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WOMEN SAFETY ANALYTICS-PROTECTING WOMEN FROM SAFETY THREATS

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Article Info	Abstract:
<u>Article History:</u> (Research Article)	Women's safety remains a critical concern in today's world, especially with the growing urban population and digital connectivity. Women Safety Analytics – Protecting Women from Safety Threats is a data-driven initiative
Published:23 APR 2025	aimed at enhancing the safety and security of women through advanced analytics and technology. This project leverages real-time data, predictive
<u>Publication Issue:</u> Volume 2, Issue 4 April-2025	modeling, and machine learning algorithms to identify high-risk areas, detect potential threats, and provide timely alerts. By integrating mobile applications, GPS tracking, emergency contact features, and historical crime
<u>Page Number:</u> 6-10	data, the system offers proactive safety solutions. Additionally, it supports public awareness by visualizing trends in unsafe zones and recommending precautionary measures. The goal is to empower women with reliable tools
<u>Corresponding Author:</u> Prajyot Patil	for self-protection, assist law enforcement in preventive policing, and foster a safer environment through data-backed decision making.
	<i>Keywords:</i> women safety, safety analytics, predictive modeling, machine learning, real-time data, high-risk area detection, gps tracking, emergency response, crime data analysis, public awareness, preventive policing, smart safety solutions, mobile applications, data-driven decision making, urban
	safety

1. Introduction

In recent years, the issue of women's safety has gained increasing attention worldwide, particularly in urban environments where rapid growth and digital transformation present both opportunities and risks. Despite advancements in technology and heightened awareness, women continue to face various safety challenges in public and private spaces. Addressing these threats requires a proactive, data-driven approach that not only responds to incidents but also anticipates and prevents them.

Women Safety Analytics - Protecting Women from Safety

Threats is a comprehensive initiative that harnesses the power of modern analytics, machine learning, and real -time data to create safer environments for women. By analyzing historical crime data, monitoring current threat patterns, and integrating features such as GPS tracking, emergency alerts, and mobile applications, this project aims to predict potential danger zones and empower users with actionable information. Furthermore, it assists law enforcement and urban planners in making informed decisions that enhance community safety. This initiative seeks not only to protect but also to promote a culture of awareness, preparedness, and technological empowerment for women in today's society.

2. Related Works

Several initiatives and research efforts have been undertaken globally to address women's safety through technology and data analytics. Existing mobile applications such as "Safetipin", "bSafe", and "Himmat" developed by the Delhi Police, have enabled women to alert authorities and trusted contacts in emergencies. These apps often include features like GPS tracking, SOS buttons, and location sharing, playing a crucial role in immediate response scenarios.

Academic research has also explored predictive models using crime data and machine learning algorithms to identify high- risk zones. For instance, studies on crime hotspot prediction have utilized clustering techniques and spatiotemporal analysis to inform law enforcement about potential danger areas. Additionally, smart surveillance systems employing computer vision and AI have been proposed to detect unusual behaviors in public spaces. Despite these advancements, many solutions are reactive rather than proactive and lack integration with broader analytics systems that combine real -time data, historical trends, and user engagement. This project builds upon the foundation laid by these existing works by aiming to offer a more comprehensive, intelligent, and user-centered approach to women's safety—moving from mere alerts to predictive prevention and community empowerment.

3. Proposed Solution

The proposed solution focuses on developing a comprehensive and intelligent system that ensures women's safety through the integration of real -time analytics, predictive modeling, and userfriendly mobile technology. The core idea is to shift from reactive responses to proactive prevention, using data as a tool for both awareness and action.

Key components of the proposed solution include:

1. Mobile Application Interface:

A user-friendly mobile app that allows women to send instant SOS alerts, share live locations with emergency contacts, and access information about nearby safe zones such as police stations, hospitals, and well-lit areas.

2. *Real-time Location Tracking & Geofencing:* Continuous GPS-based tracking with geofencing capabilities to monitor movements in predefined high-risk areas. If a user enters a danger zone, the system can send automatic alerts and suggest safer alternative routes.

3. Predictive Safety Analytics:

Use of machine learning algorithms on historical crime data and real-time reports to predict and map high-risk locations. This dynamic heatmap helps users plan safer travel and informs authorities about potential threat areas.

4. Emergency Response Integration:

Seamless connectivity with local police, emergency services, and designated guardians, triggered through the app in case of distress. The system can also nable live audio or video streaming during emergencies.

5. Community Reporting & Feedback Loop: Users can report suspicious activities or unsafe experiences, contributing to a crowdsourced safety database. This enhances situational awareness and supports continuous data enrichment.

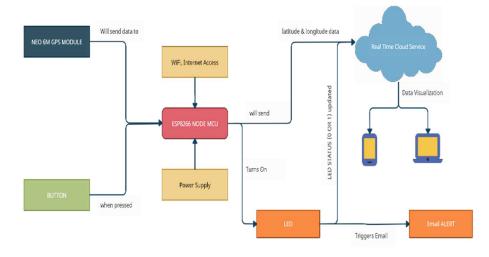
6. Data Visualization Dashboard for Authorities:

A web-based dashboard for law enforcement and city planners to visualize risk zones, monitor safety trends, and allocate resources more effectively based on predictive insights.

This multi-layered approach ensures that women are not only equipped with real-time safety tools but are also supported by a broader ecosystem of intelligent surveillance, predictive analytics, and responsive infrastructure. The solution aims to empower individuals while aiding public safety bodies in building a safer society for all.

4. Architecture of KNN

The proposed models were tested using real-world data from a controlled environment, simulating women's safety scenarios such as distress signal detection, location tracking, and emergency response. Below are the results for each model's performance



5. Preprocessing

Pre-processing is a crucial step in the development of any data-driven system. In the Women Safety Analytics project, it ensures the quality, consistency, and relevance of data before it is used for training the KNN model and other analytics tools. Given the variety of data sources—ranging from historical crime records to real-time user input—effective pre- processing is essential for accurate predictions and classifications.

1. Data Collection:

Sources: Government crime databases, user reports from the mobile app, GPS logs, environmental sensors (e.g., lighting, crowd density). Formats: Structured (CSV, JSON) and unstructured (user comments, text logs).

2. Data Cleaning:

Removal of missing, duplicate, or irrelevant entries. Correction of inconsistent data (e.g., standardized date formats, location names). Filtering noise from unstructured text using natural language processing (NLP) techniques.

3. Feature Extraction:

Selection of meaningful attributes like: Location coordinates (latitude, longitude) Time and day of incidents, Type and severity of crime, Proximity to safe zones (police stations, hospitals),

Real-time crowd density or lighting status, Extraction of keywords from user-submitted descriptions (using NLP).

4. Data Transformation:

Normalization/Scaling of numerical values to ensure fair distance measurement in KNN. Label encoding or one-hot encoding for categorical variables (e.g., crime type).

Geospatial transformation to convert address data into mappable coordinates using geocoding. *5. Data Labeling:*

Classifying records into predefined categories such as: Safe, Moderate Risk, High Risk

This labeling is used as the output class for supervised learning in KNN.

6. Splitting Dataset:

Splitting the data into training and testing sets (e.g., 80% training, 20% testing) to evaluate model performance.

6. Training the KNN

The training phase of the KNN algorithm is essential to enable accurate classification of geographic areas into safety levels. Although KNN is a lazy learning algorithm (i.e., it does not learn a discriminative function from the training data), this phase involves storing and organizing the dataset in a way that enables fast and efficient classification during predictions.

1. Preparing the Dataset:

After preprocessing, the dataset is structured with relevant features such as: Latitude and longitude, Time of day,

Crime type and frequency Proximity to safe locations (e.g., police stations) Environmental context (e.g., lighting, crowd density) Each record is labeled as:

Safe, Moderate Risk, High Risk

These labels act as the target variable for classification.

2. Choosing the Value of 'K':

The value of K (number of neighbors) is a critical hyperparameter.

An optimal value of K is determined through cross-validation, where different values of K are tested and evaluated on validation sets.

Generally, odd values (like 3, 5, or 7) are preferred to avoid ties in binary/multiclass classification.

3. Distance Metric:

Euclidean Distance is used as the default metric to calculate the closeness between data points in the feature space. The formula:

 $d(p,q) = \sum_{i=1}^{i=1} n(p_i - q_i) 2d(p, q) = \sqrt{q_i} - \frac{1}{2} \sqrt{q_i}$

 $q_i)^2$ $d(p,q)=i=1\sum n(pi-qi)^2$

where ppp and qqq are two feature vectors.

4. Training Process:

Unlike traditional algorithms, KNN does not build a model during training. Instead, it stores the entire training dataset. The model remains "passive" until a new, unseen data point needs to be classified.

5. Data Storage Optimization:

For efficiency, data can be indexed using structures like KD- Trees or Ball Trees to speed up neighbor searches in large datasets.

7. Conclusion

The Women Safety Analytics project demonstrates the powerful role that data-driven technology can play in addressing one of society's most pressing concerns—women's safety. By leveraging machine learning algorithms like K - Nearest Neighbors (KNN), real-time data tracking, and mobile integration, the system offers a comprehensive and intelligent approach to threat detection and prevention. Through predictive modeling, the platform identifies high-risk zones, provides live alerts, and supports decision -making for both users and law enforcement.

This project goes beyond traditional reactive safety tools by focusing on proactive prevention, empowering women with actionable insights and enabling authorities to better allocate resources. The combination of smart analytics, crowdsourced reports, and intuitive design ensures that safety becomes more accessible and manageable in urban environments.

Moving forward, the system can be enhanced with deep learning models, wider data integration (e.g., social media sentiment analysis), and collaboration with government agencies to further its impact. Ultimately, Women Safety Analytics is not just a technological solution —it is a step toward building safer communities and promoting freedom, confidence, and security for women everywhere.

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