

Crime Forecasting: A Spatio-temporal Analysis with Deep Learning Models

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Abstract: This study uses deep-learning models to predict city partition crime counts on specific days. It helps police enhance surveillance, gather intelligence, and proactively prevent crimes. We formulate crime count prediction as a spatiotemporal sequence challenge, where both input data and prediction targets are spatiotemporal sequences. In order to improve the accuracy of crime forecasting, we introduce a new model that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. We conducted a comparative analysis to access the effects of various data sequences, including raw and binned data, on the prediction errors of four deep learning forecasting models. Directly inputting raw crime data into the forecasting model causes high prediction errors, making the model unsuitable for real - world use. The findings indicate that the proposed CNN-LSTM model achieves optimal performance when crime data is categorized into 10 or 5 groups. Data binning can enhance forecasting model performance, but poorly defined intervals may reduce map granularity. Compared to dividing into 5 bins, binning into 10 intervals strikes an optimal balance, preserving data characteristics and surpassing raw data in predictive modelling efficacy.

Keywords: crime forecasting; time series data; deep learning; data binning

1. Introduction

Although there are many methods to predict crimes, there is no perfect solution to predict where and when crimes may occur, who may commit crimes, and who is most likely to offend or suffer in the future. The occurrence of crimes is difficult to predict, many of which cannot be described quantitatively. Near-repeat victimization (NRV)[1] pertains to an elevated risk of victimization that exhibits trends in spatiotemporal proximity. When a crime takes place at a particular location, there is an increased likelihood that additional crimes will occur in the vicinity within a given time frame. Near-repeat victimization is a fundamental concept in crime forecasting, providing a basis for understanding and predicting crime patterns.

Recently, deep learning technology is often used in crime modeling and prediction. Deep learning, ML, and computer vision offer a new way for intelligent surveillance. It mimics human approach, operates 24/7, and repeats tasks consistently once trained[2]. To address the evolving landscape of financial crime[3], group anomaly detection, graph theory, and deep learning are being combined to detect networks of malicious actors among the broader groups of users. By applying data fusion to the ConvBiLSTM model[4], Tam, S. et al. extracted vectors from tweet and crime modalities and merge them into a single representation that captures all-modality information. The study aims to use semantic knowledge from text and crime data, and transfer it to a crime-prediction model to improve its predictive ability with multi-source info. Tariq et al.[5] developed a time series forecasting model utilizing a RNN combined with LSTM to predict daily and monthly violent crime rates in Philadelphia. The integration of LSTM with RNN helps mitigate issues related to gradient explosion and gradient vanishing. Sandagiri et al.[6] proposed a framework for crime prediction, which comprises three main modules: data collection, crime detection, and crime prediction, with the Long Short-Term Memory (LSTM) neural network model serving as the proposed approach. Tasnim et al. [7] analyzed the crime forecasting problem using deep learning techniques. They proposed a fusion method based Attention-LSTM has Feature Level Fusion and Decision Level Fusion model. Introducing the Transfer learning technique reduced the training time to a certain amount.

A variety of spatiotemporal statistical techniques are commonly employed to forecast criminal incidents. Time series and deep learning techniques are useful for crime trend prediction. Incorporating spatial and temporal info in crime datasets boosts the accuracy and reliability of prediction systems[8]. Liang, W. et al.[9] proposed CrimeTensor, a tailored framework. It uses tensor learning with spatiotemporal consistency to predict crime incidents in different categories per target region. Muthamizharasan et al.[10] endeavored to predict crime rates by employing a CNN-LSTM model. In this approach, CNN was utilized to extract features from the dataset, while LSTM was leveraged to analyze the temporal relationships within long-term data. Their findings indicated that the combination of CNN and LSTM yields a robust crime prediction method, achieving high levels of accuracy. Wang and Yuan[11] utilize LSTM to forecast the daily occurrences of criminal events in Atlanta. By using LSTM, they are able to capture the dependencies in the time lag as well as the spatial distribution of these criminal events. In addition, they discuss the effects of different spatiotemporal scales on the accuracy of crime prediction.

2. Related work

2.1 1D convolutional neural networks (1D CNN)

A one-dimensional convolution kernel filter, which focuses solely on 1D data and signals, can be employed to extract convolution information from the local perceptual field through a sliding window approach. The input tensor sequence of 1D CNN is shown in 3.4. Each tensor in the sequence represents the crime data of all grids in the adjacent region of the grids to be forecast simultaneously. We process each tensor d_t using Conv1D layer. Extracting the spatial features between adjacent spots proves highly advantageous. Then, the dangerous local features can be detected and localized from the global feature.

2.2 Recurrent Neural Network (RNN)

RNNs made their debut in the 1980s, with researchers such as David Rumelhart, Geoffrey Hinton, and Ronald J. Williams making substantial contributions to their development. [12]. Two notable types of RNN models that were proposed during this time are the Hopfield networks and the Cohen–Grossberg models. RNNs represent a category of neural networks specifically engineered to manage sequential information, including time series and natural language. Unlike conventional feedforward neural networks that process data in a static, unidirectional manner, RNNs incorporate a loop within their structure, enabling them to retain an internal state and demonstrate dynamic temporal characteristics.

2.3 Long short-term memory (LSTM)

LSTM Networks were indeed proposed in 1997 by Schmidhuber, J. and Hochreiter, S.[13] Their groundbreaking paper, titled "Long Short-Term Memory," presented LSTM as a remedy to the vanishing gradient issue commonly encountered in traditional RNNs when handling extended sequences of data. The LSTM framework is constructed to capture long-term dependencies in data through the incorporation of a gating mechanism, enabling the network to retain or discard information selectively across different time durations.

A normal LSTM network consists of various memory components known as cells. A typical LSTM unit is composed of one or more memory cells along with three multiplicative gates: an input gate, an output gate, and a forget gate. The cells retain values across time intervals, while the three gates control the flow of information into and out of the cells. The LSTM model used in this article was proposed by Gers, F. A. et al. [14], and each unit activation can be calculated as follows:

$$i_t = \sigma(W_i d_t + H_i h_{t-1} + C_i c_{t-1} + b_i) \quad (1)$$

$$o_t = \sigma(W_o d_t + H_o h_{t-1} + C_o c_{t-1} + b_o) \quad (2)$$

$$f_t = \sigma(W_f d_t + H_f h_{t-1} + C_f c_{t-1} + b_f) \quad (3)$$

$$c_t = f_t c_{t-1} + i_t \tanh(W_c d_t + H_c h_{t-1} + b_c) \quad (4)$$

$$h_t = o_t \tanh(c_t) \quad (5)$$

Where tensor sequence d_t are inputs, i_t , o_t , f_t , and c_t correspond to the vectors for input gates, output gates, forget gates, and cell activations the moment t. W , C and H describe weight matrices from input to gates, cell activations to another component, and hidden vectors. b_i , b_o , b_f and b_c denote input, output, forget gates and cell activations bias vectors. σ is a *sigmoid* function.

2.4 Gated Recurrent Units (GRU)

GRUs were proposed in 2014 by a team of researchers led by Cho, K. et al.[15] The GRU was introduced as an alternative to the LSTM network, offering a more computationally efficient model with fewer parameters. The GRU streamlines the LSTM architecture by merging the forget and input gates into a unified update gate and introducing a reset gate to regulate the impact of past information. This architecture enables the GRU to selectively retain information from prior time steps, rendering it highly advantageous for tasks involving sequential data, such as language modeling, speech recognition, and time series prediction. Since its inception, the GRU has gained widespread popularity in deep learning for sequence modeling applications.

2.5 Model performance

We use RMSE (Root Mean Square Error), MAE (Mean Absolute Error) and MSE (Mean Squared Error) to measure the accuracy of forecast. RMSE is defined as follow:

$$RMSE = \sqrt{\frac{1}{N*T} \sum_{i,t} (\hat{y}_{i,t} - y_{i,t})^2} \dots\dots(6)$$

$$MAE = \frac{\sum_{i,t} |\hat{y}_{i,t} - y_{i,t}|}{N*T} \dots\dots(7)$$

$$MSE = \frac{1}{n} \sum_{t=1}^n (\hat{y}_{i,t} - y_{i,t})^2 \quad (8)$$

Where N denotes the total number of grids into which the selected area is divided, T represents the number of time slots taken into account, $y_{i,t}$ and $\hat{y}_{i,t}$ correspond to the actual and predicted crime intensity in grid i at time t , respectively.

3. Crime forecasting model specifics

3.1 Data Analysis

The crime data utilized in this study are sourced from Open Data Philly, which serves as a repository of open datasets in the Philadelphia area for a 5-year period from January 2017 through the end of December 2021. In order to demonstrate our model simply and effectively, we use all criminal records regardless of their types.

The risk expectation level at a specific location—a relative measure—is determined by aggregating risk contributions derived from historical crime data and external factors. The box plot shows differing patterns for crimes per hour in Figure 1. Crimes (regardless of type) tend to occur during the daytime and are concentrated between 8:00 p.m. and midnight. The concentration in the daytime may be mainly due to the time when the data was reported, rather than the time when the actual crime occurred, such as the most common theft. Figure 2 reflects the daily new crime cases transits with Low temporal regularity.

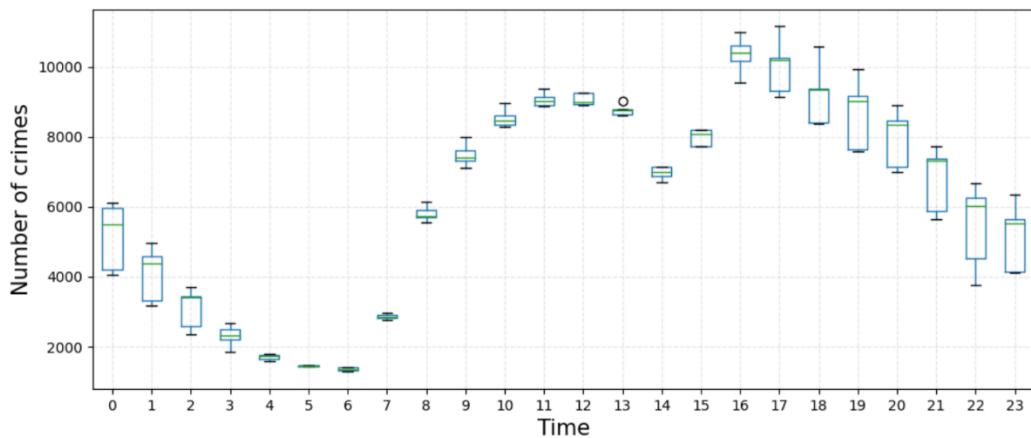


Figure. 1 Depicts hourly crime data intensity of 5 years in Philadelphia (2017-2021)

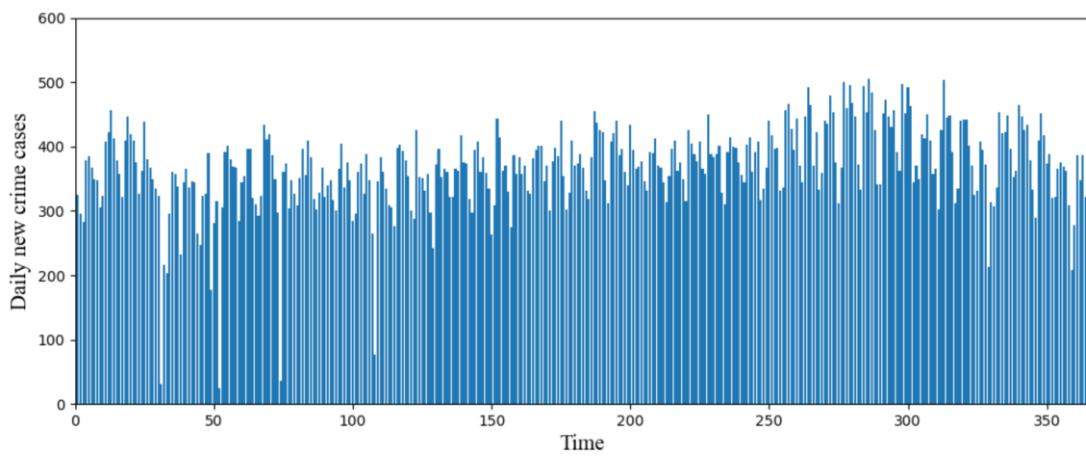
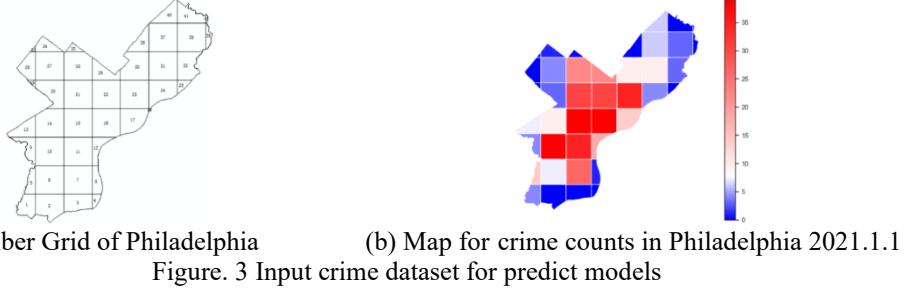


Figure. 2 Number of crimes per day in 2021 in Philadelphia

3.2 Grid Mapping

We extracted from the source data the time-stamps and the longitude and latitude of their locations. In Figure 3, We divide the Philadelphia map into grids of scale 5000m*5000m (42 cells). According to the coordinate, all crime data are appropriately mapped to each space of the grid. The number of crimes in each cell is filled with red

and blue. Red is highest count and blue is lowest.



We use roughly more than 730,000 crime records of Philadelphia from 2017 to 2021, where each record contains a lot of informative fields. The crime date and location information , such as longitude, latitude, are used in our forecasting networks. The crime data are first aggregated based on grid position and day so as to feed the model.

The initial crime dataset is denoted as $d = (d_1, \dots, d_T)$ for $t = 1 \dots T$, representing a sequence of crime quantity vectors. In the grid-based input format, the grid quantity vector at time t , $d_t = (d_1^t, \dots, d_G^t)$ for $g = 1, \dots, G$, where d_g^t signifies the total number of crimes that occurred in the g-th spatial cluster grid during time period t . These crime data vectors are derived from the original dataset, which includes the four attributes detailed in Table 1. As shown in Figure 3 for grid partitioning, the crime vector on January 1, 2021 is $d_1 = (3, 0, 0, 0, 7, 5, 15, 1, 3, 33, 29, 11, 5, 6, 37, 39, 7, 0, 0, 2, 18, 18, 29, 3, 0, 0, 3, 13, 13, 6, 6, 2, 0, 1, 0, 0, 4, 2, 0, 4, 0, 0)$. There are three criminal incidents took place in cell 1, and zero in cell 2, 3, 4, 17, 18, 24, 25, 32, 34, 35, 38, 40, 41. Using the same method, we can obtain d_2, \dots, d_{10} a crime dataset for a total of 10 days from January 2nd to January 10th. The process of merging raw data and transforming it into grid-based input datasets is illustrated in Table 2. The initial crime dataset d can be directly utilized as input for constructing the deep learning model.

Table 1 Raw dataset

point x	point y	dispatch date	objectid
39.95623732	-75.14326837	2021-9-19	9096588
40.05434623	-75.14078766	2021-9-19	9071176
39.95080482	-75.15444697	2021-9-19	9122608
40.0827525	-75.02498382	2021-9-19	9097975
39.91772028	-75.1876692	2021-9-19	9097005
...

Table 2 Grids input dataset

g1...g27	g28	g29	g30	g31	g32	g33...g42	dispatch_date
...	22	3	8	5	1	...	2021-9-19
...	21	11	14	10	3	...	2021-9-20
...	25	10	21	15	1	...	2021-9-21
...	27	11	12	17	3	...	2021-9-22
...	11	11	11	10	3	...	2021-9-23
...

3.3 Data binning

With the rise of computer science and the field of machine learning, data binning techniques have undergone further development and optimization. They are employed not only for simplifying data but also in feature engineering processes. For instance, binning simplifies data by decreasing the number of unique values it contains, which can make it easier to analyze and visualize. In machine learning, binning can be used to create new features that might be more informative for certain models, especially those that do not handle continuous data well, like decision trees. Some commonly used methods of data binning are as follows: Equal Width Binning, Equal Frequency Binning, Clustering-based Binning, Custom Binning, etc.

In this paper, we choose Equal Width Binning method based on the characteristics of time series crime data and computing resources. First, sort the number of crimes in the grid any period to find the maximum value d_{max} ,

minimum value d_{min} , the number of boxes N represents placing the data into N bins. Second, each bin maintains the crime counts in equal intervals for classification. Equation 6 calculates l which represents the interval width of the bin; Equation 7 calculates χ_n , the interval boundary values of n th box.

$$l = \frac{\chi_{max} - \chi_{min}}{N} \quad (9)$$

$$\chi_n = \chi_{min} + (n - 1)l \quad (10)$$

The value range of crime data is evenly divided into 10 intervals and 5 intervals for experiments, the data distribution is shown in the Figure 4 shows the grid crime counts of each bin (with 7 or 14 intervals between each bin) for Philadelphia in 2021. It seems obvious that the grid crime count range is within 8 (box number 0) is clearly overwhelming.

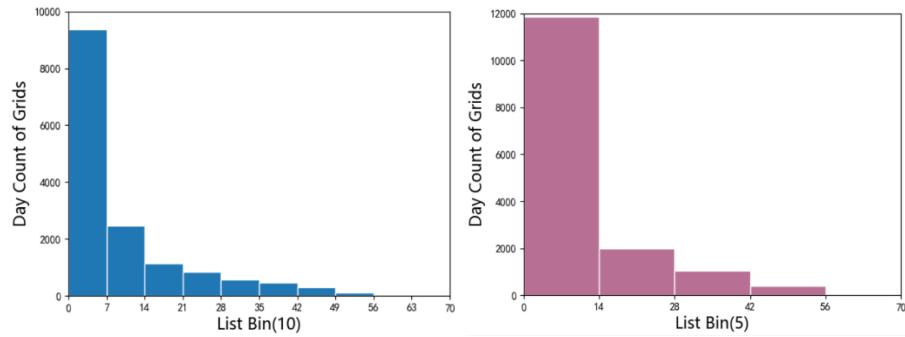


Figure.4 Bin counts of crimes in Philadelphia in 2021

3.4 Forecasting model

The architecture proposed for crime nowcasting is depicted in Figure 5. There are 1 Conv1D layer and 2 LSTM layers in this architecture. The Convolutional LSTM model learns the input data preprocessed every 8 days through the sliding window algorithm. The convolution and pooling layers of the 1D CNN improve features extraction from crime data. The LSTM layer learns a representation that analyses the nonlinear dependency over the previous event sequence. Finally, the convolutional LSTM method can output spatial-temporal crime forecasting on next time step. The prediction model performance is analyzed and evaluated by several error metrics.

In Figure 5, D represents the dataset of multidimensional vectors x_i with $i \in \{1, \dots, n\}$, where each x_i contains information on the time, the location (longitude and latitude). Assuming that the crime data is observed on a geographical area represented by an $M \times N$ grid, comprising of M rows and N columns. Within each grid cell, there exist P measurements that change over time. Because crime data is time-series, the x_i data points mapped corresponding cell are also split at times. The crime data at any time can be represented by a tensor $d \in D^{P \times M \times N}$. Given the previous I observations of a sequence of tensors $\tilde{d}_{t-I+1}, \dots, \tilde{d}_t$, predicting the most likely length- J sequence of $\tilde{d}_{t+1}, \dots, \tilde{d}_{t+J}$ in the future can be described as follows:

For crime prediction, the observation at each timestamp is a 2D two-color grid map.

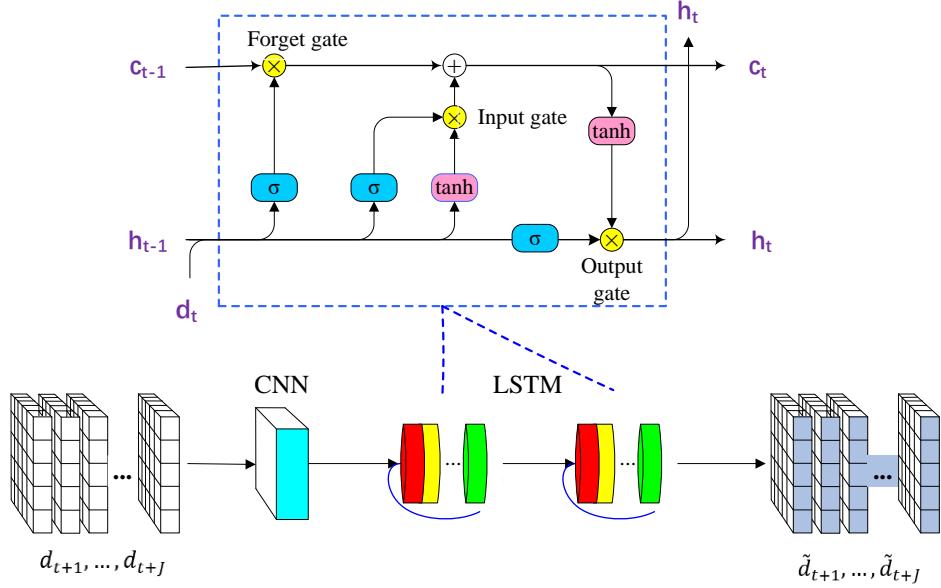


Figure. 5 The architecture of the proposed Convolutional LSTM

4. Experiments

In this section, we present a series of meticulously designed experiments aimed at assessing the accuracy and practicality of the neural network models. The experiments make use of data sources expounded upon in Section 3 for each and every model delineated in Section 2.

Table 3. Analysis results of prediction models

Data	Models	MSE	RMSE	MAE
Raw data	Convolutional LSTM	18.426174	4.292572	2.539324
	RNN	15.921171	3.990134	2.404256
	GRU	15.680926	3.959915	2.370931
	LSTM	15.526878	3.940415	2.358028
Data bin(10)	Convolutional LSTM	0.620420	0.787667	0.469292
	RNN	0.640877	0.800548	0.487625
	GRU	0.657954	0.811144	0.482966
	LSTM	0.641788	0.801116	0.484547
Data bin(5)	Convolutional LSTM	0.171270	0.413848	0.231429
	RNN	0.174156	0.417320	0.232986
	GRU	0.178365	0.422333	0.233482
	LSTM	0.177826	0.421695	0.235216

Table 3 presents the performance comparison of various neural network models, namely Convolutional LSTM, RNN, GRU, and LSTM, when applied to crime prediction. The evaluation metrics used are MSE, RMSE, and MAE.

For the raw data, the LSTM model performs the best among the models with an MSE of 15.526878, MAE of 2.358028, and RMSE of 3.940415. Lower error values imply more accurate predictions, thus LSTM seems to be the most effective for the raw data. Directly inputting raw crime data into the forecasting model would lead to prohibitively high prediction errors, thereby making the forecasting models unsuitable for practical use in real-world scenarios.

When the data is binned into 10 bins, the Convolutional LSTM model has an MSE of 0.620420, MAE of 0.469292, and RMSE of 0.787667. Error values for the RNN, GRU, and LSTM models are slightly elevated. Here, the Convolutional LSTM model shows the lowest error values among the four models, indicating better performance for this data binning.

For the data binned into 5 bins, the Convolutional LSTM model again shows relatively lower error values compared to the other models, suggesting it is more suitable for data binned into 5 bins.

Overall, the LSTM model performs best for the raw data, while for the data binned into 10 groups and 5 groups, the Convolutional LSTM model shows better performance. This indicates that the optimal choice of model

depends on the data pre-processing methods, including whether to bin the data and the number of bins.

Binning the data generally improves the performance of these neural network based models, as indicated by the reduction in MSE, RMSE, and MAE values. And a smaller number of bins (in this case, bin(5)) seems to lead to better performance compared to a larger number of bins (bin(10)) for these models.

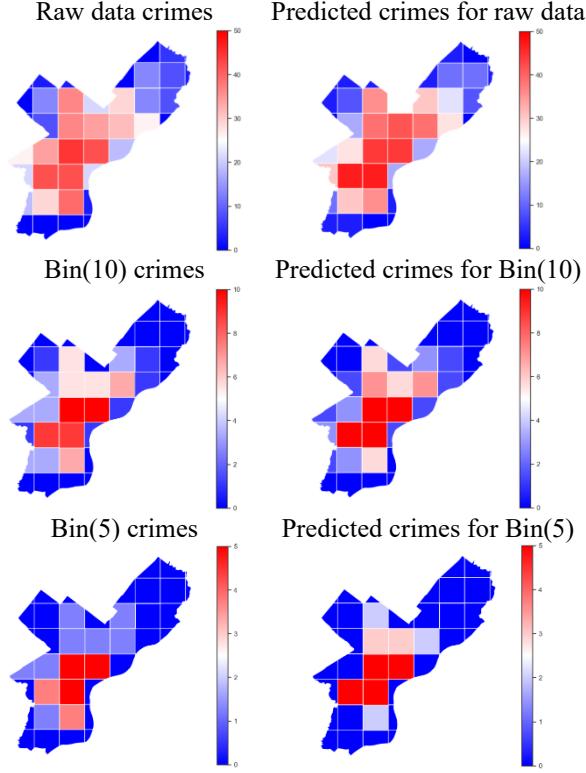


Figure. 6 Crime maps in Philadelphia on a certain day in 2021.

Figure 6 showcases different spatial crime forecasting effects with different types of crime data in Philadelphia. The color ranges from blue to red, indicating the crime quantity from low to high. Although Table 3 shows data binning significantly improves the performance of predictive models, binning crime data causes a degradation in the granularity of maps, resulting in less detailed representations. When the data is binned into 5 groups, the bin size proves overly large. As a result, the data within each bin turns out to be extremely heterogeneous. This heterogeneity poses a challenge for the model, hampering its ability to effectively capture the underlying patterns. Binning the data into 10 intervals is an optimal choice. It effectively retains the intrinsic characteristics of the data while significantly improving the performance of the predictive model compared to using raw data.

5. Conclusion

In this paper, we present a novel architecture that leverages Convolutional LSTM to accurately predict crime occurrences. The architecture utilizes spatial grids as basic units, allowing for the identification of regions where crimes regardless of type, informed by the principles of near-repeat victimization. Temporal segmentation and windowing were employed to structure the time series dataset, enabling its use for training and testing deep learning prediction models. Feeding raw crime data directly into the forecasting model would result in unacceptably high prediction errors, rendering the model impractical for real-world applications. Binning the original crime data as a preprocessing step can significantly enhance the predictive performance of deep learning models. Relative to traditional RNN, GRU, and LSTM models, the proposed Convolutional LSTM prediction model exhibits better performance, as evidenced by lower values of MSE, RMSE, and MAE. Compared to binning into 5 intervals, using 10 intervals is optimal. It retains data characteristics better and improves model performance more than raw data.

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