Spatio-temporal Crime Analysis of Bangladesh using Machine Learning Models

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Abstract. This study presents a comprehensive spatio-temporal analysis and forecasting of crime trends in Bangladesh using monthly police data from January 2019 to June 2024. This research analyzes five crime types: theft, burglary, robbery, narcotics-related offences, and gender-based violence (GBV) across ten regions, including two major metropolitan cities and eight divisions. Descriptive and exploratory analyses reveal spatial and temporal crime patterns, followed by a comparative evaluation of five forecasting models: Random Forest, XGBoost, SARIMAX, FBProphet, and LSTM. Model performance is assessed using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). Results show that model performance varies by crime type. SARIMAX demonstrated strong forecasting capabilities for stationary, auto-correlated data (e.g., theft), while FBProphet performed well for crimes with strong seasonality, such as narcotics-related offences. Random Forest demonstrated strong predictive capability for non-stationary data or stationary data with no autocorrelation, particularly for GBV, whereas LSTM (long short-term memory) underperformed, likely due to the limited dataset size. The comparative performance of the models was further validated by aggregating data in major geographic regions, where SARIMAX, FBProphet, and Random Forest maintained their superiority for theft, narcotics, and GBV, respectively. The study can be used as directives to the policy makers to have detailed knowledge on the spatio-temporal dynamics of crime and choose the right ML models for crime prediction for informed decision making to control future occurrences of crime.

Keywords: Bangladesh,spatio-temporal analysis, crime analysis, crime prediction, crime forecasting, data-driven policing, predictive policing, FBProphet, SARIMAX, random forest

1 Introduction

Spatio-temporal crime analysis is crucial in data-driven policing for strategic planning, resource allocation, and informed decision-making to control crime

M. S. Arefin et al. (eds.), *Proceedings of the International Conference on Intelligent Data Analysis and Applications (IDAA 2025)*, Advances in Intelligent Systems Research 206,
https://doi.org/10.2991/978-94-6239-664-7_67

in society. Spatio-temporal crime analysis offers a comprehensive understanding of complex characteristics of crime, including patterns, features, trends, and spatial distribution, and enhances the ability to predict future trends of criminal incidents based on historical data. Various statistical and machine learning models are being applied to analyze and forecast crime to identify future crime trends. For analyzing time series datasets, Ensemble methods like Random Forest, Adaboost, and eXtreme Gradient Boosting (XGBoost) are popularly used. In addition, traditional statistical models and tools like ARIMA, SARIMAX, Exponential Smoothing, FBProphet, and deep learning models such as LSTM, are gaining attention from scholars for forecasting time series data. Each model outperforms for data with certain properties, like ARIMA, which is best for stationary data, while the FBProphet model and LSTM are good for data with seasonality and complex non-linear patterns, respectively [22].

Real-life crime data are considered to be non-stationary, irregular, and sometimes have recurring patterns that exhibit seasonality. For example, property crimes, like theft, have the tendency to occur in certain seasons like summer or winter, depending on the area [11]. With such uncertainty in data, the prediction of crimes, based on police reports, is a challenging task. This study aims to conduct an in-depth analysis of crime identifying patterns, trends, and the relation of crime with location and time through descriptive and exploratory data analysis. It also seeks to explore the prediction of the future trend of crime in Bangladesh by analyzing time series crime data of the Bangladesh police. The study employed five machine learning models and procedures: Random Forest, XGBoost (eXtreme Gradient Boosting), FBProphet, SARIMAX, and the LSTM model. It explored the crime trend through a comparative analysis of the performance of these models in predicting crime. Therefore, law enforcement agencies will be able to identify the spatial and temporal hotspots of crime, make an informed decision about the personnel and resource allocation, and policing strategies to prevent the future occurrence of crimes, and adopt an appropriate ML model based on the characteristics of the data rather than choosing one ML model for all types of crime.

Section 2 of this paper contains a review of some previous related work and outlines the machine learning models employed in this study. Section 3 describes the proposed methodology with the experimental setup, including data collection, data preprocessing, and both descriptive and predictive analyses of the data. This is followed by the results and a discussion on the performance of machine learning models in forecasting criminal incidents in Section 4. The final section, Section 5, concludes the study, highlighting some ideas for future research.

2 Literature review

2.1 Related work

Time series data prediction is widely used for forecasting various types of data, including production rates, prices, sales, customer numbers, and temperatures.

Therefore, a substantial number of studies have been found on time series data analysis and prediction, including research on temporal crime analysis using machine learning models and mixed revelations were found on the performance of the models.

In the case of predicting crime using time series data, LSTM performed better than the ARIMA model in a study [13] that involved spatial crime analysis through forecasting high-crime hot spots for four types of crime- murder, rape, theft, and property offences in 42 districts of India. The study suggested that LSTM models outperform traditional ARIMA methods in capturing intricate crime patterns and dependencies.

According to Feng et al. [6], the performance of the FBProphet model and the LSTM model was better than that of the conventional neural network (CNN) model. The study analyzed three crime datasets of San Francisco, Chicago, and Philadelphia using statistical methods and predicted future crime incidents along with a comparison of their performance with the three years of training data. The study conducted by Hossain et al. [8] in 2022, argued that Random Forest and Adaboost show higher performance than the Decision Tree and k-nearest neighbor (KNN) algorithms in crime prediction of San Francisco city by analyzing the criminal activity dataset for 12 years. According to [15], XGBoost exhibits the highest accuracy compared to nearest neighbor, support vector machine, random forest, and decision tree in predicting crime rates for eight distinct crime categories in 19 Indian metropolitan cities.

A substantial amount of research has explored crime analysis in Bangladesh, employing both statistical and machine learning techniques. Islam et al. [10] analyzed ten years of crime data of Bangladesh from 2010 to 2019 and explored the trend, patterns, and dependencies of crimes, namely murder, narcotics, smuggling, and dacoity. Awal et al. [3] conducted a descriptive analysis to identify the pattern and trend in crime occurrence. Using linear regression, the study forecasted future crime trends across six metropolitan cities and seven administrative regions of Bangladesh, focusing on murder, theft, burglary, dacoity, robbery, women and child repression, and kidnapping. The results indicated that most crime rates have increased in parallel with population growth. Rahman et al. [16] applied various machine learning algorithms like Random Forest, Decision Tree, Support Vector Machine (SVM), Multi-Layer Perceptron (MLP) with Adam optimizer, Lasso, Bayesian, Ridge, and Linear Regression to predict crime rates in Bangladesh, specifically focusing on dacoities, robberies, and murders. The study analyzed a yearly dataset of 10 years of crime data collected by Bangladesh Police from 2010 to 2019 and concluded that the MLP with Adam optimizer performs better than the other algorithms. Sneha et al. [20] predicted the number of murder cases in Bangladesh by applying different types of regression models like XGB, Decision Tree, and Gradient-Boosting on the publicly available crime datasets of the Bangladesh police from 2010 to 2019 and concluded that ExtraTreesRegressor demonstrated the best prediction accuracy. Similarly, Nobel et al. [14] proposed a machine learning-based method, namely, the Extra Tree model, for crime prediction, of dacoity, robbery, and murder, as well as geographical areas, including metropolitan regions and divisions. In the study, the area names were given numerical values, and the features were standardised using the StandardScaler method. The proposed method used the Extra Trees Regressor model on the standardized data set and achieved 99% precision in prediction.

Most previous studies on crime analysis in Bangladesh have relied on crime dataset covering the period from 2010 to 2019. However, to better capture the evolving nature of criminal activity, analysis of more recent data is essential for understanding the complex spatio-temporal dynamics of crime. Moreover, prior research has predominantly utilized regression-based and ensemble machine learning methods for crime prediction. While these approaches have yielded useful insights, the rapid advancement of statistical and deep learning models offers opportunities to achieve higher predictive accuracy and uncover deeper temporal relationships in crime data.

Based on the above studies and findings, this present study aims to contribute to the existing literature by analyzing the most recent monthly crime data from the Bangladesh police, spanning January 2019 to 2024. The study employs descriptive analysis to explore spatial and temporal crime patterns and evaluates the forecasting performance of five widely used regression-based, statistical, and deep learning models on time series crime data. This will provide an understanding of choosing the ML model based on crime data, and will attempt to use different ML models for achieving more accuracy in crime prediction in preventive policing.

The focus of this study is to provide a comprehensive understanding of the dynamic characteristics of criminal incidents in Bangladesh by identifying their patterns, trends, and relationships related to time and location through visualization techniques. Additionally, the study also provides insights into selecting suitable machine learning models based on the statistical nature of each crime type, thereby improving the accuracy and applicability of predictive policing methods in the Bangladeshi context.

2.2 Machine Learning Models

The study employs five machine learning models for time series forecasting - Random Forest, XGBoost, SARIMAX, FBProphet, and LSTM. These models were selected based on their performance and adaptability in capturing diverse temporal patterns in time-series data. A brief overview of the models is outlined below.

Random Forest: Random forest is an ensemble learning method that aggregates predictions from multiple decision trees to produce a more accurate and stable prediction. It is a supervised learning algorithm that can be used for both classification and regression tasks. In the case of regression, the average of the predictions from multiple decision trees is used to determine the final output [4].

XGBoost: XGBoost (eXtreme Gradient Boosting) is a decision tree-based ensemble technique that utilizes gradient boosting to enhance predictive performance. It aggregates the outcomes from several individual trees to forecast data. XGBoost is known to exhibit high capability in identifying complex and nonlinear patterns of time series data [1].

SARIMAX: The Seasonal Autoregressive Integrated Moving Average with Exogenous Factors (SARIMAX) model is an improved version of the statistical model, SARIMA, by handling seasonality. It incorporates both seasonal effects and exogenous factors, which helps reduce the error values and improve the overall model accuracy, even in the case of close input and output dataset lengths. It is capable of handling sequential datasets of different size [2].

FBProphet: FBProphet, developed by Meta (formerly Facebook), is an additive time series forecasting model designed to capture nonlinear trends with strong seasonal components. It performs well with datasets exhibiting multiple seasonal patterns and missing observations. Prophet is robust to outliers and structural breaks, making it suitable for real-world forecasting applications [21].

LSTM: Long-Short Term Memory (LSTM) is an improvement of the RNN structure, mainly to solve the problem of gradient vanishing in the training process of long sequences, so that the recurrent neural network has stronger and better memory performance [9]. LSTM models can retain information over longer sequences, especially in datasets with complex patterns and nonlinear relationships [22].

By understanding the advantages and limitations of ML models and comparing their performance across different crime data, law enforcement agencies in Bangladesh will be able to choose the appropriate ML model for crime forecasting and informed decision-making.

3 Proposed Methodology

3.1 Data Collection and Preprocessing

The crime dataset for this study was collected from the official website of the Bangladesh Police[5]. The dataset contains monthly crime statistics from 2019 to 2025, of eight divisions and eight metropolitan cities of Bangladesh, for crimes like dacoity, robbery, theft, burglary, violence against women and children, murder, abduction, drug recovery, etc. Police reports often have limitations of not having a complete dataset, and the quality of the information might not be as expected, as the information can be biased in some cases, but police reports can be a good source of data for details of criminal incidents [7]. Therefore, analyzing historical crime data, such as crime type, time, location, etc., will help law

[5] https://www.police.gov.bd/en/january_2020

enforcement agencies implement proactive policing.
For this study, we extracted and analyzed the crime statistics for five types of crimes, such as property crimes (theft and burglary), violent crimes(robbery), drug-related crimes and gender-based violence in the two metropolitan cities (Dhaka Metropolitan City (DMP), Chattogram Metropolitan City (CMP)) and eight divisions (Dhaka, Chattogram, Rajshahi, Barishal, Mymensingh, Sylhet, Rangpur, and Khulna division). The two mega cities, Dhaka and Chattogram were selected for crime analysis due to their significant socio-economic importance in the country. The above crime types were chosen for three reasons.

- Property crimes such as theft, burglary, and drug-related crimes are known to have seasonal patterns in occurrence, and thus, crime data has seasonality [18]. In contrast, violent crimes like robbery display weak seasonal patterns, while gender-based crimes are generally random and do not show any seasonal pattern [5]. Thus, the time series dataset with these variations will allow us to evaluate the performance of machine learning models across various types of crime.
- Crime patterns vary not only seasonally but also spatially. For this reason, we have included data from both urban and rural areas of Bangladesh.
- Crimes with zero occurrences in different areas have been dropped, and places with zero occurrences of the above five types of crime have been omitted.

After cleaning and restructuring, the time series dataset of monthly data from January 2019 to June 2024 contains 66 records for each type of crime in each area and a total of 660 records across 10 different regions of Bangladesh. Table 1 provides a comprehensive view of crime distribution both by area and by crime type.

Area	**Burglary**	**Theft**	**Robbery**	**GBV**	**Narcotics**	**Total Crimes**
DMP	**2,724**	**6,152**	**1,578**	**8,355**	**78,396**	**97,205**
CMP	*2,006*	*4,159*	*1,184*	5,347	36,652	49,348
Dhaka div	563	1,608	272	6,741	*69,091*	*78,275*
Chattogram div	377	1,562	215	5,363	50,291	57,808
Rajshahi div	198	283	108	4,319	32,907	37,815
Khulna div	486	2,034	196	4,762	19,848	27,326
Barishal div	238	484	172	*6,843*	26,091	33,828
Sylhet div	258	682	88	2,097	10,915	14,040
Mymensingh div	271	351	63	3,819	17,005	21,509
Rangpur div	358	840	132	5,081	19,028	25,439
TOTAL	**7,479**	**18,155**	**4,008**	**52,727**	**360,226**	**442,595**

Table 1: Total Crime Cases by Areas (January 2019 to June 2024)

Preprocessing Step The preprocessing step included the following phases:

- *Aggregation:* The raw dataset listed the crimes for each month in the eight cities and eight divisions of Bangladesh. For modeling efficiency, the data for each area, year and month were aggregated into a single column, with each crime type and area name represented as columns, indexed by month and year in the time series dataset.

- For the random forest regressor and XGBoost model, the year and month were placed in two columns- year and month to use as two features, as they performed better with two features than one.
- Since the LSTM model requires normalization of data, the records were normalized before the implementation of the model, and the predicted values were rescaled.

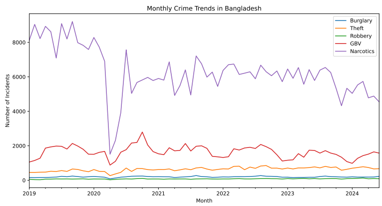
The five machine learning models were used for five types of crimes, namely theft, burglary, robbery, drug-related crimes, and gender-based violence, in the 10 regions in Bangladesh, including DMP, CMP, Dhaka, Chattogram, Rajshahi, Barishal, Mymensingh, Sylhet, Rangpur, and Khulna division.

As Bangladesh experienced political turmoil in and after July 2024, the number of police reports of crime drastically changed throughout the country due to several socioeconomic factors, including several police reports on past incidents. Thus, the crime statistics after July 2024 may not provide a clear picture of the crime dynamics and law and order situation of the country. Additionally, the performance of the crime prediction models for the period after July 2024 showed low performance with greater variance. Therefore, the records from January 2019 to June 2024 were chosen for descriptive analysis of crime, and for the forecasting experiment, records from January 2019 to December 2023 were chosen as the training set, while records from January 2024 to June 2024 were chosen as the test set.

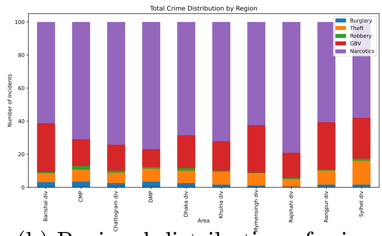
3.2 Descriptive Crime Analysis

We performed descriptive analysis to gain a deeper understanding of the dataset and its underlying patterns. Specifically, we visualized crime types, their spatial and temporal distributions, and interrelationships to explore the complex characteristics of criminal incidents. As shown in Fig. 1a, narcotic-related crimes constitute the highest number of reported crimes across regions, followed by gender-based violence, while burglary, theft, and robbery occured less frequently. The sharp decline of all the crimes during mid-2020 (from April to June) all over the country exhibits the impact of COVID-19 restrictions on both criminal incidents and the operational activities of police, although the trend regained after three months.

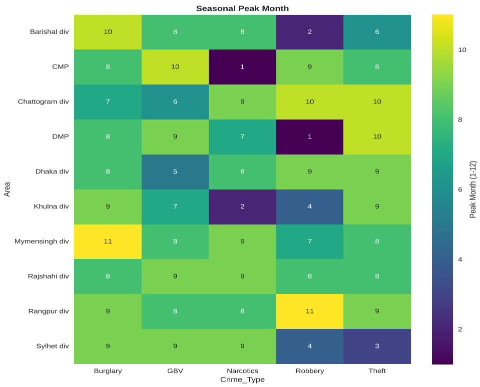
Among the regions as depicted in Fig. 1b, narcotics-related crimes are high in Rajshahi division (78.90%), Dhaka city (76.70%), and Chattogram division (74.10%) while GBV rate is high in Barishal (29.67%), Rangpur (28.85%), and Mymensingh division (28.56%). The percentage of theft is highest in Sylhet division (14.53%) while the rate is consistent in other areas (within 7-8 %). Robbery is the least reported crime across the regions, and the percentages of burglary and robbery are high in the Chattogram and Dhaka metropolitan cities, along with the Chattogram division.



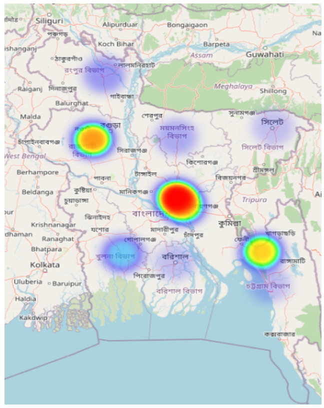
(a) Monthly crime distributions



(b) Regional distribution of crime



(c) Seasonal peak of crimes



(d) Hotspot of Narcotic-related crimes

Fig. 1: Regional and monthly distributions of crime in Bangladesh (2019-2024)

The total number of crimes in the eight divisional areas is 523582, which is higher than that of the two metropolitan cities, 138571. However, the monthly average number of property crimes (theft and burglary) in metropolitan cities (63.7) is higher than that of divisional areas (44.1). Similarly, the monthly average number of robbery and narcotics-related crime is higher (14.6 and 776.8) in metropolitan cities than that of divisions (9.4 and 677.3). This indicates the prevalence of property and violent crimes with urbanization. In contrast, the monthly average of GBV is higher (211.5) in divisions than in these two metropolitan cities (130.9).

According to the heatmap of the monthly seasonal peak of crimes shown in Fig. 1c, across the country, these five types of crime spike during August, September, and October in the year, particularly property crimes and drug-related crimes increase during this period, which suggests the exploration of the impact of season and related socioeconomic factors on crime.

The hotspot map in Fig. 1d shows the hotspot of narcotic-related crimes across the regions. Hotspots for other types of crimes are omitted to adhere to page limits.

3.3 Exploratory Data Analysis

Exploratory Data Analysis (EDA) was conducted to gain a comprehensive understanding of the features, patterns, trends, and correlations within the dataset. The analysis focused on identifying temporal and spatial characteristics, assessing data stability, and determining the degree of seasonality and stationarity across different crime types and regions.

Crimes such as theft, burglary and robbery exhibited an overall upward trend across all areas with strongest trend changes in robbery and theft cases. Moderate seasonality patterns and low residual volatility (standard deviation < 25) of data indicate the stability of these crimes over the years.

Narcotics-related crimes exhibit strong seasonality, particularly in Dhaka city, the Dhaka division, and divisions with border areas such as Rajshahi, Khulna, and Chattogram, although there is a decline in the trend in all regions. The number of residual volatility of the data indicates a significant COVID-19 impact and enforcement strategies of narcotics throughout the country.

Gender-Based Violence (GBV) shows mixed temporal trends across regions but maintained consistent seasonal patterns. The high residual volatility observed in GBV data underscores the need for continued attention and intervention from law enforcement agencies to mitigate this type of crime.

The statistical analyses included:

- The Augmented Dickey-Fuller (ADF) test was used to assess the stationarity of each time series.
- The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) were used to quantify dependencies between current and lagged values.

The results of these tests can be summarized as follows:

- The crime datasets of theft in all the regions were stationary, except for the CMP, Dhaka, and Rajshahi divisions, which exhibited variation in autocorrelation and limited seasonal patterns in the data.
- Burglary has stationary data except for the Chattogram divisions. All the datasets exhibit autocorrelation for short lag lengths, with seasonality present in most regions.
- The datasets of Robbery exhibit stationary behavior, except in the Dhaka and Chattogram divisions, and show no autocorrelation or autocorrelation at short lag lengths of data.
- Narcotics-related time series datasets were stationary, except in the Dhaka, Rajshahi, and Mymensingh divisions, and exhibited autocorrelation at both short and mid lag lengths, along with a seasonal pattern and high residual volatility.
- GBV datasets of all areas were stationary and exhibited autocorrelation for short lag lengths without seasonal patterns in most areas.

Overall, the EDA revealed distinct temporal dynamics across crime types and regions, highlighting the interplay between urbanization, enforcement intensity, and exogenous events such as the COVID-19 pandemic in shaping crime patterns over time.

3.4 Experimental Setup

To implement the machine learning models on the datasets, the experiment was conducted in a Google Colab environment, a cloud-based platform provided by Google, using Python. The exploratory analysis included data visualization, which was performed using Python.

Hyperparameters were tuned for all models except the Random Forest and XGBoost. Initially, the parameters were set to their default values and later adjusted through tuning and cross-validation in selected cases. Random Forest and XGBoost showed comparatively better performance at the default parameters.

For the FBProphet model, based on the presence of significant values in the Autocorrelation Function (ACF) plot for different lag lengths within 12 lags, the *cap* and *floor* value of the *logistic growth value* parameter was set. The value of the parameter *seasonality_prior_scale* was set to 0.03.

In the case of the SARIMAX model, the values of hyperparameters - *Differencing Order* (d) and *Seasonal Differencing Order* (D)- were set based on the stationarity of the data. For stationary data, the value of both was set to 0. For non-stationary data, the nonseasonal *Differencing Order* (d) was set, but the *Seasonal Differencing Order* (D) was set based on the presence of stationarity after differencing with nonseasonal order to avoid over-differencing. The non-seasonal and seasonal Autoregressive (AR) order and Moving Average (MA) order of the model were set based on the presence of significant values in the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plot for different lag lengths. Later, the orders were computed based on the performance of the model with a lower AIC. Tuning the parameters significantly improved the forecasting performance of the SARIMAX model [17].

For the LSTM model, tuning of the hyperparameters impacts the performance of the LSTM network [12], and the prediction values, along with error parameters, differ for different epoch sizes and learning rates [19]. Given the small size of the dataset, the experiment was conducted with the hyperparameter values shown in Table 2. The parameters were tuned by experimenting with combinations of different values and comparing their performance. Increasing the epoch size beyond 100 or the unit size did not improve the performance of the model significantly. Hence, values were chosen based on their generalized performance for all types of crime data and to avoid overfitting.

Hyperparameter	units size	activation function	dropout value	learning rate	epoch	batch_size
value	10	linear	0.03	0.02	100	50

Table 2: LSTM hyperparameter

All models were trained using time series data on crime in Bangladesh. For the LSTM model, numerical features were normalized and scaled using Min-Max Scaling techniques, while other models did not require feature scaling. The forecasting test was performed using a time-based train-test split. Models were trained on data up until December 2023 and were then tested on data from January 2024 to June 2024 to simulate real-world forecasting scenarios. Each model was evaluated using two performance metrics that are commonly applied in predictive policing research:

- *Mean Absolute Percentage Error (MAPE)* – Computed as the absolute difference between the actual and predicted value for each data point, divided by the actual value, multiplied by 100 to get a percentage, and then averaged across all data points.
- *Root Mean Square Error (RMSE)* – the square root of the mean value of the squared differences between the predicted and actual values.

The full implementation, including model training code and experiments, is available in an open-source repository [6].

4 Discussions

Five machine learning models were used to forecast five types of crimes for the next six months across ten regions in Bangladesh. The forecasting performance was measured using two performance metrics- MAPE and RMSE. The regional performance for each type of crime is shown in Tables 3, 4, 5, 6, and 7.

ML Model	Error	DMP	CMP	Dhaka	Chattogram	Rajshahi	Khulna	Barishal	Sylhet	Mymensingh	Rangpur
FBProphet	MAPE	20.31%	30.18%	11.26%	20.58%	12.75%	38.67%	22.53%	**18.15%**	**11.93%**	16.14%
	RMSE	44.04	9.76	12.75	28.29	10.42	22.29	8.1	**8.41**	**7.04**	13.29
SARIMAX	MAPE	**19.36%**	20.04%	**9.19%**	**18.23%**	8.39%	**10.60%**	**18.29%**	18.31%	17.85%	**9.51%**
	RMSE	**42.15**	6.82	**10.09**	**25.28**	7.82	**8.01**	**6.19**	8.7	7.94	**6.54**
Random Forest	MAPE	21.1%	**12.75%**	18.43%	22.54%	**4.82%**	42.34%	27.66%	26.43%	19.55%	13.72%
	RMSE	42.08	**4.78**	20.82	31.11	**4.98**	25.12	8.81	13.17	9.41	10.54
XGBoost	MAPE	21.44%	17.24%	17.79%	22.95%	7.55%	43.13%	37.52%	31.03%	24.07%	14.68%
	RMSE	42.14	6.62	22.07	34.34	7.34	25.79	11.07	15.19	11.59	11.24
LSTM	MAPE	23.33%	29.06%	25.23%	24.54%	28.61%	40.88%	28.15%	22.84%	25.66%	24.31%
	RMSE	46.34	10.3	29.47	29.7	26.49	27.2	8.05	12.56	11.94	16.15

Table 3: Performance of machine learning models area-wise: theft

ML Model	Error	DMP	CMP	Dhaka	Chattogram	Rajshahi	Khulna	Barishal	Sylhet	Mymensingh	Rangpur
FBProphet	MAPE	23.07%	36.55%	**8.57%**	23.01%	**60.2%**	21.39%	**27.57%**	60.93%	55%	**160.26%**
	RMSE	18.82	6	**3.44**	7.78	**2.94**	3.24	**5.64**	5.1	2.38	**6.66**
SARIMAX	MAPE	30.77%	**21.18%**	11.8%	**18.72%**	100.33%	25.56%	34.95%	38.99%	68.94%	200.70%
	RMSE	23.03	**3.29**	4.19	**7.44**	4.12	4.25	5.41	3.82	2.92	8.17
Random Forest	MAPE	29.57%	34.8%	11.24%	19.16%	78.52%	**20.75%**	28.33%	55.19%	17.38%	171.97%
	RMSE	21.94	4.69	4.55	6.92	3.61	**3.03**	6.52	4.56	1.08	7.52
XGBoost	MAPE	31.08%	40.79%	10.68%	22.13%	100.74%	22.32%	30.18%	56.30%	**13.33%**	177.69%
	RMSE	23.76	6.1	4.45	7.7	5.12	3.44	6.58	4.67	**1.29**	8.76
LSTM	MAPE	**15.36%**	33.22%	19.70%	19.45%	74.04%	26.21%	29.79%	**26.56%**	29.88%	204.67%
	RMSE	**12.76**	4.52	7.65	6.99	2.98	4.1	4.22	**3.1**	1.48	8.75

Table 4: Performance of machine learning models area-wise: burglary

[6] https://github.com/rroxy08/BD-crime-data

ML Model	Error	DMP	CMP	Dhaka	Chattogram	Rajshahi	Khulna	Barishal	Sylhet	Mymensingh	Rangpur
FBProphet	MAPE	**21.93%**	43.76%	28.99%	26.00%	48.52%	54.09%	**1.5**	61.31%	**31.67%**	88.65%
	RMSE	**6.58**	4.97	9.48	6	4.88	3.63	**1.35**	1.73	**1.63**	2.35
SARIMAX	MAPE	23.60%	**33.17%**	**25.62%**	24.27%	23.73%	44.74%	1.95	58.48%	35.05%	44.75%
	RMSE	7.19	**3.63**	**7.37**	6.07	2.14	1.94	1.55	1.97	1.82	1.93
Random forest	MAPE	30.47%	35.56%	30.74%	**19.24%**	**20.69%**	61.11%	1.5	**41.87%**	35.00%	**40.08%**
	RMSE	7.9	3.14	7.6	**5.6**	**1.87**	2.89	1.58	**1.83**	1.87	**1.83**
XGBoost	MAPE	38.00%	45.55%	40.71%	23.00%	20.69%	71.39%	1.5	68.65%	55.00%	49.37%
	RMSE	9.15	4.18	10.28	5.58	1.87	3.06	1.58	2.08	2.24	1.68
LSTM	MAPE	36.98%	34.59%	40.95%	35.40%	22.13%	**43.11%**	1.99	55.93%	36.16%	43.17%
	RMSE	9.93	3.99	11.12	9.84	3.13	**1.88**	1.62	1.99	1.88	1.97

Table 5: Performance of machine learning models area-wise: robbery

ML Model	Error	DMP	CMP	Dhaka	Chattogram	Rajshahi	Khulna	Barishal	Sylhet	Mymensingh	Rangpur
FBProphet	MAPE	**8.59%**	**24.82%**	13.04%	**12.69%**	10.02%	9.22%	**7.03%**	**16.29%**	39.25%	**8.68%**
	RMSE	**73.17**	**44**	136.59	**93.84**	123.14	67.89	**14.78**	**18.82**	114.46	**49.29**
SARIMAX	MAPE	17.70%	28.99%	**8.26%**	21.34%	14.95%	**8.41%**	10.83%	20.97%	45.38%	9.20%
	RMSE	139.26	50.9	**105.71**	160.2	148.65	**54.7**	21.9	22.91	123.44	57.74
Random Forest	MAPE	60.03%	27.74%	14.29%	42.55%	10.52%	11.81%	25.16%	64.14%	**15.7%**	14.57%
	RMSE	430.02	48.89	139.68	303.71	107.11	86.22	48.97	65.1	**46.97**	75.41
XGBoost	MAPE	56.73%	30.03%	14.79%	40.56%	**9.89%**	13.28%	24.43%	61.57%	16.62%	14.63%
	RMSE	409.63	52.02	142.78	295.02	**107.24**	94.49	50.45	66.17	51.63	79.9
LSTM	MAPE	84.90%	39.73%	17.34%	50.28%	17.45%	9.10%	40.42%	84.22%	32.82%	18.37%
	RMSE	604.34	100	244.6	356.39	178.81	70.86	78.67	85.88	118.59	91.01

Table 6: Performance of machine learning models area-wise: narcotics

ML Model	Error	DMP	CMP	Dhaka	Chattogram	Rajshahi	Khulna	Barishal	Sylhet	Mymensingh	Rangpur
FBProphet	MAPE	23.66%	24.71%	15.12%	27.52%	21.52%	26.23%	**24.47%**	**29.86%**	15.32%	17.9%
	RMSE	41.88	14.43	51.73	50.67	50.47	40.26	**39.1**	**13.14**	18.34	45.36
SARIMAX	MAPE	25.45%	**19.73%**	27.14%	16.54%	24.94%	31.95%	29.01%	39.77%	**10.62%**	25.83%
	RMSE	45.07	**11.96**	88.22	35.01	57.61	49.08	48.57	17.2	**14.25**	61.89
Random Forest	MAPE	**9.60%**	27.25%	**10.91%**	**8.43%**	**6.61%**	**20.83%**	31.23%	32.45%	24.83%	**17.5%**
	RMSE	**13.68**	11.36	**33.13**	**15.7**	**15.13**	**25.16**	45.44	14.17	31.74	**32.16**
XGBoost	MAPE	10.46%	25.57%	12.42%	10.68%	8.76%	23.28%	33.39%	32.76%	25.17%	18.72%
	RMSE	14.27	11.86	36.84	20.83	23.6	29.19	49.41	15.75	31.9	35.63
LSTM	MAPE	38.92%	85.62%	17.70%	40.32%	19.40%	46.73%	24.67%	76.03%	56.87%	27.45%
	RMSE	57.13	30.12	49.51	71.39	42.16	53.52	38.96	31.04	63.33	51.26

Table 7: Performance of machine learning models area-wise: GBV

ML Model	Error	Theft	Burglary	Robbery	Narcotics	GBV
FBProphet	MAPE	**5.90%**	11.08%	14.38%	6.98%	20.34%
	RMSE	**45.72**	26.55	21.56	418.1	332.49
SARIMAX	MAPE	7.97%	15.05%	**13.80%**	**6.73%**	27.31%
	RMSE	74.21	34.39	**21.08**	**393.59**	452.56
Random Forest	MAPE	6.52%	12.09%	14.94%	21.72%	**7.21%**
	RMSE	55.25	26.27	19.7	1122.89	**109.34**
XGBoost	MAPE	8.55%	13.26%	17.41%	20.71%	10.12%
	RMSE	68.88	29.48	21.04	1103.7	140.41
LSTM	MAPE	18.17%	**7.96%**	23.08%	30.39%	28.94%
	RMSE	142.41	**15.63**	32.05	1646.59	422.51

Table 8: Performance of ML models - Ten areas

For the theft and narcotics-related crime datasets, SARIMAX and FBProphet demonstrated good performance and were competitive in most regions, respectively, although the error rates of both ML models were close. For the robbery dataset, the SARIMAX, FBProphet and Random Forest performed well. In contrast, Random forest excelled for GBV-related crimes while the FBProphet model, SARIMAX, and LSTM outperformed across different regions for burglary.

The FBProphet model excelled for data sets with autocorrelation on short lag lengths, seasonal patterns, and residual volatilities, while the SARIMAX worked well for autocorrelated data with variation of lag lengths with or without seasonal patterns. The Random Forest regressor outperformed other models for datasets with nonstationary data or data with no autocorrelation, i.e., independent data from each other. Performance of XGBoost was similar to Random Forest. Although LSTM performs well for nonlinear complex data [13], it did not outperformed other models in this study, except for Burglary in three regions. The reason may be, the short-range dataset does not contain enough data to train the model fully.

The ML models were employed again to have a robust observation on prediction performance for the five types of crime by aggregating the ten areas as different geographic regions namely - Metro cities (DMP and CMP), Coastal region (Chattogram and Barishal div), Northern region (Rajshahi, Rangpur and Mymensingh division), Southern region (Khulna division), Eastern region (Sylhet division) and Central region (Dhaka division). Fig. 2 shows the comparison of ML models' performance based on Mean Absolute Percentage Error (MAPE) errors. A low value indicates less error and better performance. For the geographic regions, SARIMAX excelled for theft and Robbery, while FBProphet performed well for narcotics-related crimes. Random Forest surpassed other models in predicting GBV cases, while LSTM and Random Forest outperformed for Burglary. A similar observation is seen for the prediction of crimes by aggregating the crime data of the ten areas. The errors are shown in Table 8.

5 Conclusions and Future Work

This study presents an in-depth spatio-temporal analysis and forecasting of crime trends in Bangladesh using monthly crime data from January 2019 to June 2024. The descriptive analysis identified clear spatial patterns, such as the high prevalence of narcotics-related crimes in border divisions like Rajshahi, while property crimes concentrated in metropolitan regions, highlighting the influence of urbanization. Temporally, the data clearly captured the impact of external shocks, such as the COVID-19 pandemic, and identified varying seasonal patterns across different crime types.

The comparative evaluation of forecasting models demonstrated that there is no universally superior model. Instead, the performance of each model is highly dependent on the intrinsic characteristics of the crime data. SARIMAX demonstrated strong forecasting capabilities for stationary crime data with auto-

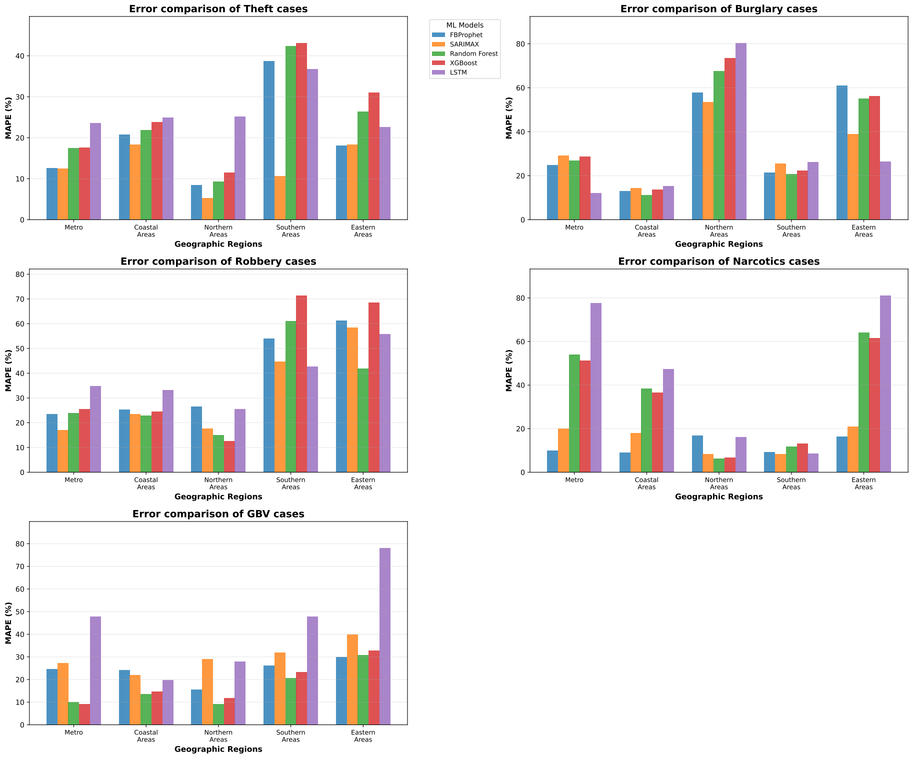


Fig. 2: Error comparison of machine learning models

correlations at different lag lengths and low residual volatility (e.g., theft). The FBProphet model performed well for crime data with short-term auto-correlation having strong seasonal patterns and high residual volatility (e.g., narcotics-related offences). Random Forest demonstrated strong predictive capability for non-stationary data or stationary data with no autocorrelation (e.g., GBV). The performance of XGBoost was similar to Random forest regressor but could not outperform it. On the other hand, the LSTM model, although effective for identifying complex non-linear patterns, likely underperformed due to the limited size of the training data. Based on the performance of the ML models clearly SARIMAX, FB prophet and Random Forest are best performing models among the five. Law enforcement agencies will have a detailed understanding of the spatial and temporal relationships of crime, along with crime hotspot identification and fluctuation over time, and will be able to adopt an effective policing strategy and make informed decisions on personnel and resource allocation to prevent future occurrences of crime. A model-selection framework based on crime type characteristics can significantly improve the accuracy of predictive policing initiatives.

Future research work can lead to several directions. One of them should incorporate exogenous factors such as socioeconomic indicators, weather, public events, and policing intensity to improve model robustness. The availability of district, upazila, and thana-level data over extended periods would benefit models in providing more reliable and comprehensive forecasts. Additionally, developing ensemble or hybrid models may lead to more robust predictions. Lastly, implementing a real-time forecasting and data visualization dashboard could transform these analytical insights into practical decision-support tools for law enforcement agencies.

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