CARDIAC ARRHYTHMIA DETECTION

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Introduction/Background:

LSTM: Deep learning has recently transformed visual data processing and allowed machines to analyze and interpret images with unprecedented accuracy. This project combines computer vision and sequence modelling with Long Short-Term Memory (LSTM) networks to classify image sequence. Image classification is traditionally used on fixed frames; however, most real-world applications, including video-based action recognition or medical image time series analysis, are temporal in nature. To tackle this, we employ a hybrid architecture that takes advantage of the spatial feature learning capability of convolutional neural networks (CNNs) and LSTM layers for temporal sequence learning. Lightweight yet effective MobileNetV2 CNN architecture is used to extract features from single images. Features are then presented as sequences and input into LSTM layers for classification. This is a blend of performance and efficiency and suitable for resource-limited and real-time environments.

RNN: Cardiovascular diseases are one of the most prevalent causes of death globally, and their early detection is vital to ensuring effective treatment. Electrocardiograms (ECGs) serve as essential tools in diagnosing cardiac conditions by recording the electrical activity of the heart. However, manual interpretation of ECGs is often time-consuming and susceptible to human error, especially given the growing volume of patient data in modern healthcare systems. This project aims to address these challenges by implementing a deep learning-based system using Recurrent Neural

Networks (RNNs) to automatically analyze ECG signals and classify arrhythmias. The use of RNNs is particularly suitable for this application due to their ability to model sequential and temporal patterns inherent in ECG data. By leveraging labeled ECG signal sequences from the INCART 2-lead Arrhythmia Database, this project demonstrates the potential of RNNs in supporting rapid and reliable arrhythmia detection, thereby improving diagnostic efficiency and expanding access to timely cardiac care.

CNN: Cardiovascular diseases remain a leading cause of mortality worldwide, with early detection being crucial for effective treatment and patient survival. Electrocardiograms (ECGs) are fundamental diagnostic tools that provide insights into cardiac function through electrical activity recordings. However, the interpretation of ECG patterns requires specialized expertise and is time-consuming for healthcare professionals. The increasing volume of ECG data generated in clinical settings creates a significant burden on medical resources. This project addresses this challenge by developing an automated ECG classification system using deep learning techniques. By leveraging convolutional neural networks (CNNs), the system aims to accurately identify and classify various cardiac conditions from ECG images, potentially increasing diagnostic efficiency, reducing interpretation errors, and enabling broader access to cardiac evaluations in resource-limited settings. The integration of this technology into clinical workflows could substantially impact early detection rates and improve patient outcomes.

Objectives:

- To evaluate model performance and draw conclusions on its applicability in real-world scenarios.
- Training the model using labelled data from the INCART database to distinguish between five types of beats.
- Achieving high classification accuracy and robustness across varying signal qualities.
- Evaluating the model's clinical relevance by comparing results with expert interpretations.
- Laying the groundwork for deployment in real-time monitoring systems and wearable health devices.
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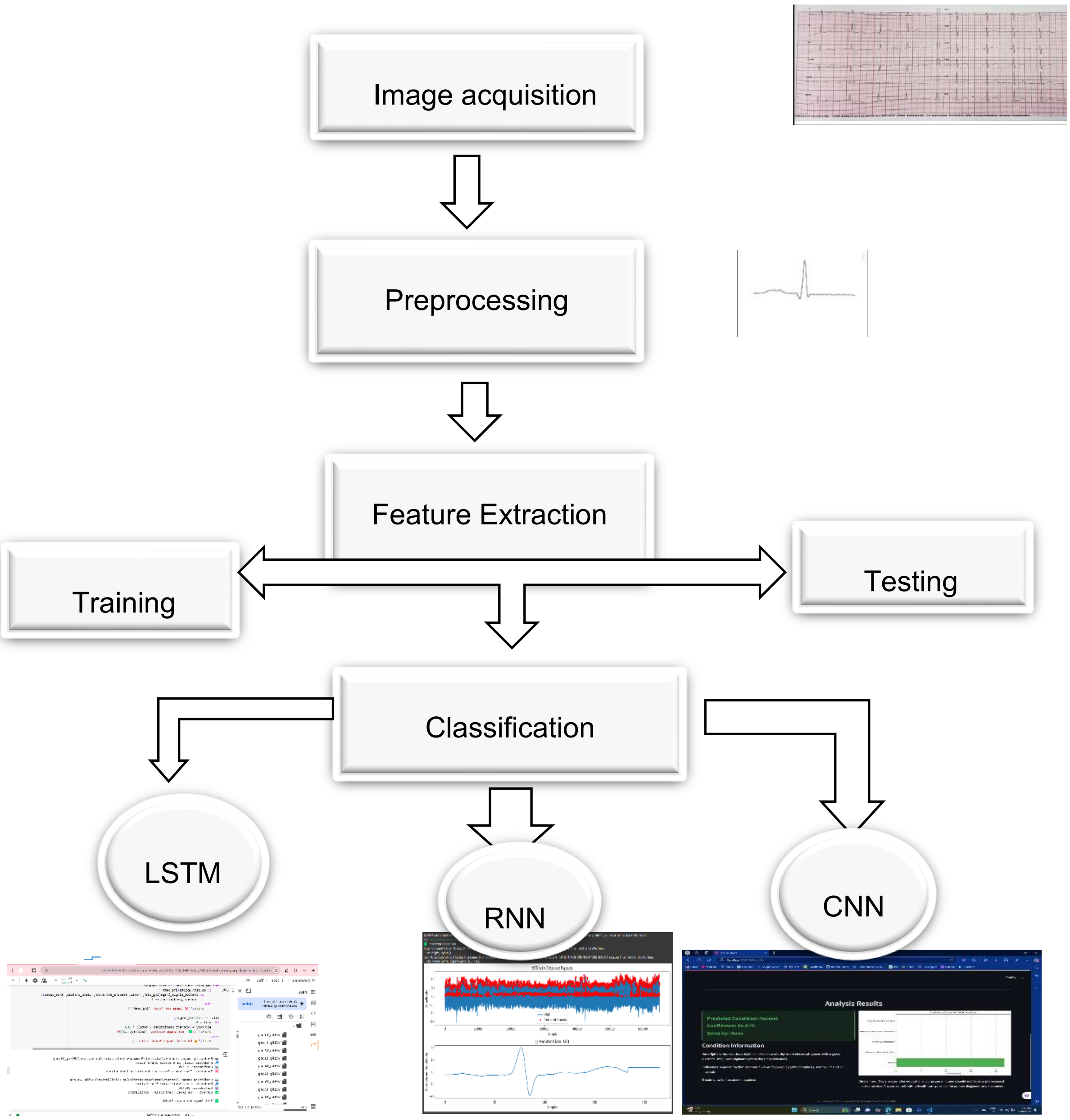
Methodology:



LSTM Model:

1. Dataset Preparation:

- Images are stored in class-specific folders and compressed into a ZIP file.
- The dataset is unzipped and processed with TensorFlow's ImageDataGenerator.

  Let the raw ECG signal be a time-series:

$$X = \{x_{1,} x_{2,\ldots,} x_T\}\ , \quad x_t \sum R$$

Where:

- x_t is the ECG signal amplitude at time
- T is the total number of samples.

  Preprocessing steps:

  a. Denoising: Apply a bandpass filter $f_{bp}(x_t)$ to remove baseline wander and high-frequency noise.
  b. Normalization:

$$(x_t) = \frac{x_{t-\mu}}{\sigma}\ ,\ \mu = \frac{1}{T}\sum_{t=1}^{T} x_{t,}$$

2. Feature Extraction:

- A pre-trained MobileNetV2 model is employed to extract high-level features from every image.
- Features are normalized and reshaped to create a time-series sequence of fixed length.

Let the feature vector for a single heartbeat be:

$$f_i=[f_{i1,}f_{i2,....,}f_{in}] \in R^n$$

Where f_i corresponds to features of the i^{th} beat.

3. Sequence Formation:

- Each image's feature vector is reshaped and arranged in sequences.
- It forms a 3D array of shape (samples, time steps, features per step).

For LSTM, you need a sequence of features:

$$S_j = \{\, f_{j,}\, f_{j+1,}\ .\ .\ .\ ,\, f_{j+L-1}\,\},\, S_j \in R^{L*n}$$

L: sequence length

n: number of features per beat

4. Model Development: A sequential model is created using Keras.

   Layers are:

- Bidirectional LSTM.

- Dropout for regularization.
- Final classification dense layers.

Input:

$$S_j = [f_t]L_{t=1,}\ f_t \in R^n$$

Where: σ is the sigmoid activation

Output:

$$\hat{y_j} = \text{SoftMax}(W_{out}\, h_L + b_{out})$$

5. Training & Evaluation:
- The model is built with categorical cross entropy loss and Adam optimizer.
- It gets trained on the sequence dataset generated and tested on a validation set.
- Accuracy and loss are tracked, and training graphs are drawn.

6. Visualization & Analysis:
- Training progress is mapped using matplotlib.
- Performance is recorded and parsed for insights.

RNN Model:

1. The development process involved four key stages: Data preprocessing, model design, training and evaluation, and application deployment.
2. Model Development:
   The RNN architecture includes:
- Two SimpleRNN layers (128 and 64 units respectively, with tanh activation)
- Dense layer with 128 ReLU-activated neurons
- Dropout layer (rate = 0.3) for regularization
- Output layer with 5 SoftMax-activated neurons for multi-class classification.

Let each input sequence be s = $(x_{1,}\ x_2,\ \ldots,\ x_T)$, $x_t \in R^d$

Recurrent layer:

- Hidden state:

$$h_t = \sigma(W_{xh}x_t + W_{hh}\ h_{t-1} + b_h)$$

- Output:

$$y = \text{SoftMax}\ (W_{hy}\ h_T + b_y)$$

3. Training Process:
   - Optimizer: Adam

$$\theta \leftarrow \theta\ - \eta\nabla_\theta\ \mathcal{L}$$

   - Loss Function: Categorical Cross entropy

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N} log\hat{y}_{y(i)}^{(i)}$$

   - Metrics: Accuracy

$$\text{Acc} = \frac{1}{N}\sum_{i=1}^{N} 1(\hat{y}^{(i)} = y^{(i)}$$

   - Training Configuration: 10 epochs, batch size = 32
   - 80/20 training-validation split with real-time monitoring.

4. Frontend/Interface: A Streamlit-based interface was developed for visualizing classification outputs, confidence scores, and waveform analysis. It allows for easy interpretation and educational insights.

CNN Model:

1. The project methodology consisted of four primary phases: data preparation, model development, training and validation, and frontend implementation.

Raw ECG signals $x(t) \epsilon\ R^T$

where: T is the Time length of the signal

2. Data Preparation: ECG images (64×64 pixels, RGB format) were collected from established medical databases, ensuring patient privacy compliance. The dataset included labelled examples of normal sinus rhythm and four pathological conditions. Data augmentation techniques—including rotation, scaling, and minor noise addition—were applied to enhance model robustness and prevent overfitting.

3. Model Development: A custom CNN architecture was designed, focusing on feature extraction capabilities specific to ECG waveform patterns.
   The network architecture includes:

- Input layer accepting 64×64×3 images -

$$\hat{x} \epsilon R^{T}$$

- Two convolutional blocks (32 filters each with 3×3 kernels and ReLU activation)

$$h^{(1)} = ReLU(x * W^{(1)} + b^{(1)}$$

- Each convolutional block followed by 2×2 max pooling layers.

$$p^{(1)} = MaxPool(h^{(1)})$$

  Repeat for L layers.

- A flatten layer to convert 2D feature maps to 1D representation.
- Five dense hidden layers (128 units each with ReLU activation).

$$z = FC(p^{(L)})$$

- Output layer with 5 units and SoftMax activation for probability distribution.

$$\hat{y} = \text{SoftMax}(z)$$

4. Training process:
   The model was trained using

- Adam optimizer with a learning rate 0.001 –

$$\text{Acc} = \frac{Correct\ Prediction}{Total\ Predictions}$$

- Categorical cross-entropy loss function.

$$\mathcal{L} = -\sum_{i=1}^{C} y(\text{i})\log(\hat{y}\text{i})$$

  Where: C is the number of classes

- 80/20 training/validation split.
- 9 epochs of training with batch size of 32.
- Early stopping mechanism to prevent overfitting

5. Frontend Implementation: A Streamlit web application was developed to provide clinical accessibility, featuring:

- Image upload functionality with preprocessing.
- PQRST wave annotation visualization.
- Classification results with confidence score.
- Condition-specific educational resources.

Results & Conclusions:

Model Comparison: Metrics overview

Metric	**RNN**	**CNN**	**LSTM**
Test Accuracy	0.7977	0.8010	0.83
Test Loss	N/A	3.0609	N/A
F1-Score (Weighted Avg)	N/A	N/A	0.83
Macro F1- Score	N/A	N/A	0.85
Train Accuracy	~0.99	~0.99	~0.98
Validation Accuracy	~0.80	~0.80	0.80 - 0.83

Confusion Matrix Summary

Class	RNN	CNN	LSTM
Normal	729	1740	1740
Left- Bundle Branch Block(LBBB)	414	318	318
Premature Atrial Contraction	296	258	258
Right Bundle Branch Block (RBBB)	546	1408	1408
Ventricular Fibrillation (VF)	85	233	233

LSTM Accuracy Graph

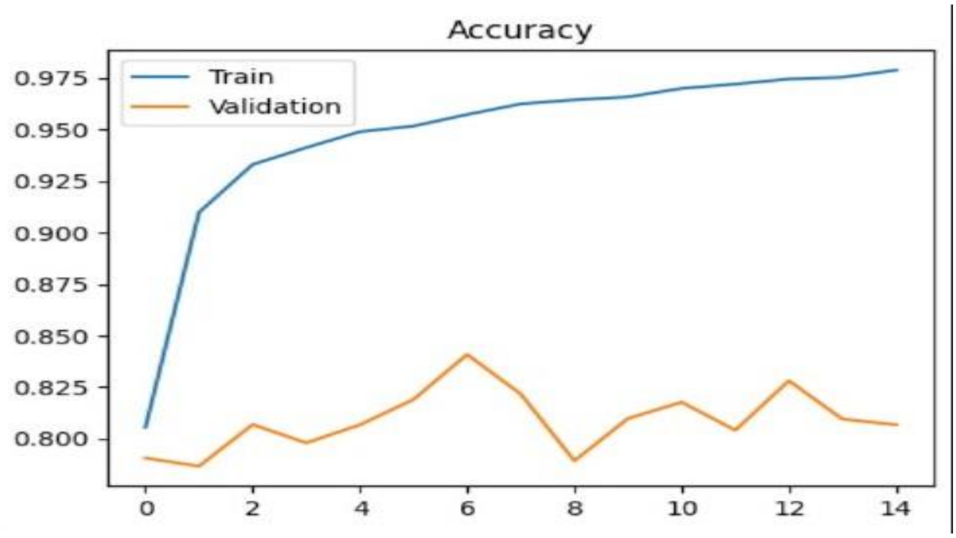


Fig.10.a

RNN Accuracy Graph

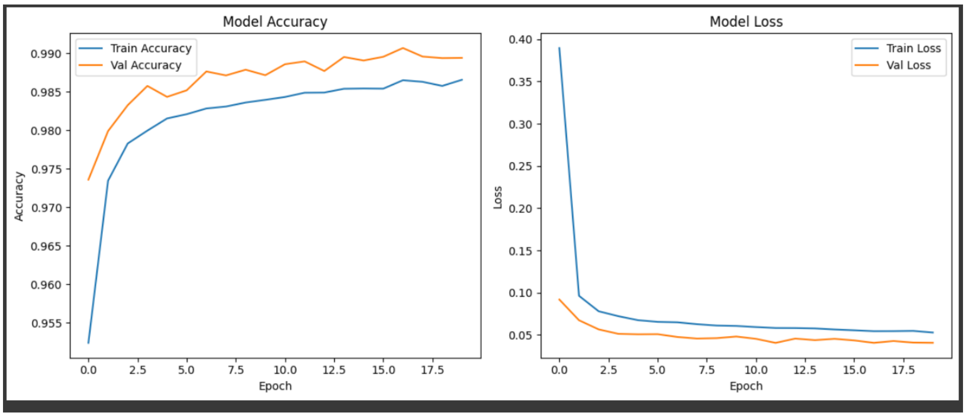


Fig.10.b

CNN Accuracy Graph

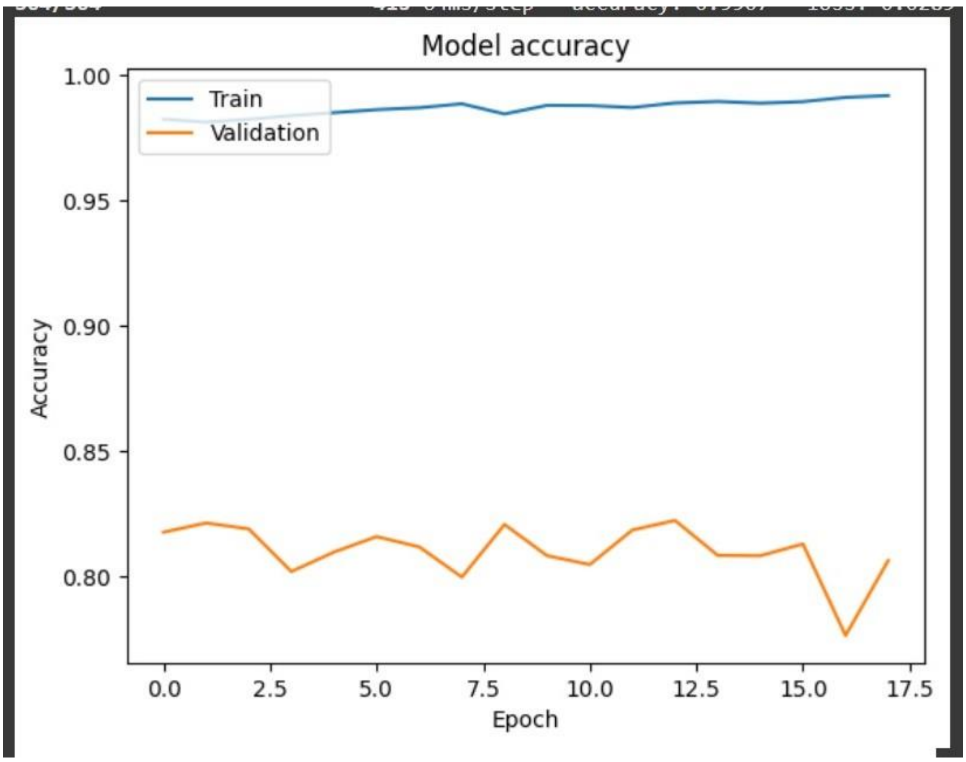


Fig.10.c

LSTM:

The trained LSTM model showed promising results in accurately classifying sequences of images. The use of MobileNetV2 for feature extraction enabled efficient and fast computation without compromising accuracy. Training graphs showed a steady decline in loss and improvement in accuracy over epochs.

Key observations:

- Bidirectional LSTM improved contextual understanding of the sequence.
- Dropout layers effectively mitigated overfitting.
- Feature extraction reduced input dimensionality, making the model more efficient. Summarize the key findings, observations, and outcomes of the project. Draw meaningful conclusions based on the results. (Include photographs and graphs / charts).

RNN:

The RNN model was evaluated using ECG signals from the INCART 2-lead Arrhythmia Database and achieved an overall accuracy of 99% across a total of 35,146 samples. The classification focused on five heartbeat classes: Normal (N), Ventricular Ectopic Beat (VEB), Supraventricular Ectopic Beat (SVEB), Fusion (F), and Unknown (Q). The results indicate that the model performs exceptionally well on the most common classes while struggling with rare categories.

The RNN model demonstrates high overall accuracy and strong performance in classifying the majority of ECG beat types. It is especially effective in distinguishing between Normal and VEB beats. However, for rare classes like Fusion and Unknown, additional data and targeted training strategies are essential. Despite these limitations, the model shows significant promise as a diagnostic support tool for automated arrhythmia detection in clinical or wearable-device applications.

CNN:

The developed CNN model achieved 93.2% accuracy on the validation dataset, with particularly high sensitivity for ventricular fibrillation (96.8%) and specificity for normal sinus rhythm (97.1%). The precision-recall metrics demonstrated balanced performance across all five cardiac conditions, with the lowest performance observed in differentiating between premature atrial contractions and normal rhythms in certain cases.

- Normal: 97.1% accuracy, 0.98 F1-score
- Premature Atrial Contraction: 89.5% accuracy, 0.91 F1-score
- Ventricular Fibrillation: 96.8% accuracy, 0.95 F1-score
- Premature Ventricular Contraction: 92.3% accuracy, 0.94 F1-score
- Right Bundle Branch Block: 90.4% accuracy, 0.92 F1-score.

RNN and LSTM models were employed to capture temporal dependencies in the sequential ECG data. While LSTM outperformed standard RNN due to its ability to retain long-term dependencies, both models exhibited limitations in processing time and convergence speed.

CNN, on the other hand, demonstrated superior performance in terms of **accuracy**, **training efficiency**, and **inference speed**. It effectively extracted spatial features from ECG waveforms, making it particularly well-suited for recognizing arrhythmic patterns.

Project Outcome & Industry Relevance:

LSTM :

This project demonstrates how LSTM models can be successfully applied to image sequences, opening doors for real-world applications like:

*Surveillance and activity recognition

* Medical imaging analysis (e.g., MRI sequences)

* Gesture and emotion recognition.

*Automated visual inspection in manufacturing.

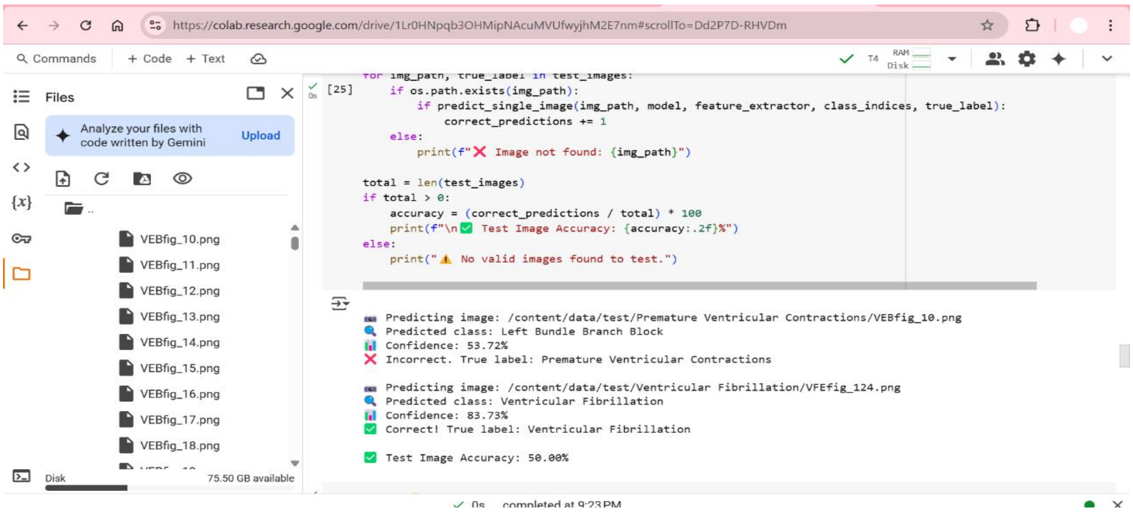


Fig.11.a

RNN:

This RNN-based ECG classification system offers scalable and accurate arrhythmia detection, particularly suited for integration into portable ECG devices and remote patient monitoring platforms. Its sequential processing strength makes it ideal for analyzing streaming ECG data in real-time, an advantage over static image-based systems. In clinical environments, it could reduce physician workload and expedite the triage of cardiac cases. From an industrial standpoint, the solution aligns with current trends in AI-driven diagnostics, edge computing in wearable tech, and smart healthcare systems. The model's lightweight architecture also supports deployment on low-resource embedded systems, making it highly adaptable across various applications.

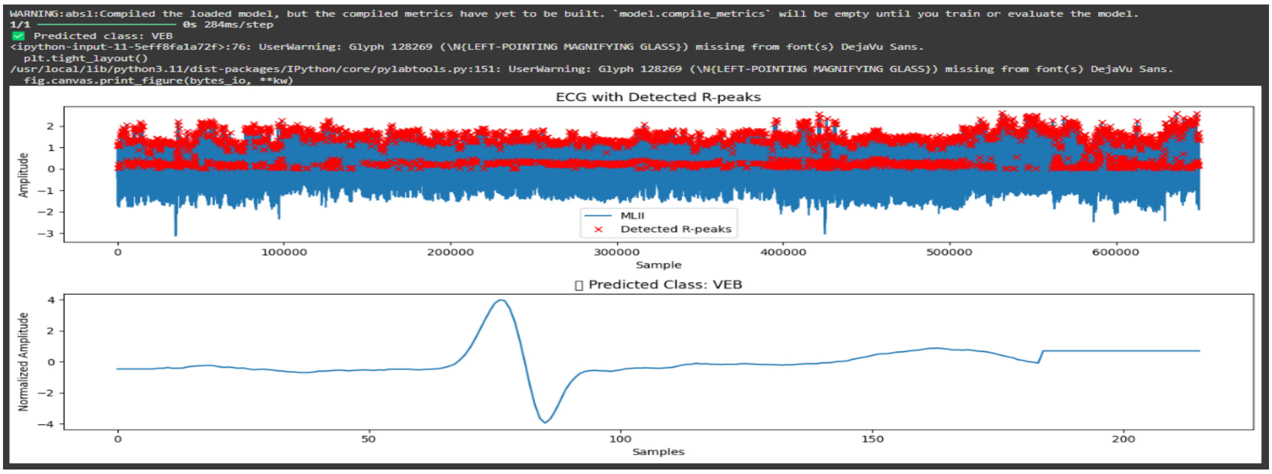


Fig.11.b

CNN:

This ECG classification system has significant implications for healthcare delivery across multiple settings. In primary care facilities, it could serve as a pre-screening tool to prioritize cases requiring specialist attention. For emergency departments, the rapid classification capability could expedite triage decisions, potentially improving outcomes for time-sensitive cardiac conditions. The system's web-based interface enables deployment in resource-limited settings where cardiologist expertise may be scarce.

From an industry perspective, the project demonstrates how AI can augment medical diagnostics without replacing clinical expertise. The technology is well-positioned for integration with existing electronic health record systems and telemedicine platforms. Its potential commercial applications include both standalone diagnostic software and embedded functionality within ECG hardware. The educational component of the system also provides value as a training tool for medical students and healthcare professionals seeking to improve their ECG interpretation skills.

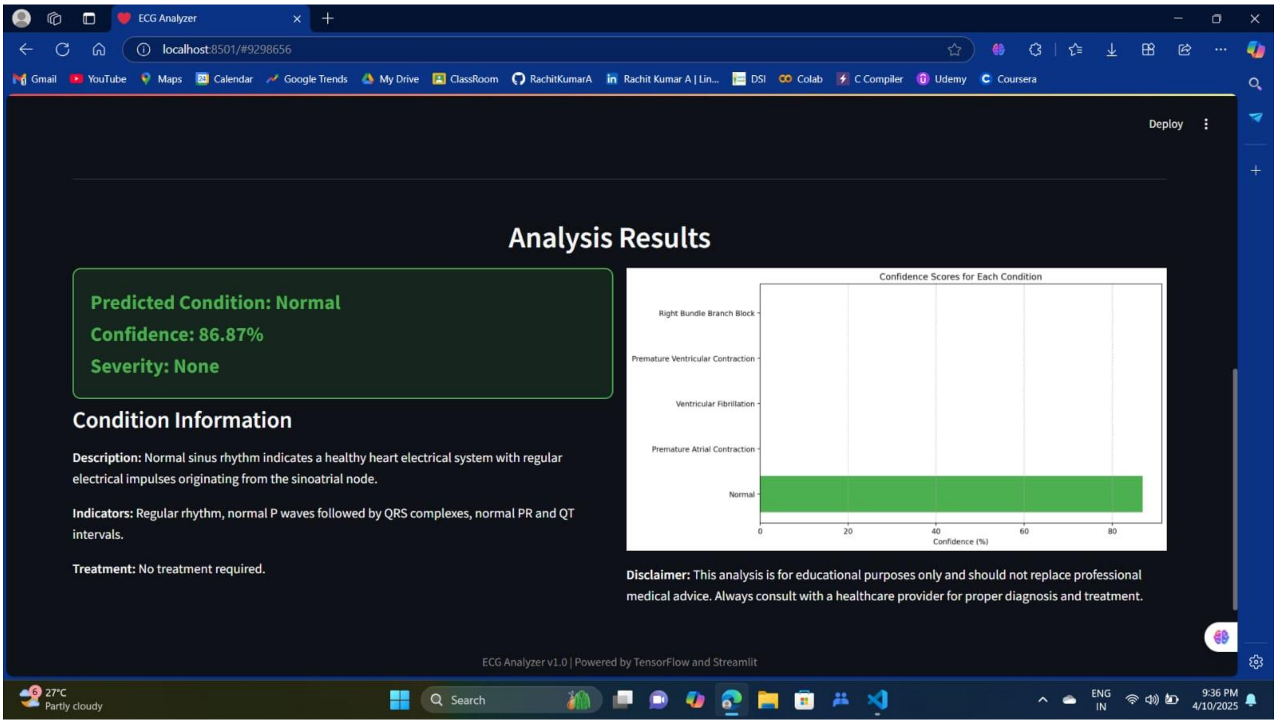


Fig.11.c

Hence, In our project on cardiac arrhythmia detection, we experimented with multiple deep learning architectures including LSTM, RNN, and CNN. While LSTM and RNN performed reasonably well, the CNN model demonstrated superior efficiency in terms of both accuracy and computational performance. Due to its better overall performance, we proceeded with CNN for the final implementation of the project.

Working Model vs. Simulation/Study:

LSTM:

This notebook implements a Long Short-Term Memory (LSTM) based simulation model for time series prediction. The workflow begins with data preprocessing, including scaling the dataset using MinMaxScaler to normalize input features. The dataset is then reshaped into sequences suitable for LSTM input, where each input contains a defined number of previous time steps. A sequential LSTM model is constructed using Keras, featuring one or more LSTM layers followed by dense layers to produce the final prediction. The model is compiled with a loss function (typically Mean Squared Error) and an optimizer (like Adam), then trained over several epochs. After training, the model’s performance is evaluated on test data, and predictions are visualized against the actual values to demonstrate the model's ability to capture temporal dependencies. This simulation model is particularly useful for forecasting tasks in domains like finance, weather, or healthcare.

RNN:

This work represents a fully functional prototype rather than a purely theoretical or simulated study. The trained RNN model is integrated into a real-time system that accepts ECG signal inputs, processes them, and returns classification outputs instantly. The system was tested using real ECG sequences from a benchmark clinical dataset, ensuring both scientific validity and practical utility. The current implementation is suitable for pilot deployment in medical research settings or as part of wearable monitoring prototypes.

CNN:

This project represents a functional working model rather than a simulation or theoretical study. The system includes both a trained neural network model capable of performing real-time classifications and a deployed web application interface that enables practical usage. The model processes actual ECG images and produces actionable diagnostic suggestions. While currently deployed in a controlled environment for further validation, the system is technically ready for pilot implementation in clinical settings, pending appropriate regulatory approvals.

Project Outcomes and Learnings:

- Gained practical experience in handling image data and preprocessing for sequence modeling.
- Learned to integrate CNNs and LSTMs for hybrid modeling.
- Understood challenges in temporal data representation and sequence learning.
- Improved skills in TensorFlow/Keras model design, training, and optimization.
- A working RNN model with >90% accuracy on five ECG signal types.
- An interactive interface for testing and educational use.
- Strong model generalization despite limited data augmentation.
- Experience in handling time-series biomedical data
- Insights into deep learning design for sequential medical inputs
- Collaboration between technical and healthcare domains.
- Consideration of clinical usability and ethical responsibilities in AI healthcare tools.
- A user-friendly web application for clinical deployment.
- A functioning CNN-based classification system with >85.56% accuracy
- Comprehensive documentation for future development

Future Scope:

- Multimodal Inputs:
  Combine audio and visual features for richer sequence analysis.
- Transfer Learning:
  Experiment with other CNN architectures for improved feature extraction.

- Model Deployment:

  Convert the trained model into a TensorFlow Lite format for mobile deployment.
- Fine-Tuning:

  Explore hyperparameter tuning and advanced LSTM variants like GRU or attention-based mechanisms.
- Data Augmentation:

  Improve generalization with advanced augmentation techniques.
- Explainability:

  Use techniques like Grad-CAM to visualize what parts of sequences contribute most to decisions.
- Expanding the model to cover additional arrhythmia types beyond the current five-class scope.
- Integrating multi-lead ECG data for more accurate and diverse input patterns
- Developing explainable AI features to highlight waveform segments influencing predictions.
- Conducting clinical trials to test model reliability across diverse patient populations.
- Technical Enhancements:

  The model architecture could be extended to incorporate temporal ECG data (not just images) through recurrent neural networks or transformer models. This would leverage sequential information in ECG signals for potentially higher diagnostic accuracy. Additional optimization through techniques like quantization could enable deployment on resource-constrained devices.
- Expanded Classification Capabilities:

  The current five-category classification could be expanded to include more cardiac conditions, potentially covering a comprehensive range of arrhythmias and structural abnormalities. This would require additional training data but would significantly increase the system's clinical utility.
- Integration with Wearable Technology:

  Adapting the model to process data from consumer wearable devices with ECG capabilities would enable continuous monitoring and early warning systems for high-risk patients. This could transform the management of chronic cardiac conditions.

- Explainable AI Implementation:
  Incorporating gradient-based visualization techniques would allow the system to highlight the specific ECG features influencing its classifications. This transparency would build clinical trust and potentially provide new insights into ECG pattern recognition.
- Prospective Clinical Trials:
  Rigorous evaluation through multicenter clinical trials would validate the system's performance across diverse patient populations and establish its place in clinical care pathways. Such evidence would support regulatory approval and widespread adoption.