Machine Learning-Based Safety System for Women with Real-Time Alerts and Geo-Tracking

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ABSTRACT

Women's safety in quickly changing urban environments is ideally served by intelligent and flexible systems that can respond and adapt quickly. Many existing security devices rely primarily on an individual activating the device or they establish a set of conditions to respond to a potential risk – they fail to recognize risk patterns that are often little or emerging. The project proposes a machine learning system which engages users' smartphone sensors and collects sensor data to monitor movement and sound alarms in real time when unusual movement is identified.

The system employs the UCI HAR dataset and incorporates accelerometers and gyroscopes to train and evaluate three classifiers: Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbor (KNN). In the essence of being reliable, a Voting Ensemble model is used with soft voting. The system also features geo-tracking and automatic messaging, simulating emergency responses by sending geo-location to selected contacts whenever high-risk activity is observed.

Evaluation was conducted using performance metrics such as precision, recall, accuracy, and F1-score, resulting in the ensemble model yielding the best results against all classifiers. The system can evolve in different ways, including applying voice distress detection, IoT links with wearables, and development of a mobile app to facilitate live personal safety for the user.

INTRODUCTION

The combination of machine learning (ML) with the technology of wearable sensors has altered the way we measure and interpret human movement in real-time. Traditional security systems have been somewhat reluctant to be applied in personal protection, especially for women. This is fundamentally driven by the reliance on established models and user actions, which become delayed and less adaptive in negative or emergency scenarios.

Many studies have examined ML-based forecasting systems in health care, education, and public safety, but nearly all utilize historical data instead of real-time data. Most single-model systems prioritize resilience and truthfulness since they are typically not able to track and cooperate with transforming human behaviors or emerging environmental conditions, and in doing so, significantly diminish the scale and reliability of the systems.

To tackle these issues, the current research offers a combined machine learning model that connects wearable sensor data with ensemble learning methods to provide continuous safety monitoring. The model will identify abnormal movement pattern, GPS position, and weather pattern, and alert family members of potential danger or accident. The hybrid machine learning model will also alert family members with the at-risk person's location whenever any unusual behavior (e.g., falling tremendously quickly, or remaining motionless for long periods) occurs.

The paving of this configuration is a sophisticated answer that fits the context and is adaptive, so as it can work effectively in various conditions. The ensemble learning allows this system to reach greater reliability in the presence of incomplete and/or noisy data.

LITERATURE SURVEY

Recent studies show a strong focus on adopting Machine Learning (ML) and Internet of Things (IoT) technologies to enhance women's safety and security systems. As an example, Paul et al. [1] proposed a sensor-driven ML framework for recognizing human physical activities and detecting threat based on motion data.

Kabir and Tasneem [2] proposed a smart wristband and a mobile application that leverages assessment of motion and context of the situation to generate automated notification alerts during emergency situations.

Ganesan and Sivakumar [3] demonstrated the vast capabilities of leveraging ML capability with IoT integration by developing an IoT-based health monitoring model for predicting cardiac problems.

Mehra et al. [4] underlined both feature extraction and classifier tuning are important aspects of successfully recognizing human activity leveraging smart sensors. Akram et al. [5] proposed a safety device for monitoring in real-time and in an alerts approach - based on an IoT approach - that employs acceleration data, GSM, and GPS modules.

A wearable device was designed by Sunehra et al.[6] based on Raspberry Pi technology with GPS and Machine learning (ML) algorithms to detect abnormal movements or abnormal activities. An emergency beacon was designed by Shobitha et al.[7] based on Arduino to provide enhanced safety for women. Arul Gandhi et al.[8] made a smart wearable device based on gyroscope and accelerometer sensors that collects data to identify type of physical activity.

Rohini and Sangeetha [9] introduced a wearable device that merges IoT and ML for tracking user movements and sending alerts via GPS and SMS.

In a similar way, Rani and Venkatesh [10] incorporated ML algorithms with GPS to build a functional real-time alert system.

Naik et al. [11] have proposed a hybrid approach to ML that would facilitate continuous health monitoring with automatic alerts as well.

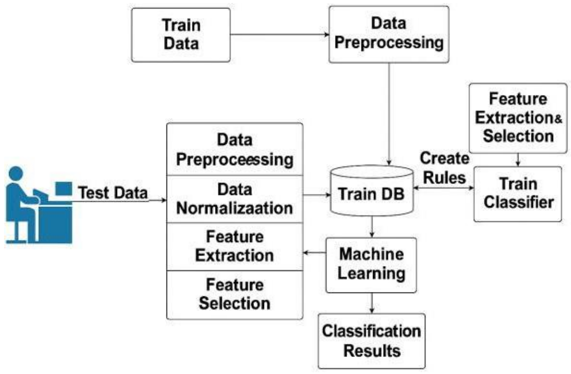
According to Jadhav et al. [12], context-aware data is important and it is essential to enhance the reliability of safety prediction using a comparison of multiple ML methods.

Naidu et al. [13] created an alarm system that offered location-outcome notifications to ML-based vulnerable zones and generated notifications automatically in emergencies.

Singh and colleagues [14] created a response system that used local data processing to minimize latency as an edge-computing supported operation.

Conversely, Jagadeesh and colleagues [15] contributed to the field with the development of an alert system based on Firebase monitoring GPS and temperature data to assess a quick, scale-able cloud alert system.

METHODOLOGY



ML, based -based Safety System

The suggested system works on top of an existing machine learning pipeline that has the ability to run in real-time to serve as an activity detector and emergency notifier. The complete system is a multi-step process of, collecting data, preprocessing the data, extracting features, training a model using the features and test data, evaluation, and finally run a real-time simulation to test the completeness of speed and accuracy across the entire process.

1. Data Collection

Data for the experiment came from the UCI Human Activity Recognition (HAR) data set. The UCI HAR dataset owns tri-axial accelerometer and gyroscope data that were gathered from the smartphone worn on the individuals. The projects indicated their activities pertaining to 6 distinct physical activities (walking, walking upstairs down stairs, seated, standing, lying minute). Each of these records had a time value, each was labeled one of the 6 activities and therefore is appropriate for the controlled activity low rate of partners for the supervised miners which is quite dependent a priori on accurately relating sensor data for activities.

2. Feature Engineering

The process of feature construction was performed to determine important features of the sensor data

* All time : mean, standard deviation, energy, skewness, kurtosis and entropy based on the raw time series signals
* All frequency : leading to the use of important frequencies, FFT coefficients and spherical entropy to describe periodic motion.

In making feature decisions we maximized the performance ability to make:

- Random Forest Importance: This was used for ranking features according to the Gini impurity decrease technique.
- Recursive Feature Elimination (RFE): This was used for the exclusion of the poorly ranked variables in favour of improving the overall performance.

3. **Data Pre-processing**

In the data preprocessing stage, it was ensured that the data could be treated fully and was directly usable for training:

•Missing values were handled: Missing values were replaced by interpolation and by the forward-fill method.

•Noise filtering: A Butterworth low-pass filter was applied, eliminating unwanted oscillations the sensor measured and smoothing this to sensor data.

•Normalization: All feature values were normalized by application of a Standard Scaler, so as to give balanced input to all classifier development.

CLASSIFICATION

In order to assess and feature four classifiers, Random Forest (RF), SVM(Support Vector Machine), K nearest neighbors (KNN) and Voting Ensembling. Random Forest is a group of decision trees that are good for high dimensions and robust to noise in the input. We have made a grid search for the hyperparameters of the model regarding number of estimators and depth of the trees..

SVM (Support Vector Machine) classifier is a margin based classifier using the RBF kernel. We began with tuning hyper parameters as C and gamma, to assist the generalization and improvement of classification; as a comparison metric.

KNN (K-Nearest Neighbors) is a non-parametric model, using euclidean measures or distance. KNN represents an additional comparison model that we can use alongside RF and SVM.

Voting Ensemble is a combination based approach of RF, SVM, and KNN classifiers with soft voting as the approach. In the present investigation, Voting Ensemble merges the probabilistic outputs of the classifiers to maximise reliability and minimise error in classification.

ALGORITHM

Python was the chosen language for the implementation of the algorithm. The analysis, training and visualisation components of the implementation relied upon several well known and generally used major libraries, namely.............., Scikit-learn, NumPy, pandas and matplotlib. The implementation of the algorithm was designed and run in a modular way which allowed for the integration of various steps of the data processing and model evaluation sequences.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Measures overall correctness.

$$Precision = \frac{TP}{TP + P}$$

Measures how many predicted positives are actually correct.

$$Recall = \frac{TP}{TP + FN}$$

Measures how many actual positives were correctly predicted.

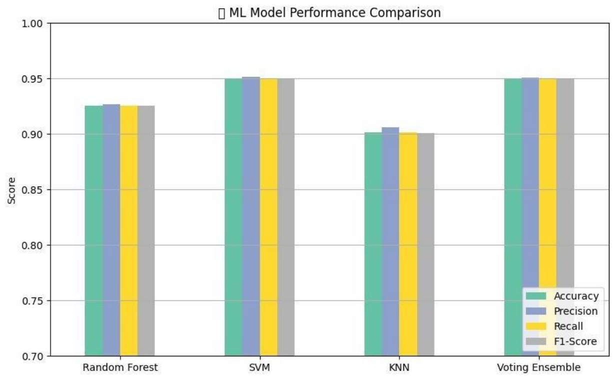
$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Harmonic mean of precision and recall.

RESULTS

Bar Graphs

The four models, Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Voting Ensemble were tested with conventional statistics, accuracy, precision, recall and f1 score. The results were shown in both tabular and graphical formats for easy assessment.



Model Performance Evaluation

The Voting Ensemble was the most stable and consistent performer out of all models. It achieved an overall accuracy of 95 percent and the precision and recall values were above 0.95 for nearly all classes of activity. Furthermore, there was a perfect score of 1.00 for "Laying." This demonstrates an extremely reliable performance for the stationary movement identificati

	Random Forest	SVM		KNN		Voting Ensemble		support
	precision	precision *nc*		precision *nc*		precision *nc*		support
Walking	0.89	0.94	0.98	0.85	0.95	0.93	0.95	496
Walking Upstairs	0.88	0.89	0.96	0.89	0.94	0.90	0.97	471
Walking Downstairs	0.97	0.94	0.94	0.95	0.98	0.98	0.89	420
Sitting	0.91	0.90	0.91	0.91	0.91	0.95	0.92	491
Standing	0.91	0.92	0.95	0.93	0.93	0.90	0.96	532
Laying	1.00	1.00	1.00	1.00	1.00	1.00	1.00	537
accuracy	0.93	0.95	0.95	0.90	0.90	0.95	0.95	2947
weighted avg	0.93	0.92	0.95	0.90	0.95	0.95	0.95	2947

Confusion Matrix Analysis

The various models were assessed regarding differential activity-type performance via confusion matrices. The ensemble model minimized confusion about closely-related classes (as an example, Walking Upstairs and Walking Downstairs), which was a necessary endpoint in a safety-based framework whereby trust is based on exactitude

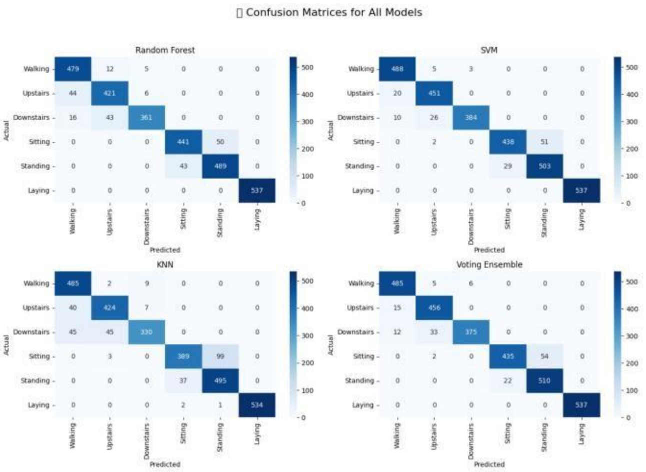
Key Points:

• Random Forest: Had a little overlap with "Sitting" and "Standing."

• SVM: Was able to separate classes more impressively but had slight difficulty with the transitional activities.

• KNN: There was more misclassification because of the affect the scaling of the distances.

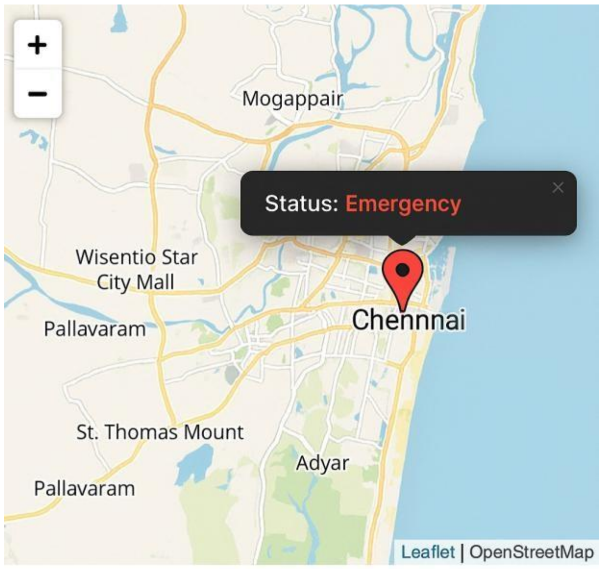
• Voting Ensemble: Corrected the majority of those problems by combining, taking advantages of the models.



Real-Time Alerts

To test responsiveness, a simulation with live data was performed. The ensemble model classified inputs rapidly without delay. When certain risks or abnormal conditions were detected—for example, sudden immobility or prolonged resting—the system would alert the user and provide GPS information to emergency contacts.

The Twilio API was leveraged to provide SMS alerting, OpenStreetMap was utilized to provide a map of the real-time location, and all alarms were recorded complete with timestamps, predicted activity, and alarm state (Safe / Alarm / Emergency). The experiment demonstrated the feasibility of the system with real-world applications with mobile and wearable platforms.



Real-Time Alert Simulation

CONCLUSION

This project introduces a cutting-edge machine learning safety system aimed at women featuring real-time activity recognition and emergency alerting. The Voting Ensemble outperformed the competing classifiers overall on all evaluation metrics of accuracy, precision, recall and F1. The location based features of GPS alerted messaging and tracking of users' location greatly enhance the practical use of the system and allow for immediate assistance in case of an emergency. The modular and scalable nature of the system allows it to be implemented in mobile and/or wearable devices while retaining low latency and effective processing time in real environments.

Contributions:

to test the systems responsiveness in real time. - A hybrid ML framework was developed for sensor-based human activity recognition. GPS location tracking and alert messaging were integrated into the final system to facilitate a user's ability to share their location during an emergency. We verified the systems efficacy using accuracy metrics and confusion matrices. Finally, simulated emergency testing was completed

Limitations:

The human activity recognition system relies solely on pre-labeled data and will need retraining for users, or re-labeling in new contexts. The precision of the GPS model can vary depending on devices and/or surroundings. Both voice-based detection and more sophisticated sensor fusion features are not currently implemented.

Future Scope:

Voice Alerting: Use NLP Modles to detect distress using speech tones and words. IoT Sensor: Use heart rate, temperature and other environmental sensors. Mobile app: Develop a cross platform mobile security app to do Continuous background checks. Edge computing: Compute data locally to reduce latency in results and to lock user privacy. Live data integration: Replace simulated data with live inputs for longer testing in the field.

REFERENCES

1. Paul, T. D., Karthik, R., & Anitha, S. (2024). *Experimental Analysis of Women Safety Management System Using IoT and ML. International Journal of Engineering Research & Technology (IJERT), 10(6).* Link
2. Kabir, A. Z. M. T., & Tasneem, T. (2020). *Safety Solution for Women Using Smart Band and CWS App. 17th International Conference on Electrical and Computer Engineering (EICT-CON), IEEE.*
3. Ganesan, M., & Sivakumar, N. (2019). *IoT-Based Heart Disease Prediction and Diagnosis Model for Healthcare Using ML. International Conference on Systems Computation Automation and Networking, IEEE.*
4. Navita Mehra et al. (2022). *ML-Based Human Activity Recognition Using Smart Sensors in IoT Environment. ResearchGate.* PDF
5. Akram, W., Jain, M., & Hemalatha, C. S. (2019). *Design of a Smart Safety Device for Women Using IoT. Procedia Computer Science, 165, 656–662.*
6. Sunehra, D., et al. (2020). *Raspberry Pi Based Smart Wearable IoT Device for Women Safety Using GPS. IEEE International Conference for Innovation in Technology (INOCON).*
7. Shobitha, M., et al. (2021). *Arduino-Based GPS Distress Beacon for Women Safety. International Journal of Scientific Research in Engineering and Management (IJSREM).*
8. Arul Gandhi, V., et al. (2023). *Smart Wearable Device for Women Safety Using Gyroscope and Accelerometer. International Journal of Innovative Technology and Exploring Engineering (IJITEE).*
9. Rohini, G., & Sangeetha, M. (2023). *Smart Wearable Device for Women Safety Using IoT and ML. International Conference on Communication and Electronics Systems (ICCES), IEEE.*
10. Rani, A. S., & Venkatesh, B. (2024). *Real-Time Alert System for Women Safety Using ML and GPS. International Journal of Research in Engineering and Technology (IJRET), 12(1).*
11. Naik, R., et al. (2018). *Hybrid ML System for Health Monitoring and Emergency Alerts. International Journal of Computer Applications.*
12. Jadhav, B. S., et al. (2025). *Assessment and Exploring of Women's Safety Using Machine Learning Techniques. International Journal of Creative Research Thoughts (IJCRT), 13(4).*
13. Naidu, G. R., et al. (2024). *Women's Safety Platform Using Machine Learning. IOSR Journal of Computer Engineering.*
14. Singh, A., et al. (2022). *Edge Computing-Based Secure Emergency Response System. International Journal of Advanced Computer Science and Applications.*
15. Jagadeesh, M., et al. (2018). *Firebase-Based Emergency Alert System with Location and Temperature Monitoring. International Journal of Engineering and Technology.*