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Department of Information Technology-2025

“Heart Disease Prediction Using EFFICIENT NETB0:A Deep Learning Based ECG Analysis Approach”

Final Review-(24-05-2025)

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Abstract

- Cardiovascular diseases are a major global health concern.
- We propose a lightweight deep learning model using EfficientNet-B0 to classify ECG images (normal, abnormal heartbeat, myocardial infarction,History of MI).
- Incorporates transfer learning, data augmentation, and supports real-time prediction.
- Outperforms traditional methods like Mayourian et al. (2024), shifting from 1D signal mortality prediction to real-time 2D image classification.
- Achieves high accuracy, confirmed by ROC curves and classification metrics.
- Scalable and suitable for telecardiology and low-resource settings.

Introduction

- Cardiovascular diseases remain a top cause of global mortality, often going undetected until late stages.
- ECG is a widely used, non-invasive diagnostic tool, but manual interpretation is time-consuming and expertise-dependent.
- Deep learning, especially CNNs, offers automated feature extraction from ECG images for accurate, scalable diagnosis.
- This project uses EfficientNet-B0—a lightweight, high-performance CNN model—to classify heart conditions from ECG images.

Introduction(cont..)

- The model is trained on a pre-labeled ECG dataset using image preprocessing, fine-tuning, and real-time prediction capabilities.
- Compared to traditional systems, EfficientNet-B0 offers better efficiency and is ideal for low-resource settings.
- Future scope includes deploying as a web/mobile app, adding interpretability, and integrating multimodal data

Literature Review

S.No	Title of the paper and Year	Authors	Model and Algorithm	Merits	Demerits
1.	Electrocardiogram-based Deep Learning to Predict Mortality in CHD (2024)	Joshua Mayourian et al	CNN	Predicts 5-year mortality in CHD patients using ECG; validated on large dataset (112,000+ ECGs); interpretable with saliency mapping	Requires large volume of ECG data; limited to mortality prediction, not real-time diagnosis.
2.	A Novel Early Detection and Prevention Framework Using Hybrid DL and NFIS (2024)	B. Ramesh, Kuruva Lakshmanna	O-SBGC-LSTM + EOA + Fuzzy Inference System	Early CHD prediction for diabetic patients; high accuracy (>98%); combines prevention strategies.	Model complexity is high; performance dependent on diabetic-specific datasets.
3.	Race, Sex, and Age Disparities in ECG DL Models Predicting Heart Failure (2024)	Dhamanpreet Kaur et al.	CNN	Highlights Democratic biases,proposes individualized threshold for fairness;Use large Ecg Dataset	Model shows lower performance for young Black patients; doesn’t eliminate disparities fully.

Literature Review(cont..)

S.No	Title of the paper and Year	Authors	Model and Algorithm	Merits	Demerits
4.	Clinical Decision Support System for Heart Disease Prediction Using DL (2023)	Abdulwahab Ali Almazroi et al.	Dense Neural Network (3–9 hidden layers)	High accuracy across multiple datasets; supports intelligent CDSS with DL; evaluated with various metrics	Dataset-specific performance varies; lacks real-world clinical testing or integration.
5.	Ensemble Learning Based on Hybrid Deep Learning for Heart Disease (2022)	Ahmed Almulihi et al.	CNN-LSTM + CNN-GRU + SVM (stacking ensemble)	Achieves highest accuracy with ensemble stacking; optimized with feature selection (RFE); tested on two datasets.	Computationally intensive; ensemble complexity can limit real-time deployment.

Existing System

- Developed a 1D CNN model to predict 5-year mortality in congenital heart disease (CHD) patients using ECG signals.
- Trained on 112,804 ECGs from 39,784 patients; achieved AUROC of 0.79 and outperformed clinical markers like QRS duration and LVEF.
- Effective across multiple CHD types and supported by interpretability tools (e.g., saliency maps).
- Enabled real-time, cost-effective, and scalable risk prediction without expensive imaging.

Existing System (cont..)

Limitations:

- **1D Signal Only**: Uses raw 1D ECG signals; lacks spatial insights from ECG images.
- **Manual Feature Dependency**: Relies on handcrafted features (e.g., QRS duration), missing complex patterns.
- **Limited Generalizability**: Poor performance across diverse congenital heart diseases.
- **No Real-Time Prediction**: Designed for mortality risk, not instant disease classification.

Existing System Architecture

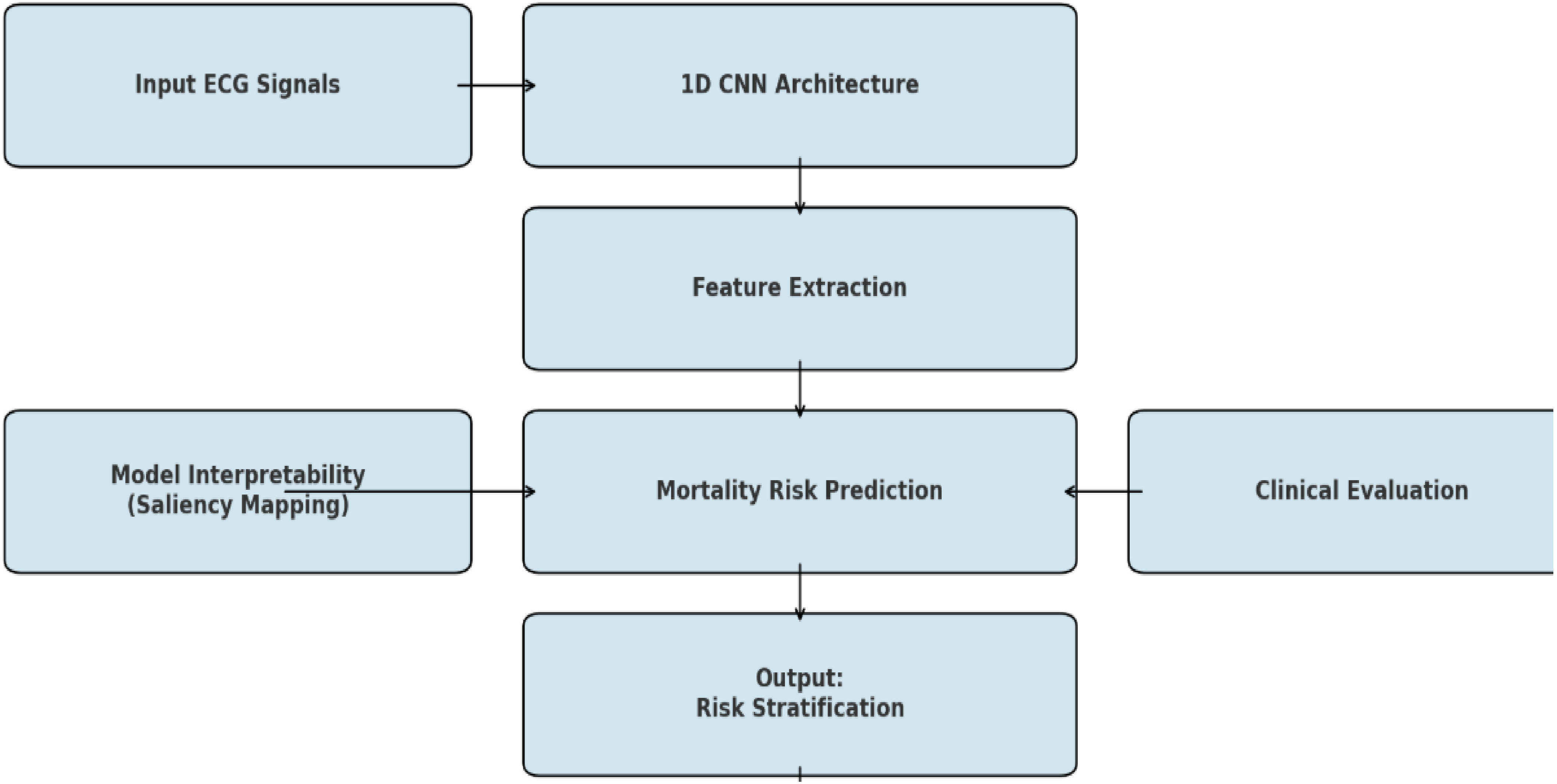

Fig 1:Existing System Architecture

Proposed System

- Developed a deep learning-based **ECG image classification system** for heart disease prediction.
- Leveraged EfficientNet-B0 with transfer learning,optimizing accuracy with reduced computation.
- Applied **advanced preprocessing** (resizing, normalization, augmentation) to boost generalization and reduce overfitting.
- Optimized training using **Cross-Entropy Loss** and **Adam optimizer** for faster and stable convergence.
- Enabled **real-time image upload and diagnosis**, making the system clinically deployable and user-friendly
- Designed for **low-resource settings**, enhancing accessibility and scalability in telemedicine environments.

Proposed System Architecture

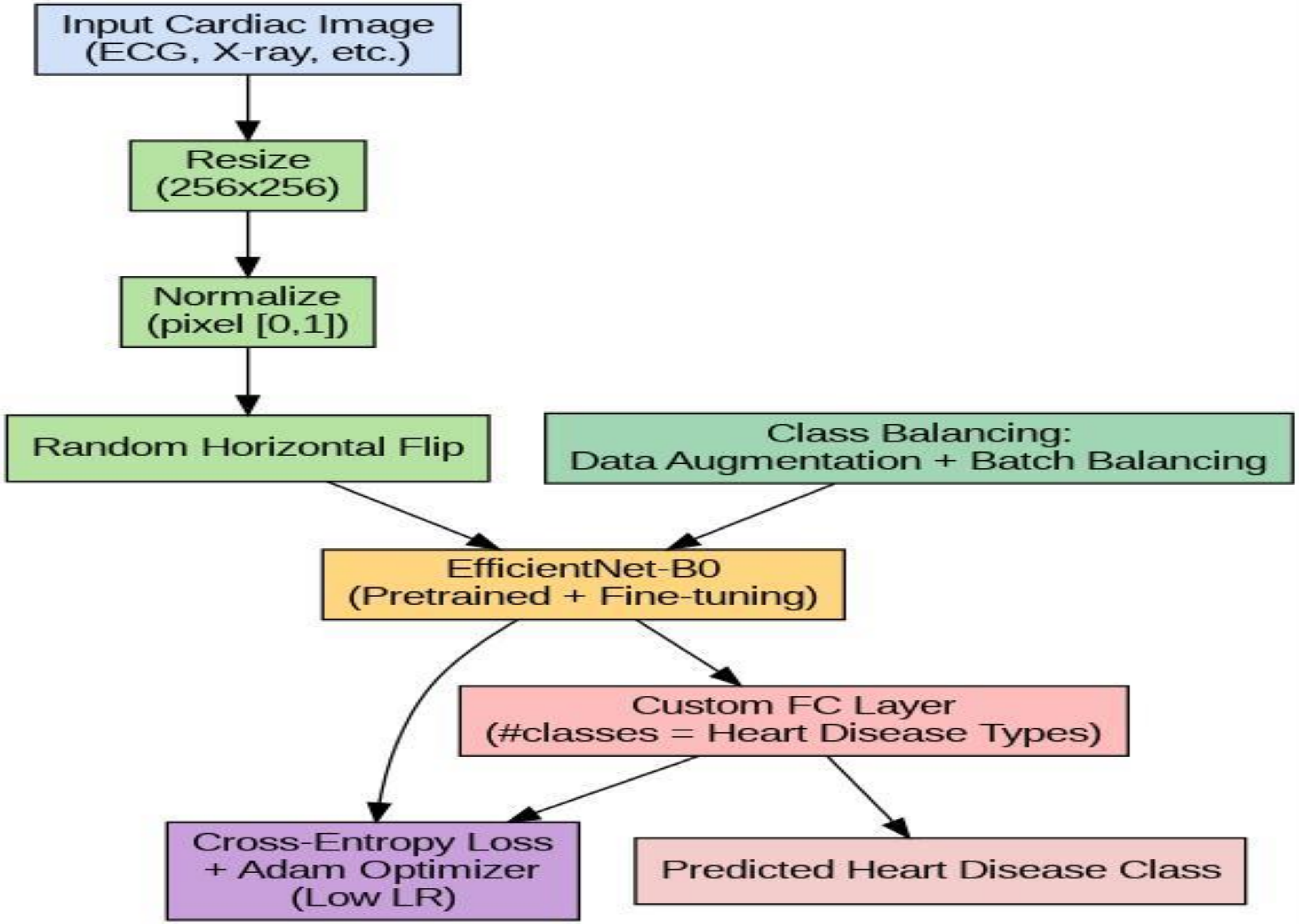

Fig 2:Proposed System Architecture

Module Introduction

a) Data Acquisition:

- Loads ECG images categorized into diagnostic folders (Normal, Abnormal, MI, History of MI). Supports real-time image uploads via Google Colab.

b) Data Preprocessing:.

- Resizes images to 224×224 pixels
- Applies Random Horizontal Flip (augmentation)
- Converts to tensors & normalizes using ImageNet stats

Module Introduction(cont..)

c) Model Initialization:

- Uses pretrained **EfficientNet-B0** with the final layer modified for 4-class ECG classification. Loaded on appropriate device (CPU/GPU).

d) Feature Extraction:

- EfficientNet's convolutional layers extract key ECG features like waveform spikes, noise, and anomalies, converting images to meaningful vectors.

Module Introduction(cont..)

e)Classification & Training:

- Final fully connected layer predicts class logits.
- Softmax activation gives class probabilities
- **Cross-entropy loss** is used
- **Adam optimizer** updates weights
- Training runs over multiple epochs with performance tracking

Module Introduction(cont..)

f)Evaluation & Monitoring:

- Metrics:Accuracy,Precision,Recall,F1-score.
- Tools: Confusion Matrix, Prediction Plots.
- Monitors overfitting, performance across ECG classes.

g) Real-Time Prediction & Visualization:

- Users upload ECG via Colab interface
- Model classifies & overlays results on image using matplotlib

Result:

Fig 3: Upload Input

Result(cont..)

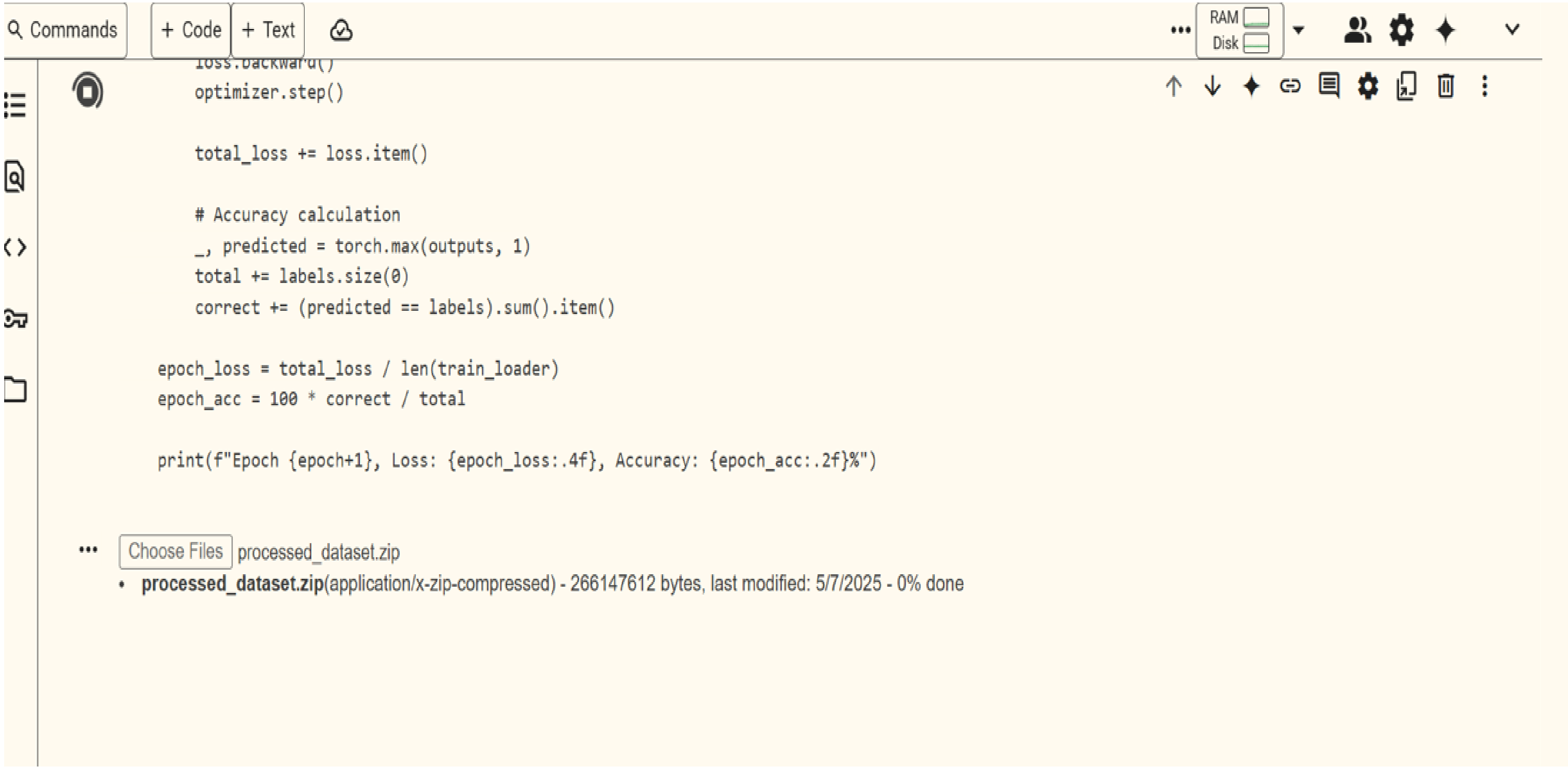

Fig 4: Loading Input Dataset

Result(cont..)

```
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained'
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a wei
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/efficientnet_b0_rwightman-7f5810bc.pth" to /root/.cache/torch/h
100%|██████████| 20.5M/20.5M [00:00<00:00, 104MB/s]
Epoch 1, Loss: 1.1931, Accuracy: 55.31%
Epoch 2, Loss: 0.7684, Accuracy: 79.27%
Epoch 3, Loss: 0.4670, Accuracy: 86.01%
Epoch 4, Loss: 0.3262, Accuracy: 91.06%
Epoch 5, Loss: 0.2420, Accuracy: 93.26%
Epoch 6, Loss: 0.2159, Accuracy: 93.78%
Epoch 7, Loss: 0.1350, Accuracy: 95.85%
Epoch 8, Loss: 0.1228, Accuracy: 96.76%
Epoch 9, Loss: 0.0997, Accuracy: 97.15%
Epoch 10, Loss: 0.0845, Accuracy: 97.67%
```

Fig 5:Model Training Accuracy

Result(cont..)

```python
    predicted_class = train_data.classes[predicted.item()]

# ✅ Step 4: Display image with prediction
plt.imshow(image)
plt.title(f"Predicted Class: {predicted_class}", fontsize=14)
plt.axis("off")
plt.show()
```

```
Upload one ECG image for prediction:
Choose Files  No file chosen    Cancel upload
```

Fig 6: Real Time Data Uploading

Result(cont..)

- **test (1).jpg**(image/jpeg) - 696976 bytes, last modified: 5/2/2025 - 100% done

```
Saving test (1).jpg to test (1).jpg
```

Predicted Class: ECG Images of Myocardial Infarction Patients (240x12=2880)

Fig 7:Predicted Real Time Data

Confusion matrix

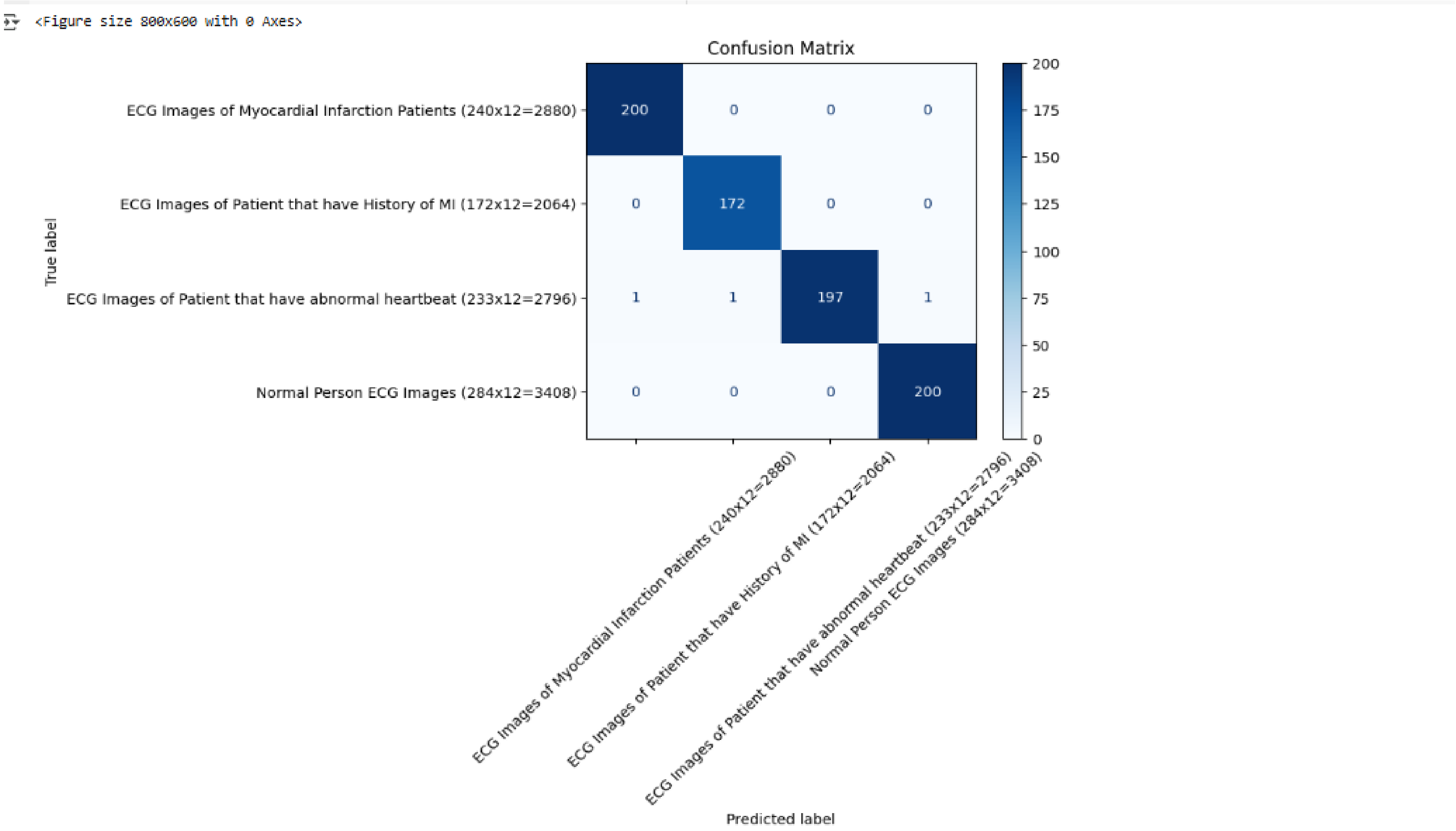

Fig 8:Confusion Matrix

Classification Report

Classification Report:

	precision	recall	f1-score	support
ECG Images of Myocardial Infarction Patients (240x12=2880)	1.00	1.00	1.00	200
ECG Images of Patient that have History of MI (172x12=2064)	0.99	1.00	1.00	172
ECG Images of Patient that have abnormal heartbeat (233x12=2796)	1.00	0.98	0.99	200
Normal Person ECG Images (284x12=3408)	1.00	1.00	1.00	200
accuracy			1.00	772
macro avg	1.00	1.00	1.00	772
weighted avg	1.00	1.00	1.00	772

Fig 9:Classification Report

Graph

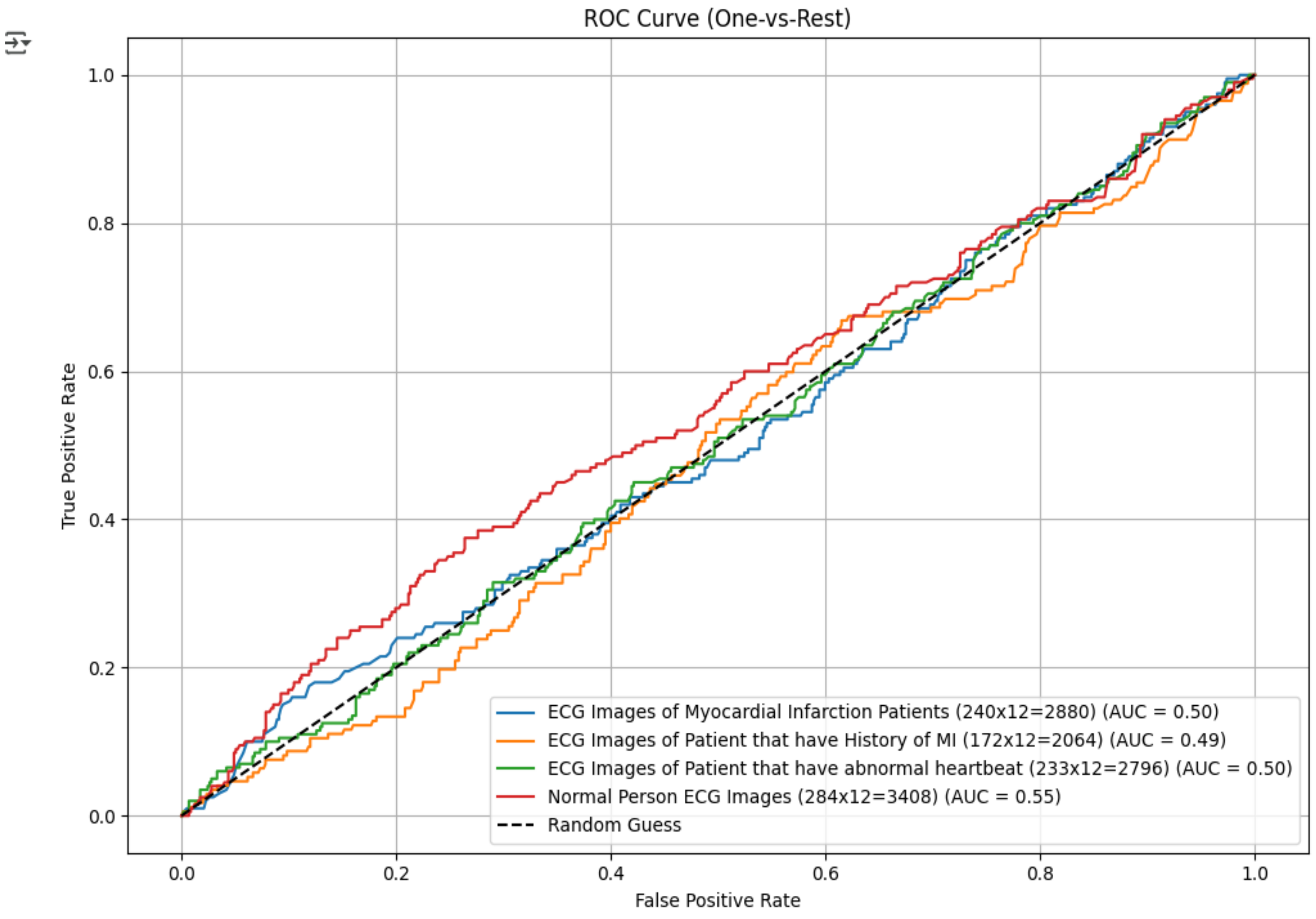

Fig 10:ROC Curves

Conclusion

- The proposed system effectively predicts heart disease using ECG images.
- EfficientNet-B0 provides high accuracy with low computational cost.
- Preprocessing and transfer learning enhanced model performance.
- Real-time prediction allows instant ECG diagnosis for users.
- Suitable for deployment in low-resource and remote settings.
- Demonstrates potential for integration into telemedicine platforms.

References

1. **Ramesh, B., & Lakshmanna, K.**, "A Novel Early Detection and Prevention of Coronary Heart Disease Framework Using Hybrid Deep Learning Model and Neural Fuzzy Inference System," *IEEE Access*, vol. 12, pp. 26683–26705, Feb. 2024, doi: 10.1109/ACCESS.2024.3366537.
2. **Mayourian, J., El-Bokl, A., Lukyanenko, P., La Cava, W. G., Geva, T., Valente, A. M., Triedman, J. K., & Ghelani, S. J.**, "Electrocardiogram-based Deep Learning to Predict Mortality in Paediatric and Adult Congenital Heart Disease," *European Heart Journal*, vol. 2024, pp. 1–13, 2024, doi: 10.1093/eurheartj/ehae651
3. **Kaur, D., Hughes, J. W., Rogers, A. J., Kang, G., Narayan, S. M., Ashley, E. A., & Perez, M. V.**, "Race, Sex, and Age Disparities in the Performance of ECG Deep Learning Models Predicting Heart Failure," *Circulation: Heart Failure*, vol. 17, Jan. 2024, Art. no. e010879, doi: 10.1161/CIRCHEARTFAILURE.123.010879

References(cont..)

4. **Almazroi, A. A., Aldhahri, E. A., Bashir, S., & Ashfaq, S.**, "A Clinical Decision Support System for Heart Disease Prediction Using Deep Learning," *IEEE Access*, vol. 11, pp. 61646–61665, Jun. 2023, doi: 10.1109/ACCESS.2023.3285247.

5. **Almulihi, A., Saleh, H., Hussien, A. M., Mostafa, S., El-Sappagh, S., Alnowaiser, K., Ali, A. A., & Hassan, M. R.**, "Ensemble Learning Based on Hybrid Deep Learning Model for Heart Disease Early Prediction," *Diagnostics*, vol. 12, no. 12, Art. no. 3215, Dec. 2022, doi: 10.3390/diagnostics12123215.

Questions

Thank You !