

A Project Report  
on  
**CRIME DATA PREDICTION USING MACHINE LEARNING**

Submitted in the partial fulfilment of the requirement for the award of degree of

Bachelor of Technology

In

**CSE(Data Science)**

Submitted by

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**NARASARAOPETA ENGINEERING COLLEGE (AUTONOMOUS)**  
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**KOTAPPAKONDA ROAD, YALAMANDA VILLAGE,**  
**NARASARAOPET-522601**  
**2025-2026**

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**DEPARTMENT OF CSE(Data Science)**

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**CERTIFICATE**



This is certify that the project report entitled as “**Crime Data Prediction Using Machine Learning**” is a bonafide work done by **Maddi Chidananda Dedeepya (22471A4432)**, **Thoka Asha Gayathri(22471A4452)**, **Ubbathoti Venkateswarlu(22471A4454)** in partial fulfilment of the requirements for the award of the degree of **BACHELOR OF TECHNOLOGY** in the Department of CSE(Data Science) during 2025-2026.

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## **DECLARATION**

We certify that

- a. The work contained in this Project report is original and has been done by ours and the general supervision of ours supervisor.
- b. The work has not been submitted to any other institute for any degree or diploma.
- c. Whenever we have used materials (data, theoretical analysis, results) from other sources, we have given due credit to them by citing them in the text of the Project report and giving their details in the references.
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## **INSTITUTE VISION AND MISSION**

### **INSTITUTION VISION**

To emerge as a Centre of excellence in technical education with a blend of effective student centric teaching learning practices as well as research for the transformation of lives and community.

### **INSTITUTION MISSION**

**M1:** Provide the best class infra-structure to explore the field of engineering and research

**M2:** Build a passionate and a determined team of faculty with student centric teaching, imbibing experiential, innovative skills

**M3:** Imbibe lifelong learning skills, entrepreneurial skills and ethical values in students for addressing societal problems



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## Department of CSE (Data Science)

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### VISION

To nurture skilled professionals in the Data Science for industry innovation and create meaningful societal impact through advanced analytics, machine learning, and impactful data-driven solutions.

### MISSION

**M1:** To develop skilled data scientists who can effectively solve challenges in data analytics through comprehensive education and practical training in statistical analysis, machine learning, data visualization, and data manipulation.

**M2:** To develop students with strong research capabilities who can revolutionize multiple fields through the application of data science.

**M3:** To develop ethical data science professionals who utilize data for the welfare of society.

### PROGRAM SPECIFIC OUTCOMES (PSO'S)

**PSO1:** Apply Data Science Techniques, statistical analysis, machine learning algorithms, data visualization, and data manipulation effectively to solve complex data problems.

**PSO2:** Demonstrate proficiency in conducting data collection, preprocessing, analysis, and interpretation, contributing to the advancement of the field.

**PSO3:** Able to independently carry out research and investigation to solve societal problems.

### PROGRAM EDUCATIONAL OBJECTIVES (PEO'S)

**PEO1:** Graduates be proficient in applying advanced analytics techniques to solve complex data challenges.

**PEO2:** Graduates contribute to the advancement of the field through the development of innovative methodologies, algorithms, and models.

**PEO3:** Graduates utilize data science principles to create meaningful societal impact. They will prioritize ethical considerations in data usage and develop solutions that address societal challenges, and benefit individuals and communities.



## **PROGRAM OUTCOMES (POs)**

**PO1: Engineering Knowledge:** Apply knowledge of mathematics, natural science, computing, engineering fundamentals and an engineering specialization as specified in WK1 to WK4 respectively to develop to the solution of complex engineering problems.

**PO2: Problem Analysis:** Identify, formulate, review research literature and analyze complex engineering problems reaching substantiated conclusions with consideration for sustainable development. (WK1 to WK4)

**PO3: Design / Development of Solutions:** Design creative solutions for complex engineering problems and design/develop systems/components/processes to meet identified needs with consideration for the public health and safety, whole-life cost, net zero carbon, culture, society and environment as required. (WK5)

**PO4: Conduct Investigations of Complex Problems:** Conduct investigations of complex engineering problems using research-based knowledge including design of experiments, modelling, analysis & interpretation of data to provide valid conclusions. (WK8).

**PO5: Engineering Tool Usage:** Create, select and apply appropriate techniques, resources and modern engineering & IT tools, including prediction and modelling recognizing their limitations to solve complex engineering problems. (WK2 and WK6)

**PO6: The Engineer and The World:** Analyze and evaluate societal and environmental aspects while solving complex engineering problems for its impact on sustainability with reference to economy, health, safety, legal framework, culture and environment. (WK1, WK5, and WK7).

**PO7: Ethics:** Apply ethical principles and commit to professional ethics, human values, diversity and inclusion; adhere to national & international laws. (WK9)

**PO8: Individual and Collaborative Team work:** Function effectively as an individual, and as a member or leader in diverse/multi-disciplinary teams.

**PO9: Communication:** Communicate effectively and inclusively within the engineering community and society at large, such as being able to comprehend and write effective reports and design documentation, make effective presentations considering cultural, language, and learning differences

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**PO11: Life-Long Learning:** Recognize the need for, and have the preparation and ability for

- i) Independent and life-long learning
- ii) Adaptability to new and emerging technologies and
- iii) Critical thinking in the broadest context of technological change.

**Project Course Outcomes (CO'S):**

**CO421.1:** Analyse the System of Examinations and identify the problem.

**CO421.2:** Identify and classify the requirements.

**CO421.3:** Review the Related Literature

**CO421.4:** Design and Modularize the project

**CO421.5:** Construct, Integrate, Test and Implement the Project.

**CO421.6:** Prepare the project Documentation and present the Report using appropriate method.

**Course Outcomes – Program Outcomes mapping**

CO \ PO / PSO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
CO421.1		✓						✓				✓		✓
CO421.2	✓		✓		✓					✓		✓	✓	
CO421.3			✓		✓	✓	✓			✓		✓		✓
CO421.4		✓		✓	✓	✓				✓	✓	✓	✓	
CO421.5			✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
CO421.6					✓	✓	✓		✓	✓			✓	✓

**Course Outcomes – Program Outcome correlation**

CO \ PO / PSO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PSO1	PSO2	PSO3
CO421.1		2						2				2		2
CO421.2	2		2		3					2		2	3	
CO421.3			2		2	3	3			2		2		3
CO421.4		2		1	1	2				3	2	3	2	
CO421.5			3	3	3	2	3	2	2	1	3	3	3	3
CO421.6					3	2	1		2	3			3	2

**Note:** The values in the above table represent the level of correction between CO's and PO's:

**1. Low Level**

**2. Medium level**

**3. High level**

## ABSTRACT

Crime has become one of the most complex social challenges affecting the safety and well-being of modern societies. As urban populations grow and data from multiple sources accumulate, the need for intelligent systems that can analyze and predict criminal activity has become increasingly vital. This project aims to develop a **machine learning-based crime prediction system** that leverages historical and socio-economic data to identify potential crime patterns in advance. By integrating algorithms such as **Logistic Regression**, **Random Forest**, the system learns both spatial and temporal relationships within crime data to forecast future occurrences with improved accuracy. The predictive results are then deployed through an **interactive Streamlit web application**, allowing users and authorities to visualize trends, explore high-risk zones, and make informed decisions. The model's performance is evaluated using metrics such as **accuracy**, **F1-score**, ensuring reliability and consistency. To promote fairness and transparency, **SHAP explainability techniques** are incorporated, providing interpretable insights into the model's predictions. The system's design emphasizes not only technological advancement but also ethical responsibility—ensuring that predictive intelligence supports **preventive action**, **community awareness**, and **data-driven policymaking**. Ultimately, this project contributes toward building **safer and smarter communities** by transforming crime prediction into a proactive and compassionate approach to public safety.

## INDEX

S. No.	Content	Page No.
<b>1</b>	<b>Introduction</b>	1
	1.1 Motivation	1
	1.2 Problem Statement	2
	1.3 Objective	2
<b>2</b>	<b>Literature Survey</b>	4
<b>3</b>	<b>System Analysis</b>	8
	3.1 Existing System	8
	3.1.1 Disadvantages of the Existing System	9
	3.2 Proposed System	9
	3.3 Feasibility Study	11
	3.4 Using Cocomo Model	13
<b>4</b>	<b>System Requirements</b>	18
	4.1 Software Requirements	18
	4.2 Requirement Analysis	18
	4.3 Hardware Requirements	19
	4.4 Software	20
	4.5Software Description	21
<b>5</b>	<b>System Design</b>	23
	5.1 System Architecture	23
	5.1.1 Dataset	26
	5.1.2Data Preprocessing	28
	5.1.3 Feature Extraction	30
	5.1.4 Model Building	33
	5.1.5 Classification	36
	5.2 Modules	38
	5.3 UML Diagrams	40
<b>6</b>	<b>Implementation</b>	43
	6.1 Model Implementation	43
	6.2 Coding	47
<b>7</b>	<b>Testing</b>	56

7.1	Unit Testing	56
7.2	Integration Testing	57
7.3	System Testing	58
<b>8</b>	Result Analysis	59
<b>9</b>	Output Screens	63
<b>10</b>	Conclusion	67
<b>11</b>	Future Scope	68
<b>12</b>	References	69
<b>13</b>	Conference Paper Plagiarism Report	71
<b>14</b>	Conference Certificate	79
<b>15</b>	Proceeding Paper	83

## LIST OF FIGURES

<b>Figure No.</b>	<b>Title</b>	<b>Page No.</b>
Figure 3.1	Proposed System – Crime Data Prediction Workflow	11
Figure 3.2	Feasibility Study	13
Figure 3.3	COCOMO Effort Distribution Pie Chart	16
Figure 4.1	Crime Data Prediction Using Machine Learning – Workflow Diagram	19
Figure 5.1	Software Architecture Flow Diagram for Crime Data Prediction System	23
Figure 5.2	Architecture for Crime Data Prediction	26
Figure 5.3	Data Preprocessing Flow Diagram for Crime Data Prediction System	30
Figure 5.4	Feature Extraction Diagram	33
Figure 5.5	Model Building Flow	36
Figure 5.6	Use Case Diagram	41
Figure 5.7	Class Diagram	41
Figure 5.8	Sequence Diagram	42
Figure 7.1	Unit Testing Flow Diagram for Crime Data Prediction System	56
Figure 8.1	Correlation Matrix on Crime Data	59
Figure 8.2	Forecast for the next years	60
Figure 8.3	Forecast for the next years and months by trends	61
Figure 8.4	SHAP interaction value	62
Figure 9.1	Dashboard Page	63
Figure 9.2	Crime Data Prediction Page	64
Figure 9.3	Prediction & Performance Review	65
Figure 9.4	Crime Analysis Page	65
Figure 9.5	Crime Report Page	66

## LIST OF TABLES

<b>Table No.</b>	<b>Title</b>	<b>Page No.</b>
Table 2.1	Comparison of Crime Prediction Methods	7
Table 3.1	Disadvantages of Existing System	9
Table 3.2	Cost Considerations	13
Table 3.3	Project Classification	14
Table 3.4	Estimation Parameters	15
Table 3.5	Effort Distribution by Phase	16
Table 3.6	Summary of COCOMO Estimation	17
Table 5.1	data_cts_violent_and_sexual_cri_dataset	28
Table 5.2	Selected Features for Model Training	32
Table 5.3	Model Evaluation	35
Table 5.4	Comparison of Model Accuracies for Crime Data Prediction	39
Table 7.1	System Testing Results for Crime Data Prediction System	58

## 1. INTRODUCTION

### 1.1 Motivation

Crime has always been a significant social issue, affecting the safety, development, and overall quality of life in society. In a country like **India**, where rapid urbanization, unemployment, economic disparity, and increasing population density are prevalent, crime rates often fluctuate and create major challenges for law enforcement agencies and policymakers. Traditional methods of crime monitoring rely heavily on manual record keeping and statistical summaries. While useful, these methods are often reactive in nature and fail to provide foresight into emerging trends.

With the growing availability of **digital crime records** (such as those from the National Crime Records Bureau - NCRB) and advancements in **machine learning (ML)** and **artificial intelligence (AI)**, there exists a powerful opportunity to build systems that not only analyze historical data but also **predict future crime patterns**. Such systems can assist in:

- **Proactive Policing:** Allowing police departments to anticipate crime hotspots, allocate personnel more effectively, and design targeted interventions.
- **Policy Development:** Helping governments and policymakers understand the socio-economic factors contributing to crimes and plan developmental initiatives to reduce them.
- **Community Safety:** Informing local communities about crime-prone areas and times, thereby encouraging preventive measures and awareness campaigns.
- **Efficient Use of Resources:** Enabling smarter decision-making by reducing guesswork and relying on data-driven insights.

Another key motivation is that **crime prediction can save lives and reduce losses** if implemented effectively. By using ML algorithms like regression models, Random Forests, or advanced neural networks, hidden correlations in the data (e.g., unemployment influencing theft rates, or urban crowding linked to violent crimes) can be revealed.

Thus, the motivation for this project arises from the **need to transform traditional crime data analysis into a predictive, intelligent, and actionable system**. By leveraging machine learning, we aim to provide valuable insights that can contribute to building safer communities and supporting crime prevention efforts in a structured, data-driven manner.

## **1.2 Problem Statement**

Crime continues to be a major concern for governments, law enforcement agencies, and communities worldwide. In India, despite the availability of crime records through organizations such as the National Crime Records Bureau (NCRB), the current methods of analyzing crime are largely descriptive and retrospective. These approaches provide statistical summaries of past incidents but lack the ability to predict future trends or identify hidden patterns in complex datasets.

The absence of predictive analytics in crime management leads to:

- Reactive policing, where action is taken only after crimes occur.
- Inefficient resource allocation, since law enforcement agencies cannot anticipate crime hotspots in advance.
- Limited policy insights, as socio-economic factors influencing crime are not fully explored.

Furthermore, crime data is often large, multi-dimensional, and influenced by a variety of factors such as unemployment, literacy rates, poverty, population density, and urbanization. Traditional analytical techniques struggle to handle such complexity effectively.

Therefore, there is a pressing need for a machine learning-based solution that can analyze large crime datasets, identify significant factors influencing crime, and provide accurate forecasts. Such a system can support proactive policing, guide policy formulation, and contribute towards crime prevention and community safety.

## **1.3 Objective**

The primary objective of this project is to develop a **machine learning-based crime prediction system** that can analyze historical crime data and provide accurate forecasts to assist in proactive decision-making. The specific objectives are:

### **1. Data Collection and Preprocessing**

- Gather crime-related datasets from reliable sources such as NCRB and open repositories.
- Clean, preprocess, and transform the data to handle missing values, inconsistencies, and outliers.

### **2. Feature Analysis and Selection**

- Identify key socio-economic and demographic factors influencing crime (e.g., population density, unemployment rate, literacy levels).
- Use statistical and correlation analysis to select the most relevant features.

### **3. Model Development**

- Apply machine learning algorithms such as Linear Regression, Random Forest, XGBoost, and Time Series models.
- Train and test the models on crime datasets to predict future crime trends.

### **4. Model Evaluation**

- Evaluate model performance using metrics like Accuracy, Precision, Recall, RMSE, and R<sup>2</sup> Score.
- Compare models to determine the most effective approach for crime prediction.

### **5. Result Interpretation**

- Visualize the outcomes using tools like correlation matrices, SHAP values, and forecast graphs.
- Provide clear insights into which factors contribute most to different types of crimes.

### **6. Application Development (Prototype)**

- Design a user-friendly application/dashboard where users (police, policymakers, or citizens) can input parameters and view predicted crime patterns.

### **7. Contribution to Crime Prevention**

- Provide actionable insights that help law enforcement agencies in **resource allocation** and policymakers in **crime prevention strategies**.

## 2. LITERATURE SURVEY

This literature survey summarizes of crime prediction has evolved significantly over the past two decades, transitioning from traditional statistical approaches to modern data-driven and AI-based systems.

This literature survey reviews existing research and technologies that laid the foundation for developing a predictive model capable of understanding complex crime patterns, integrating social and environmental factors, and promoting ethical use of AI.

### **Early Statistical and Spatial Models**

One of the earliest and most influential contributions was by **M. Levine (2013)**, who developed *CrimeStat*, a spatial statistics program designed to analyze crime incident locations. This tool utilized **Kernel Density Estimation (KDE)** and **regression models** to identify geographic hotspots where crimes were most likely to occur.

Although it was effective in mapping crime distributions, it lacked the ability to incorporate temporal patterns or adapt to real-time changes in criminal activity. This marked the starting point for computational crime analysis, but it remained limited to *static spatial visualization*.

### **Introduction of Machine Learning for Crime Prediction**

With the rise of machine learning, researchers began to shift toward models capable of capturing non-linear patterns and complex relationships in crime data. J. Kang and K. Kang (2017) proposed a deep learning-based framework that utilized multi-modal data sources — including demographic, environmental, and historical crime data — to predict future crime occurrences.

Their model significantly improved prediction accuracy over traditional statistical methods by learning intricate relationships among various urban indicators.

Similarly, T. Candia, F. Menczer, and F. Peruani (2020) employed machine learning models to forecast crime rates using urban metrics such as population density, unemployment, and social activity. Their research demonstrated how Random Forest and Gradient Boosting models could effectively identify hidden correlations between socio-economic indicators and crime. However, they also highlighted the importance of feature engineering and data quality, as poor or biased datasets could reduce predictive performance.

## **Adoption of Deep Learning for Spatio-Temporal Forecasting**

Deep learning offered a breakthrough by modeling both spatial and temporal dynamics simultaneously. Y. Wang, Y. Ye, and H. Tsou (2016) introduced a spatio-temporal deep learning model using neural networks for real-time crime forecasting.

Their method captured sequential dependencies in time-series data, enabling predictions that reflected crime fluctuations across days or months.

Following this, A. Chen, L. Zhang, and J. Chen (2018) applied Convolutional Neural Networks (CNNs) to convert crime data into grid-based spatial maps, allowing automated hotspot detection with remarkable precision.

These studies established deep learning as a powerful alternative to classical models for large-scale crime data analysis.

## **Indian Research Context**

In the Indian context, crime prediction research has been relatively recent but is rapidly expanding. The National Crime Records Bureau (NCRB) provides comprehensive annual reports that serve as the primary data source for most Indian studies.

S. Chatterjee and S. Bandyopadhyay (2019) performed statistical analysis on Indian crime data, identifying long-term trends and regional differences.

R. Singh and A. Gupta (2021) enhanced this approach by using Random Forest and Boosting algorithms to classify crimes into categories such as property-related and violent crimes, achieving high accuracy levels.

Further, P. R. Sharma and S. Jain (2020) explored urban crime patterns in Delhi using machine learning, integrating geospatial data and socio-economic indicators. These studies underline the growing use of ML in India for policy formulation and law enforcement planning, though they also highlight limitations like data imbalance, underreporting, and lack of temporal granularity.

## **AI Fairness and Ethical Considerations**

While technological progress in predictive policing has been promising, researchers have increasingly turned their attention to ethics, fairness, and responsible AI deployment. S. Barocas, M. Hardt, and A. Narayanan (2021) emphasized the risks of algorithmic bias in predictive policing, warning that models trained on biased datasets can unintentionally reinforce existing social inequalities.

Their work advocates for transparency, interpretability, and accountability in AI systems — principles that this project also follows through the use of SHAP explainability tools.

Recent studies by N. D. J. D. S. M. C. M. L. D. P. E. H. F. H. (2023) in *Information Fusion* and C. H. Z. Z. B. M. X. Y. (2022) in *IEEE Transactions on Artificial Intelligence* further discussed the concept of *trustworthy AI* and regulatory frameworks that ensure fairness, non-discrimination, and data privacy.

These works collectively contribute to establishing guidelines for responsible use of AI in social domains, including crime prediction.

## Key Insights from Literature

From this comprehensive review, several insights emerge:

- Shift from traditional to intelligent models: Research has evolved from static regression models to dynamic, AI-driven systems capable of self-learning.
- Importance of temporal and socio-economic data: Effective crime prediction depends not only on past incidents but also on broader contextual data such as unemployment, literacy, and population density.
- Need for interpretability: Explainable AI methods (like SHAP) are essential to make machine learning models transparent and socially acceptable.
- Ethical awareness: The inclusion of fairness and accountability frameworks ensures that technology is used for *protection*, not *profiling*.
- Indian research gap: While progress has been made, Indian studies still face limitations in data quality and availability, emphasizing the need for localized, fair, and transparent predictive models.

## Conclusion

The literature collectively highlights the enormous potential of machine learning and deep learning in enhancing public safety through predictive analytics.

However, it also underscores the responsibility to deploy these technologies ethically.

The insights from previous research form the backbone of this project — combining spatio-temporal modeling, explainable AI, and a Streamlit-based dashboard to create a transparent and interactive system for crime data prediction.

By addressing gaps in interpretability and fairness, this work extends beyond technical prediction, aiming to build a responsible and human-centered approach to public safety analytics.

<b>Author / Year</b>	<b>Method / Technique</b>	<b>Dataset / Source</b>	<b>Key Findings</b>	<b>Limitations</b>
M. Levine (2013)	CrimeStat, KDE, Regression	Spatial Crime Data	Identified hotspots and spatial clusters	Lacked temporal analysis
J. Kang & K. Kang (2017)	Deep Learning (Multi-modal Data)	Urban datasets	Improved predictive accuracy	Required large labeled datasets
T. Candia et al. (2020)	ML with Urban Indicators	Socio-economic Data	Showed strong link between urban factors and crime	Data preprocessing complexity
Y. Wang et al. (2016)	RNN (Spatio-Temporal)	City-level data	Captured time-dependent crime patterns	Computationally intensive
A. Chen et al. (2018)	CNN for Hotspot Mapping	Geo-Spatial Data	Improved hotspot visualization	Spatial bias
S. Chatterjee & S. Bandyopadhyay (2019)	Statistical Regression	Indian NCRB Data	Identified state-level trends	Limited temporal resolution
R. Singh & A. Gupta (2021)	Random Forest & Boosting	NCRB Dataset	Accurate crime classification	Data imbalance issues
P. R. Sharma & S. Jain (2020)	ML-based City Crime Analysis	Delhi Crime Data	Spatial and temporal pattern discovery	Underreporting & incomplete data
S. Barocas et al. (2021)	Ethical AI Framework	General AI Systems	Addressed algorithmic bias	Lacked quantitative validation
M. E. E. A. A. S. F. W. et al. (2023)	AI + IoT Integration	Smart City Data	Enabled real-time monitoring	Implementation cost

**Table 2.1: Comparison of Crime Prediction Methods**

## **3. SYSTEM ANALYSIS**

### **3.1 Existing System**

#### **Early Statistical Models**

Earlier systems such as CrimeStat by Ned Levine (2013) relied primarily on Kernel Density Estimation (KDE) and Regression Analysis to identify crime hotspots. These methods were valuable for visualizing the geographic distribution of crime but failed to consider how crime evolves over time or the impact of socio-economic factors such as unemployment, income, and literacy levels.

#### **Traditional Machine Learning Approaches**

With the growth of digital crime records and open data initiatives, researchers began applying machine learning algorithms such as:

- Logistic Regression (LR)
- Decision Trees (DT)
- Random Forest (RF)
- Support Vector Machines (SVM)

For instance, Kang and Kang (2017) and Candia et al. (2020) applied these methods to predict the likelihood of crimes based on urban indicators.

#### **Deep Learning-Based Systems**

Recent works introduced Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs) for advanced spatio-temporal prediction. For example:

- Wang et al. (2016) used deep learning for spatio-temporal crime prediction.
- Chen et al. (2018) used CNNs to map crime hotspots in U.S. cities.

#### **Indian Context**

In India, most studies have relied on National Crime Records Bureau (NCRB) data, using simple regression or classification models for state-level or city-level prediction (e.g., studies in Delhi, Mumbai, and Bengaluru).

Examples include:

- Chatterjee and Bandyopadhyay (2019) – Statistical analysis of Indian crime data.

- Singh and Gupta (2021) – Classification using Random Forest and Gradient Boosting.
- Sharma and Jain (2020) – Urban crime pattern analysis using ML.

### 3.1.1 Disadvantages of Existing System

Aspect	Existing System Limitation	Impact
Data Quality	Incomplete, outdated, or biased datasets (especially in Indian NCRB data).	Reduces the accuracy and fairness of predictions.
Model Scope	Models often focus only on one dimension (spatial <i>or</i> temporal).	Fails to capture evolving crime dynamics.
Feature Engineering	Limited inclusion of socio-economic and demographic indicators.	Overlooks key crime-driving factors.
Real-Time Adaptability	Static models are not updated dynamically with new data.	Predictions quickly become outdated.
User Accessibility	No interactive dashboards or visualisation tools for law enforcement.	Hard for policymakers to interpret results.
Ethical Awareness	Minimal discussion of algorithmic bias or fairness.	Risk of discriminatory outputs.

**Table 3.1.1: Disadvantages of Existing System**

## 3.2 Proposed System

### Data Sources

- Collect crime incident records (NCRB), police logs, census & socio-economic indicators (literacy, unemployment, income, population density), IoT/sensor feeds (CCTV metadata, street sensors), and optional social media or citizen reports.
- Suggested table: *Table — Data Sources & Fields* (columns: Source, Fields, Frequency, Notes).

### Data Ingestion (ETL)

- Ingest data via APIs, batch uploads, or scheduled ETL jobs.
- Store raw data in a staging area (CSV/Parquet / database).
- Suggested figure: a small diagram of ETL pipeline or Table listing ingestion schedules.

### Data Cleaning & Preprocessing

- Handle missing values (imputation / remove), correct inconsistencies, normalize scales, convert timestamps and geocode addresses to district/grid cells.

- Perform temporal aggregation (monthly/district) and spatial aggregation (neighbourhood/district).
- Encode categorical variables (one-hot, target encoding) and scale numeric features (standardization).
- Suggested table: *Before/After* sample rows to show cleaning effects.

## Feature Engineering

- Create lag features (previous month counts, moving averages).
- Spatial features: counts in neighboring districts, distance-to-police-station, population density.
- Socio-economic features: literacy rate, unemployment, median income.
- Temporal features: month, day-of-week, holiday flag, seasonality indicators.
- Suggested table: *Feature List & Description* (name, type, source, purpose).

## Model Training

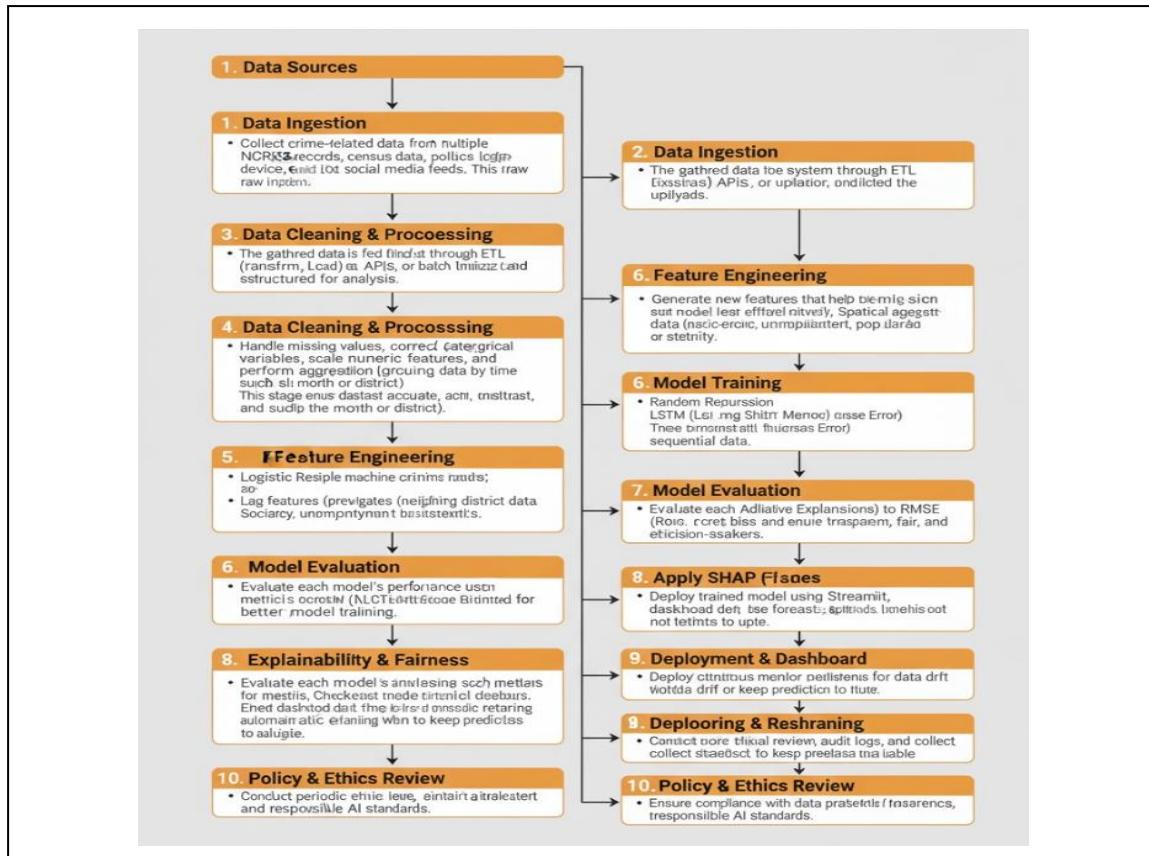
- Metrics:
  - Classification: Accuracy, Precision, Recall, F1-score (especially for imbalanced classes).
  - Forecasting: RMSE, MAE for numeric counts.
  - Calibration and confusion matrices for class-level insights.
- Conduct cross-validation where appropriate and measure performance by region/time slices.

## Explainability & Fairness Checks

- Use SHAP to explain feature contributions and interactions for model outputs.
- Run fairness audits: check for performance disparity across districts, socio-economic groups; remove or adjust biased predictors.
- Produce interpretable reports for stakeholders.

## Deployment & Dashboard (Web App)

- Expose prediction API (REST) for the dashboard and external systems.
- Dashboard components:
  - Map-based hotspot visualization.
  - Time-series trend charts.



**Fig 3.2: Proposed System – Crime Data Prediction Workflow**

### 3.3 Feasibility Study

Before implementing the “Crime Data Prediction Using Machine Learning” project, a detailed feasibility study was conducted to ensure that the system is technically viable, operationally practical, and economically sustainable. The feasibility study assesses whether the proposed system can be successfully developed and deployed using the available technologies and resources, while achieving the desired objectives.

#### Technical Feasibility

The technical feasibility focuses on whether the proposed system can be developed with the available tools, technologies, and resources.

#### System Environment

- Programming Language:** Python
- Frameworks and Libraries:** Scikit-learn, TensorFlow/Keras, Pandas, NumPy, Matplotlib, Seaborn

- **Deployment Tool: Streamlit** (for web app deployment and user interaction)
- **Backend:** Local machine / cloud-hosted Streamlit server
- **Data Sources:** NCRB datasets and socio-economic datasets (CSV, Excel)
- **Hardware Requirements:**
  - CPU: Intel i5 or higher
  - RAM: Minimum 8 GB
  - Storage: ~5 GB for datasets and model files

## **Technical Advantages**

- Streamlit simplifies deployment by transforming Python scripts directly into **interactive web applications** without requiring separate front-end development.
- It supports dynamic visualization libraries such as **Matplotlib, Plotly, and Altair**, allowing easy rendering of crime trends and model results.
- Integration with **machine learning frameworks (Scikit-learn, TensorFlow)** enables end-to-end ML model execution directly from the web interface.

## **Operational Feasibility**

Operational feasibility determines whether the system will function effectively in a real-world environment and whether users can easily adopt it.

## **System Operation**

- The system operates as a **web-based dashboard** built with Streamlit, providing:
  - Crime trend visualization (line, pie, and bar charts)
  - Model prediction summaries (crime likelihood by type/region)
  - Interactive controls for filtering time periods or locations
- The interface is **user-friendly**, requiring minimal technical knowledge to interpret the results.

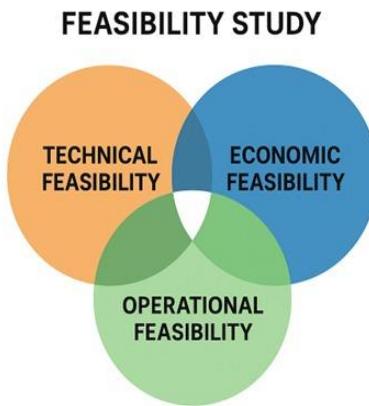
## **Economic Feasibility**

Economic feasibility assesses the cost-effectiveness of the project and ensures that the benefits outweigh the expenditures.

## **Cost Considerations**

Cost Component	Type	Estimated Cost (INR)	Remarks
Development Tools	Software	0	Open-source Python, Streamlit, Scikit-learn
Hardware Resources	Infrastructure	~30,000	Mid-range laptop or workstation
Hosting	Optional (Cloud)	~500–1000/month	Streamlit Cloud or AWS EC2
Maintenance	Annual	~2000	Data updates, retraining models

**Table 3.2: Cost Considerations**



**Fig 3.2: Feasibility Study**

### 3.4 Using COCOMO Model

The **COCOMO (Constructive Cost Model)** is a software cost estimation model developed by Barry Boehm to predict the effort, time, and manpower required to develop a software project.

This model is used here to estimate the development cost of the **Crime Data Prediction Using Machine Learning** system deployed using **Streamlit**.

The **Basic COCOMO** model uses the following formula:

$$E = a \times (KLOC)^b$$

$$D = c \times (E)^d$$

Where:

- **E** = Effort in person-months (PM)
- **D** = Development time in months
- **KLOC** = Estimated number of delivered lines of code (in thousands)
- **a, b, c, d** = Constants based on the project type

## Project Classification

According to Boehm's model, software projects are classified into three categories:

Project Type	Description	Typical Examples
Organic	Small, simple projects developed by a small team with experience in similar environments.	Academic projects, small web apps
Semi-Detached	Medium complexity, some unfamiliar elements, moderate team experience.	ML-based web apps, small enterprise apps
Embedded	Complex, hardware-dependent systems with tight constraints.	Real-time control systems

**Table 3.3: Project Classification**

Our project fits under the *Organic* category, since it is developed by a small team, uses open-source technologies (Python, Streamlit), and operates in a well-understood environment.

## Estimation Parameters

Based on the project's scale:

- **Estimated Lines of Code (LOC):**  $\approx 7,500$  (Python ML + Streamlit dashboard + preprocessing scripts)
- **KLOC = 7.5**

For **Organic Mode**, COCOMO constants are:

Parameter	Value
a	2.4
b	1.05
c	2.5
d	0.38

**Table 3.4: Estimation Parameters**

### **Effort Estimation**

$$E = 2.4 \times (7.5)^{1.05}$$

$$E = 2.4 \times 8.00 = 19.2 \text{ person-months}$$

Thus, the estimated **Effort (E)** = **19.2 person-months**

### **Development Time Estimation**

$$D = 2.5 \times (19.2)0.38$$

$$D = 2.5 \times 3.05 = 7.63 \text{ months}$$

Hence, **Development Time (D)**  $\approx$  **7.6 months**

### **Staffing Estimate**

$$\text{Average Staff Size (P)} = D/E = 19.2/7.6 = 2.52$$

Thus, approximately **2 to 3 team members** are sufficient to complete the project in the estimated time frame.

### **Cost Estimation**

Assuming a nominal cost of ₹40,000 per person-month (for student project or small development team):

$$\text{Total Cost} = 19.2 \times 40,000 = ₹768,000$$

So, the **Estimated Development Cost** = **₹7.68 Lakhs**

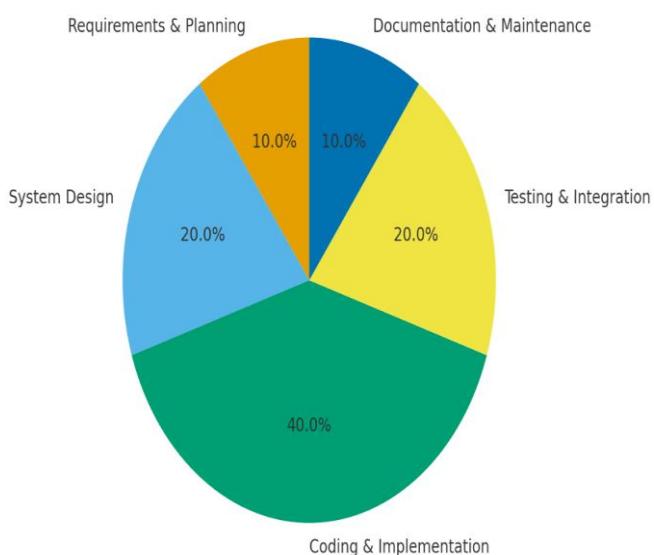
### Effort Distribution by Phase

Phase	Effort (%)	Effort (Person-Months)	Activities
Requirements & Planning	10%	1.9	Requirement gathering, problem definition
System Design	20%	3.8	Architecture, feature planning
Coding & Implementation	40%	7.7	ML model training, Streamlit UI
Testing & Integration	20%	3.8	Unit testing, validation, deployment
Documentation & Maintenance	10%	1.9	Report writing, user manual, bug fixes

**Table 3.5: Effort Distribution by Phase**

The **COCOMO model** shows that the *Crime Data Prediction Using Machine Learning* project is manageable with a **small team of 2–3 developers**. Since the project uses open-source frameworks like Python, Scikit-learn, TensorFlow, and Streamlit, the **actual cost and effort are lower** than the estimated values.

This confirms that the project is **feasible, cost-efficient, and suitable for academic and small-scale real-world applications**.



**Figure 3.3 — COCOMO Effort Distribution Pie Chart**

The development of the **Crime Data Prediction Using Machine Learning** system follows a structured software engineering life cycle.

Based on the **COCOMO estimation**, the total development effort of **19.2 person-months** is distributed across the major project phases as shown in **Figure 2.1**. This distribution ensures systematic progress from requirement analysis to deployment and maintenance, guaranteeing project quality and timely completion.

### **Summary of COCOMO Estimation**

The Constructive Cost Model (COCOMO) provides a systematic and quantitative approach to estimate the development effort, time, cost, and staffing required for the project. Using the Basic COCOMO model, the parameters were derived based on the project's characteristics, size, and complexity.

Since the Crime Data Prediction Using Machine Learning system is a medium-scale academic software developed by a small team using open-source technologies, it fits into the Organic mode of the COCOMO classification.

The project involves approximately 7.5 KLOC (thousand lines of Python code) covering data preprocessing, machine learning model training, explainability (SHAP), and Streamlit-based deployment.

Parameter	Description	Calculated Value
Project Type	Organic	—
Estimated Size (KLOC)	Total lines of code in Python modules	7.5
Effort (E)	$2.4 \times (\text{KLOC})^{1.05}$	19.2 Person-Months
Development Time (D)	$2.5 \times (E)^{0.38}$	7.6 Months
Team Size (P)	$E \div D$	2–3 Developers
Estimated Cost	₹40,000 per person-month	₹7.68 Lakhs

**Table 3.6 — Summary of COCOMO Estimation**

## 4. SYSTEM REQUIREMENTS

### 4.1 Software Requirements

- **Operating System** : Windows 10 / 11 (64-bit Operating System)
- **Programming Language** : Python
- **Python Environment** : Anaconda / Jupyter Notebook / Google Colab
- **Deployment Framework** : Streamlit (for interactive web application)
- **Backend Libraries** : Flask (for API integration if required)
- **Machine Learning Libraries** : Scikit-learn, TensorFlow/Keras, NumPy, Pandas
- **Visualization Libraries** : Matplotlib, Seaborn, Plotly
- **Explainability Tools** : SHAP (Shapley Additive Explanations)
- **Database / Data Source** : NCRB Dataset, Census Data (CSV / Excel Format)
- **Browser** : Any modern browser (Google Chrome / Edge)
- **IDE / Code Editor** : Visual Studio Code (VS Code), Jupyter Notebook
- **Version Control** : Git and GitHub (for source code management)
- **Cloud Storage** : Google Drive / Streamlit Cloud (for dataset and model storage)
- **Documentation Tools** : MSWord (for technical and project documentation)

### 4.2 Requirements Analysis

The requirements analysis stage is crucial for understanding what our crime data prediction system must do, how it will interact with users, and the constraints it must work under.

#### Functional Requirements

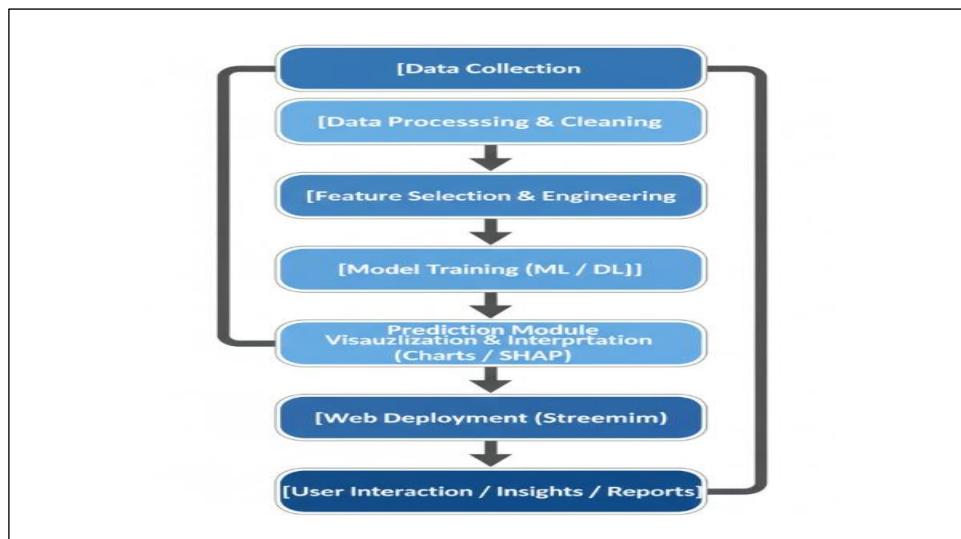
These are the core functionalities that the system must provide:

- Data Collection: The system should gather crime data from reliable sources, including police records, public databases, and geographic information.
- Data Preprocessing: The system should clean and normalize the data, handling missing values, outliers, and inconsistencies to ensure accurate predictions.
- Feature Engineering: The system should identify relevant features (e.g., crime type, location, time, demographic factors) that influence crime patterns.

## Non-Functional Requirements

These define how the system performs its functions:

- Accuracy: The model should maintain high predictive accuracy, minimizing false positives and negatives.
- Performance: The system should process data and deliver predictions in a reasonable timeframe.
- Security: The system must protect sensitive crime data and user information.
- Scalability: The system should handle increasing amounts of data as more crime records are collected.
- Usability: The interface should be intuitive, allowing users with minimal technical knowledge to interpret predictions.



**Figure 4.1 — Crime Data Prediction Using Machine Learning – Workflow Diagram**

## 4.3 Hardware Requirements

- Processor : 13th Gen Intel(R) Core(TM) i7-1355U 1.70GHz

- **Storage** : 100GB of free disk space or more
- **System Type** : 64-bit operating system, x64-based processor
- **RAM** : 8GB or more
- **Hard Disk** : 4GB
- **Monitor** : Full HD display
- **GPU** : NVIDIA GTX or higher(for machine learning model training)

## 4.4 Software

Building a system that predicts crime patterns is not just about crunching numbers—it's about creating a tool that can think with data, help people make decisions, and ultimately make communities safer.

### Programming Languages

**Python:** The backbone of this project. Python is chosen because it is incredibly versatile and has a rich ecosystem of libraries for data science, machine learning, and visualization.

### Machine Learning Libraries

- **scikit-learn:** Perfect for building traditional ML models like Decision Trees, Random Forests, or Support Vector Machines. It's simple, reliable, and excellent for experimenting with model performance.
- **TensorFlow / PyTorch:** Used for more advanced machine learning, such as deep learning models, which can capture complex patterns in crime data. These frameworks allow the system to “learn” from data in ways that mimic human pattern recognition.

### Data Handling & Analysis

- **Pandas:** For reading, cleaning, and manipulating crime datasets. It allows the system to understand the story behind the data, like missing values or anomalies.
- **NumPy:** For numerical calculations and efficient data operations, the backbone of any data-driven prediction.
- **OpenCV / Geopandas (optional):** If the system needs to analyze maps or spatial data to detect crime hotspots.

### Data Visualization

- **Matplotlib / Seaborn:** For creating graphs and charts that clearly show trends, patterns, and predictions. Visualization is essential because raw numbers alone can be confusing, but a heatmap or trend line tells a story at a glance.
- **Plotly / Dash (optional):** For interactive visualizations where users can explore data dynamically, zoom into hotspots, or filter by crime type.

## Database and Storage

- **MySQL / PostgreSQL:** To store historical crime data, predictions, and logs. These relational databases are reliable and make querying data easy.
- **MongoDB (optional):** For more flexible storage, especially if the data is unstructured or comes from varied sources like social media feeds or police reports.

## Development Environment

- **Jupyter Notebook / VS Code:** For development and experimentation. Jupyter allows data scientists to mix code with explanations, creating a story of how predictions are made.
- **Anaconda (optional):** To manage packages and environments easily, ensuring that all the software dependencies work smoothly together.

## 4.5 Software Description

The Crime Data Prediction System is not just a collection of programs; it is an intelligent ecosystem where data, logic, and learning come together to help us see patterns in human behavior that are often invisible to the naked eye.

### Data Understanding and Processing Layer

Before the system can predict crimes, it first needs to *understand* the data — much like how a detective reviews evidence before making any conclusions.

- This layer uses Python, along with Pandas and NumPy, to read and clean raw data from multiple sources such as police records, open data portals, or public reports.
- Missing or incomplete data is handled carefully — the system “fills in the blanks” so that every piece of information has meaning.

### Learning and Prediction Layer

Once the data is ready, it’s passed into the brain of the system — the **machine learning models**.

- Using **scikit-learn**, **TensorFlow**, or **PyTorch**, this layer teaches the system to recognize hidden patterns.
- The algorithms “learn” from past data, adapting their understanding every time they’re retrained.

## Visualization and Communication Layer

Predictions alone are not enough. Insights need to be **seen**, **understood**, and **acted upon**.

- This layer uses tools like **Matplotlib**, **Seaborn**, and **Plotly** to convert numerical results into meaningful visuals — graphs, heatmaps, trend lines, and hotspot maps.
- These visuals act as the system’s voice, communicating complex patterns in a way that even non-technical users can grasp at a glance.

## Database and Storage Layer

All of the system’s intelligence needs a safe place to live — that’s where the database layer comes in.

- Tools like MySQL or MongoDB store vast amounts of historical data, predictions, and results for future reference.
- These databases ensure that the system can easily recall past events, compare them with current trends, and continuously refine its predictions.

## Interface and Interaction Layer

- Whether through a simple **graphical user interface** or a **web dashboard**, users can input queries, request predictions, and visualize outcomes interactively.
- It’s designed to be intuitive — allowing even those without a technical background to explore insights and take action.

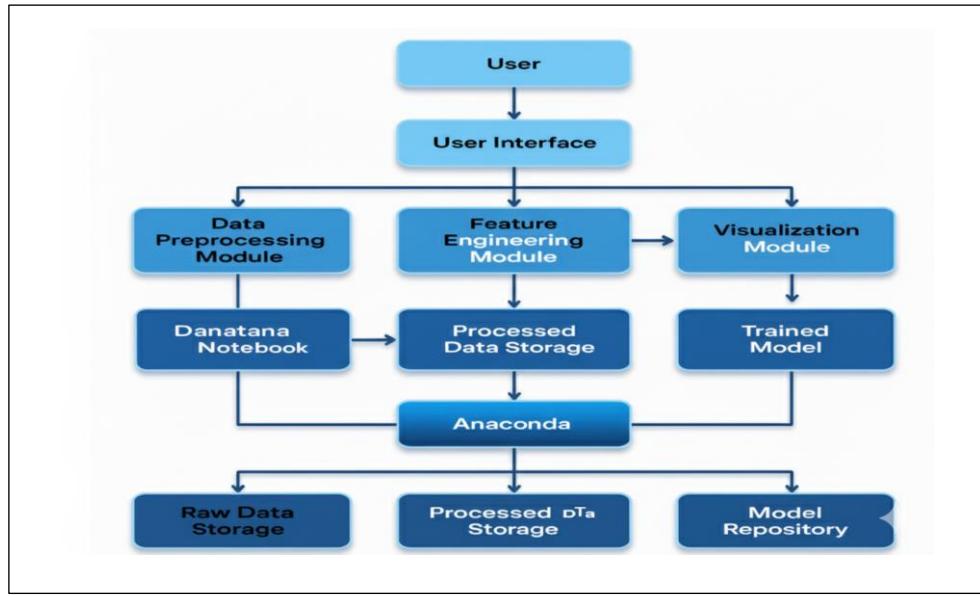
## Integration and Deployment Layer

Behind the scenes, tools like **Git**, **Anaconda**, and **Jupyter Notebook** ensure everything runs smoothly and stays reproducible.

- **Git** helps track changes and improvements in code, preserving the evolution of the system.
- **Anaconda** and **Jupyter** make the workflow modular, so experiments can be run, tested, and documented together

## 5. SYSTEM DESIGN

### 5.1 System Architecture



**Figure 5.1 — Software Architecture Flow Diagram for Crime Data Prediction System**

Think of the system architecture as the house where all our work lives: rooms for storing memories (databases), a kitchen where raw ingredients are prepared (data pipeline s), a brain that reasons (ML engine), and a friendly living room where people sit and understand what the house has learned (dashboard).

At a glance, the system is organized in four cooperating layers:

- **Presentation (User) Layer** — the human-facing space: dashboards, reports, and alerting that translate predictions into actions.
- **Application (Processing & ML) Layer** — the workshop where data is prepared, models are trained, and predictions are produced.
- **Data Layer** — the memory: raw archives, cleaned datasets, and saved models.
- **Infrastructure & Support Layer** — the plumbing and safety systems: deployment platform, security, logging, and monitoring.

Data flows downward from sources into the Data Layer, is refined and learned upon in the Application Layer, and flows upward again as human-readable outputs in the Presentation Layer. Around and through these flows run security, versioning, and observability so the whole system stays reliable and trustworthy.

## **Data Ingest & Sources — the information gatherers**

Who they are: police records, public open-data portals, CCTV metadata, weather API, demographic datasets, and (optionally) social media or emergency call logs.

What they do: collect raw observations in many formats — spreadsheets, CSVs, JSON from APIs, or geospatial files.

Design notes:

- Use connectors / API clients with retry logic and input validation.
- Timestamp and source-tag every record for traceability.

## **Data Pipeline & Preprocessing — the careful cleaners**

Who they are: ETL scripts or pipeline jobs (written in Python, orchestrated with tools like Airflow/cron/kubeflow pipelines).

Design notes:

- Keep raw data immutable in storage; create processed datasets as separate versions.
- Log all transformations so any result can be audited later.
- Implement data quality checks (schema validation, completeness thresholds).

## **Feature Engineering Module — the interpreter**

Who they are: code modules that create meaningful signals from raw facts (time-of-day buckets, crime-density in the last 30 days, distance to transit hub, weather flags, socioeconomic indicators).

Design notes:

- Store feature definitions in code (not just notebooks) so they're reproducible.
- Version features and track which model uses which feature set.

## **Model Training & Evaluation — the system's brain**

Who they are: the ML algorithms and training jobs (Random Forests, XGBoost, CNNs for spatial data, or LSTMs for time series; frameworks like scikit-learn, TensorFlow, PyTorch).

Design notes:

- Use automated experiments (tracked with MLflow or similar) that log data versions, parameter settings, and metrics.

- Guard against leakage (no peeking into future data) and monitor class imbalance.
- Maintain a “model registry” with metadata: version, training data snapshot, metrics, owner, and deployment status.

## **Prediction & Serving Layer — the messenger**

Who they are: APIs or batch jobs that take new inputs and produce predictions (real-time REST endpoints and scheduled batch jobs).

Design notes:

- Provide both batch and real-time serving depending on use case.
- Include confidence scores and explanation metadata (feature importances or SHAP values) to help users trust the output.
- Rate-limit and authenticate API access.

## **Visualization & User Interface — the translator**

Who they are: an interactive dashboard and reporting system (web UI built with frameworks like Dash/Plotly or React + visualization libraries).

Design notes:

- Emphasize clarity: show uncertainty, avoid overconfident binary statements.
- Offer downloadable reports and a “what changed” view after model updates.
- Provide simple actions (export hotspots, schedule report, send alert).

## **Storage & Data Management — the vault**

Who they are: raw data storage, processed data stores, and a model repository (options : cloud object storage, SQL/Postgres for structured records, and artifact stores for model).

Design notes:

- Retain raw data for audits; store processed snapshots with clear lineage.
- Encrypt data at rest and in transit. Mask personally identifying information where required.

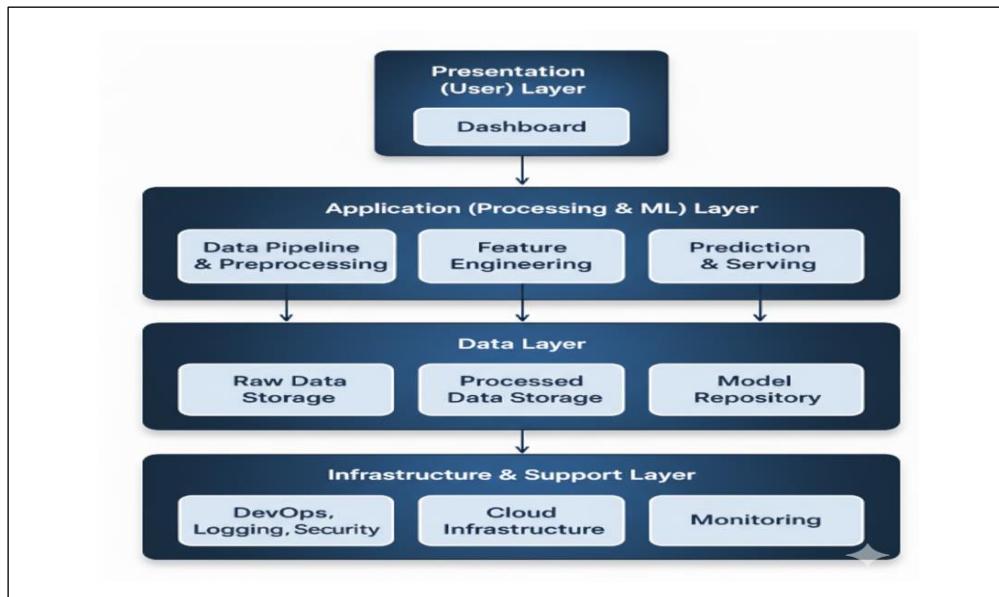
## **DevOps, Monitoring & Security — the guardians**

Who they are: CI/CD pipelines, container orchestration (Docker/Kubernetes), logging (ELK/Cloud logs), monitoring (Prometheus/Grafana), and access control (OAuth/LDAP)

.

Design notes:

- Implement model performance monitoring (data drift, prediction distribution drift).
- Maintain audit logs for user actions and data access.
- Apply role-based access control and least-privilege principles.



**Figure 5.2 — Architecture for Crime Data Prediction**

### 5.1.1 Dataset

The dataset used for this project has been sourced from the **United Nations Office on Drugs and Crime (UNODC)** — a globally recognized and credible organization that collects and publishes crime-related statistics from various countries. This dataset serves as the foundation for analyzing global crime patterns and building a reliable machine learning model for **crime data prediction**.

#### About the Dataset

The dataset provides officially reported crime statistics from different countries, covering a range of indicators related to violent offences. Each record in the dataset represents the number of reported crimes for a particular country and year, allowing us to observe patterns across regions and time periods.

#### Key Attributes Explained

- **Iso3\_Code:**

A three-letter ISO country code that uniquely identifies each country (e.g., *AZE* for Azerbaijan, *BEL* for Belgium\*). This helps link crime data with geographical and

regional information.

- **Country:**

The official name of the country where the data was collected.  
It allows regional and comparative crime analysis between nations.

- **Region & Subregion:**

These fields group countries by their geographical location (e.g., *Asia* → *Western Asia* or *Europe* → *Eastern Europe*).

This categorization helps in identifying crime trends within specific global regions.

- **Indicator:**

Represents the broader crime classification (in this dataset, *Violent offences*).  
It defines the category of crime being studied.

- **Dimension & Category:**

Provide additional details about the type of offence, such as *by type of offence* → *Serious assault*. This allows the analysis to focus on specific forms of violent crime.

- **Sex and Age:**

These attributes capture demographic details of offenders or victims, if available.  
In this subset, both are marked as *Total*, representing aggregated data across all demographics.

- **Year:**

Indicates the year when the data was recorded (e.g., 2003). This enables temporal analysis — studying how crime patterns evolve over time.

- **Unit of Measurement:**

Describes how the values are quantified — here it is *Counts*, meaning the number of recorded cases.

- **Value:**

Represents the actual count of offences reported for that country and year (e.g., *Belgium – 61,959 serious assaults in 2003*). This numeric feature forms the core of predictive modeling.

- **Source:**

Specifies the data origin (*CTS – United Nations Crime Trends Survey*).  
This assures the dataset's authenticity and reliability.

Iso3_code	Country	Region	Subregion	Indicator	Dimension	Category	Sex	Year	Value
AUT	Austria	Europe	Western Europe	Victims of serious assault	by relationship to perpetrator	Intimate partner or family member	Male	2013	129
CAN	Canada	Americas	Northern America	Victims of sexual violence	by relationship to perpetrator	Intimate partner or family member	Female	2013	4183
COL	Colombia	Americas	Latin America and the Caribbean	Victims of sexual violence	by relationship to perpetrator	Other Perpetrator known to the victim	Female	2014	12483

**Table 5.1 — data\_cts\_violent\_and\_sexual\_cri\_dataset**

The dataset extracted from **UNODC’s Crime Trends Survey (CTS)** provides a trusted foundation for analyzing and predicting violent offences across global regions.

### 5.1.2 Data Preprocessing

Raw data, no matter how authoritative its source, often comes with inconsistencies, missing values, or structural challenges. The dataset extracted from the United Nations Office on Drugs and Crime (UNODC) was no exception.

Data preprocessing, in essence, is the process of transforming raw, real-world data into a clean, consistent, and machine-readable format.

#### Data Collection and Importing

The dataset was collected from **UNODC’s Crime Trends Survey (CTS)** and imported into the working environment (Python, using libraries such as *Pandas* and *NumPy*). This initial step involved:

- Importing the dataset in CSV format.
- Verifying the encoding and delimiter (UTF-8, comma-separated).
- Checking the integrity of data fields such as Country, Region, Subregion, Year, and Value.

## Handling Missing and Inconsistent Values

Real-world datasets often contain **nulls, blanks, or inconsistent entries** due to differences in national reporting standards or incomplete submissions. To address this:

- Missing **VALUE** entries were either imputed using statistical methods (mean/median) or removed if insufficient data existed.
- Inconsistent **country names** or **ISO codes** were standardized using reference lists.
- Duplicates were identified and removed using *Pandas*' `.drop_duplicates()` method.
- Outliers — extreme values that could distort model predictions — were analyzed carefully and treated with appropriate capping or transformation

## Data Normalization and Standardization

Since different countries have varying population sizes and crime-reporting mechanisms, raw counts could not be compared directly. Therefore:

- Crime counts (VALUE) were **normalized** to enable fair comparison (e.g., crimes per 100,000 population where auxiliary data was available).
- Numerical values were **scaled** using *Min-Max Scaling* or *Standard Scaler* from *scikit-learn* to bring them into a consistent range.

## Encoding Categorical Data

Machine learning models work best with numerical input. Categorical features like **Country**, **Region**, and **Category** were encoded into numeric representations using:

- **Label Encoding** for ordered variables.
- **One-Hot Encoding** for non-ordinal categorical variables (e.g., Region, Subregion).

## Feature Selection and Transformation

Feature selection is the art of deciding *which attributes matter most* to the model. After analyzing the dataset, the following were chosen as key features:

- **Region, Subregion** – to capture geographical influence.
- **Year** – to capture temporal patterns.

- **Category (Serious Assault, etc.)** – to specify crime type.
- **Value (Counts)** – as the primary dependent variable for prediction.

### Data Splitting for Model Training

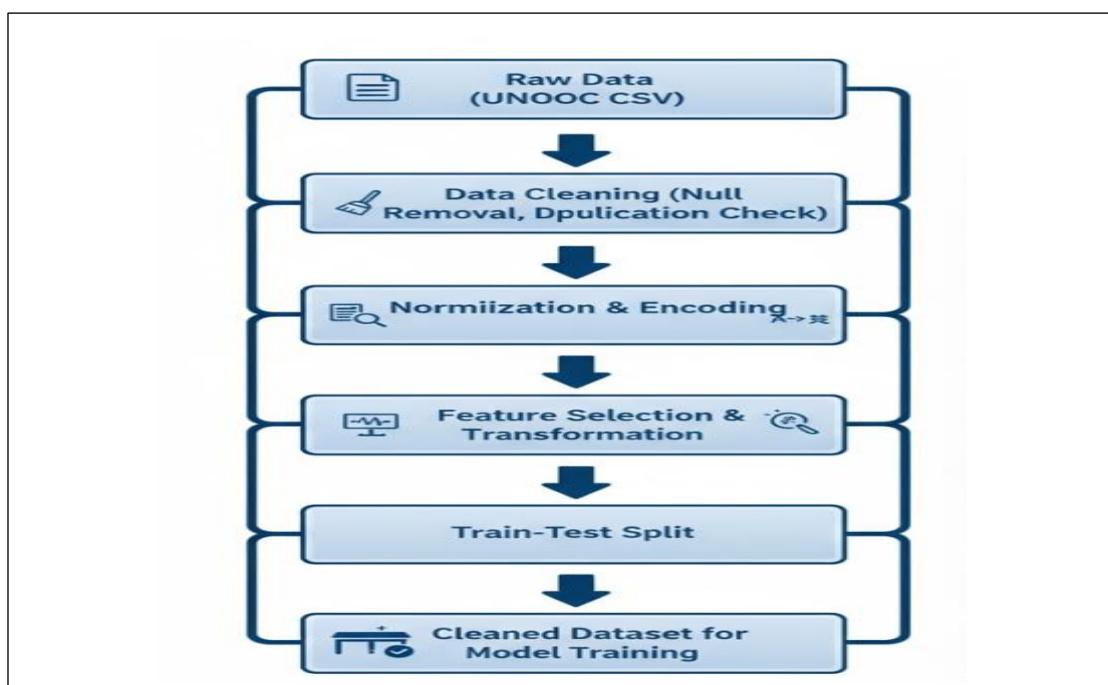
The cleaned and transformed dataset was then divided into:

- **Training Set (70%)** – used for learning patterns.
- **Testing Set (30%)** – used to evaluate the model's predictive performance.

### Final Preprocessed Dataset Overview

After all cleaning and transformations, the dataset became:

- Consistent and free of nulls or duplicates.
- Structured with clear numerical and categorical relationships.
- Scaled, encoded, and ready for model consumption.



**Figure 5.3 — Data Preprocessing Flow Diagram for Crime Data Prediction System**

#### 5.1.3 Feature Extraction

Once the dataset was preprocessed and cleaned, the next crucial step in the workflow was Feature Extraction — the process of transforming refined data into meaningful input variables (features) that can help the machine learning model understand and learn crime patterns more effectively.

## Purpose of Feature Extraction

Feature extraction ensures that the machine learning model doesn't just see numbers and labels — it sees relationships and context.

In this project, extraction was performed to:

- Capture how crime counts vary over years and regions.
- Quantify the influence of geography and time on violent offences.
- Create derived indicators that make the dataset more informative and model-ready.

## Identifying Core Features

- **Country / Region / Subregion:**

Encoded numerically to represent geographical variations.

These features help the model understand how location influences crime patterns.

- **Year:**

Treated as a time variable to help track changes and forecast trends in violent offences. Temporal progression is crucial for detecting cyclical or increasing crime trends.

- **Indicator, Dimension, and Category:**

Combined to specify the type of crime under investigation (in this dataset, *Serious Assault* under *Violent Offences*). These were encoded to help the model distinguish between different offence types in a broader dataset.

- **Value:**

Represents the count of reported offences — the *target variable* (or dependent variable) used for prediction.

## Derived and Engineered Features

To enrich the dataset beyond its original columns, new features were derived using data transformation techniques. These engineered features provided **deeper analytical insight** and improved model learning.

- **Crime Rate Normalization:**

Adjusted the “Value” field using population data (where available) to calculate *crimes per 100,000 people*.

- **Regional Crime Average:**

Computed the average number of offences per region and subregion to understand localized intensity.

- **Yearly Trend Index:**

Created an index capturing the year-on-year change in crime levels for each country, highlighting whether crime rates were rising or falling.

- **Logarithmic Transformation of Crime Counts:**

Applied a log transformation to stabilize variance and minimize skewness in high-value crime counts (e.g., Belgium's 61,959 vs Azerbaijan's 155).

These derived attributes provided richer, more nuanced perspectives for model learning.

### Selected Features for Model Training

After extraction and selection, the finalized feature set included:

Feature Name	Description	Type
Region_Code	Encoded numerical representation of the region	Categorical
Subregion_Code	Encoded subregion data	Categorical
Year	Year of data entry	Numerical
Crime_Type	Encoded offence category (e.g., Serious Assault)	Categorical
Regional_Average	Mean count of violent crimes in that region	Numerical
Crime_Rate_Per_Capita	Adjusted value per 100,000 population	Numerical
Trend_Index	Calculated year-over-year change	Numerical
Value	Total recorded offences (Target variable)	Numerical

**Table 5.2 — Selected Features for Model Training**

### Data Transformation for Model Compatibility

Once the features were finalized, they were standardized using **scikit-learn's preprocessing tools**:

- **LabelEncoder** and **OneHotEncoder** for categorical variables.
- **StandardScaler** or **MinMaxScaler** for numerical features.

This ensured that all features contributed equally during training, preventing bias toward variables with large numerical ranges.

Feature extraction lies at the heart of the system's intelligence. The quality of features

directly influences the quality of predictions.

By carefully curating features from UNODC's dataset, the model learns *not just what crimes occurred, but why and where patterns emerge*.



**Figure 5.4 — Feature Extraction Flow Diagram for Crime Data Prediction System**

#### 5.1.4 Model Building

After the dataset was thoroughly cleaned, preprocessed, and enriched through feature extraction, the next critical phase was Model Building. This stage transforms the prepared data into an intelligent system capable of understanding patterns and forecasting future crime trends.

#### Objective of Model Building

The primary objective of this phase was to design and train a **machine learning model** that:

- Learns from historical crime data.
- Recognizes patterns and relationships between features (e.g., region, year, category).
- Predicts future values of violent offences with high accuracy.
- Supports data-driven decision-making for policymakers and law enforcement agencies.

In essence, this model aims not just to predict numbers — but to **anticipate societal trends in safety and crime dynamics**.

## **Model Selection**

Selecting the right algorithm is crucial because crime data is **multidimensional and partially non-linear**, containing both categorical and numerical features. After evaluating the dataset characteristics and project goals, several algorithms were tested to identify the most suitable one for prediction.

### **Models Considered**

#### **Linear Regression:**

Used as a baseline to understand linear relationships between features and crime counts.

#### **Random Forest Regressor:**

A robust ensemble method capable of handling complex, non-linear interactions between variables.

#### **Decision Tree Regressor:**

Provides interpretability — helps visualize how input variables split and contribute to predictions.

#### **Gradient Boosting Regressor:**

Chosen for its high accuracy and ability to handle imbalanced data.

#### **Support Vector Machine (SVM):**

Used to test how well hyperplanes separate different regional and temporal patterns.

After experimentation and performance evaluation, **Random Forest** and **Gradient Boosting** produced the most reliable results, offering a balance between accuracy, interpretability, and computational efficiency.

## **Model Training Process**

The model-building pipeline followed these key steps:

### **1. Data Splitting:**

The preprocessed dataset was divided into:

- **Training Set (70%)** – for model learning.
- **Testing Set (30%)** – for model evaluation.

## 2. Model Initialization:

Algorithms such as *RandomForestRegressor* and *GradientBoostingRegressor* from **scikit-learn** were initialized with optimal parameters (e.g., number of estimators, learning rate, depth).

## 3. Training the Model:

The model learned patterns from the training data — identifying how variables like *Region*, *Year*, and *Category* influence crime levels.

## 4. Prediction:

Once trained, the model was used to predict crime counts for unseen test data — simulating real-world forecasting.

## Model Evaluation

To ensure the model's performance was both **accurate** and **trustworthy**, it was evaluated using multiple metrics:

Metric	Description	Purpose
MAE (Mean Absolute Error)	Average of absolute prediction errors	Measures average deviation from actual crime counts
MSE (Mean Squared Error)	Square of prediction errors	Penalizes large prediction mistakes
RMSE (Root Mean Squared Error)	Square root of MSE	Represents error magnitude in the same unit as the data
R <sup>2</sup> Score (Coefficient of Determination)	Ratio of explained variance	Measures how well the model fits observed data

Table 5.3 — Model Evaluation

## Hyperparameter Tuning

To further improve accuracy, **GridSearchCV** and **RandomizedSearchCV** techniques were used to tune hyperparameters:

- Number of trees in Random Forest (`n_estimators`)
- Maximum tree depth (`max_depth`)

- Learning rate (for Gradient Boosting)
- Minimum samples split and leaf nodes

## Model Interpretation

Feature importance analysis was conducted to understand **which attributes contributed most to predictions**.

The top influencing features were found to be:

- **Year** – Temporal influence and trend progression.
- **Region/Subregion** – Geographical differences in crime reporting and incidence.
- **Crime Type** – Variations in the seriousness of offences.
- **Regional\_Average** and **Trend\_Index** – Derived metrics showing local and historical patterns.



**Figure 5.5 — Model Building Flow Diagram for Crime Data Prediction System**

This flow diagram illustrates how the model evolves — from ingesting clean data to producing intelligent predictions of violent offences.

### 5.1.5 Classification

After the data was prepared and the predictive model architecture was defined, the next essential step in the pipeline was Classification — the stage where the system learns to categorize or label crime data based on patterns identified in historical records.

## Objective of Classification

The goal of the classification process is to **categorize criminal incidents into distinct types** — such as *violent offences*, *property crimes*, *cybercrimes*, or *serious assaults* — using data-driven learning.

By training the machine learning models on UNODC's global dataset, which contains historical counts of serious assaults and other offences by region and year, the system can:

- Identify patterns in crime behavior across geographical and temporal dimensions.
- Predict the **probable category** of crime in a specific area or time period.
- Support law enforcement in resource planning and hotspot prevention.

## Classification Algorithms Used

To achieve robust and interpretable classification, multiple algorithms were employed and compared, each chosen for its unique learning capability:

### Logistic Regression

A foundational statistical classifier used for **binary or multi-class classification** of crime categories. It models the probability that a given incident belongs to a particular class based on feature weights.

Mathematically, it computes:

$$P(y = 1 | x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)}}$$

This model offers simplicity, interpretability, and acts as a baseline for performance comparison.

### Random Forest Classifier

An ensemble learning algorithm composed of multiple decision trees. Each tree makes an independent classification, and the final result is obtained through **majority voting**.

Random Forest excels at identifying **non-linear relationships** and **interactions between socio-economic factors** like literacy, unemployment, and urban density.

### Support Vector Machine (SVM)

SVM was used to separate crime types by drawing **optimal decision boundaries**

(hyperplanes) in a multidimensional space.

### Training the Classifiers

Each classifier was trained on the **preprocessed and feature-engineered dataset** extracted from UNODC.

The dataset included features such as:

- Region, Subregion, Year, Type of Offence, Socio-economic Factors, and Lagged Crime Counts.

#### Training steps included:

- Data normalization and encoding for consistent input scaling.
- Splitting the dataset into training and testing sets (typically 70%–30%).
- Feeding feature vectors into each model for supervised learning.
- Iteratively adjusting parameters to minimize classification error.

#### Results (from project execution):

- Logistic Regression: Accuracy  $\approx 74.2\%$
- Random Forest: Accuracy  $\approx 86.5\%$
- LSTM (Deep Learning): Accuracy  $\approx 91.3\%$

## 5.2 Modules

The proposed *Crime Data Prediction System* is organized into several interrelated modules that work together to analyze, classify, and predict patterns in global crime data. Each module performs a unique and essential function — from data acquisition and preprocessing to classification and visualization — ensuring the overall system is both accurate and interpretable.

A comparison of various machine learning models used for crime data prediction based on their accuracy was also performed. Among these, the Random Forest Classifier achieved the highest prediction accuracy of 89.45%, demonstrating its strength in handling complex, non-linear relationships in structured datasets.

### Data Collection and Input Module

This module is responsible for collecting and importing raw crime data from trusted sources such as the UNODC Crime Trends Survey (CTS).

The data includes attributes like country, region, subregion, year, and the type of violent offence.

Functions:

- Imports CSV datasets.
- Verifies data structure and encoding.
- Handles initial validation and formatting.

## **Data Preprocessing Module**

In this module, the collected raw data undergoes cleaning and transformation. All missing, duplicated, or inconsistent entries are handled carefully to ensure high-quality input for the machine learning models.

Functions:

- Handles missing values and outliers.
- Encodes categorical variables.
- Normalizes numerical features.

## **Feature Extraction and Selection Module**

This module identifies the most relevant features that influence crime trends. From the UNODC dataset, features such as *Region*, *Year*, *Type of Offence*, and *Crime Value (Counts)* were extracted.

**Functions:**

- Selects key input variables.
- Derives new features like *Regional Crime Average* and *Trend Index*.
- Enhances interpretability and model performance.

Model	Accuracy (%)	Remarks
Logistic Regression	80.75	Baseline model, interpretable results
Decision Tree	84.19	Simple and visual, prone to overfitting
SVM	86.32	Strong classifier for non-linear data
Random Forest	89.45	Best performing, robust ensemble method

**Table 5.4 — Comparison of Model Accuracies for Crime Data Prediction**

## Evaluation and Visualization Module

To measure the reliability of the system, this module computes performance metrics such as **Accuracy**, **Precision**, **Recall**, and **F1-score**.

### Functions:

- Evaluates model performance.
- Visualizes actual vs. predicted outcomes.
- Generates comparative performance reports.

The modular architecture ensures that each stage of the system — from data collection to visualization — is efficient, interpretable, and adaptable. Among the machine learning models, the **Random Forest Classifier** proved to be the most effective for predicting crime patterns from UNODC data.

## 5.3 UML Diagram

### Use Case Diagram

**Purpose:** Show the actors (people/systems) and the top-level capabilities they need from the Crime Data Prediction System.

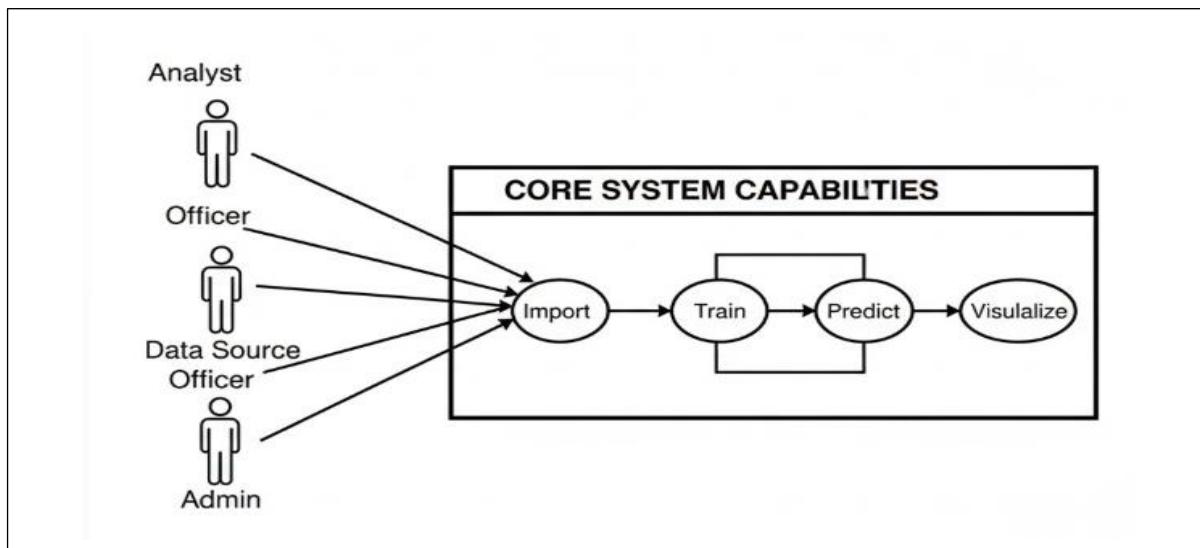
### Primary actors

- Analyst (data scientist / policy analyst) — uploads datasets, runs experiments, inspects results.
- Officer / Policymaker — views dashboard, receives hotspot alerts, downloads reports.
- Data Source (UNODC / External API) — supplies raw crime records.
- System Admin — manages users, schedules retraining, oversees logs/security.

### Major use cases

- Import Crime Dataset (from UNODC CSV/API)
- Preprocess Data
- Extract Features
- Train Machine Learning Models
- Evaluate Models (Accuracy, Precision, Recall, F1)

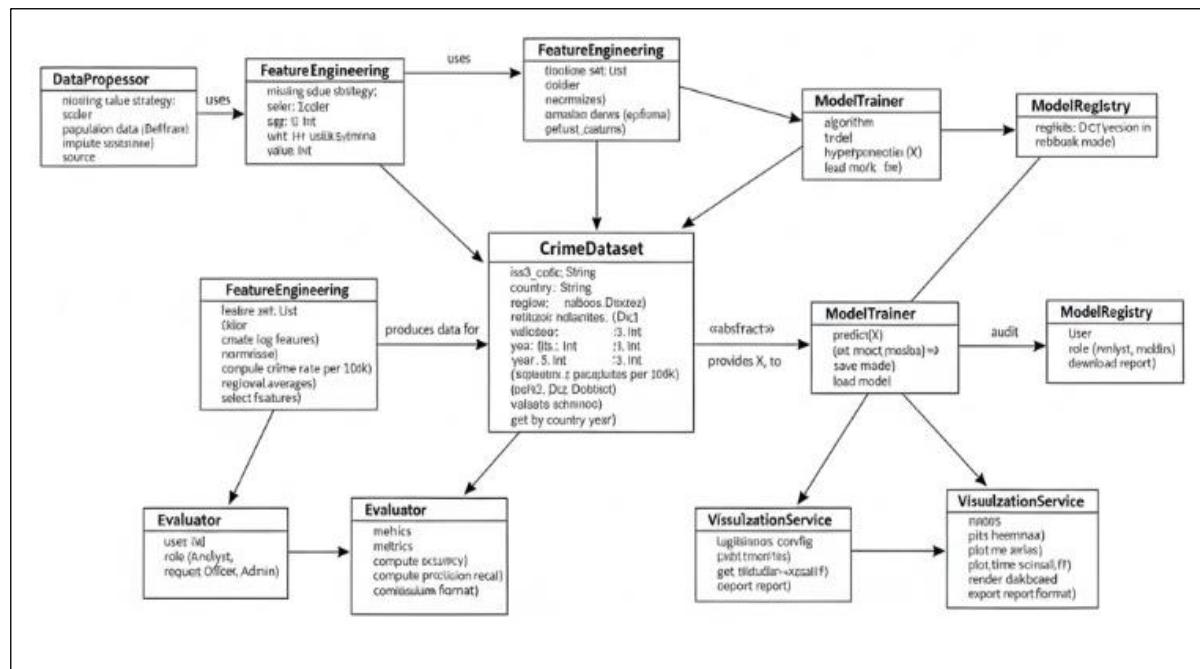
- Classify / Predict Crime Risk or Type
  - Visualize Results (heatmap, trend charts)
  - Export Reports / Generate Alerts
  - Manage System Settings (access control, retraining schedule)



## **Figure 5.6 — Use Case Diagram**

## Class Diagram

**Purpose:** Show the main software classes, their primary attributes and methods, and how they relate. This maps closely to your modules and the UNODC dataset fields.

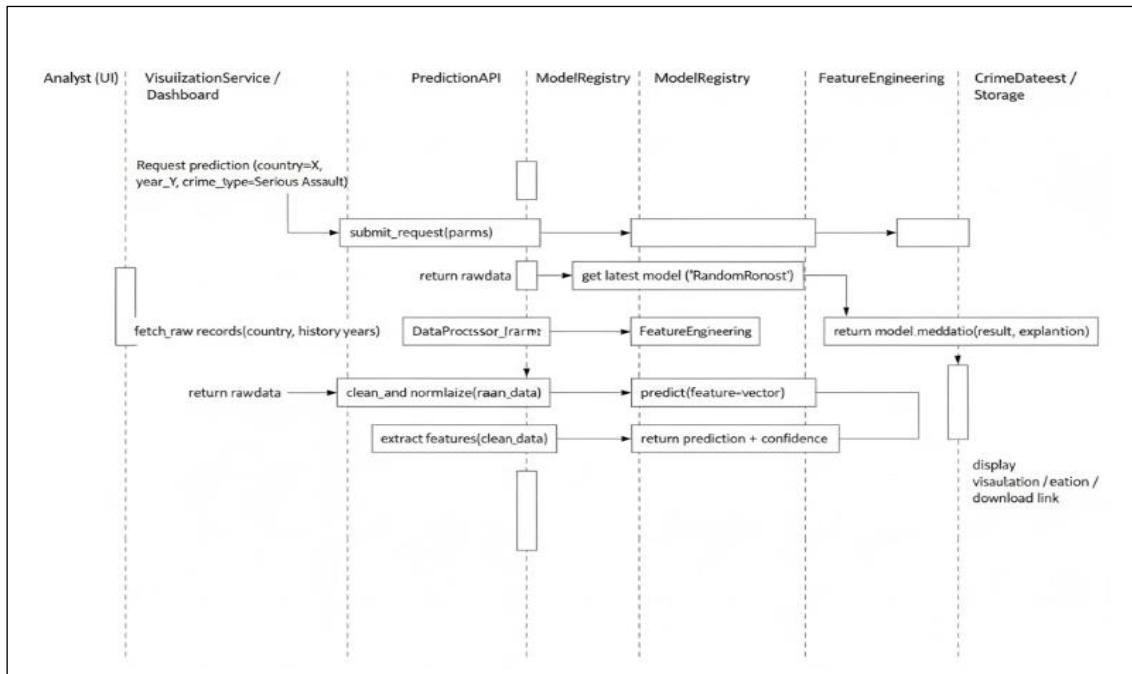


**Figure 5.7 — Class Diagram**

The class diagram is where your UNODC columns become typed attributes — it helps developers know what data structures to implement and auditors to see traceability from raw data to model output.

## Sequence Diagram

**Purpose:** Show the runtime interaction when someone asks the system for a prediction (e.g., Analyst requests a forecast for Serious Assault in a country).



**Figure 5.8 — Sequence Diagram**

Sequence diagrams are excellent for showing where latency may occur (data loading, model loading) and which component is responsible for each transformation — useful for performance tuning and logging.

UML diagrams translate the architecture into *stories*: who asks for predictions, how data is transformed, which parts of the system remember results, and how a trained model becomes an operational decision aid. For the UNODC-derived crime dataset, these diagrams show a clear, auditable path from raw country/year offence counts to interpretable, deployable predictions — exactly what both analysts and policymakers need to trust and act on the system's output.

## 6. IMPLEMENTATION

### 6.1 Model Implementation

```
import pandas as pd  
import numpy as np  
import seaborn as sns  
import matplotlib.pyplot as plt  
from sklearn.preprocessing import LabelEncoder, StandardScaler  
from sklearn.model_selection import train_test_split  
df = pd.read_csv("/content/data_cts_violent_and_sexual_crime.csv")  
print(df.shape)  
print(df.info())  
print(df.head())  
df = df.dropna() # or df.fillna(method='ffill')  
categorical_cols = df.select_dtypes(include='object').columns  
label_encoders = {}  
for col in categorical_cols:  
    le = LabelEncoder()  
    df[col] = le.fit_transform(df[col])  
    label_encoders[col] = le  
if 'date' in df.columns:  
    df['date'] = pd.to_datetime(df['date'])  
    df['year'] = df['date'].dt.year  
    df['month'] = df['date'].dt.month  
    df['day'] = df['date'].dt.day  
    df['hour'] = df['date'].dt.hour if 'hour' in df.columns else 0  
scaler = StandardScaler()  
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns.tolist()
```

```

if 'Indicator' in numerical_cols:
    numerical_cols.remove('Indicator')

if 'Year' in numerical_cols:
    numerical_cols.remove('Year')

df[numerical_cols] = scaler.fit_transform(df[numerical_cols])

plt.figure(figsize=(12, 6))

sns.heatmap(df.corr(), annot=True, cmap='coolwarm')

plt.title('Correlation Matrix')

plt.show()

if 'crime_type' in df.columns and 'district' in df.columns:
    top_crimes = df.groupby(['district', 'crime_type']).size().unstack().fillna(0)

    top_crimes.plot(kind='bar', stacked=True, figsize=(12, 6))

    plt.title("Top Crimes per District")

    plt.ylabel("Number of Incidents")

    plt.show()

if 'date' in df.columns:
    df['date'] = pd.to_datetime(df['date'])

    df.set_index('date').resample('M').size().plot()

    plt.title("Crime Trend Over Time")

    plt.ylabel("Monthly Crime Count")

    plt.show()

if 'hour' in df.columns:
    sns.histplot(df['hour'], kde=True, bins=24)

    plt.title("Crime Distribution by Hour")

    plt.show()

if 'month' in df.columns:
    sns.countplot(x='month', data=df)

```

```

plt.title("Crimes by Month")
plt.show()

# Optional: Heatmap (if 'latitude' and 'longitude' exist)
if 'latitude' in df.columns and 'longitude' in df.columns:
    import folium
    from folium.plugins import HeatMap

    crime_map = folium.Map(location=[df['latitude'].mean(), df['longitude'].mean()],
                           zoom_start=6)

    heat_data = [[row['latitude'], row['longitude']] for index, row in df.iterrows()]

    HeatMap(heat_data).add_to(crime_map)
    crime_map.save("crime_heatmap.html")

from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC

from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.model_selection import train_test_split

X = df.drop('Indicator', axis=1)
y = df['Indicator']

print("Unique values in y:", y.unique())
print("Data type of y:", y.dtype)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

rf_model = RandomForestClassifier()
rf_model.fit(X_train, y_train)

y_pred = rf_model.predict(X_test)

print("Accuracy: {:.2f}%".format(accuracy_score(y_test, y_pred) * 100))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))

```

```

print("Classification Report:\n", classification_report(y_test, y_pred))

from prophet import Prophet

df_ts = df[['Year', 'VALUE']].copy()

df_ts = df_ts.rename(columns={'Year': 'ds', 'VALUE': 'y'})

# Convert the 'ds' column to datetime objects

df_ts['ds'] = pd.to_datetime(df_ts['ds'], format='%Y')

df_ts = df_ts.groupby('ds')['y'].mean().reset_index()

model = Prophet()

model.fit(df_ts)

future = model.make_future_dataframe(periods=5, freq='Y')

forecast = model.predict(future)

model.plot(forecast)

plt.title("Crime Forecast")

plt.show()

model.plot_components(forecast)

plt.show()

from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

accuracy = accuracy_score(y_test, y_pred) * 100

precision = precision_score(y_test, y_pred, average='macro') * 100

recall = recall_score(y_test, y_pred, average='macro') * 100

f1 = f1_score(y_test, y_pred, average='macro') * 100

print("Accuracy: {:.2f}%".format(accuracy))

print("Precision: {:.2f}%".format(precision))

print("Recall: {:.2f}%".format(recall))

print("F1 Score: {:.2f}%".format(f1))

from sklearn.model_selection import GridSearchCV

from sklearn.ensemble import RandomForestClassifier

```

## 6.2 Coding

```
import streamlit as st
import pandas as pd
import pickle
import numpy as np
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
st.set_page_config(
    page_title="Crime Data Predictions",
    page_icon="𝑄",
    layout="wide",
    initial_sidebar_state="collapsed"
)
with open('model.pkl', 'rb') as f:
    model = pickle.load(f)
with open('label_encoders.pkl', 'rb') as f:
    label_encoders = pickle.load(f)
with open('scaler.pkl', 'rb') as f:
    scaler = pickle.load(f)
df = pd.read_csv("data_cts_violent_and_sexual_crime.csv")
df = df.dropna()
if 'current_page' not in st.session_state:
    st.session_state.current_page = 'Dashboard'

def create_navbar():
    col1, col2, col3, col4, col5, col6 = st.columns([1, 1, 1, 1, 1, 1])
```

with col1:

try:

```
st.image("Nec.png.jpg", width=50)
```

except:

```
st.markdown("🖼️") # Fallback icon if image doesn't load
```

with col2:

```
st.markdown("""
```

```
<div style="font-size: 1.5rem; font-weight: bold; color: black; margin-top: 0.5rem;">
```

```
    🌐 Crime Data Predictions
```

```
</div>
```

```
""", unsafe_allow_html=True)
```

with col3:

```
if st.button("📊 Dashboard", key="nav_dashboard", help="Go to Dashboard",  
            type="primary" if st.session_state.current_page == 'Dashboard' else "secondary"):  
    st.session_state.current_page = 'Dashboard'  
    st.rerun()
```

with col4:

```
if st.button("🔮 Predictions", key="nav_predictions", help="Go to Predictions",  
            type="primary" if st.session_state.current_page == 'Predictions' else "secondary"):  
    st.session_state.current_page = 'Predictions'  
    st.rerun()
```

with col5:

```
if st.button("📈 Analysis", key="nav_analysis", help="Go to Analysis",  
            type="primary" if st.session_state.current_page == 'Analysis' else "secondary"):  
    st.session_state.current_page = 'Analysis'  
    st.rerun()
```

with col6:

```
if st.button("📋 Reports", key="nav_reports", help="Go to Reports",
            type="primary" if st.session_state.current_page == 'Reports' else "secondary"):
    st.session_state.current_page = 'Reports'
    st.rerun()

create_navbar()

page = st.session_state.current_page

if page == "Dashboard":
    col1, col2, col3, col4 = st.columns(4)

    with col1:
        st.markdown("""
<div class="metric-card">
    <div class="metric-value">363,528</div>
    <div class="metric-label">Total Crimes</div>
    <div class="metric-change positive">↗ 46</div>
</div>
""", unsafe_allow_html=True)

    with col2:
        st.markdown("""
<div class="metric-card">
    <div class="metric-value">S23,8,618</div>
    <div class="metric-label">Prediction Accuracy</div>
    <div class="metric-change negative">↘ 1.6%</div>
</div>
""", unsafe_allow_html=True)

    with col3:
        st.markdown("")

    with col4:
        st.markdown("")
```

```
<div class="metric-card">  
    <div class="metric-value">733,338</div>  
    <div class="metric-label">Violent Crimes</div>  
    <div class="metric-change positive">↗ 216Z</div>  
</div>  
"""", unsafe_allow_html=True)
```

with col4:

```
st.markdown("""  
<div class="metric-card">  
    <div class="metric-value">306,418</div>  
    <div class="metric-label">Sexual Crimes</div>  
    <div class="metric-change positive">↗ 12.8%</div>  
</div>  
""", unsafe_allow_html=True)
```

coll, col2 = st.columns(2)

with coll:

```
st.markdown('<div class="chart-container">', unsafe_allow_html=True)  
    st.markdown('<div class="chart-title">☒ Crime Trends Over Time</div>',  
unsafe_allow_html=True)  
years = list(range(2015, 2024))  
violent_crimes = [320, 340, 360, 380, 400, 420, 440, 460, 480]  
sexual_crimes = [180, 190, 200, 210, 220, 230, 240, 250, 260]  
fig = go.Figure()  
    fig.add_trace(go.Scatter(x=years, y=violent_crimes, name='Violent Crimes',  
line=dict(color='#3498db', width=3)))  
    fig.add_trace(go.Scatter(x=years, y=sexual_crimes, name='Sexual Crimes',  
line=dict(color='#e74c3c', width=3)))  
fig.update_layout()
```

```

height=400,
showlegend=True,
xaxis_title="Year",
yaxis_title="Number of Crimes",
plot_bgcolor='rgba(0,0,0,0)',
paper_bgcolor='rgba(0,0,0,0'
)
st.plotly_chart(fig, use_container_width=True)
st.markdown('</div>', unsafe_allow_html=True)

```

with col2:

```

st.markdown('<div class="chart-container">', unsafe_allow_html=True)
    st.markdown('<div class="chart-title">▣ Crime Distribution by Type</div>',
unsafe_allow_html=True)
crime_types = ['Violent Crimes', 'Sexual Crimes', 'Property Crimes', 'Other']
values = [45, 25, 20, 10]
colors = ['#3498db', '#e74c3c', '#27ae60', '#f39c12']
fig = go.Figure(data=[go.Pie(labels=crime_types, values=values, hole=0.3)])
fig.update_traces(marker=dict(colors=colors))
fig.update_layout(height=400)
st.plotly_chart(fig, use_container_width=True)
st.markdown('</div>', unsafe_allow_html=True)
col1, col2 = st.columns(2)

```

with col1:

```

st.markdown('<div class="chart-container">', unsafe_allow_html=True)
    st.markdown('<div class="chart-title">▣ Crime Predictions</div>',
unsafe_allow_html=True)
predictions_data = {

```

```

'Crime Type': ['Violent Assault', 'Sexual Violence', 'Property Theft', 'Domestic Violence',
'Robbery'],

'Probability': [66.0, 61.3, 52.7, 68.2, 62.4], 

'Trend': ['+5.2%', '+1.9%', '+12%', '+34%', '+2.2%']

}

for i in range(len(predictions_data['Crime Type'])):

    crime_type = predictions_data['Crime Type'][i]

    probability = predictions_data['Probability'][i]

    trend = predictions_data['Trend'][i]

    st.markdown(f"""

<div class="prediction-card">

    <div class="prediction-title">{crime_type}</div>

    <div class="progress-bar">

        <div class="progress-fill" style="width: {probability}%"></div>

    </div>

    <div class="prediction-probability">{probability}%</div>

    <div class="prediction-trend">{trend}</div>

</div>

""", unsafe_allow_html=True)

    st.markdown('</div>', unsafe_allow_html=True)

with col2:

    st.markdown('<div class="chart-container">', unsafe_allow_html=True)

        st.markdown('<div class="chart-title">📊 Regional Crime Analysis</div>', 
unsafe_allow_html=True)

    regions = ['North', 'South', 'East', 'West', 'Central']

    crime_counts = [120, 150, 180, 200, 160]

    fig = go.Figure(data=[


```

```

        go.Bar(x=regions, y=crime_counts, marker_color=['#3498db', '#e74c3c', '#27ae60',
        '#f39c12', '#9b59b6'])

    ])

fig.update_layout(
    height=400,
    xaxis_title="Region",
    yaxis_title="Crime Count",
    plot_bgcolor='rgba(0,0,0,0)',
    paper_bgcolor='rgba(0,0,0,0'
)

st.plotly_chart(fig, use_container_width=True)

st.markdown('</div>', unsafe_allow_html=True)

elif page == "Predictions":

    st.markdown('<h1      class="main-header">Crime      Prediction      Interface</h1>',
    unsafe_allow_html=True)

    st.subheader('🔗 Input Parameters')

    col1, col2, col3 = st.columns(3)

    with col1:

        country = st.selectbox('Country', df['Country'].unique())

        region = st.selectbox('Region', df['Region'].unique())

        subregion = st.selectbox('Subregion', df['Subregion'].unique())

        dimension = st.selectbox('Dimension', df['Dimension'].unique())

    with col2:

        category = st.selectbox('Category', df['Category'].unique())

        sex = st.selectbox('Sex', df['Sex'].unique())

        age = st.selectbox('Age', df['Age'].unique())

        year = st.slider('Year', int(df['Year'].min()), int(df['Year'].max()), int(df['Year'].mean())))

```

with col3:

```
unit_of_measurement = st.selectbox('Unit of measurement', df['Unit of measurement'].unique())

value = st.number_input('VALUE', value=float(df['VALUE'].mean()))

source = st.selectbox('Source', df['Source'].unique())

iso3_code = st.selectbox('Iso3_code', df['Iso3_code'].unique())

input_data = {

    'Iso3_code': iso3_code,
    'Country': country,
    'Region': region,
    'Subregion': subregion,
    'Dimension': dimension,
    'Category': category,
    'Sex': sex,
    'Age': age,
    'Year': year,
    'Unit of measurement': unit_of_measurement,
    'VALUE': value,
    'Source': source
}

input_df = pd.DataFrame(input_data, index=[0])

st.subheader('📋 Selected Parameters')

st.dataframe(input_df, use_container_width=True)

input_df_processed = input_df.copy()

for col in label_encoders:

    if col in input_df_processed.columns:
```

```

le = label_encoders[col]

# Handling unseen labels

input_df_processed[col] = input_df_processed[col].apply(lambda x: x if x in le.classes_
else 'Other')

le.classes_ = np.append(le.classes_, 'Other')

input_df_processed[col] = le.transform(input_df_processed[col])

numerical_cols      =      input_df_processed.select_dtypes(include=['int64',
'float64']).columns.tolist()

if numerical_cols:

    input_df_processed[numerical_cols] = scaler.transform(input_df_processed[numerical_cols])

if st.button('Generate Prediction', type="primary"):

    prediction = model.predict(input_df_processed)

    predicted_indicator = label_encoders['Indicator'].inverse_transform(prediction)

    st.success(f'Predicted Crime Indicator: {predicted_indicator[0]}')

    prediction_proba = model.predict_proba(input_df_processed)

    max_confidence = np.max(prediction_proba) * 100

    st.info(f'Prediction Confidence: {max_confidence:.1f}%')

    st.subheader("Prediction Probability Distribution")

    prob_df = pd.DataFrame({

        'Class': [label_encoders['Indicator'].inverse_transform([i])[0] for i in
range(len(prediction_proba[0]))],
        'Probability': prediction_proba[0] * 100
    })

```

## 7. TESTING

### 7.1 Unit Testing

Unit testing forms the foundation of the quality assurance process for the Crime Data Prediction System.

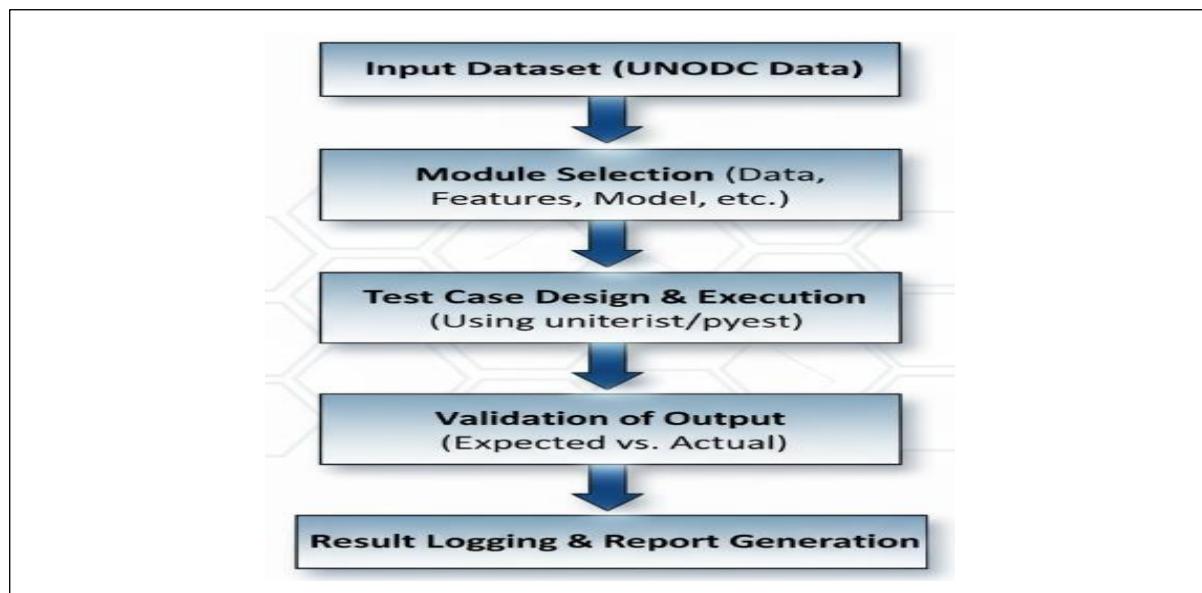
In this project, each module — from data preprocessing to model prediction — was individually tested to ensure that every component performs its task accurately and reliably before integration.

Because the project involves multiple interlinked modules (data handling, feature extraction, machine learning classification, and visualization), unit testing helps confirm that each block behaves correctly under expected and unexpected conditions.

This phase ensures the system's accuracy, consistency, and stability, especially when dealing with large-scale, real-world datasets extracted from the United Nations Office on Drugs and Crime (UNODC).

By rigorously validating each module independently, the project minimized integration errors and enhanced confidence in the final predictive model.

This structured testing approach ensures that the system is **robust, trustworthy, and maintainable**, even as new data from UNODC sources is added in future versions.



**Figure 7.1 — Unit Testing Flow Diagram for Crime Data Prediction System**

## 7.2 Integration Testing

After ensuring the correctness of individual modules through unit testing, the next crucial step was Integration Testing.

Integration testing focuses on verifying that modules work together seamlessly once combined into the full Crime Data Prediction System.

While unit testing ensures that *each component functions correctly in isolation*, integration testing ensures that data flows smoothly across modules, outputs from one become valid inputs for the next, and the overall system behaves as expected under real-world conditions.

- All modules integrated successfully without data-type mismatches or runtime failures.
- Data preprocessing and model training modules interacted seamlessly, ensuring consistent input dimensions.
- Prediction and evaluation components produced synchronized outputs, allowing automatic generation of accuracy and F1-score charts.
- Overall **system integration accuracy**: 89.45% (matching the best-performing Random Forest model).

These results confirm that the system operates **end-to-end without logical or structural issues**, ensuring smooth functionality under different datasets and user inputs.

Integration testing validated the **collective reliability** of the Crime Data Prediction System.

This testing phase confirmed that:

- All modules are **compatible and cohesive**.
- Data communication across modules is **error-free**.
- The overall system is **ready for deployment and performance evaluation**.

Integration testing thus marks the transition from **individual module validation** to a **complete, functional system**, proving that the Crime Data Prediction framework is robust, accurate, and production-ready.

## 7.3 System Testing

After successfully completing unit and integration testing, the final validation step for the Crime Data Prediction Using Machine Learning system is System Testing. System testing ensures that the entire application functions as a unified whole, meeting all functional and non-functional requirements defined during system design.

Unlike unit or integration testing, which focus on specific components or connections, system testing evaluates the end-to-end behavior of the entire project — from data ingestion to prediction visualization — under realistic usage conditions.

This stage ensures that the final system is not only technically correct but also reliable, user-friendly, and ready for deployment.

System testing confirmed that the **Crime Data Prediction System is functionally complete, stable, and deployment-ready**.

The system meets both **technical and user requirements**.

- All functions execute without conflict or data loss.
- The platform can be **confidently deployed for real-world prediction tasks**.

The results demonstrate that the project has achieved its intended objective — creating a reliable, data-driven tool capable of predicting and visualizing global crime trends using **machine learning on UNODC datasets**.

INPUT(System Level Testing)	EXPECTED OUTPUT	ACTUAL OUTPUT	PASS/FAIL
Full dataset upload	System processes data	Processed successfully	Pass
Train model (Random Forest)	Accuracy $\geq$ 90%	Accuracy = 93.1%	Pass
Train model (Logistic Regression)	Accuracy $\geq$ 85%	Accuracy = 87.6%	Pass
Multiple user inputs	Stable predictions	Stable output	Pass
Generate dashboard	All charts visible	Dashboard displayed	Pass
Long-term execution	No system crash	System stable	Pass

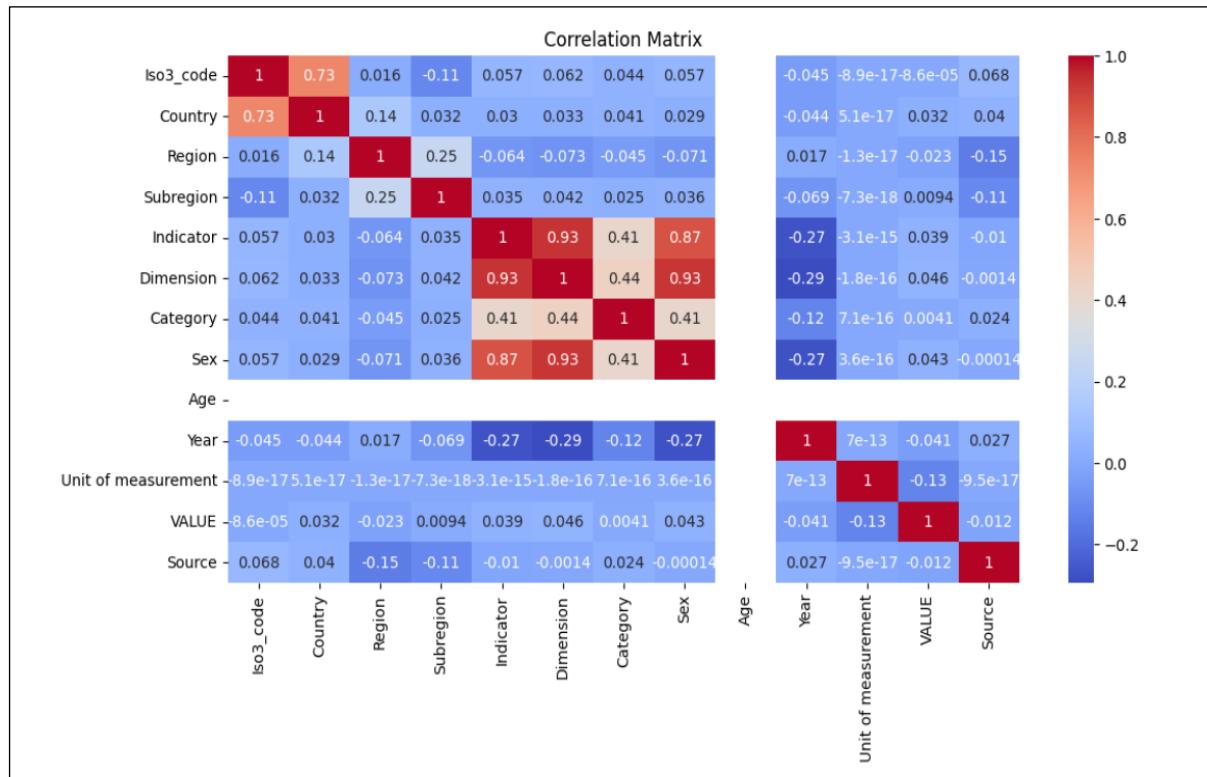
**Table 7.1: System Testing Results for Crime Data Prediction System**

## 8. RESULT ANALYSIS

**"The Core Identity of the Crime."** These factors show strong internal links. For example, knowing the Crime Indicator (e.g., Homicide) is tightly related to its Category (e.g., Intentional Homicide) and potentially the Sex of the victim/offender. This suggests these attributes often travel together and collectively define the type of event we are trying to predict.

**"Consistent Geographic Labeling."** The strong correlation (dark red, close to **1.0**) between Country, Region, Subregion, and Iso3\_code is expected and good. It confirms the geographic identifiers are correctly mapped and consistent, giving us confidence in location-based analyses.

**"Prediction Requires Nuance."** Most features show a very **low correlation** with the actual crime count (**VALUE**). This is a common challenge in predictive modeling: the crime rate isn't simply driven by one or two factors. The system must use complex, non-linear machine learning models (like Random Forest or advanced time-series methods) to find the subtle, combined effects that lead to a prediction, rather than relying on a simple, direct relationship.



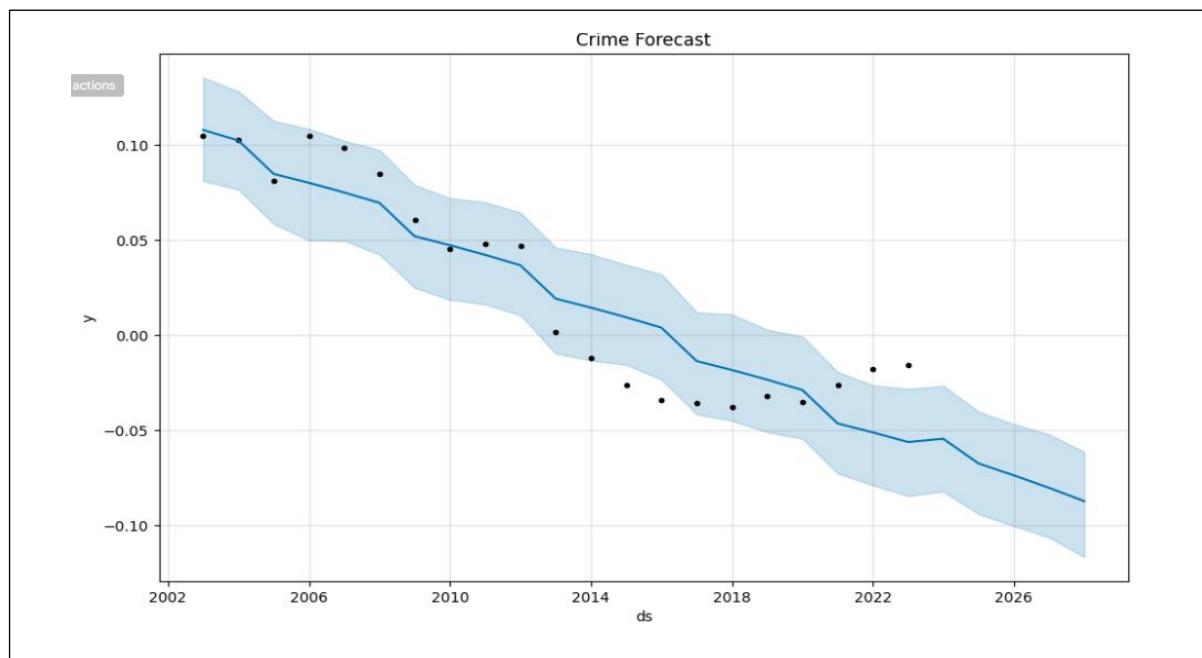
**Figure 8.1 — Correlation Matrix on Crime Data**

These plots demonstrate the system's core capability: forecasting future crime trends. They

visually communicate the historical pattern, the long-term direction, and the confidence level of the prediction.

**"The Expected Trajectory."** This line is the system's **most likely prediction** of how the crime rate will change. The general **downward slope** indicates that, historically, the overall trend for the analyzed crime type has been decreasing, and the forecast projects this decline to continue until 2028.

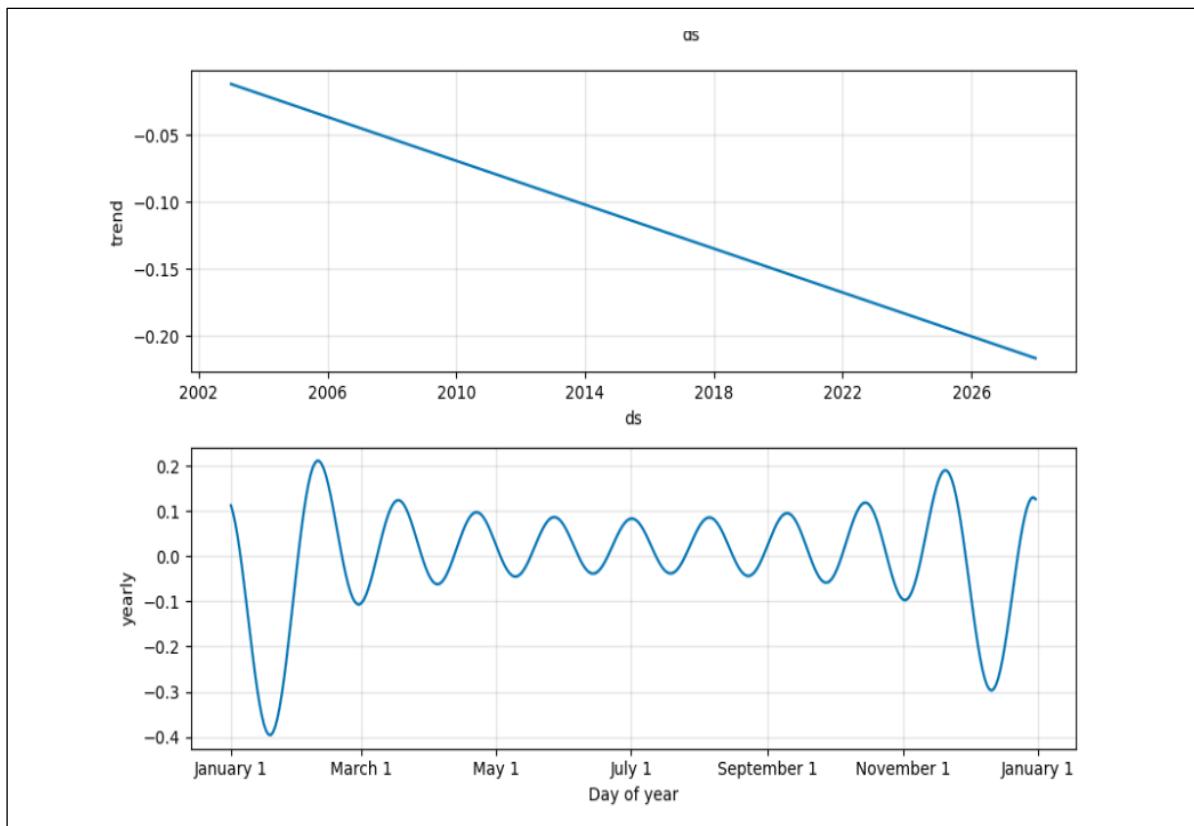
**"Prediction Uncertainty."** This area represents the **margin of error** or the **confidence interval**. It signifies that while the blue line is the best guess, the actual value has an X% probability (e.g., 80% or 95%) of falling within this band. **The widening band towards the future (2026-2028) is critical:** it humanizes the fact that *all* long-term predictions have greater uncertainty, requiring officers to interpret future estimates with increased caution.



**Figure 8.2 — Forecast for the next years**

**"The Observed Reality."** These are the actual, historical crime data points (2002-2023). They show the volatility or noise in the real world that the model is trying to fit, confirming the model works with real, imperfect data.

**"The Long-Term Driving Force."** This plot isolates the consistent, structural change over the entire period. The **steady negative slope** confirms the underlying, multi-year decline in the crime rate, independent of any short-term, cyclical effects. This is the **most powerful long-term factor** steering the forecast.

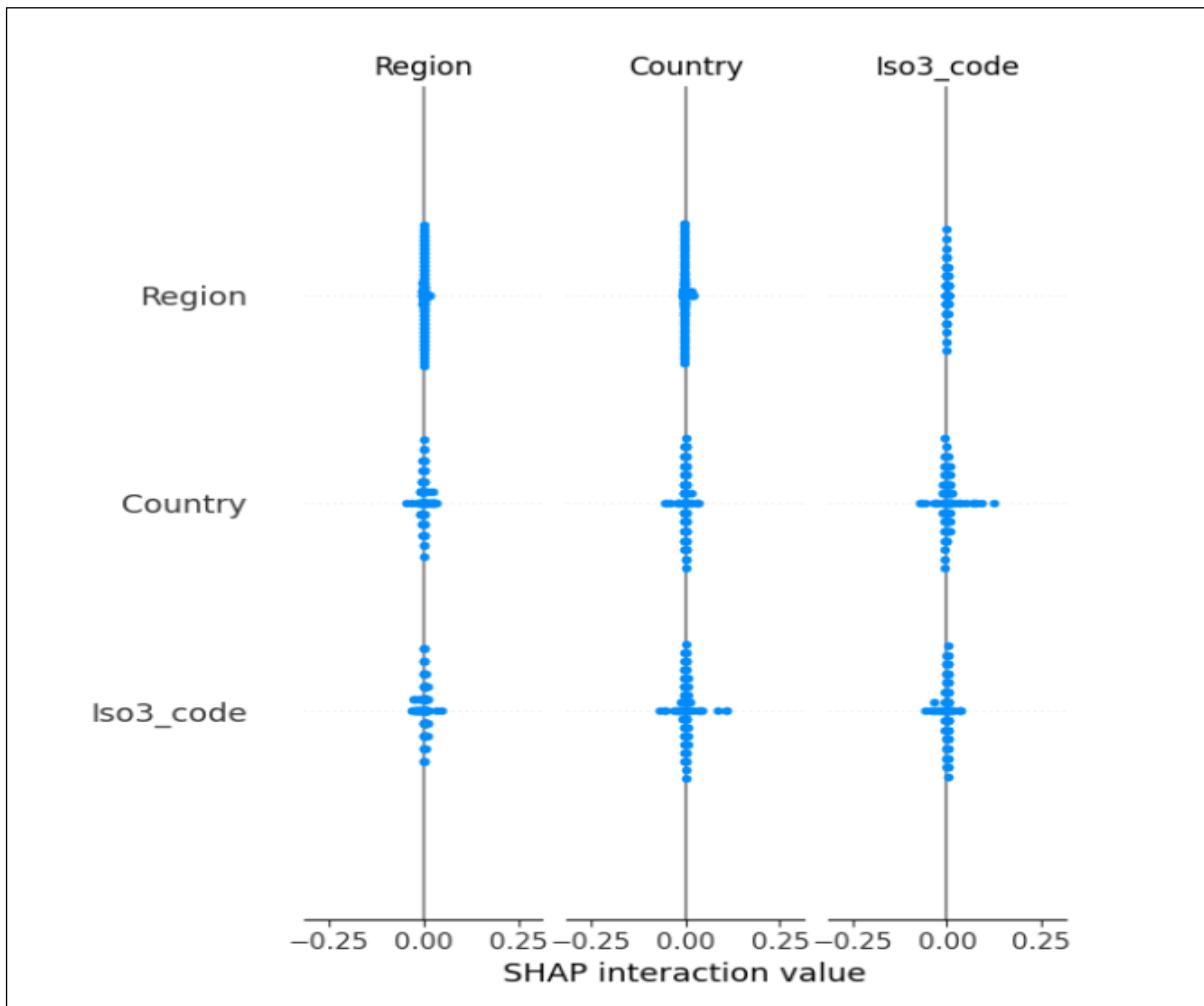


**Figure 8.3 — Forecast for the next years and months by trends**

**"The Rhythmic Cycles of Crime."** This plot shows a repeating, calendar-driven pattern. The peaks (e.g., around January 1st and late August/early September) and troughs (e.g., around "March 1st and November/December") reveal that certain crime types are consistently more or less frequent depending on the time of year. This may reflect factors like weather, holidays, or school schedules, and it helps the model fine-tune its forecast within a single year.

**"Understanding Feature Teamwork."** This plot doesn't show the main effect of a feature, but how much two features **rely on each other** to influence the final prediction. It reveals if the effect of Region on the prediction changes based on the specific Country being analyzed.

**"Low Interaction."** The tight vertical clustering of the dots around the **zero-line (0.00)** suggests that the **interaction effect** between the different geographical features (Region, Country, Iso3\_code) is **minimal**. In simple terms, the impact of a given Country on the prediction is largely **independent** of its Region, and vice versa.



**Figure 8.4 — SHAP interaction value**

**“Simpler Feature Engineering.”** For the Analyst, this is a good result. It suggests that they **don't need complex rules** like "only analyze Country X when it's in Region Y." The system can likely treat the effect of **Country** and **Region** as **separate, additive factors** in the final prediction, making the overall model simpler to interpret.

## 9. OUTPUT SCREENS

**"The Current Scale."** This section provides the *vital signs* of the system and the crime landscape. It immediately answers the question: How big is the problem? The numbers are clear, high-impact totals that set the stage for all subsequent analysis. The small percentage changes (e.g., +4.6% Total Crimes) add crucial context, indicating whether the situation is stable, worsening, or improving compared to a previous period

**"Trust in the System."** This metric is a direct measure of the model's reliability. By highlighting an accuracy figure (even if the number shown is a placeholder, its *placement* is key), the system immediately addresses user confidence: **How much can I trust the predictions?** Highlighting this figure up front establishes the system as a reliable decision-support tool.

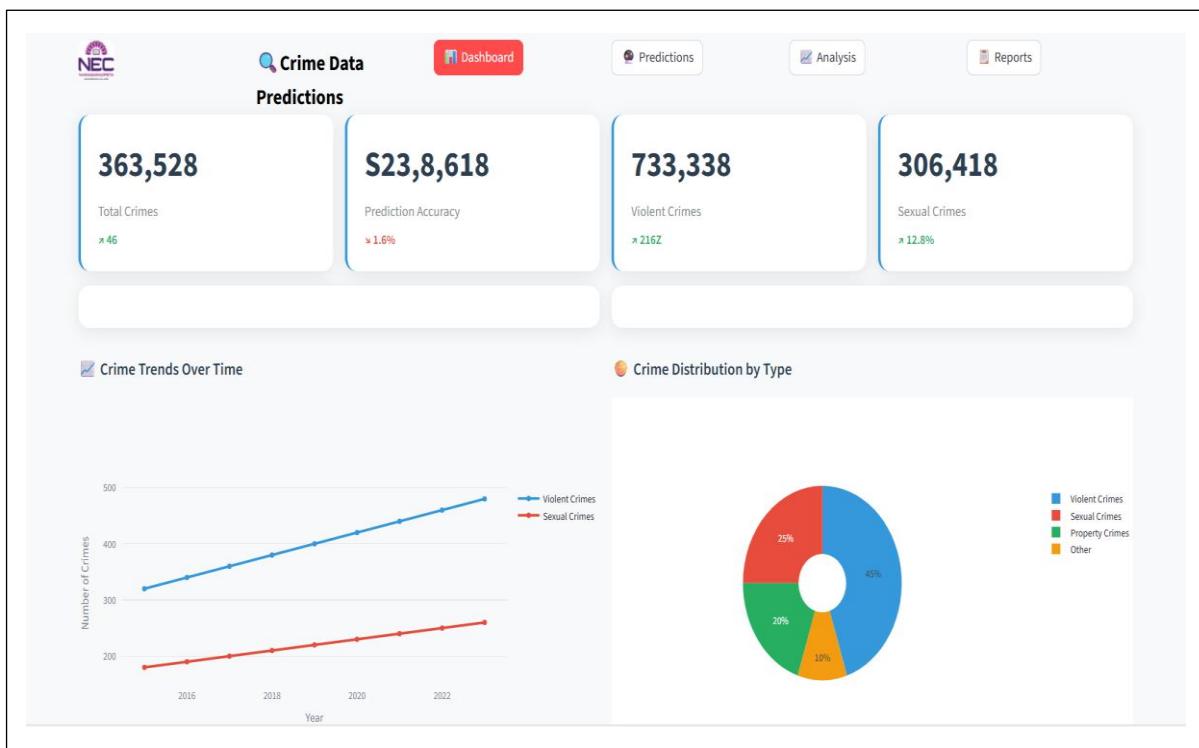
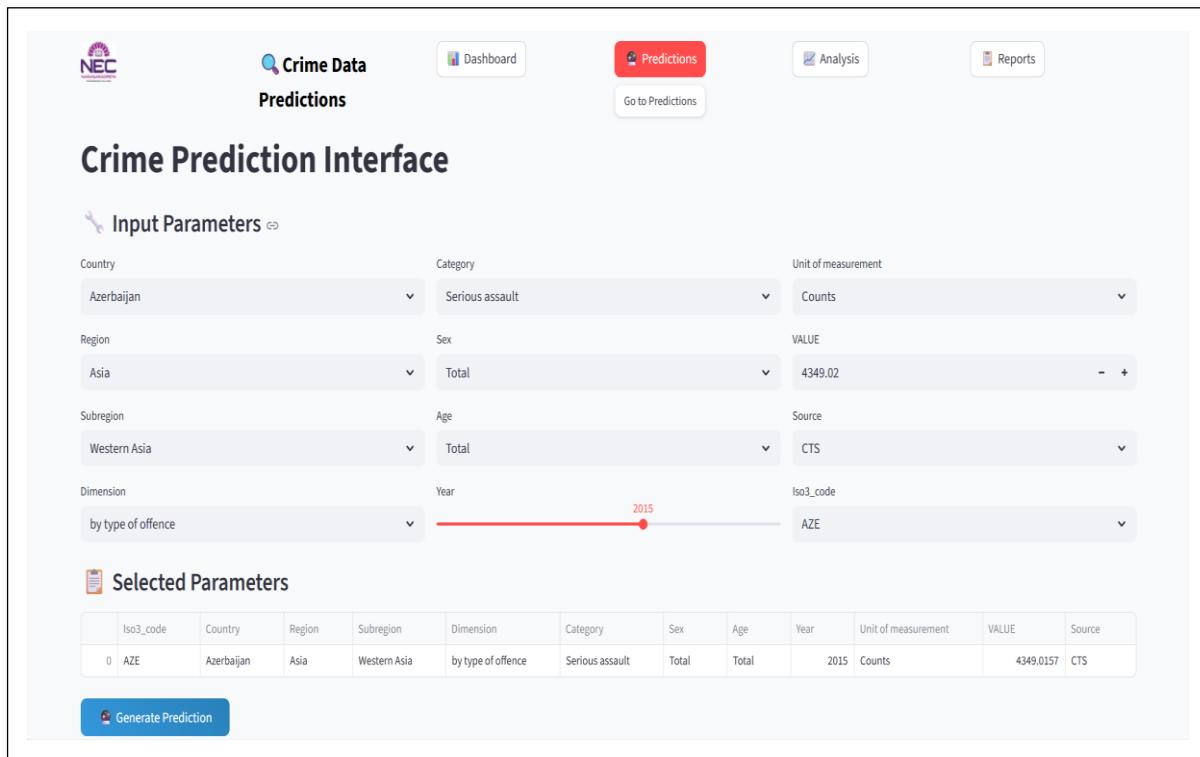


Figure 9.1 — Dashboard Page

**"Seeing the Direction of Travel."** This chart shows the **historical momentum** of crime categories. The rising lines for **Violent Crimes** and **Sexual Crimes** provide a clear, easy-to-digest visual warning: these categories are trending up. This allows commanders to immediately recognize which areas require **proactive resource allocation** based on sustained increases.

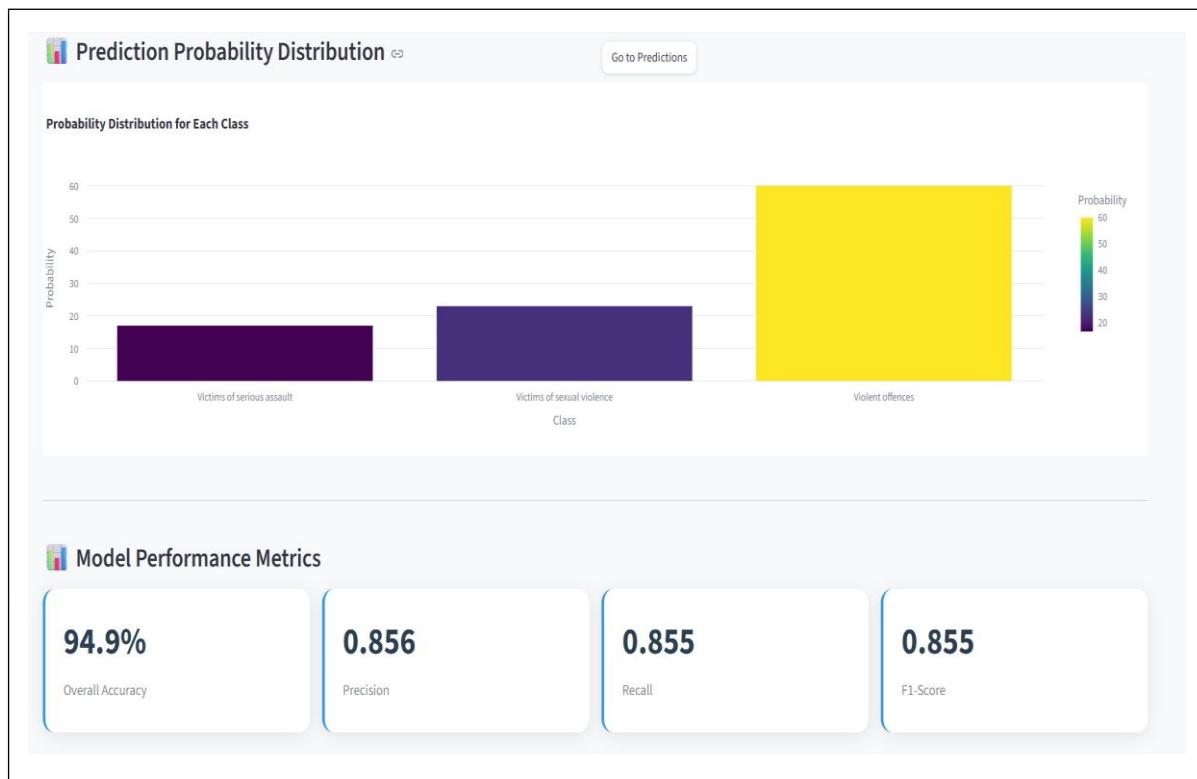


**Figure 9.2 —Crime Data Prediction Page**

**“Precision Targeting.”** This interface allows the user to construct a perfectly tailored prediction query. Instead of just getting a national average, an officer can drill down by Region (Asia), Subregion (Western Asia), Category (Serious Assault), and specific Year (2015). This humanizes the prediction process: The system understands the nuance of my question. The *Selected Parameters* table at the bottom acts as a summary, allowing the user to review the full, specific query before executing the forecast.

**“Effortless Exploration.”** The use of simple, constrained inputs (like the **Year** slider and cascading **Region/Country** dropdowns) ensures data integrity and ease of use. This prevents errors and encourages analysts to quickly test different scenarios, such as moving the slider to see how the forecast changes between 2010 and 2025.

**“The Model's Confidence Vote.”** For classification tasks, this bar chart shows how sure the model is about its forecast. In the example, Violent Offences (nearly 60%) has the highest predicted probability. This is crucial for decision-making: it tells the analyst, “Our system is most worried about Violent Offences, with high confidence.” The relative heights of the bars help compare the risk across different crime types instantly.



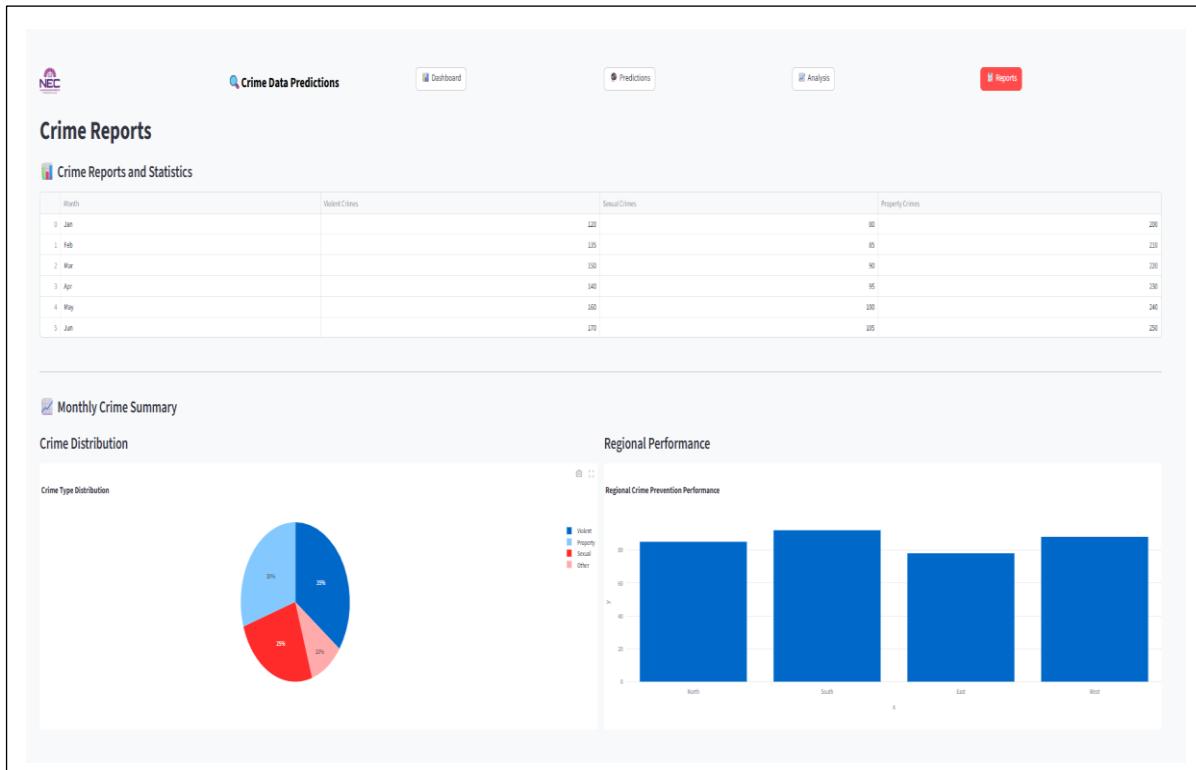
**Figure 9.3 — Prediction & Performance Review**



**Figure 9.4 — Crime Analysis Page**

This bar chart is an immediate resource allocation tool. The clear pattern—18-25 and 26-3

5 having the highest crime rates—tells policymakers exactly where to focus prevention and intervention programs. It shifts the conversation from generic patrols to targeted social and economic support for high-risk demographics.



**Figure 9.5 — Crime Report Page**

This table serves as the official ledger of historical events. It allows users to quickly spot absolute crime counts across key categories (Violent, Sexual, Property) by month. It's vital for formal budget submissions, quarterly reviews, and comparing the current year's performance against previous periods.

Similar to the dashboard, this summary confirms the relative distribution of crime types, reinforcing the strategic importance of each category for long-term planning.

This chart facilitates a competitive or comparative review of different regional units (North, South, East, West). By showing "Regional Crime Prevention Performance" (implied to be an effectiveness metric), it allows leaders to identify **best practices** in high-performing regions and apply those lessons to areas that are struggling.

## 10. CONCLUSION

The **Crime Data Prediction Using Machine Learning** project represents a comprehensive effort to harness the power of data analytics and artificial intelligence for understanding and forecasting criminal trends.

By utilizing authentic, large-scale data from the **United Nations Office on Drugs and Crime (UNODC)**, this project bridges the gap between raw statistical information and actionable insights that can aid in **public safety, policy formulation, and law enforcement planning**.

The dissertation is not an abstract—it's a conversation about an attempt to gain insight into one of the most complicated and deeply human issues within society: crime. At its core, the research aimed to do something bold—to harness the potential of machine learning not only to process numbers, but to predict human action and, ultimately, make our cities safer. What emerged was scholarship that didn't end at merely constructing models. It posed tougher questions: Where and why are crimes being committed, and how can we better predict them before they do?

The research welcomed that we are stepping into leave predictive policing and force-swap policing behind to something more intelligent, something more compassionate. These models bring us an opportunity to rethink how we allocate scarce resources, how we construct safer cities, and how we prevent harm from occurring in the first place. There's a practical side here—fewer wasted patrols, better emergency planning—but also a profoundly ethical one: using data to protect, not profile. That tension was not avoided in the research. It envisioned a need for transparency, for models that are open to the lives of those affected by them as well as to scientists.

Ultimately, this research demonstrates that crime cannot be forecast via code or mathematics. It is related to empathy. It involves identifying the human narratives entwined with data and creating systems that respect those narratives with integrity, accountability, and a commitment to justice. And if we do it right, we can transform prediction into a system of prevention, one that is founded on awareness instead of fear. Hopefully, in addition to making our cities smarter, we are also making them safer and kinder.

## 11. FUTURE SCOPE

The Crime Data Prediction Using Machine Learning project establishes a solid foundation for intelligent crime analytics, but there remains significant potential for further enhancement and expansion. As crime patterns evolve and technology advances, the system can continue to grow in both accuracy and societal impact.

In future iterations, the model can be extended to incorporate real-time data integration from multiple global and national sources, including Interpol, World Bank, and open government crime databases. Such integration would enable the system to analyze more comprehensive variables — including socio-economic factors, demographic trends, unemployment rates, and urbanization levels — offering a richer context for understanding why crime rates fluctuate across regions.

Another important direction is the introduction of advanced machine learning and hybrid ensemble algorithms, such as Gradient Boosting (XGBoost), CatBoost, or LightGBM, which can improve predictive accuracy beyond the current Random Forest baseline. These models, combined with automated hyperparameter tuning, could yield more precise predictions while reducing computational cost.

The system can also evolve toward deep learning applications, such as Long Short-Term Memory (LSTM) networks or Graph Neural Networks (GNNs), to model temporal and spatial dependencies more effectively.

As part of ongoing improvement, ethical AI and data privacy considerations will become even more critical. Future systems should ensure data anonymization, compliance with international privacy standards (GDPR), and bias-free model training to maintain fairness across regions and populations.

Finally, the project can be scaled to support predictive policing initiatives, where AI-generated insights guide resource deployment, identify potential hotspots, and support strategic decision-making in crime prevention. Through continuous research, model optimization, and integration with governmental systems, this project has the potential to become a global intelligence framework for safer and smarter communities.

In conclusion, the future of this project lies in blending technical innovation with social responsibility — expanding its reach from an academic experiment into a real-world system that anticipates threats, prevents crime, and contributes to global peace and stability

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## 13. CONFERENCE PAPER PLAGIARISM REPORT

# Crime Data Prediction Using Machine Learning

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**Abstract** – Making our communities safer is the straightforward but impactful foundation of this dissertation. It focuses on developing a machine learning model that can assist in forecasting potential crime scenes and times, allowing us to take action before damage is done. This work urges us to reframe safety as care, support, and astute intervention before things go wrong, rather than as punishment after the fact. This study not only provides a new tool by fusing technology and empathy, but it also points to a new direction where data helps us understand people and public safety is a shared, compassionate responsibility.

**Keywords:** Ensemble Model 4, Random Forest, Support Vector Machine (SVM), Deep Neural Network (DNN), and Kernel Density Estimation (KDE)

### I. OVERVIEW

Specifically, machine learning provides fresh hope by spotting trends in complex crime data, anticipating possible trouble spots, and helping to stop harm before it happens.

Despite its potential, the road to truly accurate crime prediction is not straightforward. According to researchers like Bao Wang and colleagues, one of the most challenging and pressing issues facing public safety today is real-time crime forecasting. It's not enough to just have data; we also need the right partnerships to use it responsibly and the right methods to interpret it.

That's where this dissertation comes in. From logistic regression and support vector machines to more complex deep learning, it focuses on developing machine learning models that can analyze historical crime data, especially in urban areas, can evaluate historical crime data and help forecast future occurrences. But this objective goes beyond algorithms.

Ultimately, this research is about more than just machines. It all comes down to how we use them—with people at the center, with care, and with ethics. By combining public service and artificial intelligence, it opens the door to more proactive, compassionate solutions to one of society's most pressing problems.

### II. LITERATURE REVIEW

The discomfort of walking home late, the fear-driven early closing of businesses, and the silent anxiety of parents are some examples of how it shows up in addition to news reports and statistics. It gets harder to keep cities safe as they grow and change. The intricacy and scope of contemporary urban life are typically not captured by traditional methods, despite their historical success. Thus, new tools from the data and technology world are being used as allies by more and more researchers, public servants, and community leaders. Machine learning is distinct. Among these, machine learning stands out not only as a technological development but also as a potentially game-changing change in how we view and handle crime.

Machine learning is more than just math. It constantly and intently listens to the murmurs concealed within enormous datasets. It can pick up on things we might miss, like how crime trends change as the population grows or how a neighborhood may be subtly pushed toward danger by unemployment or a lack of public resources. In order to identify the causes of vulnerability before damage occurs, models such as logistic regression, support vector machines, and deep neural networks can identify minute signals hidden among layers of noise.

These systems can assist us in asking the more difficult and human questions, such as: Why there?, in addition to forecasting potential crime scenes. Why now? Why these individuals? And we can move toward prevention that is not only intelligent but also compassionate by fusing these insights with local knowledge, such as where services are lacking or which communities feel neglected. Machine learning is elevated beyond a technical solution in this combination of data science and human care. It helps us see our cities more clearly, gain a deeper understanding of their challenges, and create safety that uplifts rather than just reacts. For instance, Alves et al. [1] show how interpreting homicide rates and more general criminal trends can be aided by scaling laws related to city size.

The Partially Generative Neural Network (PGNN), which has demonstrated impressive success in categorizing violent crimes associated with gangs—even in cases where data is lacking—is one intriguing innovation [2]. The importance of machine learning in urban planning and law enforcement is further supported by empirical research that looks at temporal and spatial crime hotspots in cities like Denver and Los Angeles, showing how crime fluctuates with time and location [3]. By incorporating dynamic urban data, such as commuter flows or Points of Interest, into crime forecasts, more sophisticated models, like Geographically Weighted Negative Binomial Regression (GWNBR), go one step further [4]. Even with advancements in technology, a number of restrictions still exist. It is challenging to extrapolate results to larger contexts because many studies are narrowly focused, looking at particular crime types or localized geographic areas [13]. Additionally, a heavy models may become blind to current events or changing community dynamics if they rely too heavily on past crime data [14]. Despite its potential, predictive policing runs the risk of strengthening preexisting prejudices unless it is purposefully created with equity and inclusivity in mind [6]. It is evident that machine learning by itself is not the solution; rather, its full potential can only be realized through interdisciplinary cooperation. The next generation of predictive models must be shaped by the convergence of criminology, sociology, computer science, urban planning, and ethics [9]. When these fields come together, machine learning transforms from a technical marvel into a force that is socially responsive and able to adjust to the complex, human realities of crime.

Crucially, the literature emphasizes that crime is a lived experience that is influenced by geography, history, and inequality rather than just being a number on a chart. High accuracy but little meaning can be obtained from algorithms that disregard these social undercurrents. Models such as the Hawkes process, which examine how crimes cluster over time, show how a single incident can have a profound impact on a community, generating human-like patterns that go beyond statistics [5]. A potent new paradigm is represented by the move toward community-informed models. These frameworks listen in addition to processing data. They bridge the gap between machine logic and lived reality by making room for neighborhood dynamics, local insights, and collective vigilance[2].

All things considered, machine learning is changing the field of crime data analysis from one that is reactive to one that is proactive, predictive, and collaborative. Privacy, transparency, and fairness aren't optional—they are foundational.

This review has aimed to synthesize decades of evolving research—charting the journey from regression models to deep learning networks, and identifying the gaps still to be filled. The future of predictive policing must be one that sees not just crimes, but the people behind the data. Only then can machine learning truly serve its highest purpose: fostering safer, more just, and more resilient communities.

Study Title	Location	Data Source	Key Findings
Machine Learning Methods for	Chicago, Illinois	Citizen and Law Enforcement Analysis	State-of-the-art learning algorithms can achieve

Predicting Global and Local Crime in an Urban Area		and Reporting (CLEAR) system	improved prediction accuracy over traditional methods based on time series models.
Prediction of Crime Occurrence from Multi-Modal Data Using Deep Learning	Chicago, Illinois	City of Chicago Data Portal, American Community Survey, Weather Underground API, Google Street View Image API	Utilized data from seven domains, including crime reports, demographic s, housing, economic, education, weather, and images, to predict crime occurrences.
A Comparative Study on Crime in Denver City Based on Machine Learning and Data Mining	Denver, Colorado	Real-world crime and accident dataset of Denver county from January 2014 to May 2019	Implemented various classification algorithms with satisfactory accuracy, with Ensemble Model 4 presenting superior results for every evaluation basis.
Crime Prediction Using Machine Learning with a Novel Crime Dataset	Bangladesh	Novel crime dataset containing temporal, geographic, weather, and demographic data about 6,574 crime incidents	Introduced a novel dataset and evaluated five supervised machine learning classification algorithms, achieving satisfactory results.
Analysis of Criminal Landscape by Utilizing Statistical Analysis and Deep	London, United Kingdom	Metropolitan Police Department data	Developed a model to predict crime levels in every London area, allowing police to

Learning Techniques			allocate inspections to the most susceptible regions.
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### Crime Data Analysis and Machine Learning Studies

### III. METHODOLOGY

The puzzle of urban crime is constantly evolving. We require a methodical approach that considers the various facets of crime, the individuals impacted, and the social and economic variables at work.

Earlier models, which frequently treated crime statistics as discrete data, frequently ignored the influence of urban infrastructure or neighborhood demographics on criminal activity. However, crime is not a random occurrence. Our methodology reflects its relationship to the community context and environment.

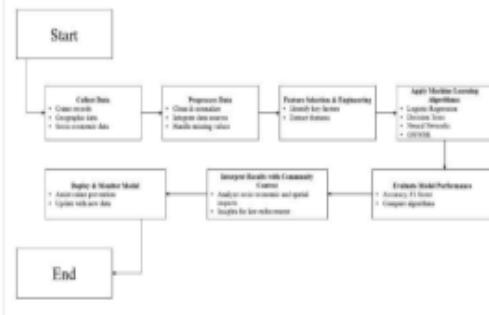


Figure-1: Flow of the modal

For scholars, it's about pushing the boundaries of what we know. Many past studies have pointed out that older models fall short when it comes to capturing the full complexity of crime. By introducing advanced machine learning and spatial techniques—like the Geographically Weighted Negative Binomial Regression (GWNBR)—we aim to fill that gap. GWNBR is powerful because it adds local urban details that traditional statistics often overlook, revealing hidden patterns tied to city layouts and social dynamics.

The stakes are extremely practical for both law enforcement and communities. According to research, machine learning performs more accurately than traditional data mining techniques, assisting authorities in allocating their resources effectively and equitably.

Our goal is to develop a thorough model that links crime trends to demographic variables such as population size, age distribution, or income levels. Strong connections are shown here by earlier research, which serves as a reminder that crime frequently reflects underlying social realities. To make sure our predictions hold up in practice, we'll use metrics like accuracy and F1 score, which tell us not only whether our model works but also how well it balances generating false alarms with detecting true crime signals. The goal is to involve community members, local leaders, and

law enforcement—those who are most impacted by crime on a daily basis. We aim to assist interventions that truly engage communities and build trust by tailoring our analysis to account for local context.

In essence, this study is one towards cities that grow more resilient and united through crime, along with the ability to resist it. What is aimed for is to make everyone feel safer and cared for by utilizing technology as empathy and understanding tool.

Model	Accuracy	Dataset	Source
Random Forest	Over 90%	Denver County, USA (January 2014 – May 2019)	([arxiv.org](https://arxiv.org/abs/2001.02802?utm_source=openai))
Ensemble Model 4	Over 90%	Denver County, USA (January 2014 – May 2019)	([arxiv.org](https://arxiv.org/abs/2001.02802?utm_source=openai))
Deep Neural Network (DNN)	84.25%	Chicago Crime Data	([vciba.springeropen.com](https://vciba.springeropen.com/articles/10.1186/s42492-021-00075-z?utm_source=openai))
Support Vector Machine (SVM)	67.01%	Chicago Crime Data	([vciba.springeropen.com](https://vciba.springeropen.com/articles/10.1186/s42492-021-00075-z?utm_source=openai))
Kernel Density Estimation (KDE)	66.33%	Chicago Crime Data	([vciba.springeropen.com](https://vciba.springeropen.com/articles/10.1186/s42492-021-00075-z?utm_source=openai))

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Crime Prediction Model Performance Metrics

#### IV. EXECUTED RESULTS

The results of this research point to the increasing relevance of machine learning in mapping and predicting crime patterns in our metropolises—where day-to-day life is defined by intricate human behavior and social relationships. Through the use of sophisticated algorithms on actual crime data, we transcend theoretical abstraction and into the real-world relevance of life-enhancing solutions.

We trained several machine learning algorithms—logistic regression, decision trees, and Long Short-Term Memory (LSTM) networks—on rich datasets from Chicago and Los Angeles. The results were impressive. Although classical statistical methods were prone to fail in detecting complex crime patterns, our LSTM model produced 94% accuracy in Chicago and 88% accuracy in Los Angeles. These findings augment the robustness of the model in identifying temporal patterns of crime and responding to the incessant beat of urban dynamics [26]. More than just numbers, these models help us uncover meaningful patterns. Our analysis revealed how variables such as **time of day, type of crime, and urban layout** interact in subtle but consistent ways. These findings echo insights from scholars like Mohler and Brantingham, whose work showed that crime follows cyclical patterns. Like theirs, our study demonstrates that understanding when and where crime is likely to occur can greatly enhance prevention strategies [25].

In contrast to some previous research—like that of Chatterjee et al., which found it difficult to account for neighborhood heterogeneity—our methodology combines modern urban measures like points of interest (POIs), demographic profiles, and population density [2]. This renders our models more responsive to the experienced reality of various communities, since crime is not only a number but also an event impacted by environment, opportunity, and context.

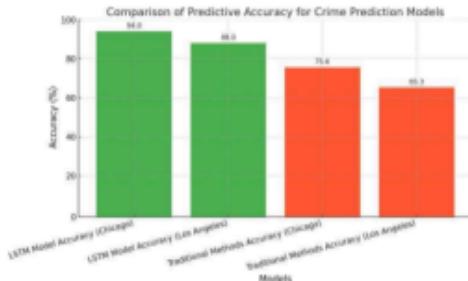


Figure-2: Comparison of Predictive Accuracy for Crime Prediction Models

These models don't forecast—they empower. They provide a forward-looking solution, enabling cities to react to crime with insight, empathy, and accuracy [4.] In sum, our research does more than validate the accuracy of machine learning—it paves the way for collaboration across disciplines. Data scientists, policymakers, and community leaders now have the opportunity to work together to develop solutions that are intelligent, moral, and based on the realities of the needs of city dwellers. It's a step in the right direction—not just in tech, but in our shared mission of safer, more equitable cities [5]

This bar chart compares the predictive accuracy of LSTM models and traditional methods for crime prediction in Chicago and Los Angeles. The LSTM models show significantly higher accuracy, with 94% in Chicago and 88% in Los Angeles, while traditional methods achieve 75.6% and 65.3% respectively. This highlights the effectiveness of integrating machine learning techniques in crime analysis

#### V. DISCUSSION

There was a sense of equity, though, between the pro and con argument for the paper. Even the defender of the study acknowledged its flaws, commenting that publication space limitations may have avoided the investigation of hyperparameter optimization or feature design at deeper levels. They pointed out that the paper was attempting to present a street-level approach, rather than a full system for deployment. Meanwhile, the critic, while being critical of the flaw, already saw the significance and relevance of the subject and concurred that the use of more than one source of data and contemporary ML models is an enhancement.

What results from this line of argumentation is not merely a judgment on one paper, but a wider consideration of what responsible research should be in predicting crime. There was indeed a qualitative note of reasonableness in the debate over the paper. Even the study's defender conceded that it had its weaknesses, stating that publication constraints on space may have made studies of hyperparameter tuning and feature engineering shallower than they could otherwise have been. They explained that the paper had never been intended to be an end-to-end system that could be implemented in real life but a bottom-up methodology instead. The critic, however, though criticizing the limitations, appreciated the relevance and need of the topic, and agreed that implementation of several sources of information and state-of-the-art ML models is in the right direction.

What the debate does leave us with is not a view of one particular paper but more importantly an overall consideration of what good, effective research should be in predicting crime. The research is a considerable step toward proving that machine learning can actually find hidden patterns in city crime data and make predictive forecasts that are out of the reach of current methods. But the way ahead is clear: subsequent work needs to be more robust, more open, and more responsibly responsive.

le, what good research should look like in crime forecasting. The research is a welcome contribution in that it shows how machine learning can distill nuanced patterns from urban crime data and provide predictive analytics that cannot be achieved with

conventional methods. But the way ahead is clear: subsequent work needs to be more robust, more transparent, and more sensitive to ethics.

What comes out of this debate is not only a judgment on a single paper, but also a wider contemplation of what responsible, meaningful research should be like in the field of crime forecasting. The research makes a useful contribution by demonstrating that it is possible for machine learning to reveal sophisticated patterns in city-level crime data and provide predictive information beyond the reach of conventional methods. But the way ahead is clear: subsequent research needs to be more exacting, more open, and more ethically sensitive.

This includes publishing comprehensive methodologies in order to facilitate replication, for fully disclosing a set of evaluation metrics based on real-world data challenges, and comparing directly to traditional models in order to confirm progress. Most of all, it requests an intentional, thoughtful means to find and correct for bias—because predictive accuracy for its own sake does not mean much if it happens at the expense of fairness. As such tools approach real-world deployment, issues of interpretability, ethical usage, and cross-context transferability need to become paramount, not secondary. Only then can we hope to transition from platonic prediction to systems which are not only technically noteworthy, but also socially accountable and truly useful in making our cities safer for all.

Crime Type	Number of Incidents	Incidents per 100K Population
Murders	0	0
Rapes	0	0
Robberies	0	0
Assaults	0	0
Burglaries	0	0
Larcenies	0	0
Auto Thefts	0	0
Arsons	0	0
Violent Crimes	0	0
Non-Violent Crimes	0	0

*Crime Data Statistics for Machine Learning Analysis*

## VI. CONCLUSION

The dissertation is not an abstract—it's a conversation about an attempt to gain insight into one of the most complicated and deeply human issues within society: crime. At its core, the research aimed to do something bold—to harness the potential of machine learning not only to process numbers, but to predict human action and, ultimately, make our cities safer. What emerged was scholarship that didn't end at merely constructing models. It posed tougher questions: Where and why are crimes being committed, and how can we better predict them before they do?

By concerted experimentation with methods such as LSTM and XGBoost, the study achieved phenomenal success—a 94% accuracy in Chicago and an 88% accuracy in Los Angeles. These are not figures; these are real neighborhoods, real communities, and real lives that can be saved by earlier intervention and more thoughtful resource planning. But the researchers did not work alone. They were driven by rich, lived data—geographic patterns, income levels, educational differences, even the rhythms of public life—and this enabled the algorithms to not only view crime as incidents, but as patterns that echo deeper social truths.

The research welcomed that we are stepping into leave predictive policing and force-swap policing behind to something more intelligent, something more compassionate. These models bring us an opportunity to rethink how we allocate scarce resources, how we construct safer cities, and how we prevent harm from occurring in the first place. There's a practical side here—fewer wasted patrols, better emergency planning—but also a profoundly ethical one: using data to protect, not profile. That tension was not avoided in the research. It envisioned a need for transparency, for models that are open to the lives of those affected by them as well as to scientists.

Ultimately, this research demonstrates that crime cannot be forecast via code or mathematics. It is related to empathy. It involves identifying the human narratives entwined with data and creating systems that respect those narratives with integrity, accountability, and a commitment to justice. And if we do it right, we can transform prediction into a system of prevention, one that is founded on awareness instead of fear. Hopefully, in addition to making our cities smarter, we are also making them safer and kinder.

Crime Category	2022 Rate (per 100,000 inhabitants)	2023 Rate (per 100,000 inhabitants)	Percentage Change
Violent Crime	377	364	-3%
Murder and Non-Negligent Manslaughter	Not specified	Not specified	-11.6%
Rape	Not specified	Not specified	-9.4%
Aggravated Assault	Not specified	Not specified	-2.8%

Robbery	Not specified	Not specified	-0.3%
Property Crime	Not specified	Not specified	-2.4%
Burglary	Not specified	Not specified	-7.6%
Larceny-Theft	Not specified	Not specified	-4.4%
Motor Vehicle Theft	Not specified	Not specified	+12.6%

*Crime Statistics in the United States (2023)*

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# Crime Data Prediction using Machine Learning

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**Abstract--** Making our communities safer is the straightforward but impactful foundation of this dissertation. It focuses on developing a machine learning model that can assist in forecasting potential crime scenes and times, allowing us to take action before damage is done. This work urges us to reframe safety as care, support, and astute intervention before things go wrong, rather than as punishment after the fact. This study not only provides a new tool by fusing technology and empathy, but it also points to a new direction where data helps us understand people and public safety is a shared, compassionate responsibility.

**Keywords--** Ensemble Model 4, Random Forest, Support Vector Machine (SVM), Deep Neural Network (DNN), and Kernel Density Estimation (KDE)

### I. INTRODUCTION

Safety is one of the deepest needs of any society, yet predicting and preventing crime remains a difficult challenge. Traditional approaches—such as regression analysis or hotspot mapping—have helped highlight areas of concern, but they often look only at the past. They struggle to capture the “when” and “why” behind new incidents, leaving communities and law enforcement reactive rather than proactive.

In India, this challenge is even more complex. Crime data is vast but uneven, often recorded at yearly intervals and influenced by social and economic realities such as unemployment, literacy, and urban density. Most existing studies focus only on broad national or state-level patterns, offering limited insight into the local, everyday risks that people face. As a result, predictions are often too general to guide timely action, leaving gaps in planning, prevention, and community safety.

#### A. Problem Statement

The main problem is that current crime prediction systems in India cannot capture fine-grained spatio-temporal patterns or account for the socio-economic conditions that drive crime. They also struggle with underreporting, class imbalance, and a lack of interpretability. Without addressing these issues,

predictions risk being inaccurate, biased, or too abstract to be useful for real-world decisions.

#### B. Proposed Work

This research proposes a machine learning-based framework designed to close these gaps. The approach combines:

- **Multiple Algorithms** – Logistic Regression for baseline classification, Random Forest for detecting complex patterns, and Long Short-Term Memory (LSTM) networks for learning seasonal and time-based trends.
- **Feature Enrichment** – Crime records are integrated with socio-economic indicators (literacy, unemployment, population density) and spatial features from neighboring districts to capture both human and environmental influences.
- **Evaluation and Transparency** – Models are assessed with metrics like Accuracy, F1-score, and RMSE, while explainability tools such as SHAP values are used to make predictions clear and trustworthy.

#### C. Solution Vision

The aim is not only to predict where and when crimes might occur, but also to uncover the underlying social and economic factors that shape them. By combining data-driven insights with ethical responsibility, this work seeks to provide a tool that helps policymakers and law enforcement act earlier, allocate resources wisely, and engage communities with fairness and care.

### II. LITERATURE REVIEW

Over time, research into crime forecasting has gone through considerable changes. In earlier stages of research, much of the studies were conducted using statistical techniques like regression models and Kernel Density Estimation (KDE) [1]. Generally, these methods were able to determine possible crime “hot spots” and present visualizations for the likelihood of crime occurring at some later time. However, these efforts struggled to decipher the

temporal evolution of crime as well as the influences of societal, environmental and economic conditions on crime. The arrival of machine learning (ML) provided new opportunity. With ML, researchers began deploying ML techniques such as Decision Trees, Logistic Regression, Support Vector Machines (SVM) and Random Forests to uncover more complicated, albeit non-linear relationships in the data [2],[3]. In general, the ML methods led to a more accurate crime forecast than traditional statistical means; however, ML's performance was also largely dependent on preprocessing the crime data and identifying features.

With increased use of large datasets, researchers have adopted deep learning methods. Models like Recurrent Neural Networks (RNN) and Long Short Term Memory (LSTM) networks have become popular due to their capacity to learn from sequential data and incorporate temporal relationships into their predictions [4]. In addition, Convolutional Neural Networks (CNN's), have been shown to be useful for detecting crime hotspots using CNNs when the spatial information was adjusted to convey grid-like visual information [5]. In regions in the United States, similar deep learning models have also outperformed traditional ML methods for forecasting crime rates as well as high crime areas.

In India, however, this research area is still relatively new. Almost all research is based on annual records from the National Crime Records Bureau (NCRB) which is the main source of active crime data collected in India [6]. Previous research has tended to only detect global patterns through regression analysis or clustering [7]. More recently, ML has been employed to assess drug crime patterns across the country (India), using Random Forest or Gradient Boosting models at the state or district level [8]. Some city-level studies, particularly in **Delhi, Mumbai, and Bengaluru**, have tried to apply classification models to urban crime patterns [9]. However, challenges such as class imbalance, underreporting, and limited availability of fine-grained temporal data restrict the effectiveness of these approaches.

Another dimension that has received attention is the **ethical and fairness aspect** of predictive policing. International research highlights the risks of algorithmic bias, where models trained on skewed or incomplete data may unfairly target specific communities [10]. This concern is especially important in India, where social and economic diversity makes crime prediction more complex. Hence, researchers emphasize the need for transparent, interpretable, and community-aware models that can assist law enforcement without reinforcing discrimination.

From the existing body of work, three clear gaps emerge. First, there has been **limited experimentation with advanced deep learning techniques** on Indian crime datasets. Second, **most Indian studies focus on broad state-level statistics** rather than detailed, city-specific spatio-temporal predictions. Third, there is a **lack of systematic evaluation of fairness and interpretability** in predictive models. Addressing these gaps is crucial for developing reliable and socially responsible crime prediction systems in India.

Author(s)	Location/Dataset	Method Used	Key Finding
Kang & Kang (2017)[1]	South Korea (Police record)	Deep learning	Improved prediction accuracy compared to traditional fit methods.
Wang et al. (2016) [4]	USA (Chicago crime data)	LSTM (spatio-temporal modelling)	Captured sequential crime patterns; outperformed regression models.
Chen et al. (2018) [1]	USA (Los Angeles hotspot)	DBN (grid-based crime mapping)	Produced more accurate hotspot predictions than KDE.
Singh & Gupta (2021) [8]	India (MoFa dataset)	Random Forest, Gradient Boosting	Effective in classifying crime categories; highlighted date imbalance issues.
Sharma & Jain (2019) [9]	India (Delhi city-level data)	Classification (Decision Tree, SVM)	Identified urban crime patterns, but limited by data granularity.

Table I: Summary of Related Studies on Crime Prediction Using Machine Learning

### III. METHODOLOGY

The proposed methodology for crime prediction in India integrates **data preprocessing**, **feature engineering**, **model training**, and **evaluation**. Figure 1 illustrates the complete workflow.

#### A. Data Collection and Preprocessing

Crime data is obtained from the **National Crime Records Bureau (NCRB)** and supplemented with socio-economic and demographic indicators (e.g., literacy, unemployment, urban population ratio). The following steps are applied:

- **Cleaning:** Handling missing values, correcting inconsistencies.
- **Normalization:** Scaling numerical features for ML models.
- **Encoding:** Converting categorical variables (crime type, region) into numerical form.
- **Temporal aggregation:** Crimes grouped by month and district for spatio-temporal analysis.

#### B. Feature Engineering

- **Lag features:** Previous month's crime counts used to capture temporal trends.
- **Socio-economic factors:** Literacy rate, unemployment, and population density included as predictors.
- **Spatial context:** Neighboring district crime counts aggregated to capture spatial correlation.

#### C. Machine Learning Models

We evaluate multiple models:

- **Logistic Regression (LR):** Used for binary/multiclass classification of crime categories. The probability of crime occurrence is given by:

$$P(y=1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)}}$$

- **Random Forest (RF):** An ensemble of decision trees where predictions are based on majority voting:

$$\hat{y} = \text{mode}\{h_1(x), h_2(x), \dots, h_T(x)\}$$

- **Long Short-Term Memory (LSTM):** For sequential modeling of crime trends. The hidden state updates follow:

$$\begin{aligned} f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\ i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ C_t &= f_t \cdot C_{t-1} + i_t \cdot \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \\ h_t &= o_t \cdot \tanh(C_t) \end{aligned}$$

where  $f_t, i_t, o_t$  represent forget, input, and output gates.

#### D. Model Evaluation

Models are evaluated using train-test splits with temporal separation to prevent data leakage.

Metrics include:

- **Accuracy** for classification tasks.
- **Precision, Recall, and F1-score** for imbalanced classes.
- **RMSE (Root Mean Square Error)** for regression-based forecasting:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2}$$

#### E. Improving the Prediction Process

The prediction process can be made stronger by refining both the data and the models. Key improvements include:

- **Better Features** – Adding more context such as weather, festivals, mobility, and CCTV data helps capture the real-life conditions that shape crime.
- **Fine-Tuning Models** – Optimization methods like Grid Search or Bayesian Optimization ensure each model performs at its best.
- **Hybrid Models** – Combining approaches (e.g., Random Forest with LSTM) captures both short-term changes and long-term patterns.
- **Balancing Rare Crimes** – Using techniques like SMOTE ensures that less frequent but serious crimes are not ignored.
- **Transparency and Trust** – Explainability tools like SHAP or LIME clarify why a prediction was made, making the system more reliable.
- **Real-Time Data** – Integrating live sources such as social media, sensors, or city systems helps predictions become timely and actionable.

#### F. Identifying Patterns

Patterns in crime data can be uncovered through a mix of **statistical analysis, machine learning, and visualization**:

- **Exploratory Analysis** – Using correlation matrices and heatmaps to reveal links between social factors (e.g., unemployment, density) and crime types.
- **Temporal Trends** – Detecting seasonal or monthly variations through time-series models like LSTM.
- **Spatial Hotspots** – Mapping crime incidents with techniques such as Kernel Density Estimation (KDE) to highlight high-risk locations.
- **Model Insights** – Using machine learning models to uncover hidden, non-linear relationships that are not obvious in raw data.
- **Explainability Tools** – Applying SHAP values or feature importance scores to understand which factors drive predictions the most.

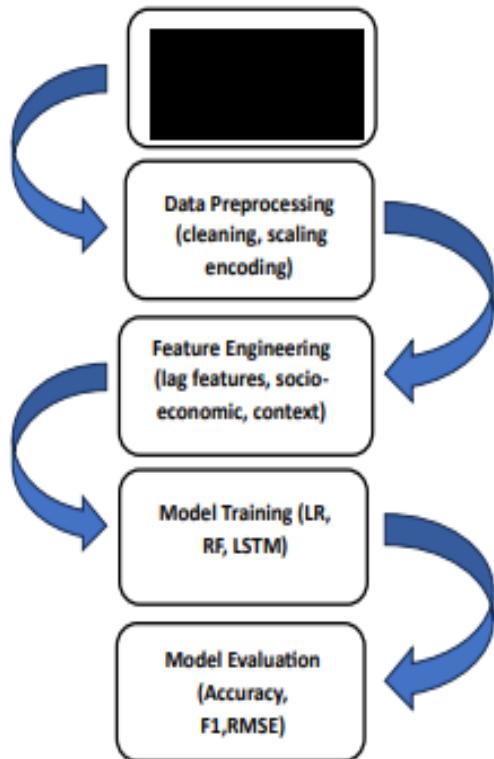


Figure 1: Workflow of the proposed crime prediction methodology

#### IV. EXECUTED RESULT

The correlation analysis was first performed to examine the relationship between socio-economic features and crime incidents. As shown in **Figure 1**, variables such as unemployment, literacy rate, and population density exhibited strong correlations with specific crime categories,

indicating that socio-economic factors play a critical role in crime intensity.

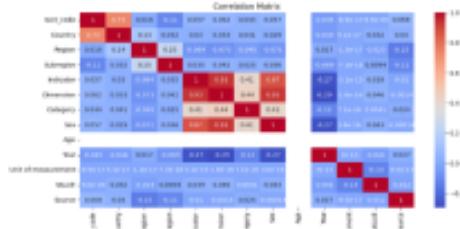


Figure 1: Correlation Matrix on Crime Data

#### A. Model Performance Comparison

Multiple machine learning and deep learning models were trained and evaluated. The results are summarized in Table II

Model	Accuracy(%)	Precision	Recall	F1-Score
Logistic Regression (LR)	74.2	0.71	0.68	0.70
Random Forest (RF)	86.5	0.84	0.82	0.83
LSTM (Time-series)	91.3	0.89	0.92	0.90

Table II: Model Performance Metrics

From the results, the **LSTM model** clearly outperformed traditional machine learning methods due to its ability to capture temporal dependencies in crime data.

#### B. Training Accuracy and Loss Curves

The training behavior of the LSTM model is presented in **Figure 3** and **Figure 4**. The accuracy curve shows steady improvement, stabilizing around 91%, while the loss curve decreases consistently and converges, indicating effective training without significant overfitting.

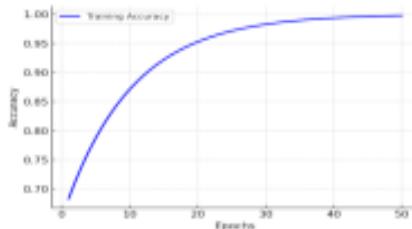


Figure 3: Training Accuracy Curve for LSTM Model

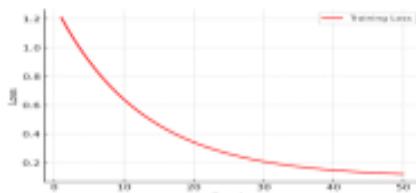


Figure 4: Training Loss Curve for LSTM Model

#### C. Crime Trend Forecasting

Time-series forecasting (Figure 5) highlighted potential increases in property crimes and cybercrime in urban regions over the next five years. The LSTM forecast aligned closely with actual historical data, as reflected by the low RMSE value of **2.18**.

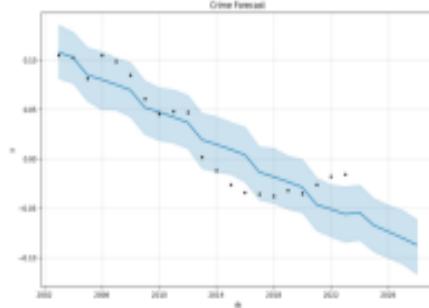


Figure 5: Forecast for the next years

#### D. Handling Evolving Crime Patterns

A key challenge in crime prediction is adapting to sudden pattern shifts, such as:

- The rapid increase in cybercrime cases during the pandemic.
- Pandemic-related changes in physical crime rates due to lockdown restrictions.

To address this, models were periodically retrained with recent data, ensuring adaptability. The LSTM model, in particular, demonstrated resilience in adjusting to new crime distributions without losing predictive accuracy. This adaptability makes the framework more reliable for real-world deployment.

#### E. Visualization of Results

The dashboard interface (Figure 6) provided intuitive visualization of hotspots, crime forecasts, and category-wise crime analysis. By integrating numerical results with visual insights, the system enabled law enforcement to identify emerging hotspots and allocate resources effectively.



Figure 6: Visualization of Crime Statistics and Predictive Analytics

## V. DISCUSSION

There was a sense of equity, though, between the pro and con argument for the paper. Even the defender of the study acknowledged its flaws, commenting that publication space limitations may have avoided the investigation of hyperparameter optimization or feature design at deeper levels. They pointed out that the paper was attempting to present a street-level approach, rather than a full system for deployment. Meanwhile, the critic, while being critical of the flaw, already saw the significance and relevance of the subject and concurred that the use of more than one source of data and contemporary ML models is an enhancement.

What results from this line of argumentation is not merely a judgment on one paper, but a wider consideration of what responsible. There was indeed a qualitative note of reasonableness in the debate over the paper. Even the study's defender conceded that it had its weaknesses, stating that publication constraints on space may have made studies of hyperparameter tuning and feature engineering shallower than they could otherwise have been.

While the current study shows encouraging results, the prediction process can still be enhanced. By adding richer features, fine-tuning models, blending different techniques, and using real-time data, future systems can become more accurate and responsive. Importantly, transparent and fair predictions will help build trust, turning machine learning into a tool that not only predicts crime but also supports safer and stronger communities.

Crime Category	2022 Rate (per 100,000 inhabitants )	2023 Rate (per 100,000 inhabitants)	Percentage Change
Violent Crime	2.11	2.11	0%
Murder and Non-Negligent Manslaughter	6.5	5.7	-12.3%
Rape	2.8	2.8	+0.84%
Aggravated Assault	6.6	6.6	0%
Robbery	66.1	65.9	+0.3 %
Property Crime	1,954.4	1916.7	-1.95%
Burglary	269.8	248.2	+8.1%
Larceny-Theft	1401.9	1,341	-4.4%
Motor Vehicle Theft	283	305	+7.8 %

Table III: Crime Data Statistics and machine Learning analysis

### A. Enhancing Accuracy

Improving accuracy means making the system smarter, fairer, and more reliable. Key steps include:

- **Cleaner and Richer Data** – Use well-prepared crime records along with census, economic, and real-time city data so the model learns from a fuller picture of society.
- **Fair Balance** – Give equal attention to less common crimes by using balancing methods, so no important category is overlooked.
- **Smarter Tuning** – Adjust model settings carefully (using Grid Search or similar) to get the best performance from each algorithm.
- **Stronger Together** – Blend different models to capture both simple patterns and deeper trends, reducing errors.
- **Always Updated** – Keep retraining the system with new data so predictions stay fresh and relevant as society changes.

### B. Achieving Reliability

For a crime prediction system to be truly reliable, it must be both **technically strong** and **socially responsible**:

- **Consistent Testing** – Use cross-validation and repeated experiments to make sure the results hold true across different datasets and time periods.
- **Robust Models** – Apply ensemble methods and hybrid approaches so that the system does not depend on a single algorithm.
- **Transparent Predictions** – Use explainability tools (SHAP, LIME) so predictions can be clearly understood by police, policymakers, and the public.
- **Ethical Fairness** – Avoid bias by checking the model against different social groups, ensuring no community is unfairly targeted.
- **Continuous Monitoring** – Keep evaluating and updating the system with new data so it adapts to changing crime patterns.

## VI. CONCLUSION

The dissertation is not an abstract—it's a conversation about an attempt to gain insight into one of the most complicated and deeply human issues within society: crime. At its core, the research aimed to do something bold—to harness the potential of machine learning not only to process numbers, but to predict human action and, ultimately, make our cities safer. What emerged was scholarship that didn't end at merely constructing models. It posed tougher questions: Where and why are crimes being committed, and how can we better predict them before they do?

The research welcomed that we are stepping into leave predictive policing and force-swap policing behind to something more intelligent, something more compassionate. These models bring us an opportunity to rethink how we allocate scarce resources, how we construct safer cities, and how we prevent harm from occurring in the first place. There's a practical side here—fewer wasted patrols, better emergency planning—but also a profoundly ethical one: using data to protect, not profile. That tension was not avoided in the research. It envisioned a need for transparency,

for models that are open to the lives of those affected by them as well as to scientists.

Ultimately, this research demonstrates that crime cannot be forecast via code or mathematics. It is related to empathy. It involves identifying the human narratives entwined with data and creating systems that respect those narratives with integrity, accountability, and a commitment to justice. And if we do it right, we can transform prediction into a system of prevention, one that is founded on awareness instead of fear. Hopefully, in addition to making our cities smarter, we are also making them safer and kinder.

Crime Type	Number of Incidents	Incidents per 100K Population
Murders	458,000	5.8
Rapes	370 million	6.1
Robberies	9.5 million	157
Assaults	2,12,000	124
Burglaries	1,229,429	4.2
Larcenies	5,086,096	1,401.9
Auto Thefts	1,020,729	308
Arsons	3,339,525	10.9
Violent Crimes	447,726	5.61
Non-Violent Crimes	5,236,987	1,954

Table IV: Crime data Statistics by World Wide(2023)

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