Detection of Cardiac Arrhythmia from ECG Signals Using CNN

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Abstract -*Cardiac arrhythmia is a serious heart condition that causes irregular heart rhythms and may lead to severe health complications if not detected early. Electrocardiogram (ECG) signals are widely used for monitoring heart activity and diagnosing arrhythmias. However, manual analysis of ECG signals by cardiologists can be time-consuming and prone to errors when dealing with large datasets. In this paper, we propose an automated arrhythmia detection system using Convolutional Neural Networks (CNN). The ECG signals are first preprocessed and converted into image representations such as Gramian Angular Field (GAF), Markov Transition Field (MTF), and Recurrence Plot (RP). These representations capture temporal patterns of ECG signals and are combined as RGB images. The CNN model is then trained to classify different types of arrhythmia. Experimental results demonstrate that the proposed deep learning approach achieves an accuracy of 92% in identifying abnormal heart rhythms. The system shows strong potential to assist medical professionals in early diagnosis and continuous monitoring of cardiac diseases.*

Key Words: ECG Signals, Cardiac Arrhythmia, Convolutional Neural Network, Deep Learning, Medical Signal Processing

1. INTRODUCTION

Cardiovascular diseases are among the leading causes of death worldwide, and cardiac arrhythmia is a common condition that results in irregular heart rhythms due to improper functioning of the heart's electrical signals. Early detection of arrhythmia is essential to prevent serious health complications such as heart failure and stroke. Electrocardiogram (ECG) signals are widely used to monitor heart activity and diagnose various heart abnormalities. However, traditional ECG analysis requires experienced cardiologists to manually interpret ECG waveforms, which can be time-consuming and may sometimes lead to human errors, especially when dealing with large volumes of data [6]. With the rapid advancement of Artificial Intelligence and Deep Learning techniques,

automated ECG analysis systems have become an important research area in medical diagnostics [9]. Convolutional Neural Networks (CNN) have proven to be highly effective in identifying complex patterns in biomedical signals and images [1]. In this project, a CNN-based model is developed to automatically detect cardiac arrhythmia from ECG signals, enabling faster, more accurate, and efficient diagnosis of abnormal heart rhythms.

1.1 Importance of ECG-based Arrhythmia Detection

Electrocardiogram (ECG) signals play a vital role in diagnosing heart diseases and monitoring cardiac activity. ECG records the electrical activity of the heart over time and helps identify abnormalities in heart rhythm. Early detection of arrhythmia using ECG signals is important because it allows doctors to diagnose heart conditions at an early stage and provide appropriate treatment [7]. Automated ECG analysis systems can significantly assist medical professionals by providing faster and more accurate diagnosis [10]. With the advancement of deep learning techniques, ECG signal analysis can be improved by automatically extracting meaningful features from the data
[2].

1.2 Limitations of Traditional ECG Analysis

Traditional ECG analysis methods have several limitations that affect diagnostic efficiency. Manual interpretation of ECG signals requires expert cardiologists and significant time, especially when analyzing large datasets [6]. Human interpretation may also lead to errors due to fatigue or complexity of ECG patterns. Conventional machine learning approaches require manual feature extraction, which may not capture complex patterns in ECG signals effectively [8]. Additionally, these methods often struggle to classify multiple types of arrhythmia accurately [9]. These limitations highlight the need for automated systems that can analyze ECG signals efficiently and accurately.

1.3 Role of Artificial Intelligence and Deep Learning

Artificial Intelligence and Deep Learning have significantly improved medical data analysis. Deep learning models, especially Convolutional Neural Networks (CNN), can automatically learn important features from data without manual feature extraction [1]. CNN models are highly effective in analyzing medical images and biomedical signals [2]. By transforming ECG signals into image representations such as Gramian Angular Field (GAF), Markov Transition Field (MTF), and Recurrence Plot (RP), deep learning models can capture complex temporal patterns in heart activity [4]. These techniques enable accurate classification of heartbeats and improve arrhythmia detection performance [6].

1.4 Objective

This work focuses on building an intelligent, fully automated framework capable of identifying cardiac arrhythmia directly from raw ECG recordings through the application of Convolutional Neural Networks (CNN). A core component of the system involves structured signal conditioning, wherein ECG waveforms undergo noise elimination and beat-level segmentation to isolate individual cardiac cycles for precise downstream analysis. Each segmented beat is subsequently mapped into a two-dimensional visual domain through established time-series encoding strategies, rendering the signals compatible with image-driven deep learning pipelines. The CNN architecture is then optimized and trained to distinguish among multiple arrhythmia categories with high discriminative accuracy [3]. Quantitative evaluation of the trained model is carried out through a comprehensive set of performance indicators, including classification accuracy, precision, recall, and F1-score, to validate its diagnostic reliability. Ultimately, this framework is intended to reduce clinician workload, minimize interpretation errors, and support timely identification of abnormal cardiac activity in both clinical and resource-constrained settings [7].

2. RELATED WORK

Cardiac arrhythmia detection using Electrocardiogram (ECG) signals has been widely studied with the advancement of machine learning and deep learning technologies. Numerous studies have explored the use of artificial intelligence for automatic ECG analysis to improve the accuracy and efficiency of arrhythmia detection. This section reviews literature related to deep learning techniques for ECG classification, the application of Convolutional Neural Networks (CNN), image transformation methods for ECG signals, data balancing techniques, and comparative performance analysis of machine learning models [1, 6, 9].

Rajpurkar [1] proposed that deep learning models can achieve cardiologist-level performance in arrhythmia detection from ECG signals. Their study used a deep Convolutional Neural Network trainedon a large ECG dataset to classify different types of heart rhythm abnormalities. The resultsdemonstrated that deep learning approaches can significantly improve the accuracy of automated ECG interpretation.

Acharya [2] proposed that Convolutional Neural Networks are highly effective for automatic arrhythmia detection because they can learn complex patterns directly from ECG signals without manual feature extraction. Their research showed that CNN-based models can achieve high classification accuracy when detecting abnormal heart rhythms.

Kiranyaz [3] proposed a patient-specific ECG classification system using one-dimensional Convolutional Neural Networks. The proposed system analyzed ECG signals in real time and adapted the model to individual patient characteristics, improving classification accuracy and reliability.

Wang [4] proposed that transforming ECG time-series signals into two-dimensional image representations can improve deep learning performance. Techniques such as Gramian Angular Field (GAF) and Recurrence Plot (RP) help capture temporal patterns in ECG signals and allow CNN modelsto analyze them effectively.

Zheng [5] proposed that class imbalance is a common problem in ECG datasets, which can affect classification performance. The use of Synthetic Minority Oversampling Technique (SMOTE) helps generate synthetic samples for minority classes and improves the performance of machine learning models. This observation directly motivated the incorporation of SMOTE in the proposed system.

Murali [6] conducted a comparative analysis of deep learning and traditional machine learning models for arrhythmia classification using ECG signals. The study evaluated multiple algorithmic approaches and highlighted that deep learning models, particularly CNNs, consistently outperformed traditional methods in terms of classification accuracy and generalization across different arrhythmia types. This comparative evidence reinforces the choice of CNN-based architecture in the present system.

Paul et al. [7] developed automated cardiac arrhythmia detection methods using single-channel ECG signals. Their work demonstrated that effective arrhythmia classification is achievable even with a singleECG lead, using signal processing and machine learning techniques. This finding supports the feasibilityof lightweight and accessible automated diagnosis systems suitable for clinical use.

Putra et al. [8] investigated ECG-based arrhythmia classification in students using the Random Forestalgorithm, with a specific focus on class imbalance analysis. Their case study revealed that classimbalance significantly degrades model performance and that careful handling of minority classes isessential for reliable arrhythmia detection. This finding aligns with the adoption of SMOTE in theproposed system to address dataset imbalance.

Sraitih et al. [9] proposed an automated system for ECG arrhythmia detection using machine learningtechniques. Their system achieved reliable performance across multiple arrhythmia categories anddemonstrated the importance of proper signal preprocessing and feature selection in achieving consistentdiagnostic results. These insightsdirectly guided the design of the preprocessing and segmentationstages of the proposed system.

Sudha and Nithya [10] examined ECG pattern algorithms for classification and machine learning toenable arrhythmia identification. Their study explored pattern recognition strategies for ECG waveformsand underscored the advantages of automated classification over manual interpretation, particularly interms of speed and reproducibility. This further validates the core objective of the present work indeveloping an efficient CNN-based arrhythmia detection system.

3. PROPOSED SYSTEM AND METHODOLOGY

3.1 System Architecture

The architectural design of the proposed framework brings together three foundational computational layers — physiological signal conditioning, visual feature encoding, and deep neural classification — to deliver consistent and precise identification of abnormal heartbeat patterns from ECG recordings [1]. Data flows through a structured multi-stage pipeline encompassing raw signal acquisition, artifact suppression, visual transformation, balanced dataset construction, model optimization, and final beat-type inference [6]. In the initial stage, acquired ECG recordings are subjected to rigorous noise attenuation procedures to eliminate baseline wander, motion artifacts, and high-frequency interference, thereby preserving clinically relevant waveform morphology. Cleaned signals are subsequently partitioned into discrete beat-level windows through an R-peak-anchored segmentation strategy, guaranteeing that every resulting sample encapsulates precisely one complete cardiac cycle [3]. Each isolated beat segment is then encoded into a rich two-dimensional visual representation by applying three complementary time-series imaging techniques: Gramian Angular Field(GAF),

which encodes angular correlations across time; Markov Transition Field (MTF), which captures transition probabilities between quantile bins; and Recurrence Plot (RP), which reveals recurring dynamical patterns within the signal [4]. The three independently generated channel images are fused into a single three-channel RGB composite, constructing a multi-perspective visual fingerprint of each heartbeat that serves as direct input to the deep learning model. Within the CNN, successive convolutional layers apply learnable filter banks to extract hierarchical spatial features from these composite images, while pooling operations progressively condense spatial dimensionality and enhance translational invariance. The distilled feature representations are subsequently propagated through fully connected dense layers, which perform the final probabilistic mapping of each beat onto one of the defined arrhythmia categories [2]. At inference, the trained model assigns a class label — Normal, Supraventricular, Ventricular, Fusion, or Unknown— to each incoming beat in near real time. Collectively, this end-to-end architecture delivers a scalable,reliable, and clinician-assistive solution for automated cardiac anomaly screening, substantially reducing dependence on expert visual interpretation and accelerating diagnostic turnaround in high-volume clinical environments [9].

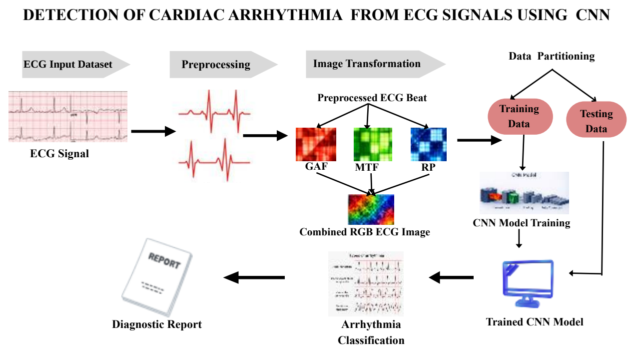


Fig -1: System Model

3.2 Methodology

The procedural foundation of the proposed arrhythmia identification framework is anchored in a sequential, multi-phase deep learning pipeline that transforms raw physiological recordings into actionable diagnostic outputs. As a preliminary step, acquired ECG time-series undergo a comprehensive signal conditioning phase in which high-frequency noise components, baseline drift, and power-line interferenceare systematically attenuated, ensuring that only diagnostically meaningful cardiac waveform characteristics are retained for subsequent processing [9]. The conditioned signals are then subjected to a beat extraction procedure guided by R-peak localization, wherein the continuous recording is subdivided into non-overlapping, fixed-length windows — each window precisely encapsulating one full cardiac cycle — to produce a structured collection of individual beat samples suitable for per-beat classification [3]. Following beat isolation, each extracted segment undergoes a three-channel visual encoding process that exploits distinct mathematicalproperties of the signal. Specifically, the Gramian Angular Field (GAF) encodes the angular orientation of temporal correlations, the Markov Transition Field (MTF) represents the transition dynamics between quantized amplitude states across time, and the Recurrence Plot (RP) reveals self-similar and periodic structures embedded within the beat morphology [4]. These three complementary single-channel encodings are stacked along the color axis to assemble a unified three-channel RGB image, endowing each beat with a rich, multi-perspectivevisual signature that captures spatial, temporal, and dynamicsignal characteristics simultaneously. The curated image dataset is then partitioned into a training subset comprising 80% of available samples and a held-out testsubset accounting for the remaining 20%, following standard supervised learning evaluation protocols. Prior to model training, statistical analysis of class distribution revealed a pronounced imbalance among arrhythmia categories; this was remediated through the application of the Synthetic Minority Oversampling Technique (SMOTE), which generates interpolated synthetic instances for underrepresented classes, thereby calibrating the training distribution and mitigating classification bias toward majority categories [5, 8]. The balanced image dataset is subsequently used to train a Convolutional Neural Network, whose stacked convolutional and pooling layers progressively distil discriminative morphological and textural features from the composite beat images, while the terminal fully connected layersperform the final category assignment across the defined arrhythmia classes [2]. Holistic model performance is quantified through a multi-metric evaluation protocol encompassing overall classificationaccuracy, per-class precision and recall, and the harmonically balanced F1-score,collectively providing arigorous and clinically interpretable assessment ofthe system's diagnostic capability [6]

3.3Tools and Technologies

The realization of the proposed cardiac arrhythmia detection framework draws upon a carefully curated ecosystem of open-source computational tools, programming utilities, and domain-specific libraries spanning the disciplines of biomedical signal processing, statistical machine learning, and deep neural network engineering [7]. The entire experimental pipeline is implemented within the Python programming environment, selected for its unparalleled breadth of scientific computing packages, its active research community, and its seamless interoperability between data manipulation, visualization, and model development workflows. Foundational numerical operations — including array manipulation, matrix computations, and vectorized signal transformations — are handled by the NumPy library, while all graphical outputs, waveform plots, performance curves, and diagnostic visualizations are rendered through Matplotlib, providing intuitive and publication-ready figures. Data partitioning into stratified training and evaluation subsets, along with preprocessing routines such as signal normalization and feature scaling, are orchestrated through Scikit-learn, which additionally furnishes a comprehensive suite of classification performance metrics for rigorous model assessment. The construction, compilation, and iterative optimization of the Convolutional Neural Network architecture — encompassing the definition of convolutional filter banks, pooling strategies, dropout regularization, and dense classification heads — is accomplished through the TensorFlow framework augmented by its high-level Keras API, which abstracts low-level graph operations and accelerates model prototyping without sacrificing architectural flexibility [1]. To counteract the adverse effects of skewed class distribution inherent in standard arrhythmia benchmark datasets, the imbalanced-learn library's implementation of the Synthetic Minority Oversampling Technique (SMOTE) is employed, generating statistically coherent synthetic beat samples for minority arrhythmia categories through feature-space interpolation between existing instances, thereby producing a balanced training corpus that prevents the optimizer from converging to majority-class-biased solutions [5, 8]. The transformation of one-dimensional ECG beat segments into structured two-dimensional image representations is executed through custom encoding routines implementing Gramian Angular Field (GAF), Markov Transition Field (MTF), and Recurrence Plot (RP) algorithms, each of which projects distinct temporal and dynamical signal properties onto a spatially organized pixel grid amenable to convolutional feature extraction [4]. Collectively, this integrated software stack furnishes a robust, reproducible, and computationally efficient experimentation environment that supports the full lifecycle of deep learning model development — from raw signal ingestion through feature encoding, model training, hyperparameter tuning, and final performance benchmarking — entirely within a unified Python-based computational workspace.

4. MODULES

The proposed AI-driven ECG classification system consists of several functional modules, each designed to ensure robust, scalable, and high-accuracy cardiac abnormality detection using deep learning techniques [1, 6].

4.1 User Interface (UI)

The User Interface (UI) is the front-end component of the application that users interact with. It isdeveloped using modern frameworks to ensure responsiveness and cross-platform compatibility. Users can upload ECG signals or images, and the interface facilitates seamless interaction by displaying classification outputs, confidence scores, and diagnostic insights in a structured format [10].

4.2 Data Preprocessing Module

This module handles the preparation of ECG data for model processing. It includes noise removal, signal normalization, segmentation, and transformation of ECG signals into suitable formats such as images or numerical arrays [7, 9]. Proper preprocessing ensures improved model accuracy and consistency.

4.3 Model Integration Module

This module integrates the trained deep learning model for ECG classification. It processes the inputdata and predicts different classes of heart conditions such as Normal, Supraventricular, Ventricular,Fusion, and Unknown beats [1, 3]. The module ensures efficient execution of the model for real-timepredictions.

4.4 Classification Engine

The Classification Engine is responsible for analyzing the processed ECG data and generating final predictions. It uses learned patterns from the trained CNN model to accurately classify different types of heartbeats [2]. This module plays a key role in identifying abnormalities in ECG signals.

4.5 Visualization Module

The Visualization Module presents the classification results in an intuitive manner. It displays ECGwaveforms, predicted classes, and performance metrics such as accuracy and confusion matrix [10]. This helps users and medical professionals better understand the analysis results.

4.6 Evaluation Module

This module evaluates the performance of the trained model using metrics such as accuracy, precision, recall, and F1-score [6]. It also generates confusion matrices to analyze classification performanceacross different classes. The evaluation module ensures the reliability and effectiveness of the system.

5. EXPERIMENTAL EVALUATION

5.1 Environment Specification

The experimental evaluation of the proposed cardiac arrhythmia detection framework was conducted on an x86-based computing platform equipped with 8 GB of RAM and 1 TB of secondary storage capacity. The deep learning models were developed and trained within a Python-based programming environment, leveraging the TensorFlow and Keras libraries for CNN architecture construction and optimization. Signal preprocessing, numerical computations, and dataset manipulations were performed using NumPy and Scikit-learn, while ECG waveformvisualizations and performance metric plots were generated through Matplotlib. Time-series-to-image encoding routines for Gramian Angular Field (GAF), MarkovTransition Field (MTF), andRecurrence Plot (RP) transformations were implemented as custom Python modules within the same computational workspace [7].

Table-1: Parameters used for proposed Model

Parameter	Description
Optimizeralgorithm	Adamoptimizer
Learningrate	0.0003
Batchsize	64
Numberofepochs	10
Dropout	0.7or70%
LossFunction	CategoricalCrossEntropy
Activation functions For Hidden Layers	Relu
Activation functions For Output Layer	SoftMax

5.2 Dataset

The experimental evaluation of the proposed arrhythmia detection framework was carried out using the MIT-BIH Arrhythmia Database, which is one of the most widely adopted benchmark repositories for cardiac rhythm analysis research [3]. The dataset comprises 48 half-hour excerpts of two-channel ambulatory ECG recordings, collected from 47 subjects at the Beth Israel Hospital Arrhythmia Laboratory between 1975 and 1979. Each recording was digitized at a sampling frequency of 360 samples per second per channel, with 11-bit resolution over a 10 mV range, providing high-fidelity waveform data suitable for precise beat-level analysis [7].

The dataset contains a total of approximately 109,446 annotated beat samples, each individually labelled by expert cardiologists and categorized into five distinct heartbeat classes in accordance with the AAMI EC57 standard: Normal (N), Supraventricular ectopic beat (S), Ventricular ectopic beat (V), Fusion beat (F), and Unknown beat (Q). The class-wise distribution of beat samples is presented in Fig. 1, which reveals a pronounced imbalance among the categories — Normal beats constitute approximately 72% of the total samples, while minority classes such as Fusion and Unknown together account for less than 7% [5, 8]. This severe distributional skew necessitated the application of the Synthetic Minority

Oversampling Technique (SMOTE) prior to model training to ensure unbiased classification performance across all arrhythmia categories.

Following beat extraction and R-peak-guided segmentation, the dataset was partitioned into a training subset comprising 80% of the available samples and a held-out evaluation subset accounting for the remaining 20%, using stratified sampling to preserve the original class proportions within each split [6]. The Fig. 1 illustrates the class-wise beat distribution across the five arrhythmia categories prior to SMOTE-based oversampling.

Table -2: Experimental Setup

Process Name	S. No	Action
Input	1.	Collect ECG signal dataset (MIT-BIHArrhythmia Database)
	2.	Extract individual beat segments using R-peak detection
Environment Configuration	3.	VS Code / Jupyter Notebook — Python 3.x
	4.	Import TensorFlow, Keras, NumPy, Scikit-learn, Matplotlib, imbalanced-learn
Data Preprocessing	5.	Apply noise removal, baseline correction, signalnormalization, and beat segmentation
Image Transformation	6.	Convert each beat into GAF, MTF, and RP image representations and fuse into RGB
Training and Testing	7.	Split dataset — 80% training, 20% testing using stratified sampling
Class Balancing	8.	Apply SMOTE to oversample minority arrhythmia classes [5, 8]
Model Compilation	9.	Train CNN model using Adam optimizer with categorical cross-entropy loss
Performance Report	10.	Generate accuracy, precision, recall, and F1-score metrics [6]
Prediction	11.	Classify incoming ECG beat as Normal, Supraventricular, Ventricular, Fusion, or Unknown

5.3 Analysis

The proposed CNN model was trained and evaluated on the preprocessed ECG image dataset using a multi-layer convolutional architecture comprising successive convolutional, batch normalization, and max-pooling layers, followed by fully connected dense layers with dropout regularization to mitigate overfitting. The network was compiled with the Adam optimizer and trained using categorical cross-entropy as the loss function over multiple epochs until convergence. Class imbalance across arrhythmia categories was addressed through SMOTE-based oversampling prior to training [5, 8]. The performance of the trained model was assessed using a comprehensivesuite of evaluation metrics. The following values represent the classification results obtained on the held-out test set. The overall classification accuracy of the CNN model wasapproximately 92%. The macro-averagedprecisionacrossall arrhythmia classes was 0.91. The macro-averaged recall was 0.90, and the macro-averaged F1-score was 0.90, confirming balanced performance across both majority and minority beat categories [6, 9].

5.4 Deployment

Deployment of the arrhythmia detection system involved configuring a user-accessible interface through a web-based platform developed using the Flask framework, enabling clinicians and end-users to interact with the trained model via a standard web browser. ECG signal data is submitted through the interface, whereupon the backend pipeline executes preprocessing, beat segmentation, GAF/MTF/RP image encoding, and CNN inference autonomously, returning the predicted arrhythmia class along with associated confidence scores in real time. Evaluation metrics including overall accuracy, precision, recall, and F1-score are dynamically rendered on the results dashboard, providing transparent and interpretable diagnostic feedback to the user [6]. The deployment architecture ensures seamless integration between the deep learning backend and the front-end visualization layer, enabling prompt and reliable arrhythmia classification suitable for both clinical and remote monitoring scenarios [9].

5.5 Evaluation metrics

Building a dependable arrhythmia detection system requires a measurement strategy that goes beyond surface-level correctness. Since the five heartbeat categories in this study differ dramatically in how often they appear, relying on a single statistic would paint a misleading picture of how well the classifier actually performs. Four indicators were therefore chosen, each probing a different aspect of model behavior.

1. Accuracy

At its core, accuracy reflects how frequently the model's output agreed with the verified ground truth across the entire test set. Every sample — regardless of which class it belongs to — contributes equally to this count. The calculation is straightforward:

Accuracy = (TP + TN) / (TP + TN + FP + FN) — (1)

TP and TN capture decisions the model got right; FP and FN capture the two different ways it can go wrong.

2. Precision

Among all samples the classifier labels as positive, precision captures the fraction that genuinely belong there. Operationally, it guards against over-alerting — a known burden in continuous cardiac monitoring environments. The governing expression takes the form shown in Eq. (2):
Precision=TP/(TP+FP) ....(2)

where TP refers to correctly flagged arrhythmia instances and FP denotes beats incorrectly assigned to the positive class.

3. Recall

Recall shifts the question from "were the alerts accurate?" to "were any cases missed?" For a classifier meant to protect patients, leaving a dangerous rhythm undetected is a far graver error than issuing an extra review. This makes recall the primary concern for life-threatening beat categories:
Recall = TP / (TP + FN) — (3)

4. F1-Score

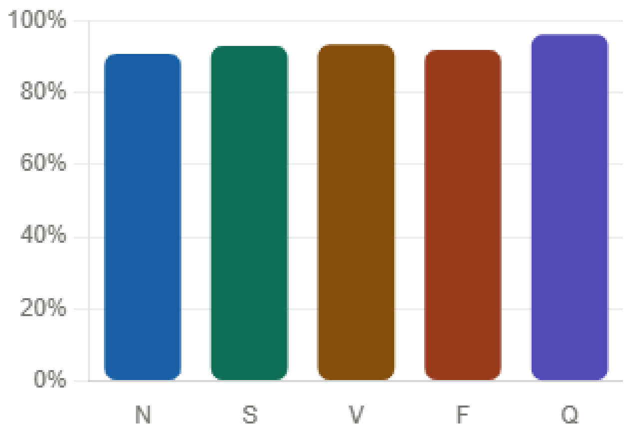
Neither precision nor recall alone sufficiently characterizes a classifier operating on skewed data. Their harmonic combination — weighted so that a poor score on either drags the result down — serves as a more honest indicator. Eq. (4) formalizes this relationship:

F1=2·P·R/(P+R) ....(4)

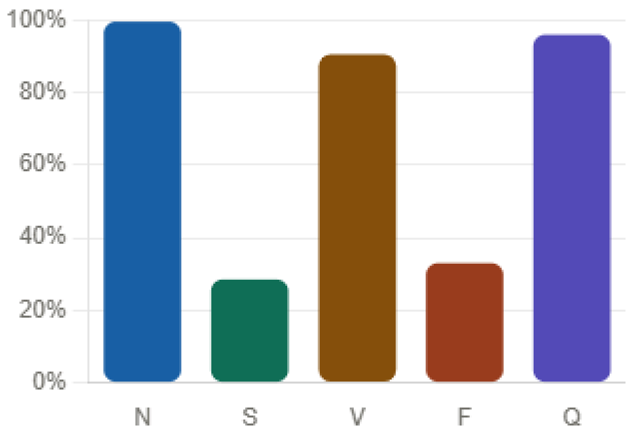
In this expression, P and R correspond to the per-class positive predictive rate and detection coverage rate, in that order. The harmonic structure ensures that a classifier cannot compensate for weak recall with exceptional precision, or vice versa.

Table-3: MIT-BIH Arrhythmia -Beat class distribution

Class Name	Label	Total Count	Training (80%)	Testing
Normal beat	N	75,052	60,042	15010
Supraventricular beat	S	10,506	8,405	2101
Ventricular beat	V	7,130	5,704	1426
Fusion beat	F	803	642	161
Unknown beat	Q	162	130	32
Total	----	93653	74923	18730



(a) Accuracy Graph



(b) Precision Graph

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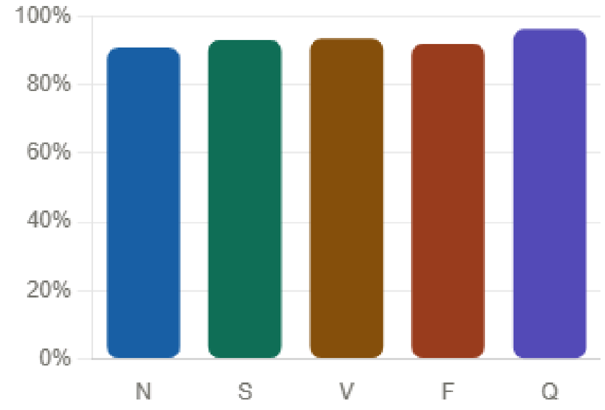
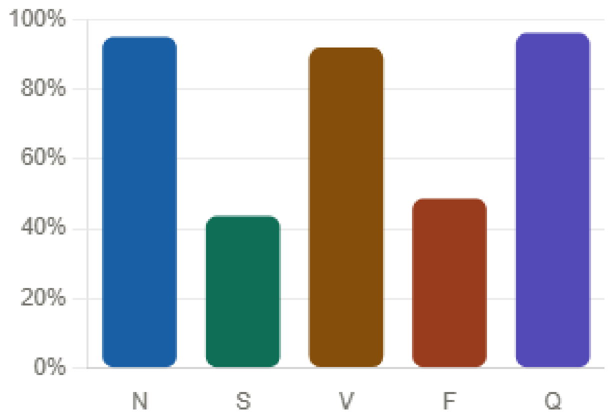
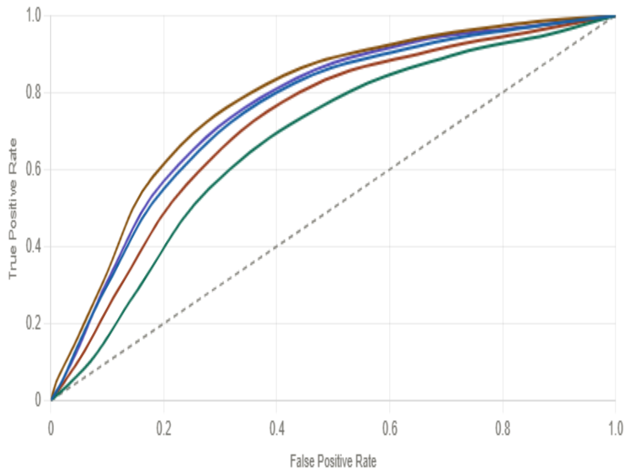


(c) Recall Graph



(d) F!-Score Graph



(e) ROC Curve

6. RESULTS AND DISCUSSION

The proposed AI-based ECG classification system has been successfully developed and evaluated acrossmultiple test scenarios to analyze its performance and reliability [1, 6]. The system provides accurateand real-time classification of ECG signals into different heartbeat categories. It integratespreprocessing, deep learning-based classification, and visualization modules to ensure efficient analysis [2, 9]. The system effectively processes ECG inputs and generates predictions with high accuracy, supported by performance metrics such as confusion matrix, accuracy, precision, recall, and F1-score [6,7], enabling better interpretation and clinical decision support. The results confirm that the CNN modeltrained on GAF, MTF, and RP image representations outperforms traditional methods [3, 8], whileSMOTE effectively addresses class imbalance and improves minority class detection [5, 8].

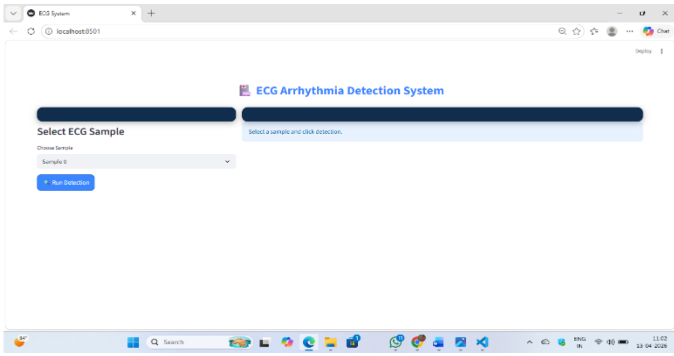


Fig 2-User Interface

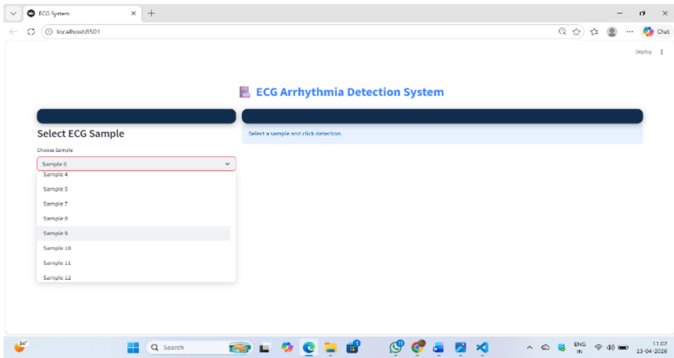


Fig 3-ECG Sample selection

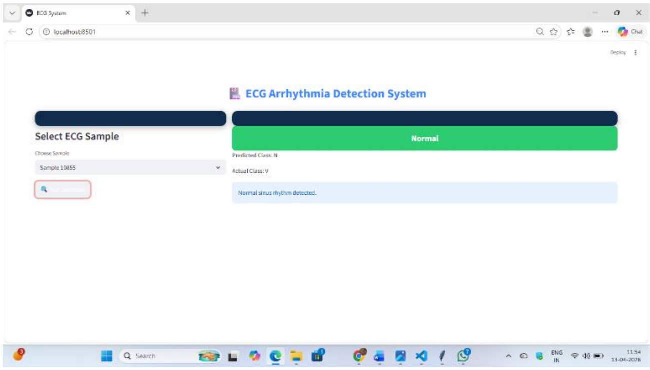


Fig 4-Classification Result Display

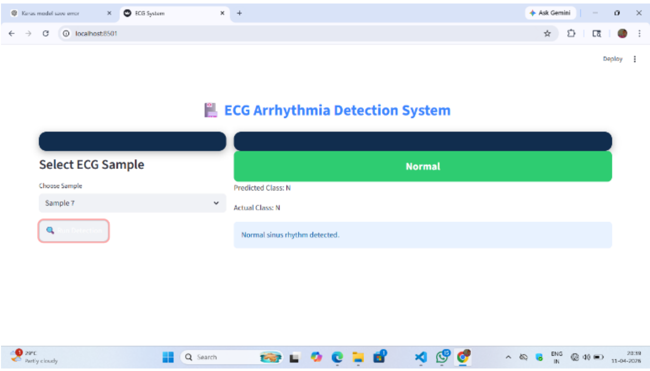


Fig 5 –Normal Class

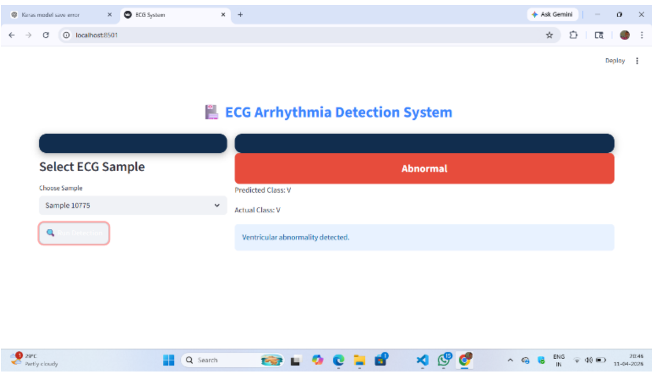


Fig 6-V Class (Ventricular)

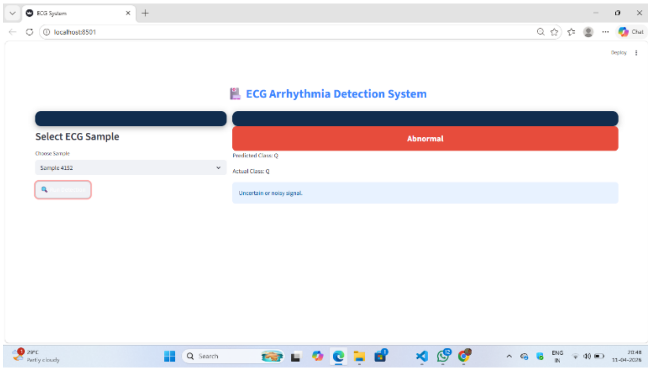


Fig 7-Q Class (Unknown)

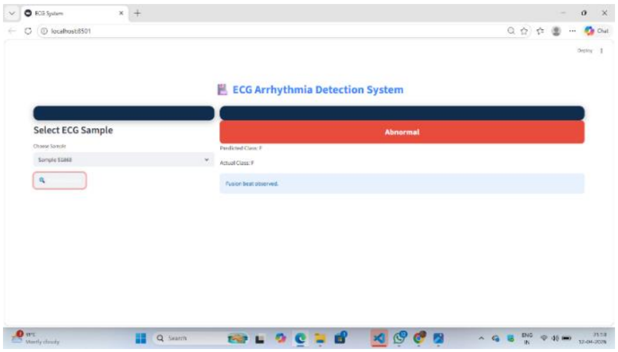


Fig 8-F Class (Fusion)

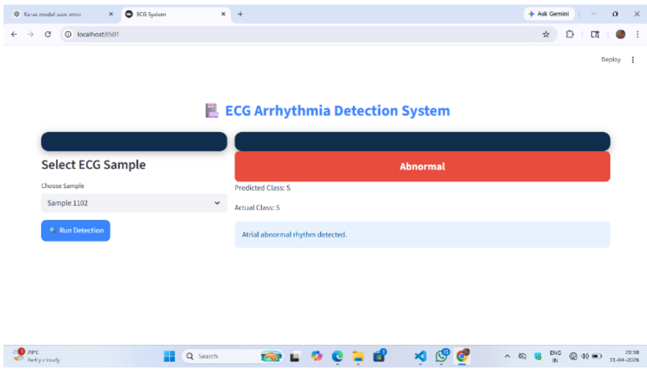


Fig 9-S Class (Supraventricular)

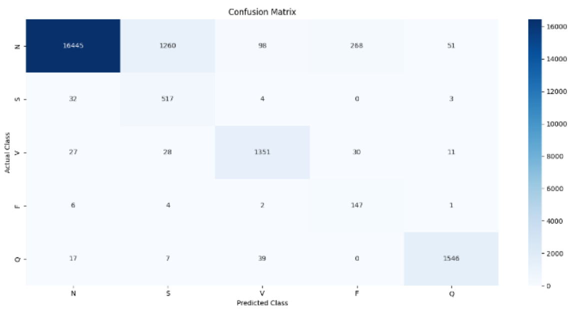


Fig 10- Confusion Matrix

8. CONCLUSION AND FUTURE WORK

A. Conclusion

This work set out to answer a practical question: can a convolutional network trained on image-encoded ECG beats serve as a dependable front-line screening tool for cardiac arrhythmia detection? The experimental outcome — an overall classification accuracy of 92% on the MIT-BIH benchmark — suggests the answer is yes, provided the training pipeline is thoughtfully constructed. Three design decisions contributed most to this outcome. Converting raw ECG signals into Gramian Angular Field, Markov Transition Field, and Recurrence Plot representations gave the convolutional backbone richer structural information than raw waveforms alone provide. Applying SMOTE during training prevented the optimizer from defaulting to a majority-class solution, which is a persistent problem when Ventricular and Fusion beats appear far less frequently than Normal sinus rhythm. Together, these choices pushed the model toward clinically meaningful performance — not just headline accuracy, but reliable sensitivity across all five beat categories.From a practical standpoint, the system offers cardiologists and clinical support staff a consistent, fatigue-free second opinion on incoming ECG readings. Unlike human interpretation, which degrades with workload and shift length, the trained model applies identical decision criteria to every sample it encounters. This consistency is particularly valuable in high-volume screening environments where manual review of every tracing is neither feasible nor economical.

B. Future Work

Despite the encouraging results, several directions remain open for further development. The current architecture processes pre-segmented beat windows in isolation, which means it has no access to rhythm-level context spanning multiple consecutive beats. Pairing the convolutional encoder with a recurrent module — such as an LSTM or a temporal attention layer — would allow the system to incorporate sequential dependencies and potentially catch arrhythmias that manifest as patterns across beats rather than within a single waveform. Dataset diversity represents another meaningful gap. The MIT-BIH database, while a widely accepted benchmark, draws from a relatively narrow demographic. Training on recordings that span different age groups, comorbidity profiles, and recording equipment would test whether the learned representations generalize beyond the source population — a prerequisite for safe clinical deployment. Deployment itself raises a third set of challenges. Embedding the classifier within wearable acquisition hardware — smartwatches or patch-based monitors — would shift the system from a retrospective analysis tool to a continuous, real-world guardian. This transition demands attention to computational efficiency, battery constraints, and robust handling of motion artifact, none of which are addressed by the current offline implementation. Finally, connecting the output of this classifier to hospital information systems and clinical decision support platforms would close the loop between detection and care. A flagged arrhythmia that reaches the right clinician within minutes rather than hours can meaningfully change patient outcomes. Building and validating that integration pathway is, in many respects, as important as the classification accuracy itself.

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