DEEP LEARNING-BASED MALARIA PARASITE DETECTION: CNN

efficient, advanced and enabling

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Jasmin Gamal Eldin

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PROBLEM OVERVIEW: WHY AUTOMATE MALARIA DIAGNOSIS?

- **The Problem:** Manual diagnosis of malaria through blood smear examination is labour-intensive and subject to human error.
- **Objective:** Automate malaria detection using deep learning to reduce diagnostic time and improve accuracy.

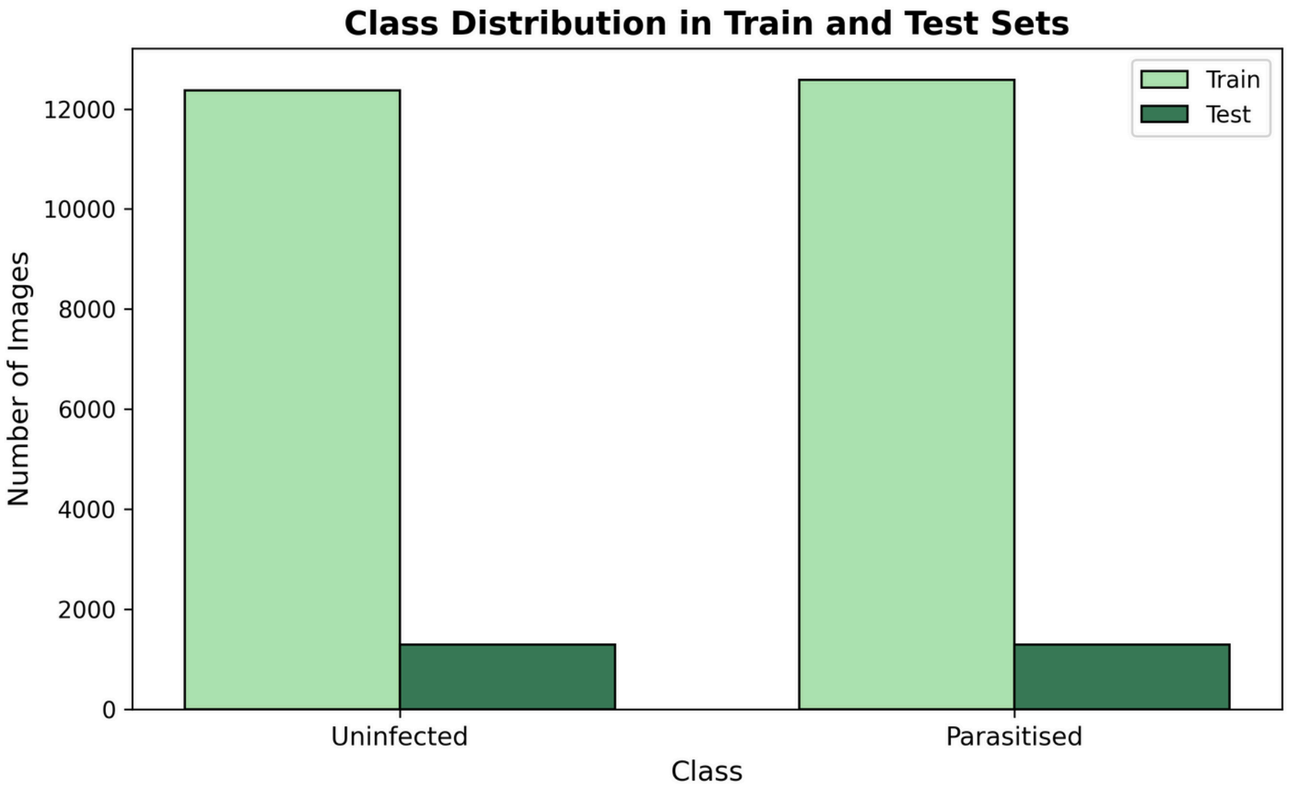
EXECUTIVE SUMMARY

- Malaria is a life-threatening disease that demands timely diagnosis.
- Manual microscopy is time-consuming and error-prone.
- We evaluated five different deep learning models for image classification.
- The Deeper CNN with added layers and capacity outperformed others in accuracy and reliability.
- We recommend deploying Deeper CNN with added layers and capacity for automated malaria detection.

DATASET OVERVIEW

Malaria Image Count

Total images in dataset: 27558



Train Image Count

train/parasitized: 12582
train/uninfected: 12376

Test Image Count

test/parasitized: 1300
test/uninfected: 1300

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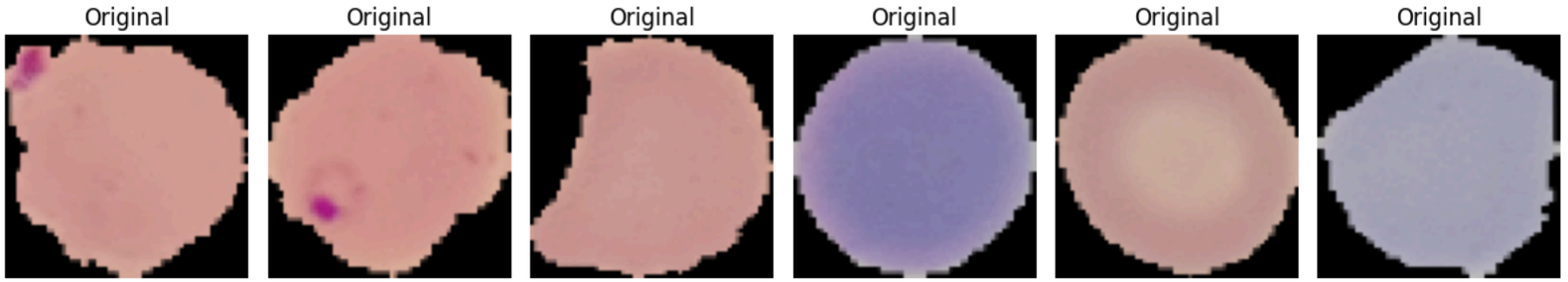
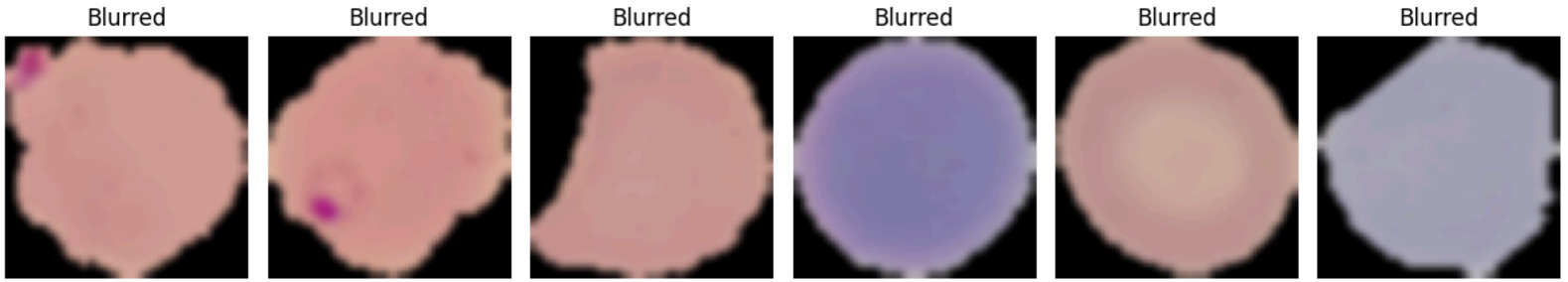
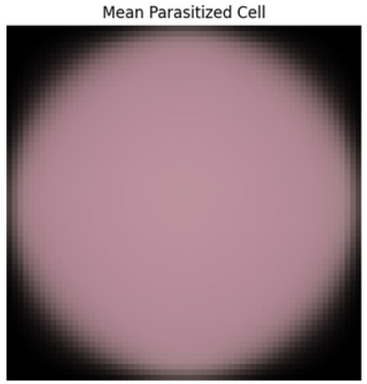
DATA PREPROCESSING PIPELINE

- Normalisation to [0,1] scale
- RGB to HSV colour space
- Gaussian blur to reduce noise

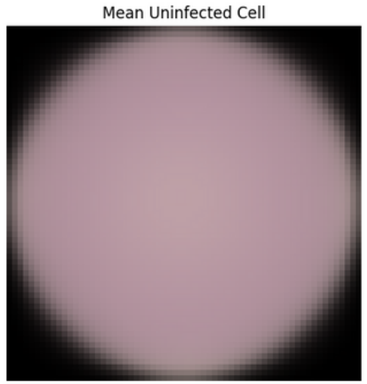




Mean image for parasitised



Mean image for uninfected



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FIVE CNN-BASED ARCHITECTURES EVALUATED

1. Base Model: Simple 2-layer CNN
2. Model 1: Deeper CNN with added layers and capacity
3. Model 2: Batch Normalisation for improved stability
4. Model 3: Augmented training data for robustness
5. Model 4: Transfer learning with VGG16

METRICS USED FOR EVALUATION

1. Accuracy
2. Precision, Recall, F1 Score
3. Confusion Matrix (TP, FP, TN, FN)
4. ROC Curve & AUC

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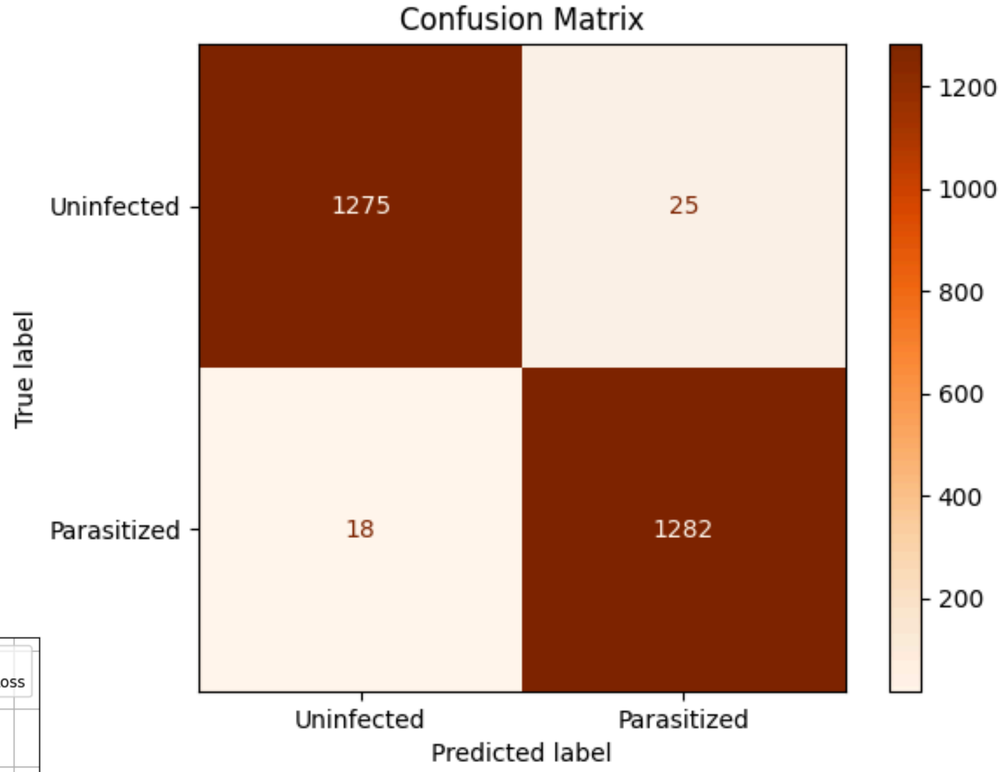
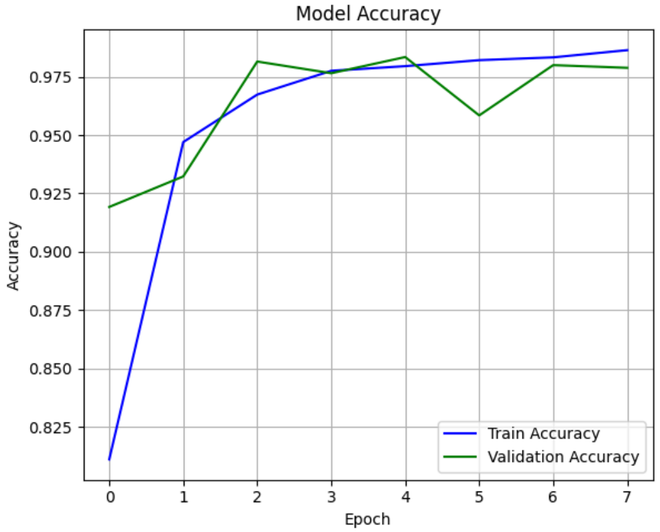
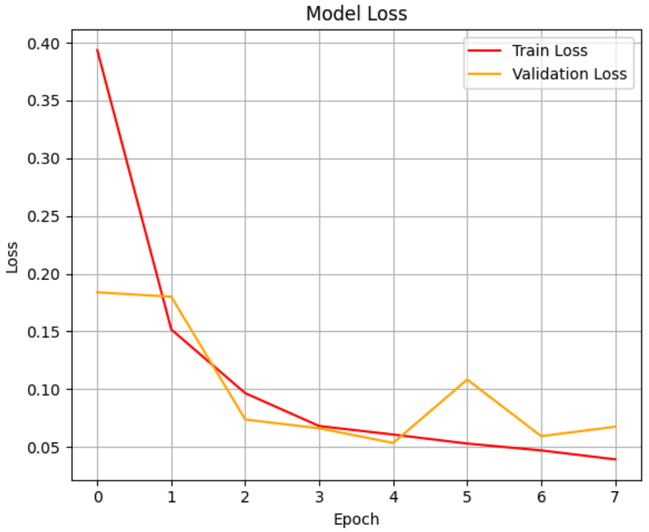
BASE CNN MODEL

- 3 convolutional layers
- ReLU activations + MaxPooling
- Flatten + Dense layers
- Final accuracy: 93%
- Signs of overfitting after 10 epochs







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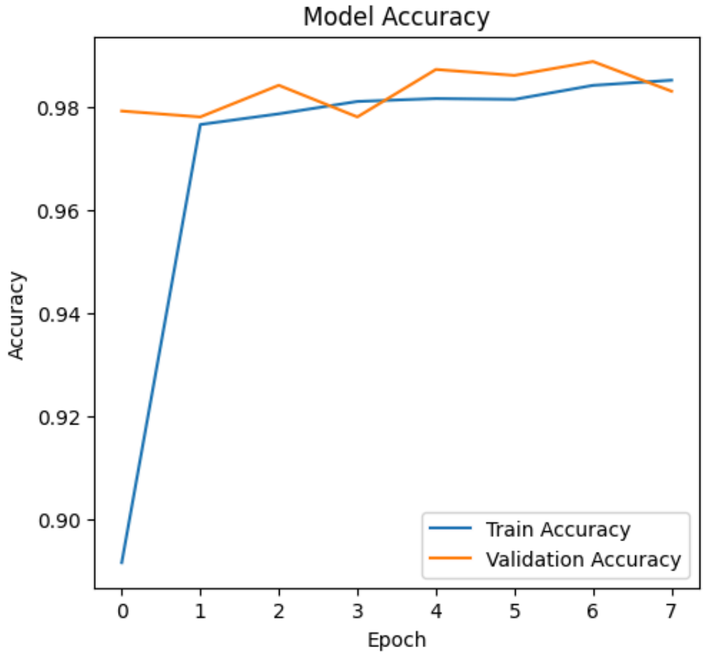
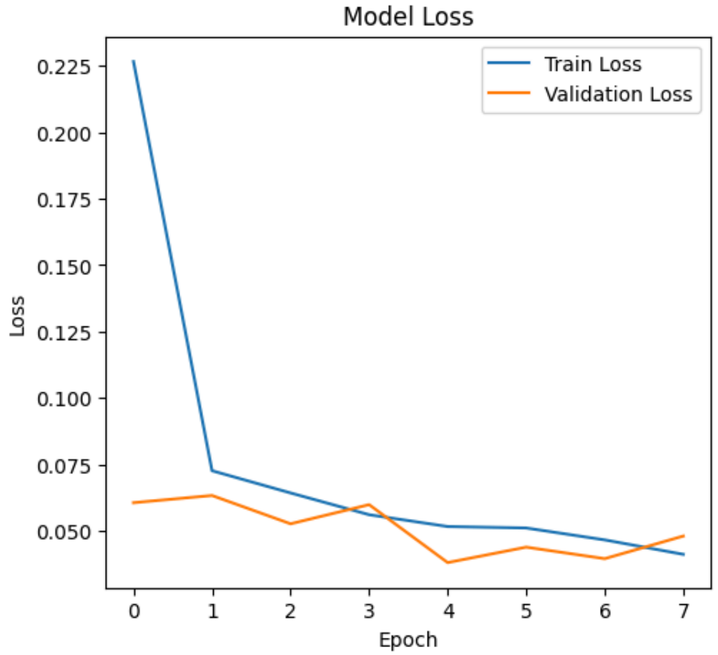
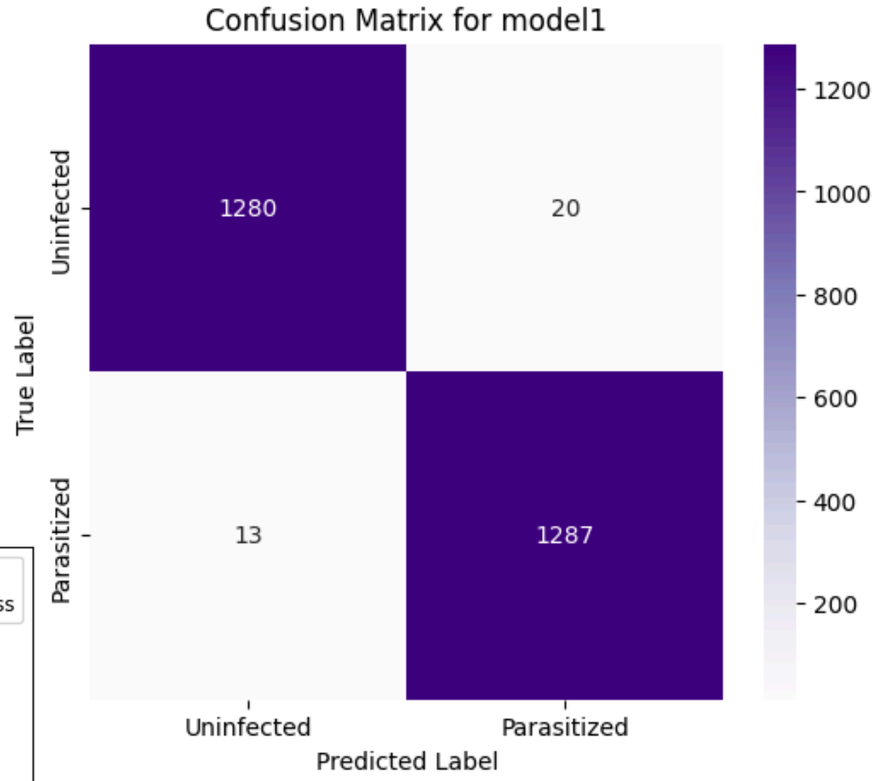
DEEPER CNN MODEL

- Increased depth (5 conv layers)
- More feature abstraction
- Improved training accuracy
- Still moderate overfitting







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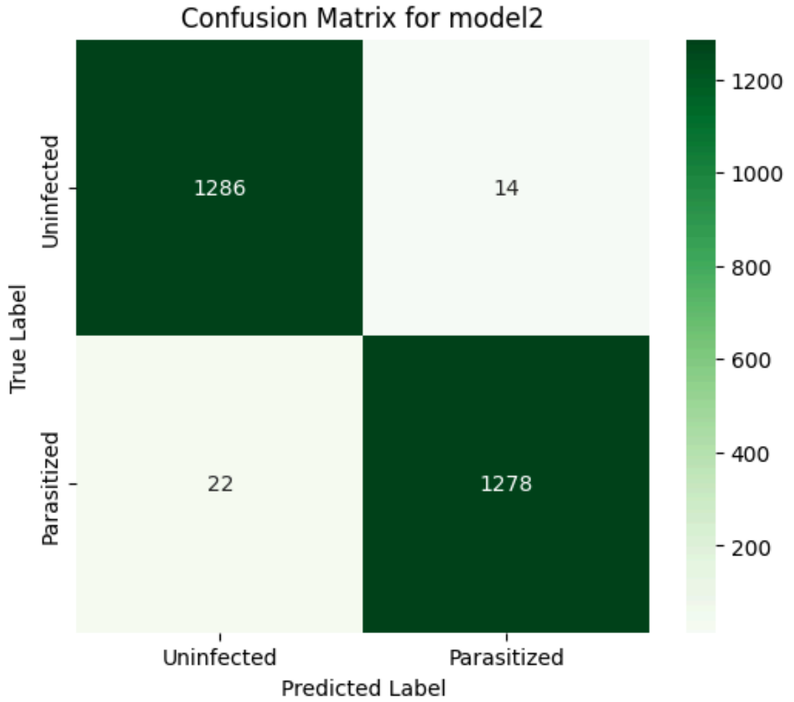
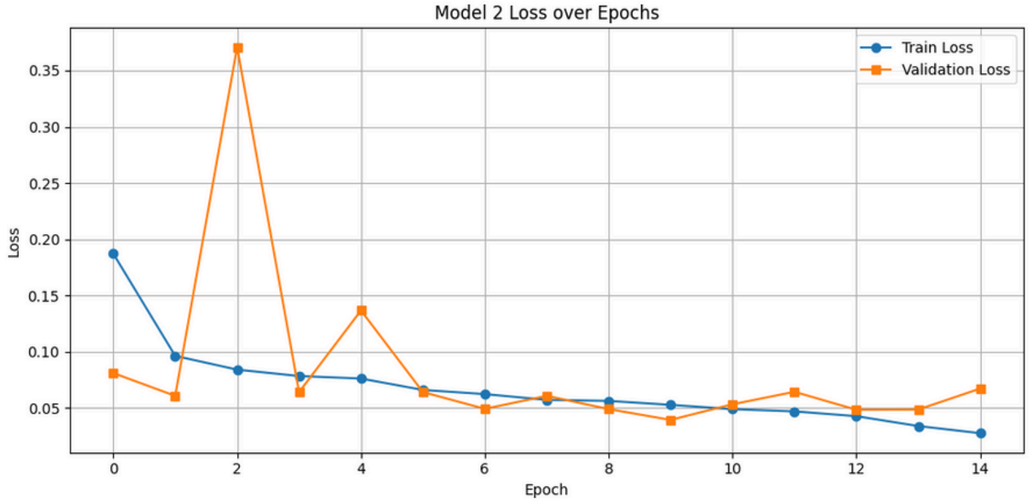
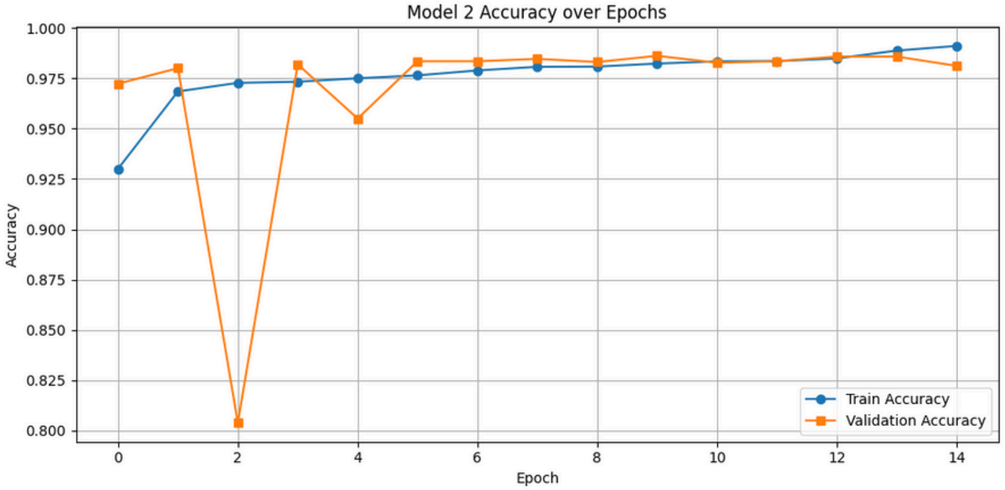
CNN AND BATCH NORMALISATION MODEL

- BatchNorm layers after conv blocks
- Stabilised training
- Reduced overfitting
- Accuracy improved marginally (94%)

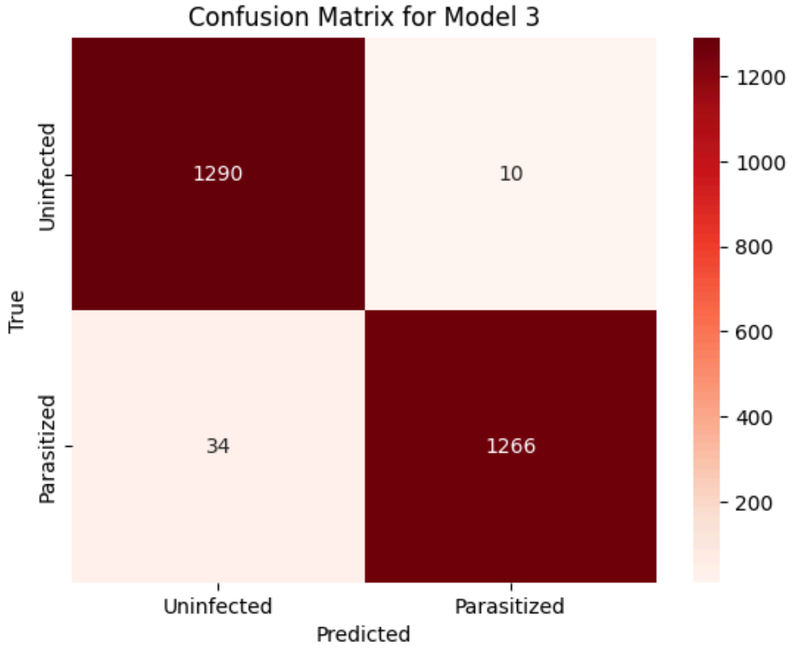


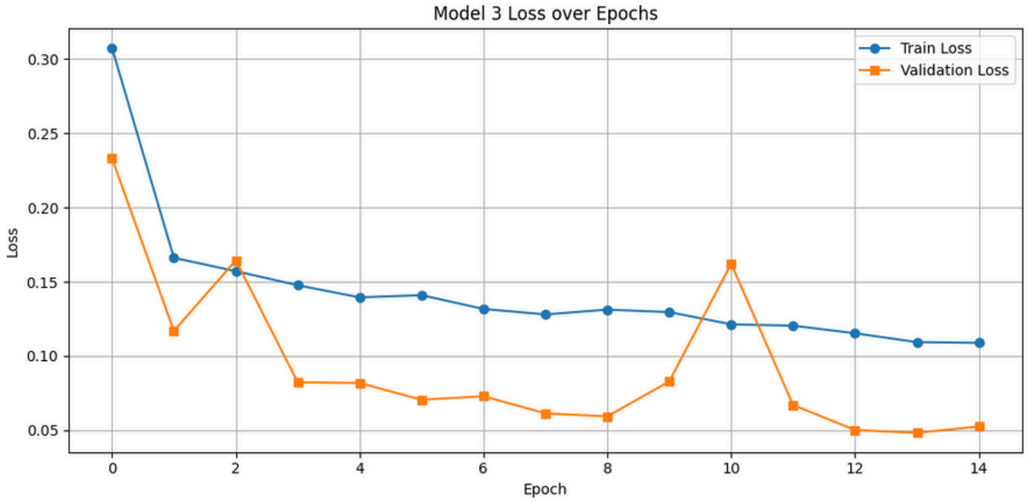


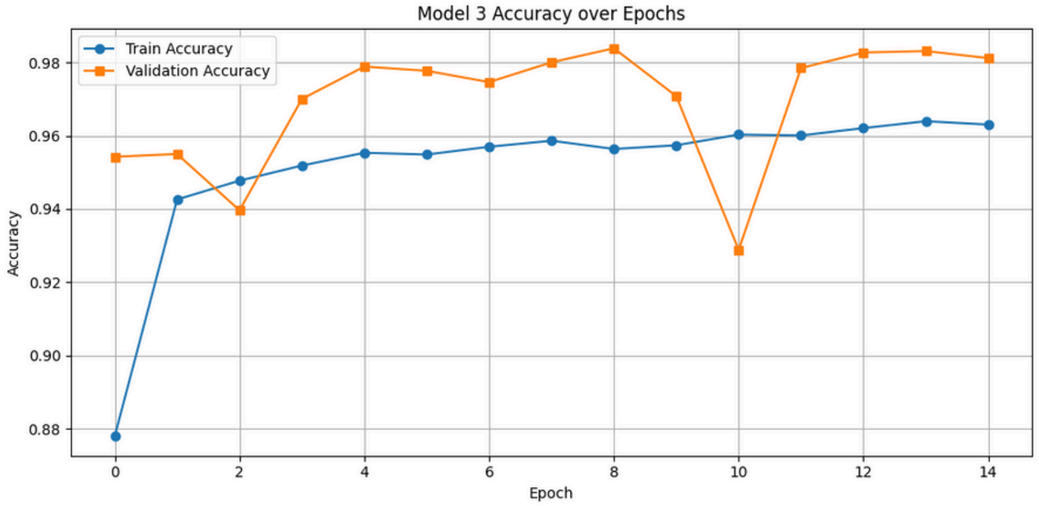


CNN AND DATA AUGMENTATION MODEL

- Added rotation, flips, zoom, brightness shift
- Better generalisation
- Validation accuracy improved to 95%

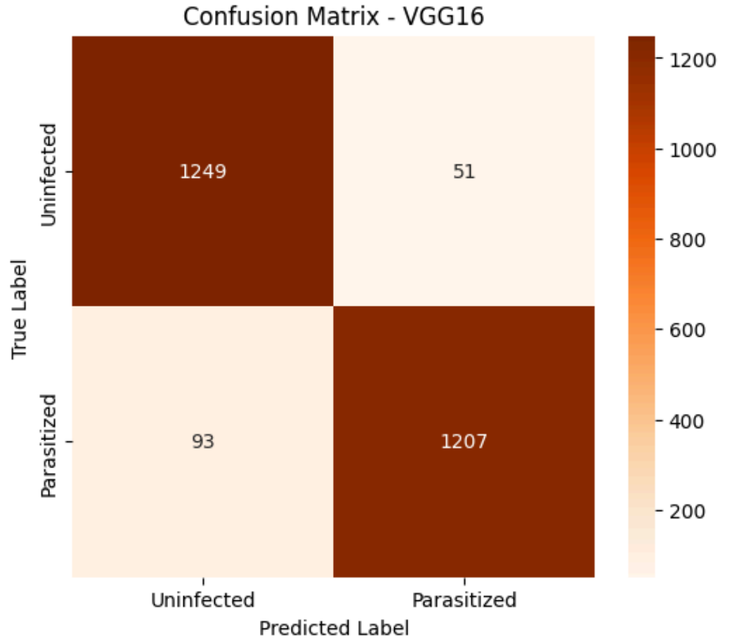


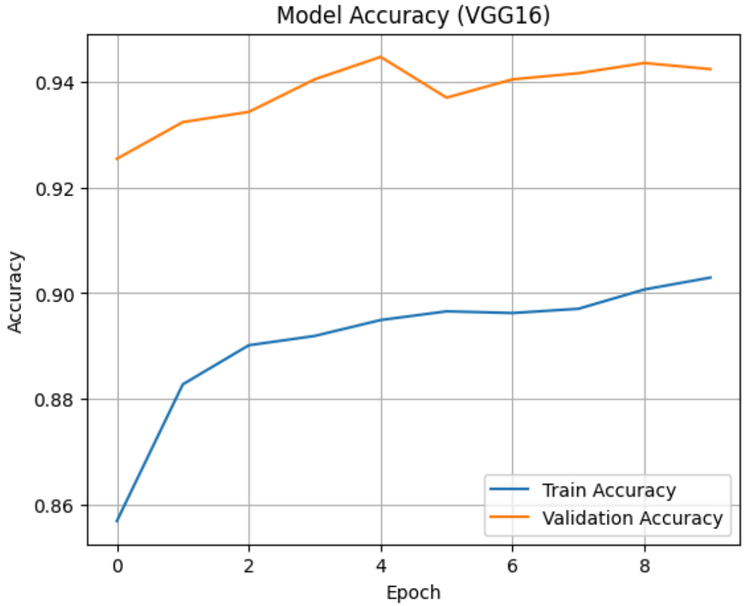


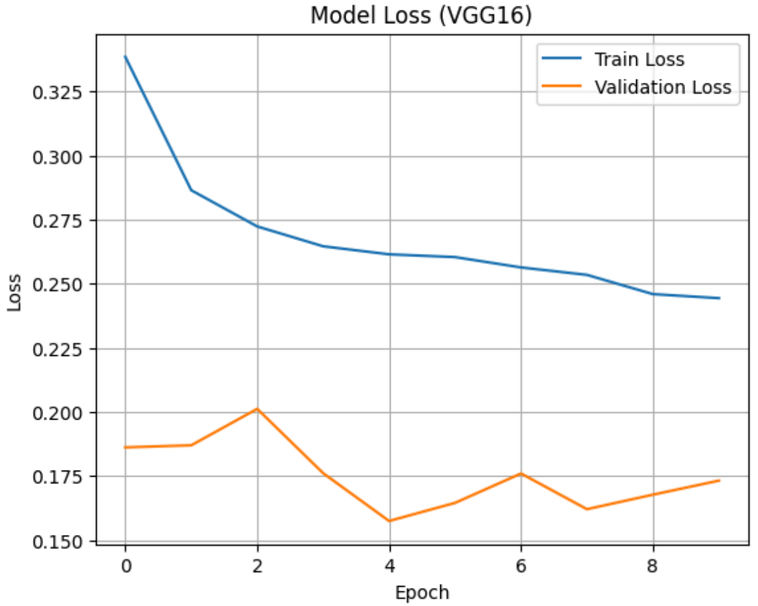


VGG16 TRANSFER LEARNING

- Pre-trained on ImageNet
- Reduced training time







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PERFORMANCE COMPARISON

Model	Accuracy	Precision	Recall	F1 Score	AUC
Base Model	98.35%	98.08%	98.62%	98.35%	0.461
Model 1: Deeper	**98.73%**	98.47%	**99.00%**	**98.73%**	**0.516**
Model 2: Batch Normalisation	98.62%	**98.91%**	98.30%	98.60%	0.464
Model 3: Data Augmentation	98.31%	**99.22%**	98.35%	98.29%	**0.516**
Model 4: VGG16	94.46%	95.95%	92.85%	94.35%	0.345

- ROC AUC values range from 0.345 to 0.516
- Indicates poor probability calibration despite high accuracy
- Model 1 & Model 3 show slightly better separation capability

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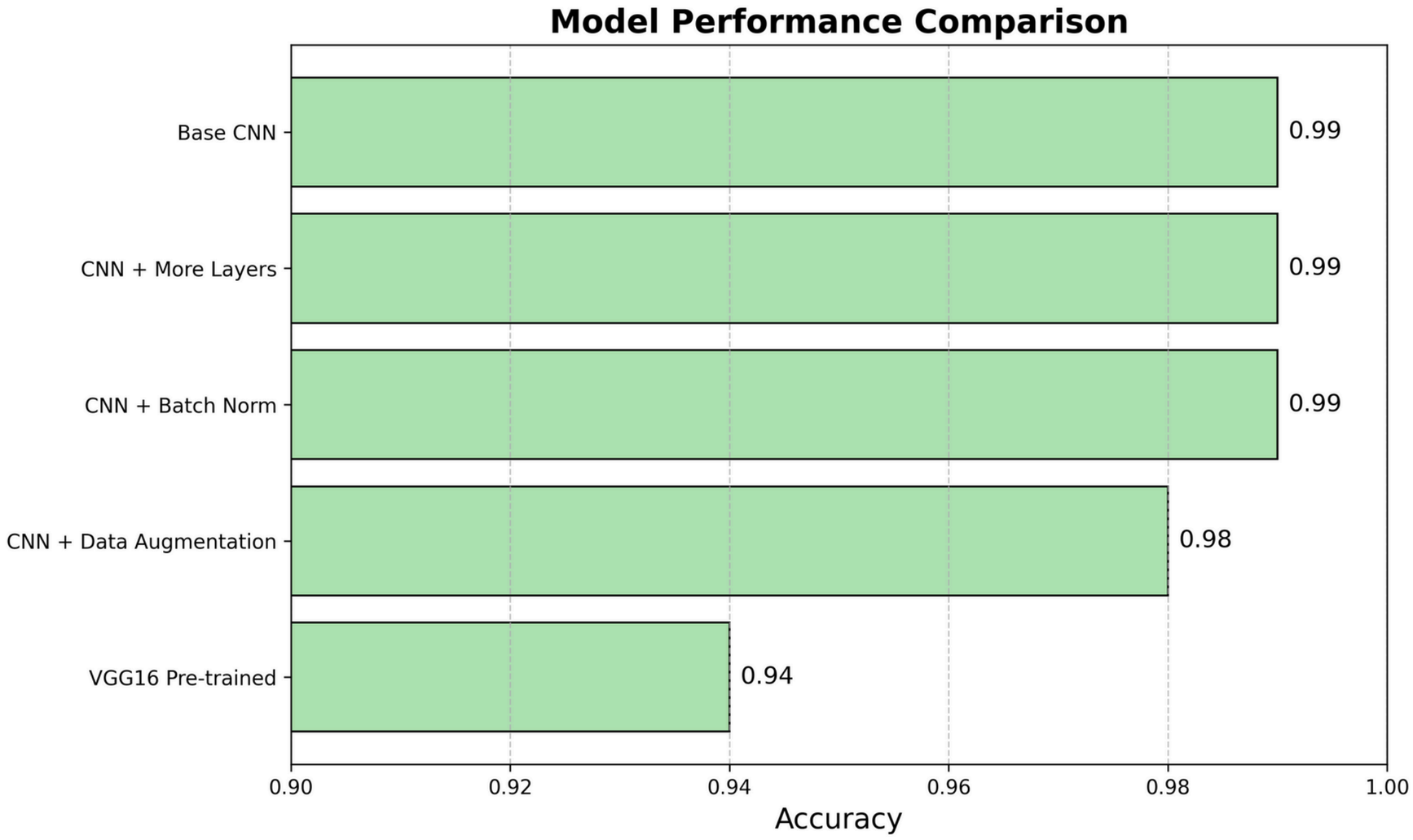
MODELS PERFORMANCE



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FINAL MODEL CHOICE: MODEL 1 (DEEPER CNN)

- Highest test accuracy (98.73%)
- Strong F1 and recall
- Balanced class-wise performance
- Efficient and straightforward to deploy

IMPLEMENTATION & FUTURE WORK

- Retrain model with field-collected data
- Improve probability calibration (e.g., Platt Scaling)
- Explore lightweight models for mobile deployment
- Integrate with diagnostic lab workflows

CONCLUSION

- CNNs show strong potential for malaria diagnosis
- Model 1 offers high accuracy and interpretability
- ROC AUC flags calibration issues addressable with further refinement
- Automation can significantly reduce diagnosis time and dependency on experts

FUTURE RESEARCH

- Real-world testing in hospital settings
- Optimisation for mobile devices
- Multi-class classification for other parasites
- Explainable AI for clinical trust

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THANK YOU FOR YOUR ATTENTION

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QUESTIONS?

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