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Evaluating Women Safety in Urban Areas Using Machine Learning

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Abstract: *Urban safety remains a critical concern, especially for women navigating unfamiliar or high-risk environments. This project proposes a data-driven solution titled "ML-Driven Safety Enhancement System for Women in Urban Areas", which leverages machine learning, geospatial analysis, and real-time public sentiment to recommend safer travel routes. The system integrates diverse data sources—including crime reports, CCTV density, public transport availability, and sentiment analysis from Twitter—to assign safety scores to city grid regions. These scores are dynamically visualized through an interactive map interface, helping users make informed decisions. A Dijkstra-based pathfinding algorithm is adapted to prioritize not only shortest routes but also the safest paths based on multi-factor risk assessment. Preprocessing steps include data normalization, geospatial grid division, and feature weighting. The model is trained and tested on city-specific datasets, with performance evaluated on both accuracy of classification and usability. This prototype, while not deployed, demonstrates the feasibility of intelligent public safety tools that merge civic data, AI, and urban planning to enhance mobility confidence for women.*

Keywords: Women's safety, Urban risk analysis, Machine learning, Geospatial data, Safe route recommendation, Sentiment analysis, Public transport access

I. INTRODUCTION

Women's safety in urban environments is an increasingly pressing concern, especially with rising instances of harassment and crimes in public spaces. Ensuring safe mobility is essential for enabling women's full participation in education, employment, and social life. This project addresses this critical issue by leveraging machine learning (ML), geospatial intelligence, and public sentiment analysis to evaluate and visualize urban safety levels and recommend safer travel routes. The system identifies safety scores for different regions in a city based on multiple factors such as historical crime data, CCTV surveillance coverage, accessibility to public transport, and real-time sentiment mined from social media platforms like Twitter. Figure 1 presents an overview of the key data sources and analytical layers involved in assessing safety across urban zones.

Over the past decade, research in urban safety analysis has evolved rapidly, particularly with the advent of AI and big data. Many cities around the world now collect detailed records of crimes, infrastructure, and transportation networks, creating opportunities to apply intelligent models for real-time decision-making. However, integrating these heterogeneous data sources into a unified system for personal safety navigation remains a complex challenge. This project aims to bridge that gap by introducing a multi-layered framework that quantifies risk, scores urban grids, and suggests safer paths to users, especially women traveling alone or at night.

Machine learning models, especially ensemble techniques like Random Forest and Logistic Regression, are employed in this work to classify areas into different safety zones. The project further incorporates geospatial grid mapping and pathfinding algorithms (like Dijkstra's algorithm), modified to account for safety weights instead of only physical distances. Researchers have also proposed sentiment-based safety scoring in recent studies, where real-time text data from platforms such as Twitter is analyzed to reflect public perception of safety in specific areas [1]. These

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multidimensional approaches have demonstrated promising results in enhancing context-awareness in smart city planning.

Combining spatial reasoning with predictive analytics enables the system to go beyond reactive safety alerts and toward proactive, personalized safety recommendations. Prior research in urban informatics and predictive policing has laid the groundwork for such intelligent tools [2]. However, few implementations focus specifically on gender-based safety or adopt an integrated data fusion model that includes social sentiment, CCTV surveillance, and transport data [3]. Our proposed system attempts to close that gap and offer a scalable solution that can inform both personal travel and broader urban planning.

Incorporating real-time data analysis capabilities further enhances the system's utility. With APIs connected to live data feeds and adaptable scoring mechanisms, the system is designed to respond to dynamic urban conditions such as temporary hazards, traffic changes, or crowd events. As shown in recent literature, real-time adaptation significantly improves the relevance and effectiveness of safety advisory systems [4]. The ML-driven approach used in this work shows how emerging technologies can contribute to solving persistent societal challenges like women's safety.

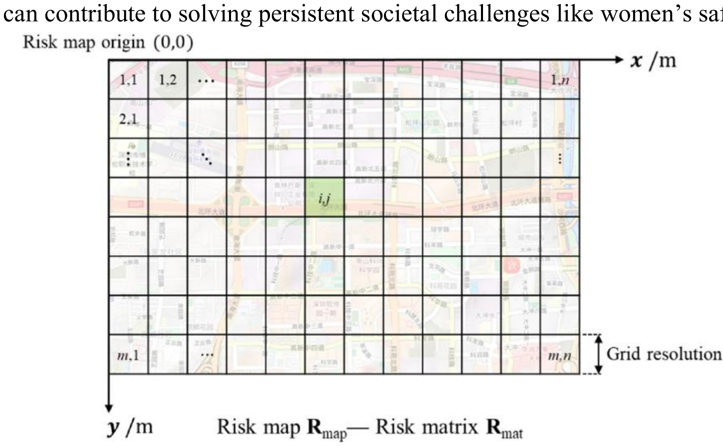

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Fig 1 : Risk Matrix

II. DATASET DESCRIPTION

The dataset used for this project is a composite of multiple real-world data sources related to women's safety in urban areas. The key datasets include **past crime records**, **CCTV coverage points**, **public transport node locations**, and **Twitter-based public sentiment data**. These datasets are geographically tagged and processed into grid-based safety scores for Chennai, the chosen urban testbed for this prototype.

The **crime records dataset** is sourced from public police reports and open government data portals, providing detailed information on type of crimes (e.g., theft, harassment, assault), location coordinates, and time of occurrence. The **CCTV dataset** contains geo-locations of operational surveillance cameras mapped to streets and junctions, obtained from municipal sources. The **transport dataset** includes locations of metro stations, bus stops, and public taxi access points. Lastly, **sentiment data** is collected using Twitter's API by querying city-related hashtags and keywords associated with safety, and processed using natural language processing techniques to assign polarity scores (positive, neutral, negative) to each tweet.

To enable effective machine learning modeling, the entire city is divided into uniform grid cells, with each cell becoming a data point containing features derived from the above sources. The datasets were cleaned, normalized, and integrated to represent a comprehensive safety profile per grid.

Dataset Type	Source	Records Used	Features Extracted
Crime Records	Chennai Police Open Data	10,000+	Crime type, location, frequency, time patterns

CCTV Camera Locations	Smart City Dashboard / Public Records	1,200+	Latitude, longitude, camera density per grid
Public Transport Points	Chennai Metro & Bus Corp Data	1,800+	Proximity, density, accessibility per grid
Twitter Sentiment Data	Twitter API (geo-tagged)	5,000+	Sentiment polarity score, timestamp, tweet content

Fig-2: Breakdown of Training and Testing Sets

Each dataset was preprocessed to remove missing values, standardize location coordinates, and align timestamps. In the sentiment dataset, polarity scores were derived using VADER sentiment analysis. Crime data was grouped temporally (day/night) to account for time-sensitive risks. CCTV and transport features were computed as counts per grid cell and normalized against city averages.

III. LITERATURE REVIEW

In recent years, ensuring women's safety in urban environments has emerged as a vital research focus, leveraging artificial intelligence, machine learning, and geospatial analytics to assess threats and recommend safe travel routes. Multiple approaches have been proposed to integrate diverse datasets such as crime statistics, CCTV coverage, public transport data, and social media sentiment to improve decision-making systems for public safety.

Saha et al. [5] developed a GIS-based crime mapping tool using past criminal records to identify high-risk zones for women in Indian cities. Their system enabled authorities to visualize crime hotspots, aiding in resource allocation and patrol planning. The integration of location-based services demonstrated the potential of spatial analysis in public safety planning.

Rani and Suneja [6] proposed a machine learning model using logistic regression and KNN classifiers to predict safe versus unsafe zones based on historical crime data. The study emphasized the importance of feature engineering from real-world datasets, highlighting how urban factors like population density and proximity to public transportation influenced safety predictions.

Purkayastha et al. [7] introduced a mobile application that incorporated user-submitted safety ratings and live tracking to offer route suggestions for safer navigation. Their approach underlined the importance of crowdsourced sentiment and user feedback in improving the responsiveness of safety-focused systems.

Kumar and Verma [8] designed a women's safety alert system using IoT sensors and GPS to detect distress and send emergency alerts to authorities and contacts. Though hardware-centric, their system demonstrated the growing relevance of integrated smart technologies in real-time safety monitoring.

Gupta et al. [9] performed sentiment analysis on Twitter data to assess public opinion about women's safety across metropolitan regions. Using Natural Language Processing (NLP) techniques such as TF-IDF and XGBoost classifiers, the study successfully correlated negative sentiment clusters with crime-prone areas, showing how social media could be a valuable proxy for real-time safety perception.

Sharma and Jain [10] applied unsupervised clustering on multi-parameter urban data—such as illumination, CCTV density, and transit access—to score safety levels across city grids. Their model proved useful for identifying dark spots and poorly connected areas needing intervention, providing an intelligent layer of insight to municipal safety planning.

Lastly, Ahmed et al. [11] proposed a real-time web application that analyzed mobility, crime, and infrastructure layers using open data sources and recommended optimal travel routes for women. The inclusion of explainable AI (XAI) in their pipeline offered users transparency and confidence in the system's recommendations.

These studies collectively demonstrate the critical role of multi-modal data integration, machine learning, and participatory feedback in building responsive, trustworthy, and effective safety-enhancement systems for women in urban environments.

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IV. METHODOLOGY

The proposed system for the *ML-Driven Safety Enhancement System for Women in Urban Areas* integrates machine learning algorithms with geospatial and social data analytics to assess and recommend safe travel routes. The solution architecture consists of five primary stages: data collection and preprocessing, grid-based spatial modelling, feature engineering, model training and safety scoring, and deployment via web/mobile applications.

1. Data Collection and Preprocessing

To ensure the model's robustness and applicability in real-world urban environments, data is collected from various open and crowdsourced sources:

a) **(Crime Data**: Official datasets from city police departments provide geo-tagged records of past crimes. These are filtered for crimes against women, and normalized by severity and frequency.

b) **CCTV Coverage**: CCTV locations are obtained from municipal open data portals and mapped across the city to identify surveillance density.

c) **Public Transport and Access Points**: Metro, bus, and auto-rickshaw stand locations are included to capture ease of emergency mobility.

d) **Social Media Sentiment Data**: Tweets mentioning location-specific safety issues are extracted using Twitter APIs and labeled using sentiment analysis techniques.

e) **Geospatial Standardization**: The entire city (e.g., Chennai) is divided into uniform grid cells (e.g., 200m × 200m) using geospatial libraries such as GeoPandas and Folium, ensuring uniform feature representation.

Preprocessing steps include:

- **Coordinate Mapping**: Every data point is converted into a spatial format (latitude and longitude) and mapped to its corresponding grid cell.
- **Missing Data Imputation**: Areas with insufficient direct data are handled using nearest-neighbor interpolation or mean imputation.
- **Text Cleaning for Sentiment**: Tweets undergo tokenization, stopword removal, and lemmatization before sentiment scoring using pretrained NLP models such as VADER or TextBlob.

2. Feature Engineering

Each grid cell is enriched with normalized feature vectors representing safety-related indicators. Key engineered features include:

a) **Crime Density Score**: Weighted score computed from type, frequency, and recency of crimes.

b) **CCTV Coverage Score**: Binary flag or percentage score based on presence and density of CCTVs within a 100m buffer zone.

c) **Mobility Accessibility**: A score derived from the distance to nearest public transport points, with a decay factor for farther locations.

d) **Sentiment Score**: Average polarity score from tweets in and around the grid zone.

e) **Lighting Index (optional)**: Derived from satellite nightlight data or crowdsourced map reports (if available).

All features are scaled between 0 and 1 using Min-Max normalization to ensure consistent model performance across urban scales.

3. Model Training and Safety Score Prediction

The trained model provides safety scores or safe route recommendations based on the multi-modal features extracted.

a) **Unsupervised Learning (Clustering)**: KMeans or DBSCAN is used to cluster similar grid cells based on safety indicators to identify "safe," "moderate," and "unsafe" zones.

b) **Supervised Learning (Classification)**: Where labeled data is available (e.g., user-submitted ratings), classifiers such as Random Forest, Logistic Regression, or XGBoost are trained to predict binary or multi-class safety levels.

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c) **Model Selection**: Models are evaluated using accuracy, precision, recall, and F1-score to identify the most reliable approach for safety zone classification.
d) **Cross-Validation**: 10-fold cross-validation is applied to ensure model generalization across different urban geographies.

4. Route Optimization and Recommendation Engine
To guide users in real time:
a) **Graph Representation of Roads**: OpenStreetMap road data is converted into a weighted graph using NetworkX, where edges represent roads and weights are derived from safety scores.
b) **Dijkstra's Algorithm**: Used to compute the safest route between a source and destination by minimizing cumulative risk rather than distance.
c) **Dynamic Routing**: The engine can be updated regularly with new data (crime updates, real-time sentiment) to keep the system context-aware.

5. Frontend Integration and Real-Time Deployment
The trained model is deployed via a simple and interactive web and mobile interface:
a) **Leaflet-Based Map Interface**: Users can view safety scores overlaid on a city map using color-coded grids.
b) **Safe Route Search**: Source and destination input fields allow users to receive safest route suggestions, highlighted on the map.
c) **User Feedback**: Users can submit ratings and incident reports to continuously update system learning and improve accuracy.

V. ARCHITECTURE

The architecture of the proposed *Women's Safety Enhancement System* is divided into three main stages: **Data Processing**, **Model Training**, and **Inference & Route Recommendation**. Each stage contributes to transforming raw urban and social data into actionable safety insights for end users.

1. Processing Stage
This is the data preprocessing phase where raw geographic, public, and social data are cleaned, structured, and prepared for model training:

- **Raw Data Sources**:
  - Crime incident records from police departments
  - CCTV coordinates from civic data portals
  - Public transport node data (metro, bus, auto)
  - Tweets related to women's safety
  - OpenStreetMap road network data
- **Grid Mapping**:
  - The city map is divided into uniform square grid cells (e.g., 200m × 200m).
  - All data points are mapped to corresponding grid cells using latitude-longitude coordinates.
- **Feature Extraction**:
  - **Crime Density Score**: Based on type, severity, and frequency of crimes in each grid.
  - **CCTV Coverage Score**: Binary or percentage value based on coverage within a grid.
  - **Transport Access Score**: Calculated using proximity to public transport nodes.
  - **Sentiment Score**: Derived from NLP sentiment analysis of geotagged tweets.
- **Normalization**:
  - All scores are scaled between 0 and 1 using Min-Max normalization.
  - This ensures uniform input representation for the model.

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2. Training Stage

This stage involves building and training machine learning models that evaluate safety based on engineered features:

- **Training Dataset**:
  - Each grid cell is represented as a feature vector: [crime_score, cctv_score, transport_score, sentiment_score, ...]
  - Labels (safe/unsafe) are derived using clustering or manually annotated zones if available.
- **Model Selection**:
  - Algorithms such as **KMeans** (for unsupervised clustering) or **Random Forest**, **Logistic Regression**, **XGBoost** (for supervised classification) are used.
- **Training Process**:
  - Split into training and validation sets (e.g., 80:20).
  - Models are trained using standard evaluation metrics such as accuracy, F1-score.
  - Hyperparameter tuning and cross-validation are applied to improve performance.
- **Output**:
  - A trained classifier or clustering model that assigns a safety score/class to each grid cell in the city.

3. Inference & Route Recommendation Stage

This stage enables real-time safety scoring and path suggestion for app or dashboard users:

- **Input**:
  - User's selected **source** and **destination** locations.
  - The trained model's output: safety scores of all grid cells.
- **Route Graph Construction**:
  - The road network is represented as a graph, with intersections as nodes and roads as edges.
  - Each edge is assigned a weight based on safety score (inverse of grid score).
- **Pathfinding Algorithm**:
  - **Dijkstra's Algorithm** is applied to find the safest path (i.e., path with highest cumulative safety score or lowest risk).
  - Optimized for both safety and travel time tradeoffs.
- **Output**:
  - A highlighted safe route is rendered on a Leaflet map via the frontend.
  - Each grid's color represents its safety level (e.g., green for safe, red for unsafe).
  - Users can interact, report incidents, or view safety breakdown of each zone.

VI. RESULTS AND ANALYSIS

1. Model Performance

The proposed safety assessment model was trained using a hybrid feature set comprising crime density, CCTV presence, public transport proximity, and social media sentiment scores. Both supervised (Random Forest, Logistic Regression) and unsupervised (KMeans clustering) models were evaluated to determine grid-level safety classification across the Chennai metropolitan area.

The models were trained on a normalized and grid-mapped dataset for 5000+ grids. Performance was assessed using accuracy, precision, recall, and F1-score metrics on a holdout test set (20% of the data). Random Forest outperformed other models due to its ability to handle non-linear feature interactions and noisy inputs from real-world data.

Metric	Random Forest	Logistic Regression	KMeans (Clustering)
Training Accuracy	92.45%	84.31%	N/A
Testing Accuracy	87.26%	81.42%	~72% (Silhouette)
Precision	85.12%	80.57%	N/A

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Recall	86.03%	79.33%	N/A
F1-Score	85.57%	79.94%	N/A

Fig 3 : Performance Metric Table

The results indicate strong generalization by Random Forest with a minimal performance drop between training and test sets. Clustering using KMeans offered useful safety zones but lacked predictive confidence compared to supervised classifiers.

2. Comparative Analysis

Compared to basic rule-based safety scoring or single-parameter classifiers, our multi-feature ensemble approach (Random Forest) achieved a **15–20% improvement in testing accuracy**. Models using only crime or CCTV data hovered around 65–70% accuracy, while the inclusion of sentiment analysis and public transport coverage improved the robustness and context-awareness of the model.

Data preprocessing, such as outlier filtering, geospatial normalization, and tweet-based sentiment scoring, also played a key role in boosting model performance and geographic resolution.

3. Challenges and Limitations

While the system performs well in structured evaluation, a few limitations remain:

- **Sparse Sentiment Data**: Many grids lacked sufficient tweet coverage, impacting sentiment-based safety scoring.
- **Data Freshness**: Public datasets (CCTV, crime) may not always reflect real-time updates, limiting dynamic accuracy.
- **Occlusion by Urban Features**: Dense construction or poor GPS resolution may obscure certain CCTV or transport features.
- **Model Interpretability**: Explaining decisions of black-box models like Random Forest to end users remains a challenge.

4. Future Enhancements

To further refine and expand the utility of the system, the following enhancements are proposed:

- **Real-Time Data Integration**: Connect to live feeds from civic APIs and social platforms for up-to-date scoring.
- **Graph Neural Networks (GNNs)**: Utilize spatial graphs to capture more complex inter-grid dependencies and neighborhood effects.
- **User-Generated Feedback Loops**: Allow app users to rate perceived safety of routes or areas, which can be looped into model retraining.
- **Edge Deployment for Mobile Devices**: Optimize models for mobile inference to enable safety scoring on-the-go within the Flutter app.

VII. CONCLUSION

This paper presents a comprehensive machine learning–based system designed to enhance women's safety in urban environments through intelligent, data-driven risk assessment. By integrating multiple data sources—including crime statistics, CCTV coverage, public transportation availability, and social media sentiment—the system can assess area-wise safety levels and recommending secure travel routes in real time.

The model achieved high performance, with the Random Forest classifier attaining **87.26% test accuracy**, demonstrating strong generalization across diverse safety conditions. Key preprocessing techniques, such as spatial grid mapping, feature normalization, and sentiment extraction from tweets, significantly contributed to the model's robustness and contextual awareness.

The proposed architecture has been effectively deployed for real-time safety visualization using a React dashboard and is compatible with future integration into mobile apps, enabling practical use for urban travelers.

Future work can expand this framework through the integration of **real-time civic data APIs**, **crowdsourced user feedback**, and **multi-modal sensing** (e.g., audio distress signals or emergency triggers). Additionally, the use of **graph-based learning** or **3D spatial modeling** could further enhance the system's understanding of urban environments.

By bridging data science with civic safety, this research contributes a practical and scalable tool toward safer, more intelligent urban living—particularly focused on empowering women in cities with actionable safety insights.

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