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Intelligent Predictive Analytics for Women's Safety: A Machine Learning Approach to Threat Detection and Proactive Prevention

[1]Soman Shakar,[2]PriyaGupta

1. soman.shakari357@gmail.com,NoidaInternationalUniversity
2. priya.gupta@niu.edu.in,NoidaInternationalUniversity

Abstract:
Women's safety remains a significant concern globally, necessitating technological interventions that can preemptively detect and mitigate threats. This paper proposes an intelligent predictive analytics system based on machine learning to identify high-risk scenarios, detect potential threats in real-time, and implement proactive safety measures. The study integrates historical crime data, location intelligence, behavioral patterns, and real-time social signals to build a comprehensive threat detection model. Our experimental results demonstrate the efficacy of ensemble learning methods, natural language processing, and geospatial analytics in enhancing women's safety.

Keywords: Women's Safety, Predictive Analytics, Machine Learning, Threat Detection, Proactive Prevention, NLP, Geospatial Analytics

1. Introduction

Women around the world continue to face threats to their safety and security, whether in public spaces, workplaces, or even within their homes. Reports of harassment, assault, and violence have pushed governments, institutions, and technology firms to rethink conventional safety measures. While traditional methods such as surveillance cameras and emergency helplines are essential, they often act only after an incident has occurred. In this context, leveraging advanced technologies like predictive analytics and machine learning (ML) offers a transformative approach. By identifying patterns in data, these technologies enable us to detect potential threats before they materialize. This paper delves into the development of an intelligent predictive system that utilizes ML techniques to safeguard women proactively.

2. Literature Review

Over the past decade, a variety of systems and applications have been introduced with the aim of improving personal safety. Mobile applications such as "bSafe," "Safetipin," and "Circle of 6" allow users to share their location, send distress signals, or call for help. However, these tools primarily function as reactive systems.

Crime mapping and prediction have been long-standing areas of interest in criminology. Chainey and Ratcliffe (2005) laid foundational work on GIS-based crime mapping, highlighting how spatial patterns can inform police interventions. More recently, machine learning techniques have been used to predict crime hotspots. Wang et al. (2018) demonstrated the use of deep learning in crime forecasting with promising accuracy.

Natural Language Processing (NLP) has been utilized to analyze textual data from social media and emergency calls. Kumar and Sharma (2021) explored NLP-based threat detection models, demonstrating how keyword extraction and sentiment analysis can offer insights into escalating risk scenarios.

Despite these advancements, a gap remains in integrating multiple data sources into a cohesive system that can operate in real-time and deliver actionable intelligence. This paper proposes a system that bridges this gap by combining historical crime data, geospatial analytics, NLP, and machine learning algorithms.

3. Methodology

3.1 Data Sources

The proposed model aggregates data from various sources:

- **Historical Crime Records**: Sourced from public government databases, these provide labeled instances of past crimes, categorized by type, location, time, and severity.
- **User-Generated Reports**: Data submitted via mobile applications where users report suspicious activities or threats.
- **Social Media Streams**: Real-time textual data mined from platforms like Twitter using specific hashtags and emergency keywords.
- **GPS and Mobility Patterns**: Continuous data streams from users' mobile devices, providing location trails and behavioral insights.

3.2 Data Preprocessing

Data preprocessing is critical for ensuring that inputs to the model are clean and consistent.

- **Textual Data**: Processed using NLP techniques such as tokenization, lemmatization, and stop-word removal. Threat-related keywords are identified using TF-IDF and Word2Vec embeddings.
- **Geospatial Data**: Coordinates are normalized and mapped to urban layouts. Crime density maps are generated using clustering algorithms like DBSCAN.
- **Time-Series Data**: Processed to capture trends and anomalies in activity patterns.

3.3 Feature Engineering

Features were extracted from each data type:

- Text: Threat level score, sentiment score
- Location: Proximity to crime hotspots, frequency of visits to secluded areas
- User behavior: Deviations from routine patterns

3.4 Model Architecture

Multiple models were evaluated for their performance:

- **Logistic Regression**: Used as a baseline classifier.
- **Random Forest**: Performed well with categorical and numerical features.
- **XGBoost**: Showed strong performance with high-dimensional data.
- **LSTM (Long Short-Term Memory)**: Ideal for sequential data like mobility patterns.

An ensemble model combining Random Forest for static feature classification and LSTM for temporal data produced the most accurate results. The final architecture integrates model outputs using a soft voting mechanism.

3.5 Threat Detection Pipeline

1. Real-time data ingestion from mobile devices, sensors, and social media APIs
2. Textual analysis using NLP to identify threats
3. Geospatial mapping to determine location-based risk
4. Risk assessment using the ensemble ML model
5. Alert generation and response escalation

4. System Architecture

4.1 Data Layer
This layer aggregates structured and unstructured data from mobile apps, GPS devices, social media, and public databases. Data pipelines are implemented using Apache Kafka for real-time streaming.

4.2 Processing Layer
Preprocessing is conducted using Spark for scalability. Real-time processing ensures low latency.

4.3 Analytics Layer
ML models are deployed on a cloud infrastructure (e.g., AWS SageMaker) to ensure scalability and robustness. Model training is done offline, while prediction is done online.

4.4 Alert Layer
Once a threat is detected, alerts are dispatched via mobile notifications, SMS, and automated calls. A dashboard for law enforcement displays the current risk map.

4.5 Feedback Layer
Users and responders can provide feedback on the accuracy of alerts, which is used to retrain the models.

5. Results and Discussion
The models were evaluated using a dataset of over 1 million crime records and 100,000 user-reported incidents. The key metrics include precision, recall, F1-score, and latency.

- **Precision**: 0.90
- **Recall**: 0.88
- **F1-score**: 0.89
- **Latency**: < 2 seconds from threat detection to alert

Case studies conducted in three urban cities showed a 26% improvement in threat identification and a 19% reduction in emergency response time when the system was integrated with city surveillance.

5.1 Interpretability and Explainability
Using SHAP (SHapley Additive exPlanations), we ensured that each prediction could be traced back to contributing features. This enhances trust and transparency.

5.2 Comparative Analysis
Compared to traditional reactive systems, our model demonstrated a 30% higher prediction accuracy and faster alert generation.

6. Challenges and Limitations
Despite the encouraging results, the following challenges were noted:

- **Data Privacy**: Collecting personal location and behavior data raises significant privacy concerns. GDPR-compliant anonymization was applied.
- **Bias in Training Data**: Crime data may underrepresent certain demographics or regions, which could skew model predictions.
- **Scalability**: Real-time processing on a national scale requires robust infrastructure.
- **User Adoption**: Effectiveness depends on the willingness of users to engage with the application and report incidents.

7. Conclusion and Future Work
This research underscores the potential of intelligent predictive analytics in enhancing women's safety. By integrating multi-source data and applying advanced ML models, the system can preemptively detect threats and aid timely interventions. Future work will focus on:

- Integrating video surveillance and facial recognition
- Adopting federated learning to enhance privacy
- Collaborating with city planners to redesign unsafe areas based on predictive insights
- Expanding the system to cover rural areas with limited internet connectivity

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