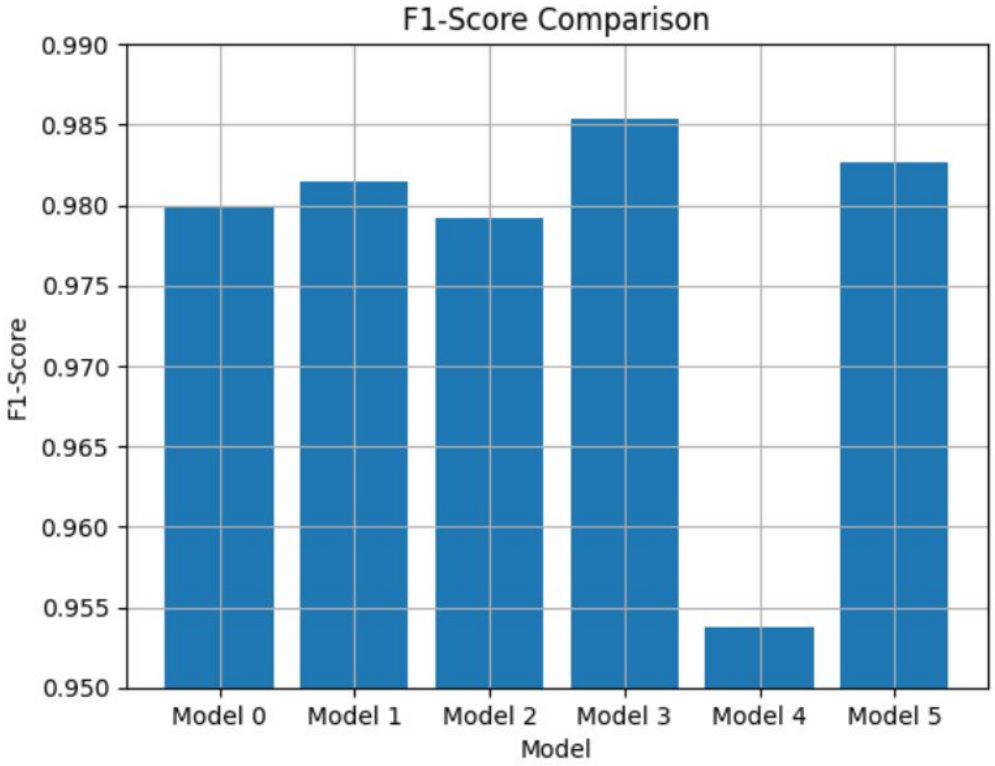


MODEL PERFORMANCE

The f1-score is the harmonic mean of Precision and Recall. It provides a measure of incorrectly classified cases.

Note:

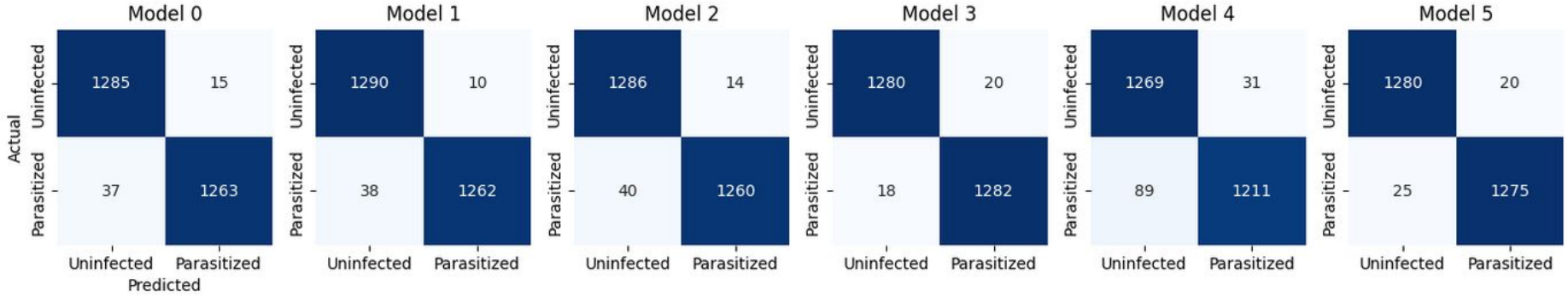
- Model 3 was trained with augmented data.
- Model 5 has the best overall f1 score.



CONFUSION MATRIX COMPARISON

Minimize Errors

- False Positive: (Type 1 Error)
- False Negative: (Type 2 Error, Missed Diagnosis)

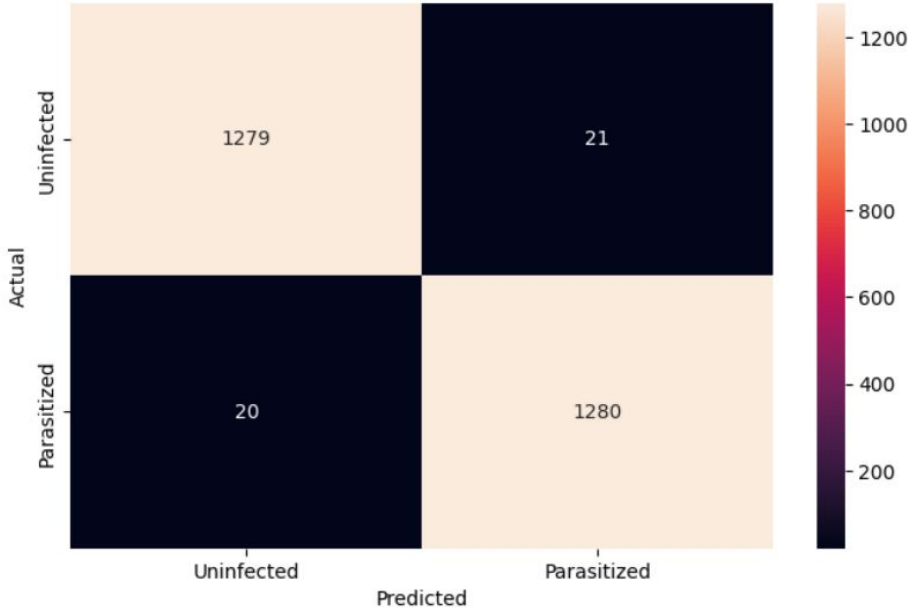


Note: Model 2 and 3 architectures are identical.

Model 3 was trained with additional augmented data.

MODEL 5 WITH AUGMENTED DATA

	precision	recall	f1-score	support
0	0.9846	0.9838	0.9842	1300
1	0.9839	0.9846	0.9842	1300
accuracy			0.9842	2600
macro avg	0.9842	0.9842	0.9842	2600
weighted avg	0.9842	0.9842	0.9842	2600



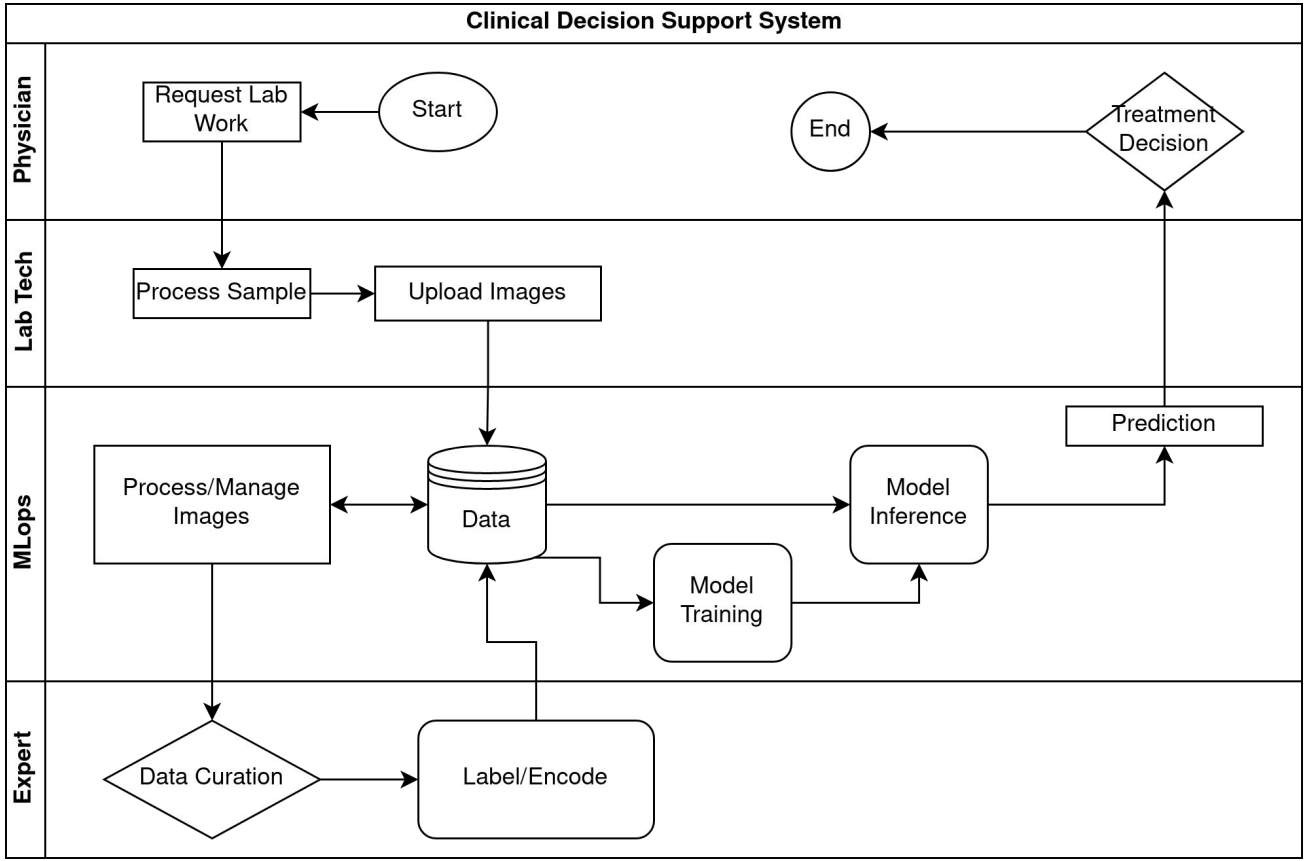
Through data augmentation we can show how our model might improve with online (out-of-core) learning. This shows that our model has potential to grow as additional training batches become available.

MODEL COMPARISON SUMMARY

Model 5 performed the best on the original dataset.

- It had the highest precision, recall, and f1 scores and the lowest false-negatives.
- The training history shows it has the potential to overfit.
- Training with an augmented dataset shows the model potential to grow in performance with additional out-of-core training.
- Reduced model complexity show potential for deployment on low-compute capacity end devices.

STAKEHOLDER BENEFITS



RECOMMENDATIONS FOR DEPLOYMENT

- Customer portal to upload images and notify results
- Server daemons to manage and present images to inference model
- Data Curation portal
- Logging for monitoring system and history of record

THANK YOU

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