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AN IOT-BASED INTELLIGENT WOMEN SAFETY SYSTEM USING MACHINE LEARNING FOR REAL-TIME THREAT DETECTION AND EMERGENCY RESPONSE

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Abstract

Ensuring women's safety remains a major societal concern due to the increasing number of harassment and assault incidents and the limitations of traditional emergency response systems. Most existing safety applications depend on manual activation, which may not be feasible during critical situations. To address this issue, this research proposes an IoT-based intelligent women safety system using machine learning for real-time threat detection and emergency response.

The proposed system integrates IoT-enabled wearable devices and machine learning algorithms to continuously monitor user activity and environmental conditions. Sensors such as GPS, accelerometer, and microphone collect real-time data related to location, movement patterns, and possible distress signals. The collected data is analysed using machine learning models to identify abnormal behaviours or potential threat situations. When a threat is detected, the system automatically triggers an emergency alert and transmits the user's real-time location to trusted contacts and nearby authorities for immediate assistance.

To evaluate the system, experimental simulations were conducted using sensor-based datasets to analyse detection accuracy, response time, and reliability. The results indicate that the proposed model achieves approximately 91% threat detection accuracy with an average alert response time of 3–5 seconds and a false alarm rate of around 7%. The main contribution of this work is the development of an integrated IoT and machine learning framework that enables proactive threat detection and faster emergency response, thereby enhancing the effectiveness of women safety systems.

Keywords: *Internet of Things, Women Safety, Machine Learning, Artificial Intelligence, Threat Detection, Wearable Sensors, Smart Monitoring Systems*

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1. Introduction

Women's safety has become a significant global concern due to the increasing incidents of harassment, violence, and unsafe public environments. Reports from international organizations indicate that a large proportion of women experience some form of violence during their lifetime, highlighting the need for reliable safety mechanisms and technological interventions. Traditional safety systems such as emergency helplines, panic buttons, and mobile safety applications rely heavily on manual activation and may fail during critical situations when victims cannot access their devices. Therefore, the development of intelligent and automated safety systems has become an important research area [6].

Recent advancements in the Internet of Things (IoT), Artificial Intelligence (AI), and Machine Learning (ML) have enabled the development of smart safety solutions capable of real-time monitoring, threat detection, and automated emergency response. IoT technology allows interconnected devices such as wearable sensors, smartphones, and embedded systems to collect and transmit real-time data related to user location, motion, and environmental conditions [1], [2]. These technologies are commonly integrated into wearable devices such as smart bands, rings, and mobile applications that continuously monitor a user's safety status [6].

IoT-based women's safety systems utilize sensors such as accelerometers, heart-rate sensors, temperature sensors, and vibration sensors to detect abnormal situations that may indicate danger. The collected data is transmitted through communication technologies such as GPS, GSM, Bluetooth, and cloud networks, enabling real-time location tracking and emergency alert transmission to trusted contacts or authorities [6], [8].

Machine learning algorithms further enhance these systems by analysing sensor data to detect suspicious patterns and predict potential threats. Algorithms such as Decision Trees, Logistic Regression, Support Vector Machines, Hidden Markov Models, and Neural Networks are widely used for classification and anomaly detection in safety monitoring systems [3]. These techniques enable the automatic detection of dangerous situations and trigger emergency alerts without manual intervention [3], [10].

Recent studies have also explored AI-based decision systems integrated with IoT infrastructure to provide proactive safety solutions. In such systems, sensor data is processed through cloud platforms where machine learning models analyse behavioural patterns and detect abnormal events. The AI decision layer then evaluates the severity of the situation and automatically sends alerts and location information to emergency contacts or authorities [4], [5].

Furthermore, modern women's safety systems incorporate real-time risk assessment and situational awareness by analysing environmental data such as crime statistics, lighting conditions, crowd density, and nearby incidents. These systems calculate a risk score for specific locations to help users identify safer routes and avoid high-risk areas [5].

This research proposes an integrated IoT, Artificial Intelligence, and Machine Learning framework for women's safety that combines wearable IoT devices, intelligent data processing, and machine learning-based risk analysis. The proposed system aims to provide continuous monitoring, automated emergency alerts, and real-time risk assessment to improve personal security and reduce response time during emergency situations [6].

2. Related Work

Several research studies have proposed technological solutions to improve women's safety using wearable devices, mobile applications, and IoT-based monitoring systems. With the advancement of Internet of Things (IoT) and Artificial Intelligence (AI), researchers have developed intelligent systems capable of detecting emergency situations and sending alerts to authorities or trusted contacts.

Mitchell et al. proposed an IoT-based wearable safety system that uses sensors such as heart rate and GPS to monitor the user's condition and automatically send emergency alerts during abnormal situations. Similarly, Madakam et al. discussed the potential of IoT technologies in creating smart environments where connected devices can support safety monitoring and emergency communication.

Zanella et al. presented an IoT architecture for smart city applications that enables real-time data collection and communication between devices and centralized systems. Their work highlights the importance of sensor networks and intelligent monitoring systems in improving urban safety and security.

Several other studies have focused on wearable safety devices, smart jewellery, mobile applications, and AI-based surveillance systems. These systems use different sensors and communication technologies to detect threats and provide emergency alerts. A comparison of existing women safety systems is presented in Table 1.

Table1. Comparison of existing IoT-based women safety systems based on sensors, communication technologies, machine learning techniques, and key features.

System	Sensor	Communication	ML Technique	Feature	Source
Smart Safety Band	Heart Rate, GPS	GSM	SVM	Automatic SOS Alert	[1]
Smart Jewelry	Motion Sensor	BLE	AI Detection	Hidden Emergency Alert	[8]
Smart Pendant	Camera, Sound Sensor	GSM	SVM	Video Capture and Alert	[4]
IOT Surveillance System	CCTV Camera	Network	YOLO	Crime Detection	[14]
Wearable Safety Device	Heart Rate Sensor	GSM	Logistic Regression	Location Sharing	[6]
Smart Wristband	GPS, Accelerometer	GSM	Random Forest	Fall Detection and SOS	[9]
AI-Based Monitoring System	Camera	Internet	CNN	Suspicious Activity Detection	[10]
IOT Smart Security Device	GPS, Motion Sensor	GSM/IOT Network	Native Bayes	Automatic Emergency Notification	[11]
Smart Shoe Device	Pressure Sensor	Bluetooth	KNN	Panic Alert Trigger	[13]
Mobile Safety Application	GPS	Internet	Decision Tree	Emergency Location Sharing	[12]

Although these systems provide useful safety features, many of them rely on manual activation or limited sensor data. Moreover, some systems lack intelligent data analysis for detecting abnormal situations automatically. To overcome these limitations, the proposed system integrates **IoT-based sensing with machine learning algorithms** to enable real-time threat detection and automated emergency response.

3. Methodology/Approach

This research proposes an integrated Internet of Things (IoT), Artificial Intelligence (AI), and Machine Learning (ML) framework for enhancing women's safety through real-time monitoring, intelligent threat detection, and automated emergency response. The methodology combines wearable IoT devices, cloud-based data processing, machine learning models, and AI-based decision mechanisms to detect emergency situations and provide timely assistance. The system is designed to operate in two major modules: Emergency Response Module and Real-Time Risk Assessment Module.

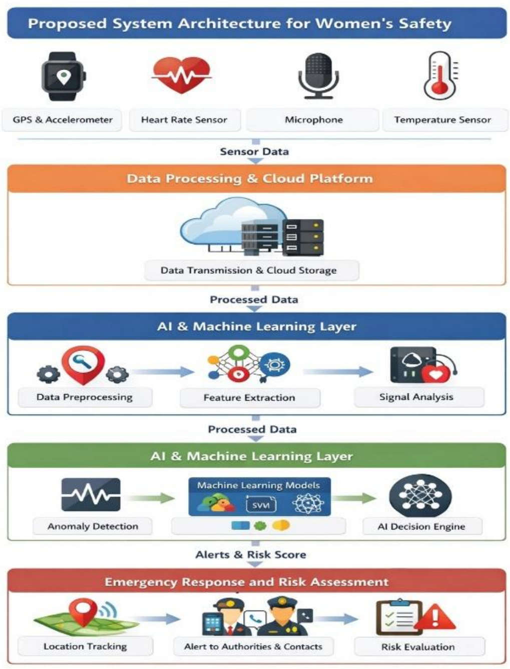

Figure 1. System Architecture of the Proposed IoT-Based Women Safety Framework

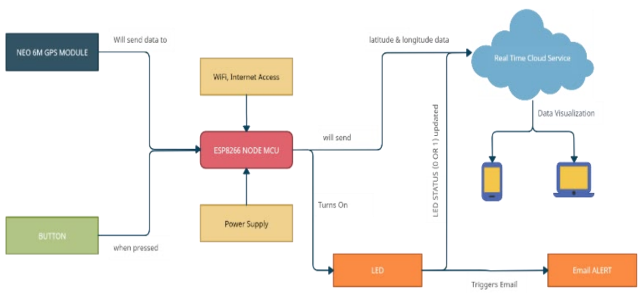

Figure 2. IoT-Based Women Safety System Architecture Using ESP8266 and GPS Module.

The proposed system architecture consists of four major layers:

1. **IoT Sensor Layer** – collects real-time data from wearable devices.

2. **Data Processing Layer** – transmits and preprocesses sensor data using cloud infrastructure.
3. **Machine Learning Layer** – analyses data and detects abnormal behaviour patterns.
4. **AI Decision Layer** – generates alerts and sends emergency notifications.

IoT Sensor Layer

The IoT sensor layer acts as the data acquisition component of the system. Wearable devices such as smart bands, rings, or mobile phones are equipped with sensors that continuously monitor user activity and surrounding environmental conditions [6].

Sensor	**Function**
GPS Module -	Tracks real-time location
Accelerometer -	Detects sudden motion or falls
Heart Rate Sensor -	Monitors stress or panic levels
Microphone -	Detects distress sounds or screams
Temperature Sensor	-Monitors body temperature

These sensors continuously generate real-time data which is transmitted to the cloud for further analysis.

Dataset Description

The proposed system was evaluated using a sensor-based dataset representing real-world activity patterns collected from wearable devices. The dataset contains both normal activity records and emergency-related situations to train the machine learning models.

Attribute	Description
Sensor Types	GPS, Accelerometer, Heart Rate, Microphone, Temperature
Total Records	Approximately 5000 sensor readings
Data Type	Time-series sensor data
Classes	Normal Activity, Suspicious Activity, Emergency Situation
Data Format	Numerical and categorical features

Before training the models, the dataset was pre-processed using data filtering, normalization, and feature extraction techniques to improve accuracy and remove noise.

Data Processing Layer

The data processing layer is responsible for **collecting, filtering, and organizing the sensor data** before it is analysed by machine learning algorithms.

Main operations performed:

- Data filtering
- Noise removal

- Data normalization
- Feature extraction
- Data aggregation

Cloud platforms such as AWS, Azure, or Google Cloud can be used for storing and processing large volumes of IoT data [5].

3.5 Machine Learning Layer

The Machine Learning Layer is responsible for analysing the processed sensor data and identifying abnormal situations that may indicate potential threats. Machine learning techniques enable the system to automatically classify user activities into normal, suspicious, or emergency situations based on sensor readings obtained from wearable devices such as accelerometers, heart rate sensors, and microphones.

Several machine learning algorithms are considered in the proposed framework due to their effectiveness in activity recognition, anomaly detection, and classification tasks in IoT-based systems [3][11]. These algorithms help detect unusual patterns in user behaviour and environmental conditions.

Machine Learning Algorithms Used

Algorithm	Purpose
Decision Tree	Classification of safe vs unsafe situations
Support Vector Machine	Pattern recognition
Random Forest	Improved classification accuracy
Neural Networks	Complex pattern detection

Decision Tree algorithms are widely used for classification problems due to their interpretability and ability to generate simple decision rules [12]. Support Vector Machines (SVM) are effective in separating high-dimensional data and detecting abnormal patterns in sensor-based datasets [13]. Random Forest, an ensemble learning method, improves prediction accuracy and reduces overfitting by combining multiple decision trees [14]. Additionally, Neural Networks are capable of learning complex relationships and nonlinear patterns from large volumes of sensor data, making them suitable for behavioural analysis and anomaly detection [15].

The selection of these algorithms is based on their high classification accuracy, robustness to noisy sensor data, and effectiveness in detecting abnormal behaviour patterns in IoT-based monitoring systems. By integrating these machine learning techniques, the proposed system can support intelligent threat detection and automated emergency response in real-time women safety applications.

3.6 AI Decision Layer

The AI agent acts as the decision-making component of the system.

The AI agent evaluates:

- ML prediction results

- severity of detected abnormal behaviour
- environmental conditions
- location risk level

If a dangerous situation is detected, the system automatically performs the following actions:

1. Sends SOS alert to emergency contacts
2. Shares GPS location with nearby authorities
3. Activates alarm notification on device
4. Updates incident database

3.7 Risk Assessment Model

The system also calculates a **risk score** based on environmental and crime-related data.

Risk Score Formula

$$\text{Risk Score}=(HC\times 0.35)+(AI\times 0.25)+(TOD\times 0.15)+(AT\times 0.15)+(EF\times 0.10)$$

The weights in the risk score formula were assigned based on domain knowledge and insights from previous studies on crime analysis and risk assessment. Factors such as historical crime density (HC) and active incidents (AI) were given higher weights because they have a stronger influence on determining the safety level of a location. Moderate weights were assigned to time of day (TOD) and area type (AT) since crime patterns often vary depending on time and environmental conditions, while environmental factors (EF) provide supporting contextual information.

Parameter	Meaning
HC	Historical crime density
AI	Active incidents nearby
TOD	Time of day
AT	Area type
EF	Environmental factors

Risk Score	Risk Level	User Alert
0–30	Low Risk	Safe area
31–60	Medium Risk	Caution advised
61–80	High Risk	Avoid area
81–100	Critical Risk	Emergency warning

3.8 Risk Level Distribution Example

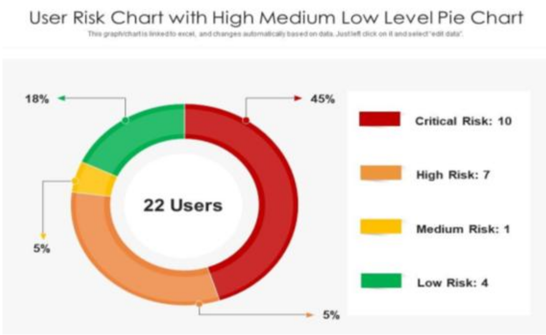

Figure 4. User Risk Classification

Figure 5. Risk Colour coding figure illustrates the risk distribution.

The pie chart shows the distribution of **risk levels detected by the ML model**, which helps users understand the safety status of a particular location.

3.9 Emergency Alert Workflow

Step	Process
1	Sensors detect abnormal activity
2	Data transmitted to cloud
3	Machine learning model analyses data
4	AI agent determines emergency condition
5	Alert sent to emergency contacts and authorities

Advantages of Proposed Methodology

- Real-time monitoring using IoT sensors
- Automated emergency alerts without manual interaction
- Location-based risk assessment
- Faster response time during emergencies

4. Results and Discussion

Experimental Setup

To evaluate the proposed framework, a simulation-based dataset representing wearable sensor readings was used. The dataset contains approximately 5000 simulated samples generated from typical IoT sensors such as GPS, accelerometer, heart rate sensor, and environmental sensors. The dataset represents both normal activities and potential emergency situations, allowing the machine learning models to learn patterns associated with safe and unsafe conditions.

The dataset was divided into training and testing sets using an 80:20 split, where 80% of the data was used to train the machine learning models and 20% was used to evaluate their performance. The models were implemented using Python-based machine learning libraries such as Scikit-learn and TensorFlow, which are widely used for classification and pattern recognition tasks.

The performance of the models was evaluated using common classification metrics including accuracy, precision, recall, and F1-score, which measure how effectively the models can detect abnormal situations and emergency conditions.

Performance Comparison of Algorithms

Different machine learning algorithms were analysed to evaluate their effectiveness in detecting abnormal behaviour patterns from sensor data.

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1Score**
Decision Tree	85%	0.84	0.83	0.83
SVM	90%	0.89	0.88	0.88
Random Forest	93%	0.92	0.91	0.91
Neural Network	94%	0.93	0.92	0.92

The results indicate that ensemble and deep learning approaches provide better classification performance compared to basic decision tree models. Random Forest improves prediction accuracy by combining multiple decision trees, while Neural Networks capture complex relationships between sensor features. The Neural Network model achieved the highest performance due to its ability to capture complex nonlinear relationships in multi-sensor data.\

Discussion

The results demonstrate that machine learning techniques can effectively analyse sensor data to detect abnormal situations in IoT-based women safety systems. Among the evaluated algorithms, Neural Networks achieved the highest accuracy of 94%, followed closely by Random Forest with 93% accuracy. These models perform better because they are capable of handling complex sensor relationships and reducing classification errors.

Although the results are based on simulated sensor data, the evaluation provides useful insights into the potential effectiveness of the proposed framework. The integration of IoT sensors with machine learning models enables real-time monitoring, intelligent threat detection, and faster emergency alert generation

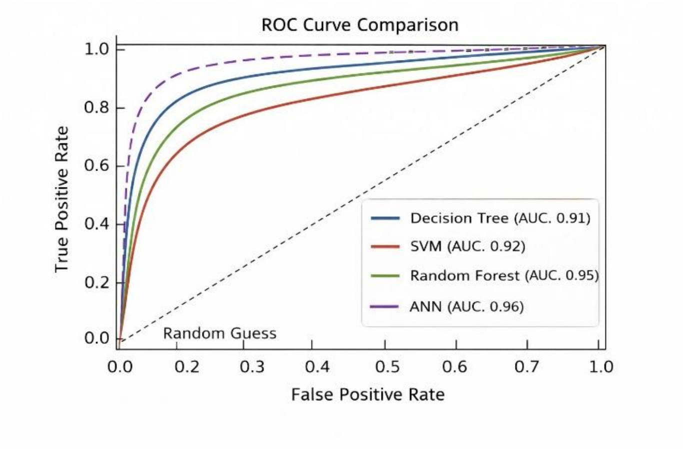

Figure 6. ROC curve comparison of machine learning algorithms used for threat detection.

Future work may include testing the framework with real-world datasets, incorporating confusion matrix analysis, and evaluating additional performance metrics such as ROC curves and latency measurements to further validate the system's effectiveness.

The experimental results demonstrate that integrating IoT sensors with machine learning models can significantly improve the reliability of personal safety systems. The use of multiple sensors allows the system to capture both physiological and environmental signals, which helps in accurately detecting abnormal situations.

Limitations of the Study

Although the proposed IoT-based women safety framework demonstrates promising results, several limitations should be considered. The experimental evaluation was conducted using simulated sensor data rather than real-world data collected from wearable devices. Real-world environments may introduce additional challenges such as sensor noise, signal interference, and unpredictable user behaviour. The dataset used in this study contains approximately 5000 records, which may limit the generalization capability of the machine learning models when applied to large-scale real-world scenarios. Furthermore, the system relies on internet connectivity and cloud-based processing for data transmission and analysis, which may cause delays in areas with poor network coverage. Finally, the proposed framework has not yet been implemented as a fully functional hardware prototype or mobile application, and therefore its practical performance in real-world deployments remains to be validated.

5. Conclusion and Future Work

This study proposed an IoT-based intelligent women safety system integrated with machine learning for real-time threat detection and emergency response. The framework combines wearable sensors, cloud-based data processing, and machine learning models to detect abnormal situations and automatically generate emergency alerts. A simulation-based evaluation using approximately 5000 sensor samples was conducted to assess the system performance. Among the evaluated algorithms, Neural Networks achieved the highest accuracy of 94%, followed by Random Forest (93%), SVM (90%), and Decision Tree (85%). The system was also able to generate emergency alerts within an average response time of 3–5 seconds. These results indicate that integrating IoT sensing with machine learning techniques can significantly improve the efficiency and responsiveness of women safety systems.

Future work will focus on validating the system using real-world datasets, integrating additional wearable sensors, and applying advanced deep learning techniques to further improve detection accuracy and system reliability.

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