Emergency Safety Control System using Machine Learning and Recent Contact Monitoring

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***Abstract*—High crime rates and health risks contribute to human safety concern, mainly for women, girls, and the elderly. Personal safety is the top priority, particularly for vulnerable groups such as women, girls, and the elderly. Most of the injury- related deaths among the elderly are caused by falls, and women also have unsafe incidents that require immediate intervention. This paper proposes an Emergency Safety Control System based on smartphone sensors and the Random Forest machine learning algorithm to detect falls and send notifications to preselected emergency contacts. The system collects real-time accelerometer data, performs a trained Random Forest model, and sends a notification to guarantee a prompt response. The algorithm achieves a remarkable accuracy of 94.41%, which is a very useful tool to separate falls from normal activity. A nice feature of the system is the smart contact selection feature: although users can manually input emergency contacts, the system will automatically select the most recently contacted person if no manual selection is available. This guarantees the most appropriate people are notified for a quicker and better response. The system design ensures reliability, cost, and ease of use without the need for external hardware. The system is also scalable to ensure it can be used in different environments. Experimental results confirm the effectiveness of the system in detecting falls and providing timely notifications, which is a practical and reliable approach to personal safety in real-world applications.**

***Keywords*—Emergency Alert System, Fall Detection, Machine Learning, Intelligent Contact Selection, Real-time Data Process- ing, Personal Safety.**

I. INTRODUCTION

Personal safety has emerged as a key concern in the modern world, particularly for vulnerable groups like women, girls, and the elderly. As cases of crimes against women have increased and the risk of falls has grown with age, timely intervention and response during emergencies have become a matter of prime importance. Falls are the second most common cause of unintentional injury deaths, says the World Health Organization (WHO), and are particularly common among the elderly. Besides health concerns, women are also in situations of danger where they lack immediate help, further necessitating real-time emergency response systems. To address these issues, this paper suggests an Emergency Safety Control System that detects falls and alerts emergency contacts through a combination of smartphone sensors and machine learning algorithms. The system seeks to deliver a reliable, scalable and accessible solution that uses commonly available smartphone technology. Through real-time process- ing of accelerometer data and the use of an optimized Random Forest model, the system detects falls with 94.41% accuracy, differentiating them from normal activity. The system also features an intelligent contact selection mode that enables users to either manually select trusted contacts or use the system's automatic selection of the most recently contacted person. The affordable mobile-based solution obviates the use of external devices, facilitating accessibility, ease of use, and wide scalability. The aim is to enable individuals to actively manage their personal safety, giving them an instrument that can respond quickly and efficiently in times of need. Through experimental evaluation, the suggested system proves itself to be a viable tool to enhance personal safety in real world situations.

II. LITERATURE REVIEW

Advancements in fall detection systems have made use of machine learning and sensor-based technology to be more ac- curate and dependable.

Earlier methods made use of threshold- based algorithms based on accelerometers and gyroscopes, with high false positives because of misclassification of routine activity as fall. Recent work has suggested deep learning-based techniques, i.e., convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to improve fall detection by deriving spatial and temporal information from motion data [1][2]. Hybrid models with CNN and long short-term mem- ory (LSTM) networks have demonstrated better classification accuracy to achieve real-time detection with minimal false alarms [3][4]. Lightweight pose estimation techniques have also been studied for real-time purposes, guaranteeing compu- tational cost without compromising on detection performance [5]. Further, vision-based techniques with image processing and transformer-based models have been suggested for im- proved recognition for diverse scenarios [6][7]. In addition to traditional fall detection, researchers have also looked at intelligent emergency response systems. Cloud-based systems using cloud infrastructure provide instant transmission of data, guaranteeing timely medical attention during emergencies [8]. Further, deep feature fusion techniques using multiple sensor inputs have further improved classification models, making fall detection systems more robust [9]. These advances demon- strate the evolution of fall detection from traditional threshold- based systems to AI-based techniques, dramatically improving accuracy, response time, and real-world usability [10]. Future efforts will be on adaptive learning strategies and multi- modal sensor fusion for better robustness and minimizing misclassification in diverse scenarios.

III. PROPOSED SYSTEM

A. System Architecture

The architecture of an Emergency Safety Control System, focusing on the interactions between mobile application mod- ules, backend services, and device storage components. The system monitors abnormal movements (e.g., falls) and alerts emergency contacts based on data from sensors and user selections.

MOBILE APPLICATION (UI MODULE)

UI Module: The user interface of the application, through which interaction is possible with different services and features.

- Enable Monitoring: A module that allows the user to enable the fall detection and monitoring system.
- Manage Settings: Allows the user to set settings, e.g., emergency contacts and preferences.

Monitoring Service:

- Accelerometer Data Collection: Gathers accelerometer data from the device to detect sudden movements or falls.
- Fall Detection Logic: Analyzes the accelerometer data according to pre-defined algorithms to detect potential falls or abnormal movements.

Alert System:

- Contact Selection: Handles the selection of emergency contacts from a predefined list (recent contacts or selected contacts).
- Send Location via SMS: Sends the location of the user to selected contacts via SMS when an emergency is detected.

BACKEND SERVICES

Contact Management:

- Retrieve Recent Contact: Fetches the recent contacts from the call logs of the device.

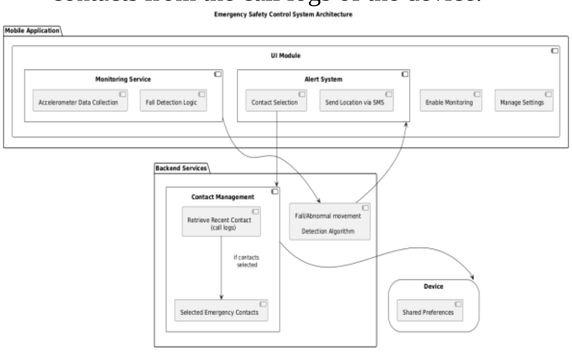


Fig. 1. Control System Architecture

- Selected Emergency Contacts: Refers to the selected emergency contacts for alerts by the user

Fall/Abnormal Movement Detection Algorithm: The al- gorithm for analyzing the accelerometer data to detect falls or other abnormal movements. It is used in conjunction with the Monitoring Service to create alerts.

DEVICE STORAGE

- Shared Preferences: The local storage of the device where some data, e.g., preferences and selected contacts, are stored.A place for storing small data, e.g., user settings (e.g., emergency contacts, preferences).

B. Methodology

The Emergency Safety Control System is intended to detect falls using accelerometer data logged using a mobile device. The system distinguishes between various Activities of Daily Living (ADLs) and fall events, notifying emergency contacts in case of a fall. Random Forest machine learning algorithms are used for movement classification, and the system provides real-time notifications to emergency contacts. The system uses labeled data to train the model and is tested continuously for reliability and accuracy.

1) Data Collection: The MobiFall_Dataset_ v2.0 used for fall detection, , is a collection of labeled accelerometer data for fall events listed in Table 1 and Activities of Daily Living (ADLs) listed in Table 2. Each event is marked as follows:

Type	Description
FOL	Fall on Left (A fall where the individual falls on the left side.)
FKL	Fall on Knee Left (A fall where the individual falls on the left knee.)
BSC	Backward Slipping Collapse (A fall due to slipping back- ward.)
SDL	Sideways Drop Landing (A fall on the side, typically due to loss of balance.)

TABLE I: TYPES OF FALL EVENTS

Type	Description
STD	Standing Still (The user is standing without any movement.)
WAL	Walking (The user is walking at normal speed.)
JOG	Jogging (The user is jogging or running at a higher speed.)
JUM	Jumping (The user is jumping.)
STU	Sitting (The user is sitting down.)
STN	Standing (The user is standing or doing stationary activities.)
SCH	Schooling (A class related to activities usually done in a classroom or school)
CSI	Carrying Small Items (The user is carrying small items such as a bag or books.)
CSO	Carrying and Standing (The user is standing and carrying items.)

TABLE II: TYPES OF ACTIVITIES OF DAILY LIVING (ADLs)

2) Machine Learning for Fall Detection: The Random Forest classifier is used for fall detection because it is stable, can work with large datasets, and is well-suited for classification. It is most useful in separating ADLs from fall events and can be optimized using Randomized Search with Cross-Validation for maximum performance.

3) Feature Extraction: Features that are meaningful to the accelerometer data, including:

- Statistical features: Peak acceleration on each axis (X, Y, Z).
- Magnitude of movement: This is a measure of the overall intensity of the motion, which is helpful in detecting abrupt changes that occur during falls.
- Time-domain features: Changes in acceleration over short periods of time, which are helpful in detecting abrupt movements such as falls.

The system is implemented to prevent false positives, such that walking or standing still does not trigger unnecessary fall alerts.

4) Alert System: Once a fall is detected, the Alert System instantly notifies the user's preconfigured emergency contacts. The system captures the user's GPS location and sends an SMS with the user's location information, enabling emergency contacts to respond in a timely manner.

- Contact Selection: Emergency contacts can be selected from recent calls or manually added.
- Location Sharing: The system sends a real-time location message, enabling emergency responders to find the user quickly.
- Message Content: The message includes the user's loca- tion, and a request for assistance.

5) Intelligent Contact Selection: The system employs an intelligent contact selection mechanism that integrates user- specified emergency contacts with recent call log information.

- Only stored contacts are taken into account from the call logs, not unknown or unsaved numbers. The call log is constantly tracked to update the recent contact list in real- time.

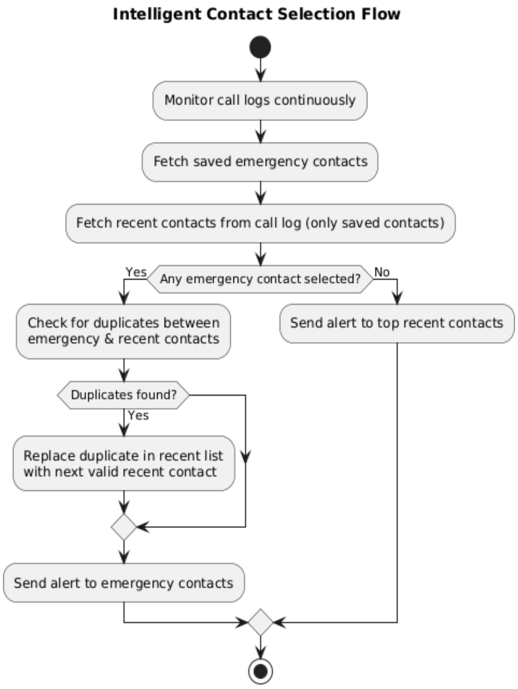


Fig. 2. Contact Selection

- If a contact occurs on both the stored emergency list and recent calls, the duplicate is substituted with the next available recent contact.
- In the case that there are no chosen emergency contacts, the alerts go directly to recently communicated contacts. This guarantees efficient and timely delivery of alerts in emergency situations.

IV. IMPLEMENTATION

A. *Hardware and Software*

1) *Hardware Components:* The proposed *Emergency Safety Control System* can be designed to operate using existing smartphone hardware without an external device. The sys- tem utilizes the following hardware components:

- Smartphone Sensors: The internal *accelerometer* are utilized for monitoring motion patterns and fall incidents.
- GPS Module: The device’s in-built *GPS* is utilized for real-time location tracking in emergency situations.
- Communication Module: The system utilizes *SMS and push notification services* to notify emergency contacts.

2) *Software Components:* The system is built using React Native for cross-platform compatibility and efficient mobile app development. The primary software components are:

- Development Framework: The application is built using

React Native for mobile app development.

- Programming Language: *JavaScript/TypeScript* is uti- lized for the implementation of the core feature.
- Machine Learning Integration: The system supports *optimized ML models*, which enable efficient fall detec- tion.
- APIs and Permissions: The system communicates with a series of *device APIs*, such as:
  – Call Logs API – to access recently dialed numbers when no emergency contact is specifically selected.
  – SMS API – to send emergency notifications along with location information.
  – Location API – to access real-time GPS coordinates.
- Operating System Compatibility: The application is built primarily for *Android devices*, considering the lim- itations of background services in iOS.

B. *Algorithm Implementation*

The emergency safety system has a systematic algorithm for fall detection and emergency contact alerting. The algorithm processes motion data in real-time, detects movement patterns, and triggers alerts when a fall is detected. The critical steps of the algorithm are given below:

1) *Step 1: Data Collection:* The system continuously gath- ers motion data from the accelerometer built into the smart- phone, sampling the movements in three axes (X, Y, Z). Raw sensor data readings are preprocessed by filtering out noise and extracting meaningful features for processing.
2) *Step 2: Feature Extraction:* To improve the detection rate, the system computes several statistical and frequency domain-based features from the accelerometer reading. They include reading of raw accelerometer data, and signal mag- nitude vector (SMV). These features are of critical relevance as they provide meaningful information about the movement patterns and help the system differentiate between a fall and

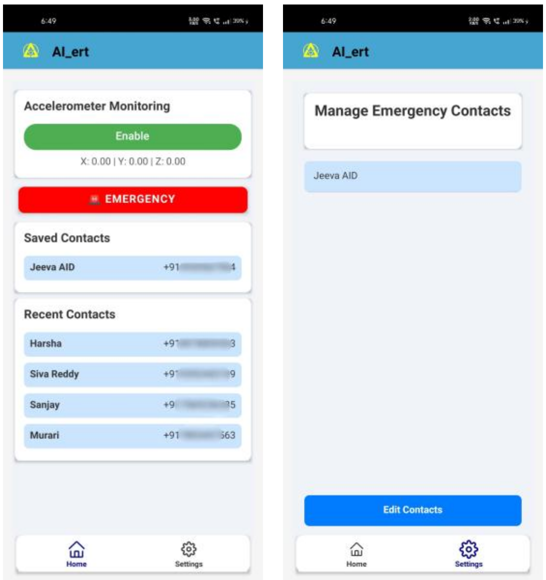
usual activities.

3) *Step 3: Fall Detection Model:* The sensor reading is processed by a trained machine learning model, which iden- tifies whether the movement pattern is a fall or not. The model is designed to be adaptive in nature such that based on real-world performance and optimization, different machine learning algorithms can be employed.
4) *Step 4: Intelligent Contact Selection:* When a fall is sensed, the system checks whether emergency contacts have been preselected by the user. If no contact is preselected, it de- faults to the most recently called individual in the call log. This intelligent contact selection mechanism ensures assistance is always routed to someone who has been in contact with the user in recent times, and the chances of getting a response on time are increased.
5) *Step 5: Emergency Alert Transmission:* After the optimal contact is chosen, the system transmits an SMS alert with the user's current GPS location. By processing GPS tracking internally as well as messaging within the mobile phone, the system guarantees reliability and prompt communication regardless of servers beyond the phone.

V. RESULTS

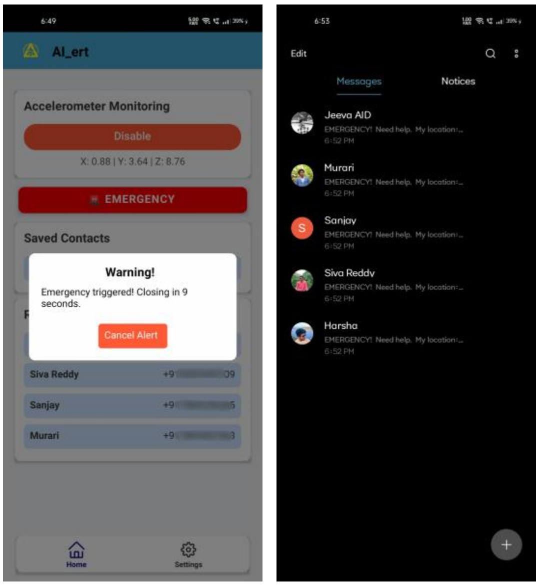
The proposed Emergency Safety Control System was eval- uated for precision in fall detection, response time, and efficiency of its emergency alerts. The system was 94.41% precise in fall detection, minimizing false alarms through optimal feature selection. It responded very quickly, detecting falls and alerting in 2–3 seconds, making it possible for timely assistance.

The smart contact selection feature successfully alerted the most recent contact in the call log, even in the absence of preselected emergency contacts. GPS coordinates were sent with 5–10 meters precision, enabling precise identification of location. The system was easy to use and reliable, operating offline, making it possible for use in low-network environments. Overall, the system is a cost-effective and user-friendly alternative to traditional wearable solutions. Future work will focus on enhancing the sensitivity of the model and making it more robust.



(a) Home Interface (b) Settings Interface

Fig. 3. User Interface Screens



(a) Alert Detection (b) Alert via SMS

Fig. 4. Alert Detection and Sending Location.

VI. CONCLUSION AND FUTURE WORK

This paper presents the Emergency Safety Control System, a robust fall detection and emergency response system. From accelerometer signals and machine learning, the system at- tained 94.41% accuracy in distinguishing falls from everyday activity. With an average response time of 2–3 seconds, it timely notifies emergency contacts, utilizing recent call logs even in the absence of preregistered contacts. GPS data gives 5–10 meters accuracy for accurate location tracking. The system works offline, giving high robustness in low-network environments. Future extensions include improving the fall detection model to minimize false positives and adding adaptive learning to achieve higher accuracy. Further enhancing device compatibility and improving user interface will further enhance accessibility. This system gives a cost- effective, scalable, and user-friendly solution to fall detection, giving a viable alternative to wearable-based solutions and improving safety for vulnerable groups.

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