



Article Info

Date Received: 14 / 03/ 2026
Date Revised: 01/04/2026
Available Online: 18 /04 /2026

SMART CRIME ANALYTICS AND HIGH-RISK ZONE FORECASTING SYSTEM USING HISTORICAL CASE RECORDS AND GEO VISUALIZATION

Dr. A Ramamurthy¹, K. Devi Chandrakala², M. Hemalatha³, P. Karunkar⁴, P. Murali Krishna⁵.

1. Professor , Department of Computer Science & Engineering, DNR College of Engineering & Technology, Balusumudi, Bhimavaram -534 202, W.G. Dist , Andhra Pradesh, INDIA.

2,3,4,5. Student, Department of Computer Science & Engineering, DNR College of Engineering & Technology, Balusumudi, Bhimavaram -534 202, W.G. Dist , Andhra Pradesh, INDIA.

10.5281/zenodo.19641260

ABSTRACT

The Smart Crime Analytics and High-Risk Zone Forecasting System is an intelligent data analytics platform developed using Streamlit, Pandas, and Folium to analyze historical crime datasets and forecast high-risk areas through geo-visualization and temporal trend analysis. The system enables users to upload crime records, apply city and crime-type filters, and visualize spatial crime patterns via interactive heatmaps and marker clusters. It computes risk levels by aggregating incident frequencies or clusters and presents monthly crime trends for predictive insights. By integrating data preprocessing, geospatial mapping, and predictive analytics, the platform aids law enforcement agencies in strategic decision-making, crime prevention, and resource optimization. In addition, the system incorporates automated data cleaning and validation mechanisms to handle missing values, inconsistent entries, and duplicate records, ensuring high data quality and reliability of analysis. It also supports real-time dashboard updates and dynamic visual analytics, allowing stakeholders to monitor evolving crime patterns and rapidly respond to emerging threats. Furthermore, the platform is designed with scalability and modular architecture, enabling integration with external data sources such as demographic statistics, weather data, and surveillance inputs to enhance predictive accuracy and long-term strategic planning.

Keywords: Interactive Data Upload & Filtering, Data Preprocessing & Cleaning, Geospatial Crime Visualization, High-Risk Zone Identification, Temporal Trend Analysis, Predictive Analytics Integration, Real-Time Dashboard Monitoring.



1. INTRODUCTION

1.1 BRIEF INFORMATION

There are several crimes that are happening in our country. But many of the people might not be aware of such crimes that are occurring in the different parts of the world. The crime related activities can severely affect socio-economic activities of a society too. Thus, definitely there is a need for a system that can provide all the necessary information's to the people. The primary aim of crime data analysis is to assist the operations of a police departments as well as enforcement departments. This may include criminal investigation, crime prevention, reduction strategies and problem solving. The different operations that are performed for the purpose of crime data analysis are data collection, data pre-processing, visualization and trends prediction.

After data collection and pre-processing, including data filtering and normalization, Google maps based geo-mapping of the features are implemented for visualization of the statistical results and time series modeling are utilized for future trends analysis. For the entire process we took the crime data that has been occurred in the different parts of our country. This data also includes the year wise information about the different crimes. The different crimes that are happening around us can be alerted always as well as the paper can also represent different crimes such as crime against women and children, murder, kidnap. Thus, through this we can easily identify the crime prone areas.

Big Data analytics is that the method of collecting, organizing and analyzing massive sets of data to discover patterns and other useful information. Big Data analytics can better help the organizations to understand the information in the crime data. There are several ways to analysis such a huge amount of data. The detailed visualization of the crime data has also pictorially represented with in this paper.

The issues regarding the crime pattern deals with predicting the hidden crimes with in the country. The crime rate is increasing day by day and the crime patterns are always changing. Thus, the behaviors in crime are difficult to be predicted. As a result, crime prediction with in an area was not an easy task. But now a days it has become more popular to use different methodologies for such a purpose.

The predictive model which is based on a neural network Long Short-Term Memory (LSTM), where a small group of attributes are trained, which further enables the prediction of the class label in the validation stage. This shows a high percentage of prediction accuracy also. The LSTM model is being widely used and it is preferred more than the

1.2 PURPOSE

The purpose of the Smart Crime Analytics and High-Risk Zone Forecasting System is to develop an intelligent platform that can analyze large volumes of historical crime data and transform it into meaningful insights. By using data analytics, visualization techniques, and geomapping tools, the system identifies crime patterns, trends, and high-risk zones across different regions. It enables users to upload crime datasets, filter them based on various parameters such as city and crime type, and



visualize the results through interactive heatmaps and charts. The ultimate goal is to assist law enforcement agencies and decision-makers in understanding crime behavior, improving situational awareness, and taking proactive steps to ensure public safety.

1.3 MOTIVATION

The motivation for developing this system arises from the growing complexity and volume of crime data in modern society. Traditional crime analysis methods are often manual, time-consuming, and lack the ability to provide quick and accurate insights. With the advancement of technology and the availability of data-driven tools, there is a strong need to adopt smarter solutions for crime analysis and prediction. This project is inspired by the potential of data analytics, machine learning, and visualization techniques to uncover hidden patterns and trends in crime data. By leveraging these technologies, the system aims to improve the efficiency of crime detection, enhance predictive capabilities, and support better resource allocation for law enforcement agencies.

1.4 PROBLEM STATEMENT

In many regions, existing crime analysis systems are limited in their ability to provide real-time insights, accurate forecasting, and intuitive visualization of crime data. Law enforcement agencies often face challenges in identifying crime hotspots, predicting future incidents, and allocating resources effectively due to the lack of advanced analytical tools. Additionally, the absence of user-friendly interfaces and interactive visualizations makes it difficult to interpret complex datasets. Therefore, there is a need for a comprehensive system that can process historical crime records, perform risk analysis, and present the results in a clear and interactive manner. The proposed system addresses these challenges by integrating data preprocessing, cluster.

2. LITERATURE REVIEW

Crime forecasting has evolved from traditional ARIMA-based statistical models to advanced hybrid machine learning frameworks. While ARIMA effectively captures linear trends and seasonality, it struggles with nonlinear patterns and sudden socioeconomic changes. Machine learning models improve nonlinear prediction but often lack strong temporal modeling and interpretability. Hybrid ARIMA-ANN models combine both approaches, where ARIMA models linear components and ANN captures nonlinear residuals. The reviewed study shows that this hybrid model outperforms traditional classifiers in accurately identifying high crime risk periods

2.1 Predictive Policing Using Self-Exciting Point Process Models

AUTHORS: O.Mohler.

Mohler and his co-authors conducted one of the most influential studies on predictive policing using statistical and mathematical models. Their research focused on applying self exciting point process models to predict crime occurrences, similar to how earthquake aftershocks are predicted. They demonstrated that crime events are not random but often cluster in space and time, meaning that one crime can increase the likelihood of another nearby. Their findings showed that predictive models



could significantly improve police patrol strategies and reduce crime rates when compared to traditional policing methods. This study laid the foundation for modern...

2.2. Hybrid ARIMA-ANN Model for Crime Risk Forecasting

AUTHORS: PAUL LACOBESCU

Paul Iacobescu and Ioan Susnea proposed a hybrid ARIMA-ANN model for crime risk forecasting, which combines the strengths of statistical and machine learning approaches. In their study, they used historical crime data along with socioeconomic and environmental factors such as unemployment, income levels, and climate conditions to improve prediction accuracy. The ARIMA model was used to capture linear trends and seasonal patterns, while the Artificial Neural Network (ANN) handled complex nonlinear relationships in the residual data. Their results demonstrated that the hybrid model outperformed traditional models like logistic regression, decision trees, and support vector machines in terms.

2.3. Time Series Forecasting Techniques and ARIMA Models

AUTHORS: R.J.Hyndman

Hyndman and Athanasopoulos provided a comprehensive understanding of forecasting techniques in their work on time series analysis. They extensively discussed models like ARIMA and their applications in various domains, including crime forecasting. Their research emphasized the importance of identifying trends, seasonality, and cyclic patterns in time-based data. They also highlighted the limitations of purely statistical models when dealing with complex real-world problems. Their work serves as a strong theoretical foundation for integrating statistical models with machine learning approaches, such as hybrid ARIMA-ANN models, to achieve better predictive performance.

2.4. Intelligence-Led Policing and Crime Analysis

AUTHORS: J.H. Ratcliffe

Ratcliffe introduced the concept of intelligence-led policing, which focuses on using data analysis and crime intelligence to guide law enforcement decisions. His work emphasized the importance of crime mapping, hotspot analysis, and data-driven strategies for effective policing. He argued that traditional reactive policing methods are less effective compared to proactive approaches that rely on crime data analysis. His research supports the idea that systems like crime analytics dashboards and forecasting tools can significantly improve decision-making and resource allocation in police departments.

2.5 Hotspot Policing and Crime Reduction Strategies

AUTHORS: D. Weisburd

Weisburd and Telep conducted extensive research on hotspot policing and its effectiveness in reducing crime. Their study showed that crime is often concentrated in specific geographic areas, known as hotspots, and targeting these areas can lead to significant reductions in crime rates. They provided empirical evidence supporting the use of spatial analysis and focused policing strategies.



Their work strongly supports the development of geo-visualization systems and heatmaps, which are essential components of modern crime analytics platforms.

2.6 Spatio-Temporal Modeling of Crime Data

AUTHORS: D.E. Brown

Wang and Brown worked on spatio-temporal modeling techniques for analyzing criminal incidents. Their research focused on understanding how crime varies across both space and time. They developed models that can identify patterns, trends, and relationships between different variables affecting crime. Their study highlighted the importance of combining spatial data (location) with temporal data (time) to improve the accuracy of crime prediction systems. This work contributed significantly to the development of modern geo-visualization and crime mapping techniques.

3. PROPOSED SYSTEM

The method processes CSV crime datasets by preprocessing (cleaning missing values, date formatting), filtering by city/crime type/date, computing risk levels (high/medium/low via frequency quantiles), clustering for hotspots, and generating temporal trends. It employs Random Forest for predictions and K-Means for zone grouping, outperforming manual analysis with automated, interactive insights. Key steps in the Smart Crime Analytics system begin with users uploading crime datasets through the intuitive Streamlit dashboard interface. The backend then processes this data using Pandas for efficient filtering by criteria like city or crime type and aggregation to compute statistics such as incident frequencies. Folium subsequently generates interactive visualizations including heatmaps and marker clusters overlaid on geographic maps to highlight spatial patterns. Finally, the integrated ML model typically Random Forest leverages features like city and crime type inputs to predict future incident counts and risk levels.

3.1. System Architecture Overview

The architecture features a Streamlit frontend for interactive UI (login, upload, filters, dashboards), Python backend for data handling (Pandas/NumPy), ML integration (Scikit-learn Random Forest), and Folium for geo-visualization, with CSV/MySQL storage. Data flows from upload → preprocessing → analysis → visualization, supporting admin/police/public roles.

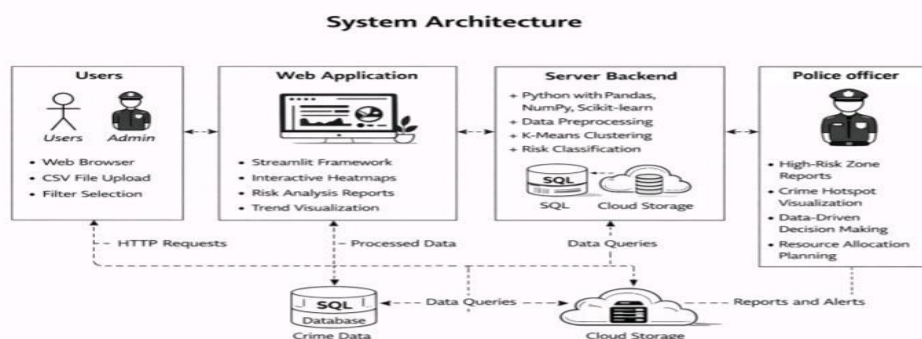


Fig: 3.1 System Architecture

System Architecture



The system architecture is designed to analyze crime data and identify high-risk zones using a web-based interface, machine learning backend, and cloud-supported storage. The architecture consists of four major components: Users, Web Application, Server Backend, and Police Officer Interface, integrated with SQL Database and Cloud Storage.

1. Users

Users include general users and administrators who interact with the system through a web browser. They can upload crime datasets in CSV format, apply filters, and request analysis. The user interface allows easy selection of parameters such as location, crime type, and time period. All requests are sent to the web application via HTTP.

2. Web Application

The web application is developed using the Streamlit framework. It acts as the middle layer between users and the backend server. This component provides interactive heatmaps, risk analysis reports, and trend visualizations. It receives user input, sends data to the backend for processing, and displays the processed results in graphical format.

3. Server Backend

The server backend handles data processing and machine learning operations. It is implemented using Python libraries such as Pandas, NumPy, and Scikit-learn. The backend performs data preprocessing, feature extraction, and K-Means clustering to identify crime hotspots. Risk classification is applied to categorize areas into low, medium, and high-risk zones. The backend interacts with SQL database and cloud storage to fetch and store data.

4. Database and Cloud Storage

The SQL database stores structured crime data including location, time, and crime type. Cloud storage is used for storing large datasets, processed outputs, and generated reports. The backend performs data queries to retrieve required information and saves processed results for future use.

5. Police Officer Interface

Police officers use the system to view high-risk zone reports and crime hotspot visualizations. The interface helps in data-driven decision making, resource allocation, and patrol planning. Alerts and reports generated by the system assist authorities in proactive crime prevention.

3.2. Use Case Diagram



Fig: 3.2 Usecase Diagram

Here's the complete UML use case diagram for the Smart Crime Analytics system. Here's what's captured:

Three actors with their distinct scopes — Admin (system management), Police Officer (operational intelligence), and Public User (read-only access).

Admin use cases (purple): login/authenticate, manage users & data, configure risk settings, audit system logs.

Police Officer use cases (teal): view crime heatmaps, view alerts & reports, plan patrol routes, monitor live dashboard.

Public User use cases (blue): view crime statistics, search crime records, download reports.

Shared system use cases (amber) form the core analytics pipeline — upload dataset → validate & clean data → filter data → analyze trends (ML) → generate risk forecast — connected via «include» relationships. The «extend» relationship from "Generate risk forecast" and "View alerts" to "Send alerts" (coral) models the conditional notification behaviour. The dashed horizontal lines separate the three actor zones, and the system boundary rectangle encloses all use cases as part of the platform.

3.3.4 Class Diagram (Simplified)

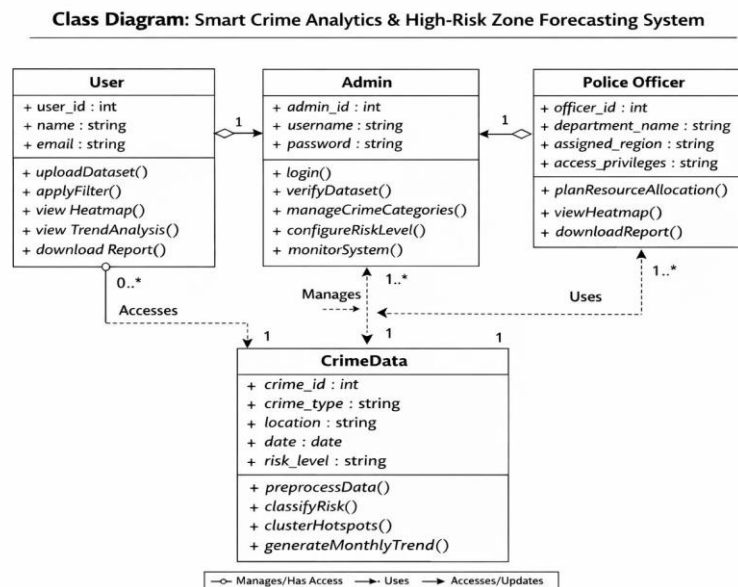


Fig: 3.3 Class Diagram

This class diagram faithfully reproduces your ASCII sketch with proper UML notation:

Three actor classes (purple) in a row — User, Admin, PoliceOfficer — each split into the standard three compartments: class name, attributes, and methods.

Aggregation arrows (<>—>) connect User → Admin → PoliceOfficer horizontally, with the open diamond on the source side and 1 * multiplicity labels exactly as in your sketch.

MLTrainingModel (amber) sits below, with dashed dependency arrows pointing up to all three actor classes — matching the ^ arrows from your original diagram — showing that the ML model depends on all three actors.

3.3 Activity Diagram

The activity diagram shows the workflow of the Smart Crime Analytics System. The process starts with the user uploading a dataset, followed by data validation. If the data is invalid, the process stops; if valid, filters are applied. The system then processes the data, generates heatmaps and reports, and finally displays the results for viewing and download.

4. RESULTS



NEW USER REGISTRATION

The screenshot shows a dark-themed registration form titled "Register" with a document icon. It contains three input fields: "Username", "Password", and "Confirm Password", each with a corresponding label and a toggle eye icon for the password fields. Below the fields is a "Register" button and a "Back to Login" button.

LOGIN

The screenshot shows a dark-themed login form titled "Login" with a lock icon. It contains two input fields: "Username" and "Password", each with a corresponding label and a toggle eye icon for the password field. Below the fields is a "Login" button and a "Create New Account" button.

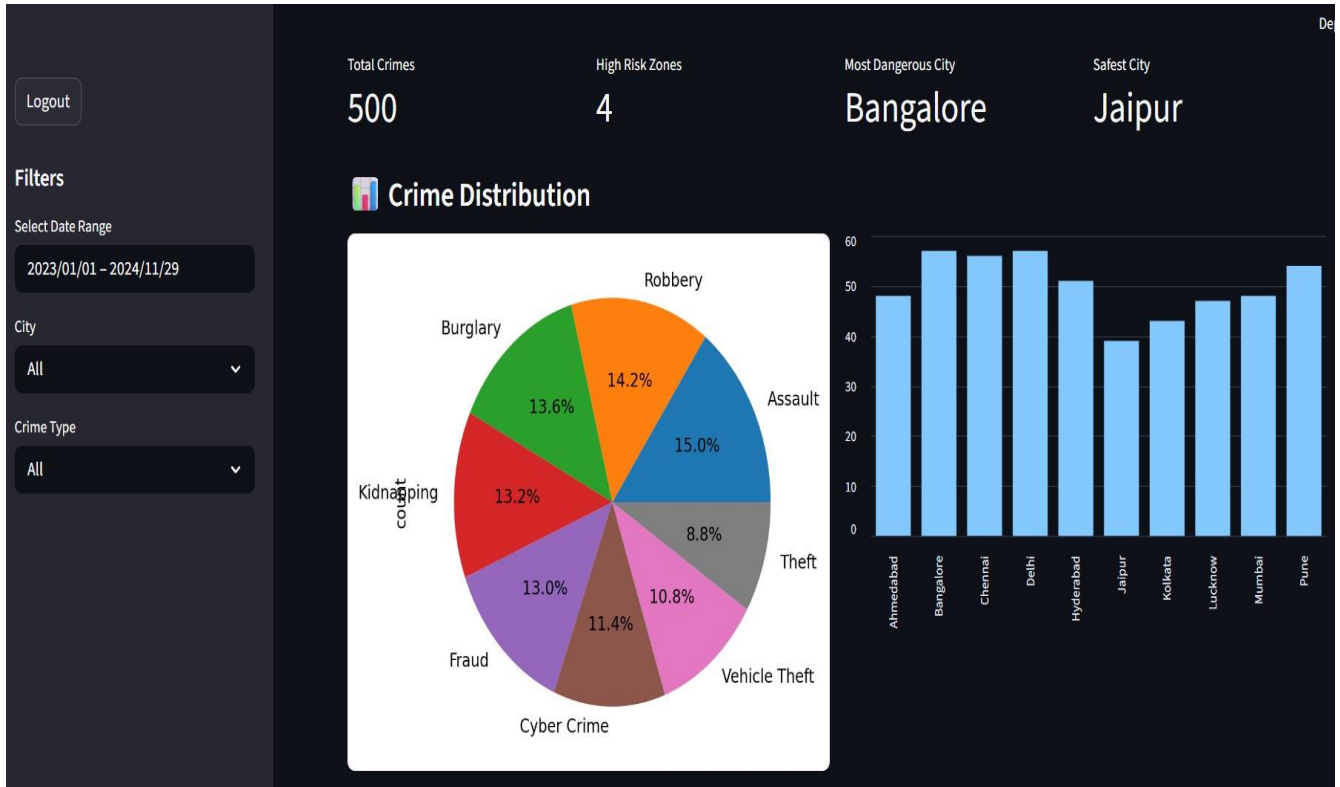


DASHBOARDS

The screenshot shows a dark-themed dashboard interface. On the left, there is a sidebar with a 'Logout' button. The main content area features a title 'AI Smart Crime Analytics Dashboard' with a small car icon. Below the title, there is a section for 'Upload Crime Dataset CSV'. This section includes a large grey box with the text 'Drag and drop file here' and 'Limit 200MB per file • CSV', accompanied by a cloud upload icon. To the right of this box is a 'Browse files' button. Below the upload area, there is a blue button labeled 'Upload dataset to begin'.



PIE CHARTS AND BAR DIAGRAMS

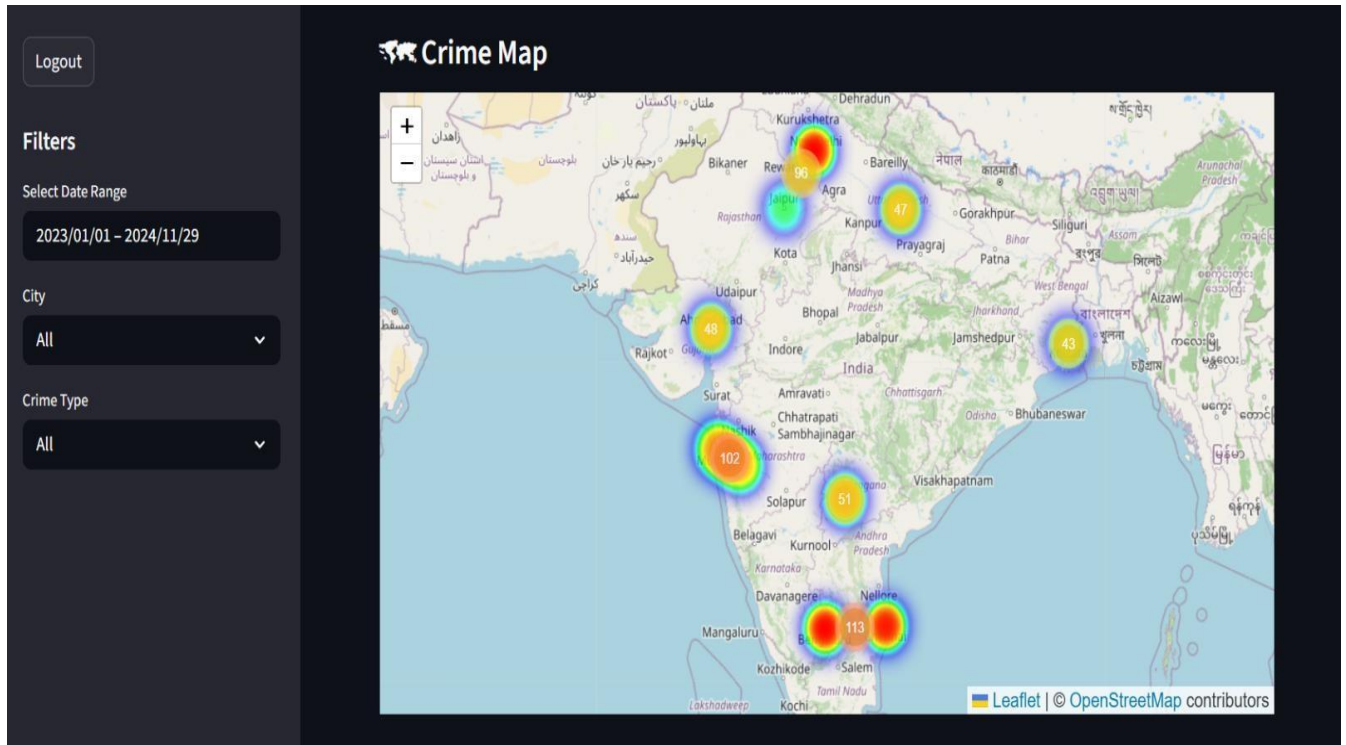


MONTHLY CRIME TRENDS





MAP VISUALIZATION



AI PREDICTION

The figure shows the 'AI Prediction' interface. It includes a sidebar with filters and a main prediction area. The filters are:

- Logout
- Filters
- Select Date Range: 2023/01/01 - 2024/11/29
- City: All
- Crime Type: All

The main prediction area shows a map of the Nellore region with a heatmap overlay. Below the map, the following options are selected:

- Select City: Lucknow
- Select Crime: Burglary

A 'Predict Crime Risk' button is present. The prediction results are displayed in a green box:

- Predicted Crime Count: 47
- Low Risk



CONCLUSION:

The Smart Crime Analytics and High-Risk Zone Forecasting Dashboard developed using Streamlit effectively visualizes and analyzes crime data to identify trends and high-risk areas. The system allows users to upload a dataset (such as `crime_dataset_india.csv`) and interactively filter information by city, crime type, and date range. It performs data preprocessing, visual exploration, and temporal analysis, giving users the ability to view filtered crime records and explore geospatial crime patterns. The integration of Folium maps provides both heatmaps and clustered crime markers, enabling users to easily pinpoint crime hotspots and understand regional distribution patterns.

Additionally, the dashboard's analytical components, such as the Risk Score/Cluster Summary and Monthly Crime Trend visualization, help users assess the frequency and evolution of crimes over time. Cities with higher report counts—like Delhi, Mumbai, and Bangalore—are identified as higher-risk zones, while the time-series chart reveals stable or fluctuating monthly crime trends. Overall, the project successfully combines data analytics, visualization, and geographic intelligence to support data-driven decision-making for law enforcement agencies, making it a practical and insightful crime analysis tool.

FUTURE SCOPE:

The Smart Crime Analytics and High-Risk Zone Forecasting Dashboard can be further enhanced by integrating machine learning and predictive analytics to forecast potential crime occurrences based on historical patterns, population density, weather conditions, and socio-economic indicators. Incorporating real-time data feeds from police records, social media, and IoT-enabled surveillance systems can make the system dynamic and responsive to evolving crime scenarios. Additionally, implementing Natural Language Processing (NLP) could enable automated extraction of crime-related information from news articles and police reports, enriching the dataset and improving analysis accuracy.

In the future, the dashboard could evolve into a comprehensive decision-support system by adding modules for criminal profiling, anomaly detection, and automatic alert generation for high-risk zones. Integration with mobile and web-based GIS applications can allow law enforcement officials to access crime insights on the go. Advanced visualization techniques, such as 3D geospatial mapping and AI-powered heatmaps, can also enhance the interpretability of complex data. Furthermore, collaboration with government and public safety organizations could lead to policy-level insights and preventive action planning, making the system a cornerstone for building safer and smarter cities.



REFERENCES

1. Wang, X.; Brown, D.E. The spatio-temporal modeling for criminal incidents. *Secur. Inf.* **2012**, *1*, [\[CrossRef\]](#)
2. Ratcliffe, J.H. *Intelligence-Led Policing*; Routledge: Oxfordshire, UK, 2016. [\[CrossRef\]](#)
3. Susnea, I.; Pecheanu, E.; Cocu, A.; Istrate, A.; Anghel, C.; Iacobescu, P. Non-Intrusive Monitoring and Detection of Mobility Loss in Older Adults Using Binary Sensors. *Sensors* **2025**, *25*, 2755. [\[CrossRef\]](#)
4. Mohler, G.O.; Short, M.B.; Malinowski, S.; Johnson, M.; Tita, G.E.; Bertozzi, A.L.; Brantingham, P.J. Randomized Controlled Field Trials of Predictive Policing. *J. Am. Stat. Assoc.* **2015**, *110*, 1399–1411. [\[CrossRef\]](#)
5. Hyndman, R.J.; Athanasopoulos, G. *Forecasting: Principles and Practice*; OTexts: Melbourne, Australia, 2021.
6. Weisburd, D.; Telep, C.W. Hot Spots Policing: What We Know and What We Need to Know. *J. Contemp. Crim. Justice* **2014**, *30*, 200–220. [\[CrossRef\]](#)
7. Camacho-Collados, M.; Liberatore, F. A Decision Support System for predictive police patrolling. *Decis. Support Syst.* **2015**, *75*, 25–37. [\[CrossRef\]](#)
8. Gorr, W.; Harries, R. Introduction to crime forecasting. *Int. J. Forecast.* **2003**, *19*, 551–555. [\[CrossRef\]](#)
9. Dakalbab, F.; Abu Talib, M.; Abu Waraga, O.; Bou Nassif, A.; Abbas, S.; Nasir, Q. Artificial intelligence & crime prediction: A systematic literature review. *Soc. Sci. Humanit. Open* **2022**, *6*, 100342. [\[CrossRef\]](#)
10. Zhang, G.P. Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing* **2003**, *50*, 159–175. [\[CrossRef\]](#)
11. Monthly Statistical Bulletin of Galatji County. Available online: <https://galati.insse.ro/produse-siservicii/publicatii-statistice/> (accessed on 21 May 2025).
12. Activity Reports of the Galatji County Police Inspectorate. Available online: <https://gl.politiaromana.ro/ro/informatii-publice/transparen-institu-ional/rapoarte-de-activitate> (accessed on 21 May 2025).
13. He, H.; Garcia, E.A. Learning from Imbalanced Data. *IEEE Trans. Knowl. Data Eng.* **2009**, *21*, 1263–1284. [\[CrossRef\]](#)
14. Fernández, A.; García, S.; Galar, M.; Prati, R.C.; Krawczyk, B.; Herrera, F. *Learning from Imbalanced Data Sets*; Springer International Publishing: Cham, Switzerland, 2018. [\[CrossRef\]](#)