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Research Article

Using Information Technology for Comprehensive Analysis and Prediction in Forensic Evidence

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ABSTRACT

With the escalation of cybercriminal activities, the demand for forensic investigations into these crimes has grown significantly. However, the concept of systematic pre-preparation for potential forensic examinations during the software design phase, known as forensic readiness, has only recently gained attention. Against the backdrop of surging urban crime rates, this study aims to conduct a rigorous and precise analysis and forecast of crime rates in Los Angeles, employing advanced Artificial Intelligence (AI) technologies. This research amalgamates diverse datasets encompassing crime history, various socio-economic indicators, and geographical locations to attain a comprehensive understanding of how crimes manifest within the city. Leveraging sophisticated AI algorithms, the study focuses on scrutinizing subtle periodic patterns and uncovering relationships among the collected datasets. Through this comprehensive analysis, the research endeavors to pinpoint crime hotspots, detect fluctuations in frequency, and identify underlying causes of criminal activities. Furthermore, the research evaluates the efficacy of the AI model in generating productive insights and providing the most accurate predictions of future criminal trends. These predictive insights are poised to revolutionize the strategies of law enforcement agencies, enabling them to adopt proactive and targeted approaches. Emphasizing ethical considerations, this research ensures the continued feasibility of AI use while safeguarding individuals' constitutional rights, including privacy. The anticipated outcomes of this research are anticipated to furnish actionable intelligence for law enforcement, policymakers, and urban planners, aiding in the identification of effective crime prevention strategies. By harnessing the potential of AI, this research contributes to the promotion of proactive strategies and data-driven models in crime analysis and prediction, offering a promising avenue for enhancing public security in Los Angeles and other metropolitan areas.

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1. INTRODUCTION

In the recent past, criminology has demonstrated phenomenal developments in increasing our knowledge concerning criminal conduct throughout humans' lifespans. Criminal behavior is defined as an order issued by the perpetrator that leads to causing harm that requires the legislator to intervene to punish it, or it is the external physical activity that constitutes the crime, or it is every movement issued by the offender to achieve the commission of his crime, and this movement is subject to change according to the crime committed by the offender. There is no crime without criminal behavior, because the law does not punish mere intentions and desires.(1)

This process has been enhanced by the adoption of the life-course criminology framework that provides a rich insight into the complex interplay between individual characteristics, social factors and environmental cues influencing criminal behavior [1]–[3]. This theoretical framework has been successfully applied by researchers to various types of crime, and their research demonstrates that a small share of hardcore offenders is responsible for most crimes [3]–[11].

In Los Angeles, often portrayed as a city of fame and cultural diversity along with sizeable economic success characterized by the glittering film industry stands an eternal plague that dominates the dramatic landscape – crime [12]. It is in this City of stardom – a place where sunlit roads and historical charming figures rub shoulders with the daily affairs of various forms of criminal habits, from minor thefts to property crimes including organized violence and cybercrimes [13]. For a well-rounded and integrated strategy in the management of crime, given that the city is constantly changing its face, criminal activities too are bound to mutate demanding creative measures which should be dynamic for better recognition as well as counteracting and preventing it.

Crime in Los Angeles does not have a common architecture – it can be perceived as ever-changing mosaics that are shaped by inequality, geography and the interplay of streets [14]. The evolving character of crime [15] creates a great challenge for traditional methods of criminal analysis, based on manual data processing and elementary statistical models that never cease to miss the realities of modern urban life.

In the field of criminal law It is "a set of substantive and formal rules that determine crimes and penalties, how to initiate a criminal case in its stages, issue a ruling, appeal it, up to a retrial, and pardon the rulings "([2]), predictability has been viewed in a positive light [16]–[19]. Indeed, uncertainty([3]) is frequently regarded as an enemy of the rule of law [20], [21]. This threat may also emerge if cases with the same or similar enough material circumstances are treated differently [18], [22]–[24] and if prosecutors and judges could create new crimes in order to punish behavior they do not condone. However, as new applications of AI for use in the legal field are being developed at a steady pace [25]–[27] another type of predictability has arisen and this form is not viewed exclusively positively [28]–[34].

The crime scene has long ceased to be a combination of time, place and evidence where people were. It now consists of digitalization with information systems all over the world permeating everything. One fact is that the legislation concerning modification of data without authorization [35] in addition to more and more evidence such as domination by smart homes, infrastructure facilities manufacturing based on cities case investigations or forensic proofs are not connected with one locality anymore [36].

[1]) See. Dr. Dhari Khalil Mahmoud, Al-Wajeez fi Sharh Penal Code, General Section, Al-Qadisiyah Printing House, Baghdad, without mentioning the year of publication, p. 66. Dr. Maher Abd Shawish, General Provisions in the Penal Code, University Press, Mosul, 1990, p. 188. Article (28) of the Iraqi Penal Code (111) of 1969, as amended.

[2]) Dr. Hilali Abdullah Ahmed, The General Theory of Criminal Proof, a comparative study between the Latin and Anglo-Saxon procedural systems and Islamic law, Volume Two, Dar Al-Nahda Al-Arabiya, 1987, p. 623

[3]) Legal certainty is considered one of the pillars of the principle of criminal legitimacy, because of the protection it provides for individual rights and freedoms, as those addressed must be aware, aware, and aware when applying it to them. Legal certainty, in return, requires judicial certainty, as legal certainty has no value unless it is supplemented by judicial certainty when applying these texts. On the accused, legal security addresses both the legislator and the judge equally. Accordingly, judicial certainty is a mental or rational state that confirms the existence of the truth, and this is achieved through what the judge deduces through the various means of perception through what is presented to him of the facts of the case based on criminal evidence and investigations, and the perceptions and possibilities that are imprinted in his mind of a high degree. High confidence in the assertion, ruling out the possibility of any doubt or skepticism regarding that final outcome that the judge reached in his ruling.

Dr. Iman Muhammad Ali Al-Jabri, The Certainty of the Criminal Judge, a comparative study in the laws of Egypt, the Emirates, and Arab and foreign countries, Mansha'at Al-Ma'arif, Egypt, Alexandria, 2005, p. 141. Judge Dr. Samir Alia, Guidelines in Criminal Cases, research published in Sawt Al-Jami'ah Magazine, second issue, 2011, pp. 35-36.

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In this restricted setting, the advent of AI provides a revolutionary paradigm for multidimensional crime analysis [37]. This intricate and broad net of criminal activity calls for a creative solution that is far beyond the scope of what traditional approaches can possibly offer. With its ability to handle large numbers of data, understand complex patterns and foresee futuristic trends AI is a lighthouse in public safety. The combination of advanced technologies and the long-lasting fight against crime provides a special overview, not only revealing current events but also predicting emergent risks before they present themselves [38].

However, while criminal jurisdictions are giving in to the new trend of using AI-based methods globally as many worldwide trends dictate a more extensive usage, France has turned on bans for judicial analytics and implemented prompted criminal responsibility [39]. In particular, the new law appearing in Article 63 of the Justice Reform Act does not allow announcing the plots that lie under judges' behaviours patterns [40]. Apparently, the origin of the ban can be traced back partly to comparisons that used any type of machine learning (ML) in reference to behavior at individual judge level for asylum cases finding massive differences between people involved [41]. In the US as well, problems of ownership and copyright over Court decision data have led to legal wrangles [34], [42], [43].

Los Angeles, a city that is often viewed as the home of dreams full of aspirations finds itself in the tight grip of this criminal system nexus with global poverty inequality and urban development [44]. Moreover, cases of violent offenses [45], white-collar criminal conduct [46] and property crimes including burglaries or car theft fall into the same paradigm [47]. It is, therefore, evident to suggest that the crime profiles defined by all neighborhoods and communities are unique as such demand unprecedented solution design extending far-beyond conventional approaches fit for a size (one).

It is therefore crucial to examine the spatiotemporal dimension of crime in Los Angeles. Every neighborhood has its own combination of problems and character, from the busy streets downtown to those hidden in the hillside. Moreover, the biotemporal aspect that is dependent on a range of factors including day time and seasonality as well as significant events increases the diversity of crime scenes [48]. A retrospective and reactive crime It represents "a deviation in human behavior, that is, it is illegal behavior because it represents an assault on a right or interest protected by Sharia law or the system issued based on it"([4]) analysis may not be able to untangle such intricacy of this gossamer pattern.

The invention of AI [49], is a technological wonder that can analyze large volumes of data, pinpoint minute details and create patterns based on the knowledge they have. From the angle of crime analysis, AI exceeds human limitations by providing a futuristic perspective. In essence, AI utilizes ML algorithms [50], which allow systems to learn from past data and recognize trends that become the basis for forecasts with unparalleled accuracy.

Investigating cybercrime authors [51] state that recent forensic studies have produced significant findings as to how to conduct criminal investigations related to computer information. Scientific meaningful information about the predictability of some features in these criminal acts has been provided by such studies. Based on this information, researchers should generate both general and specific models of the opposed processes. It is proposed here that this issue will be addressed through forensic computer modeling in the ever-advancing scenery of science and technology.

In addition, the lines within cybersecurity are becoming more indistinct among law enforcement and national security in public versus private security as there are several reasons why a closer relationship between cybercrime and cybersecurity is required [52]. Although providing specific recommendations for dealing with such challenges is quite problematic, the authors actively reflect on these trends and expect to stimulate further interdisciplinary research activity as well as policy innovation in this sphere. Additionally, as cybercrime is getting more persistent with each day there's also a growing need for the forensic investigations of such crimes. On the other hand, forensic readiness from a systematic preparatory point of view on how possible future research would occur in software development has only seen recently. So, there are lots of challenges and open questions [53]; For these reasons we were begins to work in this paper.

Starting from the base of AI's capacity to classify various crime types and understand them, a truly exhaustive analysis is laid out [54]. AI is enabled by crime codes, descriptions and modus operandi to examine the nuanced morphology of the crimes. Further, predictive modelling makes it possible for AI to identify future crime trends allowing law enforcers to adopt preventative measures aimed at thwarting threats.

Lastly, Transparency is also a valid concern [55]–[60] for AI concerning this problem area that should be considered in the future with regards to opacity as well. Furthermore, The transfer of data from the models trained with one dataset to another is also a very interesting area that deserves further work in relation to ML [61], [62].

[4]) Fadhel Nasrallahawad, LaPeinde Mort revue de, justristeLannec 12, No.4, 1988, P.19. Dr. Muhammad Ali Sweilem, The Theory of Defending Criminal Responsibility, a fundamental analytical and applied comparative study, al-Ma'arif, Alexandria, Egypt, 2007, p. 100.

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2. DATASET

The dataset of our work deals with the documentation of crimes reported from Los Angeles for the years 2020 until the end of 2023, and its size is 852950 records. The database includes a variety of important parameters that make for the complex crime dynamics in this city. Key Parameters: Division Number, dates, area information crime details victim status weapon and codes collected from [63].
This dataset is an important tool for researchers and policy practitioners who can explore the crime patterns, trends and correlations that are taking place in Los Angeles. The fact that detailed parameters are incorporated makes in-depth investigations possible, Such as the time criterion: which is meant here the time during which the perpetrator waited until the victim arrived to carry out his crime, and the spatial criterion, which shows the perpetrator sitting or stationing in a specific place waiting for the victim ([5]) which supports the formulation of appropriate crime prevention and intervention tactics. It is recommended that analysts rely on the dataset documentation for a fuller understanding of the variables and methods used. When working with crime datasets for analysis, ethical treatment of sensitive data matters.

3. DATA EXPLORATION

This step examines the data from the chosen information source. To deal with this stage, we will complete the following tasks: Crime victims' age data given in Fig 1 shows that most reside between the ages of 20 and 40 years.

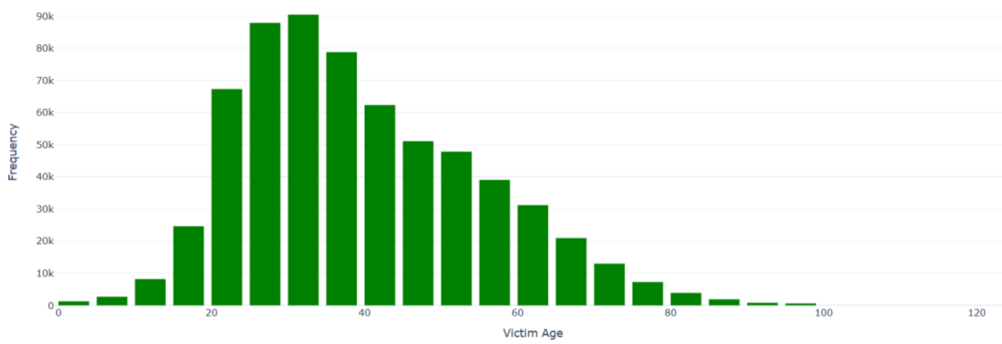

Fig. 1. Distribution of Victim Age

Figure 2 shows the number of victims in different years and hence depicts trends of victimization over four years.
In 2023, an evident hike in victims was noticeable compared to all the previous years – a notable increase of up to 234,436. In 2023, there were a total of 209581 victims, which was a substantial decrease from the previous year. This reduction, however, can be a sign of effective crime prevention strategies and better law enforcement activity or socioeconomic conditions improvements that contribute to safety. In 2021, the number of victims remained relatively constant at 209451. This uniformity implies that the determinants of victimization were fairly stable through this time span. In 2020, the number of victims increased moderately to 199,482. This may be attributed to a number of factors such as changes in population, economics or crimes ([6]). The monthly distribution of victims was as follows: The most common month in terms of the number of victims is October with 75,464 people killed. During the summer there are moderate hourly rates of victimization in July (75,429), August (75.072) and June (72891). In December, the number

[5]) Crime is a phenomenon that long preceded criminal law, as it was committed individually or collectively before there was a written text or fixed legislation. It is a phenomenon inherent to human society in terms of time and place. Fadhel Nasrallah awad, La Pein de Mort revue de, justriste Lannec 12, No.4, 1988, P.19.
[6]) Supporters of natural law believe that justice in criminal law requires adopting the closest solutions to one issue. When judging a specific case, all personal circumstances (economic, environment, population, nature of the crime, etc.) that led to the existence of this case must be taken into account. Justice, in this sense, is equality in ruling on relations between individuals whenever their circumstances are the same, while always taking into account the human aspect, as well as the personal circumstances that surround the individual in every criminal case. See: Dr. Fahd Al-Kasasbeh, "Means and Controls of the Criminal Judge's Discretionary Power in Punitive Individualization," Journal of Sharia and Law Sciences, 60, Volume 42, First Issue 2015, pp. 346-347 and beyond. See: Dr. Abdul Majeed Ibrahim Selim: The discretionary authority of the legislator (a comparative study), New University House, Alexandria, 2010, p. 363.

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of victims decreases significantly and amounts to 55341. The figures suggest that the number of victims gradually declined from February (68, 679) to November (69, 960).

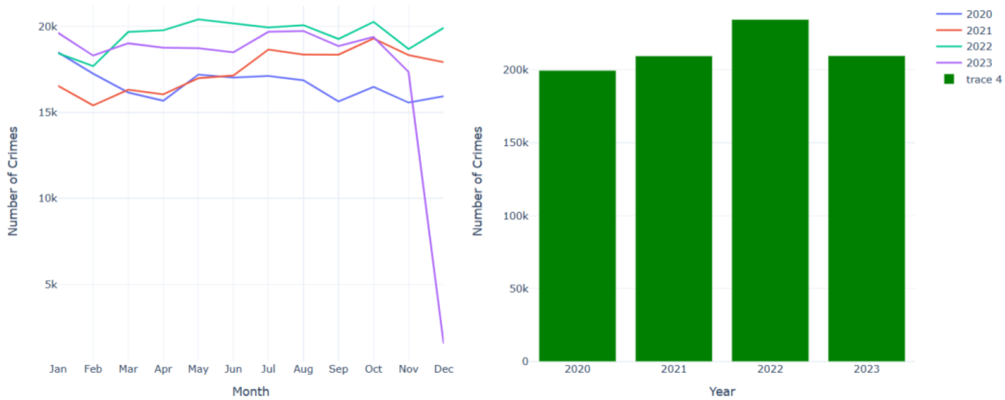

Fig. 2. Monthly Crime Frequency and Yearly Crime Distribution

The hourly distribution of victims is represented in Figure 2. The time of committing the behavior is one of the descriptions that attach to the behavior and distinguish it from any other behavior, as the legislator sometimes stipulates that the behavior constituting the crime must be committed within a specific time ([7]). Here's a concise analysis of the results: Victimization spikes during evening hours especially it was from 17:00 to 21:00 (5 PM-9 PM). The highest number of victims is reported at 17:0 minutes (49,576) and falls throughout the night. But the highest date for victimization peaks is at midnight. The number of victims decreases during the late-night and early morning hours, reaching its lowest point at 5:00 (5 AM). The data shows a gradual increase in victimization from 13:00 (1 AM) o'clock to 10:00 (10 AM). Although the figures are less when compared to the nighttime, this upsurge may be attributed to the start of busy hours including commuting and more people in public settings. There is a dip in victimization during the midday hours, particularly from 11:00 – 14:00 From 11-2 This might be linked to higher exposure, busy daytime pursuits and perhaps police presence during the day.

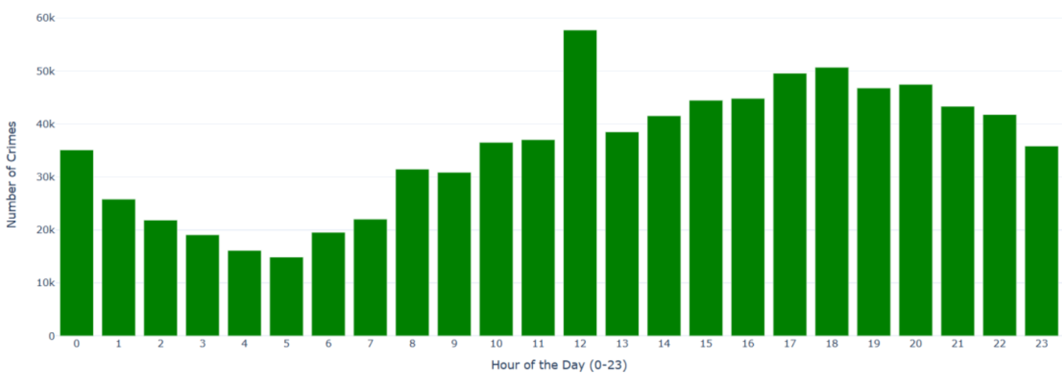

Fig. 3. Crime Distribution by Hours of the Day

[7]) Time is an element related to the outside world and is measured according to the seasons of the year, days, or hours of the day. We find, for example, that French law criminalizes hunting during certain seasons of the year. See. Adel Azer, The General Theory of Crime Circumstances, International Press, Cairo, 1976, pp. 10-11.
There are crimes in which time is considered an element in the legislative model that indicates the seriousness of the criminal. Time is included as an element in the legislative model on several occasions. Time may be an element in the crime that cannot be carried out without it, or time is considered an aggravating circumstance, as in theft crimes, if the crimes are committed between sunset. The sun and its rising indicate the danger of the offender. See Ibrahim Eid Nayel, Penal Code, General Section, General Theory of Crime, Dar Al Nahda Al Arabiya, Cairo, 2022, p. 109.

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Figure 4 specifies the victim breakdown by gender. The figures show a greater proportion of male victims reported at 351,362 cases. The number of reported female victims is also substantial – 313,468.

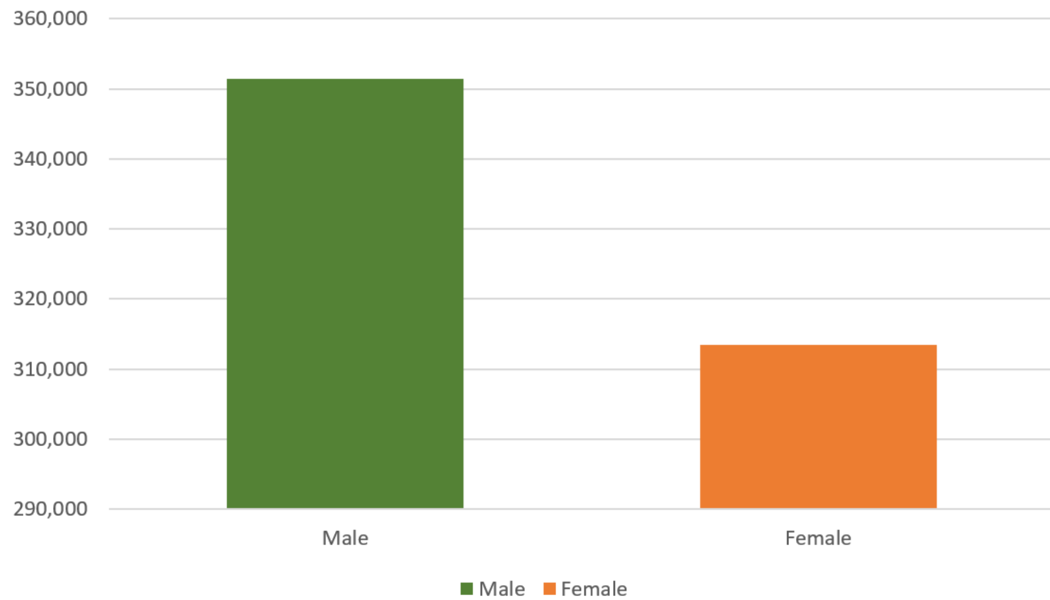

Fig. 4. Victim's Sex Distribution

The number of recorded incidents for specific crimes is shown in Figure 5 The conclusions are summarized as follows: VEHICLE - STOLEN:91,473 incidents, ATTERY - SIMPLE ASSAULT, HEFT OF IDENTITY:53,467 incidents, BURGLARY FROM VEHICLE:52,611 incidents, BURGLARY:1,961 incidents, VANDALISM - FELONY ($400 & OVER, ALL CHURCH VANDALISMS):51,826 incidents, ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT:48,876 incidents, HEFT PLAIN - PETTY ($950 & UNDER):43,402 incidents, INTIMATE PARTNER - SIMPLE ASSAULT:42,729 incidents, and THEFT FROM MOTOR VEHICLE - PETTY ($950 & UNDER): 32,875 incidents.

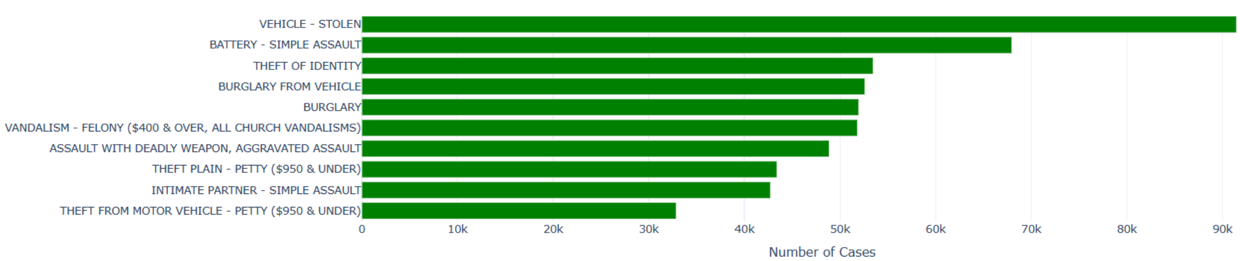

Fig. 5. Top 10 Crime Descriptions

The different weapons used in crimes are illustrated in Figure 6 below ([8]). Here's an analysis of the results: The large number of incidents reported as "Unknown" weapons (556,202) implies that it is difficult to identify or report

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[8]) The principle in criminal investigation does not take into account the method of committing the crime. However, if a certain method stipulated by the legislator in the legislative model for the crime is required to achieve the criminal behavior, then the behavior must be consistent with what the legislator requires in the criminal act. The investigator is also interested in the method of committing the crime in other cases, so committing the behavior in a certain way has an aggravating effect on the crime. He notes that there is a difference between the means by which the criminal behavior is committed, which is the tool or machine used to commit it, and the method by which the behavior is carried out, which is a characteristic attached to itself. Behavior: In many cases, the legislator is interested in committing

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information on the specific weapon types used. This absence of information could hamper detailed analyses and effective crime prevention strategies. The “strong-arm” cases are quite common and involve acts such as the use of hands, fists feet or bodily force with about 159021 reported incidences. The category of “Unknown Weapon / Other Weapon” includes 31,728 cases and shows poor specificity in reporting. A substantial amount of incidents include verbal threats (21,767), without weapons used. The total number of incidents involving handguns (18,350), semi-automatic pistols (6.672) and unknown guns (6,049)- all showing that firearm-related crimes are still a challenge in any given country Crimes related to bladed weapons (11,623), such as knives measuring less than 6 inches and other types of knives constitute a large share of reported cases.

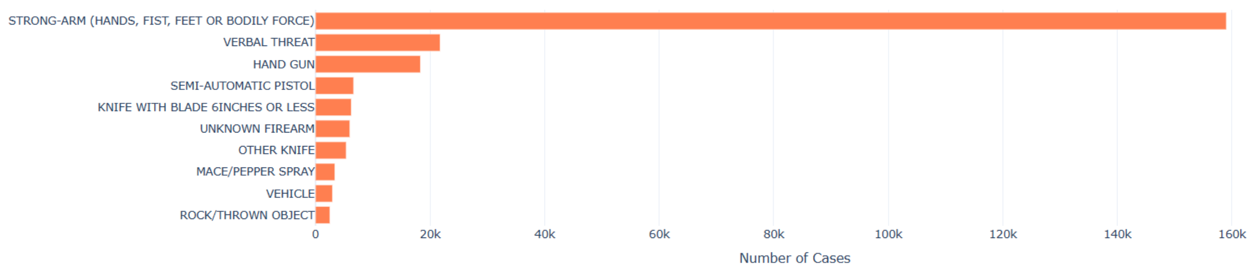

Fig. 6. The 10 Tops Weapons Used in Crimes

The statistics also reveal the case results as resolved or unresolved. In particular, there were 683107 Not Solved Cases and 169843 incidents which have been solved. Such details give a glimpse of how reported cases are disposed of, revealing the effectiveness of investigation efforts or obstacles in resolving these incidences. In order to fully understand the factors affecting resolution rates and possible ramifications for law enforcement policies, additional analysis with supporting information is indispensable. In the wake of this, Figure 7-a shows Percent Cases by Victim Sex and Resolution Status; Figure 7-b showcases Percent Cases by Area Name and Resolution Status while Figure 7-c displays percentage cases based on Crime Description and resolution status. These visual representations work to improve the clarity and interpretability of data, allowing for a more nuanced investigation into factors driving resolution.

Fig. 7. Cases of Victims with Details

some crimes in a specific way, especially those that affect honor, prestige, morals, or public order, enhancing the criminal’s danger by the type of weapon or crime tool. See: Abdel Fattah Mustafa Al-Saifi, Conformity in the Field of Criminalization, University Press House, Alexandria, Egypt, 2017, p. 69. See: Ibrahim, Muhammad Jibril, Night and Criminal Law, Journal of Human and Natural Sciences, Issue (5), Volume (3), 2022, p. 35.

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4. MODEL DEVELOPMENT

In the modern day, ML has become a unique field in research among different fields, especially in crime and law enforcement. Located in one of the largest and most diverse city by way of Los Angeles, It has a number of criminal problems to sort out. As a result, ML algorithms are used not only to forecast future crimes but also to improve preventive actions. This paper demonstrates how to apply four major ML algorithms, such as Stochastic Gradient Descent (SGD), K-Nearest Neighbors (KNN), Naive Bayes (NB), and Logistic Regression (LR) are used for crime forecasting in Los Angeles.

4.1. DATASET COLLECTION

The quality of input data for training any ML model defines its triumph. There is a need for relevant data which may include the history of crime statistics, socioeconomic factors and geographical characteristics that can be used in predicting criminal activities within Los Angeles. Selecting these parameters and changing them to get important input features for fitting the ML model is called feature engineering.

4.2. PREPROCESSING

When preprocessing, eliminating redundancy in crime data sets is vital to being able to analyse it with accuracy for informed selection [16]. To begin with, the data cleaning process starts by defining criteria for duplication that is accurate and includes attributes such as location date or information about an incident. Data profiling makes it possible to accurately identify patterns and outliers. Consistency is also promoted by standardized crime descriptions while handling missing values increases the reliability of the data. The use of distinguishing identifiers such as incident IDs makes accurate distinctions across records possible. Organizations can enhance their data integrity by adapting to the situation of crime datasets so that any form or structure regarding it will be able for the actual study and in this way ensure good decisions are reached as far as criminal information is concerned. This simplified system helps maintain the integrity of data and prevent duplication because no one is able to maintain authentic datasets which support criminal-related issues.

4.3. EXTRACTING FEATURES

Feature extraction is one of the most important concepts in crime prediction using ML. When working with ML models, we use LabelEncoder [64], [65] to encode respective variables from the categorical form into numerical format. Here's a breakdown of the features:

- Area: This refers to the place of crime.
- Crime code: The crime committed.
- Victim sex: The gender of the victim. We binarize this, having 0 for males and 1 for females.
- Victim descent: This refers to the ethnic or cultural roots of the victim.
- Weapon code: We similarly code this feature tag as 'crime_code' if it is a weapon crime.
- Hour: The time at which the crime was committed.
- Reported delay: The gap between the commission of a crime and its reporting.
- Days after reported: The time elapsed since the crime was reported.

Table 1 presents the first 5 records with selected features. Figure 8 shows the distributions, 2D distributions, time series, and values of these features.

Table 1: The First 5 Records with Selected Features

ID	area	Crime code	Victim sex	Victim descent	Weapon code	Hour	Reported delay	Days after reported
0	3	624	0	1	58	22	0	1471
1	1	624	1	16	59	3	0	1477
2	1	845	3	10	77	12	60	1374
3	15	745	0	9	77	17	0	1478
4	19	740	3	10	77	4	0	1478

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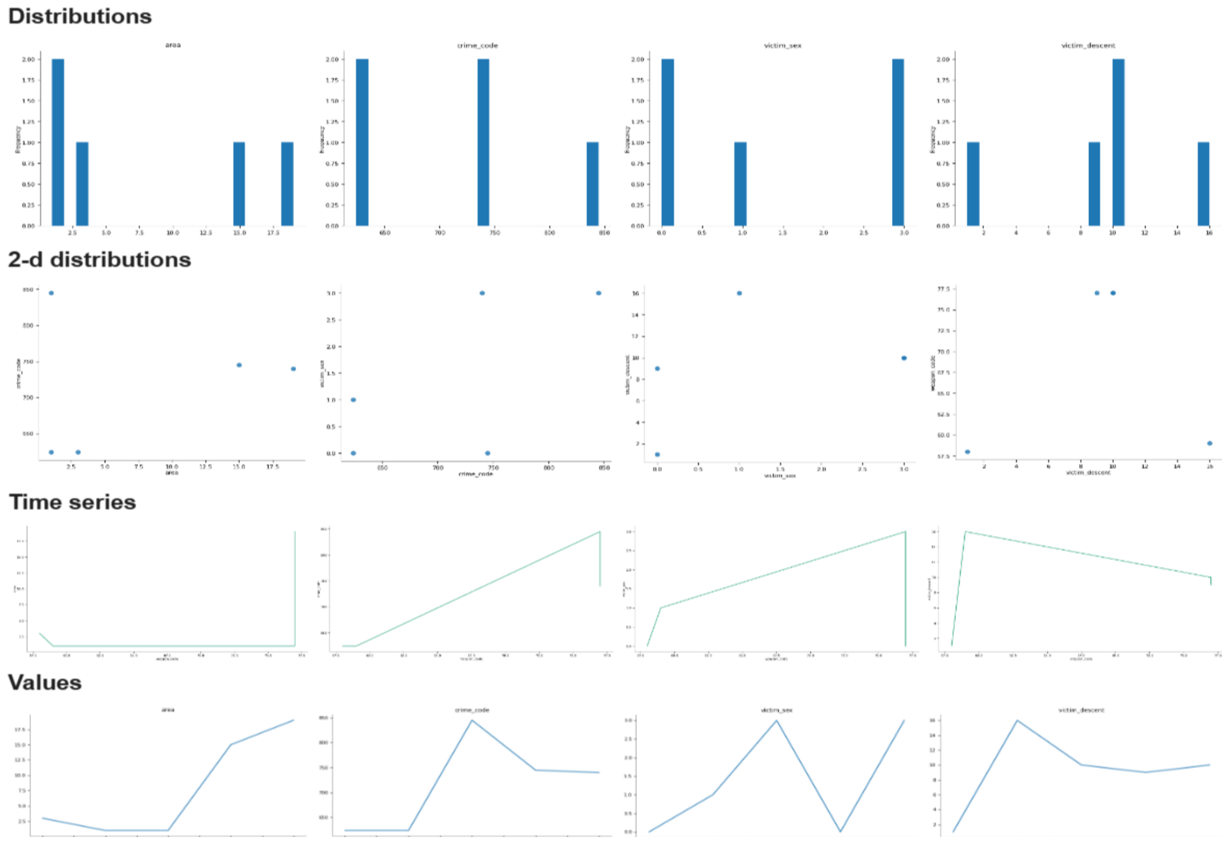

Fig. 8. Distributions, Time series, and Values of the Features

4.4. ML CLASSIFIERS

ML algorithms are essential for helping law enforcement organizations anticipate and stop criminal activity in the field of crime prediction. In order to forecast crimes in Los Angeles, this study focuses on applying four well-known classifiers: SGD, KNN, NB, and LR. We focus on evaluating these classifiers' performance and determining which model works best for predicting crimes in a complicated metropolitan setting. We can assist law enforcement organizations in choosing the best model to improve crime prevention efforts in a dynamic urban setting by comparing these classifiers. The results might also be useful for future investigations into how best to use ML techniques for public safety and crime prediction.

4.5. EVALUATION OF PERFORMANCE

One measure, accuracy, is employed to assess the effectiveness of the models. This metric works to evaluate the models' predictive capabilities and their ability to minimize both false positives and false negatives in crime prediction. Accuracy computes the ratio of successfully predicted instances to total instances, which assesses the model's overall correctness based on the following formula:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}} \quad (1)$$

- True Positive (TP): The forecasted outcome aligns with the factual result. Essentially, both the predicted and actual values are positive.
- True Negative (TN): The projected outcome matches the actual result. In simpler terms, both the predicted and actual values are negative.
- False Positive (FP): The forecasted outcome is incorrect. In other words, the predicted value is positive, but the actual value is negative.

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- False Negative (FN): The anticipated outcome is incorrect. To clarify, the predicted value is negative, but the actual value is positive.

5. RESULTS AND DISCUSSION

In this study, we employed four popular ML classifiers, namely LR, KNN, NB, and SGD, to predict outcomes on our dataset. The dataset was split into 70% for training and 30% for testing. The accuracy scores obtained for each classifier were as follows: LR (0.79), KNN (0.81), NB (0.79), and SGD (0.80). Classification accuracy is a crucial metric for evaluating the performance of a classifier. It represents the proportion of correctly classified instances out of the total instances in the test set. The results indicate that the KNN classifier achieved the highest accuracy among the selected models with a score of 0.81, closely followed by SGD with 0.80. LR and NB exhibited slightly lower accuracies, scoring 0.79 each. Figure 9 below presents these results.

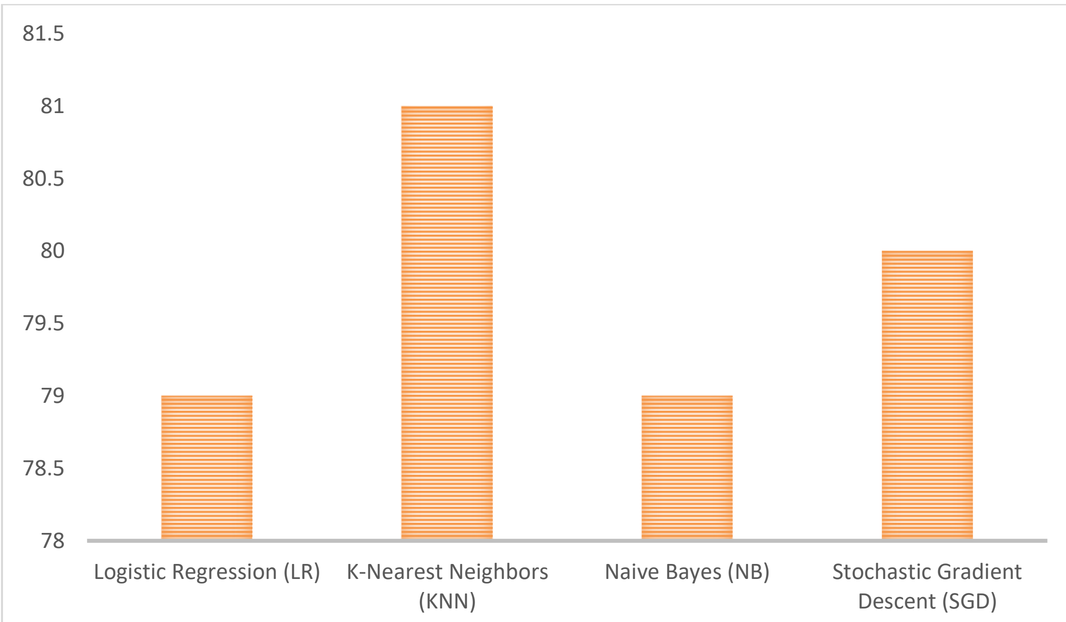

Fig. 9. Accuracy of ML Classifiers

The variation in accuracy across classifiers is attributed to their inherent strengths and weaknesses, as well as their assumptions and parameter settings. Logistic Regression assumes a linear relationship between features and the log-odds of the response variable, while KNN relies on proximity-based relationships. NB makes the assumption of independence between features, and SGD optimizes a linear model using stochastic gradient descent.

In conclusion, the choice of a classifier should be based not only on accuracy but also on the nature of the problem, interpretability, and computational efficiency. The results obtained in this study provide valuable insights into the relative performance of the selected classifiers on the given dataset, serving as a foundation for more in-depth analysis and optimization.

However, the dataset used in this study is unique, as no previous research on its contents has been carried out. It covers crimes from early 2020 to late 2023. This distinctive dataset has resulted in the present state-of-the-art for this crime topic in its outcomes. Through the utilization of previously not used data, this study establishes a standard that provides unique knowledge regarding crime prediction and prevention, thus serving as an essential contribution to furthering our understanding of criminal activity in Los Angeles during such a period.

6. CONCLUSION

This study undertook a comprehensive analysis of crime data in Los Angeles spanning the years 2020 to 2023. Given the vast volume of data, ML techniques were employed to effectively analyze and classify crime patterns. The intricacies of the dataset were addressed through the utilization of four classifiers: LR, KNN, NB, and SGD. Following a rigorous comparison and evaluation of these classifiers, KNN emerged as the most effective model for predicting crime patterns in Los Angeles over the specified time frame. In this context, KNN demonstrated exceptional accuracy

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and precision in recognizing crime patterns. Nonetheless, future research endeavors will seek to identify additional features or refine existing ones to further enhance the accuracy of predictive models. Exploring socio-economic conditions, climate factors, or other variables could provide deeper insights into crime patterns. This research stands to enhance the current initiatives aimed at improving public safety and fostering the development of proactive crime prevention strategies for Los Angeles, as well as other metropolitan areas.

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