AI-Driven Emergency Alert System Using ECG Signal Classification and Voice Assistance

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BONAFIDE CERTIFICATE

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ABSTRACT

Today's world, ensuring women's safety remains a pressing challenge, especially in situations where physical or verbal communication is restricted. To address this issue, this project proposes a novel AI-powered SOS system that utilizes real-time ECG signal analysis to detect abnormal heart activity, which often occurs under conditions of stress, fear, or threat. Unlike conventional safety solutions that rely on manual intervention (such as pressing a button or making a call), this system operates autonomously and intelligently by continuously monitoring the user's physiological signals.The core of the system employs a Convolutional Neural Network (CNN) model trained to recognize deviations from normal ECG patterns that may indicate danger or panic. Once an anomaly is detected, the system automatically triggers a safety protocol which includes sending the user's live GPS location to emergency contacts and authorities. Additionally, the system is integrated with voice assistance to provide verbal alerts and instructions, ensuring immediate action even when the victim is unable to respond physically.The backend is enhanced using the Gemini API to support natural language processing and improve real-time decision-making capabilities. The project is designed to be lightweight, scalable, and suitable for edge deployment on devices such as smartphones, smartwatches, or compact microcontrollers like Raspberry Pi or NVIDIA Jetson Nano. By incorporating AI, IoT, and biomedical signal processing, this system provides a proactive, cost-effective, and life-saving solution for women's safety.The proposed solution is not just a technological innovation but a meaningful step towards empowering women with a non-intrusive, always-on, and intelligent personal safety companion. Its potential applications span across multiple domains, including public safety, healthcare, personal security, and smart wearables, making it a highly impactful and socially relevant project.

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Initially we thank the Almighty for being with us through every walk of our life and showering his blessings through the endeavor to put forth this report. Our sincere thanks to our Chairman **Mr. S. MEGANATHAN, B.E, F.I.E.**, our Vice Chairman **Mr. ABHAY SHANKAR MEGANATHAN, B.E., M.S.,** and our respected Chairperson **Dr. (Mrs.) THANGAM MEGANATHAN**, **Ph.D.,** for providing us with the requisite infrastructure and sincere endeavoring in educating us in their premier institution.

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LIST OF ABBREVIATIONS

S. No	ABBR	Expansion
1	AI	Artificial Intelligence
2`	API	Application Programming Interface
3	ECG	Electrocardiogram
4	CNN	Convolutional Neural Network
5	GPS	Global Positioning System
6	ML	Machine Learning
7	DFD	Data Flow Diagram
8	NLP	Natural Language Processing
9	Iot	Internet of Things
10	GUI	Graphical User Interface
11	ML	Machine Learning
12	SMS	Short Message Service
13	SOS	Save Our Souls / Emergency Distress Signal
14	CSV	Comma-Separated Values

CHAPTER 1

INTRODUCTION

1.1 GENERAL

Safety is a fundamental human right, yet many women across the globe continue to face threats to their personal security—especially in situations where they are unable to call for help. In moments of extreme stress, fear, or physical restraint, traditional emergency systems that require manual activation are often ineffective. There is a pressing need for intelligent, autonomous systems that can identify distress signals from the body itself and respond instantly, without requiring user intervention. This project proposes an AI-based Women Safety SOS System that monitors ECG signals in real-time to detect abnormal heart activity indicative of distress. Leveraging a Convolutional Neural Network (CNN) model trained on ECG datasets, the system identifies critical abnormalities with high accuracy. Once such a pattern is detected, the system automatically shares the user's live location with a trusted emergency contact and simultaneously activates a voice assistant to guide or calm the user.The solution integrates biomedical signal processing, machine learning, geolocation tracking, and Google's Gemini API for natural language-based voice interaction. This multi-disciplinary approach not only bridges the gap between technology and personal safety but also empowers women by ensuring they are never truly alone during emergencies—even when they are unable to speak or act.

1.2 OBJECTIVE

This project intends to develop and implement an AI-based real-time SOS alert system designed specifically for women’s safety by analyzing ECG (Electrocardiogram) signals. The system is engineered to automatically detect signs of physiological distress—such as elevated or abnormal heart activity—using a trained convolutional neural network (CNN) model. Upon detecting such patterns, it instantly triggers an emergency protocol that includes sending the live GPS location to a pre-registered emergency contact and activating a voice assistant for immediate user guidance or alert.The core idea is to enable a hands-free emergency response mechanism that does not rely on the victim's ability to manually operate a device during a critical situation. By integrating biomedical signal processing, geolocation tracking, AI-based prediction models, and Google’s Gemini API for natural language voice interaction, the system ensures timely action even in hostile or restrictive environments.The application is scalable, energy-efficient, and can be embedded in wearable devices, making it ideal for real-world deployment. Ultimately, this project aims to enhance personal safety, reduce response time, and empower women by providing a smart, proactive, and accessible safety net in both urban and rural scenarios.

1.3 EXISTING SYSTEM

Various systems have been proposed to improve personal safety through emergency alerts, ranging from wearable health monitors to AI-based solutions. One example is the smartwatch-based system, which tracks heart rate and sends alerts when abnormalities are detected. While these systems focus on general health monitoring, they lack specialized features for women’s safety, such as location tracking and real-time voice assistance during emergencies. The Women Safety SOS System aims to address this gap by analyzing ECG signals for distress detection, sending location-based alerts, and activating a voice assistant, offering a more comprehensive and proactive solution.

CHAPTER 2

LITERATURE SURVEY

[1] ECG Classification Using Deep Neural Networks:

This review paper discusses various types of deep neural networks (DNNs) used for ECG classification. It covers different architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and more advanced hybrid models that combine different neural networks. The paper provides insight into the strengths and limitations of these models for detecting heart abnormalities, including arrhythmias, and offers a comprehensive guide for applying DNNs to ECG signal analysis.

[2] Automated ECG Classification Using a Deep Neural Network Model:

This paper proposes an automated system that employs deep neural networks for classifying ECG signals into different categories, including normal and abnormal heart rhythms. The authors focus on the design and implementation of a deep learning-based classifier, which can be used for real-time ECG analysis. The study demonstrates the effectiveness of CNNs and RNNs in identifying arrhythmic patterns and abnormal heart activities that trigger emergency alerts.

[3] ECG Arrhythmia Classification Using a Convolutional Neural Network (CNN):

In this paper, the authors propose a CNN-based method to classify arrhythmias in ECG signals. CNNs are particularly useful for analyzing time-series data like ECG, and the paper shows how the model's ability to learn hierarchical features makes it effective in detecting subtle abnormal patterns in ECG signals. The proposed system can be integrated into real-time health monitoring systems to detect irregular heartbeats and issue alerts when necessary.

[4] A Real-Time ECG Classification Algorithm for Heart Disease Detection: Using Support Vector Machine:This paper offers a literature review on the application of deep learning for ECG classification. It provides an in-depth analysis of CNN, RNN, Long Short-Term Memory (LSTM) networks, and hybrid models, discussing their strengths and weaknesses in processing ECG signals. The paper also addresses challenges such as noise in ECG data and proposes techniques for overcoming these challenges, offering valuable insights for researchers working on real-time ECG-based detection systems.

[5] ECG Signal Processing and Classification Using Wavelet Transform and Neural Networks:

The authors in this paper present a combined approach to ECG signal classification, integrating wavelet transforms for feature extraction and neural networks for classification. The wavelet transform is used to extract frequency domain features from the ECG signal, which are then fed into a neural network model for classification. This method is effective in detecting various heart abnormalities like atrial fibrillation, making it a useful approach for emergency alert systems.

[6] Real-Time ECG Classification Using Hybrid Machine Learning Algorithms:

This study explores hybrid machine learning algorithms for real-time ECG classification. It combines various models, including decision trees, SVMs, and neural networks, to improve the accuracy and reliability of abnormal heart condition detection. By using hybrid approaches, the paper shows how combining the strengths of different algorithms can lead to better performance, particularly in emergency alert systems where real-time analysis is crucial.

[7] An AI-Based Heart Disease Prediction System Using ECG Signals:

This paper introduces an AI-based system for predicting heart disease from ECG signals. The system uses machine learning models to analyze the signals and identify abnormalities that may indicate conditions like coronary artery disease or arrhythmias. The model can issue early warnings for patients at risk, making it an essential tool for preventive healthcare. The authors demonstrate how the system can be used in conjunction with wearable ECG devices for continuous monitoring.

[8] Deep Learning for ECG Classification: A Review of the Literature:

This paper offers a literature review on the application of deep learning for ECG classification. It provides an in-depth analysis of CNN, RNN, Long Short-Term Memory (LSTM) networks, and hybrid models, discussing their strengths and weaknesses in processing ECG signals. The paper also addresses challenges such as noise in ECG data and proposes techniques for overcoming these challenges, offering valuable insights for researchers working on real-time ECG-based detection systems

[9] A Novel ECG Signal Classification Approach Using Convolutional Neural Networks and Data Augmentation:

In this paper, the authors propose a novel method that combines CNNs with data augmentation techniques to improve the accuracy of ECG signal classification. Data augmentation helps address issues of limited ECG data by artificially increasing the size of the dataset, which is particularly beneficial for training deep learning models. This approach is shown to enhance the model's ability to detect rare arrhythmic events, improving the overall detection accuracy.

[10] Heart Disease Classification Using ECG and Machine Learning: This paper provides a comparative study of several machine learning algorithms, including SVM, KNN, and decision trees, for ECG signal classification. The study emphasizes the importance of selecting the right algorithm for heart disease detection, as each algorithm has its strengths and weaknesses depending on the type of ECG data. The authors conclude that while deep learning models tend to perform better, traditional machine learning algorithms can still be effective for less complex ECG classification tasks.

[11] ECG Signal Classification Using Deep Convolutional Neural Networks: The focus of this paper is on using deep CNNs for classifying ECG signals. CNNs are well-suited for analyzing time-series data like ECG due to their ability to automatically learn hierarchical features. The authors demonstrate how a deep CNN model can accurately classify various heart conditions, including arrhythmias and other abnormalities, providing a robust solution for real-time heart monitoring and emergency alert systems.

[12] Arrhythmia Classification in ECG Signals Using Deep Learning Models: This paper delves into the application of deep learning models for classifying arrhythmias in ECG signals. The authors compare several models, including CNN, LSTM, and hybrid models, and demonstrate how deep learning methods can improve the accuracy of arrhythmia detection. The study highlights the potential of these models for use in wearable ECG monitoring devices that can alert healthcare providers in case of abnormal heart patterns.

[13] ECG Classification Using Long Short-Term Memory Networks (LSTM): This paper focuses on using Long Short-Term Memory (LSTM) networks for classifying ECG signals. LSTMs are particularly effective for time-series data,

and the paper demonstrates how LSTMs can capture long-term dependencies in ECG signals, making them highly effective for detecting arrhythmias and other heart abnormalities. The authors propose that LSTM-based models can be integrated into real-time health monitoring systems for continuous, automated detection.

[14] ECG Signal Classification Using Random Forest Classifier and Feature Extraction Techniques:

This study presents the use of Random Forest (RF) classifiers for ECG signal classification. RF is a popular machine learning model known for its robustness and accuracy. The paper discusses various feature extraction techniques, including time-domain and frequency-domain methods, which are used to process raw ECG signals before classification. The study concludes that RF classifiers can achieve high accuracy in detecting abnormal heart rhythms.

[15] Real-Time Heart Disease Detection Using Wearable ECG Sensors and Machine Learning:

This paper explores the integration of wearable ECG sensors with machine learning models for real-time heart disease detection. The authors propose a system where the ECG signals from a wearable device are analyzed in real-time using machine learning algorithms to detect heart conditions like arrhythmias. The paper highlights the importance of real-time analysis for timely intervention and prevention.

[16] Early Detection of Arrhythmias Using Machine Learning Models for ECG Classification:

The authors propose a machine learning-based approach for the early detection of arrhythmias using ECG signals. By analyzing raw ECG data with machine learning algorithms like SVM and CNN, the system can detect arrhythmias before they develop into severe conditions. This early detection capability can trigger timely alerts for emergency medical intervention.

[17] ECG Signal Preprocessing and Feature Extraction Techniques for Heart Disease Classification:

This paper provides a comprehensive overview of preprocessing and feature extraction techniques for ECG signal analysis. Preprocessing techniques such as noise filtering, normalization, and segmentation are discussed, along with feature extraction methods like wavelet transform and principal component analysis (PCA). The authors emphasize the importance of these techniques for improving the accuracy of heart disease classification.

[18] Predictive Analysis of ECG for Detecting Heart Conditions Using Deep Learning:

In this paper, the authors use deep learning algorithms, particularly CNNs and LSTMs, for predictive analysis of ECG signals. The goal is to detect heart conditions early by analyzing ECG data in real-time. The authors demonstrate how their model can predict future heart conditions based on past ECG data, providing a predictive alert system that can trigger an SOS response for emergency medical assistance.

[19] Wireless ECG Monitoring System Using Machine Learning for Arrhythmia Detection:

This paper discusses a wireless ECG monitoring system that uses machine learning algorithms to detect arrhythmias. The system allows for continuous monitoring of ECG signals and can trigger alerts when abnormal heart patterns are detected.

CHAPTER 3
PROPOSED SYSTEM

3.1 GENERAL

The ECG-based SOS project proposes a robust AI-driven real-time heart abnormality detection and emergency alert system that continuously monitors heart activity using wearable ECG devices. The system leverages advanced signal processing techniques to clean and prepare ECG data, which is then analyzed using machine learning models like CNNs and LSTMs to detect conditions such as arrhythmias or other cardiac abnormalities. Upon detecting an anomaly, the system triggers automatic alerts to medical professionals or emergency responders, ensuring immediate attention. The solution integrates cloud computing for data storage and continuous model improvement, offering scalability and adaptability across healthcare, fitness, and emergency response sectors. This real-time monitoring and alert system empowers individuals to receive timely medical intervention, improving overall health outcomes and promoting proactive heart health management.

3.2 SYSTEM ARCHITECTURE DIAGRAM

The system architecture for the **ECG-based SOS project** (Fig. 3.1) is designed to monitor real-time heart activity using ECG signals, enabling timely emergency alerts in case of abnormal heart patterns. The architecture starts with the acquisition of raw ECG data from wearable devices, which are then preprocessed to filter noise and extract key features, such as PQRST waves and heart rate. This preprocessed data is passed through machine learning models, typically CNNs that analyze the heart's electrical activity to detect abnormalities such as arrhythmia. Once an abnormality is detected, the system triggers an alert, including the user's location and medical details, for emergency responders. The back-end infrastructure is built using Flask for API management, with MongoDB storing user data and session logs. The system's scalability is ensured with modular components designed to handle high-throughput data processing and low-latency alerts. The machine learning model continuously improves over time by incorporating new data, enhancing the accuracy of anomaly detection. Performance is measured based on latency, detection accuracy, and the system's ability to operate autonomously without human intervention, ensuring quick and reliable responses in emergency situations.

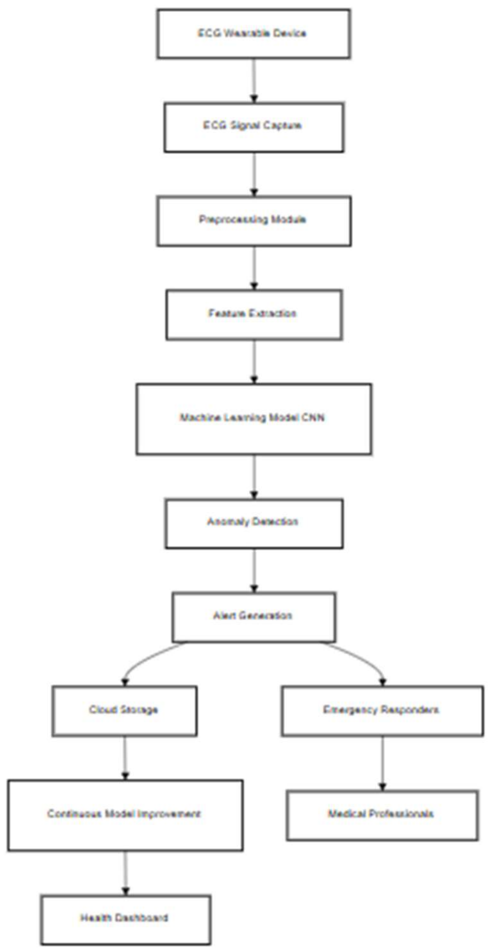


Fig 3.1: System Architecture

3.3 DEVELOPMENTAL ENVIRONMENT

3.3.1 HARDWARE REQUIREMENTS

The hardware requirements outlined below define the specifications necessary to build and deploy the ECG-based SOS system. These specifications ensure sufficient processing power for ECG signal acquisition, feature extraction, model inference, and alert generation in real-time.

Table 3.1 Hardware Requirements

COMPONENTS	SPECIFICATION
PROCESSOR	Intel Core i3 or higher
RAM	8 GB RAM
ECG SENSOR	High-quality ECG sensor
POWER SUPPLY	+5V power supply
DISPLAY UNIT	LED Display or LCD Monitor
AUDIO INPUT	High-quality Microphone

3.3.2 SOFTWARE REQUIREMENTS

The software requirements define the tools, platforms, frameworks, and libraries essential for developing and executing the ECG-based SOS system. This includes libraries for signal processing, machine learning, and alert generation. Additionally, tools for cloud storage, dashboard management, and back-end infrastructure are also specified.

Table 3.2 Software Requirements

COMPONENTS	SPECIFICATION
OPERATING SYSTEM	Windows 10 / Ubuntu 20.04 or higher
FRONTEND	ReactJS,CSS
BACKEND	Flask (Python)
DATABASE	MongoDB
ECG SIGNAL PROCESSING	SciPy, NumPy, Matplotlib
MACHINE LEARNING	TensorFlow
ALERT SYSTEM	Twilio API

3.4 DESIGN OF THE ENTIRE SYSTEM

3.4.1 ACTIVITY DIAGRAM

The activity diagram (Fig. 3.2) illustrates the workflow of the ECG-based SOS system, starting from the continuous capture of ECG signals through a wearable device. The signals are preprocessed to remove noise and normalize data, followed by feature extraction of key indicators like heart rate and waveform patterns. These features are fed into a trained machine learning model (CNN/LSTM) that detects abnormalities in real-time. If an anomaly is identified, the system immediately generates an alert and notifies emergency responders or medical professionals. Simultaneously, the data is stored in the cloud for tracking and improvement, and a health dashboard is updated for medical review. If no issue is found, monitoring continues seamlessly. This automated flow ensures rapid response to cardiac emergencies using AI.

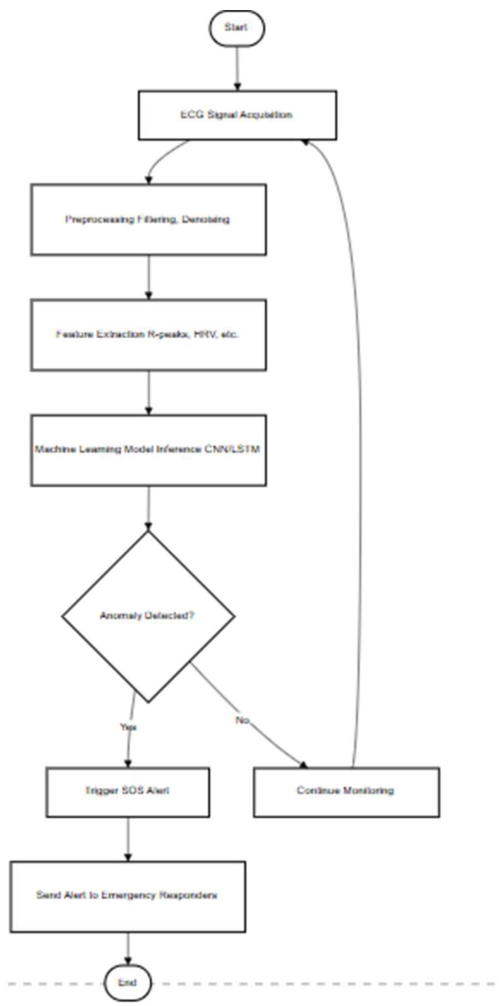


Fig 3.2: Activity Diagram

3.4.2 DATA FLOW DIAGRAM

The data flow diagram (Fig. 3.3) explains how ECG signals are processed to generate real-time alerts. The system starts by capturing ECG data from a wearable device. The signal is then preprocessed to remove noise and standardized for analysis. Key features are extracted and sent to a machine learning model (CNN/LSTM), which checks for anomalies. If abnormal heart activity is detected, an alert is triggered and sent to emergency responders and healthcare professionals. The data is also saved in cloud storage for future analysis and model improvement. A health dashboard provides real-time insights, and fallback mechanisms are in place to manage errors or false detections.

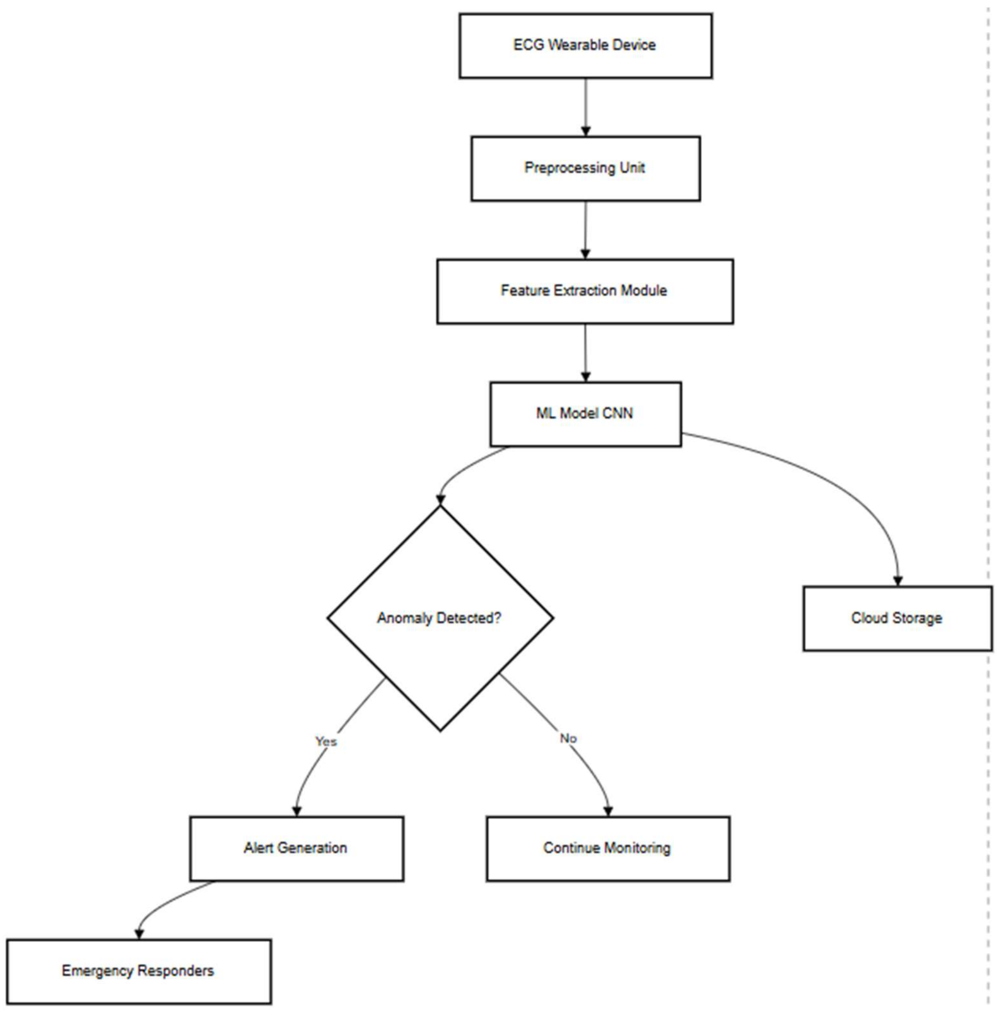


Fig 3.3:Data Flow Diagram

3.5 STATISTICAL ANALYSIS

The comparative analysis table below outlines the distinctions between traditional medical alert systems and the proposed AI-powered ECG-based SOS system designed specifically for women's safety. The proposed solution incorporates intelligent real-time ECG monitoring, machine learning-based anomaly detection, and automated alert mechanisms, reducing reliance on manual response or delayed detection. By integrating high-accuracy sensors, cloud-based dashboards, and medical-grade AI models, the system ensures rapid and reliable emergency detection, making it more robust, scalable, and life-saving.

Table 3.3 Comparison of features

Aspect	Existing System	Proposed System	Expected Outcomes
Emergency Detection	Manual panic button or delayed help	Real-time ECG monitoring with ML-based anomaly detection	Faster response, especially during unconscious or critical situations
Intelligence	Rule-based or threshold monitoring	AI/ML (CNN) models trained on ECG abnormalities	Adaptive and personalized alerting mechanism
Alert Mechanism	Manual or SMS-based alerts	Automated alerts to guardians, cloud dashboards, and nearby responders	Reduced delay and increased reach
Wearable Integration	Limited or bulky devices	Lightweight ECG wearables integrated with mobile devices	Comfortable and continuous usage
Medical Relevance	Not context-aware	Health-grade signal analysis with medical professional notification	Improved health awareness and safety support
Deployment Flexibility	Restricted	Scalable to public spaces	24/7 availability

The **AI-Powered Women Safety SOS System** eliminates the need for manual monitoring, providing real-time alerts with no human intervention. Using **CNN models** for ECG analysis, the **Gemini API** for location tracking, and **voice assistance**, it ensures faster, more accurate emergency responses. This system is especially valuable for enhancing women's safety with scalable, immediate, and context-aware alerts.

Figure 3.4 shows a **comparative analysis** of conventional systems versus the proposed solution, highlighting clear advantages in **automation**, **real-time detection**, **accuracy**, and **user experience**.

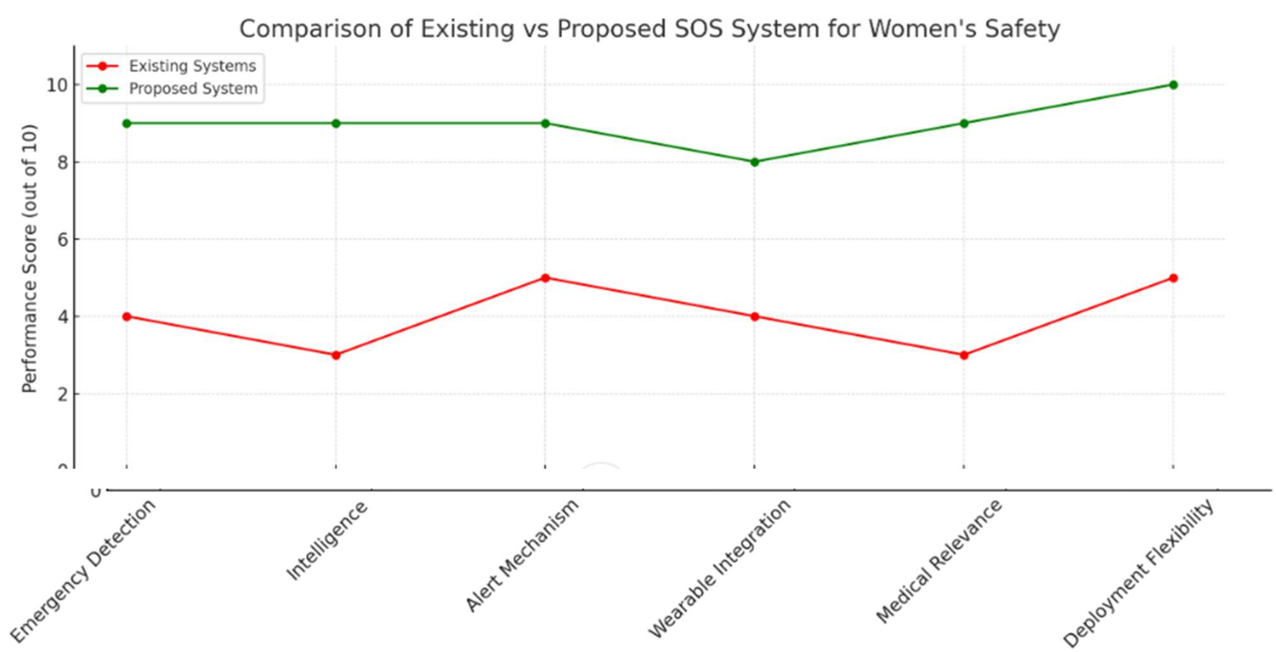


Fig 3.4 : Comparison Graph

CHAPTER 4

MODULE DESCRIPTION

The architecture of the **AI-Powered Women Safety SOS System** is designed to ensure real-time, reliable safety alerts by analyzing ECG signals. The system integrates machine learning and real-time location tracking to provide immediate assistance in emergency situations. It includes the following key components:

4.1 SYSTEM ARCHITECTURE

4.1.1 USER INTERFACE DESIGN

The sequence diagram (Fig. 4.1) illustrates the interaction between users and the system. ECG signals are captured from the user's wearable device and processed in real-time through the CNN model. If an anomaly is detected, the system automatically triggers an alert with the user's location details, which are sent to emergency contacts. Voice assistance provides additional guidance during the emergency. The system ensures a seamless user experience with easy-to-navigate interfaces for monitoring and emergency response.

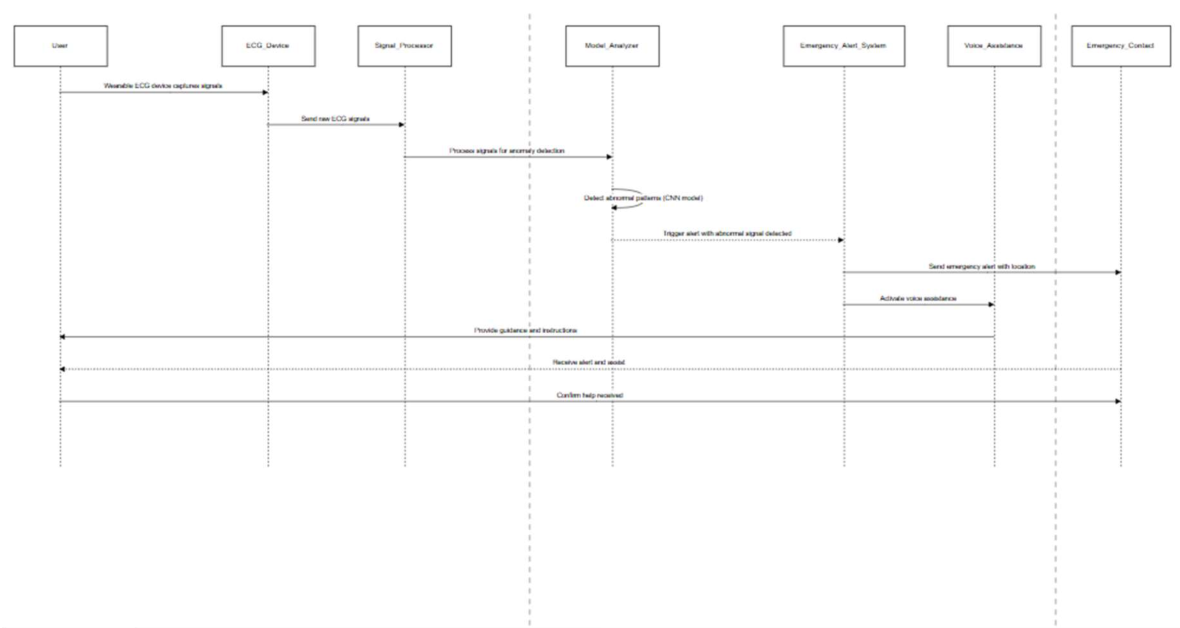


Fig 4.1: SEQUENCE DIAGRAM

4.1.1 BACK END INFRASTRUCTURE

The backend handles several critical modules: ECG signal processing, anomaly detection, location tracking, voice assistance, and alert management. Flask serves as the web framework for API interactions. MongoDB is used to store structured data such as user profiles, session logs, and alert histories. Real-time location tracking and communication is facilitated through WebSocket API or REST API. The backend is designed to be scalable, with low-latency communication for fast response times.

4.2 DATA COLLECTION AND PREPROCESSING

4.2.1 Dataset and Data Labelling

The system requires datasets containing **ECG signals** labeled with corresponding abnormal patterns indicative of health risks. The dataset also includes **user information**, such as age and gender, to ensure context-aware anomaly detection. These datasets are curated from publicly available ECG databases and custom data collection.

4.2.2. Data Preprocessing

Raw ECG data undergoes heavy preprocessing to ensure accurate detection:

- **Noise reduction** from ECG signals
- **Normalization** to standardize readings
- **Segmentation** to isolate important signal features
- **Tokenization and lemmatization** for text processing (if applicable)

4.2.3 Feature Selection

Key features from the ECG signals are selected for processing:

- **Heart rate variability** and **frequency domain features** to detect abnormalities
- **Contextual filtering** based on user's medical history and alert preferences

4.2.4 Classification and Model Selection

The system uses the following models:

- **ECG Signal Analysis**: **CNN models** for abnormality detection
- **Anomaly Detection**: Trained on labeled ECG signals
- **Location Tracking**: Integration with **Gemini API** for accurate, real-time location data
- **Voice Assistance**: Integrated text-to-speech for emergency guidance
- **Model Evaluation**: Performance is measured by accuracy of anomaly detection, real-time alert response, and voice clarity.

4.2.5 Performance Evaluation and Optimization

Model performance is continually evaluated based on:

- **Anomaly detection accuracy**
- **Response time** for emergency alerts
- **User feedback** from individuals using the system in real-world scenarios The system undergoes regular updates to reduce latency and improve accuracy.

4.2.6 Model Deployment

The trained models are deployed via **Flask** and integrated with **WebSocket API** for real-time interaction. **Avatar animations** or **voice assistance** are triggered during emergency alerts and displayed on mobile or wearable devices.

4.2.7 Centralized Server and Database

The system utilizes a **centralized server** to store:

- **User profiles** and **ECG signal data**
- **Alert logs**, **location history**, and **system feedback**

- All data is managed using **MongoDB**, ensuring fast access and flexible schema management.

4.3 SYSTEM WORK FLOW

4.3.1 User Interaction:

Users activate the system via wearable devices or mobile apps. The ECG signal is continuously monitored and analyzed for abnormalities. When an anomaly is detected, the system triggers an alert, sends the user's **location to emergency contacts**, and activates **voice assistance** for additional guidance.

4.3.2 ECG Signal Recognition and Translation:

Once an abnormality is detected, **voice assistance** provides guidance to the user, while the system sends an **emergency alert** to predefined contacts. The alert includes location data, ensuring immediate attention.

4.3.3 Voice Assistance and Emergency Alerts:

These dynamic actions are presented in real-time using an hourly made 3D avatar on screens of holographic devices. The avatar possesses facial expressions and bodily gestures that stuff a lot of feelings and linguistic facts about the language.

4.3.4 Real-Time Display and Feedback:

The system logs data in real-time, monitoring **ECG signal accuracy** and system responses. User feedback is continuously collected to ensure the system is user-friendly and adaptive to individual needs.

4.3.5 Continuous Learning & Improvement:

The system incorporates continuous learning, adjusting to regional variations, user interactions, and evolving health standards.

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENT

6.1 CONCLUSION

With the rise in safety concerns, especially among women, there is a growing need for intelligent, responsive systems that can operate independently in critical moments. This project addresses that urgency by introducing a real-time, AI-powered SOS system that leverages ECG signal analysis to detect abnormal physiological patterns typically associated with distress. Using a deep learning-based CNN model for anomaly detection, integrated with Gemini API for contextual analysis, the system autonomously triggers emergency alerts, sends precise location information, and activates voice-based assistance for immediate guidance and help.Unlike traditional safety applications that rely solely on manual activation or wearable triggers, this system is proactive—responding based on biometric input, ensuring that even unconscious or restricted users can receive assistance. The use of real-time preprocessing, location services, and scalable backend infrastructure makes it a cost-effective, adaptable solution for diverse environments.The project has far-reaching social impact, particularly in enhancing personal safety, promoting independence, and potentially reducing response time in emergency scenarios. Its ability to integrate with emergency services and adapt to other vulnerable user groups—including the elderly and individuals with medical conditions—positions it as a promising step toward a safer, AI-augmented society.

6.2 FUTURE ENHANCEMENT

Future enhancements for the proposed AI-based women safety SOS system could significantly expand its accuracy, adaptability, and real-world applicability across diverse user groups and settings. A major advancement would be the integration of multi-sensor fusion, combining ECG signals with additional biometric indicators such as body temperature, pulse rate, or skin conductance to increase the reliability of distress detection and reduce false positives.To enable two-way support, voice or haptic feedback systems can be enhanced to allow users to confirm alerts, cancel false triggers, or provide contextual responses even under constrained conditions. Emotion recognition through ECG pattern analysis or facial monitoring can further refine the model's ability to distinguish stress from normal fluctuations, leading to more precise emergency activation.

Customizable user profiles could be introduced, where individuals can set sensitivity thresholds, preferred emergency contacts, and location-specific responses. Regional language voice assistance and multilingual alert generation can make the system more inclusive across linguistic boundaries.Additionally, lightweight, edge-deployable models on hardware like Raspberry Pi or NVIDIA Jetson Nano can bring offline capabilities to areas with poor connectivity, ensuring uninterrupted operation in remote zones. Integration with smart wearables, such as fitness bands or smart rings, can offer seamless, discreet deployment without additional hardware.

The system can also benefit from machine learning pipelines with continuous learning, where user feedback and real-world usage data (anonymized and secured) help retrain models to adapt to evolving user behavior and stress indicators.Synchronizing with law enforcement, hospital, and public safety networks can enable automatic routing of alerts to the nearest responders, while geofencing can add contextual relevance by adapting alert behavior based on the user's location.

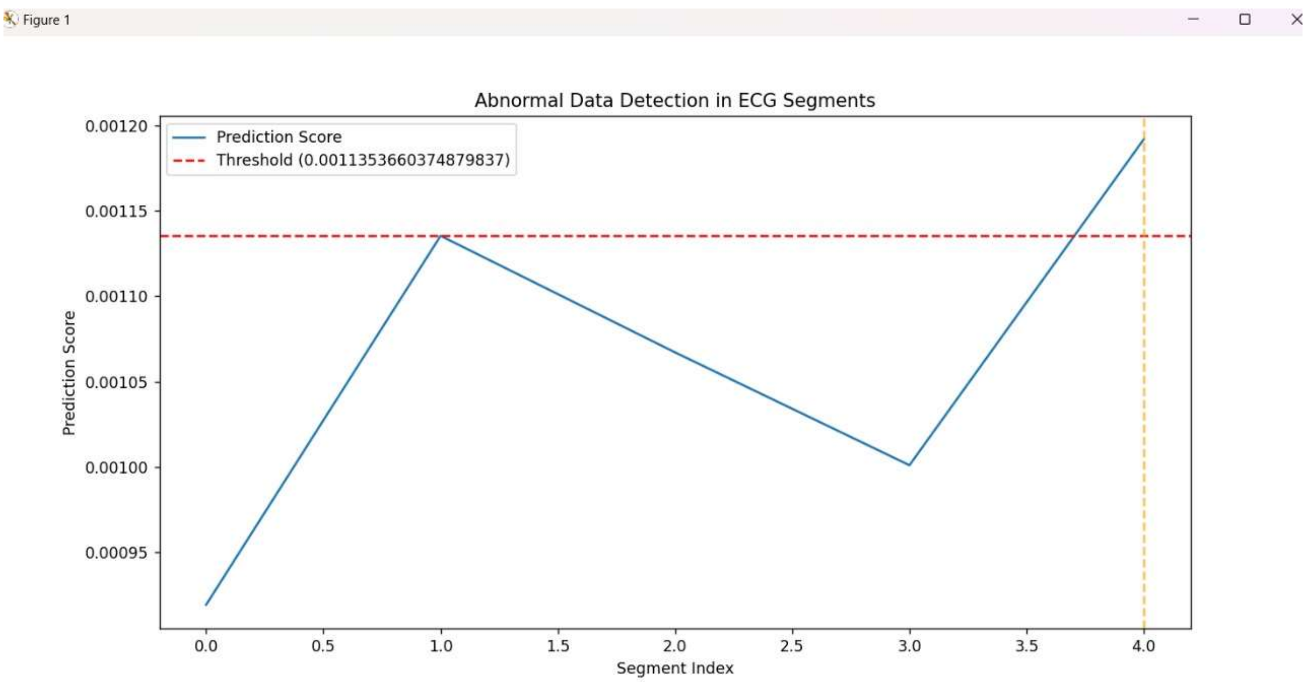
CHAPTER 5
IMPLEMENTATION AND RESULTS

5.1 IMPLEMEMTATION

The implementation of the SOS Women Safety System using ECG and AI involves a systematic integration of hardware, machine learning, and real-time communication technologies. The system begins with ECG signal acquisition, where sensors such as the AD8232 or smart wearable devices continuously monitor the user's heart activity. These signals are transmitted to a microcontroller or smartphone via Bluetooth or Wi-Fi. To ensure signal clarity, preprocessing techniques such as bandpass filtering and baseline correction are applied to remove noise and artifacts. The preprocessed data then undergoes feature extraction, where critical metrics like RR intervals, QRS complex duration, heart rate variability, and PQRST patterns are derived. These features are fed into a trained Convolutional Neural Network (CNN) model which has been developed using annotated ECG datasets to detect abnormal patterns that may indicate stress or danger.Upon detecting anomalies, the system transitions into the alert mechanism phase. It uses Google's Geolocation API or the device's GPS module to fetch the real-time location of the user. This location, along with a distress message, is immediately sent to predefined emergency contacts via SMS API integration and can also be transmitted to nearby authorities or guardians. Additionally, voice assistance is enabled through a text-to-speech engine to guide or inform the user during critical situations. The platform is built using Python for backend logic, Flask or FastAPI for the web server interface, and integrated with Whisper or Gemini API for enhanced speech understanding if needed. The system is lightweight and can also be deployed on edge devices like Raspberry Pi or NVIDIA Jetson, making it suitable for offline or remote use. Overall, the implementation ensures a real-time, intelligent, and responsive SOS system that enhances women's safety through biometric monitoring and AI-powered automation.

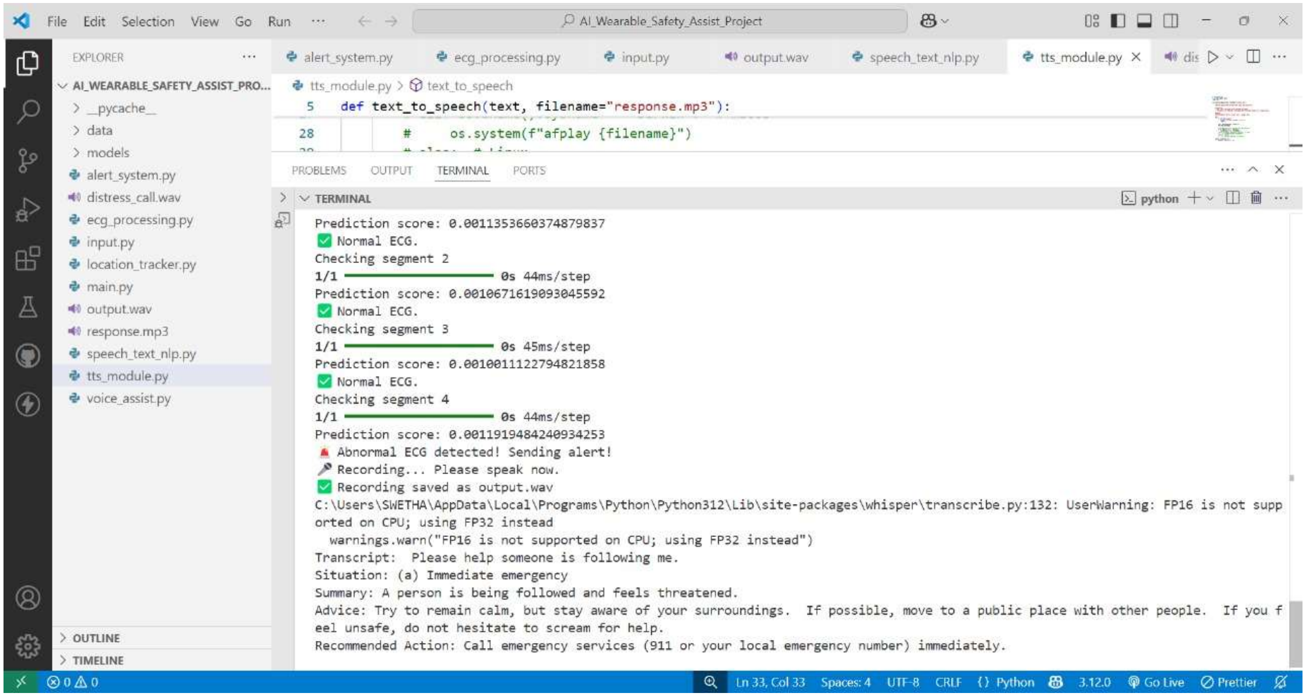
5.3 OUTPUT SCREENSHOTS

The screenshot under this section showcases the graph of an ECG signal where abnormal patterns are detected. The plotted graph clearly illustrates significant deviations in heart activity, such as irregular QRS complexes or variations in heart rate. These anomalies are flagged by the system's trained CNN model, which continuously monitors real-time ECG input to identify stress or panic-induced patterns. When such an abnormal pattern is detected, it triggers the emergency response system. This graphical representation is crucial for validating the system’s accuracy and demonstrates how the AI model differentiates between normal and emergency signals**.**



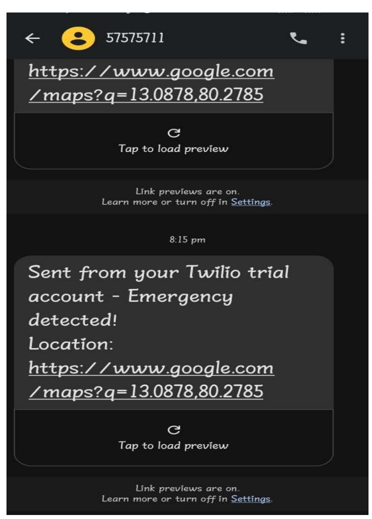
3.1 Abnormal ECG Pattern Detection – Graph Output

The voice assistance screenshot displays the system’s response when an abnormal ECG signal is detected. Upon detection, the voice assistant is activated to audibly inform the user of the triggered SOS alert and guide them with safety instructions or verbal cues. This feature enhances accessibility and provides reassurance to the user during high-stress situations. The voice assistance is implemented using text-to-speech conversion, and the message output is customized to deliver clear and prompt guidance in the user's preferred language.



3.3 Location Message Transmission

This screenshot captures the actual emergency message sent via SMS or online alert containing the user’s real-time location. The system uses GPS or Google Maps API to pinpoint the user's exact coordinates. The message typically includes a predefined SOS statement followed by the location link or address, enabling emergency contacts or authorities to respond quickly.



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