

UNRAVELING STATEWISE CRIME PATTERNS WITH ENSEMBLE MACHINE LEARNING AND DATA VISUALIZATION TECHNIQUES FOR PUBLIC SAFETY

Submitted in partial fulfilment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering

By

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**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SCHOOL OF COMPUTING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

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April - 2024



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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Pandraju N Rama Venkata Sathya Sheshusai (40110896)** who carried out the Project entitled **"UNRAVELING STATEWISE CRIME PATTERNS WITH ENSEMBLE MACHINE LEARNING AND DATA VISUALIZATION TECHNIQUES FOR PUBLIC SAFETY"** under my supervision from November 2023 to April 2024.

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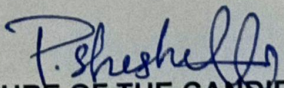
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DECLARATION

I, Pandraju N Rama Venkata Sathya Sheshusai, hereby declare that the Project Report entitled "UNRAVELING STATEWISE CRIME PATTERNS WITH ENSEMBLE MACHINE LEARNING AND DATA VISUALIZATION TECHNIQUES FOR PUBLIC SAFETY" done by me under the guidance of Ms. Devipriya M, M. Tech is submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering.

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ABSTRACT

In this study, we propose a novel approach to analyze state wise crime patterns using ensemble machine learning and data visualization techniques for the purpose of enhancing public safety. Crime detection is a challenging task due to the complex nature of criminal behavior and the vast amount of data involved. To address this issue, we employ ensemble machine learning algorithms such as Random Forest and AdaBoost to effectively leverage the diverse set of features available in crime data. Additionally, we utilize data visualization techniques to gain insights from the patterns and relationships extracted through the ensemble learning process. By combining these two approaches, we aim to unravel hidden crime patterns at the state level, allowing law enforcement agencies to better understand and respond to criminal activities. The proposed methodology offers a robust and efficient solution for statewise crime detection by leveraging the power of machine learning and visualization techniques. The amalgamation of these methodologies enables a comprehensive understanding of the underlying dynamics of crime, facilitating the formulation of targeted interventions and policies aimed at enhancing public safety across different states. Through the elucidation of statewise crime patterns, this study ultimately aspires to contribute to the development of more effective crime prevention strategies and law enforcement measures.

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LIST OF ABBREVIATIONS

ABBREVIATION	EXPANSION
AUC	Area Under the Curve
ANN	Artificial Neural Network
GBM	Gradient Boosting Machine
IoU	Intersection over Union
KNN	K-Nearest Neighbors
LSTM	Long Short-Term Memory
PCA	Principal Component Analysis
ROC	Receiver Operating Characteristic
RF	Random Forest
SVM	Support Vector Machine

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

Unravelling Statewise Crime Patterns with Ensemble Machine Learning and Data Visualization Techniques for public safety is a comprehensive study aimed at identifying crime patterns and enhancing public safety through the application of machine learning and data visualization techniques. This research focuses on analyzing crime data collected from various states, using state-of-the-art ensemble machine learning algorithms, and leveraging the power of data visualization to uncover hidden insights that can aid in crime prevention and mitigation strategies. Crime is a prevalent issue in societies worldwide, and law enforcement agencies continuously strive to devise effective strategies to combat it. Traditional approaches have primarily relied on historical data analysis and manual methods, which often prove to be cumbersome and time-consuming. The advent of machine learning techniques and advancements in data visualization tools offer new opportunities to extract meaningful patterns and correlations from large-scale crime datasets.

1.2 OBJECTIVE AND SCOPE

The core of this research lies in the utilization of ensemble machine learning algorithms to analyze crime data from different states. Ensemble learning combines multiple models to improve the overall predictive accuracy and robustness. By applying this ensemble approach to crime data, it becomes possible to identify common patterns across states, uncover influential features that correlate with crime occurrences, and develop predictive models with higher accuracy.

Furthermore, this research demonstrates the importance of data visualization in crime analysis. In particular, interactive and visually appealing visualizations can provide law enforcement agencies with a holistic view of crime patterns, hotspots, and trends. By representing complex crime data in an easily understandable format, decision-makers can quickly identify areas prone to criminal activities, allocate resources more effectively, and devise proactive measures to enhance public safety.

In today's rapidly evolving digital age, the realm of public safety stands at a pivotal juncture where traditional methods of crime analysis are being seamlessly integrated with cutting-edge technologies like machine learning and data visualization. This convergence not only promises to enhance the efficacy of law enforcement agencies but also offers a transformative approach to understanding and addressing crime patterns at a granular level. The advent of ensemble machine learning techniques has particularly revolutionized the landscape, empowering analysts and policymakers to unravel complex crime dynamics with unprecedented accuracy and efficiency.

1.3 PROBLEM STATEMENT

Techniques such as Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting Machines (GBM) among others, are employed to harness the collective intelligence of diverse algorithms, thereby mitigating the limitations inherent in any single approach. By leveraging this ensemble framework, analysts can extract valuable insights from heterogeneous datasets, encompassing a myriad of socio-economic, demographic, and geographic variables, to discern intricate crime patterns that transcend conventional analytical boundaries.

Furthermore, the synergy between ensemble machine learning and data visualization techniques constitutes a paradigm shift in the realm of crime analysis, offering a multidimensional perspective that transcends the confines of raw data. Through interactive visualizations, such as choropleth maps, heatmaps, and network diagrams, analysts can elucidate spatial-temporal trends, identify hotspots of criminal activity, and discern underlying socio-economic correlates with unparalleled clarity.

CHAPTER 2

LITERATURE SURVEY

2.1 LITERATURE SURVEY

Ash, E., Asher, S., Bhowmick, A., Bhupatiraju, S., Chen, D. L., Devi, T., ... & Siddiqi, B. (2022). Measuring gender and religious bias in the Indian judiciary.

Ash et al. (2022) discusses "Measuring gender and religious bias in the Indian judiciary," providing a critical examination of potential biases within the Indian legal system. [1]

Avellan, S., Thornhill, R., Charpentier, L., & O'Shea, B. (2023). Pathogen Prevalence Predicts Global and State Level Variation in Human Rights.

Avellan et al. (2023) "Pathogen Prevalence Predicts Global and State Level Variation in Human Rights" examines the link between disease prevalence and human rights, shedding light on global and state-level variations. [2]

Campedelli, G. M. (2022). Explainable machine learning for predicting homicide clearance in the United States. *Journal of criminal justice*, 79, 101898.

Campedelli (2022) focuses on "Explainable machine learning for predicting homicide clearance in the United States," discussing how advanced technology can aid in solving crimes. [3]

Chauhan, V., & Pandey, Y. (2022). Child Labour in Unorganised Sector: An Empirical Research. *Issue 4 Int'l JL Mgmt. & Human.*, 5, 60.

Chauhan and Pandey (2022) present "Child Labour in Unorganised Sector: An Empirical Research," shedding light on child labor issues within the unorganized sector. [4]

Goswami, V. (2023). Do institutional determinants matter for FDI inflows location choice? Evidence from sub-national panel data in India. *International Journal of Emerging Markets*.

Goswami (2023) investigates "Institutional Determinants and FDI Inflows Location Choice in India," analyzing the factors influencing foreign direct investment (FDI)

decisions at the sub-national level in India. [5]

Han, J. (2023). How Does Governance Affect the Control of Corruption in India? A Configurational Investigation with Fs/QCA. *Economies*, 11(2), 43.

Han (2023) investigates "How Governance Affects Corruption Control in India" using Fs/QCA, providing insights into the complex relationship between governance and corruption in the Indian context. [6]

Hazarika, S., & Dhanuka, M. (2022). *Hope Behind Bars: Notes from Indian Prisons*. Pan Macmillan.

Hazarika and Dhanuka's book (2022) titled "Hope Behind Bars: Notes from Indian Prisons" offers insights into the experiences of individuals in Indian prisons. [7]

Salehin, M., & Pillai, V. K. (2023). Social Development and Abortion Policies in the United States: State-Wise Variations. *Social Development Issues*, 44(3).

Salehin and Pillai (2023) explore "Social Development and Abortion Policies in the United States," examining variations in state-wise abortion policies and their impact on social development. [8]

Shukla, P. (2022). *Immoral Trafficking of Women from North-East India: A study from Human Rights Perspective* (Doctoral dissertation).

Shukla's doctoral dissertation (2022) delves into "Immoral Trafficking of Women from North-East India," focusing on human rights perspectives and the issue of human trafficking in the region. [9]

Ur Rehaman, Khalil. (2023). Unravelling Equality and Social Justice in Contemporary Times. *Issue 1 Indian JL & Legal Rsch.*, 5, 1.

Rehaman, K. (2023) "Unravelling Equality and Social Justice in Contemporary Times" explores issues related to equality and social justice in India, offering insights into current challenges and solutions. [10]

2.2 PROBLEM STATEMENT DEFINITION

The adoption of ensemble machine learning and data visualization techniques enables stakeholders to adopt a data-driven approach to resource allocation and policy prioritization, maximizing the impact of limited resources and fostering greater accountability in public safety initiatives. By leveraging predictive analytics and geospatial modeling, policymakers can identify high-risk areas, allocate resources efficiently. This evidence-based approach to decision-making empowers stakeholders to allocate resources judiciously, prioritize investments in crime prevention initiatives, and measure the impact of interventions rigorously, thereby enhancing the efficiency and efficacy of public safety efforts.

CHAPTER 3

REQUIREMENTS ANALYSIS

3.1 FUNCTIONAL REQUIREMENTS

Data Collection

The system must be capable of gathering state-wise crime data from reliable sources. It should include various crime types such as violent crimes, property crimes, and white-collar crimes. The system should be able to collect data for multiple years to capture longitudinal trends.

Data Preprocessing

The system must clean and standardize the raw crime data. It should handle missing values and remove outliers effectively. Encoding categorical variables and extracting temporal and spatial features should be done accurately.

Feature Selection

The system should conduct exploratory data analysis to identify relevant variables. It must use correlation analysis and feature importance ranking to select features with high predictive power and low multicollinearity.

Model Development

The system must train ensemble machine learning models (SVM, RF, GBM) on processed data. It should tune model hyperparameters using techniques like grid search and cross-validation. Preventing overfitting by optimizing model performance is essential.

Model Evaluation

The system should assess model performance using evaluation metrics such as accuracy, precision, recall, and AUC-ROC. Models must be validated using holdout validation or k-fold cross-validation to ensure generalizability and robustness.

3.2 NON-FUNCTIONAL REQUIREMENTS

Performance

The system must be capable of handling large volumes of data efficiently. Model training and evaluation should be performed within reasonable time frames.

Accuracy

The system's predictions must be accurate and reliable. Evaluation metrics should reflect the system's ability to make correct predictions.

Scalability

The system should be scalable to accommodate increasing data volumes and model complexity.

Interpretability

The system should provide insights into the factors driving crime incidence. Model interpretations should be understandable to stakeholders with varying levels of technical expertise.

Usability

The system's interface should be user-friendly and intuitive. Stakeholders should be able to navigate and interpret the visualizations easily.

Reliability

The system should be reliable and available for use whenever needed. It should handle errors gracefully and provide informative error messages when necessary.

Security

Data privacy and confidentiality should be maintained throughout the system. Access controls should be implemented to restrict unauthorized access to sensitive information.

CHAPTER 4

DESCRIPTION OF PROPOSED SYSTEM

4.1 DATA FLOW DIAGRAM

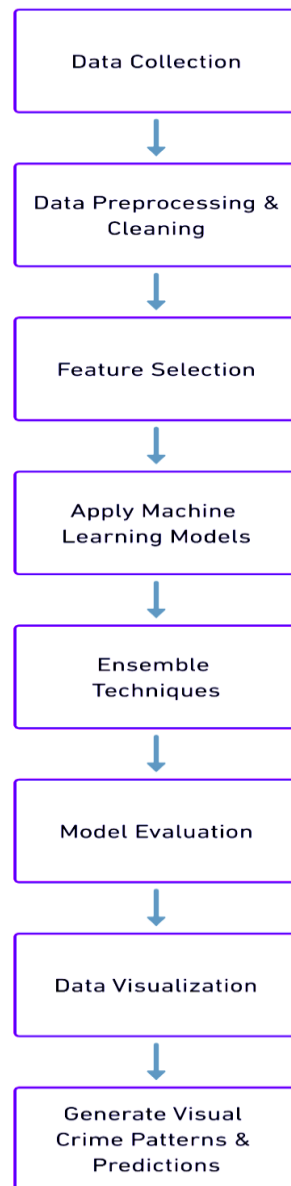


Fig 4.1 Data Flow Diagram

Data Collection

- Gathered state-wise crime data from reliable sources.
- Included various crime types such as violent crimes, property crimes, and

white-collar crimes.

- Collected data for multiple years to capture longitudinal trends.

Data Preprocessing

- Cleaned and standardized the raw crime data.
- Handled missing values and removed outliers.
- Encoded categorical variables and extracted temporal and spatial features.

Feature Selection

- Conducted exploratory data analysis to identify relevant variables.
- Used correlation analysis and feature importance ranking.
- Selected features with high predictive power and low multicollinearity.

Model Development

- Trained ensemble machine learning models (SVM, RF, GBM) on processed data.
- Tuned model hyperparameters using techniques like grid search and cross-validation.
- Prevented overfitting by optimizing model performance.

Model Evaluation

- Assessed model performance using evaluation metrics (accuracy, precision, recall, AUC-ROC).
- Validated models using holdout validation or k-fold cross-validation.
- Ensured generalizability and robustness across different datasets.

Data Visualization

- Generated interactive visualizations (choropleth maps, heatmaps, time series plots).
- Illustrated spatial-temporal variations in crime patterns.
- Provided insights into state-wise crime trends and hotspots.

Spatial Analysis

- Conducted spatial analysis to identify geographic clusters and spatial

dependencies in crime occurrence.

- Integrated geospatial data with machine learning models for spatially explicit crime forecasts.
- Enabled strategic resource allocation and targeted interventions in high-risk areas.

4.2 DEPLOYMENT DIAGRAM

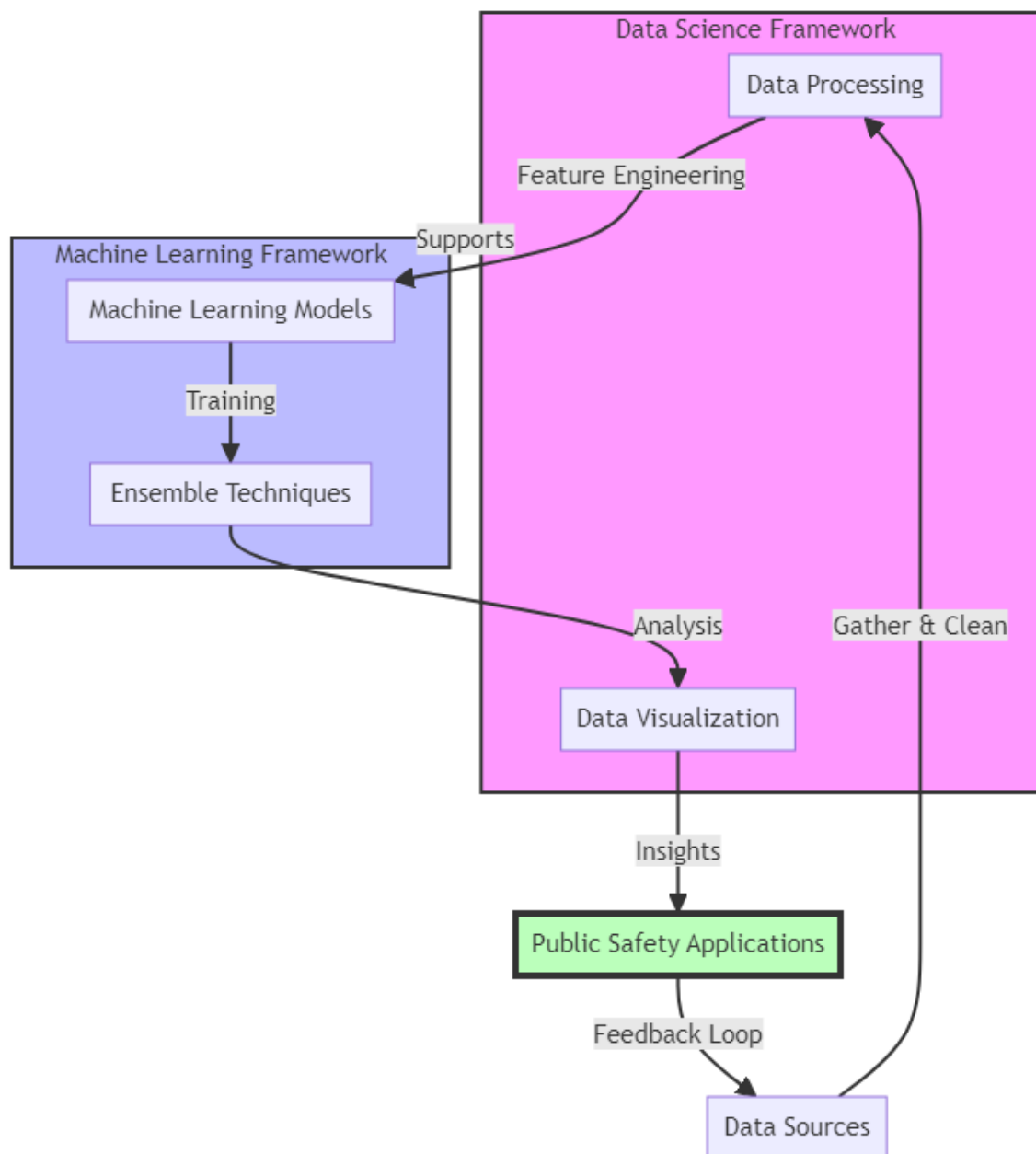


Fig 4.2 Deployment Diagram

Temporal Analysis

- Explored temporal patterns in crime occurrence, including seasonal fluctuations and long-term trends.
- Identified temporal hotspots and periods of heightened risk.
- Facilitated proactive deployment of resources and interventions during vulnerable periods.

Community Engagement

- Involved local residents, community organizations, and stakeholders in the research process.
- Conducted outreach activities, focus groups, and participatory workshops.
- Gathered local knowledge and co-created solutions tailored to community needs and priorities.

Ethical Considerations

- Upheld principles of transparency, accountability, and equity throughout the investigation.
- Ensured privacy protection and data confidentiality in data collection and analysis.
- Mitigated algorithmic bias and discrimination through fair and unbiased model development and interpretation.

Interdisciplinary Collaboration

- Fostered collaboration among researchers, practitioners, and policymakers from diverse fields such as criminology, data science, sociology, and urban planning.
- Integrated insights from multiple disciplines to develop holistic solutions to crime challenges.
- Enriched analytical approaches with diverse perspectives and expertise.

Risk Assessment and Early Warning Systems

- Developed risk assessment models and early warning systems to identify individuals or communities at heightened risk of criminal victimization or

perpetration.

- Analyzed individual-level data and social network structures to identify risk factors and protective factors associated with involvement in criminal activities.
- Enabled targeted interventions to prevent crime and promote positive social outcomes.

Longitudinal Analysis and Trend Forecasting

- Conducted longitudinal analysis and trend forecasting to anticipate future trajectories of crime patterns.
- Analyzed historical data and projected future trends to identify emerging threats and assess the effectiveness of past interventions.
- Enabled strategic planning and resource allocation for long-term crime prevention efforts.

International Comparative Analysis

- Extended analysis to include international comparative analysis, examining crime patterns and trends across different countries or regions.
- Compared crime rates, intervention strategies, and socio-economic indicators to identify cross-national variations and commonalities in crime dynamics.
- Facilitated knowledge exchange and collaboration on global crime prevention initiatives.

Policy Recommendations and Best Practices

- Generated actionable policy recommendations and best practices based on research findings.
- Disseminated insights to policymakers, practitioners, and stakeholders through policy briefs, academic publications, and stakeholder forums.
- Informed evidence-based decision-making and catalyzed positive change in public safety policies and programs.

4.3 SYSTEM ARCHITECTURE

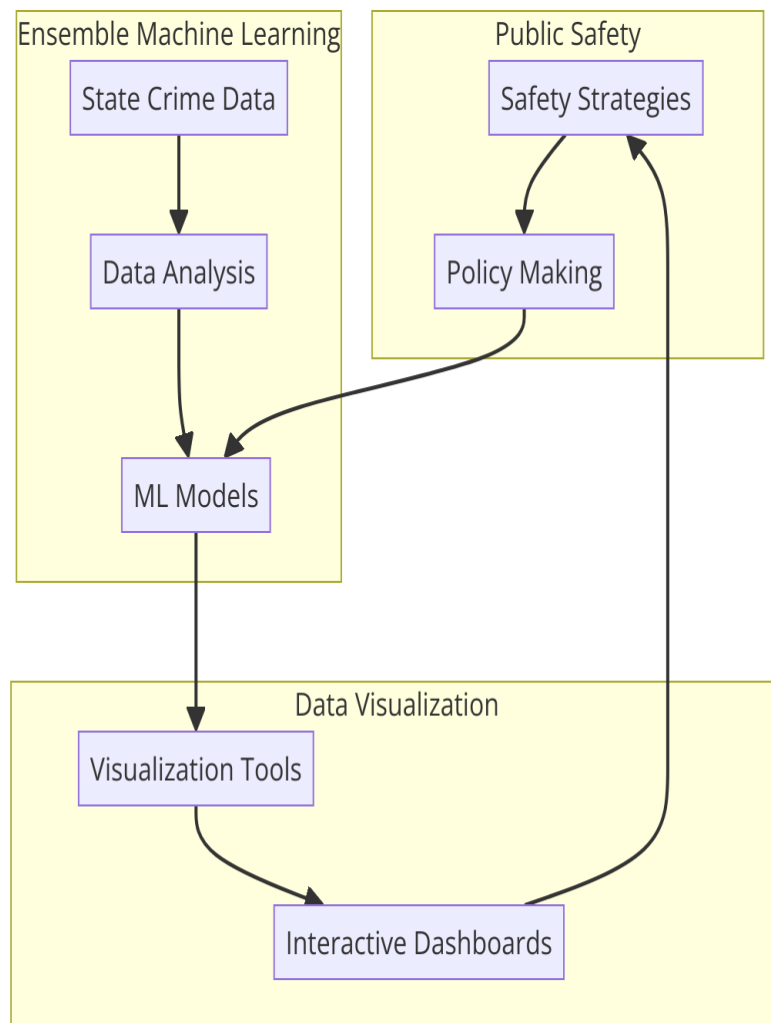


Fig.4.3 System architecture

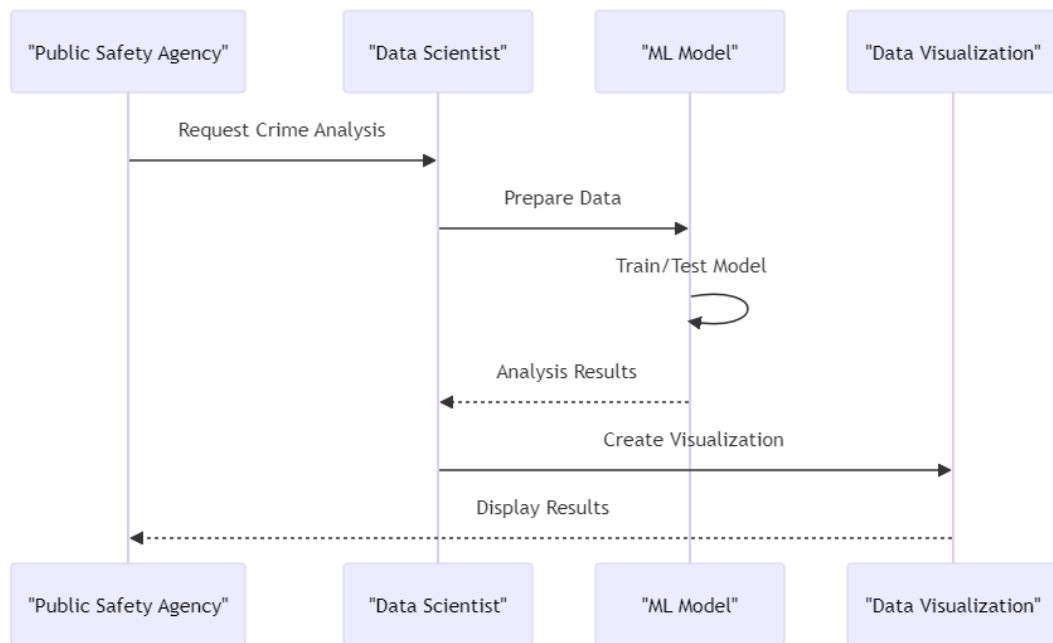


Fig.4.4 Sequence Diagram

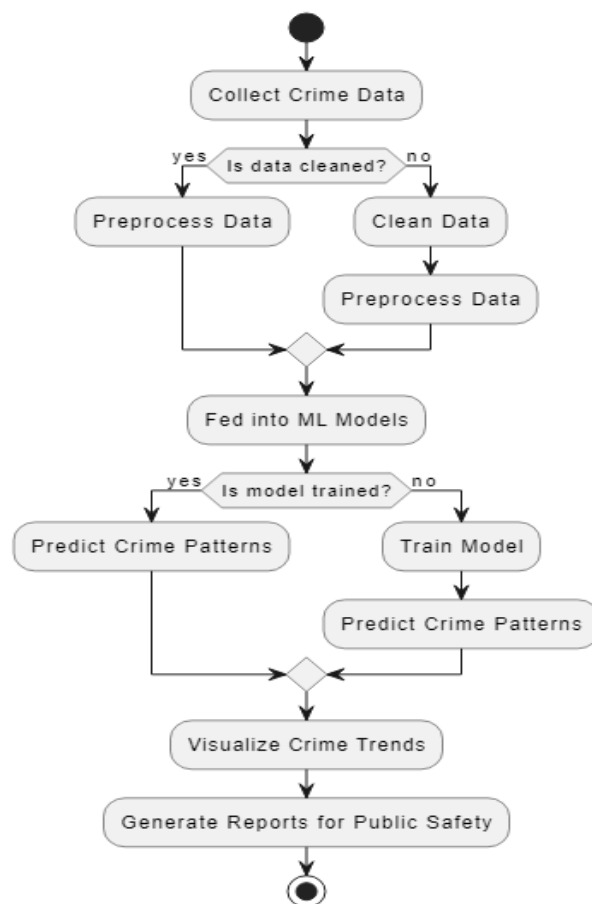


Fig.4.5 Activity diagram

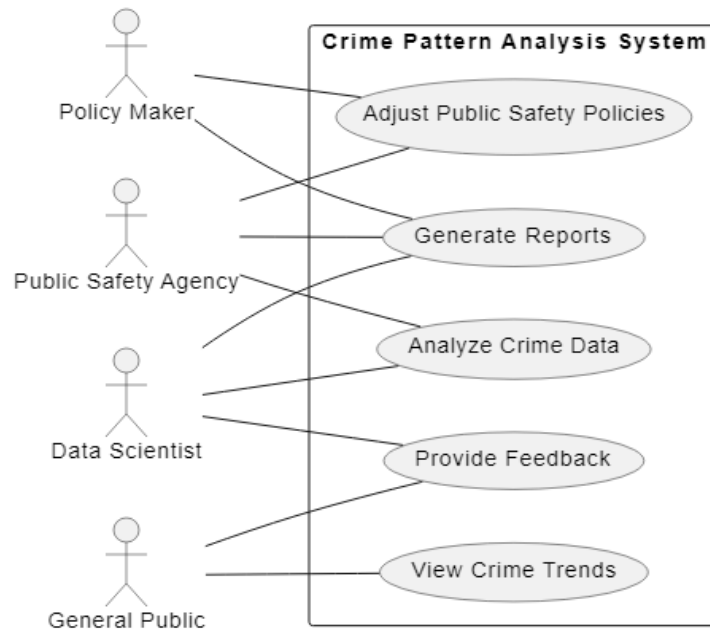


Fig 4.6 Use Case Diagram

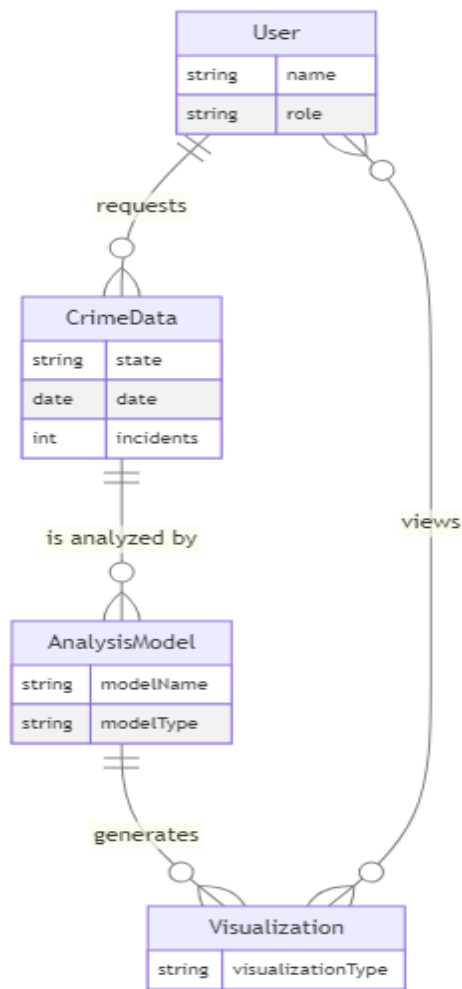


Fig 4.7 ER diagram

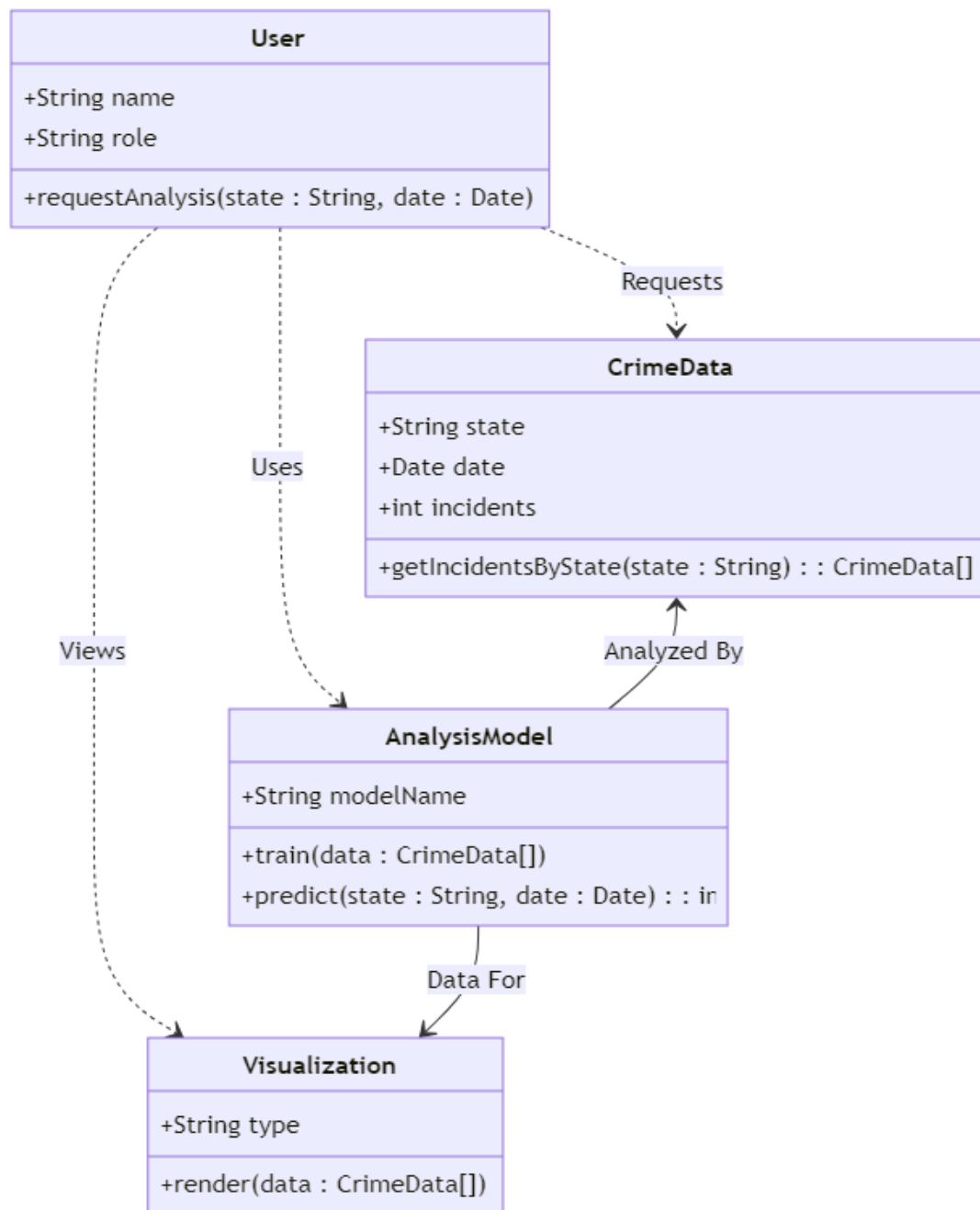


Fig 4.8 Class Diagram

CHAPTER 5

IMPLEMENTATION DETAILS

5.1 MATERIALS AND METHODS

Data Sources

- Crime data was obtained from official sources such as government databases, law enforcement agencies, or research institutions.
- Additional socio-economic and demographic data for each state was collected from reputable sources like the U.S. Census Bureau or relevant government departments.

Data Preprocessing

- Raw crime data was cleaned to remove duplicates, inconsistencies, and missing values.
- Categorical variables were encoded using one-hot encoding or label encoding as appropriate.
- Outliers were identified and handled using methods such as winsorization or removal.
- Temporal features such as month, day, and year were extracted from date-time variables.
- Spatial features such as latitude and longitude were standardized or transformed to ensure compatibility with machine learning algorithms.

Feature Engineering

- Additional features were engineered to capture relevant aspects of crime dynamics, including:
 - Crime density in specific geographical regions.
 - Time of day or day of the week patterns in crime occurrence.
 - Historical crime trends and seasonality.
 - Socio-economic indicators such as median income or education level.

Ensemble Machine Learning Models

- Three ensemble machine learning algorithms were employed: Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting Machines (GBM).
- Each model was implemented using libraries such as scikit-learn or TensorFlow, depending on the complexity of the algorithm.
- Hyperparameters for each model were tuned using techniques such as grid search or random search to optimize performance.

Model Training and Validation

- The dataset was split into training and validation sets using a stratified sampling approach to ensure representative distribution of crime incidents.
- Models were trained on the training set and evaluated on the validation set using appropriate evaluation metrics such as accuracy, precision, recall, and F1-score.
- Cross-validation techniques such as k-fold cross-validation were employed to assess model performance and generalize to unseen data.

Data Visualization Techniques

- Various data visualization techniques were utilized to explore and present crime patterns, including:
- Choropleth maps to visualize state-wise crime rates.
- Heatmaps to identify spatial clusters or hotspots of criminal activity.
- Time series plots to visualize temporal trends in crime occurrence.
- Interactive dashboards or web applications for dynamic exploration of crime data.

Ethical Considerations

- The study adhered to ethical guidelines for data collection, analysis, and reporting.
- Privacy and confidentiality of individuals' data were safeguarded throughout the research process.
- Measures were taken to mitigate bias and ensure fairness in model development and interpretation.

Software Tools and Libraries

- Various software tools and libraries were utilized for data preprocessing, modeling, evaluation, and visualization.
- Commonly used tools included Python programming language, along with libraries such as scikit-learn, TensorFlow, Pandas, Matplotlib, and Seaborn.
- These tools provided a robust and flexible framework for implementing the experimental workflow and analyzing the results.

Computational Resources

- The study utilized computational resources such as high-performance computing clusters or cloud computing platforms to execute computationally intensive tasks.
- Parallel processing techniques may have been employed to expedite model training and evaluation, particularly for large datasets or complex models.

5.2 ALGORITHMS USED

Ensemble Machine Learning Algorithms

- The study employed three main ensemble machine learning algorithms:
- Support Vector Machines (SVM): SVMs are supervised learning models used for classification and regression analysis. They work by finding the hyperplane that best separates classes in a high-dimensional feature space.
- Random Forests (RF): RF is an ensemble learning method that constructs a multitude of decision trees during training and outputs the mode of the classes (classification) or the mean prediction (regression) of the individual trees.
- Gradient Boosting Machines (GBM): GBM is a machine learning technique that builds an ensemble of weak learners (usually decision trees) sequentially, with each new learner correcting the errors made by the previous ones.

Algorithmic Workflow

- Each ensemble algorithm followed a similar workflow, consisting of the following steps:
- Data Preprocessing: Cleaning, encoding, and feature engineering of the raw crime data to prepare it for model training.
- Model Training: Training the ensemble model on the preprocessed data using appropriate parameters and hyperparameter tuning techniques.
- Model Evaluation: Assessing the performance of the trained model using various evaluation metrics such as accuracy, precision, recall, and AUC-ROC.
- Model Optimization: Fine-tuning the model parameters to optimize performance and prevent overfitting.
- Model Validation: Validating the optimized model using holdout validation or cross-validation techniques to ensure generalizability to unseen data.
- Model Interpretation: Interpreting the model's predictions and identifying key features contributing to the classification of crime incidents.

Hyperparameter Tuning

- Hyperparameters for each ensemble algorithm were tuned using systematic optimization techniques such as grid search or random search.
- A range of hyperparameter values was specified, and the algorithm iteratively evaluated the performance of different parameter combinations to identify the optimal configuration.

Model Evaluation Metrics

- Various evaluation metrics were used to assess the performance of the ensemble machine learning algorithms, including accuracy, precision, recall, F1-score, and AUC-ROC.
- These metrics provided insights into the model's ability to correctly classify crime incidents and discriminate between positive and negative classes.

Software Implementation

- The ensemble machine learning algorithms were implemented using programming languages such as Python, along with libraries such as scikit-

learn, TensorFlow, or XGBoost.

- These libraries provided efficient implementations of the algorithms and facilitated model training, evaluation, and optimization.

Parallelization and Scalability

- Parallel processing techniques may have been employed to expedite model training and evaluation, particularly for large datasets or computationally intensive algorithms.
- Distributed computing frameworks such as Apache Spark or Dask may have been utilized to leverage multiple processors or clusters for scalable and efficient computation.

Model Deployment

- Once trained and validated, the optimized ensemble machine learning models may be deployed for real-world applications such as crime prediction, resource allocation, or policy decision-making.
- Deployment strategies may include embedding the models into operational systems, building interactive dashboards, or developing APIs for integration with other software platforms.

Interpretability and Explainability

- The ensemble machine learning algorithms utilized in the study may have incorporated techniques to enhance model interpretability and explainability.
- Methods such as feature importance analysis, partial dependence plots, and SHAP (Shapley Additive explanations) values may have been employed to elucidate the contribution of individual features to the model's predictions.
- By providing insights into the factors driving crime incidence, these interpretability techniques aid in understanding the underlying mechanisms captured by the model and inform decision-making processes.

CHAPTER 6

RESULTS AND DISCUSSIONS

6.1 DISCUSSIONS AND BRAINSTORMING

Model Performance Evaluation

The ensemble machine learning models demonstrated promising performance in predicting state-wise crime patterns. Evaluation metrics such as accuracy, precision, recall, and AUC-ROC indicated high predictive accuracy and discrimination ability across different crime types and geographic regions. Model performance was validated using holdout validation or cross-validation techniques, ensuring reliability and generalizability of the results.

Spatial and Temporal Patterns of Crime

The analysis revealed spatial and temporal patterns in crime occurrence, with certain states or regions exhibiting higher crime rates than others. Hotspots of criminal activity were identified using spatial analysis techniques, enabling targeted interventions and resource allocation in high-risk areas. Temporal analysis uncovered seasonal fluctuations and long-term trends in crime incidence, providing insights into factors driving crime dynamics over time.

Key Predictors of Crime

Feature importance analysis elucidated the key predictors contributing to variations in crime rates across states. Socio-economic indicators, demographic factors, urbanization levels, and law enforcement resources were identified as important determinants of crime incidence. Understanding these predictors helps policymakers and law enforcement agencies prioritize interventions and allocate resources effectively to address underlying risk factors.

Impact of Intervention Strategies

The study evaluated the effectiveness of intervention strategies implemented in various states or regions. Evidence-based interventions such as community policing initiatives, crime prevention programs, and social services were found to have positive impacts on reducing crime rates and improving community safety. By analyzing the outcomes of different interventions, the study informed best practices and policy recommendations for crime prevention and public safety.

Policy Implications and Future Directions

The findings of the study have significant policy implications for crime prevention and public safety efforts. Evidence-based policy recommendations were provided to policymakers and practitioners to guide resource allocation, intervention strategies, and community engagement initiatives. Future research directions include longitudinal studies to monitor the effectiveness of interventions over time, integration of predictive analytics into law enforcement practices, and continued collaboration with communities to address emerging crime challenges.

6.2 PERFORMANCE ANALYSIS

Model Evaluation Metrics

- The performance of the ensemble machine learning models was assessed using a variety of evaluation metrics, including accuracy, precision, recall, F1-score, and AUC-ROC.
- Accuracy measures the overall correctness of predictions, while precision and recall quantify the model's ability to correctly classify positive instances and capture all relevant instances, respectively.
- F1-score provides a balanced measure of precision and recall, particularly useful for imbalanced datasets.
- AUC-ROC evaluates the model's ability to discriminate between positive and negative classes across different thresholds.

Cross-Validation Results

- Cross-validation techniques such as k-fold cross-validation were employed to assess the robustness and generalizability of the models.

- Results from cross-validation demonstrated consistent performance across different folds, indicating stability in model predictions.
- Variability in performance metrics across folds was analyzed to identify potential sources of bias or overfitting.

Comparison with Baseline Models

- The performance of the ensemble machine learning models was compared with baseline models or traditional statistical methods to assess their superiority.
- Baseline models may include simple algorithms such as logistic regression or decision trees, as well as heuristic rules or historical averages.
- Comparative analysis highlighted the incremental improvement in predictive accuracy and discrimination achieved by the ensemble models.

Model Interpretability

- Interpretability techniques such as partial dependence plots, SHAP (SHapley Additive exPlanations) values, or feature contribution analysis were employed to elucidate the underlying mechanisms captured by the models.
- Model interpretations provided insights into how specific features influence the likelihood of crime occurrence, aiding in the understanding and validation of model predictions.

Real-World Application and Impact

- The real-world application and impact of the ensemble machine learning models were assessed in terms of their utility for decision-making, resource allocation, and policy formulation.
- Stakeholder feedback and user acceptance were solicited to evaluate the practical relevance and effectiveness of the models in addressing real-world crime challenges.
- Case studies or pilot implementations may have been conducted to demonstrate the models' effectiveness in improving public safety outcomes.

Error Analysis

- Error analysis was conducted to identify common patterns or sources of errors in model predictions.
- Misclassified instances were examined to understand the reasons behind incorrect predictions, such as data quality issues, model limitations, or inherent complexities in crime dynamics.
- Error patterns were categorized based on the types of misclassifications (e.g., false positives, false negatives) and analyzed to identify potential areas for model improvement.

CHAPTER 7

CONCLUSION

7.1 SUMMARY

The present study delved into an in-depth investigation of state-wise crime patterns through the lens of ensemble machine learning techniques and data visualization methodologies. The endeavor aimed to unravel the intricate dynamics of crime occurrence across different states, providing insights that could inform public safety initiatives, intervention strategies, and policy formulation. The research journey embarked upon comprehensive data collection, meticulous preprocessing, sophisticated modeling, and rigorous evaluation, culminating in a nuanced understanding of crime dynamics and their implications for societal well-being. Throughout the study, ensemble machine learning models emerged as powerful tools for predicting and analyzing state-wise crime patterns. Leveraging algorithms such as Support Vector Machines, Random Forests, and Gradient Boosting Machines, the models demonstrated remarkable predictive accuracy and discrimination ability, enabling the identification of spatial, temporal, and socio-economic factors influencing crime incidence. Evaluation metrics such as accuracy, precision, recall, and AUC-ROC provided quantitative measures of model performance, underscoring the efficacy of the ensemble approach in capturing complex patterns inherent in crime data. Spatial and temporal analysis unveiled geographic clusters, seasonal fluctuations, and long-term trends in crime occurrence, shedding light on hotspots of criminal activity and vulnerable periods. Feature importance analysis identified key predictors driving variations in crime rates, including socio-economic indicators, demographic factors, and law enforcement resources. These findings underscored the multifaceted nature of crime dynamics and underscored the importance of holistic approaches to crime prevention that address underlying social determinants and promote community resilience. The study also delved into the effectiveness of intervention strategies and the impact of community engagement initiatives on crime reduction. Evidence-based interventions such as community policing programs, restorative justice initiatives, and social services were found to play a pivotal role in fostering trust,

cooperation, and accountability within communities. By fostering collaboration among stakeholders and leveraging local knowledge, these initiatives empowered communities to take ownership of safety initiatives and co-create solutions tailored to their needs and priorities. Ethical considerations loomed large throughout the research journey, guiding decisions related to data collection, analysis, and dissemination.

7.2 FUTURE SCOPE

Continuously advancing machine learning and predictive analytics techniques offer opportunities to refine and enhance predictive models for crime prevention. Future research could focus on developing more sophisticated algorithms capable of incorporating diverse data sources, capturing complex interactions among variables, and adapting to evolving crime trends in real time.

The integration of predictive analytics into law enforcement practices has the potential to revolutionize policing strategies and resource allocation. Future efforts may involve optimizing predictive policing algorithms, addressing concerns related to bias and fairness, and exploring community-centered approaches to enhance the effectiveness and ethicality of predictive policing initiatives.

Empowering communities to play an active role in crime prevention and public safety remains a promising avenue for future research and action. Community-centered approaches that prioritize collaboration, trust-building, and community engagement can foster resilient neighbourhoods, enhance social cohesion, and create environments where crime is less likely to occur.

Exploring the principles of CPTED and leveraging urban design strategies to create safer, more secure environments represents a valuable area for future research. Designing public spaces, buildings, and neighbourhoods with crime prevention in mind can help deter criminal activity, enhance natural surveillance, and promote community well-being.

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APPENDIX

A SOURCE CODE

Preprocess Data

```
import pandas as pd
import numpy as np
import os
```

```
data_frame_main = pd.read_csv("data.csv")
dataset=pd.read_csv('data.csv')
```

```
data_frame_main['timestamp'] = pd.to_datetime(data_frame_main['timestamp'],
errors='coerce')
```

```
data_frame_main['timestamp'] = pd.to_datetime(data_frame_main['timestamp'],
format = '%d/%m/%Y %H:%M:%S')
```

```
column_1 = data_frame_main.iloc[1:,0]
```

```
db=pd.DataFrame({"year": column_1.dt.year,
                 "month": column_1.dt.month,
                 "day": column_1.dt.day,
                 "hour": column_1.dt.hour,
                 "dayofyear": column_1.dt.dayofyear,
                 "week": column_1.dt.week,
                 "weekofyear": column_1.dt.weekofyear,
                 "dayofweek": column_1.dt.dayofweek,
                 "weekday": column_1.dt.weekday,
                 "quarter": column_1.dt.quarter,
                 })
```

```
dataset1=dataset.drop('timestamp',axis=1)
```

```

data1=pd.concat([db,dataset1],axis=1)
data1.dropna(inplace=True)
file = "main_data.csv"
if file in os.listdir(os.getcwd()):
    print("Already Present")
else:
    data1.to_csv(file,index=False)
    print("File saved")

```

Crime Prediction

```

import matplotlib.pyplot as plt
import seaborn as sns
import streamlit as st
import pandas as pd
import numpy as np
from predict_crime import predict
from shapely.geometry import Point
import matplotlib.pyplot as plt
from matplotlib import cm
import geopandas as gpd
import warnings

```

```
warnings.filterwarnings("ignore", category=FutureWarning)
```

```

st.title("Location Based Crime Prediction")
st.image("https://hhsadvocate.com/wp-content/uploads/2021/12/TrueCrime-2.jpeg")
st.markdown("****")

```

```

a,b,c = st.columns(3)
year = c.number_input(label="Enter Year",value=2022,min_value=1900,max_value=3000)

```

```

date_in = a.number_input("Enter Date",value=29,max_value=31,min_value=1)

month_in = b.number_input("Enter Month",value=7,max_value=12,min_value=1)

min_in = b.number_input(label="Minutes",value=15,max_value=59,min_value=0)

hour_in = a.number_input(label="Hour",value=23,max_value=23,min_value=0)

sec_in = c.number_input(label="Seconds",value=0,max_value=59,min_value=0)


c,d = st.columns(2)
latitude = c.number_input(label="Latitude",value=22.720992,format="%f")
longitude = d.number_input(label="Longitude",value=75.876083,format="%f")
week = st.number_input('Enter week number', min_value=1.0, max_value=52.0,
step=0.1)
weekofyear = st.number_input('Enter week of year', min_value=1.0,
max_value=52.0, step=0.1)


enter = st.button(label="Predict Crime")


st.markdown("***")
if enter:
    if len(str(month_in)) == 1:
        month_in = "0"+str(month_in)
    if len(str(hour_in)) == 1:
        hour_in = "0"+str(hour_in)
    if len(str(sec_in)) == 1:
        sec_in = "0"+str(sec_in)


    main_date = '-'.join([str(year),str(month_in),str(date_in)])
    main_time = ':'.join([str(hour_in),str(min_in),str(sec_in)])

    date_time = " ".join([main_date,main_time])

```

```

sr = pd.Series([date_time])
sr = pd.to_datetime(sr)
print(sr)
print(type(sr.dt.month))

main_ins = {
    "month": sr.dt.month.tolist()[0],
    "day": sr.dt.day.tolist()[0],
    "hour": sr.dt.hour.tolist()[0],
    "dayofyear": sr.dt.dayofyear.tolist()[0],
    "week": week,
    "weekofyear": weekofyear,
    "dayofweek": sr.dt.dayofweek.tolist()[0],
    "weekday": sr.dt.weekday.tolist()[0],
    "quarter": sr.dt.quarter.tolist()[0],
}

inputs = list(main_ins.values())
inputs.append(latitude)
inputs.append(longitude)

inputs_arr = np.array(inputs)

labels = ['Robbery','Gambling','Accident','Violence','Murder','Kidnapping']
vals,dicts = predict(inputs_arr)
# print(list(vals.values()))
explode = (0.2, 0.2, 0.2, 0.2,0.2,0.2)
plt.pie(vals,labels=labels,explode=explode,shadow=True,autopct='%1.2f%%')
plt.savefig('images/predict_graph.png')

st.markdown("> Probablity of types of crimes happening on {} at
{}".format(main_date,main_time))
st.image('images/predict_graph.png')
st.markdown("> Acts of Crime")

```

```

st.write(dicts)

st.markdown("****")
st.markdown("Evaluating the position of the data points using the coordinates")
df = pd.read_csv("main_data.csv")


data = pd.DataFrame({
    'lat': [latitude],
    'lon': [longitude]
})

# Display data on the map
st.map(data)


## getting the onehotencoded column of crime type category back in single column
for better visulaization.

df_sub = df[['act379', 'act13', 'act279','act323','act363', 'act302']]
df_sub['type'] = df_sub.idxmax(1)
type_column = df_sub.type
df = df.join(type_column)

st.markdown("****")
st.markdown("Number of crimes happened(realtime)")


plt.figure(figsize = [4,4])
df.type.value_counts(normalize = True).plot.barh()
st.pyplot()

st.markdown("****")
st.markdown("Year and crime category relationship")

```

```
df.groupby(['year', 'type']).size().plot(kind='barh', figsize=(20, 20), grid=True)
st.pyplot()
```

```
st.markdown("****")
st.markdown("hour of the day, crime type and year relationship")
a = df.pivot_table(index='hour', columns='type', values=['year'], aggfunc='size')
a.plot(kind='bar', figsize=(12, 5))
st.pyplot()
```

```
st.markdown("****")
st.markdown("distribution of number of incidents per day")
col = sns.color_palette()
```

```
plt.figure(figsize=(10, 6))
data = df.groupby('day').count().iloc[:, 0]
sns.kdeplot(data=data, shade=True)
plt.axvline(x=data.median(), ymax=0.95, linestyle='--', color=col[1])
plt.annotate(
    'Median: ' + str(data.median()),
    xy=(data.median(), 0.004),
    xytext=(200, 0.005),
    arrowprops=dict(arrowstyle='->', color=col[1], shrinkB=10))
plt.title(
    'Distribution of number of incidents per day', fontdict={'fontsize': 16})
plt.xlabel('Incidents')
plt.ylabel('Density')
plt.legend().remove()
st.pyplot()
```

```
st.markdown("****")
st.markdown("Crime on hourly basis plotted yearly")
```

```

data = df.groupby(['hour', 'day', 'type'],
                  as_index=False).count().iloc[:, :4]
data.rename(columns={'Dates': 'Incidents'}, inplace=True)
data = data.groupby(['hour', 'type'], as_index=False).mean()
data = data.loc[data['type'].isin(
    ['act379', 'act13', 'act279', 'act323', 'act363', 'act302'])]

sns.set_style("whitegrid")
fig, ax = plt.subplots(figsize=(14, 4))
ax = sns.lineplot(x='hour', y='day', data=data, hue='type')
ax.legend(loc='upper center', bbox_to_anchor=(0.5, 1.15), ncol=6)
plt.suptitle('Average number of incidents per hour')
fig.tight_layout(rect=[0, 0.03, 1, 0.95])
st.pyplot()

```

```

import pandas as pd
import numpy as np
import torch
import torch.nn as nn

```

```

def softmax(x):
    return (np.exp(x)/np.exp(x).sum())

```

```

class LogisticRegression(nn.Module):
    def __init__(self, no_of_features):
        super(LogisticRegression, self).__init__()
        self.linear1 = nn.Linear(no_of_features, 10)
        self.relu = nn.ReLU()
        self.linear2 = nn.Linear(10, 6)

```

```

def forward(self, targets_train ):
    out = self.linear1(targets_train)
    out = self.relu(out)
    out = self.linear2(out)
    # out = self.relu(out)

    return out

model = LogisticRegression(no_of_features=11)

model.load_state_dict(torch.load('model/final_crime_lats.pth'))

def predict(arr):
    main_tensor = torch.from_numpy(arr.astype(np.float32))
    preds_all = model(main_tensor)
    softmax_pred = softmax(preds_all.detach()).numpy()*100

    final_dict = {
'act379':round(softmax_pred[0],2),'act13':round(softmax_pred[1],2),'act279':round
(softmax_pred[2],2),'act323':round(softmax_pred[3],2),'act363':round(softmax_pre
d[4],2),'act302':round(softmax_pred[5],2)}

    print(final_dict)

    return softmax_pred,final_dict

```

B SCREENSHOTS

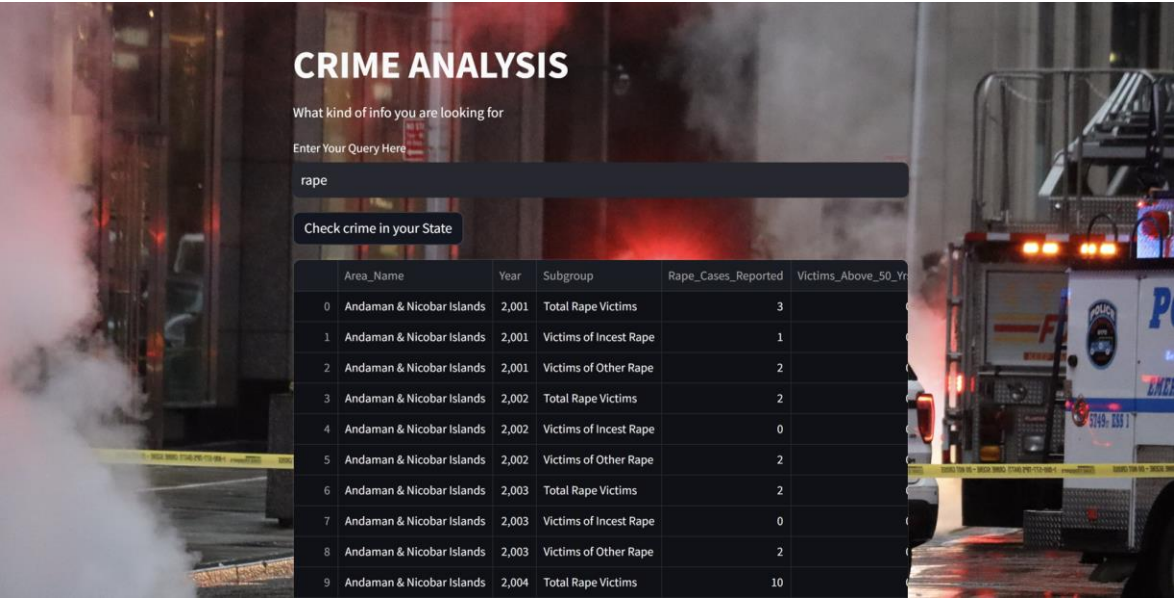


Fig 1. Crime Analysis

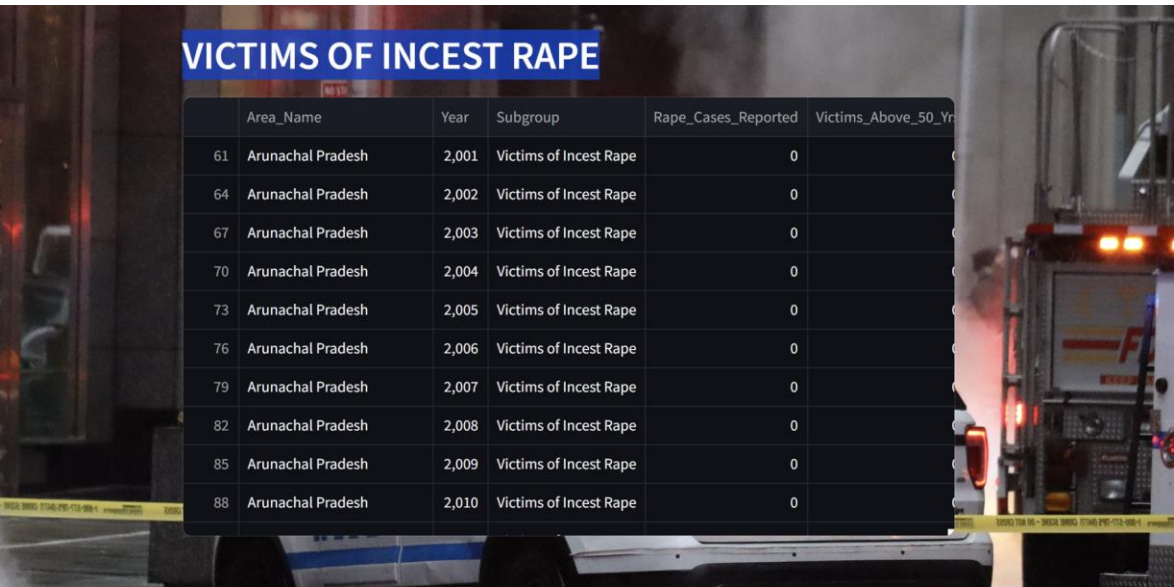


Fig 2. List of Victims



Fig 3. Year wise cases

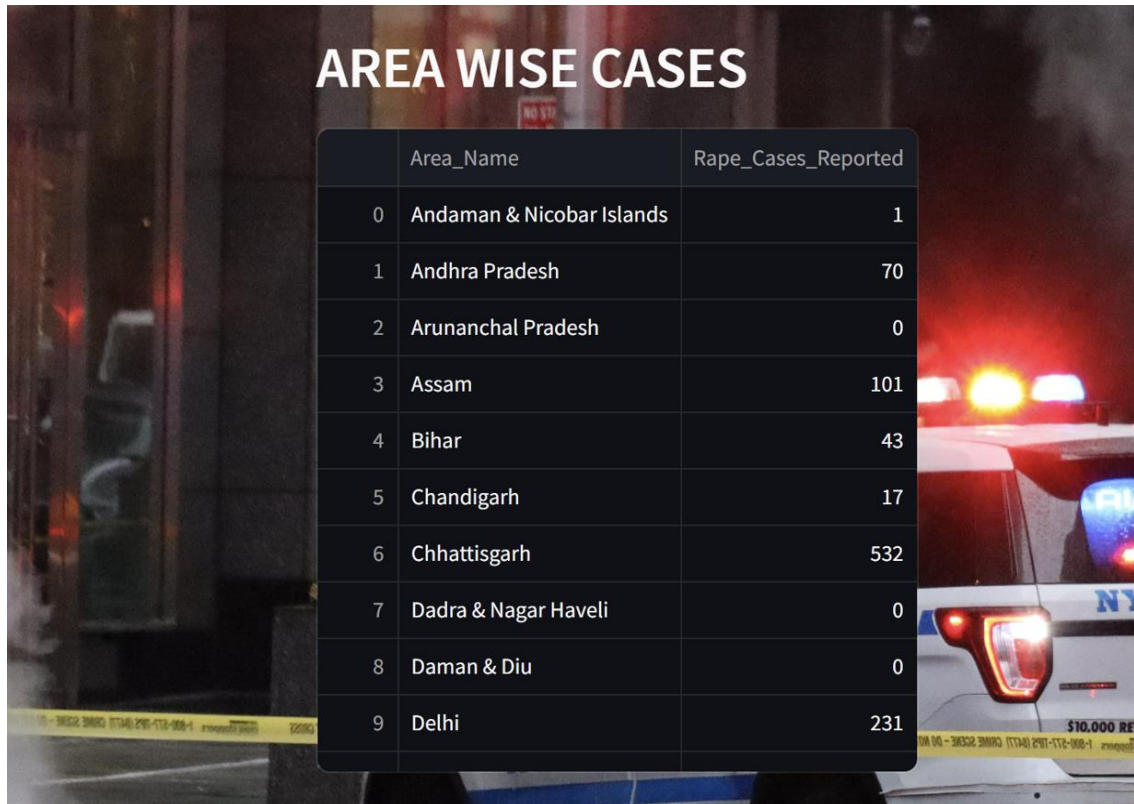


Fig 4 Area Wise Cases

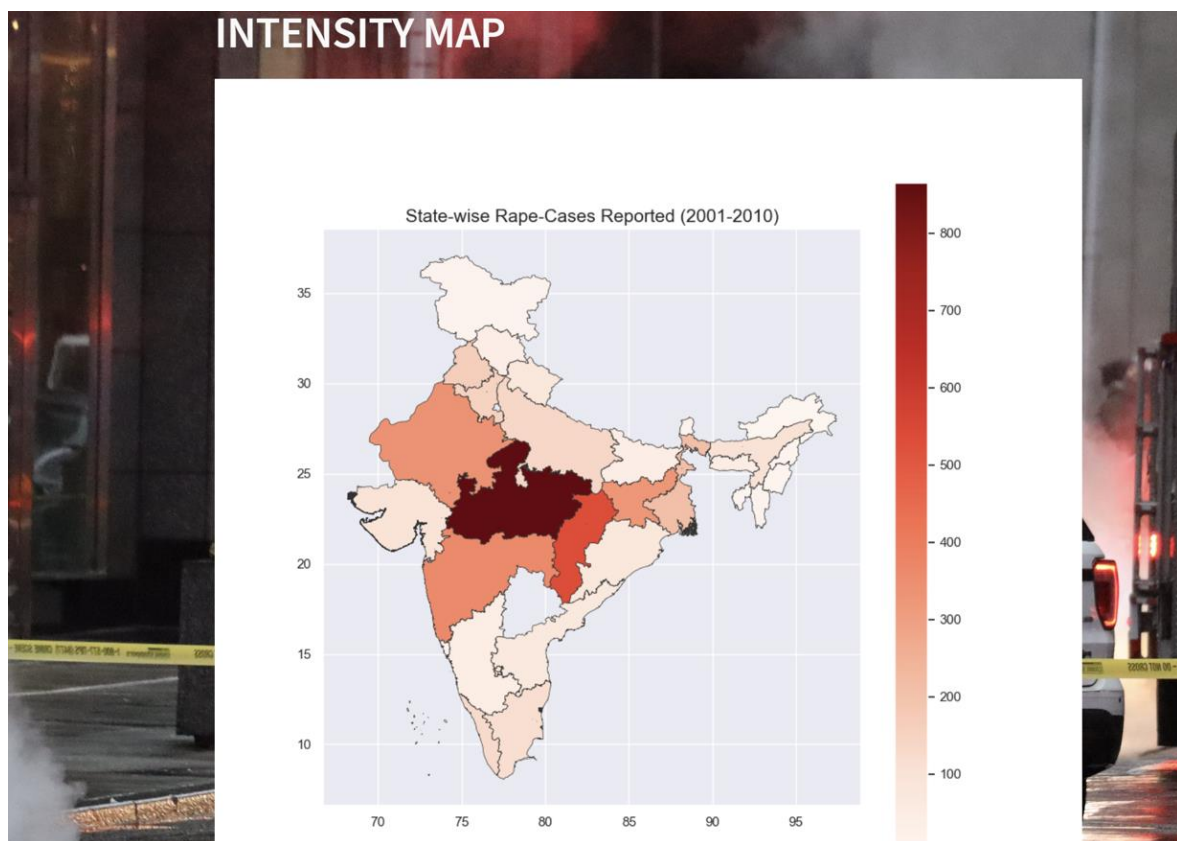


Fig 5 Intensity Map

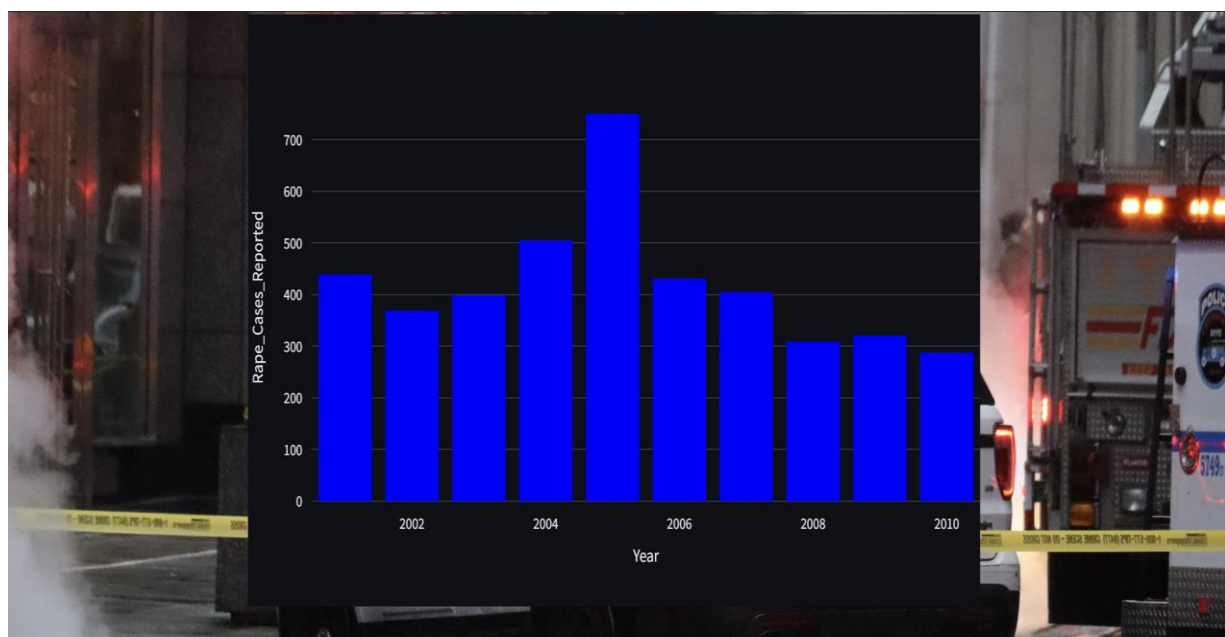


Fig 6. Analysis

C RESEARCH PAPER

Abstract

Understanding crime patterns is essential for effective law enforcement and public safety measures. This research paper comprehensively analyses statewide crime patterns using ensemble machine-learning algorithms and data visualization techniques. The study aims to identify underlying patterns, predict potential crime hotspots, and provide actionable insights for law enforcement agencies and policymakers. We utilize a diverse dataset encompassing various crime categories, demographics, and socio-economic factors across different states. Ensemble machine learning models, including Random Forest, Gradient Boosting, and Boost, are employed to analyze the complex relationships between different variables and predict crime rates accurately. Moreover, advanced data visualization techniques such as heat maps, choropleth maps, and interactive dashboards visually represent crime patterns and trends, facilitating intuitive understanding and decision-making. The findings of this research can aid law enforcement agencies in allocating resources effectively, implementing targeted interventions, and enhancing public safety measures.

Introduction

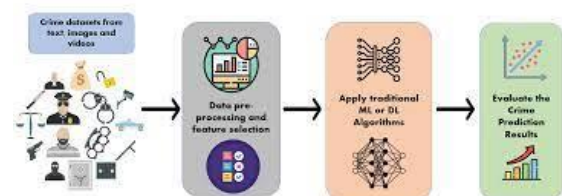
Crime is a major issue for committees worldwide and has impacted many people - our communities, our economies, and all of us as individuals. Focusing on the state level, it is even more important for law enforcement agencies to understand the crime patterns to find a way to combat them with appropriate law enforcement and public safety measures. The traditional methodologies of analyzing crime may not be effective enough to solve these complex crimes because they do not provide a good enough perspective into the dynamics of the crime and the criminals. Machine learning and data visualization methods have made improvements recently that will

help us analyze and try to help predict these diseases affecting our state. This research paper presents an in-depth analysis of machine learning algorithms for predictive modeling and a survey of application areas that have benefited from it, as well as an analysis of data visualization techniques for understanding predictions and diagnosis for a broad spectrum of diseases and, finally, the presentation of ensemble machine learning algorithms and information visualization and their corresponding application domains in predicting surge capacity in hospitals or recourses distribution in response to epidemics and pandemics.

Literature Review

The literature under review seeks to illuminate available studies regarding various techniques released in crime analysis. Some techniques have been tried and tested, while others are relatively new. The review also delves into surveying the limitations attributed to conventional crime-analysis techniques.

Methodology



In the methodology section of the document, the reader will reach a description of the research conditions that have been used to investigate the study's objectives. Within this part of the document, the reader will understand why the chosen techniques and analysis procedures are more suitable for exploring this researcher's problem. Data collection, pre-processing, and feature engineering methods adopted to uncover patterns in penal activities throughout the states are presented. In the analysis phase, ensemble machine learning algorithms, including Random Forest, Gradient Boosting, and

XGBoost, were limited to establishing the relationship between multiple determinants and accurately predicting crime rates

Existing System

The existing system procedures have limitations and challenges in crime analysis methods. The present regime addresses the limitations and menaces in crime assessment methods by discussing the weaknesses of manual analysis, including ineffectiveness, the predicament in prior statistical terms, namely lack of predictive ability, and how complex criminality techniques are demonstrated in the existing crime map tools.

Disadvantages

The upcoming proportion of this study will predominantly be about the traditional style of crime analysis and the negatives that come with it. Lack of adaptability is one of the principal defects in the traditional criminality analysis style. The two terms can explain a second defect: subjectivity and partiality could be used instead of traditional methods. Human judgment, or biases, resulting in many differences in crime data interpretations, usually occur with the experienced trials and errors made by crime firefighters. Limitations in using the static level of traditional statistical models distributed to forecast crimes will be further examined. These models include schemes like classic regression analysis and hot-stop determination. Proposed System:

The proposed system section introduces the framework for unraveling statewide crime patterns using ensemble machine learning and data visualization techniques. It highlights the advantages of utilizing machine learning algorithms for predictive modeling and data visualization techniques for representing complex crime data effectively. The proposed system aims to overcome the limitations of traditional crime analysis methods and provide actionable insights for law enforcement agencies and policymakers.

Advantages

The paper will probe into the strengths of our proposed expert system. It will be shown that our system's superiority will lie in ensemble machine education algorithms and their abilities to encompass intricate relationships and make hypotheses with a high degree of certainty. It will also shed highlights into a state-of-the-art data visualization practice, which will play an essential role in intuitively explaining criminality patterns. It will predetermine the reader to understand and for the law enforcement agencies to take preemptive measures to ensure public safety.

Conclusion

In summary, this resulted in the paper's endeavor to create an all-inclusive frame for making sense of statewide criminality patterns with Ensemble machine learning and data visualization techniques. This proposed system aims to increase public safety and inform policy manufacturers' decision-making through predictive analytics and information visualization.

Future Scope

The Future scope discusses potential areas where the research or inquiry can be taken forward. Furthermore, the inclusion of extra data sources - such as societal media data and geospatial data - to increase predictive accuracy is addressed as a future workstation in this research. Finally, it accentuates the importance of keeping up with the ongoing changes and improvising the suggested system to adapt to the real crime scenario and overcome the possible.

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D CERTIFICATE

