WGU MSDA Capstone

Identifying Malaria in Patient Blood Samples Using Convolutional Neural Networks

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Personal Introduction

Colton B. Horton

- Master's student at Western Governors University studying Data Analytics.
- Living in Utah.
- Bachelor's degree in microbiology from Brigham Young University.
- My background in both data analytics and biology inspired this capstone project.

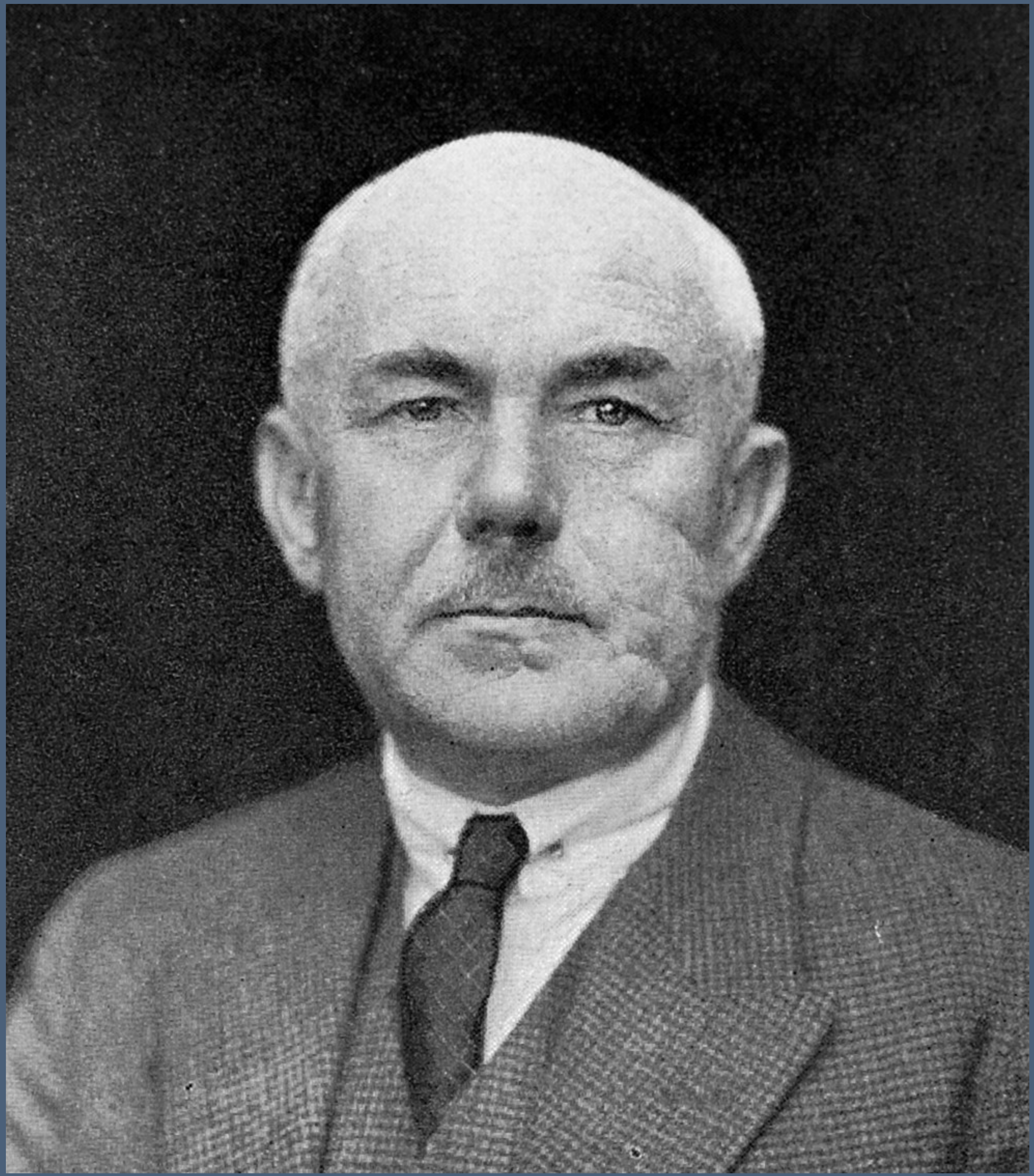
Research Problem

Malaria

A Global Health Challenge

- Malaria is a blood-borne infection caused by *Plasmodium* parasites and carried by mosquitoes. [1]
- It kills hundreds of thousands of people every year around the world. [2]
- It is a curable infection, but diagnosis remains a barrier to treatment, particularly in resource-limited areas. [1]

https://www.flaticon.com/free-icon/malaria_773852



https://en.wikipedia.org/wiki/Gustav_Giemsa

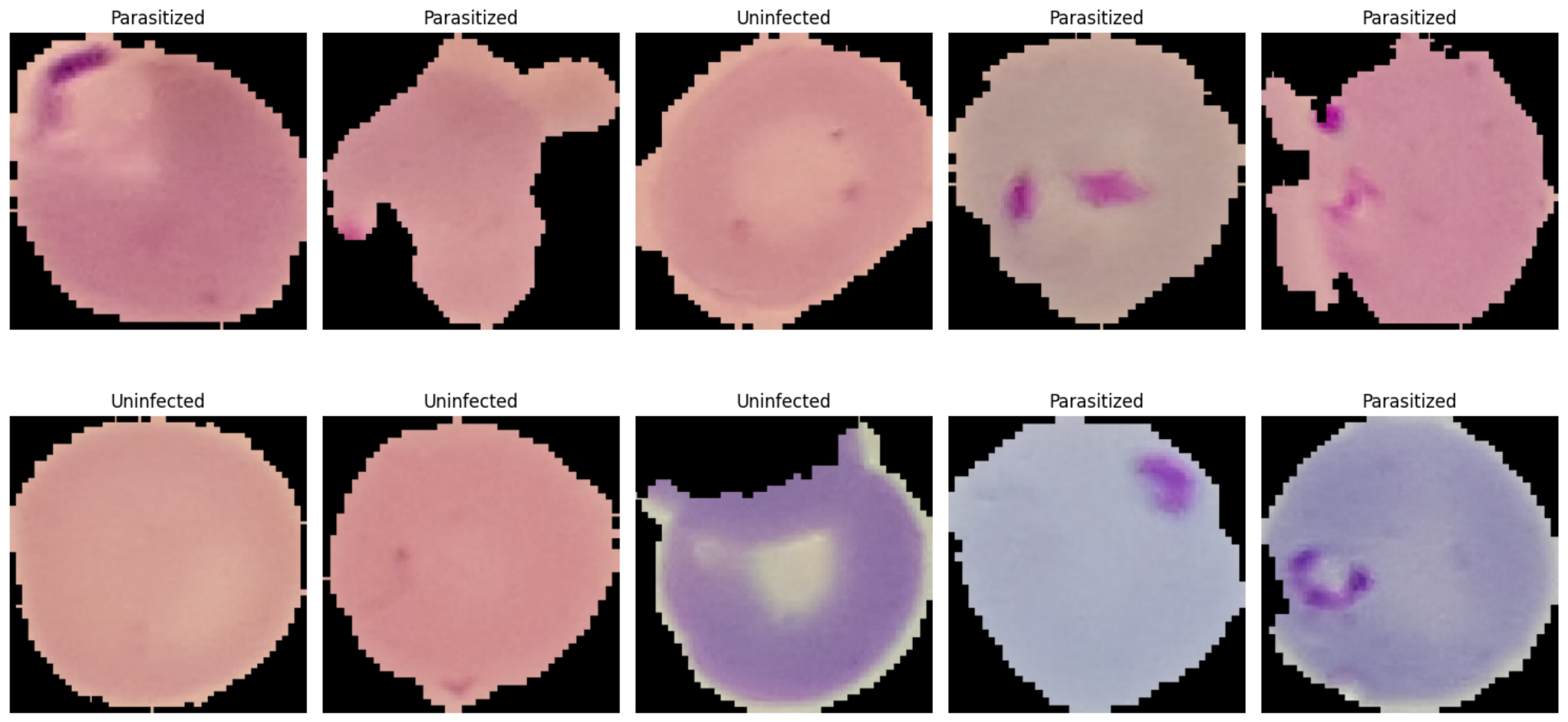
Malaria

Current Diagnostics

- In 1904, Gustav Giemsa created a staining protocol that analyzes human blood under a microscope for the presence of *Plasmodium* parasites. [3]
- It remains the gold standard for diagnosis today. [1]
- The diagnosis accuracy of Giemsa-stained blood samples, analyzed by trained microbiologists is ≈ 90%. [4]

Malaria

Giemsa Stain Example Images



https://www.kaggle.com/datasets/iarunava/cell-images-for-detecting-malaria

Malaria

Research Question

- Developing a quicker diagnostic tool that does not rely on trained microbiologists may: [5]
  - Increase speed to diagnosis.
  - Improve access to treatment.
  - Potentially decrease malaria mortality.
- Can a deep learning model be used as an alternative diagnostic tool to potentially achieve these outcomes?
  - The deep learning model of choice will be a "convolutional neural network."

Hypotheses

Null hypothesis:

- Convolutional neural networks **can not** predict cells infected with malaria with statistical significance, achieving at least 90% accuracy.

Alternative hypothesis:

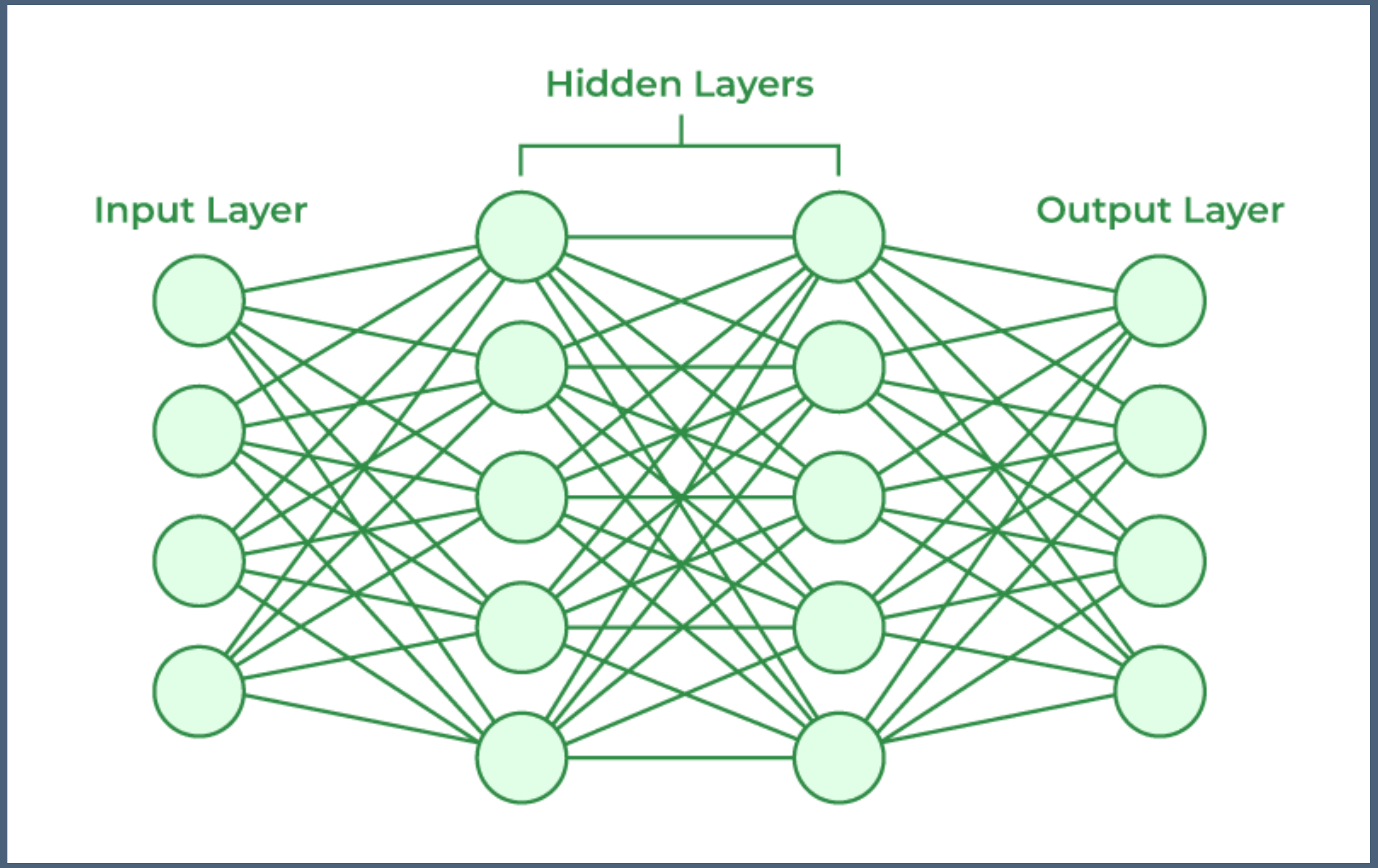
- Convolutional neural networks **can** predict cells infected with malaria with statistical significance, achieving at least 90% accuracy

Data Analysis

Model Building

General Neural Networks

- Neural networks were inspired by the connections in the human brain. [6]
- The goal of a neural network is to learn complex patterns in data.
- Consists of interconnected layers of nodes (or neurons) that identify these relationships.
- There are 3 types of layers: Input, hidden, and output.
  - The hidden layers are the heavy lifters.



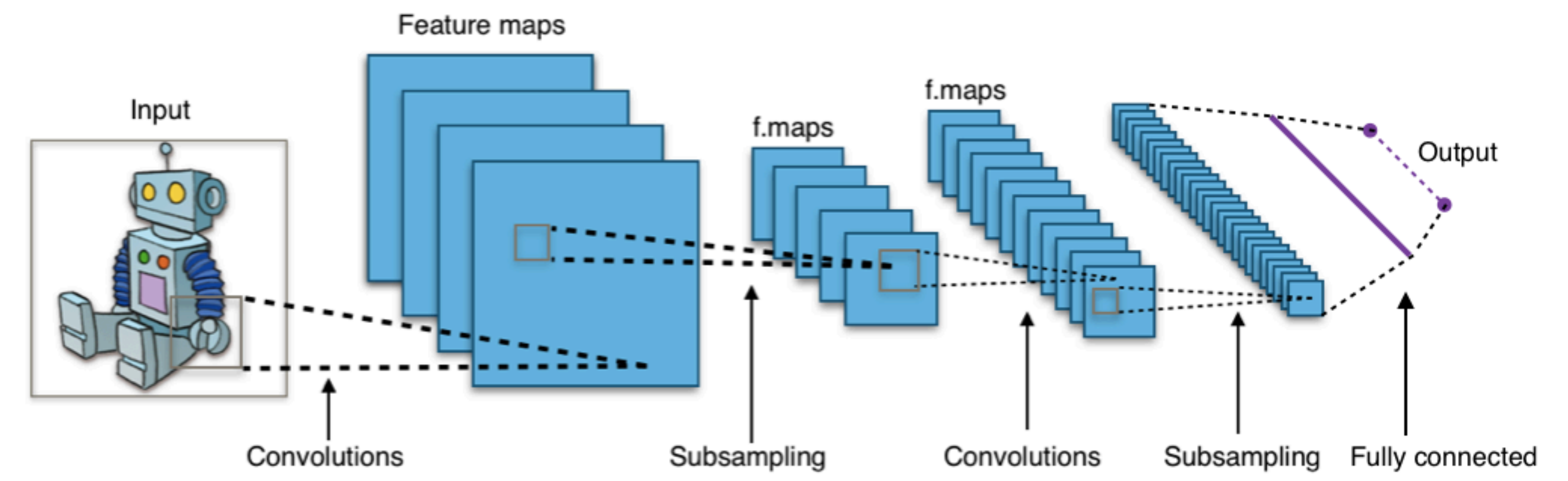
https://www.geeksforgeeks.org/artificial-neural-networks-and-its-applications/

Model Building

Convolutional Neural Networks (CNNs)

- CNNs are great for working with images, perfect for this project! 7
- A "convolution" is a mathematical process that transforms an image into another one called a "feature map."
  - The image in the upper right shows an edge-detection convolution / feature map.
- CNNs processes images through the use of many feature maps.

https://en.wikipedia.org/wiki/Kernel_(image_processing)



https://en.wikipedia.org/wiki/Convolutional_neural_network

Model Building

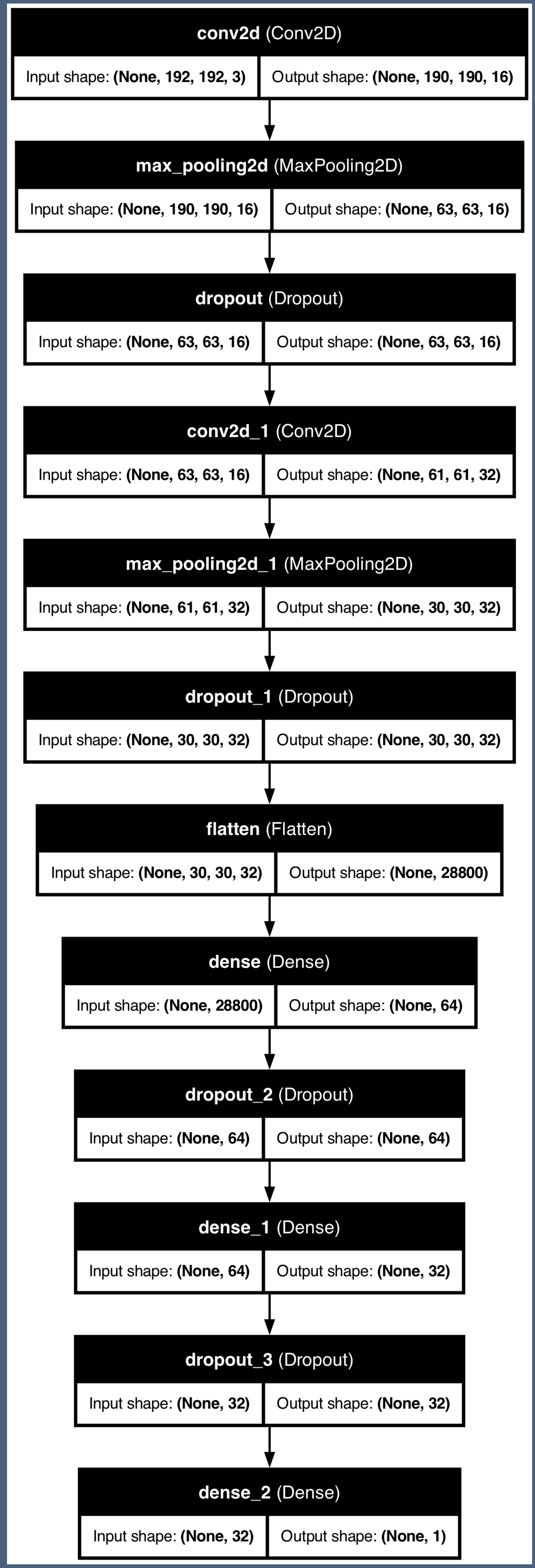
Sequential Model Building

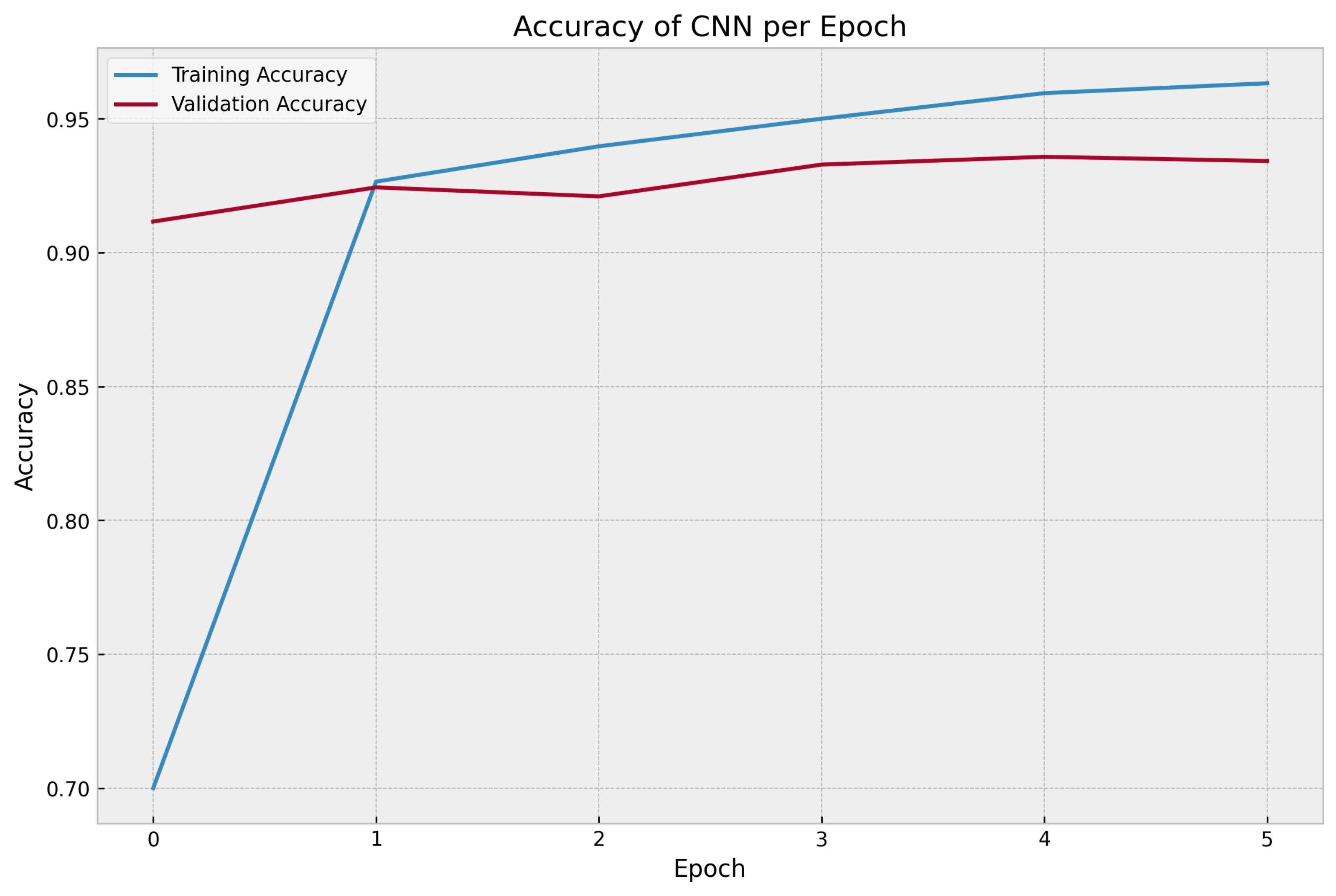
- Neural networks are very complex and require careful consideration when building them. [8]

- For this project, I will be building the model one layer at a time and analyzing how it impacts predictive performance.

  - Once the predictions are no longer improving, the model building process can stop.

Final Model Architecture





Final training accuracy: 96.4%
Final validation accuracy: 93.4%

Model Building

Final Model

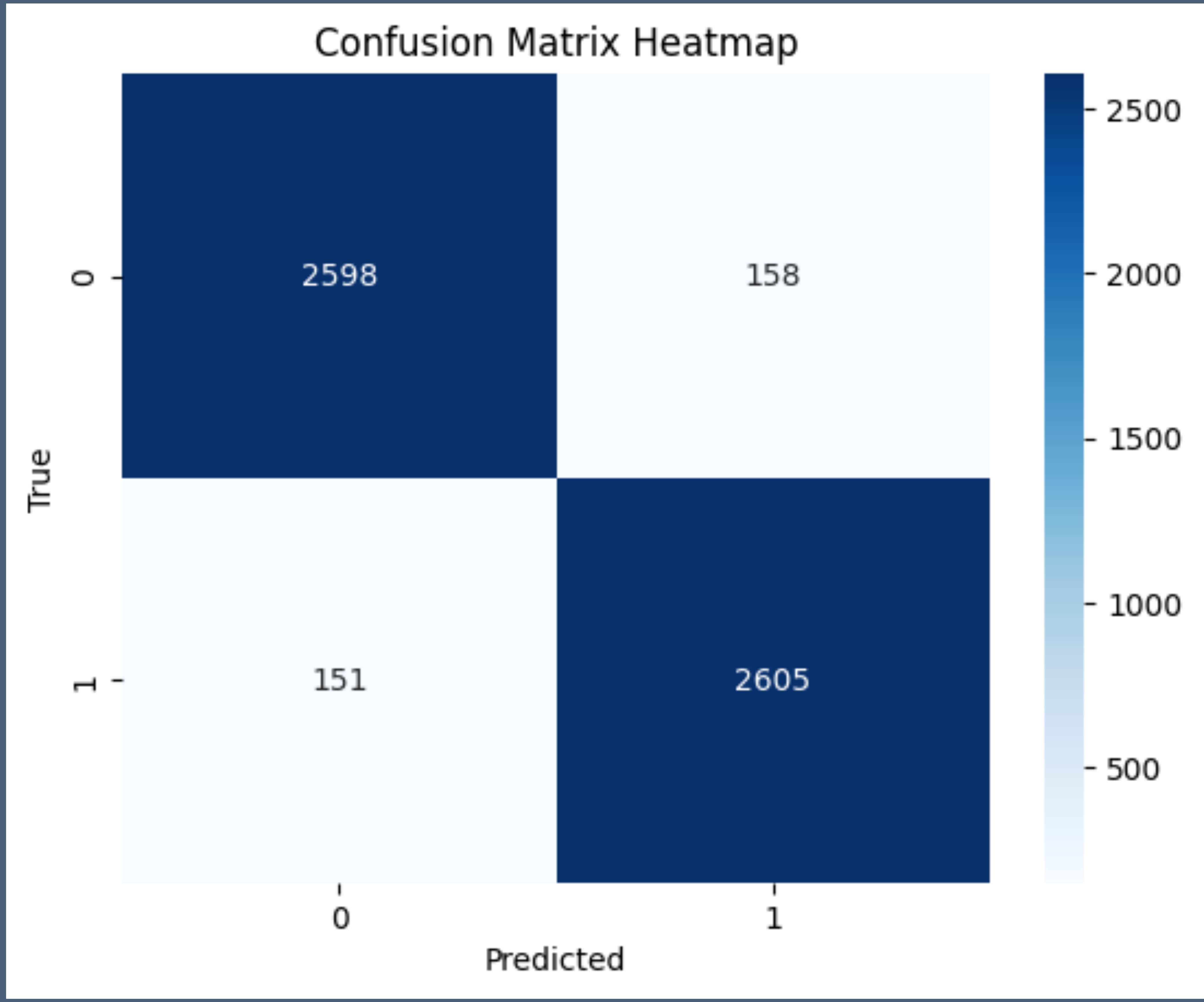
- Before fitting CNNs, data are split into training, validation, and testing subsets. 9
  - The training and validation subsets are used for fitting the neural network, the testing subset is used for a final examination of the model.
- CNNs are trained in batches called "epochs" 10
  - The accuracy can be examined for each epoch of the training process.
- The final model architecture can be seen on the left as well as the accuracy progression of the training process.

Findings

Results

Predictions From Testing Images

- Chi-square p-value of the predictions confusion matrix: approximately zero.
- Overall model accuracy: 94.4%.
- False positive and false negative rate are both approximately 5.6%.
- Reject the null hypothesis:
  - CNNs **can** predict cells infected with malaria with statistical significance, achieving at least 90% accuracy.



Limitations

Technological Requirements

- While CNNs boast strong predictive performance, they require the proper technology to host them at testing sites.
- Local infrastructure may not support this requirement.
- Each testing location will have unique challenges and addressing them will require careful consideration.
  - Creating portable, self-sufficient diagnostic devices independent of infrastructure.

Proposed Actions

CNN implementation

- Partner with humanitarian and medical aid programs to assess how and where the CNN can address needs and relieve strain on the medical system.

  - Ensure the CNN is integrated into existing healthcare frameworks for effective and sustainable implementation in resource-limited settings.

Expected Benefits

Enhanced Diagnostics and Global Health Impacts

- Implementing this model could benefit resource-limited areas by providing individuals with a fast and effective malaria diagnostic tool.
- By increasing the ease of receiving a diagnosis, it could improve the outcomes of malaria patients all around the world by empowering them to get treatment sooner (or at all).
- This project also underscores the benefit that deep learning models can have in the medical field, both in resource-limited areas as well as resource-abundant areas.
  - Successful implementation could help support more medical deep learning research.

References

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Thank You!