MALARIA DETECTION

PRESENTATION OF MALARIA DETECTION IN BLOOD CELLS

INTRODUCTION
OBJECTIVES AND DISCOVERIES FOR PROCESS

THE CONTEXT

Malaria is a life-threatening disease caused by Plasmodium parasites and early detection is crucial for effective treatment. Accurate and timely diagnosis can significantly reduce mortality rates especially in regions with limited medical resources.

THE PROBLEM FORMULATION

The task is to use data science particularly Deep learning and image processing techniques to classify blood cells as either parasitized or uninfected.

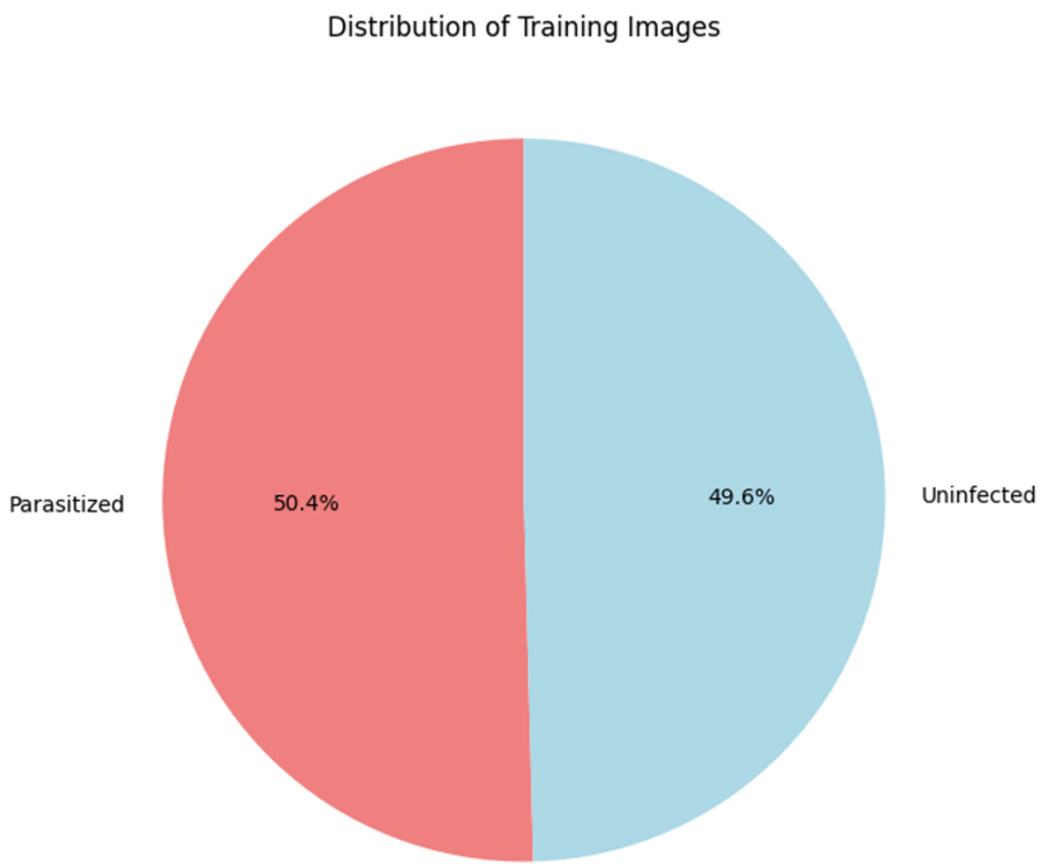
The goal is to build a model that maximizes accuracy and minimizes false diagnoses with low computation cost.

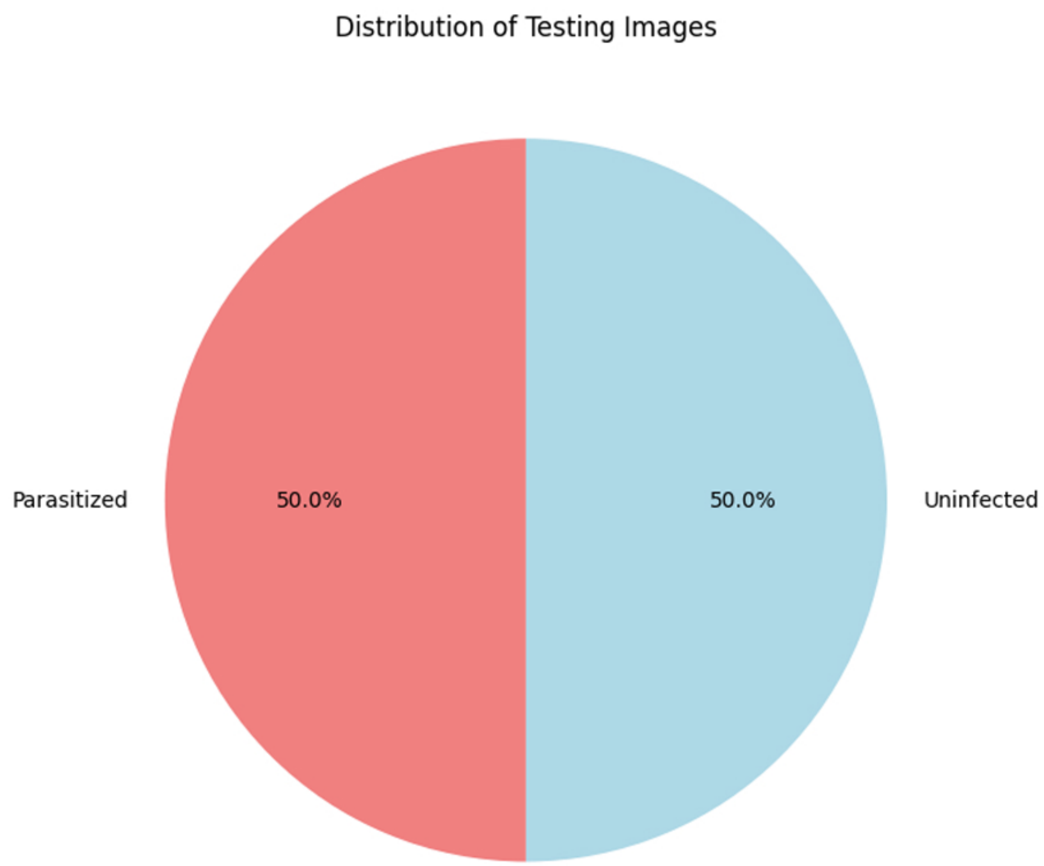
THE OBJECTIVES

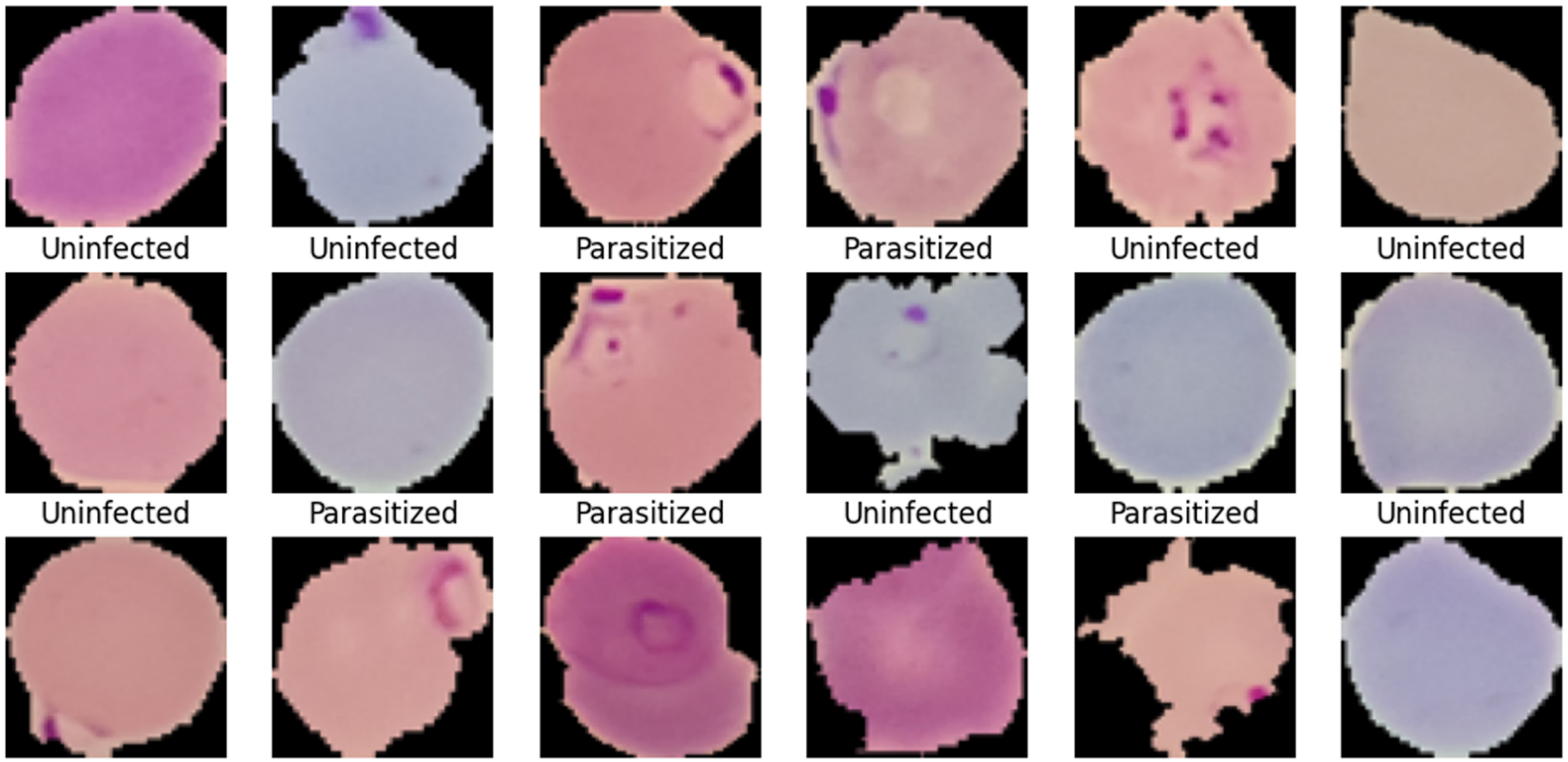
The primary aim is to develop an accurate and efficient model that can automatically detect malaria-infected cells from microscopic images.

This model should assist healthcare professionals in countries with limited resources in diagnosing malaria quickly and accurately.

BLOOD CELL IMAGES ANALYSIS OF INPUT DATA IMAGERY







DATA SET

Parasitized and Uninfected are the 2 categories of colored images that have been taken from microscope, with a total of 24,958 for training and 2,600 for testing.

STANDARDIZED IMAGE SIZE

All images are resized to 64x64 pixels with 3 channels (RGB), ensuring uniformity for efficient model performance.

IMAGE CLARITY AND BOUNDARIES

In general the images are clear with distinct boundaries between cells and background aiding in accurate shape differentiation.

COLOUR VARIATION

Noticeable color contrast exists between parasitized (more contrast) and uninfected cells (more uniform color), which will assist our model for classification.

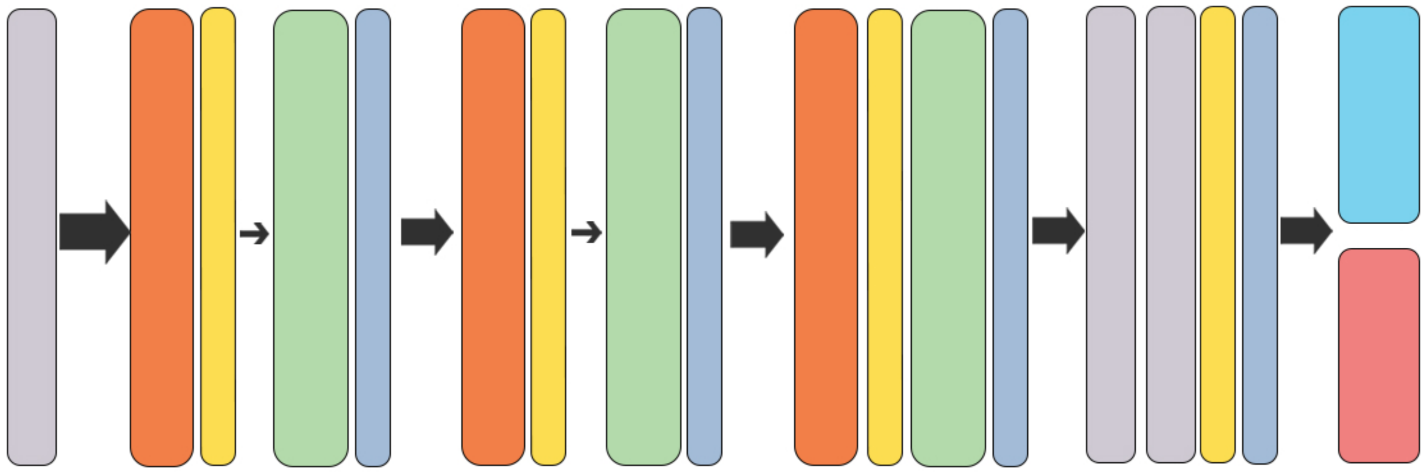
BALANCED DATA SET

The training set has a slight majority of parasitized images while the test set is perfectly balanced.
This balance will prevent bias during training and will ensure equal testing across classes.

MODEL BUILDING

MODEL COMPARISON TRAINED ON ORGINAL IMAGES

BASE MODEL



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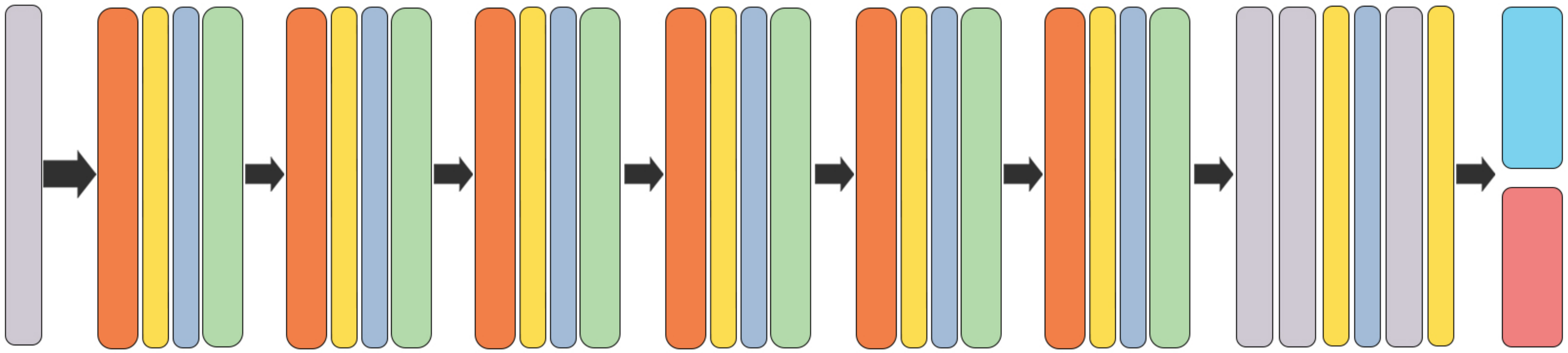
Total params: 1,058,786 (4.04 MB)
Trainable params: 1,058,786 (4.04 MB)
Non-trainable params: 0 (0.00 B)
```

MODEL 1



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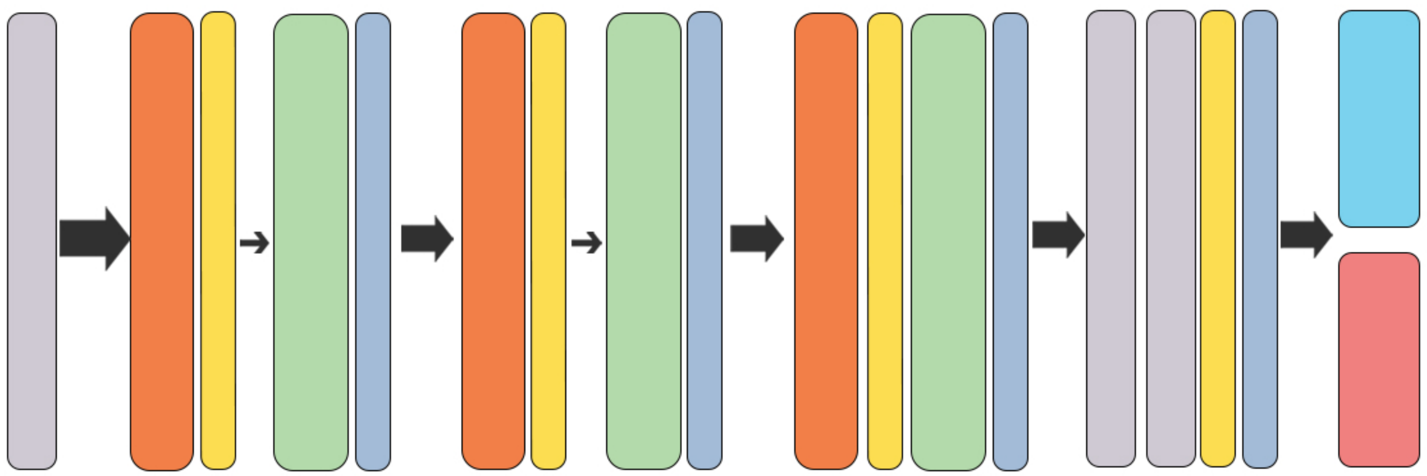
Total params: 946,722 (3.61 MB)
Trainable params: 945,826 (3.61 MB)
Non-trainable params: 896 (3.50 KB)
```

MODEL 2



```
Total params: 1,069,506 (4.08 MB)
Trainable params: 1,069,506 (4.08 MB)
Non-trainable params: 0 (0.00 B)
```

INPUT | CONV | RELU / LEAKY RELU | DROPOUT / BATCHNORM | MAX POOLING | OUTPUT

BASE MODEL

Base Model uses smaller 2x2 kernels and a simpler architecture with fewer filters,
leading to a model with a moderate number of parameters.
Training Accuracy: 98.12% with a loss of 0.0660.
Test Accuracy: 98.31% with a loss of 0.0684.
Confusion Matrix: 18 false positives, 26 false negatives,
Metrics: Precision, recall, and F1-score around 0.98

MODEL 1

Model 1 is more complex with more layers BatchNormalization & LeakyReLU activations
and larger dense layers aiming for deeper learning despite fewer total parameters.
Training Accuracy: 99.02% with a loss of 0.0355.
Test Accuracy: 97.69% with a loss of 0.0655.
Confusion Matrix: 52 false positives, 8 false negatives.
Metrics: Precision, recall, and F1-score are 0.98

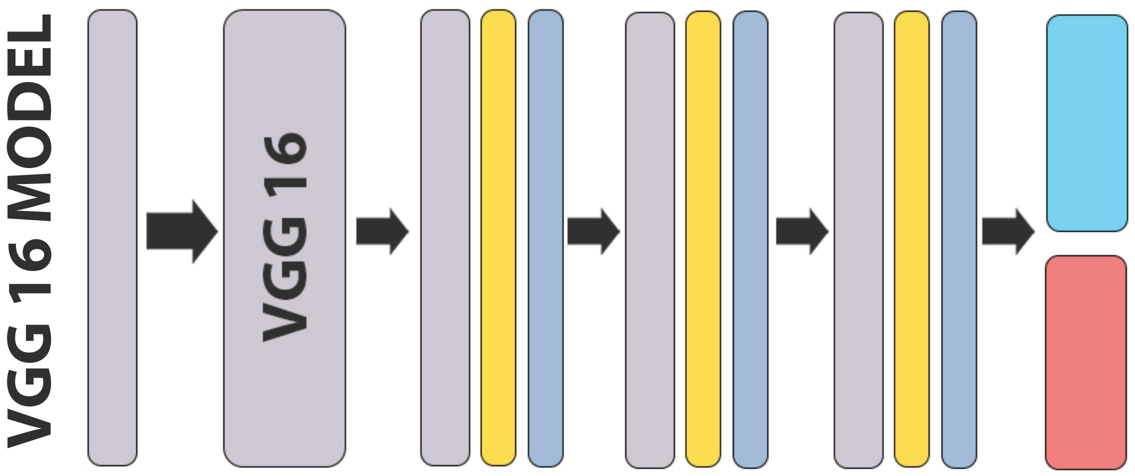
MODEL 2

Model 2 is similar to the Base Model but with larger 3x3 kernels and a slightly
higher parameter count designed to capture more detailed spatial features.
Training Accuracy: 98.46% with a loss of 0.0520.
Test Accuracy: 98.12% with a loss of 0.0641.
Confusion Matrix: 27 false positives, 22 false negatives.
Metrics: Precision, recall, and F1-score are 0.98

CONCLUSION

Based on the above we can see that the Base model has the highest performance for our case

MODEL COMPARISON TRANSFER LEARNING TRAINED ON ORGINAL IMAGES

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Trainable params: 14,714,688 (56.13 MB)
Non-trainable params: 0 (0.00 B)
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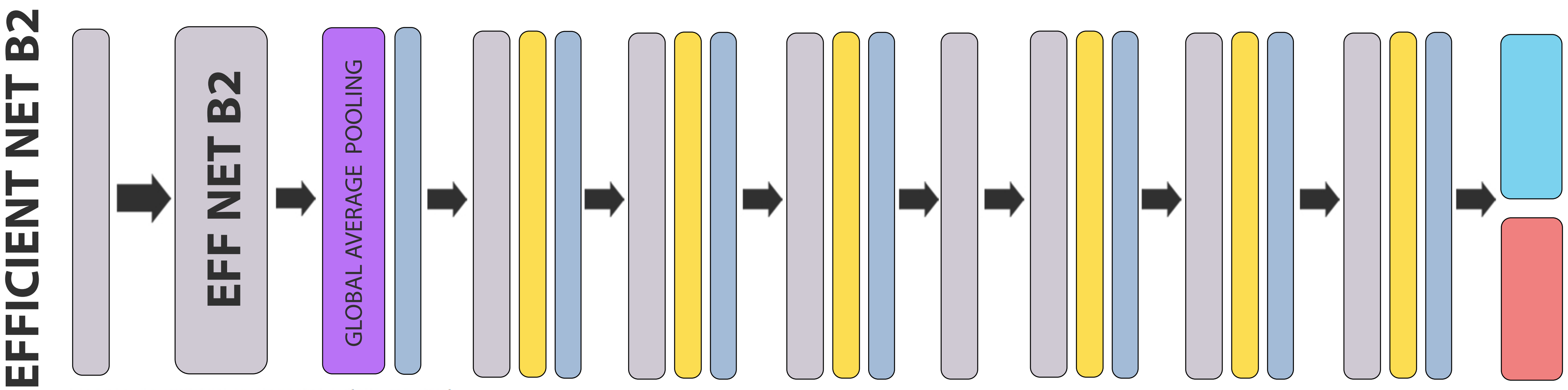


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Total params: 7,768,569 (29.63 MB)
Trainable params: 7,700,994 (29.38 MB)
Non-trainable params: 67,575 (263.97 KB)
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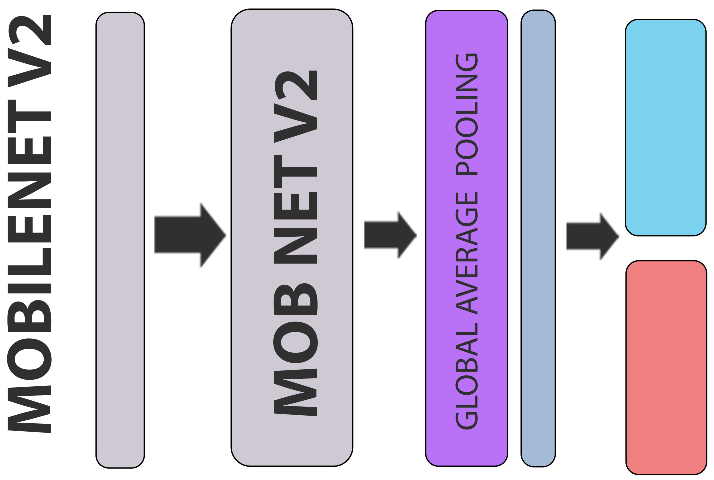
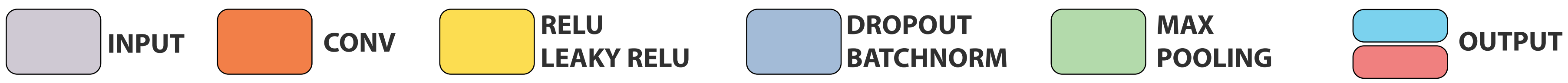




VGG 16 MODEL

VGG16 Model uses a series of dense layers with 256, 128, and 64 neurons before the final classification layer.

Training Accuracy: 95.20% with a loss of 0.1227.

Test Accuracy: 93.19% with a loss of 0.2023.

Confusion Matrix: 128 false positives, 49 false negatives.

Metrics: Precision, recall, and F1-score around 0.93 for both classes.

EFFICIENT NET B2

EfficientNetB2 Model also uses 256, 128, and 64 neuron dense layers similar to VGG16 but with a focus on efficiency.

Training Accuracy: 95.92% with a loss of 0.1053.

Test Accuracy: 95.96% with a loss of 0.1165.

Confusion Matrix: 49 false positives, 56 false negatives.

Metrics: Precision, recall, and F1-score are 0.96 for both classes.

MOBILE NET V2

MobileNetV2 Model does not use intermediate dense layers; instead, it applies Global Average Pooling followed by a small output layer, making it more computationally efficient.
The model includes fine-tuning after initial training, achieving strong generalization with the highest test accuracy.

Training Accuracy: 96.78% with a loss of 0.3813.

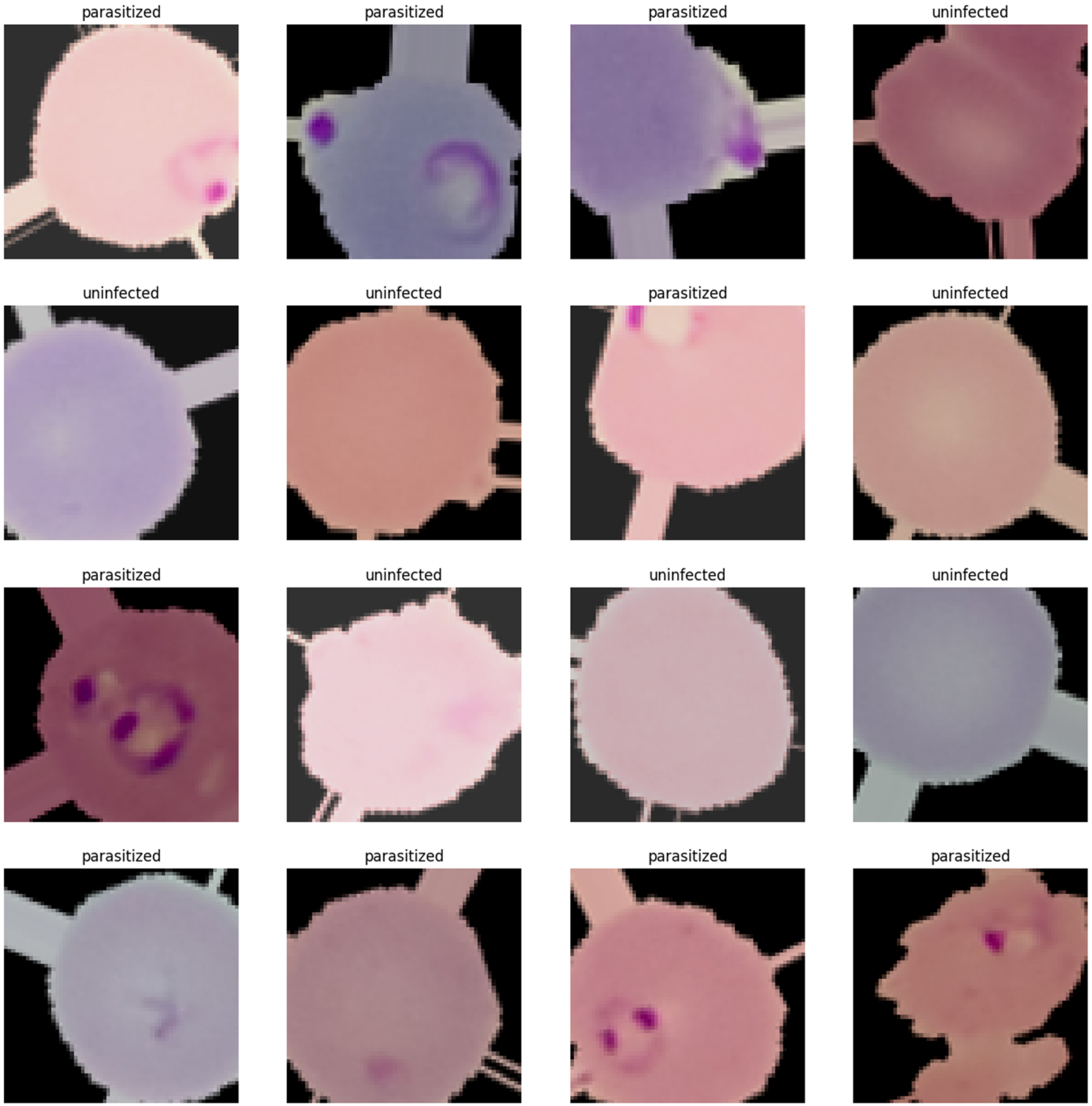
Test Accuracy: 97.00% with a loss of 0.3078.

Confusion Matrix: 33 false positives, 45 false negatives.

Metrics: Precision, recall, and F1-score are 0.97 for both classes.

DATA AUGMENTATION

EVALUATION OF AUGMENTED DATA



ROTATION

The images appear to be rotated, as seen in the varying angles of the cells.

FLIPPING

Both horizontal and vertical flipping are likely applied, given the variation in cell orientation.

COLOUR SHIFTS

There are noticeable changes in color across the images, which aligns with the use of the channel_shift_range parameter in the ImageDataGenerator.

TRANSLATION

The cells appear to be shifted within the frame, consistent with the width_shift_range and height_shift_range parameters.

INCREASED VARIABILITY

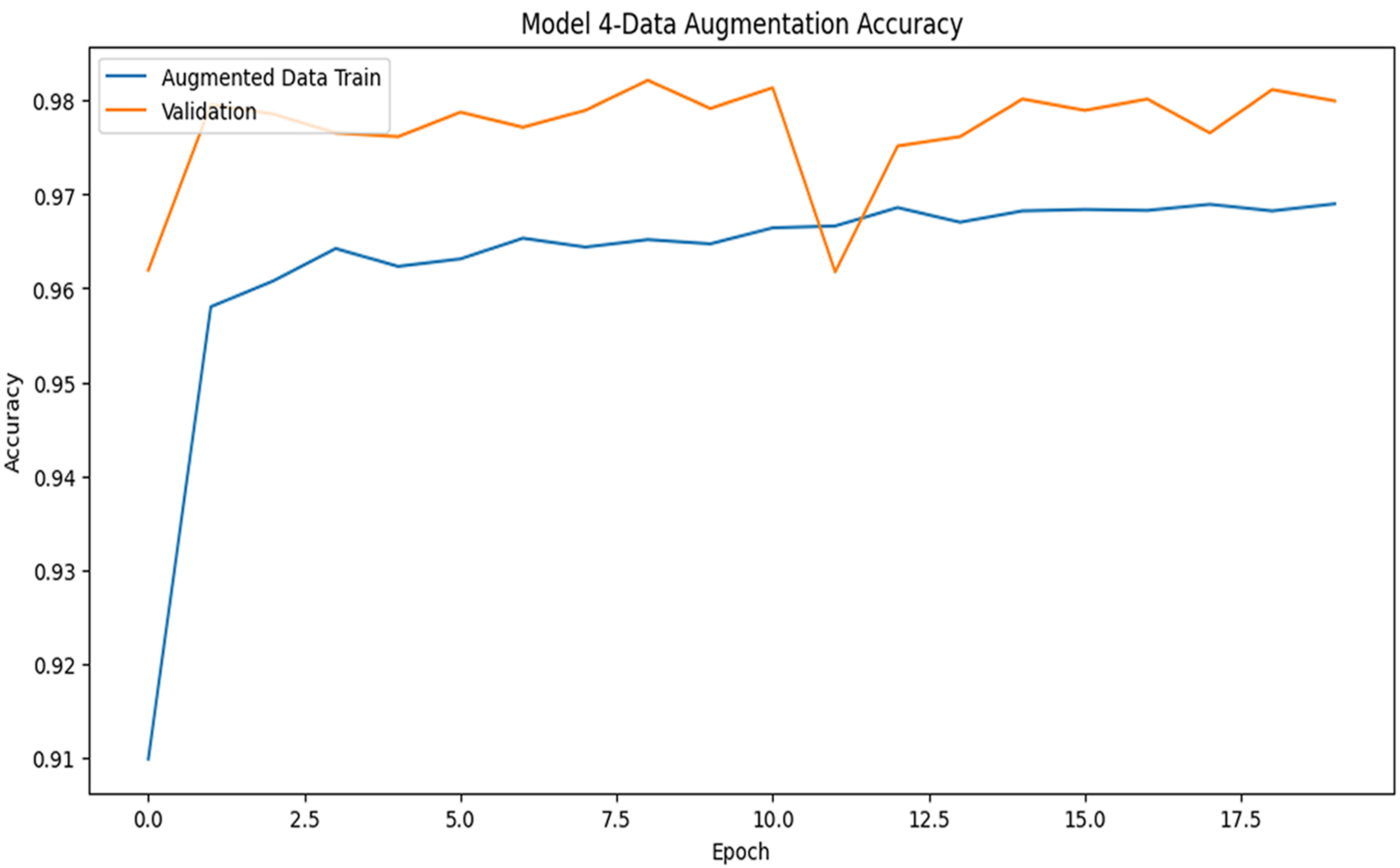
The augmentations introduce variations in the dataset, helping the model learn more robust features rather than overfitting to specific orientations or colors of cells.

BALANCED CLASSES

The augmentations are applied equally to both "parasitized" and "uninfected" cells, ensuring that both classes benefit from the increased variability.

PREFERRED MODEL

PREFERRED MODEL ARCHITECTURE AND HISTORIC OUTPUT



DEEP CONVOLUTIONAL MODEL

Capture complex features from augmented data, improving generalization and handling variability.

BATCH NORMALISATION

Stabilizes training, reduces overfitting, and maintains consistent accuracy.

LEAKYRELU ACTIVATION

Prevents "dying ReLU" issue, ensuring effective learning throughout training.

LARGE DENSE LAYERS (1024 & 512 NEURONS)

Provides capacity to integrate and refine features, leading to high accuracy.

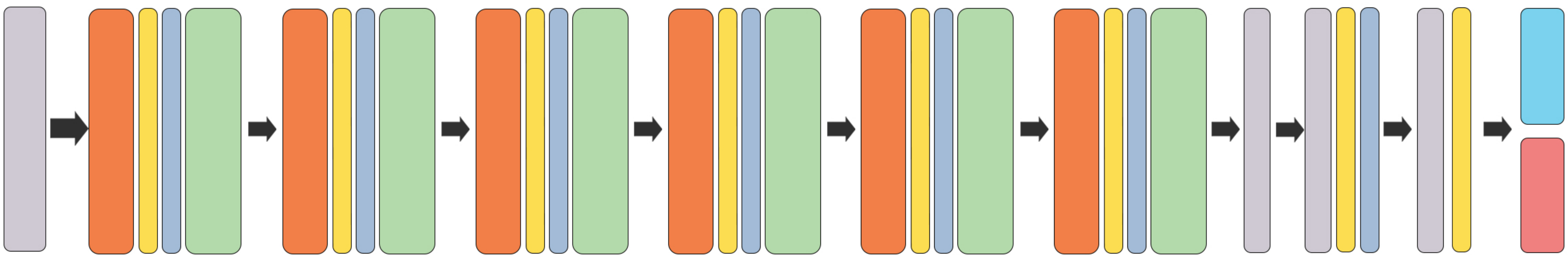
DROPOUT REGULARISATION

Prevents overfitting, promotes better generalization, and supports robust performance.

TRAINING HISTORY

- The rapid improvement at the first epoch which quickly increases indicates that the model adapts to the augmented data.
- Train Loss decrease indicates that the model continues to optimize and fit the training data better over time
- The minimal gap between training and validation accuracy confirms that the model is not overfitting.

MODEL 4



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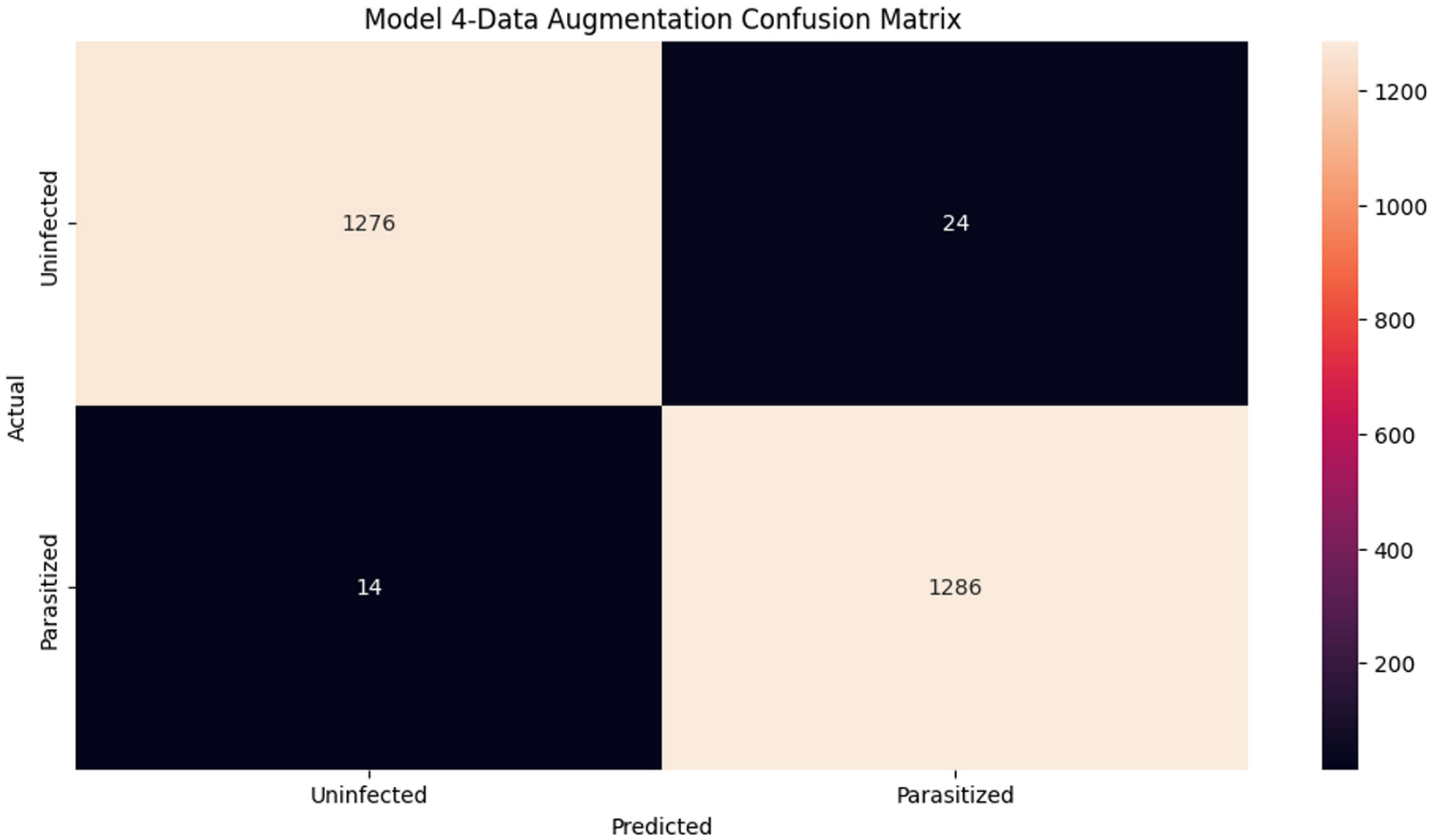
Trainable params: 945,826 (3.61 MB)
Non-trainable params: 896 (3.50 KB)
```

INPUT | CONV | RELU LEAKY RELU | DROPOUT BATCHNORM | MAX POOLING | OUTPUT

CONFUSION MATRIX TRANSFER LEARNING TRAINED ON ORGINAL IMAGES




```
82/82 ━━━━━━━━━━━━━━━━━━━━ 7s 89ms/step
              precision    recall  f1-score   support

           0       0.99      0.98      0.99      1300
           1       0.98      0.99      0.99      1300

    accuracy                           0.99      2600
   macro avg       0.99      0.99      0.99      2600
weighted avg       0.99      0.99      0.99      2600
```

OBSERVATION

Since Model 4 has the same architecture as Model 1 but was trained with data augmentation, it's insightful to compare the impact of the augmented data on the model's performance.

Training Accuracy: 98.91% with a loss of 0.0461.
Test Accuracy: 98.54% with a loss of 0.0469.
Confusion Matrix: 24 false positives, 14 false negatives.
Metrics: Precision, recall, and F1-score are 0.99 for both classes.
Conclusion:
Model 4 benefits from data augmentation being the top performer with excellent generalization, efficient use of architecture, and minimal misclassifications.

GENERALISATION CAPABILITIES

Average 6-k cross-validation accuracy: 0.98
Average 6-k cross-validation loss: 0.049

Cross-validation accuracy on augmented data: 0.96
Cross-validation loss on augmented data: 0.087

PREFERRED MODEL WHY MODEL FOUR WAS CHOSEN

HIGH ACCURACY IN MEDICAL DIAGNOSIS

Our Model demonstrates a high accuracy in distinguishing between parasitized and uninfected blood cells ensuring reliable malaria diagnosis.

ADAPTABILITY TO COMPLEX TASKS

The Model's adaptability is crucial for handling rare or challenging cases in medical diagnostics

RELIABLE PERFORMANCE

With low rates of false positives and negatives our Model ensures accurate diagnoses leading to accurate efficient medical treatments.

COMPUTATIONAL EFFICIENCY MATTERS

Its computational performance allows for high accuracy in resource limited environments making it practical for deployment in malaria prone areas.

THANK YOU