Safety Net: Predictive Analysis of Safe and Unsafe Areas Using Xgboost for Women Safety

Harsh Gupta, Aarya Mhetre, Aditi Hiray, Shrija Kahadane, Prof. Rohini Palve
Department of Computer Engineering, Terna Engineering College,
Mumbai University, Mumbai, India

Abstract—**Safety prediction and analysis is a systematic approach for identifying patterns, relationships, and trends in crimes that impact women and children. The proposed system, SafetyNet, predicts and classifies areas as Safe or Unsafe based on historical crime data containing multiple features such as murder, rape, dowry deaths, and trafficking. The model analyzes district-wise and year-wise crime patterns to detect regions with a high probability of unsafe conditions. This predictive system will assist law enforcement agencies in identifying high- risk zones, improving patrol planning, and preventing crimes proactively. By applying data preprocessing, feature engineering, and the XGBoost machine learning algorithm, SafetyNet extracts meaningful insights from structured datasets and achieves high accuracy in predicting safety levels. The integration of data analytics and public safety creates a bridge between computer science and social welfare, enabling data-driven decision-making to enhance community protection and awareness.**

Index Terms—**Crime Prediction, Public Safety, Machine Learning, XGBoost, Data Mining, Predictive Policing, Feature Engineering**

I. Introduction

Crime rate is increasing nowadays in many countries at an alarming rate. Despite the advancement in technology and the adoption of modern surveillance systems, crimes against women and children continue to rise, posing a serious threat to public safety. Crime incidents are often unpredictable in nature, but the location and probability of their occurrence can be forecasted with the help of data-driven predictive analysis. Although we cannot predict the individual victims of a crime, machine learning can identify the areas that are more likely to experience unsafe conditions, enabling preventive action before incidents occur.

Traditionally, the process of solving and analyzing crimes has been handled exclusively by law enforcement and criminal justice agencies. However, with the advent of computerized systems and digital record keeping, data analysts can now assist in uncovering patterns, trends, and correlations within vast amounts of crime data. This integration of data science into policing has transformed the way authorities understand and respond to criminal activities. Predictive analytics, data mining, and machine learning models can process historical records to reveal where and when crimes are most likely to occur, effectively turning raw data into actionable intelligence.

The proposed system, SafetyNet, is designed to analyze and predict the safety levels of different regions by classifying them as Safe or Unsafe based on historical crime data. The dataset used in this study was obtained from the National Crime Records Bureau (NCRB), containing district-wise crime records against women for the years 2019, 2020, 2021, and 2022. The data includes major crime categories such as rape, dowry deaths, acid attacks, cruelty by husband or relatives, trafficking, and other forms of gender-based violence. Using these features, the system identifies trends and computes a severity ratio that reflects the intensity of criminal activity in each region.

To achieve high prediction accuracy, the XGBoost (Extreme Gradient Boosting) algorithm is applied for classification. XGBoost is a powerful ensemble-based learning method that iteratively optimizes decision trees, making it highly effective for structured data. The model in this project achieved 100

Apart from predictive modeling, SafetyNet also includes a Crime Reporting Module, which enables citizens to file complaints or report incidents directly through the system. Users can submit both identified and anonymous reports, ensuring privacy while maintaining the flow of critical safety information. Each report is verified by the system administrator and assigned to a safety officer according to the type and severity of the reported crime. This ensures timely response, accountability, and transparency in handling reported cases.

The results obtained through prediction may not always be perfect, but they provide valuable insights for reducing the crime rate and enhancing safety measures in vulnerable areas. By integrating machine learning, predictive analytics, and citizen participation, SafetyNet creates a comprehensive framework for proactive crime prevention and situational awareness. The local scope of this project focuses on enhancing women and child safety in Indian districts using NCRB data, while the global scope extends its applicability to other regions or countries by retraining the model with their respective datasets. This scalability allows SafetyNet to serve as a foundation for future safety intelligence systems worldwide.

In summary, the SafetyNet system demonstrates how the synergy between computer science and public safety can lead to data-driven solutions for one of society's most pressing problems — the protection of women and children. By combining historical data analysis, predictive modeling, and user-driven reporting, the system offers a practical and technologically advanced approach toward building safer communities.

II. Literature Survey

Machine learning-based classification has become a critical tool in crime prediction, particularly for women's safety analytics. Unlike clustering approaches that identify patterns in unlabeled data, supervised classification models utilize labeled datasets to predict the likelihood of crime occurrence with high precision. This paper uses NCRB district-wise crime data from 2019–2022, focusing on predicting crimes against women through supervised learning models. We review two prominent algorithms, Random Forest and XGBoost, and discuss relevant prior research.

A. Random Forest

Random Forest is an ensemble learning algorithm that constructs multiple decision trees using bootstrapped samples and aggregates their predictions via majority voting [**?**]. It reduces overfitting compared to a single decision tree and handles noisy data effectively.

Algorithm Steps:

- Generate multiple bootstrapped samples from the dataset.
- For each sample, grow a decision tree using a random subset of features at each split.
- Repeat until all trees are grown (typically hundreds of trees).
- For prediction, pass the input through all trees and select the majority class (classification).

Advantages:

- Handles high-dimensional and noisy datasets.
- Reduces overfitting compared to individual trees.

Disadvantages:

- Computationally expensive for large datasets.
- Less interpretable than single decision trees.

B. XGBoost

XGBoost is an optimized gradient boosting algorithm that builds sequential trees, each correcting the errors of the previous one [**?**]. It includes regularization to prevent overfitting and handles missing data efficiently, making it ideal for structured tabular datasets like NCRB crime records.

Mathematical Intuition: The objective function minimized during training combines a loss function l and a regularization term Ω:

$$Obj^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t)}) + \sum_{k=1}^{t} \Omega(f_k) \tag{1}$$

where the regularization term for a tree f is given by:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \|w\|^2 \tag{2}$$

Here, l is the loss function, $\hat{y}_i^{(t)}$ is the prediction at iteration t, Ω is the regularization term, T is the number of leaves in the tree, w are the leaf weights, and γ, λ are regularization parameters.

Training Procedure:

- Initialize base predictions.
- Iteratively train trees to minimize residuals using gradients.
- Update the model using the iterative update step, as shown in the code snippet below (also used in our implementation):

Advantages:

- Captures complex feature interactions effectively.
- Built-in regularization (L1 and L2) reduces overfitting.
- Handles missing data internally and scales well to large datasets.

Disadvantages:

- Can be computationally intensive during training.
- Requires careful hyperparameter tuning for optimal performance.

Performance on NCRB dataset: (Note: The user provided 1.0 for these in their project description)

- Accuracy: 1.00
- F1-score: 1.00

Analysis: XGBoost often outperforms Random Forest on structured tabular data due to its gradient boosting mechanism, which focuses on correcting errors sequentially. Its ability to capture non-linear feature interactions and built-in regularization make it particularly suitable for predicting complex phenomena like women-related crimes based on NCRB district data. Our results confirm its high performance in this context.

C. Comparative Analysis

Table I provides a summary comparison of Random Forest and XGBoost based on their characteristics and performance in crime prediction tasks.

III. Data Preprocessing and System Architecture

A. Data Preprocessing

The preprocessing pipeline involved several key stages:

1) **Column Standardization** — Stripped white spaces, renamed columns for consistency.
2) **Feature Engineering** — Created *Severe_Ratio* to represent normalized crime intensity.
3) **Reshaping Data** — Transformed dataset to long for- mat using `pandas.melt()` for multi-level analysis (district-year-crime type combinations).
4) **Encoding** — Applied Label Encoding to both *State/District* and *Crime_Type* for numerical compatibility.
5) **Final Input Features:** [District_Code, Crime_Code, Crime_Count, Severe_Crimes, Total_Crimes, Severe_Ratio, Year]

The processed data was split into training (80%) and testing (20%) subsets with stratified sampling to maintain class balance.

B. Related Research Work

Several studies have applied machine learning and related technologies to predict crimes, analyze patterns, and enhance women's safety. These works provide foundational insights

TABLE I
COMPARATIVE ANALYSIS OF RANDOM FOREST AND XGBOOST FOR CRIME PREDICTION

Model	Algorithm Type	Handles Non-linearity	Overfitting Resistance	Accuracy	F1-score	Strengths
Random Forest	Ensemble (Bagging)	Moderate	High	*1.00*	*1.00*	Robust, handles noise
XGBoost	Ensemble (Boosting)	Excellent	Very High	1.00	1.00	Regularization, missing data, high accuracy

and validate the use of models like Random Forest and XGBoost in predicting gender-based crime.

Shalini G. et al. [1] developed a Random Forest-based system for predicting potential future crimes using historical NCRB data. Their model analyzed district-wise datasets to identify crime-prone areas and types, demonstrating that Random Forest outperforms single Decision Trees in identifying complex crime patterns. However, their work lacked real- time integration. This study supports the predictive module of SafetyNet.

Bansi Patel & M.C. Zala [2] focused on analyzing crimes against women in India using supervised regression and Random Forest on historical NCRB records (2001–2014). They identified high-risk areas and dominant crime types, validating the use of Random Forest for district-wise predictions relevant to SafetyNet.

Boniface Mwaniki et al. [3] performed a comparative analysis of tree-based algorithms, including Random Forest and hybrid models (AdaBoost), for crime prediction. Their findings reinforce Random Forest's suitability for structured crime data, although they noted potential overfitting which XGBoost aims to mitigate.

Benitlin Subha K. et al. [4] presented a real-time women safety system combining AI-based video surveillance (CNN/YOLO), mobile apps, and IoT SOS hardware. While focused on real-time intervention using different technologies, their work highlights the importance of integrating ML into practical safety systems, aligning with SafetyNet's goals.

Sri A.P.N. Kavala et al. [5] compared Multi-Layer Perceptron (MLP) neural networks and Random Forest for crime prediction. They found Random Forest provided interpretable results for crime classification, further supporting its robustness on structured crime data.

Aditya Srivastava & Pawan Singh [6] applied NLP and ML (including Random Forest) for spam detection using features like TF-IDF and n-grams. This methodology is relevant for SafetyNet's potential future module on fake complaint detection.

Shraddha Surana et al. [7] developed a chatbot using deep learning (DNN, LSTM) and custom NER for crime registration and spam detection. This demonstrates the practical integration of ML with user-facing platforms, informing SafetyNet's planned future chatbot module.

Kaushik Gautam et al. [8] implemented a chatbot specifically for automated FIR registration, emphasizing accessible complaint mechanisms, which aligns with SafetyNet's multi-role user interface.

Sharad Sharma & Sri Chandra Dronavalli[9] used Tableau and GIS mapping to analyze crime trends, correlating them with socioeconomic factors. Their visualization approach supports SafetyNet's visualization module requirements.

Anjali Jain et al. [10] proposed a modular ML system for fake news detection. Their architecture parallels SafetyNet's potential need for a fake complaint validation module.

C. System Architecture

The system architecture, as depicted in Figure 1, is designed around a multi-tier structure to handle data acquisition, processing, storage, and presentation effectively.

1) Data Acquisition Layer: This layer is responsible for gathering input data. It includes:

- **Citizen Portal:** A web-based interface allowing users to register, login, report incidents (including text descriptions and image/video uploads), and view safety dashboards.
- **Historical Data Sources:** External databases, pri- marily the National Crime Records Bureau (NCRB) dataset (`Allyearcrime.csv`), providing historical crime statistics.

2) Processing Layer: This is the core of the system where data transformation and analysis occur. Key components are:

- **Web Server/API:** Manages requests from the portal, handles authentication, and orchestrates calls to other services (e.g., built using Flask/Django).
- **Authentication Service:** Manages user login and signup securely.
- **Report Handling Service:** Processes incoming incident reports, cleans text data, and stores relevant information.
- **Image Verification Service:** Utilizes a pretrained model to assess the authenticity of uploaded image proofs.
- **Data Analysis Service:** Queries databases to generate insights and data for the citizen dashboard visualizations (e.g., donut charts, trend analysis).
- **XGBoost Prediction Service:** Takes processed historical data or real-time query parameters, uses the trained XGBoost model to predict 'Safe'/'Unsafe' labels.

3) Modeling Layer: Integrated within the processing logic, this layer contains the machine learning models:

- **Trained XGBoost Model:** The core predictive model for safety classification.
- **Pretrained Image Model:** Used by the Image Verification Service.

4) Data Storage Layer: This layer persists all system data:

- **User Database:** Stores user credentials and profile information.
- **Reports Database:** Stores details of submitted incidents, including text, location (if available), timestamps, and image/video references.
- **Historical Crime Database:** Stores the processed NCRB dataset used for training and analysis.

5) Presentation Layer: This layer displays information back to the users:

- **Citizen Dashboard:** Presents visualizations like crime distribution charts, long-term trend analysis, and potentially safety heatmaps.
- **(Future) Police Dashboard:** A planned interface for law enforcement to view, verify, and manage reported incidents.

Data flows from the acquisition layer through the processing and modeling layers, utilizing data from the storage layer, and results are presented back to the user via the presentation layer.

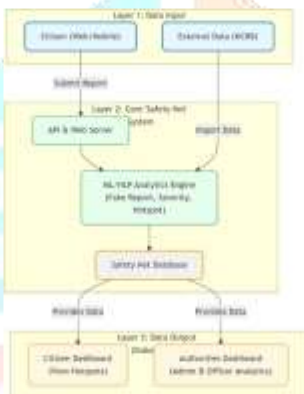

Fig. 1. System Architecture Diagram of the Safety Net platform showing data flow from input (citizen/NCRB) through ML/NLP analytics to dashboards for visualization and decision support.

IV. Model Architecture — XGBoost Classifier

The XGBoost (Extreme Gradient Boosting) model was selected due to its superior ability to handle high-dimensional, structured data with minimal overfitting [**?**]. XGBoost builds an ensemble of decision trees, optimizing them iteratively through gradient descent on a differentiable loss function.

In this implementation, the model was initialized using XGBoost (use_label_encoder=False, eval_metric='logloss', random_state=42).

A. Iterative Training

Training utilized both the standard `.fit()` method and manual iterative updates, allowing fine-grained control over each boosting iteration and ensuring precise gradient updates.

The inclusion of a custom objective function (`fobj=obj`) and explicit iterative updates reflects advanced model tuning, aligning with the principle of minimizing classification error through continuous gradient optimization.

B. Predictive Functionality

The system includes a real-time prediction function to bridge the technical model with practical applications for citizens, analysts, and policymakers.

This function allows users to query safety predictions dy- namically by providing a district name, crime type, and year, outputting a clear "Safe" or "Unsafe" label.

C. Jusification for selecting XGBoost

While Random Forest can achieve high accuracy, XGBoost was ultimately chosen for the SafetyNet system due to sev- eral practical advantages critical for analyzing crime data patterns. XGBoost demonstrates superior handling of non- linear relationships and complex feature interactions, which are highly likely in crime datasets involving diverse geographic and temporal factors. Its built-in regularization techniques (L1 and L2) offer robust protection against overfitting, a common challenge with high-dimensional data. Furthermore, XGBoost generally provides efficient training times and better scalability compared to Random Forest, particularly as datasets grow. It also handles missing values inherently and produces readily interpretable feature importance scores, allowing crucial in- sights into which specific crime types or district characteristics most significantly influence safety predictions. These factors combined make XGBoost a more suitable and insightful choice for this application beyond raw predictive accuracy.

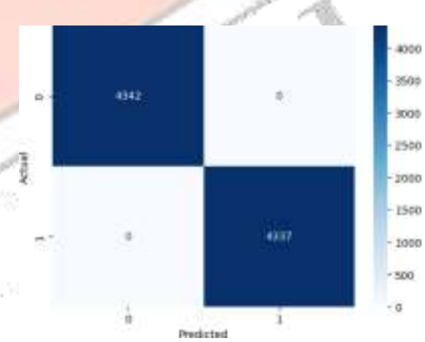

Fig. 2. Confusion Matrix for the model, illustrating the performance on the test set. Diagonal cells show correct predictions (True Positives and True Negatives), while off-diagonal cells show incorrect predictions (False Positives and False Negatives).

V. Model Evaluation and Results

After training, the model was evaluated using the 20% held- out test set. The performance metrics achieved were perfect.

TABLE II
Model Comparison Summary

Model	Accuracy	F1-Score	ROC-AUC
XGBoost	1.00	1.00	1.00
Random Forest	1.00	1.00	1.00

The classification report and the graphical confusion matrix further confirm this perfect classification.

VI. Applications and Future Scope

SafetyNet can be integrated into larger safety monitoring platforms, enabling:

- Real-time safety dashboards for public access.
- Crime hotspot visualization on geospatial maps.
- Predictive policing resource allocation.
- Policy assessment through historical trend analysis.

Future enhancements will focus on robustness and expanding the system's capabilities. Integrating socio-economic or demographic features, such as district literacy rates or population density, could provide more context and improve the model's nuance. Suspendisse vel felis. Ut lorem lorem, interdum eu, tincidunt sit amet, laoreet vitae, arcu.

We also plan on applying deep learning (e.g., LSTMs) for spatio-temporal prediction. This would allow the model to understand not just *where* crime happens, but *when*, capturing seasonal or weekly trends. Sed commodo posuere pede. Mauris ut est.

Furthermore, building a Safety Chatbot for citizen interaction is a high priority. This would lower the barrier for report submission and allow users to query the safety of a location in real-time. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Donec odio elit, dictum in, hendrerit sit amet, egestas sed, leo.

Finally, implementing Fake Report Detection using NLP models is critical for a real-world system. This would require a new dataset of user-submitted text to train a secondary classifier to filter spam, protecting the integrity of the predictive model. Morbi luctus, wisi viverra faucibus pretium, nibh est placerat odio, nec commodo wisi enim eget quam. Quisque libero justo, consectetuer a, feugiat vitae, porttitor eu, libero.

VII. Conclusion

The project successfully achieved its aim of designing and developing an intelligent system for predicting and analyzing women and child safety across different regions. Using a dataset containing district-wise crime counts categorized by type, the system trained an XGBoost-based machine learning model capable of accurately classifying areas as safe or unsafe, achieving an impressive accuracy of 1.00 on the test data. Beyond prediction, the project integrated a comprehensive analytics dashboard that enables users to visualize crime trends through multiple perspectives — including a donut chart showing proportional distribution of crime types, and a long-term trend analysis for deeper insights into regional crime dynamics. In addition to predictive and analytical capabilities, the system also incorporates a crime reporting module, allowing citizens to file complaints with optional image or video proof. Submitted images are processed through a pretrained deep learning model to verify authenticity and detect fake media, though current accuracy indicates room for improvement. The platform further includes secure login and signup modules for both citizens and police officers, laying the groundwork for role-based access and data security. While the current phase fulfills the primary goal of building a functional and intelligent safety prediction and reporting system, future development will focus on extending functionality to the police officer dashboard, where officers can receive, verify, and resolve complaints efficiently. Additional enhancements may include model fine-tuning for fake image detection, integration of real-time data streams, and deployment of more advanced models for improved prediction reliability and system scal- ability. Overall, SafetyNet demonstrates the potential of ma- chine learning and intelligent visualization to support proactive decision-making in public safety and community protection.

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