Crime Type and Occurrence Prediction using Machine Learning Algorithm

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ABSTRACT
With the rapid growth of urban populations and the increasing complexity of social structures, crime prediction has become an essential task in ensuring public safety and effective law enforcement. This project, titled "Crime Type and Occurrence Prediction Using Machine Learning", aims to leverage historical crime data and advanced machine learning algorithms to predict both the type of crime and the likelihood of its occurrence in a given location and time frame. The system utilizes supervised learning techniques to analyze features such as crime location, time, previous occurrences, weather conditions, and socio-economic factors. By training models like Random Forest, Support Vector Machine (SVM), and Logistic Regression on crime datasets, the system can classify various types of crimes—such as theft, assault, vandalism—and estimate the probability of a crime taking place. This predictive approach can be used by law enforcement agencies to allocate resources more effectively, increase patrol in high-risk areas, and ultimately prevent crime before it happens. Additionally, the system can serve as a decision-support tool for city planners and policymakers by providing insights into crime trends and patterns. The integration of machine learning into crime analysis demonstrates the potential for technology to play a crucial role in modern policing, enhancing public safety through data-driven intelligence and proactive response..

Keyword: Random Forest, Support Vector Machine (SVM), and Logistic Regression.

INTRODUCTION

Crime is one of the major challenges faced by urban and rural communities alike across the globe. As populations continue to grow and urbanization expands, there has been a parallel increase in criminal activities ranging from thefts and burglaries to violent assaults and cybercrimes. Law enforcement agencies often struggle with limited resources, time constraints, and a reactive approach to crime investigation. In such a scenario, predictive analytics and machine learning (ML) offer a revolutionary way to transition from reactive policing to proactive crime prevention.

The idea of predicting crimes based on patterns derived from historical data is not new. However, with the advancement in computational power and the availability of large-scale datasets, it is now possible to develop intelligent systems capable of forecasting where and what type of crime is likely to occur, as well as estimating the likelihood of its occurrence. These insights can significantly aid police departments, government agencies, and policymakers in devising targeted interventions.

This work, titled "Crime Type and Occurrence Prediction Using Machine Learning", aims to develop a model that can predict two major aspects:
The type of crime – such as robbery, assault, vandalism, drug-related crimes, etc. The likelihood of occurrence – determining if a crime is likely to happen at a particular location and time. By using machine learning algorithms on features such as time of day, day of the week, location coordinates, weather conditions, population density, past crime frequency, and socioeconomic indicators, we can derive patterns that are not easily visible to human analysts. The project emphasizes not only on classification (i.e., crime type) but also on probabilistic forecasting (i.e., crime occurrence), making it a dual-purpose solution for law enforcement analytics. The Need for Predictive Crime Modeling Traditional law enforcement heavily relies on human intuition and after-the-fact investigation. While these techniques are valuable, they lack the capacity to foresee and prevent crimes before they happen. Moreover, the manual analysis of data is time-consuming and prone to oversight, especially when working with large volumes of crime records.
With machine learning, vast amounts of structured and unstructured crime-related data can be processed, analyzed, and interpreted at high speed and accuracy. Supervised learning techniques such as Decision Trees, Random Forest, Logistic Regression, Support Vector Machines (SVM), and advanced models like XGBoost and Neural Networks can be trained on labeled crime datasets to classify crime types. Simultaneously, techniques such as classification probability estimation and time series analysis can be used to predict the occurrence of crimes in future timeframes.

PROBLEM STATEMENT

Predicting crime is a difficult and sensitive function for law enforcement agencies, as it assists in the effective allocation of resources, the prevention of crimes, and improving the public safety The conventional methods of crime prediction heavily depend on subjective examination of past crime data, which is potentially labor-intensive, error-incurred, and incapable of coping with instantly shifting crime trends. The issue becomes even greater with the increased volume and variety of sources of data, such as geographic locations, socio-economic conditions, time-based trends, and even social media behaviour. Moreover, forecasting both the nature and incidence of crimes in real-time with high precision is still an open problem. The main issue is the lack of predicting the precise time and location of crime occurrences with adequate precision, resulting in ineffective law enforcement resource allocation. Compounding the problem is the absence of comprehensive data that integrates spatial, temporal, and social factors to make meaningful predictions. Furthermore, the skewness in crime data—with certain types of crime being heavily underrepresented—tends to result in model biases and poor performance, particularly for less common but more serious crimes. This study aims to overcome these challenges by using Machine Intelligence (MI), in the form of Machine Learning (ML) algorithms, to predict both crime type and occurrence with greater accuracy. Using historical crime data, temporal patterns, socio-economic factors, and geographic data, the focus is to come up with models that can generate actionable knowledge about where and when particular crimes are expected to take place. This will benefit law enforcement agencies by making informed decisions to avoid crime, streamline patrolling processes, and distribute resources accordingly, all toward improving public safety. The challenge is aggravated by the requirements of obtaining reliable and precise real-time forecasts dealing with voltile crime patterns that evolve over time and across different regions.

OBJECTIVES

To Collect and Preprocess Crime Data:
Gather historical crime datasets from reliable sources and clean the data to ensure quality and consistency for analysis.

To Develop a Predictive Model Using Random Forest:
Build and train a Random Forest classifier to accurately predict the type of crime and the likelihood of its occurrence based on various features such as location, time, and other relevant attributes.

To Evaluate Model Performance:
Assess the accuracy, precision, recall, and other performance metrics of the Random Forest model to ensure reliable predictions.

To Create an Interactive Visualization Dashboard:
Develop a user-friendly Streamlit-based dashboard that provides city-wise crime data visualization, enabling users to explore crime patterns and trends geographically.

To Provide Real-Time Insights for Law Enforcement and Citizens:
Deliver actionable insights through prediction and visualization to assist law enforcement agencies in resource allocation and help citizens stay informed about crime trends in their areas.

To Enhance Public Safety and Crime Prevention:
Use predictive analytics to enable proactive measures against crime, reducing crime rates and improving community safety.

LITERATURE SURVEY

1. 1.Forecasting Crime with Deep Learning by Alexander Stec and Diego Klabjan (2018): This study utilized deep neural networks to predict daily crime counts in Chicago and Portland, incorporating additional datasets like weather and public transportation to enhance prediction accuracy.
2. 2.Deep Learning for Real-Time Crime Forecasting by Bao Wang et al. (2017): This research adapted a deep learning spatio-temporal predictor to forecast crime distribution in Los Angeles, demonstrating the effectiveness of deep learning models in real-time crime prediction.
3. Patel and Thakkar (2016) conducted a study titled *“Machine Learning Approaches to Predict and Detect Crime,”* in which they explored the effectiveness of various machine learning algorithms in crime prediction. Using the UCI crime dataset, they compared the performance of Random Forest, Support Vector Machine (SVM), and Naive Bayes classifiers. The evaluation was based on standard metrics such as precision and recall. Their findings revealed that the Random Forest algorithm significantly outperformed the other methods, achieving higher accuracy and reliability in predicting criminal activity. This study highlights the potential of ensemble learning techniques, particularly Random Forest, in enhancing predictive policing strategies.
4. In their 2016 study titled *“Machine Learning Approaches to Predict and Detect Crime,”* Patel and Thakkar examined the effectiveness of several machine learning algorithms in predicting and detecting criminal activities. They utilized the UCI crime dataset to compare the performance of Random Forest, Support Vector Machine (SVM), and Naive Bayes classifiers. The results demonstrated that Random Forest outperformed the other algorithms in terms of both precision and recall, indicating its superior ability to accurately classify and predict crime-related data. This research underscores the value of using ensemble methods like Random Forest in crime analytics for more accurate and reliable crime prediction.

5. In the 2013 study titled *"Crime Analysis and Prediction Using Data Mining,"* Chitra and Seenivasagam applied data mining techniques to analyze and predict criminal activity using real crime datasets. The research focused on the use of clustering algorithms such as K-Means and classification methods like Decision Trees to identify patterns and forecast future crime occurrences. Notably, the study emphasized crime data from India and demonstrated that incorporating socio-demographic attributes significantly enhanced the accuracy of crime prediction models. This work highlights the importance of contextual and demographic factors in developing effective crime analysis systems.

PROPOSED SYSTEM

Crimes are the significant threat to the humankind. There are many crimes that happens regular interval of time. Perhaps it is increasing and spreading at a fast and vast rate. Crimes happen from small village, town to big cities. Crimes are of different type – robbery, murder, rape, assault, battery, false imprisonment, kidnapping, homicide. Since crimes are increasing there is a need to solve the cases in a much faster way. The crime activities have been increased at a faster rate and it is the responsibility of police department to control and reduce the crime activities. Crime prediction and criminal identification are the major problems to the police department as there are tremendous amount of crime data that exist. There is a need of technology through which the case solving could be faster. "Here we are proposing a new Random forest based feature section algorithm for avoid the nosie information for feature engineering by using this we can achieve the best accuracy".

- The above problem made me to go for a research about how can solving a crime case made easier. Through many documentation and cases, it came out that machine learning and data science can make the work easier and faster.
- The aim of this project is to make crime prediction using the features present in the dataset. The dataset is extracted from the official sites. With the help of machine learning algorithm, using python as core we can predict the type of crime which will occur in a particular area.
- The objective would be to train a model for prediction. The training would be done using the training data set which will be validated using the test dataset. Building the model will be done using better algorithm depending upon the accuracy. (XGBoost, AdaBoost,Random Forest, KNN)classification algorithms will be used for crime prediction. Visualization of dataset is done to analyze the crimes which may have occurred in the country. This work helps the law enforcement agencies to predict and detect crimes in Chicago with improved accuracy and thus reduces the crime rate.

SYSTEM ARCHITECTURE

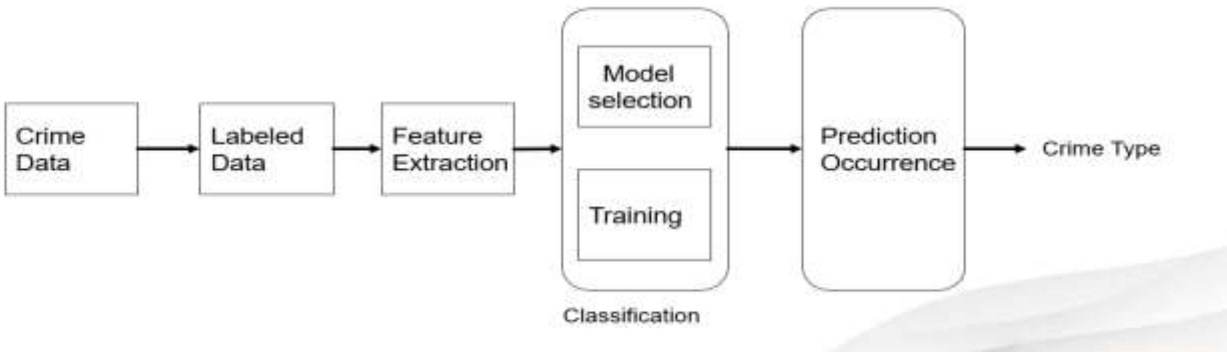

Fig 1. System architecture

1. **Crime Data**
- This is the raw dataset containing various information related to crimes — such as date, time, location, type of crime, suspect/victim details, etc.
- It serves as the foundation for training the model.
2. **Labeled Data**
- From the raw crime data, this stage involves assigning labels — i.e., specifying the target output such as the type of crime (e.g., theft, assault, robbery).
- This transforms the data into a supervised learning format, where both input features and corresponding output labels are available.
3. **Feature Extraction**
- Important features are selected from the dataset to reduce noise and improve model performance.
- Examples: extracting time of day, crime location zone, or weather conditions during the event.
- This step helps in feeding only the most relevant data into the model.
4. **Classification Block (Model Selection + Training)**
- This section is divided into two steps:
  - Model Selection: Choosing the appropriate algorithm for classification (e.g., Decision Tree, SVM, Random Forest, Naive Bayes).
  - Training: Feeding the extracted features and labeled data into the model so that it can learn the patterns associated with different crime types.
5. **Prediction Occurrence**
- Once the model is trained, it is used to predict the occurrence or type of crime based on new input data.
- This block represents the inference or deployment phase of the model.
6. **Crime Type (Output)**
- The final output is the predicted type of crime, which can help law enforcement agencies anticipate and prepare for specific types of criminal activity.

IMPLEMENTATION:

- Data Set Reading and Inspection.
- Text Preprocessing.
- Analysis.
- Classification
- Evaluation.

Data Set Reading and Inspection:

The dataset can be taken from the Kaggle repository. The dataset contains homicide entries collected from the FBI's supplementary Homicide Report.From the dataset, the significant features like State, Year, Month, Crime Type, Crime Solved, Victim Gender, Victim Age, Victim Race, Victim Count and Weapon are chosen as the input features for the system. The record collected is almost 63000. The features Perpetrator Age, Perpetrator Gender and Relationship of the perpetrator with the victim are chosen as the target variable to be predicted by the system.

Text Preprocessing:

Once the dataset is collected, it must be pre-processed to get the clean dataset. The pandas and NumPy libraries are available in python for the pre-processing. it is removing of empty values from the dataset or repeated records should be removed.

Analysis:

The analysis includes the graphical representation of different values to analyse the dataset property. The different graphs are plotted by Matplotlib libraries. The graphical analysis gives a direction towards the prediction.

RESULTS AND DISCUSSIONS

Figure 2. Login page

Crime Type and Occurrence Prediction Using Machine Learning Algorithm. This system is designed to predict various types of crimes and their occurrences using machine learning techniques. The login window features a user-friendly interface with input fields for both username and password, where the entered password is masked for security. It includes three buttons: "Login" to authenticate the user, "Cancel" to reset or exit the login process, and "Register" for new users to create an account.

ReportNumber	DateReported	DateofOccurrence	CrimeCode	City
40160	31-07-2024 17:00	7/31/2024 7:00	31-07-2024 17:19	193
40159	1/8/2024 19:00	7/31/2024 6:00	31-07-2024 11:05	311
40158	2/8/2024 3:00	7/31/2024 5:00	31-07-2024 21:33	423
40157	31-07-2024 14:00	7/31/2024 4:00	31-07-2024 04:14	300
40156	1/8/2024 16:00	7/31/2024 3:00	31-07-2024 05:05	312
40155	1/8/2024 11:00	7/31/2024 2:00	31-07-2024 12:59	532
40154	31-07-2024 17:00	7/31/2024 1:00	31-07-2024 21:42	567
40153	2/8/2024 11:00	7/31/2024 0:00	31-07-2024 03:46	568
40152	1/8/2024 0:00	7/30/2024 23:00	30-07-2024 23:10	106
40151	1/8/2024 23:00	7/30/2024 22:00	31-07-2024 19:41	430
40150	31-07-2024 19:00	7/30/2024 21:00	31-07-2024 15:43	161
40149	1/8/2024 4:00	7/30/2024 20:00	31-07-2024 17:38	479
40148	2/8/2024 18:00	7/30/2024 19:00	30-07-2024 21:30	345
40147	2/8/2024 9:00	7/30/2024 18:00	30-07-2024 19:32	400
40146	31-07-2024 22:00	7/30/2024 17:00	31-07-2024 00:01	539
40145	31-07-2024 22:00	7/30/2024 16:00	31-07-2024 12:30	508
40144	2/8/2024 4:00	7/30/2024 15:00	31-07-2024 01:51	362
40143	1/8/2024 22:00	7/30/2024 14:00	30-07-2024 16:55	237
40142	1/8/2024 4:00	7/30/2024 13:00	31-07-2024 03:26	365
40141	31-07-2024 02:00	7/30/2024 12:00	30-07-2024 12:44	157
40140	31-07-2024 08:00	7/30/2024 11:00	30-07-2024 13:35	393
40139	31-07-2024 11:00	7/30/2024 10:00	30-07-2024 19:27	138
40138	31-07-2024 18:00	7/30/2024 9:00	30-07-2024 18:36	317
40137	1/8/2024 9:00	7/30/2024 8:00	30-07-2024 18:02	459
40136	31-07-2024 05:00	7/30/2024 7:00	30-07-2024 21:51	417
40135	31-07-2024 02:00	7/30/2024 6:00	30-07-2024 12:21	389
40134	30-07-2024 22:00	7/30/2024 5:00	30-07-2024 05:27	459
40133	30-07-2024 10:00	7/30/2024 4:00	31-07-2024 03:00	328
40132	30-07-2024 08:00	7/30/2024 3:00	30-07-2024 22:45	144
40131	31-07-2024 00:00	7/30/2024 2:00	30-07-2024 23:21	534
40130	30-07-2024 09:00	7/30/2024 1:00	30-07-2024 06:26	373
40129	30-07-2024 07:00	7/30/2024 0:00	30-07-2024 19:48	594
40128	31-07-2024 23:00	7/29/2024 23:00	30-07-2024 14:44	272
40127	31-07-2024 23:00	7/29/2024 22:00	30-07-2024 09:16	369
40126	1/8/2024 2:00	7/29/2024 21:00	30-07-2024 05:05	591
40125	1/8/2024 11:00	7/29/2024 20:00	30-07-2024 11:02	504

Figure 3. Dataset

This dataset includes detailed information on crime reports, with columns such as Report Number, Date Reported, Date of Occurrence, Crime Code, and City. Each entry represents a unique crime incident. The data captures both when the crime occurred and when it was reported. This allows analysis of time-based patterns and delays in reporting. The Crime Code indicates the type of crime, which can be used as a label in classification models. The City field helps in identifying geographic crime hotspots. Time features like hour, day, and month can be extracted from the date fields. These features are useful for building machine learning models. Possible applications include predicting crime types and occurrence. This dataset supports both classification and time-series analysis for crime forecasting.

Figure 4..Main Screen

The main screen displays the core interface of the crime prediction system. It features several buttons such as “Load Dataset,” “Preprocessing,” “Feature Engineering,” “Prediction,” and “Dashboard.” These options represent key stages in the machine learning pipeline. Users can upload datasets, clean and process data, select important features, and run predictions. The dashboard provides a visual summary of prediction results. The interface is designed to be user-friendly and intuitive. It simplifies complex ML tasks for users with minimal technical expertise. The background image of a police car reinforces the system's focus on crime analysis and law enforcement.

```
🔍 Crime Occurrence Prediction Report:

              precision    recall  f1-score   support

           0       0.18      0.03      0.05       102
           1       0.97      1.00      0.98      3164

    accuracy                           0.97      3266
   macro avg       0.57      0.51      0.52      3266
weighted avg       0.94      0.97      0.95      3266
```

Figure 5 Crime occurence report

This image shows a classification report generated by a machine learning model evaluating crime occurrence predictions. It includes key metrics like precision, recall, f1-score, and support for two classes:
Class 0: No crime occurred
Class 1: Crime occurred
Formulas used for the occurrence prediction

1.Precision = TP / (TP + FP)
TP: True Positives
FP: False Positives

2. Recall (Sensitivity)
Recall = TP / (TP + FN)
FN: False Negatives

3. F1-Score
F1-score = 2 * (Precision * Recall) / (Precision + Recall)

4. Accuracy
Accuracy = (TP + TN) / (TP + TN + FP + FN)

5.Macro Average
Macro Avg = (Metric1 + Metric2 + ... + MetricN) / N

- N = Number of classes
- Metric = Precision or Recall or F1 for each class

6. Weighted Average
Weighted Avg = (Metric1 * Support1 + Metric2 * Support2 + ... + MetricN * SupportN) / (Support1 + Support2 + ... + SupportN)

- Metric = Precision or Recall or F1
- Support = Number of true instances for each class

Crime Type Prediction Report:

	precision	recall	f1-score	support
ARSON	0.04	0.04	0.04	147
ASSAULT	0.06	0.08	0.07	153
BURGLARY	0.07	0.06	0.07	173
COUNTERFEITING	0.04	0.04	0.04	154
CYBERCRIME	0.04	0.04	0.04	146
DOMESTIC VIOLENCE	0.06	0.06	0.06	158
DRUG OFFENSE	0.01	0.01	0.01	153
EXTORTION	0.04	0.05	0.05	149
FIREARM OFFENSE	0.02	0.03	0.03	156
FRAUD	0.05	0.06	0.05	159
HOMICIDE	0.05	0.05	0.05	131
IDENTITY THEFT	0.04	0.05	0.05	150
ILLEGAL POSSESSION	0.05	0.04	0.05	157
KIDNAPPING	0.05	0.05	0.05	151
PUBLIC INTOXICATION	0.07	0.06	0.06	148
ROBBERY	0.04	0.04	0.04	147
SEXUAL ASSAULT	0.06	0.06	0.06	153
SHOPLIFTING	0.08	0.06	0.07	152
TRAFFIC VIOLATION	0.06	0.06	0.06	154
VANDALISM	0.02	0.02	0.02	123

Figure 6..Crime type prediction Report

The image shows a Crime Type Prediction Report in the form of a classification performance metrics table. It evaluates how well a machine learning model predicts different types of crimes based on three key metrics: **precision**, **recall**, and **f1-score**, along with the **support** (number of actual occurrences for each crime type). Here's a breakdown:

Key Metrics:

1. **Precision**: Measures the accuracy of positive predictions (how many predicted crimes of a type were correct).
   Example: For ASSAULT, precision is 0.06, meaning only 6% of predictions labeled as "ASSAULT" were correct.
2. **Recall**: Measures the model's ability to find all actual instances of a crime type (how many actual crimes of a type were correctly predicted).
   - Example: For BURGLARY, recall is 0.06, meaning only 6% of actual burglaries were identified.
3. **F1-Score**: A balance between precision and recall (harmonic mean). Useful for imbalanced datasets.
   - Example: CYBERCRIME has the highest F1-score (0.04), but this is still very low.
4. **Support**: The number of actual occurrences of each crime type in the dataset.
   - Example: DOMESTIC VIOLENCE has 158 instances.

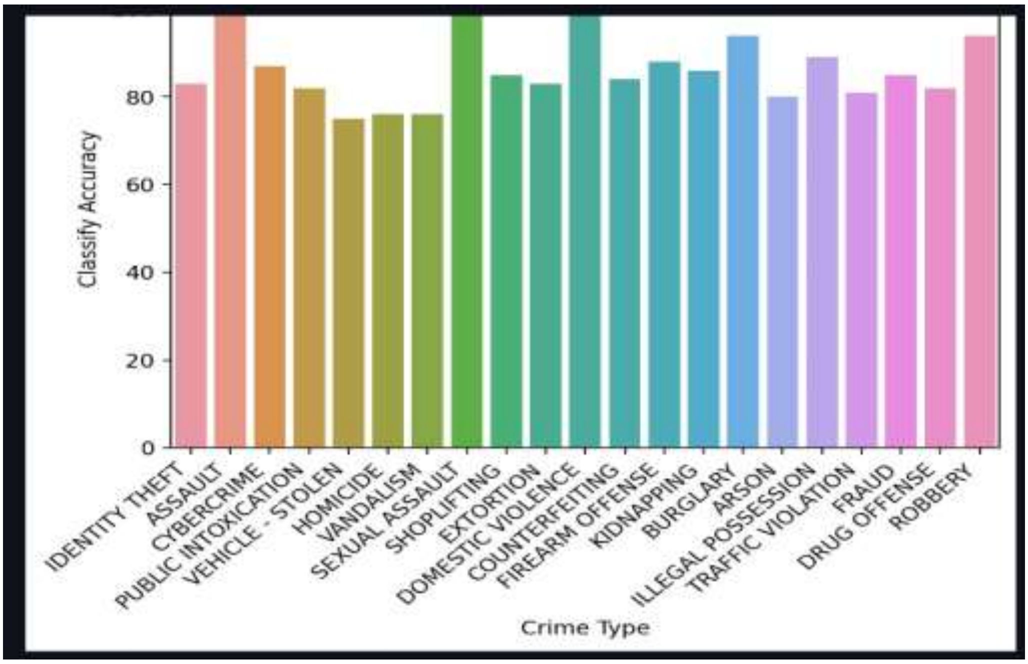

Fig 7. C rime Analysis

This bar graph visualizes the number of different types of crimes recorded in Bangalore. The y-axis represents the count of crimes, while the x-axis lists various crime descriptions. Each bar corresponds to a specific crime type, and its height indicates the number of times that crime was reported.

The graph shows that the crime types with the highest counts have bars that extend to approximately 175-200, while others are much lower, with some close to zero. This suggests that certain types of crimes are more prevalent than others in Bangalore. The graph is a snapshot of crime data, making it easier to spot the most common categories visually.

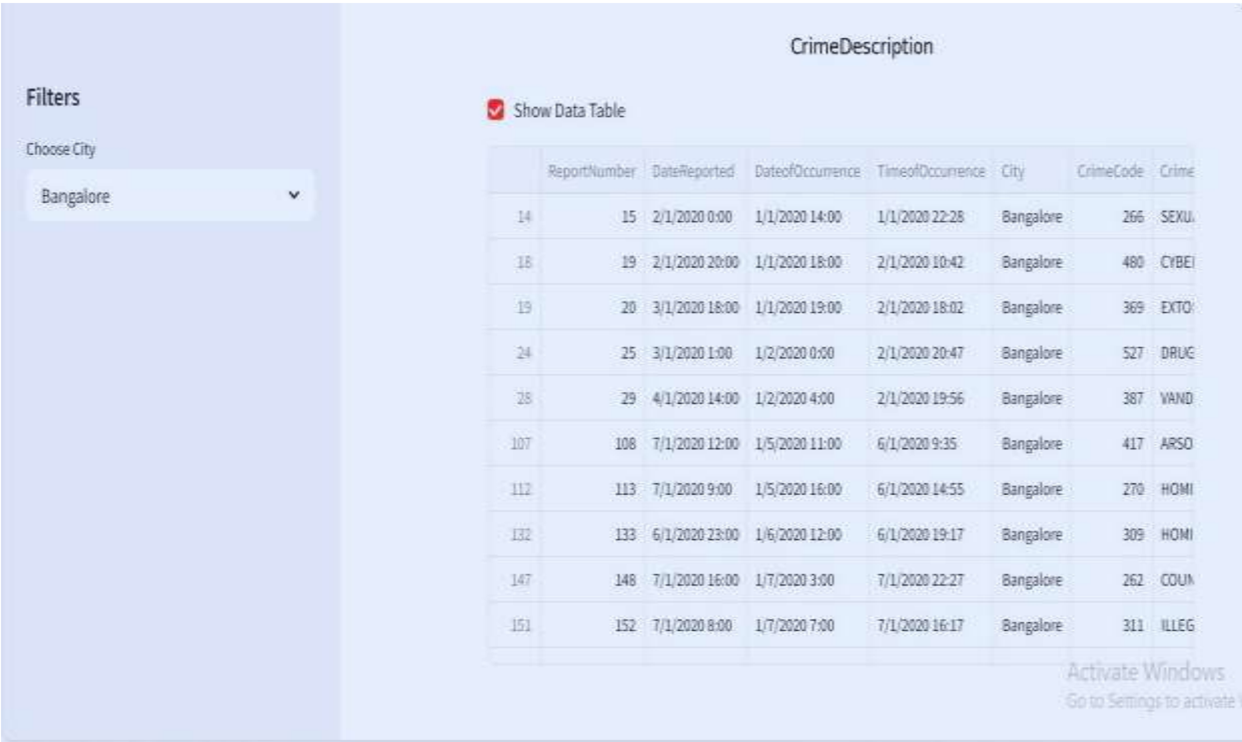

Figure 8. streamlit dashboard

This page is part of a crime data visualization dashboard designed to help users analyze crime patterns in different cities. It features a filter section where users can select a city—Bangalore is chosen in this example—and a data table that displays detailed crime records for the selected location. The table includes columns such as the report number, date reported, date and time of occurrence, city, crime code, and a description of the crime (such as sexual assault, cybercrime, or extortion). A checkbox labeled "Show Data Table" allows users to toggle the visibility of the data. This dashboard helps users, such as law enforcement agencies or analysts, to explore crime trends by reviewing when and where crimes happened, what types of crimes were reported, and how they are categorized. It provides a clear and interactive way to understand crime data for better safety planning and decision-making.

CONCLUSION

The development of a crime type and occurrence prediction system using Random Forest and Streamlit demonstrates the powerful potential of machine learning in enhancing public safety and law enforcement efficiency. By leveraging historical crime data and advanced predictive algorithms, this system provides valuable insights into crime patterns and potential future incidents, enabling proactive measures to mitigate risks. The integration with Streamlit offers an interactive and user-friendly platform for visualizing crime data city-wise, making it accessible to stakeholders and decision-makers. This project not only highlights the effectiveness of Random Forest in handling complex, multi-dimensional datasets for classification but also underscores the importance of data-driven approaches in crime analysis. While the system shows promising accuracy and practical application, there remains room for further improvements by incorporating real-time data and advanced analytics. Overall, this predictive model serves as a significant step towards smarter policing and community safety, supporting timely interventions and informed decision-making. Continued enhancements and wider adoption of such technologies can contribute to safer urban environments and better crime management strategies in the future.

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