Crime Risk Prediction Using Sequential Minimal Optimization Algorithm

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Abstract— One of the most significant and pervasive issues in our society is a crime, and preventing it is a crucial task. An increasing crime factor leads to an imbalance in the constituency of a country. Crime prediction and forecasting is a challenging task for law enforcement agencies to prevent crimes in the future. In recent years, machine learning algorithms have been used to analyze crime data and provide useful insights to predict and prevent future crimes. In this paper, we propose a crime risk prediction and forecasting system using a sequential minimal optimization algorithm, a popular support vector machine algorithm that can be used for classification and regression tasks. We demonstrate the effectiveness of the SMO algorithm and LSTM model on a real-world crime dataset and compare its performance with other commonly used machine learning algorithms. Our results show that the SMO algorithm and LSTM model gives faster and more variety of visualizations for crime trend prediction and forecasting.

Keywords—Crime risk prediction, Sequential Minimal Optimization, Forecasting, Machine learning

I. INTRODUCTION

Crime risk prediction is a challenging problem in the field of enforcement. The ability to predict crime risks can help law enforcement agencies to allocate their resources effectively and prevent crime before it occurs. Traditional crime prediction methods rely on expert knowledge and statistical analysis, which are often subjective and time-consuming. Machine learning algorithms have been increasingly used for crime risk prediction due to their ability to learn patterns and make accurate predictions. In recent years accurate crime prediction is crucial for the effective prevention of criminal acts. Predicting crime types and hot spots from past patterns presents various computational challenges and opportunities. While machine learning-based crime prediction is currently the mainstream analysis approach, few studies have systematically compared different machine learning methods. Machine learning algorithms have shown their ability to process non-linear rational data and handle high-dimensional data with faster training speed, enabling them to extract data characteristics. Despite considerable research efforts, there is still a lack of literature on the relative accuracy of crime prediction for large datasets in multiple cities. Recent studies suggest that implementing different models can address challenges related to predicting and forecasting violent acts in high crime-density areas. Crime data typically demonstrates data seasonality, indicating the potential significance of criminal activities that have evolved over the year. Previous studies have used various machine learning algorithms to predict crime, including Random Forests, Support Vector Machines, and Decision Trees. This paper proposes the use of the Sequential Minimal Optimization (SMO) algorithm for crime risk prediction in three major cities: Chicago, Philadelphia, and San Francisco.SMO is a popular support vector machine algorithm known for its ability to handle large datasets and high-dimensional feature spaces. Forecasting is done with the use of LSTM. Analyzing crime data requires time series analysis, which involves generating visual patterns using deep learning algorithms, particularly Long Short-Term Memory (LSTM) as compared to ARIMA. In practice, LSTM is more suitable for time series forecasting as it requires only a single fitting and does not require parameter optimization .It aims to predict the risk of crime and forecast future crime incidents based on historical crime data.

II. RELATED WORK

Previous research has shown that machine learning algorithms such as decision trees, random forests, and support vector machines can be effective for crime risk prediction. These algorithms have been used to predict various types of crimes, including burglary, robbery, and drug-related offenses.

1. Unsupervised Domain Adaptation for Crime Risk Prediction Across Cities

This paper proposes an unsupervised domain adaptation method for crime risk prediction across cities, which utilizes adversarial training and feature alignment techniques to learn domain-invariant representations of crime data. The authors highlight the challenges of adapting crime risk models across different cities and discuss existing approaches to crime risk prediction and domain adaptation. The experimental evaluation of the proposed method on crime data from three different cities shows that it outperforms several baselines in terms of accuracy and robustness to domain shifts. The authors conclude by discussing the contributions and limitations of their work and suggest potential avenues for future research.

2. *Dynamic road crime risk prediction with urban open data*

In this piece, proposes a machine learning approach to predicting road crime risk using urban open data. The authors emphasize the potential of urban open data as a source of information for crime risk prediction in urban areas. They review existing approaches to road crime risk prediction, discuss the use of urban open data in crime prediction, and propose a machine learning pipeline that incorporates various data sources, including crime statistics, traffic volume, and weather data. The authors compare their approach to several baseline models and show that it outperforms them in terms of accuracy and efficiency. Finally, the authors conclude by discussing the contributions and limitations of their work, as well as potential avenues for future research. They highlight the importance of dynamic road crime risk prediction and the potential of urban open data as a source of information for crime prediction in urban areas.

3. *Risk Prediction of Theft Crimes in Urban Communities*

The authors provide an overview of crime prediction and highlight the importance of theft crime prediction in urban areas. They review existing approaches to crime prediction, including traditional statistical models and machine learning techniques. The authors then describe their approach, which involves feature selection, data preprocessing, and the use of several machine learning models for prediction. The results section presents the experimental evaluation of the proposed approach using data from a city in Mexico. The authors compare their approach to several baseline models and show that it outperforms them in terms of accuracy and efficiency. Finally, the authors discuss the limitations of their work and potential avenues for future research, emphasizing the need for more comprehensive and diverse datasets to improve crime prediction in urban areas.

4. *Crime Type and Occurrence Prediction using Machine Learning Algorithm*

This proposes a machine learning approach to predicting crime type and occurrence in urban areas. The authors provide an overview of crime prediction and the challenges associated with it, such as the lack of accurate and up-to-date data. They review existing approaches to crime prediction, including traditional statistical models and machine learning techniques. The authors describe their approach to crime type and occurrence prediction using machine learning algorithms. They propose a feature selection and engineering process to extract relevant features from the input data. They also describe the crime type and occurrence prediction models, including decision trees, random forests, and support vector machines. Finally, the authors discuss the limitations of their work and potential avenues for future research, emphasizing the need for more comprehensive and diverse datasets to improve crime prediction.

5. *Smart Policing Technique With Crime Type and Risk*

This paper addresses the challenge of reducing crime rates by proposing a machine learning-based smart policing technique that predicts crime types and associated risks. The authors also review studies on the use of geographic information systems (GIS) and other data sources to identify crime hotspots and patterns. Proposed smart policing technique, which uses a machine learning pipeline that incorporates various data sources, including crime data, demographic data, and geographic data. The authors also discuss the feature engineering process, the models used for prediction, and the evaluation metrics and proposed smart policing technique, which uses a machine learning pipeline that incorporates various data sources, including crime data, demographic data, and geographic data. The authors also discuss the feature engineering process, the models used for prediction, and the evaluation metrics. Finally, they highlight the potential of their smart policing technique in improving policing efficiency and reducing crime rates and suggest that it could be extended to other domains beyond crime.

6. *Domain Adversarial Transfer Network for Cross-Domain Fault Diagnosis*

This paper presents a new approach to fault diagnosis using domain adaptation and deep learning techniques. The authors address the challenges associated with cross-domain diagnosis and introduce their proposed method, which uses domain adversarial transfer learning to learn domain-invariant representations of sensor data and improve diagnosis accuracy. The methodology section describes the domain adversarial transfer network for fault diagnosis, which consists of an encoder-decoder architecture with a domain discriminator. The results demonstrate the effectiveness of the proposed method on two datasets from different domains, and the authors suggest potential applications beyond industrial systems.

III. PROPOSED SYSTEM

We proposed the SMO algorithm and LSTM model to predict and forecast crimes which help to make the decision-making process easier for law enforcement agencies. Big Data Analytics (BDA) is a new way to analyze data and extract information and their relationships in a variety of application areas. However, dealing with vast volumes of available data presents several issues in public policy. As a result, new methodologies and techniques for analyzing this heterogeneous and multi-sourced data are required. Big data analytics (BDA) has long been used and researched in the disciplines of data science and computer science. The notion of big data in BDA, its analytics, and the issues that come with engaging with it. On the research gaps and issues associated with criminal data mining. Furthermore, this project provides insight into data mining for detecting patterns and trends in crime that may be used correctly, as well as a resource for novices in the research of crime data mining. As a result, managing and analyzing massive amounts of data is extremely tough and complex. To improve the efficiency of crime detection, appropriate data mining techniques must be used. Numerous data mining applications, particularly those that use the Apriority method discover the most efficient association rule and decrease processing time. Furthermore, numerous strategies have been created.

A. Data Collection

Data collection is the process of gathering and measuring information from countless different sources. Collecting data allows you to capture a record of past events so that we can use data analysis to find recurring patterns. We have collected the dataset from Gaggle and UCI repositories. Therefore the dataset includes Chicago, Philadelphia, and San Francisco. Fig 1. shows the overview of the Chicago dataset, Fig 2. shows the overview of the Philadelphia dataset, and Fig 3. shows the overview of the San Francisco dataset.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	ID	Case Numl	Date	Block	IUCR	Primary Ty	Descriptio	Location D	Arrest	Domestic	Beat	District	Ward	Communit	FBI Code	X Coordi
2	12013914	JD191103	01/22/202	008XX W J	890	THEFT	FROM BUI	APARTMEI	FALSE	TRUE	1915	19	46	3	6	116995
3	12014538	JD191889	########	066XX S LC	1153	DECEPTIVI	FINANCIAI	RESIDENCI	FALSE	FALSE	723	7	6	68	11	117318
4	12015249	JD192661	01/22/202	045XX N C	1310	CRIMINAL	TO PROPEI	RESIDENCI	FALSE	FALSE	1724	17	33	14	14	115323
5	12015175	JD192579	########	002XX W L	810	THEFT	OVER $50(	OTHER (SP	FALSE	FALSE	122	1	42	32	6	117460
6	12134619	JD331224	########	007XX E 9(	2826	OTHER OF	HARASSMI	RESIDENCI	FALSE	FALSE	633	6	8	44	26	118275
7	12016034	JD193556	########	018XX N W	1153	DECEPTIVI	FINANCIAI	APARTMEI	FALSE	FALSE	1434	14	32	22	11	116026
8	11970262	JD138268	01/31/202	042XX W D	820	THEFT	$500 AND	OTHER (SP	TRUE	FALSE	2534	25	37	23	6	114799
9	11940213	JD102425	########	010XX W 7	3710	INTERFERI	RESIST/OB	STREET	TRUE	FALSE	612	6	17	71	24	117091
10	12016589	JD193997	01/24/202	067XX S PA	820	THEFT	$500 AND	RESIDENCI	FALSE	FALSE	722	7	6	68	6	117373
11	12016436	JD193883	########	007XX W 5	2825	OTHER OF	HARASSMI	RESIDENCI	FALSE	TRUE	935	9	20	61	26	117233
12	12016706	JD194198	01/20/202	028XX N SA	1153	DECEPTIVI	FINANCIAI	RESIDENCI	FALSE	FALSE	1412	14	35	21	11	115422
13	12017743	JD195242	########	098XX S EL	890	THEFT	FROM BUI	RESIDENCI	FALSE	TRUE	511	5	8	50	6	118462
14	12017996	JD195553	01/27/202	050XX W A	820	THEFT	$500 AND	STREET	FALSE	FALSE	1533	15	28	25	6	114270
15	12018457	JD196013	01/16/202	063XX S CH	1130	DECEPTIVI	FRAUD OR	RESIDENCI	FALSE	FALSE	312	3	20	42	11	118166
16	12013828	JD191019	########	044XX S LA	281	CRIMINAL	NON-AGGI	APARTMEI	FALSE	FALSE	814	8	22	56	2	114377
17	12004464	JD180179	01/17/202	008XX S FI	2820	OTHER OF	TELEPHON	RESIDENCI	FALSE	TRUE	123	1	25	32	08A	117500

Fig 1. Overview of the Chicago dataset

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	objectid	dc_dist	psa	dispatch_c	dispatch_c	dispatch_t	hour_	dc_key	location_b	ucr_gener	text_gene	point_x	point_y	lat	lng
2	79	77	A	########	########	14:43:00	14	2.02E+11	0 BLOCK P	600	Thefts	-75.2307	39.88388	39.88388	-75.2307
3	80	77	A	########	########	09:24:00	9	2.02E+11	0 BLOCK P	600	Thefts	-75.2307	39.88388	39.88388	-75.2307
4	389	26	3	########	########	11:34:00	11	2.02E+11	2500 BLOC	600	Thefts	-75.1238	39.982	39.982	-75.1238
5	735	3	3	########	########	03:08:00	3	2.02E+11	2100 BLOC	600	Thefts	-75.1627	39.92328	39.92328	-75.1627
6	752	25	4	########	########	12:42:00	12	2.02E+11	700 BLOCK	500	Burglary N	-75.1441	40.00212	40.00212	-75.1441
7	1472	6	2	########	########	17:01:00	17	2.02E+11	1300 BLOC	600	Thefts	-75.1624	39.95404	39.95404	-75.1624
8	1384	24	2	########	########	18:00:00	18	2.02E+11	2000 BLOC	300	Robbery N	-75.1117	39.9938	39.9938	-75.1117
9	1702	25	1	########	########	02:04:00	2	2.02E+11	1200 BLOC	300	Robbery Fi	-75.1472	40.01496	40.01496	-75.1472
10	1948	16	1	########	########	22:30:00	22	2.02E+11	3000 BLOC	600	Thefts	-75.1837	39.95541	39.95541	-75.1837
11	2534	6	3	########	########	17:29:00	17	2.02E+11	0 BLOCK D	600	Thefts	-75.1435	39.94619	39.94619	-75.1435
12	2773	2	2	########	########	02:58:00	2	2.02E+11	700 BLOCK	600	Thefts	-75.104	40.0306	40.0306	-75.104
13	2999	12	1	########	########	04:00:00	4	2.02E+11	7300 BLOC	400	Aggravate	-75.2418	39.91277	39.91277	-75.2418
14	4825	7	3	########	########	17:06:00	17	2.02E+11	13500 BLC	600	Thefts	-75.0137	40.13143	40.13143	-75.0137
15	5827	3	2	########	########	17:38:00	17	2.02E+11	0 BLOCK M	600	Thefts	-75.1462	39.9244	39.9244	-75.1462
16	5828	3	2	########	########	11:09:00	11	2.02E+11	0 BLOCK M	600	Thefts	-75.1462	39.9244	39.9244	-75.1462
17	5829	3	2	########	########	17:43:00	17	2.02E+11	0 BLOCK M	600	Thefts	-75.1462	39.9244	39.9244	-75.1462
18	5830	3	2	########	########	16:28:00	16	2.02E+11	0 BLOCK M	600	Thefts	-75.1462	39.9244	39.9244	-75.1462
19	5837	3	2	########	########	13:17:00	13	2.02E+11	0 BLOCK M	600	Thefts	-75.1462	39.9244	39.9244	-75.1462
20	6269	9	3	########	########	13:08:00	13	2.02E+11	2500 BLOC	600	Theft from	-75.1788	39.96663	39.96663	-75.1788
21	5921	3	2	########	########	15:04:00	15	2.02E+11	0 BLOCK M	600	Thefts	-75.1462	39.9244	39.9244	-75.1462
22	4144	39	1	########	########	18:59:00	18	2.02E+11	4200 BLOC	600	Thefts	-75.1964	40.00953	40.00953	-75.1964
23	4692	15	3	########	########	10:30:00	10	2.02E+11	3500 BLOC	300	Robbery N	-75.0427	40.03743	40.03743	-75.0427

Fig 2. Overview of the Philadelphia dataset

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Incident D.	Incident D.	Incident Ti	Incident Ye	Incident D.	Report Dat	Row ID	Incident ID	Incident N	CAD Numb	Report Typ	Report Typ	Filed Onlin	Incid
2	########	########	04:00	2020	Tuesday	########	9E+10	900124	2.06E+08		II	Coplogic Ir	TRUE	
3	########	########	15:00	2020	Friday	########	8.99E+10	898768	1.91E+08		IS	Initial Supplement		6
4	########	########	20:10	2020	Monday	########	9.04E+10	903588	2.06E+08		II	Coplogic Ir	TRUE	
5	########	########	20:15	2020	Thursday	########	9.53E+10	953244	2E+08		IS	Coplogic S	TRUE	
6	########	########	04:46	2020	Thursday	########	8.87E+10	887129	2E+08		VS	Vehicle Supplement		
7	########	########	02:04	2020	Wednesda	########	9.54E+10	953779	2.06E+08		II	Coplogic Ir	TRUE	7
8	########	########	03:38	2020	Saturday	########	9.72E+10	971639	2E+08	2E+08	IS	Initial Supplement		6
9	########	########	03:38	2020	Saturday	########	9.72E+10	971639	2E+08	2E+08	IS	Initial Supplement		6
10	########	########	00:00	2020	Sunday	########	9.54E+10	954186	2E+08	2.02E+08	II	Initial		
11	########	########	09:00	2020	Wednesda	########	9.55E+10	955210	2.06E+08		II	Coplogic Ir	TRUE	
12	########	########	12:00	2020	Wednesda	########	9.73E+10	972550	2.01E+08	2.03E+08	VI	Vehicle Initial		
13	########	########	12:00	2020	Thursday	########	9.73E+10	972591	2.01E+08	2.03E+08	VI	Vehicle Initial		7
14	########	########	18:00	2020	Friday	########	9.56E+10	956069	2.06E+08		II	Coplogic Ir	TRUE	
15	########	########	19:17	2020	Friday	########	9.56E+10	956444	2E+08	2E+08	IS	Initial Supplement		7
16	########	########	20:05	2020	Wednesda	########	9.56E+10	956438	2E+08	2E+08	IS	Initial Supplement		
17	########	########	19:17	2020	Friday	########	9.56E+10	956444	2E+08	2E+08	IS	Initial Supplement		
18	########	########	16:05	2020	Tuesday	########	9.56E+10	956435	2E+08	2E+08	IS	Initial Supplement		
19	########	########	20:05	2020	Wednesda	########	9.56E+10	956438	2E+08	2E+08	IS	Initial Supplement		7

Fig 3. Overview of the San Francisco dataset

From those patterns, predictive models are built using machine learning algorithms that look for trends and predict future changes.

B. Data Preprocessing

This data is in the form of the number of cases recorded all over the cities throughout the year. The data is in unprocessed form and contains some wrong as well as missing values. Hence preprocessing of data is a crucial task in order to bring the data in proper and clean form. Pre-processing of data includes data cleansing and Preprocessing. The dataset is classified into various groups based on certain characteristics of the data object. We selected the following features for our experiments: location, time of day, day of the week, and type of crime. These features have been shown to be important predictors of crime.

C. Narrative Visualization Prediction with SMO

We actualize the shortest Crime record linkage Profile information between two nodes in this module. Like the node-keyword index, only Crime record linkage Profile information from nodes with a Crime record linkage Profile weight less than a certain threshold is saved. The reason for the Node-Node index is that in a text-based database, the number of different words contained within the region of threshold Crime record linkage Profile weight of a node is quite big in comparison to the number of nodes present in the region. Combining narrative visualization with the Sequential Minimal Optimization (SMO) algorithm can effectively explore and communicate complex crime data. Narrative visualization can display crime rates over time, the distribution of different crimes in neighborhoods, and correlations with various factors of crime. By using the SMO algorithm, it's possible to identify complex relationships between different variables that may not be immediately obvious. Fig 4. shows the visualization of crime cases in Chicago. Fig 5. shows the visualization of crime cases in Philadelphia. Fig 6. shows the visualization of crime cases in San Francisco. Fig 7. shows the hourly crime trend of the three cities. Fig 8. shows the monthly statistics of crimes. This combination creates a more complete understanding of crime patterns, which can inform law enforcement and policymakers in developing crime prevention and intervention strategies.

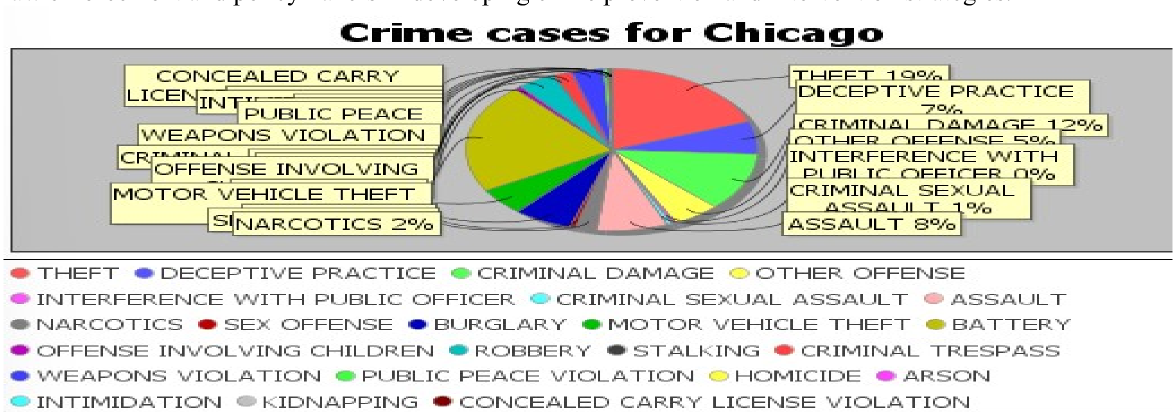

Fig 4. Visualization of crime cases in Chicago.

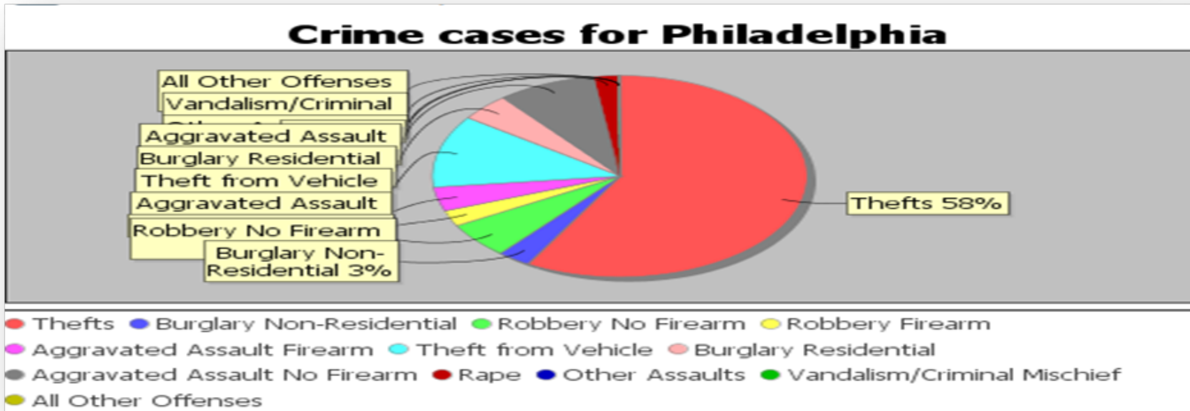

Fig 5. Visualization of crime cases in Philadelphia.

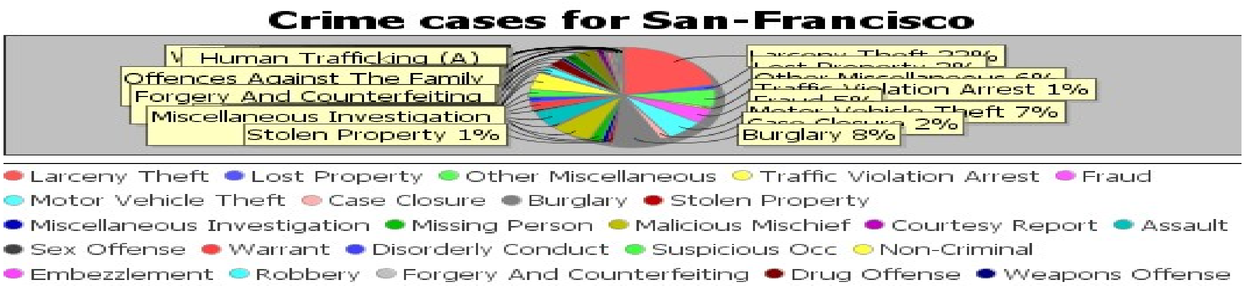

Fig 6. Visualization of crime cases in San Francisco.

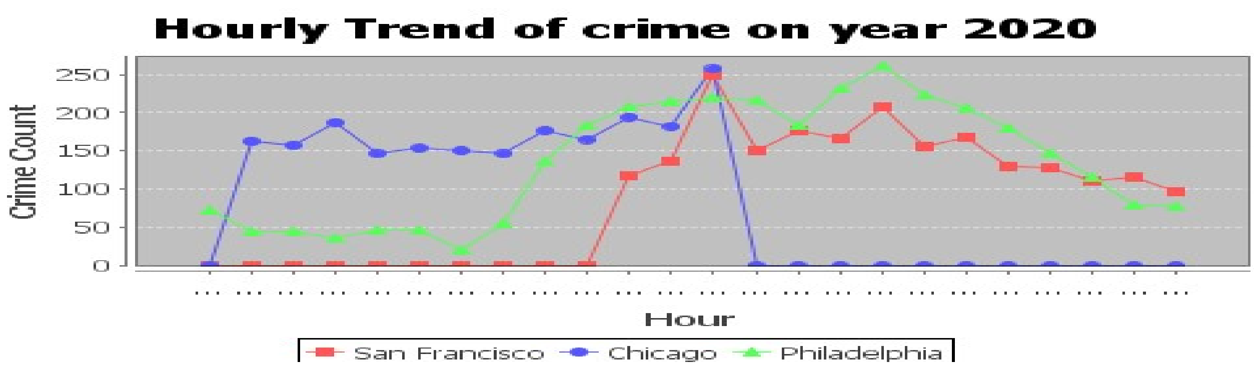

Fig 7. Hourly prediction of crime in three cities

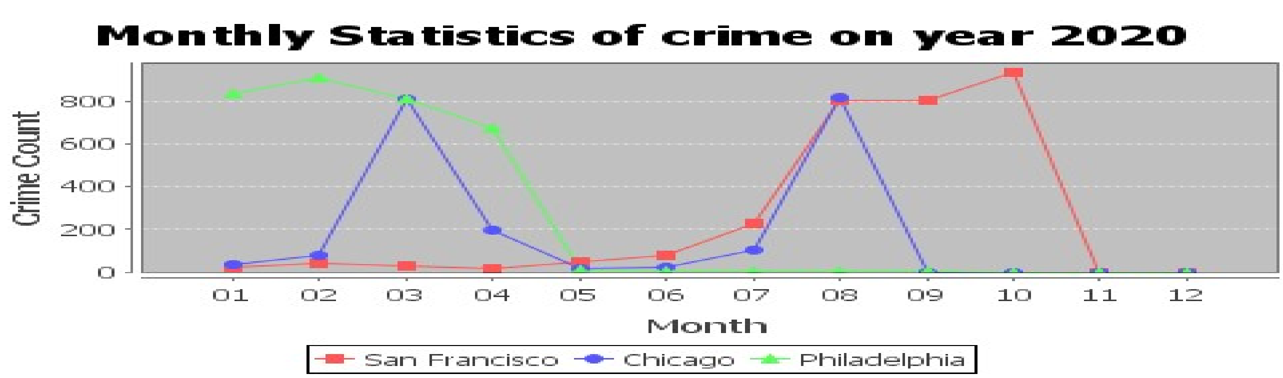

Fig 8. Monthly statistics of crime in three cities

D. Forecasting

The LSTM model is an effective neural network for analyzing time-series data and has gained popularity in crime prediction. By analyzing historical crime data, LSTMs can accurately forecast future crime trends and capture complex relationships between variables. Fig 9. shows the forecasting results of crime trends in three cities. Fig 10. shows the comparison graph of SMO and LSTM by means of RMSE and correlation. Its ability to account for seasonality and cyclical patterns allows law enforcement to allocate resources accordingly. LSTMs can also be used for identifying high-risk areas and predicting recidivism. By using deep learning techniques like LSTM, law enforcement can make informed decisions and work towards creating safer communities.

```
@relation SanFranciscoTestingData

@attribute Date numeric
@attribute Month numeric
@attribute Year numeric
@attribute CrimeCount numeric

@data
1,1,21,12
2,1,21,12
3,1,21,15
4,1,21,17
5,1,21,15
6,1,21,14
7,1,21,10
```

Fig 9. Forecasting results of crime in three cities with date, month, year, and crime count.

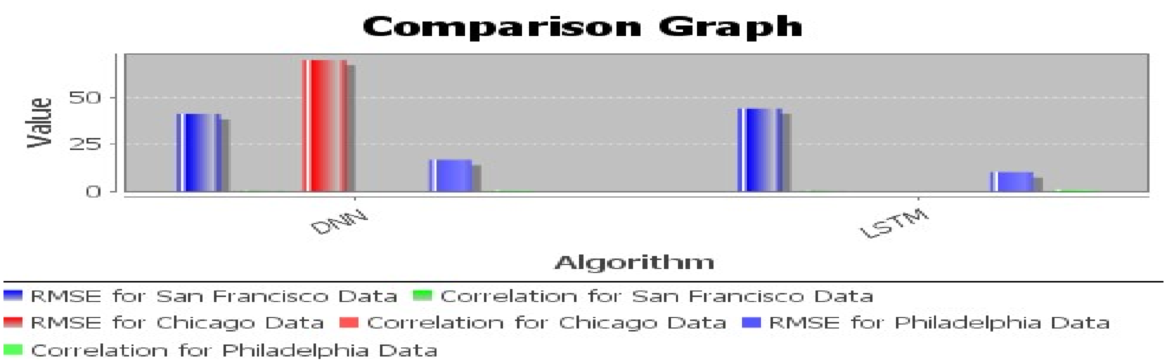

Fig 10. Comparison graph of SMO and LSTM

IV. CONCLUSION AND FUTURE WORK

In this paper a series of state-of-the-art big data analytics and visualization techniques were utilized to analyze crime big data from three US cities, which allowed us to identify patterns and obtain trends. The results show that the proposed system can achieve high accuracy in predicting crime risk and can forecast future crime incidents with reasonable accuracy. By exploring the neural network algorithm SMO, and the deep learning algorithm LSTM, we found that both perform better than conventional neural network models. We also found the optimal time period for the training sample to be 3 years, in order to achieve the best prediction of trends in terms of RMSE and spearman correlation. Optimal parameters for the prediction and forecasting models are also determined. Additional results explained earlier will provide new insights into crime trends and will assist both police departments and law enforcement agencies in their decision-making. In the future, we plan to complete our ongoing platform for generic big data analytics which will be capable of processing various types of data for a wide range of applications. We also plan to incorporate multivariate visualization graph mining techniques and fine-grained spatial analysis to uncover more potential patterns and trends within these datasets. Moreover, we aim to conduct more realistic case studies to further evaluate the effectiveness and scalability of the different models in our system.

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