Biomedical Signal Processing

Mini Project

Arrhythmia Detection

Introduction

- **What is an Electrocardiogram (ECG)?**
  - A test that records the heart’s electrical activity.

- **Why is ECG Important?**
  - Helps detect arrhythmias by analyzing electrical patterns.

Introduction

- **What is Arrhythmia?**
  - A condition where the heart beats irregularly, too fast, or too slow.
- **Importance of Detection**
  - Early detection prevents complications like stroke and heart failure.
  - Machine learning models help automate and improve diagnosis.

Motivation

- **Prevents Serious Health Complications:**
  - Early detection can prevent stroke, cardiac arrest, and heart failure.
- **Improves Quality of Life:**
  - Timely treatment allows patients to manage symptoms better.
- **Supports Clinical Decision-Making:**
  - Assists doctors in diagnosing and treating arrhythmia efficiently.
- **Reduces Healthcare Costs:**
  - Early intervention minimizes the need for expensive emergency treatments.

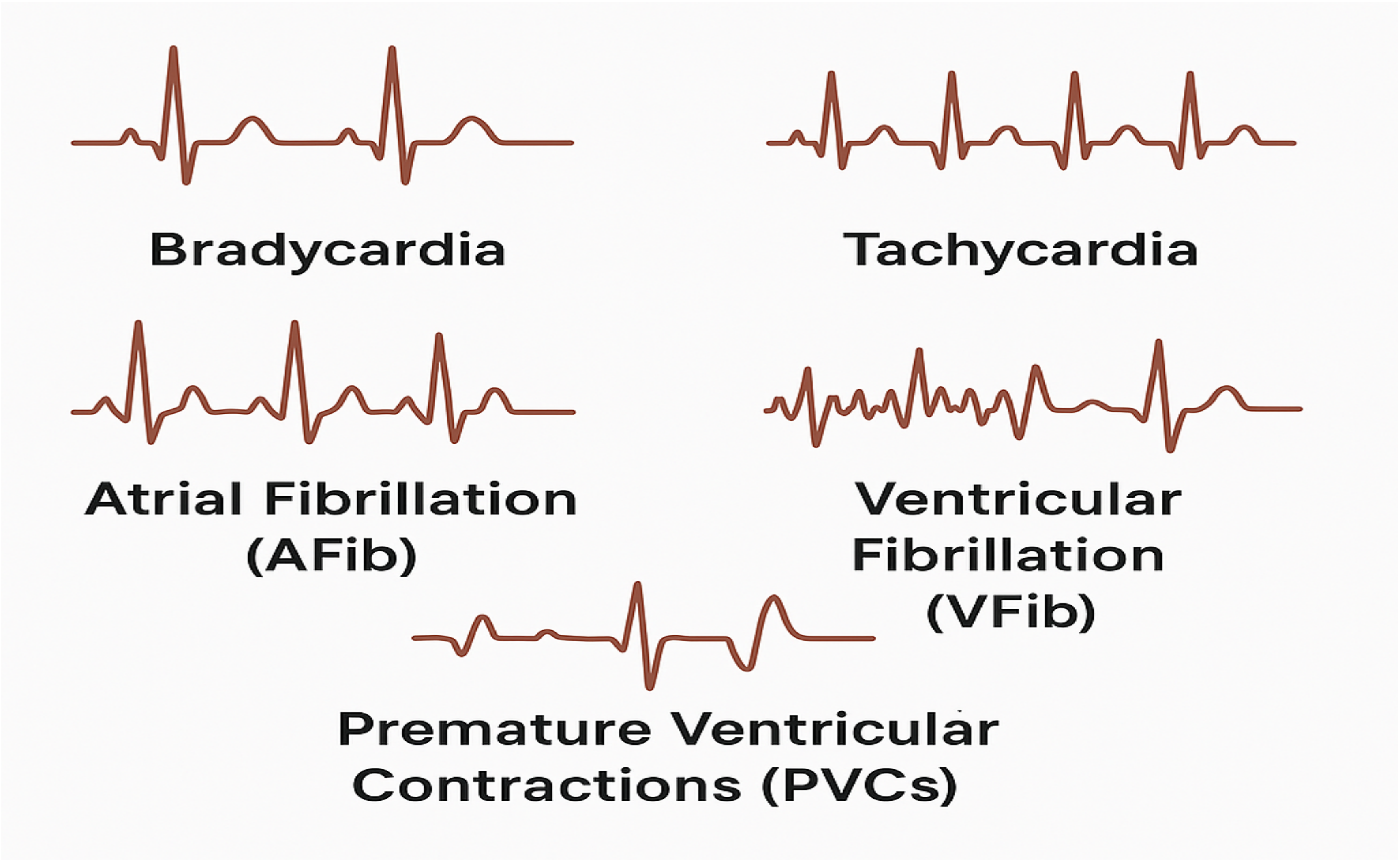
Objectives

- **Develop a CNN-based model** for detecting arrhythmia from ECG signals.
- **Utilize the MIT-BIH dataset** to train and test the model.
- **Improve classification accuracy** between normal and abnormal heart rhythms.
- **Demonstrate model performance** using evaluation metrics such as accuracy, precision, recall, and F1-score.
- **Contribute to healthcare advancements** by providing an automated arrhythmia detection system.

Types of Arrhythmia

- **Bradycardia:** Slow heart rate (< 60 BPM)
- **Tachycardia:** Fast heart rate (> 100 BPM)
- **Atrial Fibrillation (AFib):** Irregular, rapid heart rhythm
- **Ventricular Fibrillation (VFib):** Disorganized electrical signals in ventricles
- **Premature Ventricular Contractions (PVCs):** Extra, abnormal heartbeats

Types of Arrhythmia



MIT-BIH Dataset

- **About the Dataset**
  - Developed by **MIT-Beth Israel Hospital**
  - Contains **48 half-hour ECG recordings** with different arrhythmias
  - Includes **normal and abnormal heartbeats**

Methodology

1. Data Preprocessing

- **Feature Extraction:** First 187 columns as features
- **Labeling:** Last column as class label (Normal = 0, Abnormal = 1)
- **Balancing:** Equal samples of normal and abnormal beats
- **Normalization:** StandardScaler used for feature scaling
- **Reshaping for CNN:** (Samples, 187, 1) format

Methodology

2. CNN Model Architecture

- **Layers Used:**
  - **Conv1D:** Extracts ECG features
  - **MaxPooling1D:** Reduces dimensionality
  - **Flatten:** Converts 2D to 1D
  - **Dense Layers:** Fully connected neural layers
  - **Dropout:** Reduces overfitting
- **Activation Functions:**
  - **ReLU:** For hidden layers
  - **Sigmoid:** For output (binary classification)

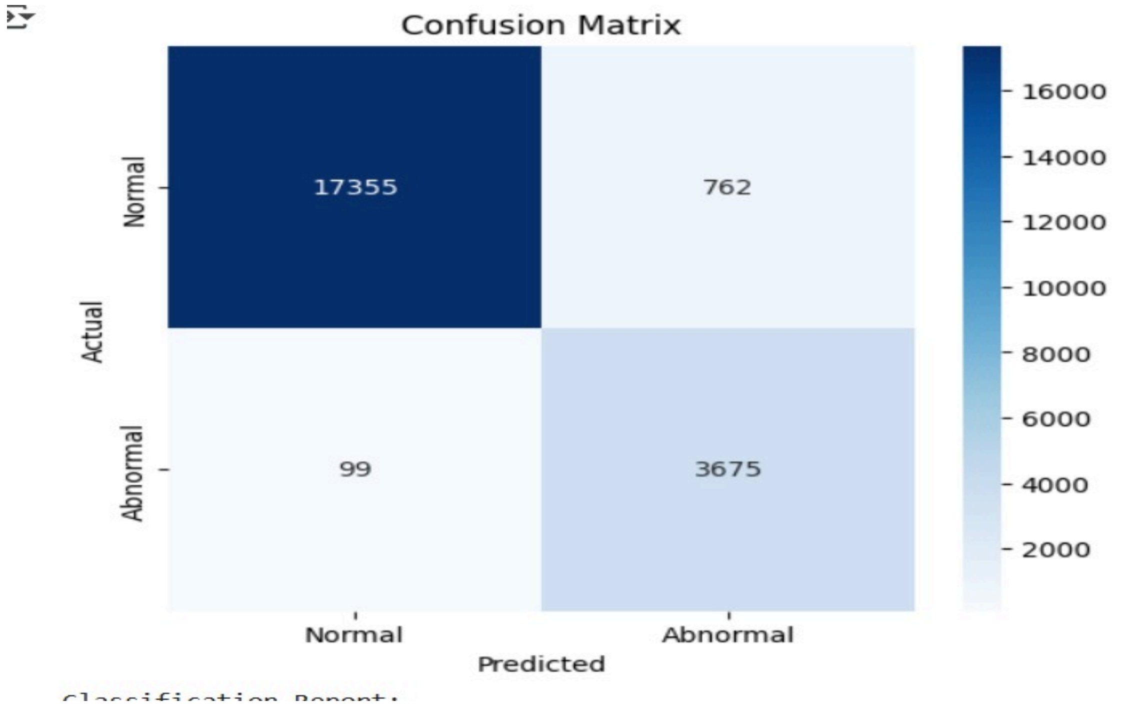
Methodology

3. Training and Evaluation

- **Training Parameters:**
  - **Epochs:** 50
  - **Batch Size:** 32
  - **Validation Split:** 20%
- **Loss Function:** Binary Crossentropy
- **Optimizer:** Adam
- **Performance Metrics:**
  - **Accuracy:** Measures correct predictions
  - **Confusion Matrix & Classification Report:** Precision, Recall, F1-score

Results

- **Confusion Matrix :**



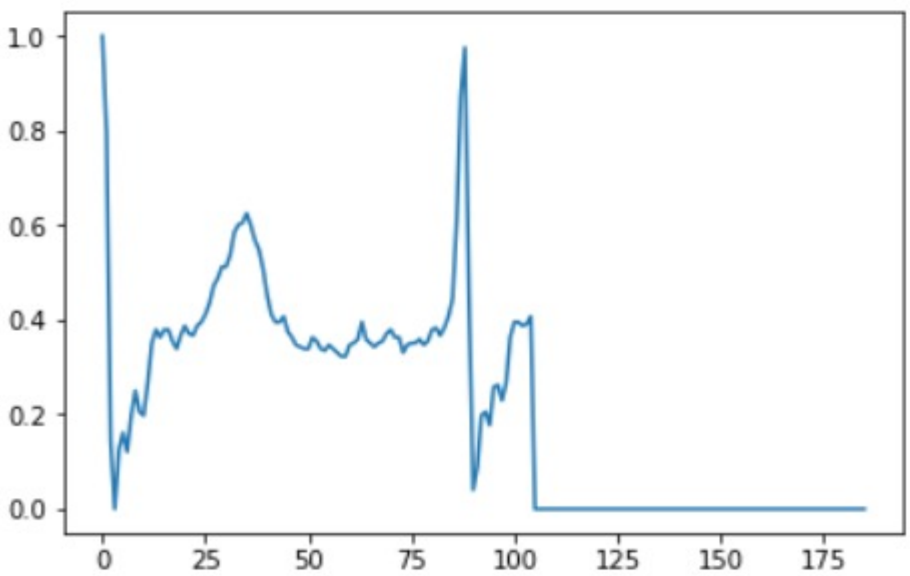
High recall is crucial (as we don’t want to miss actual abnormal cases).

Results

- **Classification Report :**

```
Accuracy: 0.9607
Precision: 0.8283
Recall: 0.9738
```

- **Arrhythmia predicted by model :**



Discussions

- **Strengths of the Model:**
  - High accuracy in distinguishing normal and abnormal heart rhythms.
  - Effective feature extraction using CNN architecture.
  - Balanced dataset improves performance and reduces bias.
- **Challenges & Limitations:**
  - Requires large datasets for better generalization.
  - Potential overfitting due to limited training data.
  - Model performance may vary based on ECG noise and signal quality.

Conclusion

- CNN effectively classifies arrhythmia vs. normal.
- High accuracy achieved with balanced dataset.
- The model demonstrates potential for real-world applications in ECG-based arrhythmia detection.
- AI-powered detection can assist healthcare professionals in early diagnosis and intervention.

Future Work

- **Enhance Model Performance:**
  - Experiment with advanced deep learning techniques (e.g., LSTM, Transformer models for sequential data).
  - Implement data augmentation techniques to improve generalization.
- **Real-Time Arrhythmia Monitoring:**
  - Deploy the model on wearable ECG monitoring devices.
  - Develop a mobile or web-based application for real-time classification.
- **Expand Dataset Coverage:**
  - Collect and integrate more diverse ECG datasets.
  - Include different age groups and medical conditions for better generalizability.

References

- **MIT-BIH Arrhythmia Dataset**

- **TensorFlow & Keras Documentation**

- https://www.kaggle.com/code/gregoiredc/arrhythmia-on-ecg-classification-using-cnn