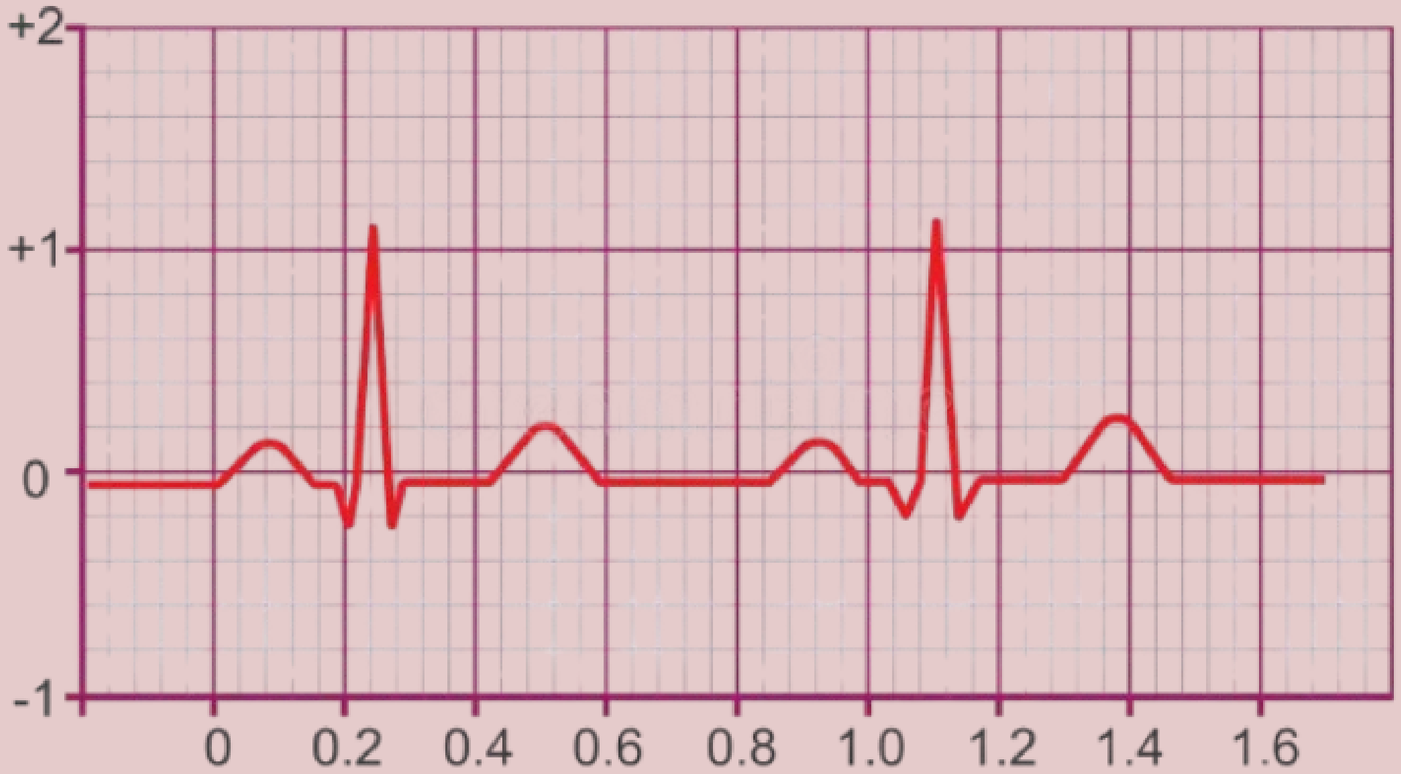
ECG SIGNAL CLASSIFICATION USING DNN



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Introduction

- Cardiovascular diseases are the leading cause of death worldwide.
- ECG is widely used to detect heart abnormalities.
- Manual ECG analysis is time-consuming and prone to human error.

Problem Statement:

To develop an automated system that classifies ECG signals as Normal or Abnormal using Deep Learning.

What is ECG?

ECG (Electrocardiogram) records the electrical activity of the heart.

Main components:

- P wave – Atrial depolarization
- QRS complex – Ventricular depolarization
- T wave – Ventricular repolarization

Abnormal changes in these waves indicate heart problems.

Deviations from normal ECG patterns indicate potential cardiac conditions. Irregularities in wave amplitude, duration, or rhythm can reveal arrhythmias, ischemia, or structural heart problems.

Normal ECG

Regular rhythm with consistent P-QRS-T patterns

Abnormal ECG

Irregular patterns indicating cardiac dysfunction

Project workflow

Start

↓

Upload ECG Dataset (CSV)

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Preprocessing
- Remove NaN
- Feature-Label Separation
- Binary Conversion
- Standardization

↓

Train-Test Split (80-20)

↓

Build Deep Neural Network
- Dense + ReLU
- Dropout
- Softmax Output

↓

Train Model (Adam Optimizer)

↓

Evaluate Accuracy

↓

Predict Test Data

↓

Borderline Detection (Confidence < 60%)

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Generate Outputs
- Accuracy
- Confusion Matrix
- Percentage Graph

End

DNN block

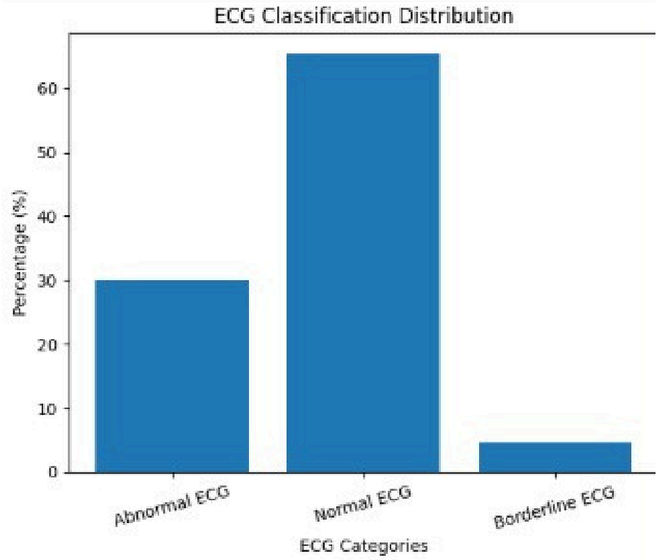
1. **Dense layer** (Fully connected layer)
2. **Activation Function: ReLU (Rectified Linear Unit)**
3. **Dropout Layer: (0.3)** Randomly disables 30% neurons during training, to prevent overfitting.
4. **Output Layer**
5. **Loss Function**
6. **Adam Optimizer** (It adjusts learning rate automatically, is one of the best optimizers for deep learning.)

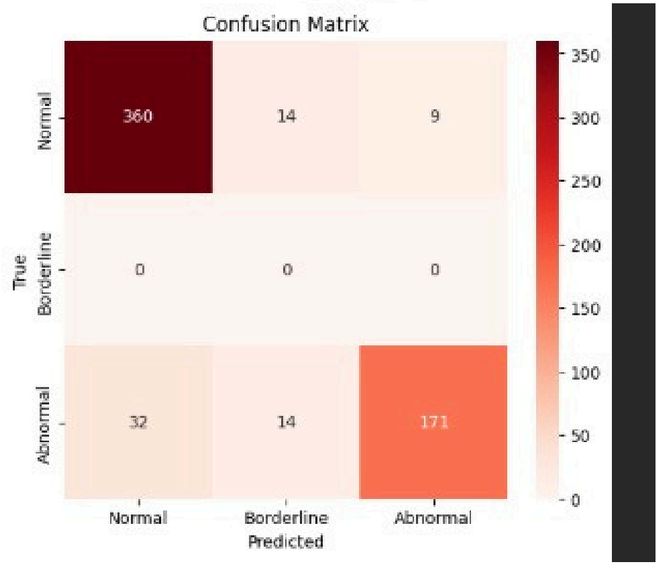
1. **Forward Propagation**
2. **Input → Hidden layers → Output**
3. **Loss Calculation**
4. **Compare predicted vs actual**
5. **Backpropagation**
6. **Calculate gradients**
7. **Weight Update**
8. **Using Adam optimizer**
9. **Repeat for 25 epochs**
10. **This is how the network learns ECG patterns.**

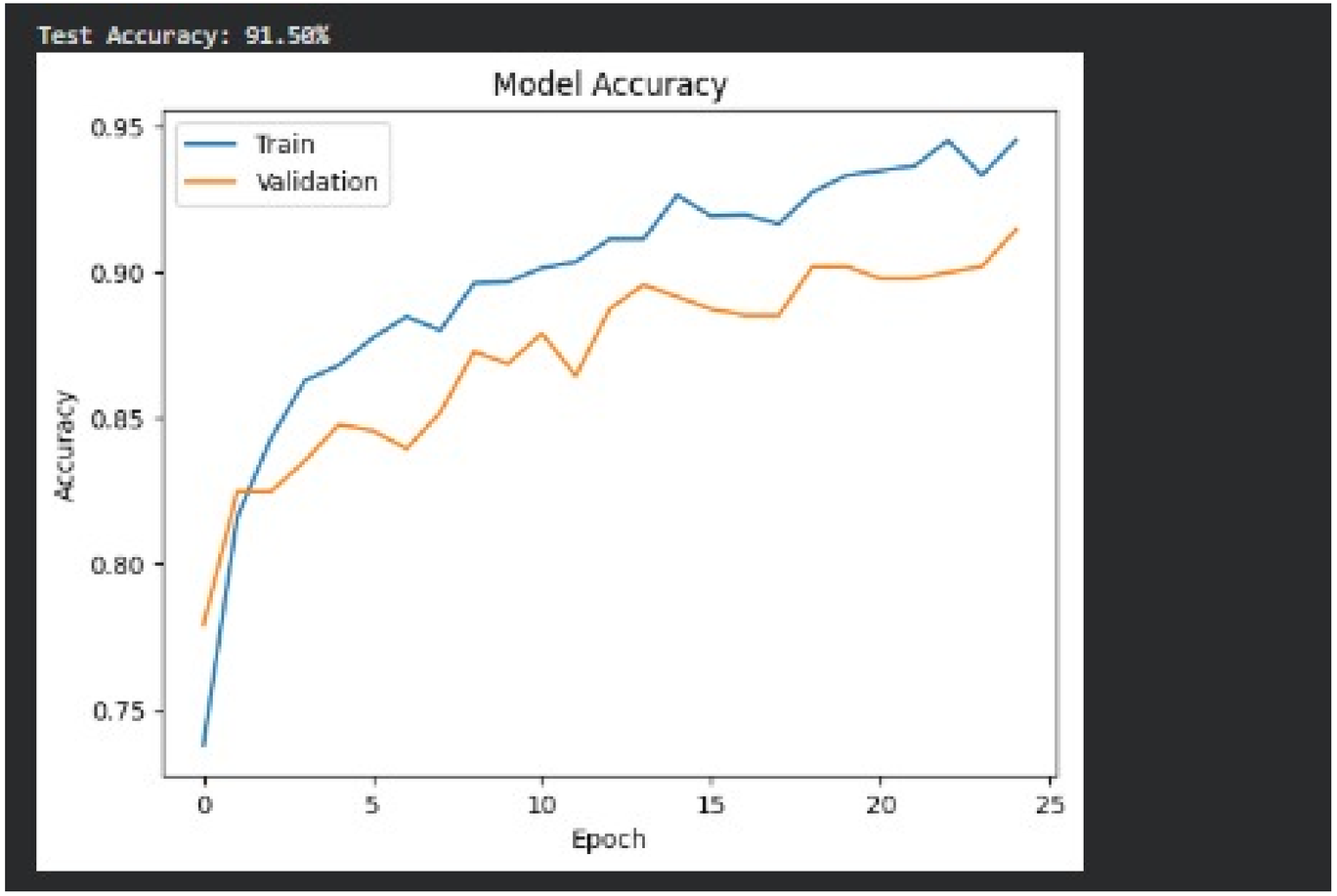
- **Input layer (implicit)**
- **Hidden Layer 1 → 128 neurons**
- **Hidden Layer 2 → 64 neurons**
- **Output Layer → 2 neurons**

It learns features automatically.
thats why deep learning

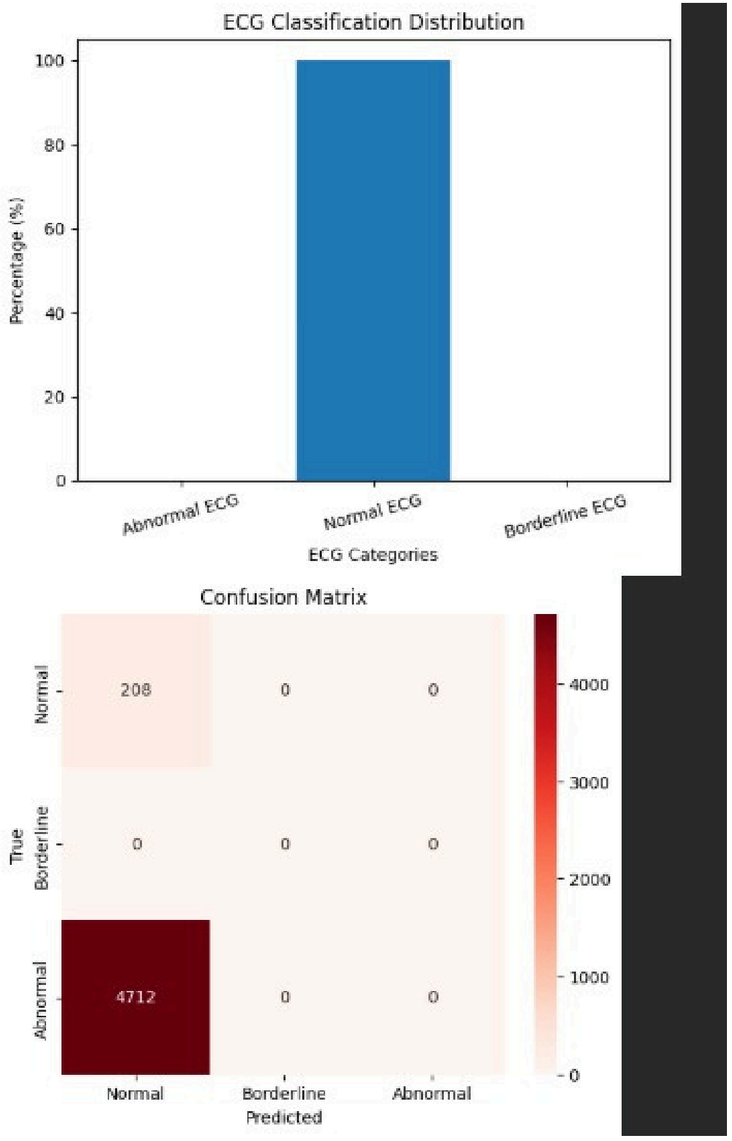
OUTPUT

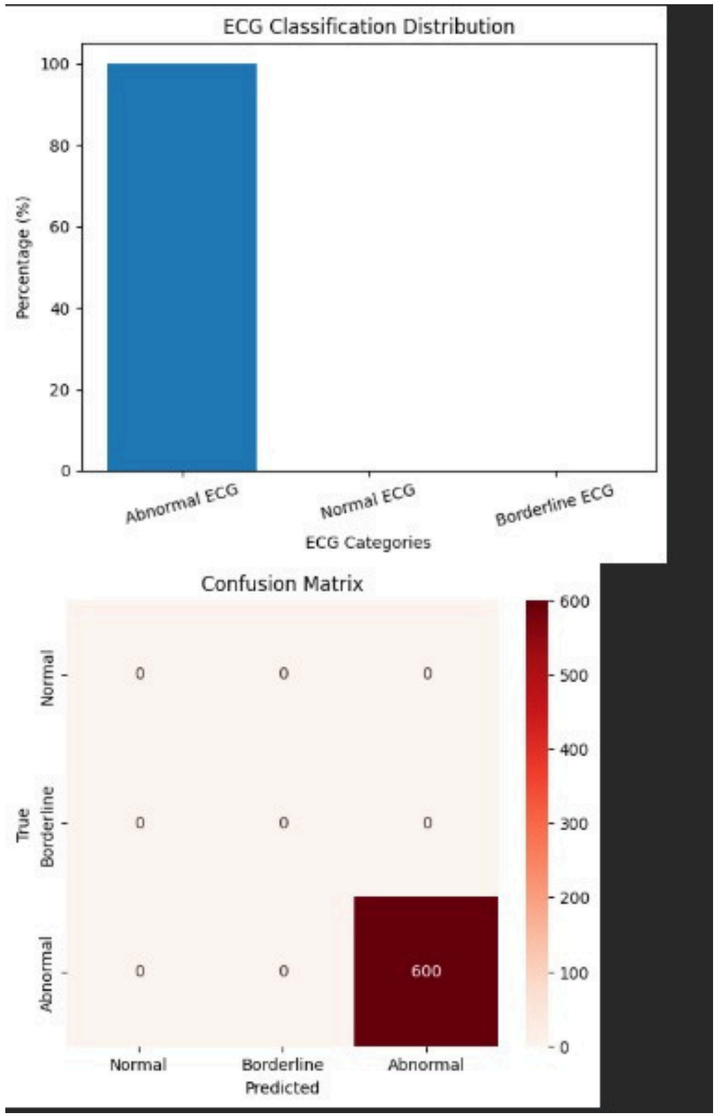

ECG Classification Distribution
Percentage (%)
0
10
20
30
40
50
60
Abnormal ECG
Normal ECG
Borderline ECG
ECG Categories


Confusion Matrix
Normal
Borderline
Abnormal
True
360
14
9
0
0
0
32
14
171
Normal
Borderline
Abnormal
Predicted
350
300
250
200
150
100
50
0

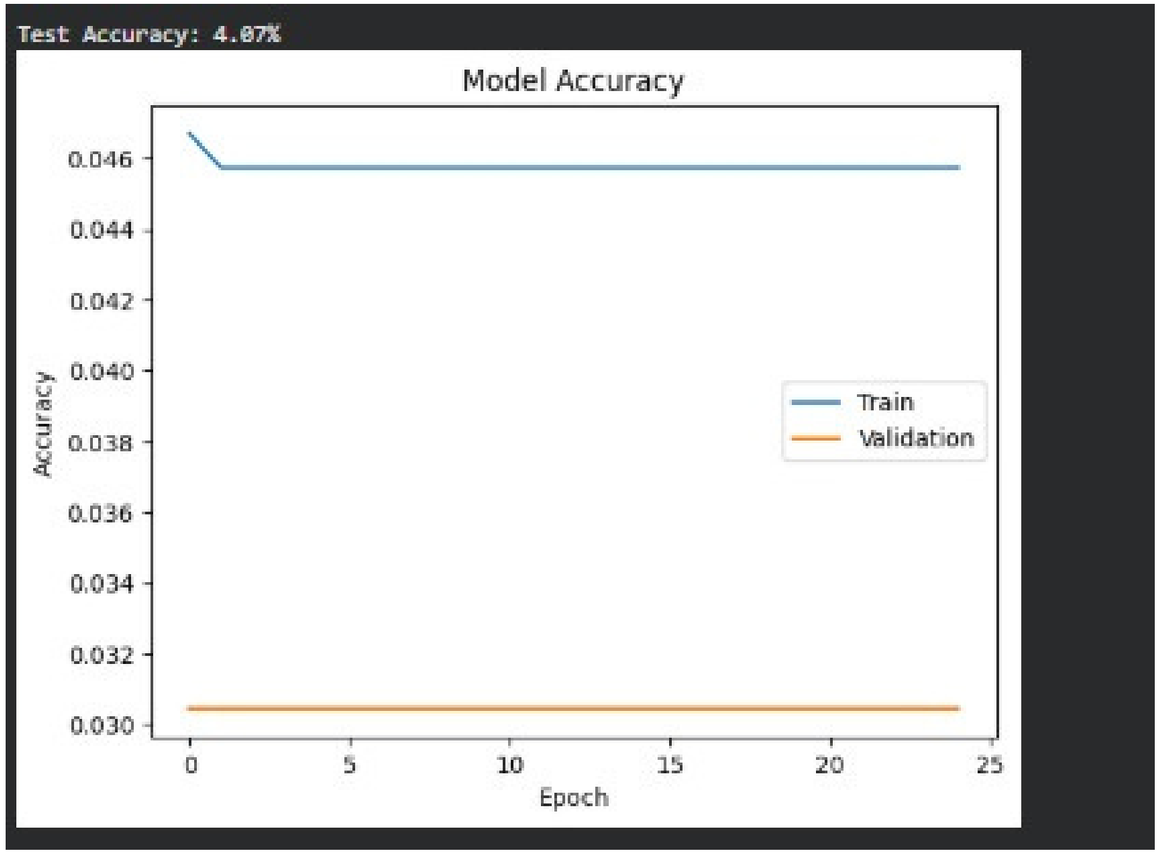

Test Accuracy: 91.50%
Model Accuracy
Train
Validation
Accuracy
0.95
0.90
0.85
0.80
0.75
0
5
10
15
20
25
Epoch

OUTPUT

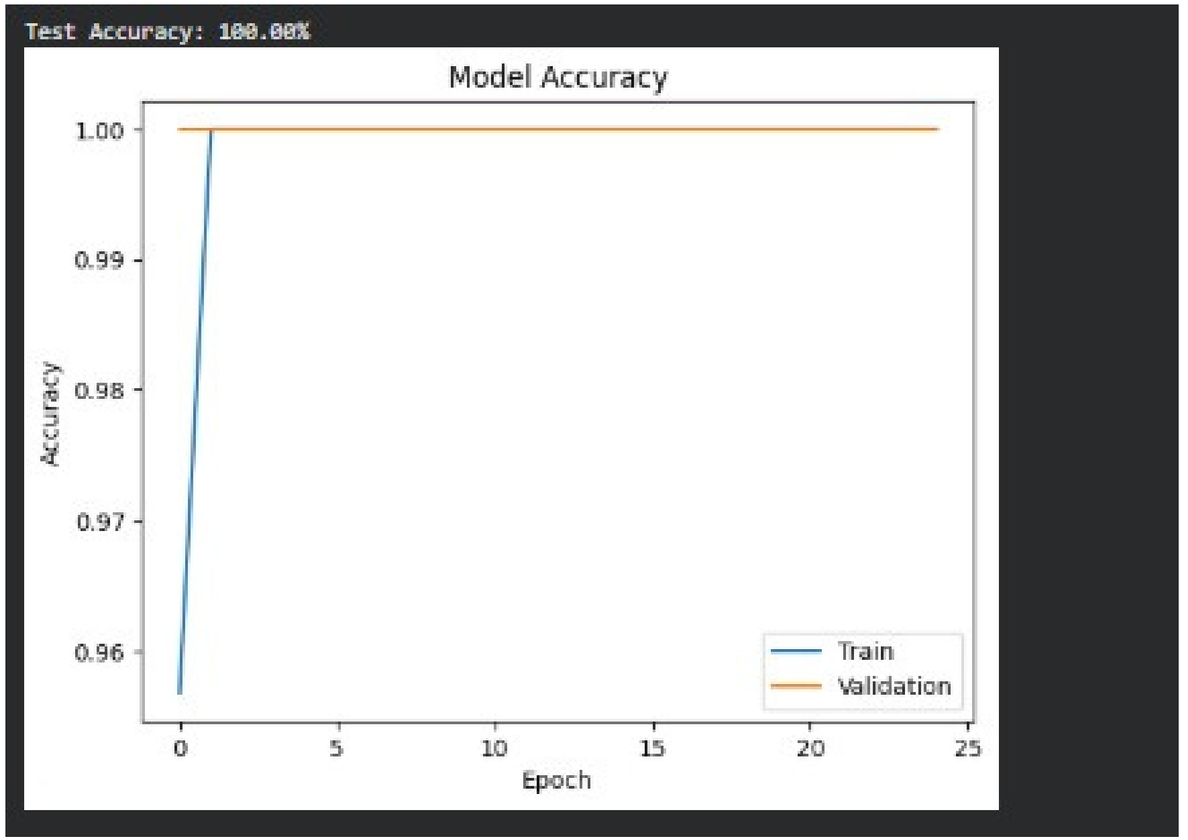

ECG Classification Distribution
Percentage (%)
0
20
40
60
80
100
Abnormal ECG
Normal ECG
Borderline ECG
ECG Categories
Confusion Matrix
True
Normal
Borderline
Abnormal
208
0
0
0
0
0
4712
0
0
Normal
Borderline
Abnormal
Predicted
4000
3000
2000
1000
0


ECG Classification Distribution
Percentage (%)
0
20
40
60
80
100
Abnormal ECG
Normal ECG
Borderline ECG
ECG Categories
Confusion Matrix
True
Normal
Borderline
Abnormal
0
0
0
0
0
0
0
0
600
Normal
Borderline
Abnormal
Predicted
600
500
400
300
200
100
0

ACCURACY



Normal



Abnormal

Conclusion

Project Outcomes

1. Objective Achieved

- Developed a Deep Neural Network (DNN) model for ECG signal classification.
- Successfully classified ECG signals into Normal and Abnormal categories.

2. Performance

- Achieved approximately 91% test accuracy.
- Confusion matrix used to evaluate classification performance.
- Implemented confidence-based Borderline detection for uncertain predictions.

3. Key Observations

- Data preprocessing and normalization significantly improved performance.
- Class imbalance affects prediction results.
- False negatives are critical in medical diagnosis and require careful analysis.

THANKYOU!