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Crime Rate Prediction System -An Experiment with Denver Crime Dataset Using Machine Learning Technique

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ABSTRACT

In recent years the nation Nigeria has experienced an increasing rate of criminality in the six geopolitical zones. Different crimes ranging from kidnapping, herdsmen attack, banditry, killings and so on. These activities have generated fear in the minds of the citizens thereby disrupting individuals, communities and their economic activities. This has affected both foreign and local investors in investing in the state. The overall effect on the socio-economic growth of the nation is unbearable. This paper presents a supervised machine learning technique for crime prediction using the Random Forest classifier algorithm and visualisation on the Denver crime dataset. The Denver crime dataset was used in this research due to its completeness and the lack of comprehensive dataset in the Nigerian police department. The prediction classification applied in this piece of work was based on the most frequent crime type, hotspot and crime count. The finding shows that the year 2022 experienced more crime related issues and theft crime was observed to be the highest while District 3 and 6 were seen as crime hotspots.

Keywords: Crime, Prediction, Machine Learning, Random Forest

I. INTRODUCTION

In recent years the rising rate of criminal activities in Nigeria is becoming alarming. There have been different cases of crime related issues in all the geopolitical zones which are daily reported in the news media. The most prevalent crime ranges from kidnapping, herdsmen attack, banditry, human trafficking, molestation, killings and so on. Partly, this could be attributed to the proliferation of firearms in the hands of criminals and also due to technological advancement and sophisticated methods employed by criminals. Crime is any act or omission declared to be socially detrimental to the State and is forbidden by the law and is liable for punishment by the state (Herring, 2014; Emmanuel, 2011). Özsungur defines crime as the violation of social norms that are considered harmful to the society and punishable by law (Özsungur, 2022). However, these different types of crime as spelt out by the state including burglary, robbery and child

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molestation have been in an upswing, while more heinous crimes like herdsmen attack, banditry, murder, kidnapping, sexual abuse, and gang-related offences have also been seen in a disturbingly increasing order (Ariel et al., 2016). These criminal activities carried out by men and women has generated significant concern in the entire nation. This research seeks to harness the power of machine learning for crime prediction. The essence is to provide a valuable insight in identifying patterns that will not only expedite the identification of perpetrators but also to provide a deeper understanding of crime-ridden areas. Moreover, one efficient approach for crime prevention is the identification of crime hotspots which are areas with high criminal activities. Adopting machine learning techniques in this research will allow for the analysis of crime data to understand critical information relating to various criminal incidents and their characteristics. From this, predictions can be made as to whether a crime follows an established pattern or if a new modus of operandi has emerged, which will potentially forewarn law enforcement agencies of impending criminal activities. Criminal activities does not only disrupt the lives of individuals and communities but also hinder economic growth by discouraging investment, tourism, and overall socio-economic development. As a result, the inability to accurately predict and mitigate these crimes has detrimental effects on Nigeria's economy as foreign and domestic investments are deterred and valuable resources are carted away from productive sectors to address security concerns.

II. RELATED WORKS

Historically, crime analysts relied on manual, labour-intensive processes for crime prediction (Abraham et al. 2021). This involves applying some statistical techniques for finding the mean, median, mode and standard deviation in making possible prediction of crime occurrence. The advent of computing technologies marked a paradigm shift in automating the process thereby facilitating more efficient analysis of crime data. Sherman et al. (1989) laid the foundation for technological advancements in crime analysis by introducing the concept of "hotspots," identifying concentrated areas of criminal activities (Brantingham et al. 2020). This seminal work set the stage for the integration of technology to identify spatial patterns in crime, a precursor to predictive policing.

The emergence of Geographic Information Systems (GIS) represents a watershed moment in crime analysis. GIS enables law enforcement agencies to visualize crime data, identify hotspots, and allocate resources strategically (Zhou et al. 2014; Chainey & Ratcliffe, 2013). This technological innovation enhances the analytical capabilities of crime analysts, providing a spatial context to criminal activities. The integration of databases and data mining techniques further accelerated the evolution of crime analysis. Chainey (2014) explored the application of data mining technique to crime data, enabling the identification of patterns and trends. This technological leap paved the way for predictive modeling, as algorithms could now analyze historical crime data to forecast future occurrences (Farsi et al. 2018). Machine learning algorithms have become instrumental in crime analysis, particularly in predictive policing models. Application of machine learning techniques to identify patterns in criminal behavior was implemented in (Mandalapu et al. 2023). The continuous refinement of these algorithms, coupled with the increasing availability of big data, has empowered predictive policing models to make more accurate forecasts based on historical crime patterns.

Moreover, the integration of real-time data streams has added a dynamic dimension to crime analysis. Technologies that enable the processing of live data, such as social media monitoring and sensor network contributes to more responsive and adaptive crime analysis. Real-time information enhances situational awareness allowing law enforcement agents to address emerging threats promptly (Yin et al. 2012; Yang et al. 2013). The convergence of these technological advancements has given rise to the contemporary landscape of predictive policing. Predictive models fuelled by sophisticated algorithms and comprehensive datasets can forecast where and when crimes are likely to occur (Shah et al. 2021; Oatley, 2022; Dakalbab et al. 2022). The literature on technological advancements in crime analysis highlights the pivotal role of these innovations in enhancing the proactive capabilities of law enforcement agencies allowing for targeted interventions and resource optimization.

However, this evolution is not without challenges. Ethical considerations, privacy concerns, and the potential for algorithmic biases underscore the importance of responsible and transparent implementation (Konda, 2022; Tatineni, 2019). As technology continues to advance, the literature calls for ongoing scrutiny and adaptation of ethical frameworks to ensure the responsible use of predictive policing technologies in the ever-changing landscape of crime analysis. The exploration of the concept of crime reveals a rich and nuanced understanding that extends beyond mere legal definitions. Legally, crime is encapsulated as any act or omission that breaches established laws and attracts punitive measures by the state (Moiseienko,2024; McGrath, 2015; Masake, 2019). This definition is firmly rooted in legal frameworks, and provides an in-depth insight into the classifications of criminal offences and the intricate principles governing criminal liability. Nevertheless, the definition of crime transcends its legal boundaries and extends into sociological and political spheres. Eglin & Hester, (2015) introduces a sociological perspective, asserting that crime is not only a violation of legal norms but also a breach of social norms deemed detrimental to the fabrics of society, thus warranting legal consequences. This perspective underscores the dynamic interplay between legal and societal values in shaping perceptions of deviant behaviour. On the other hand Wyner and Casini (2017) presented a political lens through which crime is viewed as a social construct strategically employed by those in power to exert control over marginalized groups. This perspective unveils the intricate socio-political dynamics influencing the definition and enforcement of criminality and emphasizing the role of power structures in shaping societal perceptions. The multifaceted nature of the term "crime" unveiled portrays it as a complex interplay in the legal, sociological, and political dimensions. The discuss between scholars and theorists on the topic of crime enriches the understanding of crime wherewith providing an holistic perspective that acknowledges its varied manifestations in society (Fassin, 2017; Hayward, 2017). This broadened conceptualization serves as a foundational framework for the subsequent exploration of related works in crime prediction models and their applications in law enforcement.

Contemporary law enforcement strategies experienced significant advancement with the introduction of crime prediction models (Brayne, 2020; Kennedy et al. 2018; Korystin and Svyrydiuk, 2021). However, this is possible with availability of crime data. Specifically, crime prediction models with respect to predictive policing, have generated reasonable attention in recent years. Waardenburg et al. (2018) applied predictive policing strategies with specific interest on hotspot areas for crime prevention. The research draws attention to the very important role of spatial and temporal analysis in establishing crime patterns thereby providing law enforcement agencies with a valuable tool for strategic allocation of resources and interventions. The concept of machine learning and crime prediction was explored in (Kadar et al., 2019). The research presented an advanced technique that integrates spatial and temporal factors enabling the refinement and enhancement of data-driven approaches to crime prediction. The integration of various components including geographical information and historical crime data enables crime prediction models to be more precise and gives an actionable insights for law enforcement agencies (Moses & Obi, 2022).

The application of crime prediction models showcase a new era of proactive law enforcement. The integration of artificial intelligence and machine learning techniques has propelled the design and development of more refined crime prediction models that capable of identifying complex patterns and trends in crime data (Apene et al. 2024; Mandalapu, 2023). These models are more sophisticated and goes beyond the traditional reactive techniques enabling law enforcement agencies to forecast and intercept criminal activities before their occurrence (Singh et al. 2024). Moreover, crime prediction models are not limited to a specific geographical location but its application is universal. As being evidenced in various research studies. The basic principles in these models can be applied in diverse settings and data thereby providing a universal framework for crime prevention. Crime prediction models are generally valuable tool for law enforcement agencies in terms of their scalability and adaptability. They foster collaborative techniques for managing and mitigating criminal activities. However, application of crime prediction models is also associated with certain challenges and ethical considerations. Ethical implications of predictive policing was examined in (Jorgensen, 2022). The research findings highlighted potential biases and discriminatory outcomes linked with these models. The responsible deployment of crime prediction models require spontaneous evaluation of its fairness, accountability and transparency to law enforcement practices. Research in this area of studies reveal a landscape distinguished with continuous innovation with careful examination for ethics. Application and commitment to these models showcase an advancement in law enforcement practices thereby utilizing technology to strengthen public safety as well as advance resource allocation. It stand as a ground breaking force to prevent unnecessary occurrence of criminal activities.

III.METHODS AND MATERIAL

The methodology provides a systematic and transparent approach to data collection, analysis, and interpretation, ensuring the reliability and validity of the research findings. This section provides a concise yet comprehensive introduction to the overall approach of the research.

Dataset

The dataset used for this research was collected from Denver Police Department, of the United States. This dataset was used in this research due to lack of comprehensive crime data in the various states of Nigeria. The dataset provides a rich repository of information encompassing various crime categories, timestamps, and geographical coordinates. Its selection was driven by the need for a diverse and well-documented dataset that could support the study objectives in crime prediction and machine learning. The dataset can be accessed in the Kaggle site: https://www.kaggle.com/datasets/paultimothymooney/denver-crime data/download?datasetVersionNumber=465.

The dataset was retrieved from 2018 to 2023. They contain a substantial amount of records of 386,865 distinct instances of reported offences. The retrieved data is presented in a tabular form in rows and columns where we have 6540 rows and 22 columns (see the Denver dataset in Figure 3.1). The dataset is diverse and heterogeneous in nature.

1	incident_	offense_i	offense_c	offense_c	offense_t	offense_c	first_occurrence_date	last_occurrence_date	reported_date	incident_	geo_x	geo_y	geo_lon	geo_lat	district_id	precinct_i	neighbort	is_crime	is_traffic	victim_count
2	2.02E+08	2.02E+14	2999	0	criminal-r	public-dis	2/10/2022 02:50		2/10/2022 03:16	1107 N SA	3140929	1692612	-104.999	39.73396	1	123	lincoln-pa	1	0	1
3	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	7/7/2021 21:02		7/8/2021 00:55	815 16TH S	3142470	1697098	-104.993	39.74625	6	611	cbd	1	0	1
4	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	10/29/2020 01:30		10/29/2020 04:31	4745 N FEI	3133352	1710396	-105.026	39.78289	1	111	berkeley	1	0	1
5	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	9/6/2018 17:00	9/6/2018 23:00	9/7/2018 09:58	65 S FEDEF	3133534	1685797	-105.025	39.71536	4	411	barnum	1	0	1
6	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	5/8/2020 05:00	5/8/2020 18:30	5/13/2020 10:00	12295 E AL	3184065	1710782	-104.845	39.78308	5	521	montbellc	1	0	1
7	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	10/8/2020 02:26		10/8/2020 03:43	2100 W 30	3137149	1701888	-105.012	39.75948	1	113	highland	1	0	1
8	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	4/18/2020 06:30		4/18/2020 06:30	1272 N PE	3146039	1693575	-104.981	39.73652	6	623	capitol-hi	1	0	1
9	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	6/28/2022 17:56		6/28/2022 17:56	2980 E 35T	3153838	1704189	-104.953	39.76553	2	212	clayton	1	0	1
10	2.02E+10	2.02E+16	2999	0	criminal-r	public-dis	6/6/2020 01:00	6/6/2020 05:00	6/6/2020 13:29	900 N MAI	3155851	1691502	-104.946	39.73067	2	213	congress-j	1	0	1
11	2.02E+10	2.02E+16	2999	0	criminal-r	public-dis	7/14/2022 02:01	7/14/2022 02:04	7/14/2022 02:49	2540 N DC	3148172	1699978	-104.973	39.75407	2	211	whittier	1	0	1
12	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	9/2/2022 21:30	9/3/2022 06:55	9/3/2022 11:07	10 N SHER	3125808	1686311	-105.053	39.71688	4	411	barnum-w	1	0	1
13	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	8/11/2019 22:30		8/12/2019 00:28	200 16TH S	3143897	1695450	-104.988	39.7417	6	611	cbd	1	0	1
14	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	7/21/2021 16:41		7/21/2021 16:41	5TH ST / W	3138188	1694755	-105.009	39.73988	1	123	lincoln-pa	1	0	1
15	2.02E+08	2.02E+14	2999	0	criminal-r	public-dis	1/22/2022 18:30	1/22/2022 19:00	1/22/2022 20:40	21444 E 46	3214093	1709787	-104.738	39.77971	5	523	gateway-g	1	0	1
16	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	3/30/2022 21:25		3/31/2022 00:27	8101 E NO	3170283	1711719	-104.894	39.78592	5	511	central-pa	1	0	1
17	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	9/17/2019 17:00		9/17/2019 17:52	18635 E 43	3204908	1708296	-104.771	39.77582	5	523	gateway-g	1	0	1
18	2.02E+10	2.02E+16	2999	0	criminal-r	public-dis	5/8/2020 11:00	5/9/2020 11:05	5/9/2020 12:40	1460 S BR(	3144336	1676621	-104.987	39.69001	3	313	platt-park	1	0	1
19	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	4/22/2020 13:00	4/22/2020 13:30	4/22/2020 15:15	1550 N OG	3147801	1695259	-104.974	39.74112	6	621	north-cap	1	0	1
20	2.02E+08	2.02E+14	2999	0	criminal-r	public-dis	2/12/2022 22:45	2/13/2022 08:00	2/13/2022 09:16	1014 S FEI	3133754	1679544	-105.025	39.69819	4	412	athmar-pa	1	0	1
21	2.02E+10	2.02E+16	2999	0	criminal-r	public-dis	7/13/2021 06:30	7/13/2021 08:00	7/13/2021 08:53	1649 N DC	3147971	1695800	-104.974	39.7426	6	621	north-cap	1	0	1
22	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	8/16/2020 17:15		8/16/2020 18:23	621 17TH S	3143478	1697084	-104.99	39.74619	6	611	cbd	1	0	1
23	2.02E+10	2.02E+16	2999	0	criminal-r	public-dis	8/1/2020 13:30	8/1/2020 14:00	8/5/2020 11:56	1346 N OS	3139376	1694039	-105.004	39.7379	1	123	lincoln-pa	1	0	1
24	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	6/6/2021 23:45		6/7/2021 01:12	1800 LARII	3142075	1698868	-104.995	39.75111	6	612	union-sta	1	0	1
25	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	7/8/2021 00:00	7/8/2021 00:54	7/8/2021 01:57	2449 W DU	3135673	1701938	-105.017	39.75964	1	113	highland	1	0	1
26	2.02E+10	2.02E+16	2999	0	criminal-r	public-dis	7/23/2021 03:45	7/23/2021 04:30	7/23/2021 15:00	461 S MAG	3165635	1683296	-104.911	39.70798	3	322	washingtc	1	0	1
27	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	6/10/2022 14:57	6/10/2022 23:45	6/11/2022 00:50	3203 N QU	3167444	1703321	-104.904	39.76292	2	221	northeast	1	0	1
28	2.02E+09	2.02E+15	2999	0	criminal-r	public-dis	6/27/2021 21:05		6/27/2021 23:26	7507 E 36T	3168518	1705033	-104.901	39.7676	5	512	central-pa	1	0	1

Figure 3.1: A sample of Denver Police Crime Dataset

The multifaceted nature of this dataset allows for a nuanced exploration of various aspects related to criminal activities. The columns collectively provide a comprehensive set of attributes that can be used for detailed analysis and prediction in the context of crime data. Each column contributes to a unique insight into the nature and characteristics of reported offences. This repository of information forms the foundation for the analytical phases of the research, facilitating a thorough examination of crime patterns, trends, and predictive modelling. The data range and distribution were analysed to ensure that it fell within expected parameters. This helped to identify any outliers or anomalies that might indicate potential errors or biases in the dataset.

Random Forest Classifier Algorithm

Random forest classifier is a supervised learning algorithm that combines the results of multiple decision tree classifiers to generate a single output. It is a simple, flexible, diverse and an easy to use machine learning algorithm for both classification and regression analysis. Random forest classifier is a meta estimator that improves prediction accuracy by averaging the sub-outputs of the decision tree classifiers thereby controlling overfitting. The basic features that defines this algorithm is its ability to construct varying simple decision trees during the training phase and extracting the majority votes at the classification stage. The beauty of it is the voting process which has the effect of reducing the undesirable property of overfitting training data in the decision trees. It has the ability to display some level of unpredictability with respect to the final training model structure. In this study the classifier randomly select a combination of features from every node to grow a tree. Then the bagging method randomly generate the training dataset by extracting with replacement of N ensample with N as the size of the original training dataset. By retrieving the most common vote class from the classifiers in the forest. The Gini index is used for attribute selection which measure the impurity of attributes based on classes. The Gini index can be expressed as: $\sum\sum_{j\neq i}(f(C_i,T)/|T|)(f(C_j,T)/|T|)$ Where $f(C_i,T)/|T|$ is the probability that the selected case is a member of the C_i class. Therefore, applying a combination of features the decision tree grows to its maximum depth without pruning based on new training data. Mingers, (1989) and Pal and Mather, (2003) highlights that the performance of a tree based classifiers is not affected by the choice of pruning methods adopted and also not the attribute selection measures.

IV. RESULTS AND DISCUSSION

In this research the Random Forest classifier algorithm was implemented for crime prediction. The model exhibited a notable accuracy of 76.7%, indicating that it accurately predicted crime outcomes in approximately 7 out of 10 cases. The Random Forest algorithm, with default parameters such as the number of trees (`n_estimators`), maximum depth of the trees (`max_depth`), and others were employed to handle complex relationships within the data to mitigate the overfitting problem. The default parameters for Random Forest include`n_estimators=100`, `max_depth=None`,`min_samples_split=2`, `min_samples_leaf=1`,`max_features='auto'`, `bootstrap=True`, and `random_state=None`. See table 4.1 for the model performance.

Table 4.1 Model performance

	Precision	recall	f1-score	support
0	0.6	0.51	0.55	25891
1	0.71	0.85	0.77	41023
2	0.46	0.19	0.27	7220
accuracy			0.67	74134
macro avg	0.59	0.52	0.53	74134
weighted avg	0.65	0.67	0.65	74134

The precision, recall, and F1-score values for each class provide a more clear understanding of the model's performance, especially considering the imbalanced nature of the dataset. For instance, the model demonstrates higher precision and recall for Class 1, indicating better predictive accuracy for this category. Class 2, however, exhibits lower precision and recall values suggesting challenges in accurately predicting instances of this class. This analysis, coupled with the classification report, provides a comprehensive overview of the Random Forest model's strengths and areas for potential improvement in predicting crime outcomes.

Examining the correct and incorrect cases involve further analysis of the model predictions and understanding the factors that influenced its decision making process. Upon examination it was clear that certain patterns contribute to the correctness or incorrectness of the classifications. The model performs well in predicting instances of Class 1, which corresponds to a precision of 0.71 and recall of 0.85. This indicates that the model is effective at identifying and correctly classifying this particular type of crime. The features that contribute to these correct predictions may include location-related variables, time of day, and historical crime data. In Class 0 the precision and recall of 0.60 and 0.51 respectively correct. This shows that the data might have exhibited clear patterns or characteristics that distinguish it from other classes. These patterns could be specific geographical locations, certain time of the day, or unique combinations of feature values. For Class 2, the model struggled as reflected in its precision and recall values of 0.56 and 0.29. This suggest the challenges in accurately identifying this type of crime. The features contributing to these incorrect predictions may be less pronounced or more subtle, making it difficult for the model to generalize effectively. An analysis of false positives and false negatives reveals specific scenarios where the model falters. For example, false positives in Class 2 predictions may occur when certain features align with those of Class 0 or Class 1. Understanding the misclassification can guide feature engineering or model adjustments.

In visualizing the distribution of crimes each year from 2018 to 2023 provides a valuable insight to understanding the evolution of crime patterns over the years (see figure 4.1 crime pattern chart). The frequency of occurrence of crime as exhibited shows a consistent upward trend.

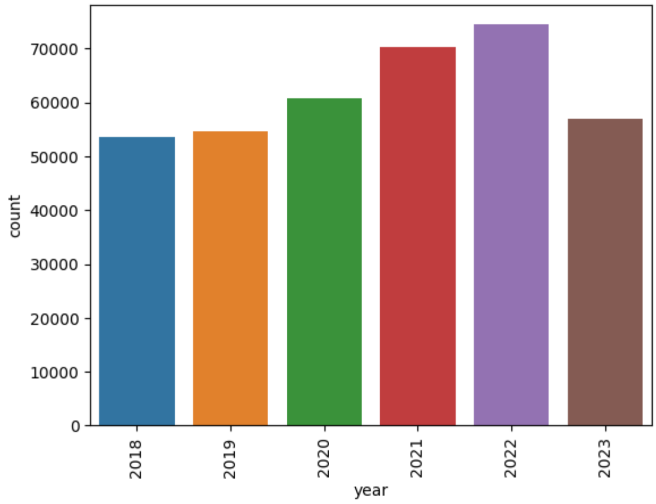

Figure 4.1: Chart Showing Crime Patterns

Offence categories were visualized in Fig 4.2 which illustrates that offences related to theft are significantly predominant in the dataset occupying a considerable portion of the overall crime landscape.

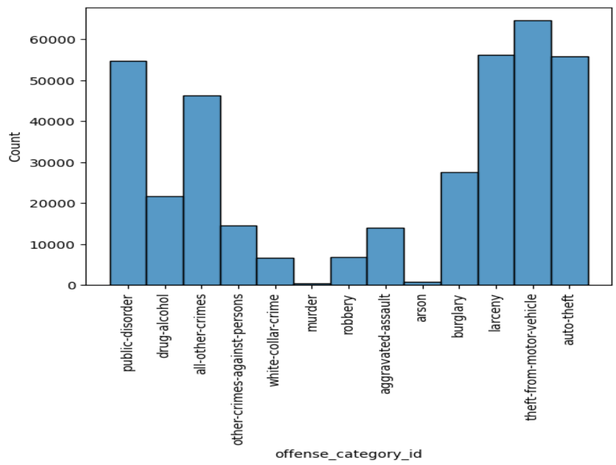

Figure 4.2: Chart Showing Visualization of Offence

Also in visualizing crime count in Figure 4,3, we observed that District **6** and **3** are the highest contributors to crime counts, which indicates that these areas are potential crime hotspots while District **7** stands out with notably low crime counts.

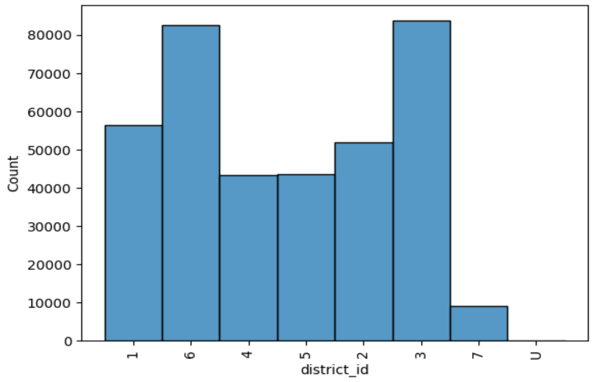

Figure 4.3: Chart Showing Crime Counts

V. CONCLUSION

The research applied the supervised machine learning technique (Random Forest Classifier Algorithm) to identify patterns in Denver crime dataset to predict crime based on most prevalent crime type, crime hotspots and crime count. In this work the Random Forest Classifier combines the classification of multiple decision tree results into a single output thereby taking average of the sub-outputs of the different classifiers. Three classification were considered, in which the first classification had a precision score of 0.60 and a recall of 0.51 with F1-score of 0.55 performance. While the second class had a better precision of 0.71 and a recall of 0.85 with F1-score of 0.77. The obtained result was visualised in terms of crime distribution, offence category, and crime count. In visualising crime distribution, it was observed that the year 2022 experience more criminal activities. Theft as a crime came highest in offence categorization while in crime count Districts 6 and 3 were identified as potential crime hotspot whereas District 3 had low crime count. However, the research do not address other important issues like spatio-temporal and time. In future we will address these issues and apply other machine learning algorithms like K-nearest neighbour, naive bayes, recurrent neural network (RNN) and convolutional neural network for further experimentation.

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