Crime Analysis and Forecasting: Integrating Machine Learning with Population Density and Economy

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Abstract

This research examines the analysis and forecasting of crime rates using machine learning methods, while taking into account the impact of economic indicators and population density characteristics. A prediction model is the main goal of this project in order to assist policymakers and law enforcement organizations in making effective decision about crime prevention and resource allocation. Despite the fact that crime analysis has been the topic of substantial research, little focus has been placed on how economic and population characteristics interact to predict crime. Our study examines the connections between these socioeconomic factors and crime rates in an effort to close this gap. We get statistics from the World Bank, Macrotrends for this. We strive to offer a more thorough knowledge of the factors driving crime by using a holistic approach that takes into consideration population density and economic data. Our work uses machine learning techniques, specifically regression models, to evaluate and forecast crime rates in accordance with the accepted methodology in the field. To model the links between crime and all of the above socio-economic factors, we use regression analysis. Using this method, we can develop prediction models that can provide insightful information about the dynamics of crime and its relationship to factors such as population density and economic situations. This research has the potential to significantly advance society in a number of ways. by having a greater understanding of the complex connection between population density, economic position attainment and crime. This may consequently result in better resource allocation, greater efficacy of crime prevention strategies, and ultimately safer and more secure communities.

Index Terms: Bangladesh, crime prediction, analysis, Bangladesh police, ACLED, crime report

Acknowledgements

Thanks to Almighty Allah. This work would not have been possible without the input and support of many people over the last trimesters. We would like to express our gratitude to everyone who contributed to it in some way or another. First, we would like to thank our academic advisor, Iftekharul Abedeen. Our sincere gratitude goes to our honorable class teacher Prof. Dr. Al-Sakib Khan Pathan. We also thank our group members, seniors, and classmates. Last but not least, we owe our family, including our parents, for their unconditional love and immense emotional support.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

In a world which evolves quickly, studying and reducing crime are the most important things that can be done to keep people safe and improve society. The main ideas of this thesis are about analysing and predicting crime using machine learning and two important factors: changes in the population and economic growth. The main goal of this study, which is focused on our country, is to fully observe, analyse, and predict crime patterns. This will help people in law enforcement and community development make better decisions and take more proactive steps. By combining technology, population, and economic indicators, our research aims to provide useful information for making societies safer and more resilient.

1.1 Project Overview

This project tries to look into how to analyse and forecast crime, with a focus on how to use machine learning techniques along with population change and economic growth as important factors in our country. We want to use complex algorithms to find hidden patterns in crime data and make prediction models that show how changes in population, the economy, and criminal activity are all connected in complex ways. Our goal is to give law enforcement and policymakers a full picture of crime patterns through time series analysis and creative data analysis. This will allow them to take proactive steps for public safety and community development. Our project aims to provide useful tools for dealing with and reducing crime problems in our specific social and economic setting by combining ideas from different fields.

1.2 Motivation

The idea for this study came from a deep understanding of how important it is to deal with the complicated problems that crime causes in our society. As technology changes and cities change quickly, the old ways of looking at crime need to be updated. Using population change and economic growth along with machine learning as important factors aims to start a new era of proactive crime prevention and community development.

We get ideas for how to make the public safer from the way predictive modelling can help us predict and stop criminal activities. By looking into how crime patterns are connected to how the population and economy are changing all the time, we hope to give law enforcement and policymakers useful information. The goal of this research is not only to improve academic knowledge, but also, and this is more important, to give our communities useful tools to help them deal with and reduce the effects of crime. We hope that this multidisciplinary project will make a real difference in making societies safer and more resilient.

1.3 Objectives

There are clear goals built into this project to:

1. Predict Crime Patterns: - Use population and economic data to build machine learning models that can predict how crime will happen in the future.

2. Understand Temporal Trends: - Use a regression model to look at crime data and find out how it changes over time.

3. Visualise Key Statistics:- Do exploratory research to make important crime statistics for cities look good on a screen.

4. Support Decision-Making: Give law enforcement and policymakers useful information so they can make smart choices about how to stop crime.

5. "Contribute to Community Development": To help with community development, look into how crime patterns, population changes, and economic growth are connected.

These goals are meant to help us learn more about how crime works and give people who have a stake in community safety and intervention useful tools for making things better.

1.4 Methodology

Using a systematic approach and different machine learning techniques to look at crime patterns in Bangladesh is how this research project is being done. These are the main steps:

1. Data Collection: - Get a variety of datasets from the Bangladesh Police website and ACLED, such as crime records, population data, and economic indicators that are relevant to the chosen regions.

2. Data Preprocessing: - Clean and preprocess the collected data to make sure it is consistent and reliable. This includes fixing any missing values or outliers that could affect how well the model works.

3. Feature Engineering: - Take out and choose the important parts of the dataset, focusing on variables that have to do with crime, population growth, and Bangladeshi economic indicators.

4. Model Selection: – Come up with a list of machine learning models that are best fit for the crime data and the study's goals. These models should include Regression, Decision Tree, Random Forest, K-Means Clustering, and Naïve Bayes.

5. Train the models: Use the preprocessed dataset to train each chosen model, making sure that the parameters are optimised to improve performance and accuracy.

6. Evaluate the models: Use metrics like accuracy, precision, recall, and F1-score to rate each model's performance and make sure you get a full picture of how well they can capture crime patterns in Bangladesh.

This method is specifically designed for the unique dataset that comes from the Bangladesh Police website and ACLED. Its goal is to give specific information that can be used to analyse and predict crime in the country.

1.5 Project Outcome

By the end of this research project, we hope to have produced useful results that will help law enforcement and help people in third-world countries understand how important it is to analyse crime. These are the expected results:

1. Advanced Predictive Models: Use advanced machine learning models to look at crime and predict patterns by combining changes in the population and the economy. The goal of these models is to give law enforcement agencies proactive information that they can use for planning strategies and allocating resources.

2. Making Informed Decisions for Law Enforcement: Giving law enforcement agencies actionable intelligence that helps them stop and deal with crime by making informed decisions. It is expected that law enforcement strategies will work better when population and economic factors are combined with machine learning.

3. Community Development Insights: These are details about how crime patterns, population changes, and economic growth are all connected in third-world countries. The goal of the project is to provide useful information that policymakers can use to guide community development efforts and improve the health of society as a whole.

4. Increasing the safety of the public: The project's goal is to improve public safety by proactively finding crime patterns through the use of machine learning techniques. This result is very important for making places safer and raising people's quality of life.

5. Building up people's skills in third-world countries: A focus on building up third-world countries' abilities, with a focus on sharing knowledge and skills related to crime analysis. The project's goal is to give these countries the tools they need to take a more proactive approach to crime management by showing them the benefits of combining machine learning with demographic and economic data.

In short, the project's results are in line with a larger goal of using machine learning to make the world a better place. The study wants to have a big and long-lasting effect on how we understand and deal with crime. It will do this by teaching third-world countries how data-driven insights can change things and helping law enforcement stop crimes before they happen.

1.6 Organization of the Report

There is a title page. Then there is the abstract and the acknowledgment. Then, there is a table of contents. In the table of contents, the first chapter, Introduction, has a section named Project overview, a section called Motivation, a section called Objectives, a section called Methodology, Chapter two is Background, and there is a Preliminaries section. Then, the literature review section. Inside the literature review section. The next chapter, the name is Dataset. Then there is the Complex engineering problem chapter. The last chapter is the conclusion chapter. Two sections are there which are a Summary and future work.

Chapter 2

Background

[*Must be present in FYDP-1 Report and also in Final Report*]

Every chapter should start with 1-2 sentences on the outline of the chapter.

2.1 Preliminaries

In this section, you have to provide the necessary background knowledge to understand the rest of the report [**?**].

2.2 Literature Review

This section will contain you literature review.

2.2.1 Similar Applications

Put a summary of similar web applications, mobile apps similar to your work.

2.2.2 Related Research

2.3 Literature Review

For our research, there are some related literature reviews which include the Author's Year Site, Study Description, Method Adopted, and Results.

Authors Year Site	Study Description	Method	Result
Empirical Analysis for Crime Prediction and Forecasting Using Machine Learning and Deep Learning Techniques (2021)	The paper aims to improve crime prediction and forecasting using machine learning and deep learning techniques on Chicago and Los Angeles crime datasets.	The paper applies eight machine learning algorithms, namely logistic regression, SVM, Naïve Bayes, KNN, decision tree, MLP, random forest, and XGBoost, to achieve high prediction accuracy for crime types and hot spots23.	The paper also performs time series analysis using LSTM and ARIMA models to capture the temporal patterns and trends of crime data. The paper provides exploratory data analysis to visualize the key statistics, such as crime rate, crime count, crime density, and crime types for both cities.
Public decision support for low population density areas: An imbalance-aware hyper-ensemble for spatio-temporal crime prediction (2019)	To develop machine learning models for spatio-temporal crime prediction that can handle extreme class imbalance and low population density regions1.	To propose a hyper-ensemble that combines under-sampling and ensemble learning techniques to improve the hit rate and prediction accuracy index (PAI) of crime hotspots2.	To demonstrate that the hyper-ensemble outperforms common baselines and achieves a hit rate of 24.6 % and a PAI of 4.932 at 5 % coverage area.
Socio-economic, built environment, and mobility conditions associated with crime: a study of multiple cities (2020)	The paper aims to explore the relationship between crime rates and various neighborhood characteristics.	A Bayesian model is employed to assess the impact of these features on crime rates.	The model's performance is evaluated under various feature combinations, revealing city-specific patterns.
Luigi Di Stefano et al. (March 2004) [?]	Image and vision computing, Area-based algorithms & Photometric properties.	Single Matching Face (SMP). Bidirectional Matching (BM). Real-time stereo applications.	Can't deal with the border-localization problem. Relies only on SMP. Sometimes detect unreliable matches.
Comparison of Machine Learning Algorithms for Predicting Crime Hotspots (2020)	To Compare the predictive power of six machine learning algorithms for crime hotspot prediction, using historical crime data and built environment covariates.	The authors applied KNN, random forest, SVM, naive Bayes, CNN, and LSTM models to forecast the crime hotspots in a town in southeast China, using two-week time units and 150m x 150m grid units1. They also added POI density and road network density as covariates to the LSTM model to examine their effects.	The authors found that the LSTM model outperformed the other models in terms of hit rate and hit efficiency. They also found that the addition of built environment covariates improved the prediction accuracy of the LSTM model.
Crime Prediction and Monitoring in Porto, Portugal, Using Machine Learning, Spatial and Text Analytics (2022)	Patterns in Porto, Portugal, based on official police data from 2016 to 20181. They also review the relevant literature on crime mapping, hot-spotting, and prediction, and highlight	Also used machine learning methods, such as random forest, lasso regression, decision tree and support vector machine, to forecast and predict crime occurrences based on contextual factors.	Additionally, they used natural language processing methods, such as topic modeling and sentiment analysis, to extract information from tweets related to crime and insecurity.

Authors Year Site	Study Description	Method Adopted	Limitations
Economic Crime Detection Using Support Vector Machine Classification (2021)	The paper proposes a method to detect fictitious enterprises, which are business entities that are created or acquired to cover up illegal or prohibited activities.	the article based on the Support Vector Machine (SVM) classification, a machine learning technique that can separate data into two classes.	Paper compares SVM methods—linear, polynomial, radial. Best: polynomial (100% train, 99.7% test). Confusion matrices show results. Suggests method for public sector software to combat economic crimes, spot fictitious enterprises.
Prediction on the Combine Effect of Population, Education and Unemployment on Criminal Activity Using Machine Learning (2022)	The paper explores the correlation of violent crime rate with population, education, and unemployment in areas where majority of the inhabitants are afro Americans1.	The paper uses multiple linear regression (MLR) to analyze the data and predict the crime rate2.	The paper also performs cross-validation and confusion matrix to evaluate the accuracy of the model.
Crime Analysis And Prediction Using Machine Learning, 2022	The paper employs SVM and Python libraries for crime analysis, prediction, and visualization in India. It utilizes historical data, discusses SVM applications, and outlines future work to enhance prediction accuracy.	The authors used SVM (Support Vector Machine) algorithm to predict the future crime occurrences based on the past data.	The paper's performance is poor and unreliable, and it needs significant improvement and validation to be considered a credible contribution to the field of crime analysis and prediction.
Crime forecasting: a machine learning and computer vision approach to crime prediction and prevention 2021	The article explores ML and computer vision for crime prediction, reviewing law enforcement technologies and comparing ML algorithms' performance on crime datasets. It highlights the applications and challenges of computer vision in crime forecasting and its synergy with ML and deep learning.	Decision tree,KNN,Naïve Bayes classifier,Autoregressive integrated moving average (ARIMA),Regression model,Random Forest.	It highlights the applications and challenges of computer vision in crime forecasting and its synergy with ML and deep learning.
AN APPROACH TO CRIME DATA ANALYSIS: A SYSTEMATIC REVIEW, February, 2018	The webpage reviews data mining techniques for crime analysis, proposing a CRISP-DM methodology and addressing challenges.	SVM, ANN, Nearest Neighbor, Decision tree, Naïve Bayes and Neural network	The paper systematically reviews data mining techniques for crime data analysis,covering types of crime, data sources, methods, and challenges.

Chapter 3

Data Set

3.1 Dataset Analysis.

Our dataset was compiled from the websites of the Bangladesh Police and ACLED. The data for the Bangladesh Police website spans the years 2010 to 2019 and includes 15 attributes. For ACLED, we obtained 30,000 samples.

3.1.1 Year vs Population

Year	Total Population
2000	129193327
2001	131670484
2002	134139826
2003	136503206
2004	138789725
2005	140912590
2006	142628831
2007	144135934
2008	145421318
2009	146706810
2010	148391139
2011	150211005
2012	152090649
2013	154030139
2014	155961299
2015	157830000
2016	159784568
2017	161793964
2018	163683958
2019	165516222
2020	167420951
2021	169356251
2022	171186372

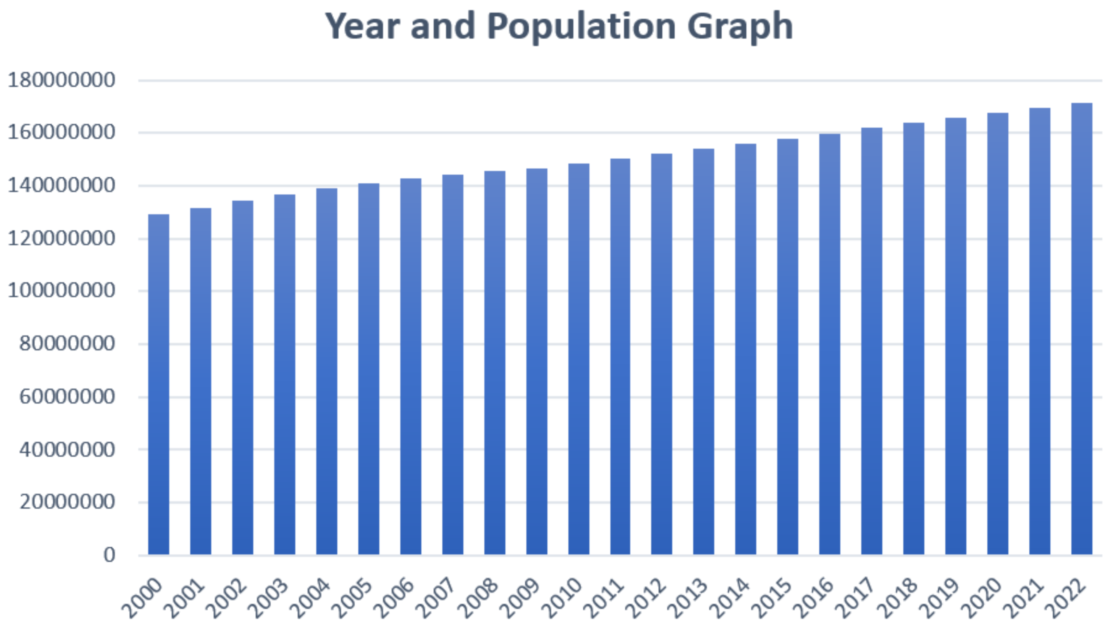

Figure 3.1: Year vs Population.

3.1.2 Year vs GDP Per Capital

Year	GDP Per Capital
2000	330
2001	310
2002	190
2003	290
2004	350
2005	490
2006	540
2007	590
2008	510
2009	410
2010	440
2011	520
2012	520
2013	470
2014	470
2015	530
2016	580
2017	530
2018	610
2019	670
2020	230
2021	570
2022	600

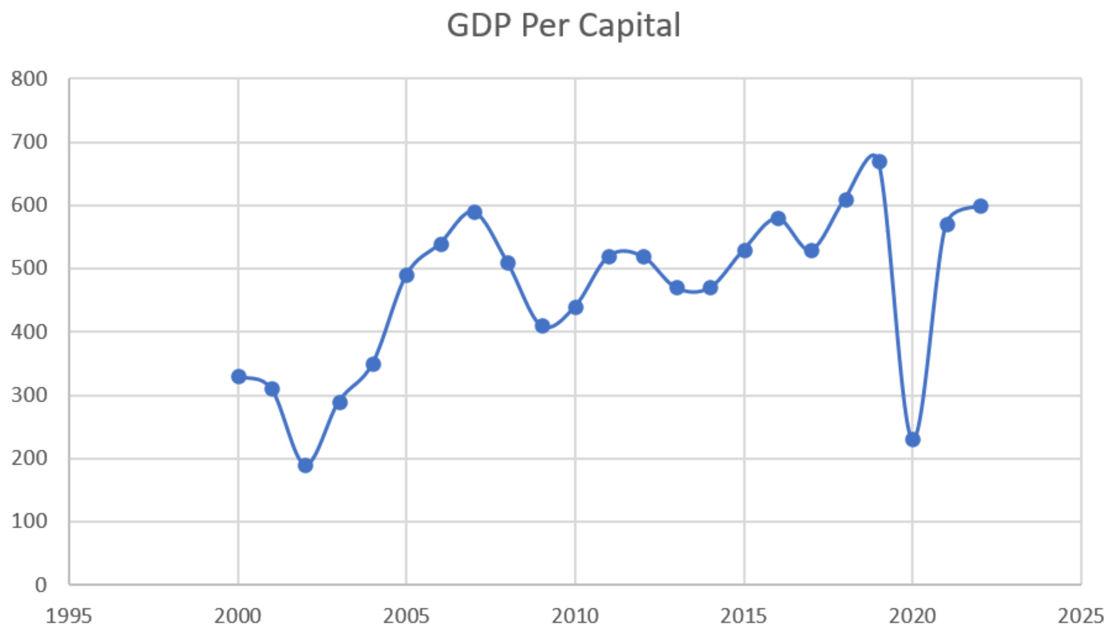

Figure 3.2: Year vs GDP Per Capital.

3.1.3 Year vs Dacoity

Year	Dacoity
2010	656
2011	650
2012	593
2013	613
2014	651
2015	492
2016	408
2017	336
2018	262
2019	32

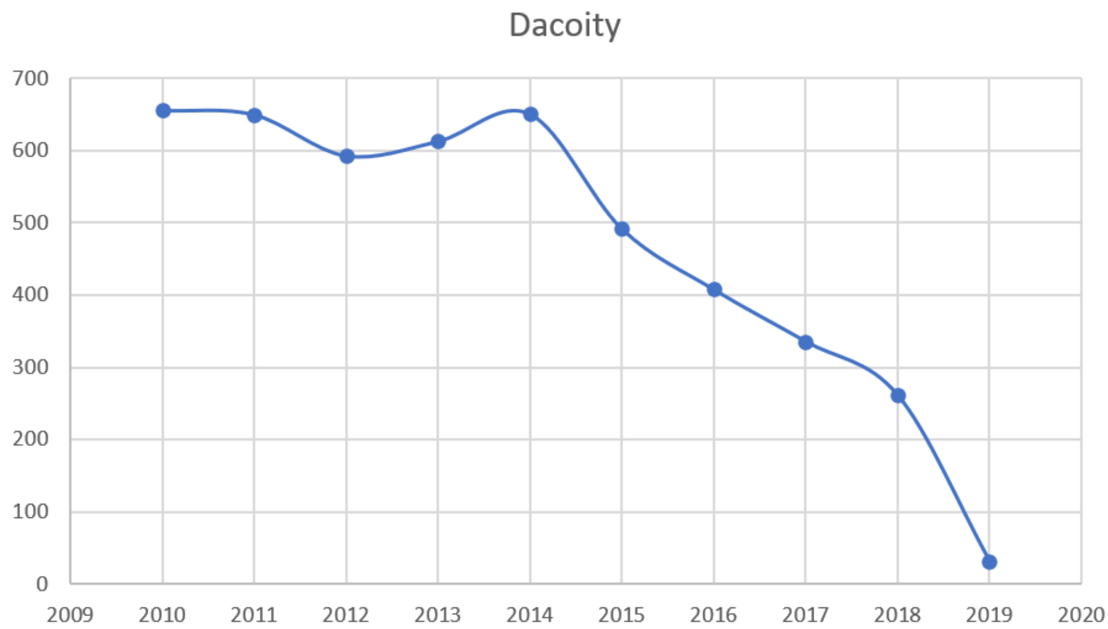

Figure 3.3: Year vs Dacoity.

3.1.4 Year vs Robbery

Year	Robbery
2010	1059
2011	1069
2012	964
2013	1021
2014	1155
2015	933
2016	722
2017	657
2018	562
2019	68

3.1.5 Year vs Speed Trial

Year	Speed Trial
2010	1666
2011	1863
2012	1907
2013	1896
2014	1716
2015	1549
2016	1052
2017	1045
2018	922
2019	48

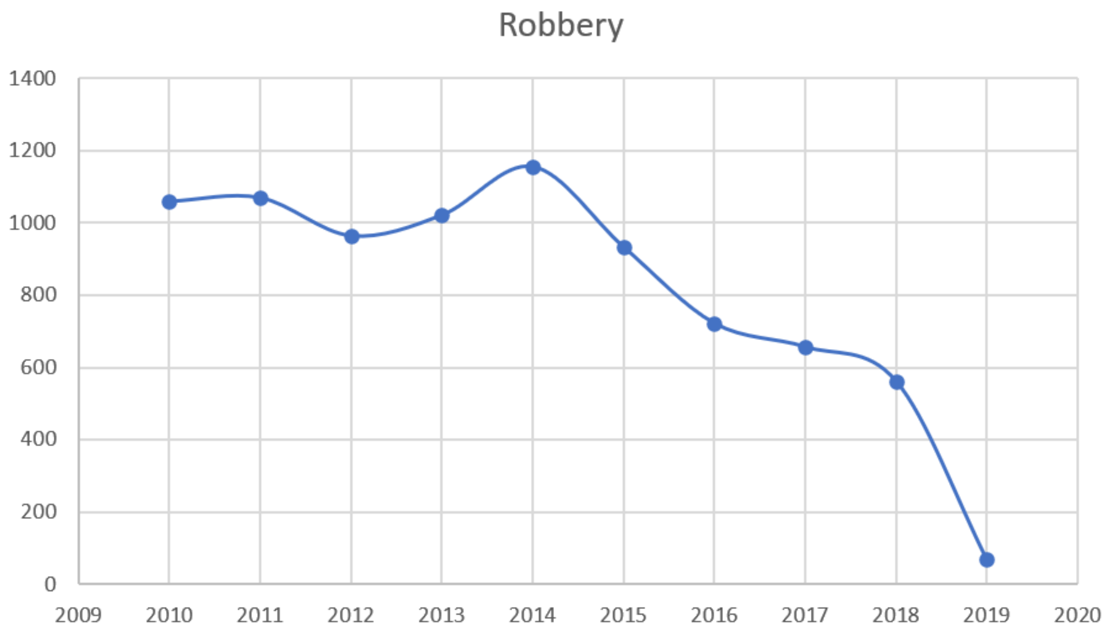

Figure 3.4: Year vs Robbery.

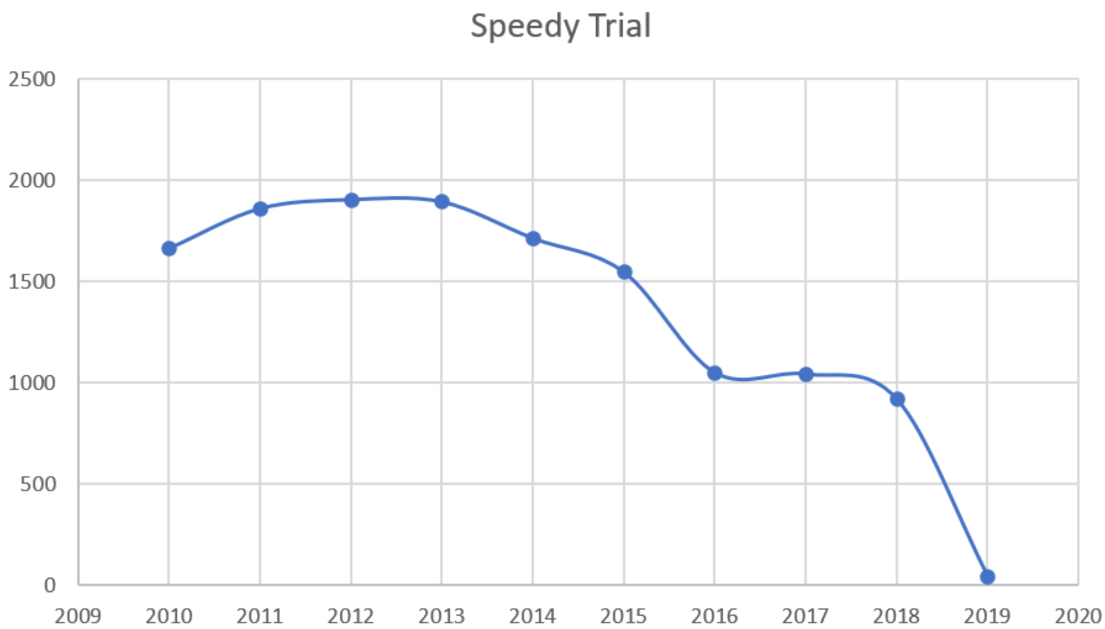

Figure 3.5: Year vs Speed Trial.

3.1.6 Year vs Riot

Year	Riot
2010	130
2011	109
2012	94
2013	172
2014	79
2015	93
2016	53
2017	23
2018	26
2019	1

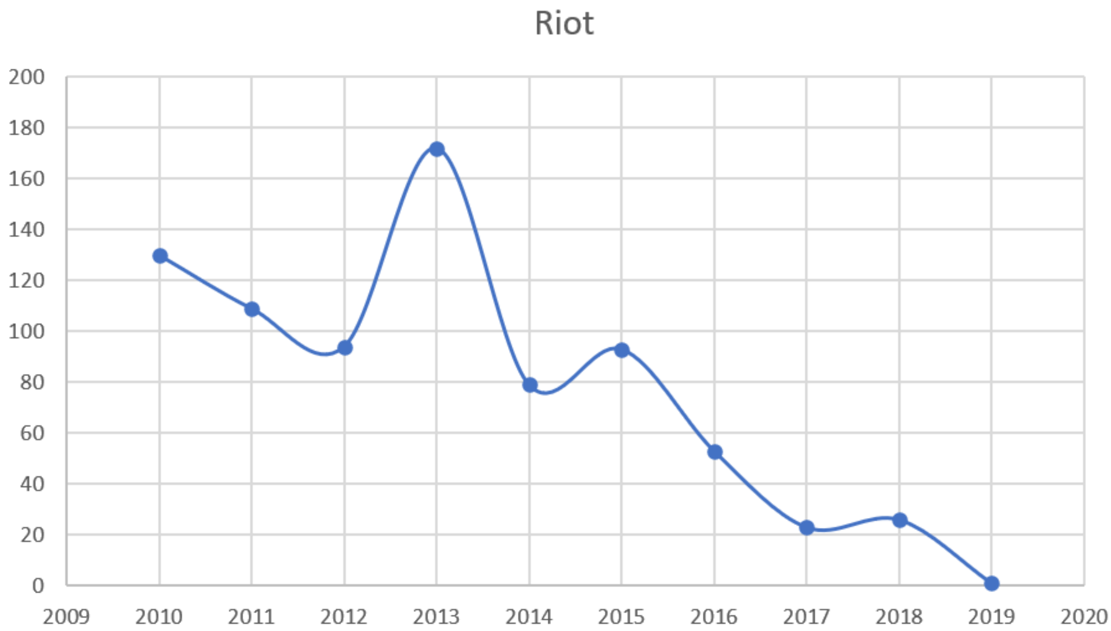

Figure 3.6: Year vs Riot.

3.1.7 Year vs Women Abuse

Year	Women Abuse
2010	17752
2011	21389
2012	20947
2013	19601
2014	21291
2015	21210
2016	18446
2017	17073
2018	16253
2019	1139

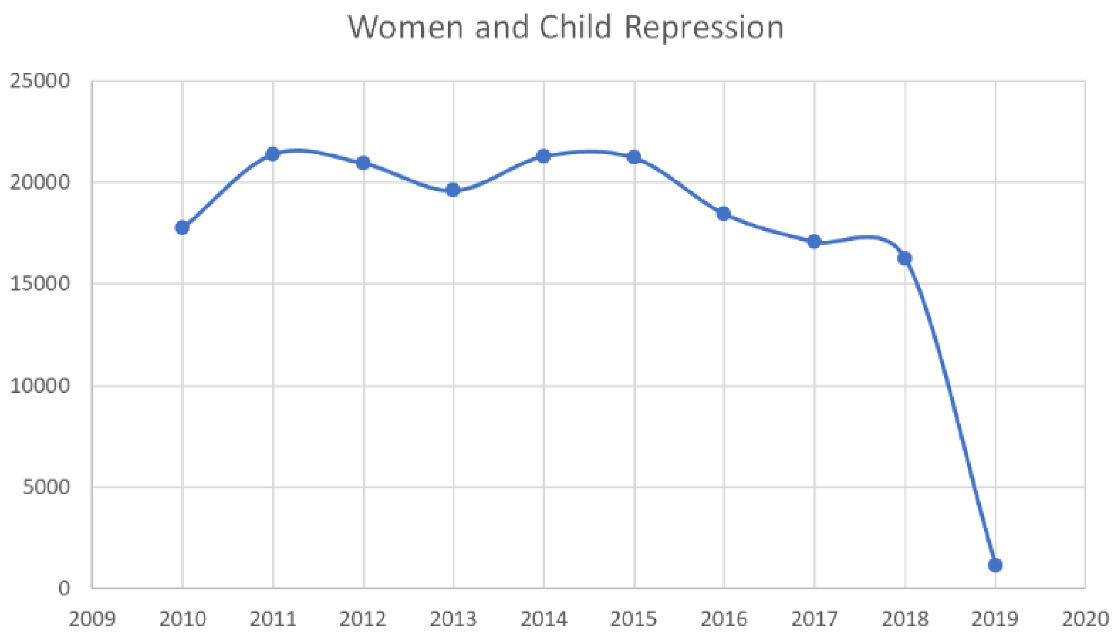

Figure 3.7: Year vs Women Abuse.

3.1.8 Year vs Kidnapping

Year	Kidnapping
2010	870
2011	792
2012	850
2013	879
2014	920
2015	805
2016	639
2017	509
2018	444
2019	46

3.1.9 Year vs Police Assault

Year	Police Assault
2010	473
2011	581
2012	659
2013	1257
2014	702
2015	634
2016	521
2017	543
2018	811
2019	69

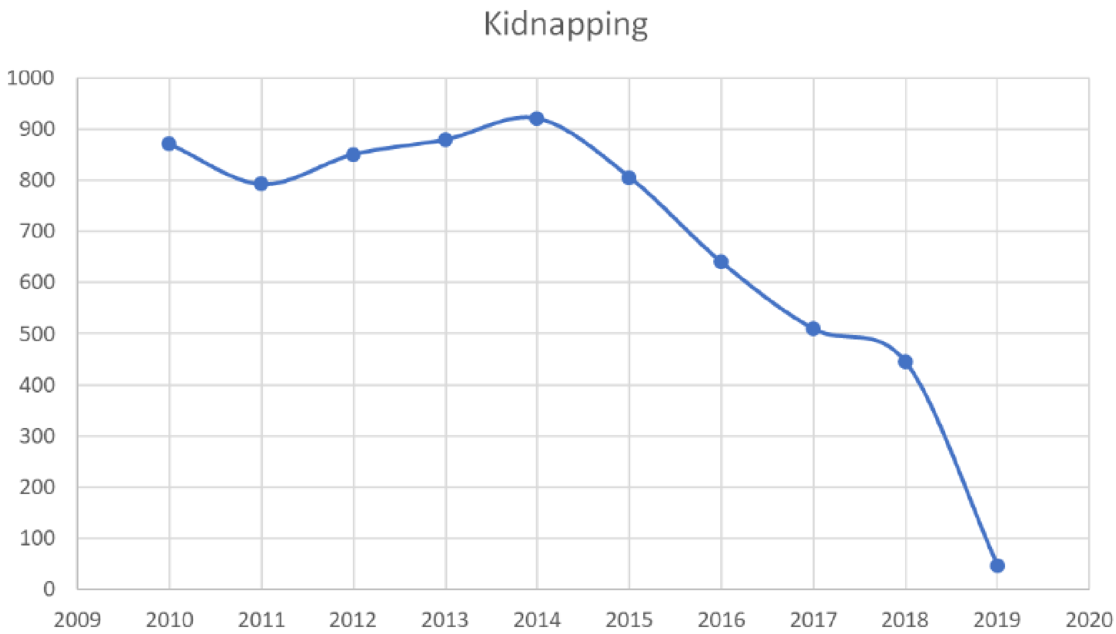

Figure 3.8: Year vs Kidnapping.

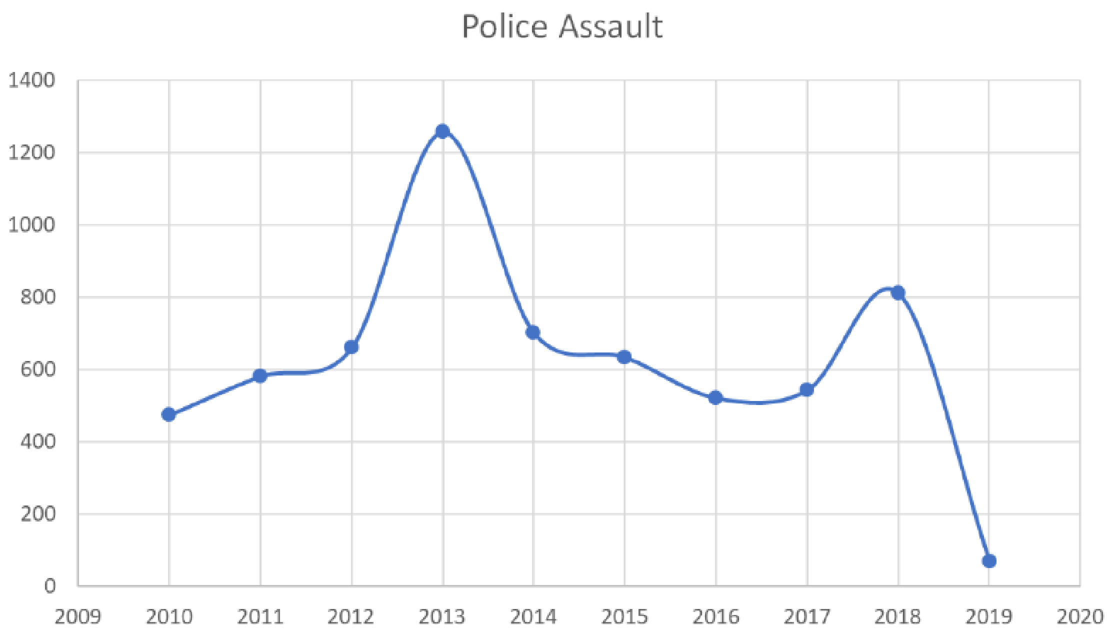

Figure 3.9: Year vs Police Assault

3.1.10 Year vs Burglary

Year	Robbery
2010	3101
2011	3134
2012	2927
2013	2762
2014	2809
2015	2495
2016	2213
2017	2163
2018	2137
2019	174

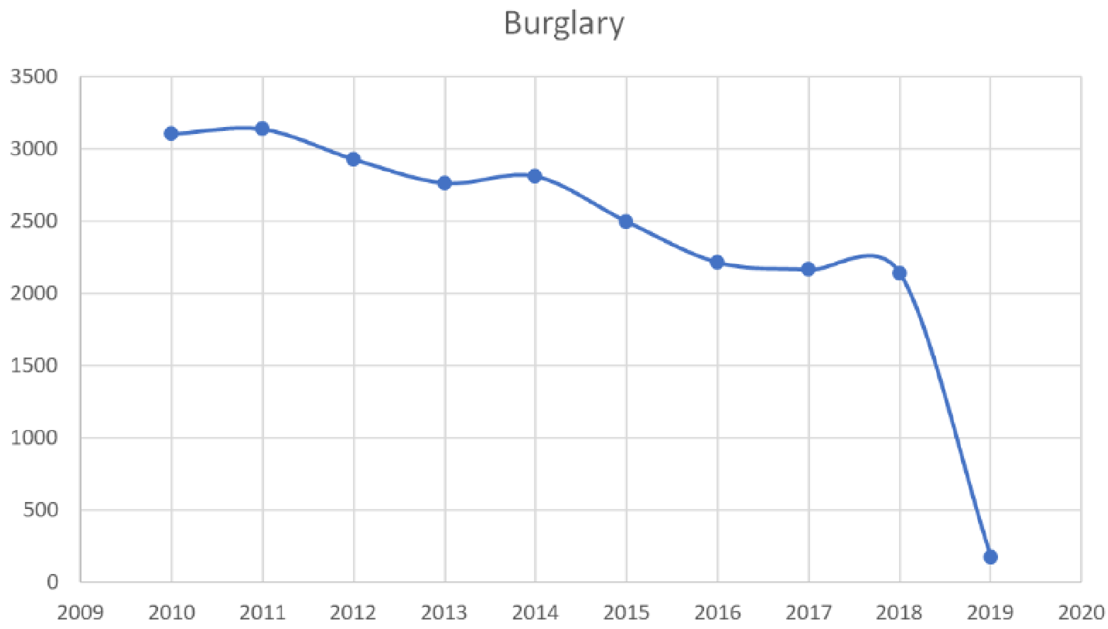

Figure 3.10: Year vs Burglary

3.1.11 Year vs Theft

Year	Theft
2010	8529
2011	8873
2012	8598
2013	7882
2014	7660
2015	6821
2016	6110
2017	5833
2018	5561
2019	494

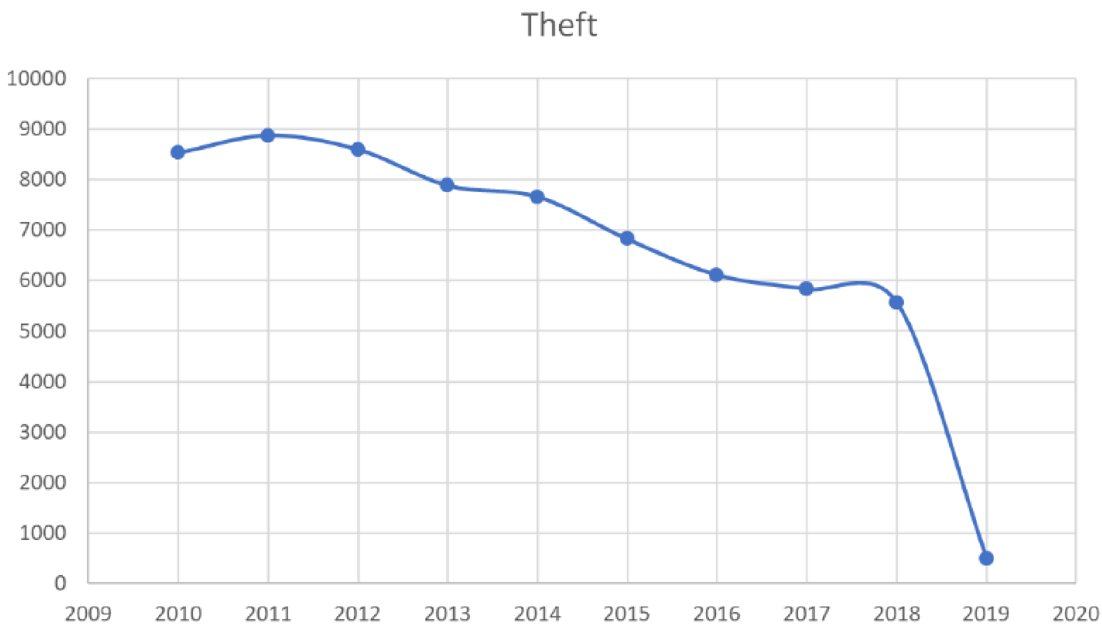

Figure 3.11: Year vs Theft

3.1.12 Year vs Other Cases

Year	Other Cases
2010	87139
2011	88355
2012	96112
2013	93930
2014	90400
2015	84117
2016	77747
2017	74645
2018	69736
2019	5428

3.1.13 Year vs Arms Act.

Year	Arms Act
2010	1575
2011	1269
2012	1511
2013	1517
2014	2023
2015	2079
2016	2291
2017	2208
2018	2515
2019	174

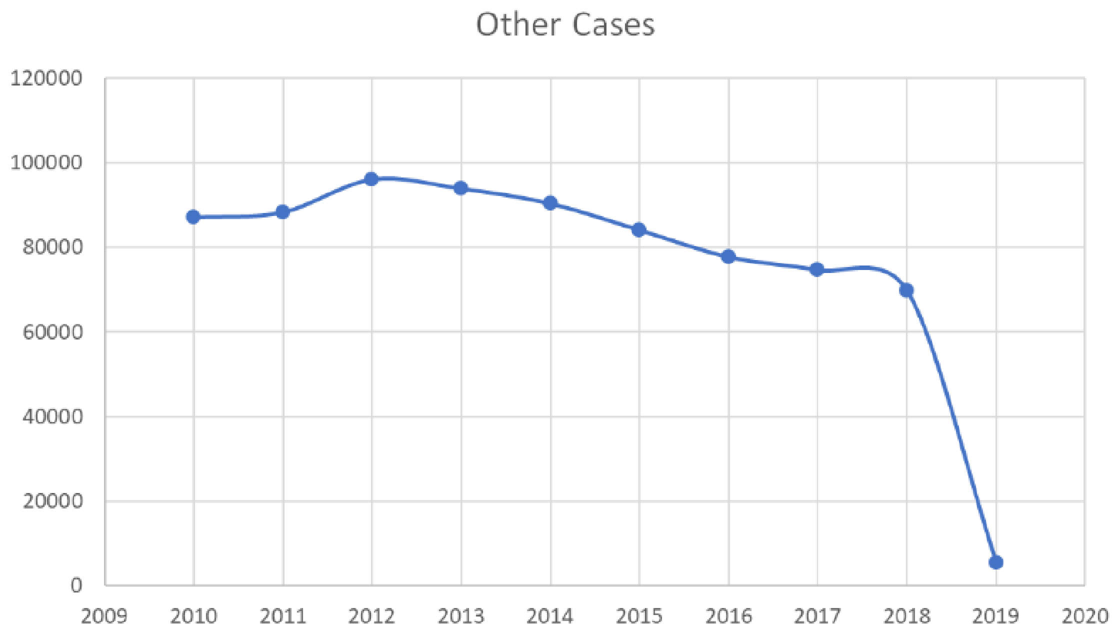

Figure 3.12: Year vs Other Cases

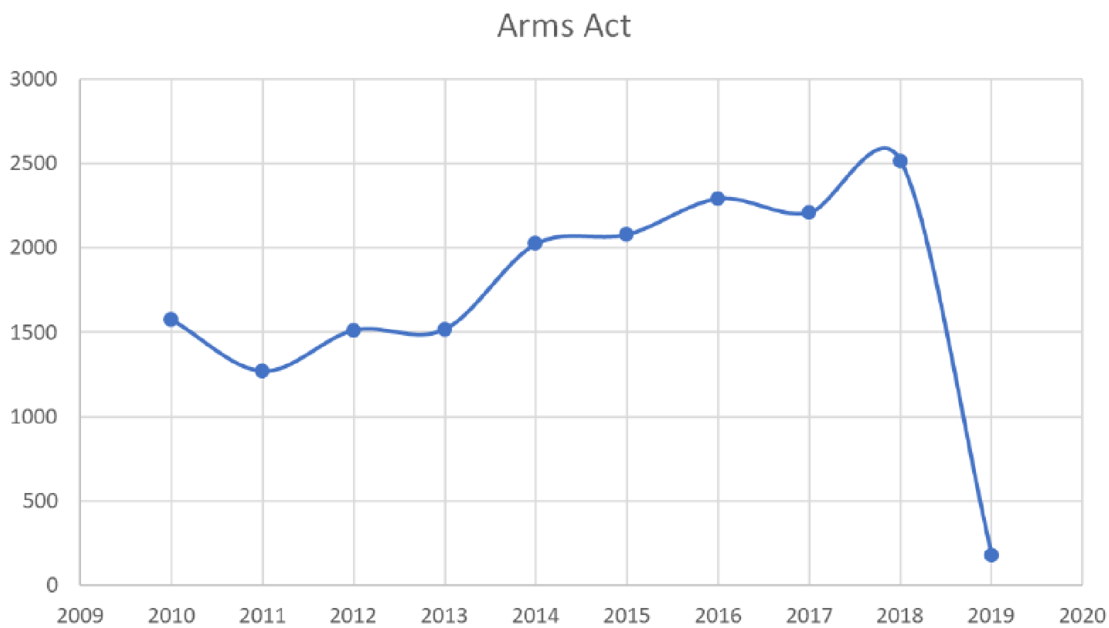

Figure 3.13: Year vs Arms Act

3.1.14 Year vs Explosive

Year	Explosive
2010	253
2011	207
2012	289
2013	1007
2014	520
2015	725
2016	487
2017	362
2018	1310
2019	30

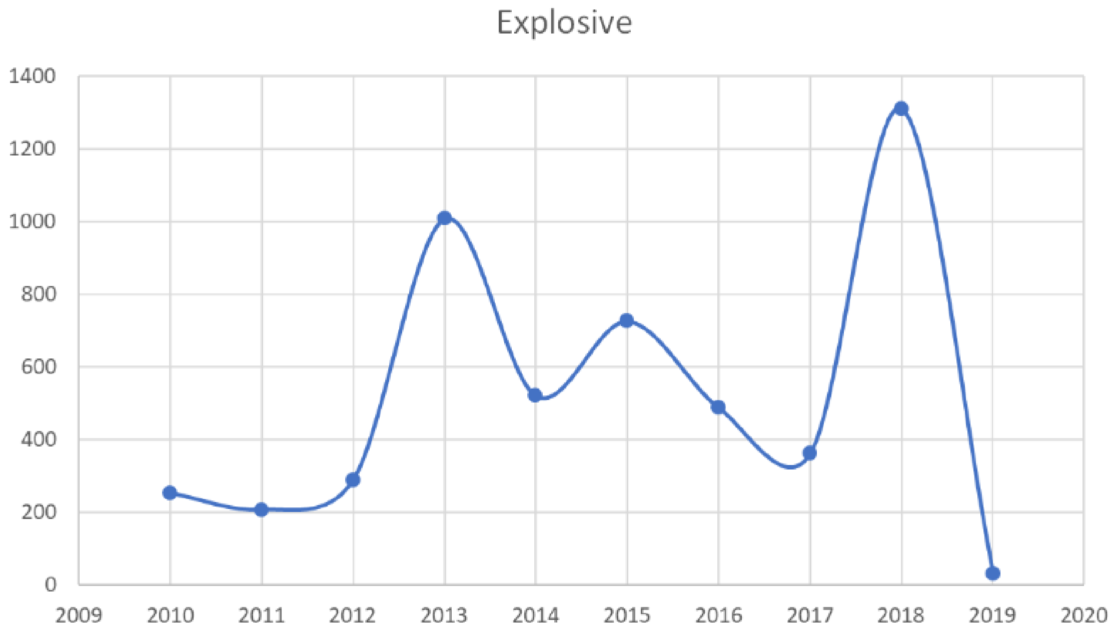

Figure 3.14: Year vs Explosive

3.1.15 Year vs Narcotics

Year	Narcotics
2010	29344
2011	31696
2012	37264
2013	35832
2014	42501
2015	47666
2016	62208
2017	98984
2018	112549
2019	9069

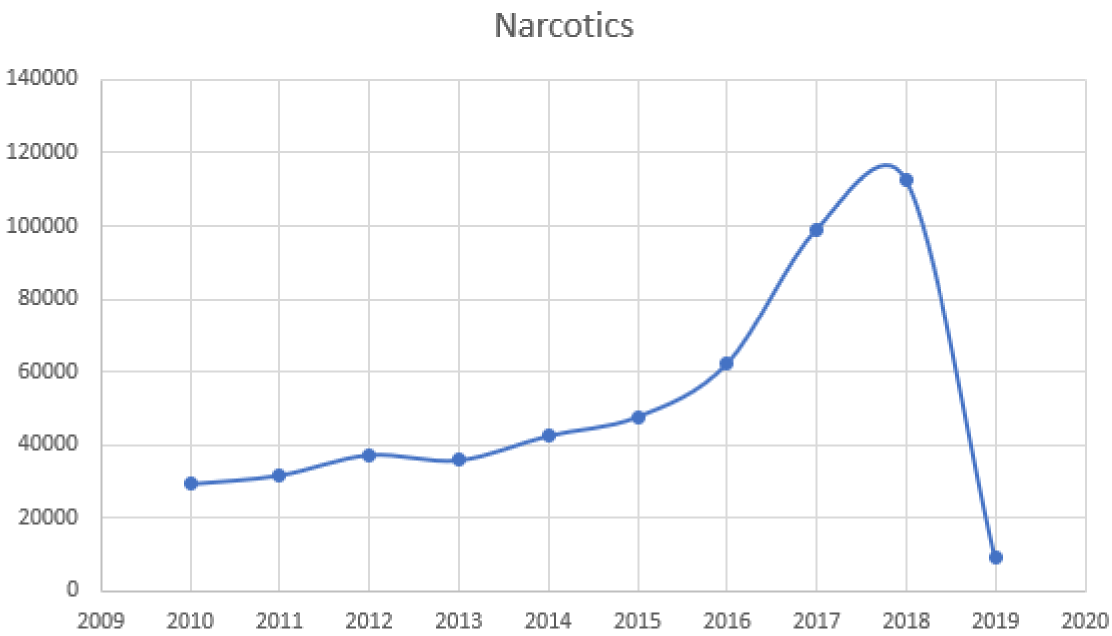

Figure 3.15: Year vs Narcotics

3.1.16 Year vs Smuggling

Year	Smuggling
2010	6363
2011	5714
2012	6578
2013	6437
2014	6788
2015	6179
2016	4680
2017	5599
2018	4501
2019	361

3.2 Dataset Preprocessing.

We split up the data and created a subset to determine the relationship between crime and population.

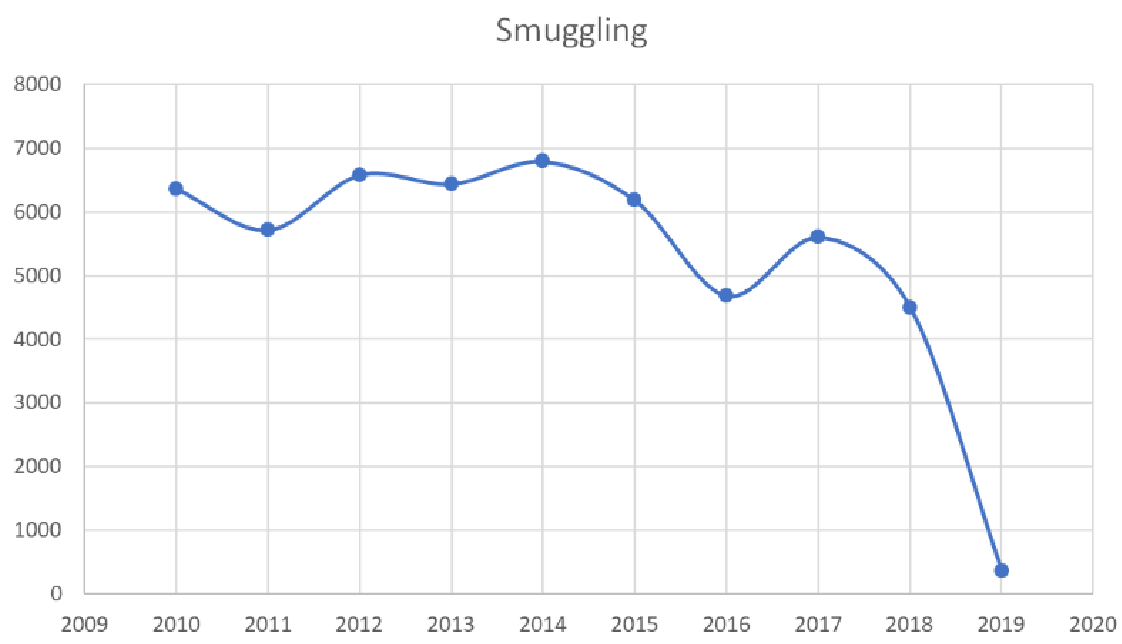

Figure 3.16: Year vs Smuggling

3.2.1 Arms Act

Year	Total Population	GDP Per Capital	Arms Act
2010	148391139	440	1575
2011	150211005	520	1269
2012	152090649	520	1511
2013	154030139	470	1517
2014	155961299	470	2023
2015	157830000	530	2079
2016	159784568	580	2291
2017	161793964	530	2208
2018	163683958	610	2515
2019	165516222	670	174

3.2.2 Burglary

Year	Total Population	GDP Per Capital	Burglary
2010	148391139	440	3101
2011	150211005	520	3134
2012	152090649	520	2927
2013	154030139	470	2762
2014	155961299	470	2809
2015	157830000	530	2495
2016	159784568	580	2213
2017	161793964	530	2163
2018	163683958	610	2137
2019	165516222	670	174

3.2.3 Dacoity

Year	Total Population	GDP Per Capital	Dacoity
2010	148391139	440	656
2011	150211005	520	650
2012	152090649	520	593
2013	154030139	470	613
2014	155961299	470	651
2015	157830000	530	492
2016	159784568	580	408
2017	161793964	530	336
2018	163683958	610	262
2019	165516222	670	32

3.2.4 Explosive

Year	Total Population	GDP Per Capital	Explosive
2010	148391139	440	253
2011	150211005	520	207
2012	152090649	520	289
2013	154030139	470	1007
2014	155961299	470	520
2015	157830000	530	725
2016	159784568	580	487
2017	161793964	530	362
2018	163683958	610	1310
2019	165516222	670	30

3.2.5 Kidnapping

Year	Total Population	GDP Per Capital	Kidnapping
2010	148391139	440	870
2011	150211005	520	792
2012	152090649	520	850
2013	154030139	470	879
2014	155961299	470	920
2015	157830000	530	805
2016	159784568	580	639
2017	161793964	530	509
2018	163683958	610	444
2019	165516222	670	46

3.2.6 Murder

Year	Total Population	GDP Per Capital	Murder
2010	148391139	440	3988
2011	150211005	520	3966
2012	152090649	520	4114
2013	154030139	470	4393
2014	155961299	470	4514
2015	157830000	530	4037
2016	159784568	580	3591
2017	161793964	530	3549
2018	163683958	610	3830
2019	165516222	670	351

3.2.7 Narcotics

Year	Total Population	GDP Per Capital	Narcotics
2010	148391139	440	29344
2011	150211005	520	31696
2012	152090649	520	37264
2013	154030139	470	35832
2014	155961299	470	42501
2015	157830000	530	47666
2016	159784568	580	62208
2017	161793964	530	98984
2018	163683958	610	112549
2019	165516222	670	9069

3.2.8 Other Cases

Year	Total Population	GDP Per Capital	Other Cases
2010	148391139	440	87139
2011	150211005	520	88355
2012	152090649	520	96112
2013	154030139	470	93930
2014	155961299	470	90400
2015	157830000	530	84117
2016	159784568	580	77747
2017	161793964	530	74645
2018	163683958	610	69736
2019	165516222	670	5428

3.2.9 Police Assault

Year	Total Population	GDP Per Capital	Police Assault
2010	148391139	440	473
2011	150211005	520	581
2012	152090649	520	659
2013	154030139	470	1257
2014	155961299	470	702
2015	157830000	530	634
2016	159784568	580	521
2017	161793964	530	543
2018	163683958	610	811
2019	165516222	670	69

3.2.10 Riot

Year	Total Population	GDP Per Capital	Riot
2010	148391139	440	130
2011	150211005	520	109
2012	152090649	520	94
2013	154030139	470	172
2014	155961299	470	79
2015	157830000	530	93
2016	159784568	580	53
2017	161793964	530	23
2018	163683958	610	26
2019	165516222	670	1

3.2.11 Robbery

Year	Total Population	GDP Per Capital	Robbery
2010	148391139	440	1059
2011	150211005	520	1069
2012	152090649	520	964
2013	154030139	470	1021
2014	155961299	470	1155
2015	157830000	530	1155
2016	159784568	580	722
2017	161793964	530	657
2018	163683958	610	562
2019	165516222	670	68

3.2.12 Smuggling

Year	Total Population	GDP Per Capital	Smuggling
2010	148391139	440	6363
2011	150211005	520	5714
2012	152090649	520	6578
2013	154030139	470	6437
2014	155961299	470	6788
2015	157830000	530	6179
2016	159784568	580	4680
2017	161793964	530	5599
2018	163683958	610	4501
2019	165516222	670	361

3.2.13 Speed Trial

Year	Total Population	GDP Per Capital	Speed Trial
2010	148391139	440	1666
2011	150211005	520	1863
2012	152090649	520	1907
2013	154030139	470	1896
2014	155961299	470	1716
2015	157830000	530	1549
2016	159784568	580	1052
2017	161793964	530	1045
2018	163683958	610	922
2019	165516222	670	48

3.2.14 Theft

Year	Total Population	GDP Per Capital	Arms Act
2010	148391139	440	8529
2011	150211005	520	8873
2012	152090649	520	8598
2013	154030139	470	7882
2014	155961299	470	7660
2015	157830000	530	6821
2016	159784568	580	6110
2017	161793964	530	5833
2018	163683958	610	5561
2019	165516222	670	494

3.3 Complex Engineering Problem

3.3.1 Knowledge Profile

This section will concentrate on the knowledge profile process, which compiles information on a project's qualities.

3.2.15 Women and child Repression

Year	Total Population	GDP Per Capital	Women and child Repression
2010	148391139	440	17752
2011	150211005	520	21389
2012	152090649	520	20947
2013	154030139	470	19601
2014	155961299	470	21291
2015	157830000	530	21210
2016	159784568	580	18446
2017	161793964	530	17073
2018	163683958	610	16253
2019	165516222	670	1139

Profile	Description	Status
K1	Natural Sciences applicable to our project	No
K2	Required Mathematical or Computational analysis	Yes
K3	Engineering Fundamentals that need to be sustained	Yes
K4	Specialist in-depth knowledge required	Yes
K5	Engineering Design and Front-end work	Yes
K6	Engineering practices required to be upheld	Yes
K7	Comprehensive Engineering Ethics and real-life impacts and Implications	Yes
K8	Literature and website research on related projects	Yes

3.3.2 Complex Problem Solving

Table 3.1: Mapping with complex problem-solving.

Attribute	Status	Problem Description
P1 (Depth of Knowledge)	Yes	The Mathematical terms & data analysis are included(k2). Implementation of word matching and searching (k3,k4). Web-based front end, interface and database management (K5) and keeping the project safe and cost-efficient (K6). (K8) helps us find the limitation and need to improve our paper.
P2 (Range of Conflicting Requirements)	Yes	Wide-ranging or conflicting technical, engineering, and other issues are common in many fields and require careful consideration to find a solution that satisfies all stakeholders. It may involve trade-offs, compromises, and a deep understanding of the various factors to arrive at a satisfactory answer.
P3 (Depth of Analysis)	Yes	There are no websites where students can find an admission solution with just a few steps. We are trying to provide an easy solution.
P4 (Familiarity of issues)	Yes	Students need to give their information correctly. It could be biased by social pressure even after getting a proper solution from our site.
P5 (Extent of applicable codes)	Yes	Professional engineering codes and maintain standards for their projects. They continuously evolve to keep pace with changes in industry and society, resulting in engineering projects that are safe, dependable, and socially responsible.
P6 (Extent of stakeholder involvement and conflicting requirements)	Yes	Students and University authorities are stakeholders. Stakeholders may want different features or services where developers try to solve those problems and give a better solution.
P7 (Interdependence)	Yes	The project's interdependent components include the admission system, data collection, and database creation. Subsystems work independently as front-end interface development, web scraping, Laravel & React, etc.

3.3.3 Engineering Activities

Table 3.2: Complex Engineering Activities.

Attribute	Status	Complex Engineering Problems have characteristics P1 and some or all of P2 to P7:
A1 (Range of resources)	Yes	We will use web scraping for data collecting of universities, also including students' academic results and the location as a record to get the nearest University, devoted back-end developers to handle bugs and maintenance, servers, and funding to maintain the servers to store data.
A2 (Interaction Level)	Yes	If any students fill the requirements form with incorrect information, the algorithm may not suggest a suitable institution or undergraduate program.
A3 (Innovation)	Yes	This system is designed to be user-friendly and hassle-free, where users get all kinds of admission knowledge and guidance, and even users can interact with a support team if required.
P4 (Familiarity of issues)	Yes	Students need to give their information correctly. It could be biased by social pressure even after getting a proper solution from our site.
A5 (Consequences for society and the environment)	Yes	Students need help with choosing universities and programs. Also, they always need more time to decide about institution ranking and long-distance location.
A6 (Familiarity)	Yes	This computer-assisted method makes it more convenient to navigate a situation for a community to learn about a better solution in getting admission process.

Chapter 4

Conclusion

Finally, this research project tried to shed light on the complicated world of crime analysis and prediction by combining machine learning with important factors like population growth and changes in the economy. The journey has been shaped with a strong focus on Bangladesh, taking into account the special challenges and chances that come up in this setting.
The goal of the project was to help law enforcement agencies be more proactive by using advanced predictive models like Regression, Decision Tree, Random Forest, K-Means Clustering, and Naïve Bayes. Our results help us understand crime patterns and how they change over time, but it's important to note that they don't cover all crimes. For example, they don't cover money laundering, human trafficking, cybercrime, or online bullying.
We are still fully committed to helping people understand how crime works in third-world countries. The new information not only helps police, but it also raises awareness about how important it is to make decisions based on data to keep communities safe and help them grow.

4.1 Limitation

The project is mostly about crime patterns that are related to general illegal activities. It doesn't look into specific areas like money laundering or trafficking people. The analysis is not as complete because these specific crimes were not included. The project doesn't look at digital crimes like cyberbullying and other cyber offences. Because these crimes are so complicated, they need more in-depth analysis than what the project is doing now, which is mainly looking at common crime patterns.

4.2 Future Work

To make room for future research, studying digital crimes like cybercrime and online bullying is still uncharted territory that needs special care. The accuracy and reliability of crime predictions could be improved by adding more socioeconomic variables to predictive models and using a larger dataset. Additionally, working with law enforcement to use machine learning in the real world and keep testing it against changing crime patterns is a promising way to make it a practical part of crime prevention strategies.

Chapter 5

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