

# Reliable AI-Powered ECG Anomaly Detection and Decision Support System for Instantaneous Medical Monitoring

Rajeswari P

Electronics Engineering Department  
Anna University-MIT Campus  
Chennai, India  
rajeswaripeee@ieee.org

K Mariammal

Department of Electronics Engineering  
Anna University-MIT Campus  
Chennai, India  
mariammal@annauniv.edu

**Abstract**— Primarily in remote and resource-constrained areas, accurate and timely healthcare tracking has become crucial for the early identification of cardiac problems. The Reliable equipped with artificial intelligence ECG anomaly detection and decision support framework presented in this paper integrates XGBoost, Artificial Neural Network (ANN), simulated vital monitoring, and real-time interaction technologies. Before extracting significant statistical and morphological properties such rolling mean, variability, slope, minimum, and maximum values, ECG data from the MIT-BIH Arrhythmia Database are preprocessed to eliminate baseline drift and high-frequency noise. To increase the resilience and accuracy of classification, a hybrid ANN–XGBoost model is created. The suggested method detects ECG anomalies with 98.6% accuracy, 98.1% precision, 97.8% recall, and a 97.9% F1-score. A real-time visualization dashboard based on Streamlit and a WhatsApp alert system that uses the Twilio API to enable emergency notifications in three to five seconds are also included in the framework. The findings of the experiment show enhanced interpretability, dependability, and real-time health monitoring capabilities.

**Keywords**— ECG anomaly detection, Reliable AI, ANN, XGBoost, IoMT, Decision Support System, Real-time healthcare monitoring, AI-enabled networks.

## I. INTRODUCTION

Early diagnosis and ongoing monitoring are crucial for efficient healthcare management because cardiovascular illnesses rank among the world's top causes of death. Although ECG signals are frequently utilized to identify heart problems, accurate interpretation frequently necessitates advanced healthcare infrastructure and skilled medical understanding. By offering benchmark ECG recordings for analysis and research, the MIT-BIH Arrhythmia Database has made a substantial contribution to the advancement of automated ECG analysis systems [1].

ECG categorization methods now perform better thanks to recent developments in artificial intelligence and machine learning. Strong scalability and resilience have been shown by XGBoost in biological data categorization applications [2]. Convolutional neural network algorithms (CNNs), in particular, have demonstrated great efficacy in learning intricate ECG patterns and enhancing the accuracy of heartbeat categorization [3]. The capacity of the classification of ECG frameworks to generalize across various datasets has been further improved using transfer learning techniques [4]. Furthermore, interpretable AI techniques have been put forth to enhance clinical trust and transparency in automated medical facilities [5]. While reducing overfitting problems, hybrid frameworks that include advanced machine learning and augmenting techniques have also improved classification performance [6].

In an effort to help physicians with rule-based medical analysis, DSS are being included more and more into intelligent healthcare systems [7]. Similar to this, real-time healthcare communication and remote patient monitoring have been made possible by Internet of Healthcare Things (IoMT)-based monitoring platforms [8]. Medical monitoring techniques real-time visualization and user interactivity have been further enhanced by streamlit-based healthcare dashboards [9]. Enhanced accessibility and healthcare interaction effectiveness have also been shown by mobile and IoT-connected healthcare frameworks [10], [11]. In addition, recent research has emphasized the significance of intelligent anomaly detection and AI-driven healthcare analytics for applications including remote patient monitoring [12]–[14].

Despite these developments, the majority of current ECG monitoring systems prioritize classification accuracy and frequently lack multi-parameter monitoring, dependable real-time deployment, interpretable healthcare judgments, and quick communication methods. Overall healthcare dependability is limited since most systems can not successfully integrate electrocardiogram analysis with physiological indicators like body temperature and SpO<sub>2</sub>. Furthermore, current methods frequently lack user-friendly monitoring dashboards and real-time alarm systems.

This work recommends a Reliable AI-enabled ECG anomaly detection and decision support framework that incorporates ANN, XGBoost, simulated vital monitoring, and real-time communication technologies in order to overcome these constraints. The suggested solution integrates rule-based decision support, real-time visualization, instantaneous WhatsApp alarm delivery, multi-parameter healthcare evaluation, and ECG anomaly detection. By utilizing AI and communication technologies to provide intelligent, dependable, and real-time clinical monitoring, the proposed work is in line with the conference topic RAIN—Reliable AI-enabled Networks. The study is structured as follows: Section I: Overview and Review of Literature The suggested approach, which includes processing of signals, typical feature extraction, and hybrid modeling, is explained in Section II. The findings, discussion, performance assessment, and comparative analysis are presented in Section III. The work is determined with future research directions in Section IV.

## II. METHODOLOGY

According displayed in Fig. 1, the suggested Robust AI-enabled healthcare tracking framework is made up of several stages for intelligent ECG evaluation and real-time patient monitoring. To facilitate reliable healthcare evaluation, the platform integrates real-time communication, simulated

physiological monitoring, hybrid machine learning models, and ECG signal preprocessing.

## 2.2 Signal Preprocessing and Noise Elimination

Annoying disturbances such as muscle distortions, baseline drift, and power-line interference are common in ECG signals and can impact classification performance. A filter with a band with a cutoff range of 0.5–40 Hz is used to eliminate low-frequency and high-frequency noise components in order to enhance signal quality. In order to preserve amplitude consistency during analysis, the ECG signals are normalized after filtering. Prior to feature extraction, superfluous signal markers and irrelevant annotations are also eliminated. Fig. 1 shows the entire preprocessing and computational method.

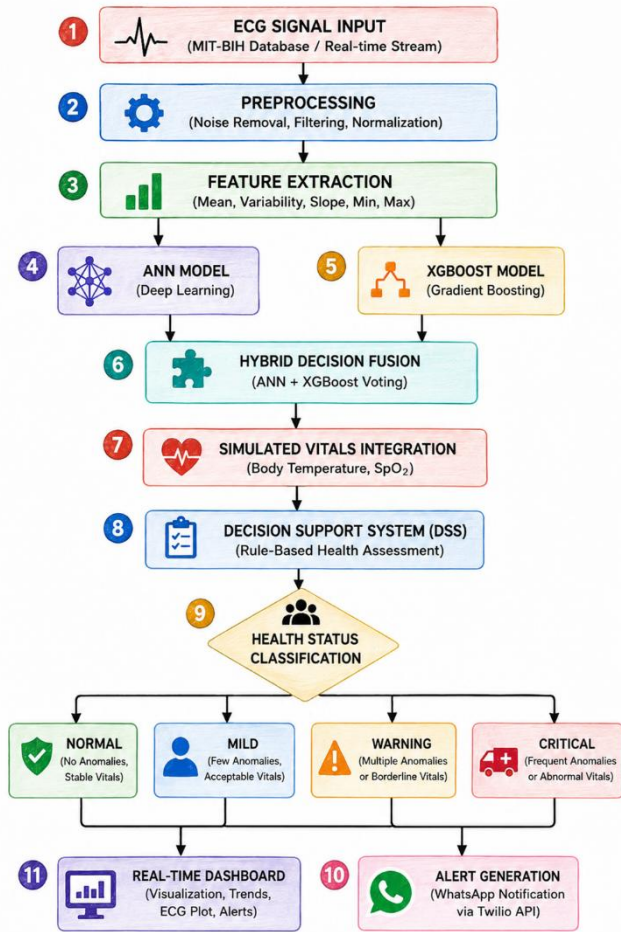


Fig. 1. Proposed system flowchart for ECG Anomaly Detection and Decision Support

## 2.3 Feature Extraction

The ECG signals are examined using a sliding windowed feature extraction technique to identify significant statistical and waveform-related features. Each signal segment's rolling mean, variability, slope, minimum value, and maximum value are among the features that are extracted. Waveform trends, amplitude fluctuations, and sudden signal alterations linked to cardiac problems are all well represented by these characteristics. Table 1 lists the features that were extracted and the descriptions that go with them.

TABLE I. EXTRACTED FEATURES

| Si.No: | Feature               | Description                             |
|--------|-----------------------|---|
| 1      | Rolling Mean          | Represents baseline trend of the signal |
| 2      | Variability (Std Dev) | Measures fluctuation in amplitude       |
| 3      | Slope                 | Detects rapid changes in the waveform   |
| 4      | Minimum               | Lower bound of signal in window         |
| 5      | Maximum               | Upper bound of signal in window         |

## 2.4 ANN-Based Heartbeat Classification

In order to differentiate between normal and pathological ECG heartbeats, an ANN is created. The input layer, several hidden layers with ReLU activated functions, and an output layer with sigmoid activation functions make up the network design. The ANN model aids in precise anomaly detection by effectively learning nonlinear correlations found in ECG signals.

## 2.5 XGBoost-Based Classification

XGBoost has been integrated into the system to enhance classification resilience because to its great generalization capabilities and effective handling of nonlinear biological data [2]. Using gradient boosts techniques, the model builds several decision trees one after the other, reducing overfitting while increasing prediction accuracy.

## 2.6 Hybrid Decision Fusion

A majority polling method is used to combine the outputs produced by ANN with XGBoost. The final choice is classified as abnormal if either approach predicts the existence of an irregular heartbeat. This hybrid fusion approach reduces inaccurate classifications and increases overall reliability.

## 2.7 Simulated Physiological Monitoring

The monitoring construction incorporates simulated physiological indicators, such as temperature and SpO<sub>2</sub> levels, to improve healthcare relevance. SpO<sub>2</sub> levels range from 88% to 100%, and temperature readings originate between 36.5°C and 38.5°C. In order to facilitate thorough patient assessment, these factors are continuously monitored in conjunction with ECG analysis.

## 2.8 Decision Support System

Normal, Mild, Warning, and Critical are the four categories into which a rule-based the Decision Support System (DSS), divides patient states. Table 2 provides a summary of the DSS's health classification criteria. The DSS enhances interpretability and facilitates trustworthy clinical decision-making by combining physiological parameters with ECG abnormality data.

## 2.9 Real-Time Alert Communication

An alert message with the anomalous count, body temperature, SpO<sub>2</sub> level, and timestamp is automatically created whenever the framework detects Warning signs or Critical health circumstances. The Twilio API is used to send the notice over WhatsApp. According to Table 5's response time analysis, alert delivery takes three to five seconds. Fig. 5 shows the real-time notification interface.

TABLE II. HEALTH STATUS CLASSIFICATION RULES

| Si.No: | Health Status | Rules                                       |
|--------|---------------|---|
| 1      | Normal        | No anomalies and vitals within normal range |
| 2      | Mild          | Few anomalies and vitals normal             |
| 3      | Warning       | Multiple anomalies or borderline vitals     |
| 4      | Critical      | Frequent anomalies or abnormal vitals       |

### 2.10 Real-Time Visualization Dashboard

Real-time analysis of ECG signals, reported abnormalities, corresponding physiological variables, and comprehensive patient status is provided by a Streamlit-based dashboard. The dashboard facilitates remote health care surveillance and decision-making with interactive charts, live monitoring tools, and trend analysis.

## III. RESULTS AND DISCUSSION

### 3.1 Classification Performance

An 80:20 train-test split is used to evaluate the suggested hybrid ANN-XGBoost framework. Table 3 provides an overview of the performance measures derived from the experimental investigation. The framework shows dependable performance in ECG anomaly identification with 98.6% accuracy, 98.1% exactness, 97.8% retention, and a 97.9% F1-score.

TABLE III. PERFORMANCE METRICS

| Si.No: | Metric    | Value (%) |
|--------|-----------|-----------|
| 1      | Accuracy  | 98.6      |
| 2      | Precision | 98.1      |
| 3      | Recall    | 97.8      |
| 4      | F1-Score  | 97.9      |

### 3.2 Confusion Matrix Evaluation

The classification capabilities of the suggested model in differentiating between normal and pathological heartbeats is demonstrated by the confusion matrix displayed in Fig. 2. With extremely low false prediction rates, the framework accurately detects 945 benign beats and 915 aberrant beats. These findings validate the hybrid categorization approach's stability and efficacy.

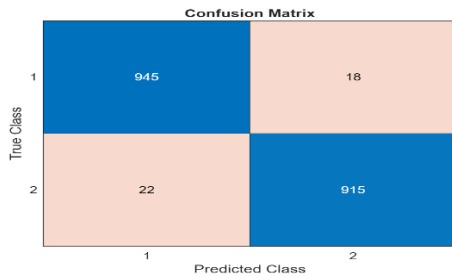


Fig.2. Confusion Matrix

### 3.3 ROC Curve

The postulated framework's capacity for discrimination is illustrated by the ROC curve shown in Figure 3. Excellent

separability between the normal and pathologic heartbeat classes across various threshold values is indicated by the Area Under the Curve (AUC) metric value of almost 0.99.

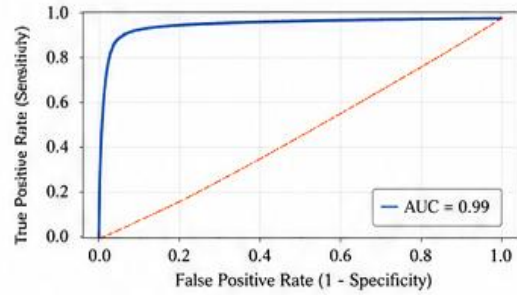


Fig.3. ROC Curve

### 3.4 ECG Anomaly Visualization

Precisely evident in Fig. 4, discovered anomalies are directly indicated on an ECG waveform for better interpretability. Clinicians and users can more successfully identify irregular heartbeat locations with the use of this display. The reliability of medical evaluation and decision-making is further enhanced by the combination of ECG examination with simulated physiological monitoring.

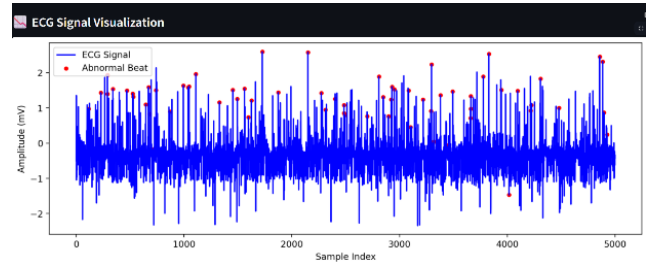


Fig.4. ECG Signal with Detected Anomalies

### 3.5 MATLAB Baed ANN Evaluation

The ANN model's predictive power and computational efficiency are validated by the MATLAB performance study presented in Table 4. Reliable learning behavior and efficient classification capacity are demonstrated by the network's low MSE value and convergence within 35 epochs.

TABLE IV: MATLAB PERFORMANCE ANALYSIS

| Si.No: | Parameter              | Value  |
|--------|------------------------|--------|
| 1      | Mean square error(MSE) | 0.012  |
| 2      | ROC-AUC Score          | 0.99   |
| 3      | Convergence Epochs     | 35     |
| 4      | Training Time          | 18.7 s |

### 3.6 Real-Time Response Analysis

The performance time analysis shown in Table 5 illustrates the suggested framework's near real-time potential. While alert production and communication take about a period of three to five seconds ECG decoding and DSS inspection are

finished in one second. These findings demonstrate that the framework is appropriate for time-sensitive medical monitoring applications.

TABLE V: EXECUTION TIME ANALYSIS

| Si.No: | Operation              | Time (s) |
|--------|------------------------|----------|
| 1      | ECG Processing         | <1       |
| 2      | Classification(Hybrid) | 1        |
| 3      | DSS Evaluation         | <1       |
| 4      | Alert Generation       | 3-5      |

### 3.7 Real-Time WhatsApp Notification System

The ability to deliver real-time alerts about health issues via WhatsApp is a major improvement added to this system. When the DSS detects significant health threats, including multiple ECG aberrations or abnormal vital signs, this notification system is immediately activated. The system gathers vital health information into a structured message, including body temperature, baseline SpO<sub>2</sub> levels, and the overall number of anomalies. Using the Twilio API, this message is instantly sent via WhatsApp to the registered contact. In real-world assessments, the notifications were sent out in a matter of seconds, suggesting that this approach is ideal for prompt response, especially in situations where ongoing physical observation is impractical. Figure 3 illustrates how the Twilio API is used to generate alerts using WhatsApp.

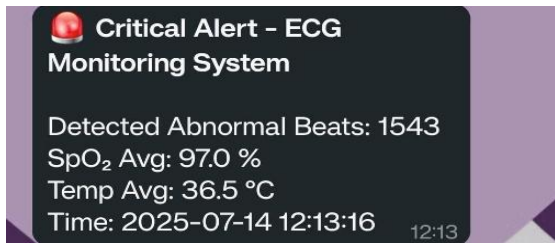


Fig.5. Whatsapp Alert Message

### 3.7 Comparative Performancer Analysis

The proposed framework is compared to current CNN-based ECG classification systems [3] and IoMT healthcare monitoring frameworks [8] in the comparative study presented in Table 6. In contrast to traditional methods, the suggested system integrates real-time communication, intelligent decision support, multi-parameter physiological monitoring, and accurate ECG anomaly detection into a single framework. For real-world healthcare applications, the integration of DSS-based healthcare evaluation, dynamic visuals, and instant WhatsApp notifications greatly enhances realistic convenience, interpretability, and monitoring reliability.

TABLE VI. Comparison With Existing Works

| Parameter                 | [3] CNN-Based ECG Model | [8] IoMT Health Monitoring System | Proposed System (This Work)    |
|---------------------------|-------------------------|-----------------------------------|--------------------------------|
| Approach                  | Deep CNN                | IoT + Cloud Monitoring            | Hybrid ANN + XGBoost           |
| Dataset Used              | MIT-BIH                 | Real-time sensor data             | MIT-BIH + Simulated Vitals     |
| Classification Accuracy   | 96–98%                  | Not focused                       | 98.6%                          |
| Model Type                | Deep Learning           | IoT Framework                     | Hybrid ML + DL                 |
| Feature Engineering       | Automatic (CNN)         | Not applicable                    | Statistical + Morphological    |
| Interpretability          | Low                     | Medium                            | High (DSS-based)               |
| Real-Time Monitoring      | No                      | Yes                               | Yes                            |
| ECG Signal Processing     | Yes                     | Limited                           | Advanced                       |
| Multi-Parameter Vitals    | No                      | Yes                               | Temperature + SpO <sub>2</sub> |
| Decision Support System   | No                      | No                                | Fully Implemented              |
| Health Classification     | Binary                  | Basic                             | 4-level (Normal–Critical)      |
| Alert Mechanism           | No                      | Limited                           | Instant (3–5 sec)              |
| Visualization             | No                      | Basic Dashboard                   | Interactive Dashboard          |
| Deployment                | Offline Model           | Cloud-based                       | Web-based (Streamlit)          |
| Scalability               | Medium                  | High                              | High                           |
| Computational Complexity  | High                    | Medium                            | Optimized Hybrid               |
| Suitability for Rural Use | Limited                 | Moderate                          | High                           |

## IV. CONCLUSION AND FUTURE WORK

The scalable AI-assisted ECG detection of anomalies and decision support system that combines ANN, XGBoost, simulate vital surveillance, and real-time communication methods for cognitive healthcare applications was provided in this research. With a precision of 98.6%, accuracy of 98.1%, retention of 97.8%, and a F1 rating of 97.9%, the suggested hybrid framework showed excellent classification performance, demonstrating its efficacy in detecting ECG abnormalities. By enabling thorough health assessment transcend ECG analysis alone, the incorporation of simulated physiological data like body temperature and SpO<sub>2</sub> improved the system's clinical relevance. Additionally, by classifying patient states into Normal, Mild, Warning, and Critical levels, the rule-based Decision Support System demonstrates enhanced interpretability. The base was further reinforced by the Twilio-enabled WhatsApp alert system and the Streamlit-based monitoring dashboard, which enable real-time visualization and quick emergency communication in three to five seconds. The suggested framework offers better reliability, multi-parameter monitoring capabilities, interpretability, and real-time deployment applicability, according to a comparison with current methods. Consequently, by facilitating trustworthy AI-driven health care communication and monitoring, the system offers a workable and scalable solution for global healthcare monitoring and is consistent with the conference theme of

RAIN – Reliable AI-enabled Networks. Future research will concentrate on incorporating wearable IoMT sensors in real-time, growing the ECG dataset for better generalization, and applying edge AI approaches for scalable and low-power healthcare monitoring systems.

#### ACKNOWLEDGEMENT

The authors acknowledge Anna University for facilitating this study through the Anna Research Fellowship (ARF), Lt.No.CFR/ARF-Jul2024/AR1.

#### REFERENCES

- [1] G. B. Moody and R. G. Mark, "The impact of the MIT-BIH Arrhythmia Database," *IEEE Eng. Med. Biol. Mag.*, vol. 20, no. 3, pp. 45-50, May-Jun. 2001. <https://doi.org/10.1109/51.932724>
- [2] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. on Knowl. Discov. Data Min.*, San Francisco, CA, USA, 2016, pp. 785-794. <https://doi.org/10.1145/2939672.2939785>
- [3] S. Acharya, U. R. Acharya, Y. Hagiwara, J. H. Tan, and M. Adam, "A deep convolutional neural network model to classify heartbeats," *Comput. Biol. Med.*, vol. 89, pp. 389-396, Dec. 2017. <https://doi.org/10.1016/j.combiomed.2017.08.022>
- [4] M. Kachuee, S. Fazeli, and M. Sarrafzadeh, "ECG heartbeat classification: A deep transferable representation," in *Proc. IEEE Int. Conf. Healthc. Inform. (ICHI)*, 2018, pp. 443-444. <https://doi.org/10.1109/ICHI.2018.00092>
- [5] J. Kwon and Y. Kim, "An interpretable deep learning model for ECG-based heart disease classification," *IEEE Access*, vol. 8, pp. 168559-168570, 2020.
- [6] S. R. M. Prakash and S. Patil, "Arrhythmia classification using a hybrid CNN-XGBoost model," *Int. J. Recent Technol. Eng. (IJRTE)*, vol. 8, no. 4, pp. 1244-1248, Nov. 2019.
- [7] M. A. Kabir and C. Shahnaz, "A decision support system for cardiac arrhythmia detection using ensemble classifiers," in *Proc. 20th Int. Conf. Comput. Inf. Technol. (ICCIIT)*, 2017, pp. 1-6.
- [8] S. Mahapatra, S. Panda, and R. Kumar, "IoMT based patient health monitoring system using cloud computing and wearable sensors," in *Proc. IEEE Int. Conf. IoT Connected Technol.*, 2021, pp. 183-187. <https://doi.org/10.3233/APC200178>.
- [9] Streamlit Inc., "Streamlit: The fastest way to build data apps." [Online]. Available: <https://streamlit.io/>
- [10] D. Han and L. Chen, "Design and implementation of a mobile health monitoring system," *IEEE Sens. J.*, vol. 21, no. 5, pp. 5752-5760, Mar. 2021.
- [11] P. Ingale, "Enhancing Patient Care and Monitoring Using AI and IoT in Healthcare," *European Chemical Bulletin*, 2023.
- [12] A. Chaudhari, "A Review of Artificial Intelligence for Predictive Healthcare Analytics and Healthcare IoT Applications," *Lecture Notes in Networks and Systems*, Springer, 2023. [https://doi.org/10.1007/978-981-99-3177-4\\_42](https://doi.org/10.1007/978-981-99-3177-4_42)
- [13] P. Jayant, E. Vincent, Mohana, M. Moharir and A. K. A R, "Smart Health Monitoring and Anomaly Detection Using Internet of Things (IoT) and Artificial Intelligence (AI)," 2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), Coimbatore, India, 2024. <https://doi.org/10.1109/ICoICI62503.2024.10696283>
- [14] S. Ahamed, "An Intelligent IoT Enabled Health Care Surveillance Using Machine Learning," *International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*, 2022. <https://doi.org/10.1109/ACCAI53970.2022.9752648>
- [15] K. G. Mallikarjuna, "Smart Health Monitoring System for Elderly People," *Lecture Notes in Electrical Engineering*, Springer, 2024. [https://doi.org/10.1007/978-981-99-8646-0\\_12](https://doi.org/10.1007/978-981-99-8646-0_12)