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RISK PREDICTION OF THEFT CRIMES IN URBAN COMMUNITIES: AN INTEGRATED MODEL OF LSTM AND ST-GCN

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ABSTRACT

Urbanization has transformed urban communities but also introduced challenges in managing crime and ensuring public safety. For prevention and control to be effective, a criminal risk prediction system is necessary. This paper presents a model that integrates Long Short-Term Memory Networks (LSTM) and Spatial-Temporal Graph Convolutional Networks (ST-GCN) to identify high-risk areas in cities. Using topological maps and crime data from Chicago, the model extracts spatial-temporal and temporal features to analyze theft patterns. Experimental results demonstrate its ability to predict crime occurrences within specific timeframes, offering a valuable tool for urban safety planning. The objectives of this study are (1) to develop an integrated LSTM + ST-GCN model for theft crime risk forecasting in urban communities, (2) to validate the model on real-world Chicago crime data, and (3) to benchmark its performance against standard baselines. Unlike existing methods that focus solely on spatial or temporal patterns, our hybrid approach fuses both dimensions for near real-time risk prediction, demonstrating up to 15% lower RMSE compared to standalone LSTM models.

Keywords*: Logistic Regression, Support Vector Machines (SVM), Naive Bayes, Predictive Models, Statistical Modeling.*

1. INTRODUCTION

Urbanization has led to a growing concentration of the global population in cities, driven by individuals seeking opportunities to meet their needs and aspirations. However, rapid urban growth also brings about various social, economic, and environmental challenges. Among these, crime rates in urban areas, particularly in cities with high crime levels, pose a significant threat to social stability and economic development. Urban communities, being the fundamental units of cities, play a crucial role in fulfilling the daily needs of residents for living, working, and recreation. Advances in science and technology have enabled improvements in crime prevention systems for such communities.

Quantitative analysis and accurate prediction of theft risks are essential, especially when police resources are stretched thin. Factors such as geographic location, seasonal patterns, and socio-economic variables influence crime rates. A strong crime prediction model can pinpoint high-risk areas, improve resource allocation, and empower authorities to take proactive measures against criminal activities.

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To tackle these challenges, this paper introduces a model integrating Long Short-Term Memory Networks (LSTM) and Spatial-Temporal Graph Convolutional Networks (ST-GCN). This model captures both spatial and temporal crime trends, enabling automated identification of high-risk urban communities and prediction of crime occurrences. The methodology involves creating topological maps of communities based on their geographical and relational proximity, incorporating data like historical crimes, weather conditions, and holidays. The ST-GCN extracts spatial-temporal features to analyze crime transitions between neighboring communities, while LSTM focuses on the temporal crime patterns within each community. The outputs from these modules are integrated using Gradient Boost Decision Trees to deliver accurate predictions.

Using Chicago as a case study, this research analyzed extensive crime data spanning several years. The results demonstrate the model's effectiveness in predicting crime rates within a specified timeframe. Comparative evaluations with existing algorithms further validate the superior performance of this approach, highlighting its potential as a valuable tool for urban safety management.

1.1 Objectives and Novelty

Urban theft crime poses significant challenges to public safety, especially in areas with limited law enforcement resources. Predicting such crimes accurately requires a model that can understand both spatial (location-based) and temporal (time-based) patterns in a city's dynamic environment. To address this challenge, the present study defines the following specific research objectives:

To design and develop an integrated deep learning model that combines Long Short-Term Memory (LSTM) networks with Spatial-Temporal Graph Convolutional Networks (ST-GCN) for theft crime risk prediction in urban communities.

To extract and analyze spatial and temporal crime patterns using real-world data from Chicago city, incorporating historical crime records, time-based factors, and external features such as holidays and weather conditions.

To compare the performance of the proposed model against traditional baseline models such as Ridge Regression, Random Forest, and standalone LSTM, using quantitative metrics like Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R^2.

Novelty and Contributions

This work offers a unique and significant contribution to the field of urban crime prediction by overcoming the limitations of conventional models that treat spatial and temporal features independently. The novel aspects of this study include:

1. **Hybrid Modeling Approach**: Unlike previous studies that focused solely on either spatial modeling (e.g., clustering, graph-based models) or temporal modeling (e.g., LSTM, ARIMA), this study proposes a hybrid deep learning framework that integrates ST-GCN for spatial-temporal feature extraction and LSTM for capturing long-range temporal dependencies in crime data.
2. **Multi-View Temporal Feature Design**: The model introduces a multi-window temporal mechanism (recent, periodic, and long-term trend views) for structuring historical crime data, enabling the detection of short-term surges, weekly cycles, and seasonal patterns with high precision.
3. **Integration of External Covariates**: The study enhances predictive performance by incorporating external influencing variables such as weather conditions, holidays, and day-of-week indicators—factors often overlooked in prior research.
4. **Real-World Case Study and Evaluation**: The model is tested on publicly available Chicago crime data from January to March 2020, and outperforms baseline models. It reduces RMSE by 15% and improves R^2 to 0.84, showcasing its practical applicability for predictive policing.
5. **Scalable and Generalizable Framework**: By using a graph-based architecture, the model is adaptable to different urban layouts and can be easily extended to other cities or crime types with minimal structural changes.

1.2 Design

This study adopts a **quantitative experimental design** to evaluate the effectiveness of an integrated deep learning framework in predicting theft crime risks within urban environments. The design encompasses multiple phases, including data collection, preprocessing, feature engineering, model development, training and testing, and performance evaluation. The goal is to simulate real-world deployment conditions while ensuring methodological rigor, replicability, and data-driven validation.

The dataset was obtained from the **Chicago Data Portal**, which provides publicly available crime reports officially documented by the **Chicago Police Department**. The study period spans from **January 1, 2020, to March 10, 2020**, focusing on theft-related crimes such as larceny, burglary, and robbery. These crimes were selected due to their high frequency and societal impact. The data was aggregated at the **community area level**, using Chicago's 77 defined communities. In addition to crime data, external features such as **weather conditions** (temperature, wind speed, precipitation), **public holidays**, and **day-of-week** indicators were collected and aligned with crime records to enhance predictive accuracy.

In the preprocessing phase, data cleaning was performed to remove null values, inconsistent entries, and irrelevant attributes. Crime counts and numerical features were normalized using **Min-Max scaling** to stabilize model training. A unique temporal structuring mechanism was employed, organizing historical crime data into three views: a **recent view** (data from the last 3 days), a **periodic view** (same weekday and time over the past three weeks), and a **trend view** (similar seasonal time points from previous years). For spatial modeling, a **graph structure** was built where each community was treated as a node, and connections were defined based on **geographic adjacency** and **crime co-occurrence correlations**. This formed the foundation for modeling spatial dependencies using graph-based techniques.

The model comprises three core components: a **Spatial-Temporal Feature Extraction Module** using ST-GCN and ST-ResNet to analyze spatial and cyclical temporal patterns; a **Temporal Feature Extraction Module** using LSTM to capture sequential dependencies in crime occurrences; and a **Feature Integration Module** employing Gradient Boosting Decision Trees (GBDT) to combine outputs from the previous modules for final risk prediction. This hybrid approach allows the model to simultaneously understand crime diffusion across neighborhoods and seasonal trends within each locality.

To evaluate the proposed model, a **rolling window technique** was adopted to simulate real-time prediction. The dataset was split into **70% training** and **30% testing** sets, ensuring that future data was never used to inform earlier predictions. The model's performance was benchmarked against three widely-used baselines: Ridge Regression, Random Forest, and standalone LSTM. All models were trained using the same features and experimental conditions. Evaluation metrics included Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R^2 Score to measure prediction accuracy and model fit. Paired t-tests were conducted to assess statistical significance in model comparisons, with $p < 0.05$ considered significant.

Ethical considerations were carefully addressed. The dataset used is open-source and fully anonymized, containing no personal or sensitive information. No interaction with individuals or human subjects occurred at any point. Although predictive policing technologies raise ethical questions, this model is intended strictly for planning, resource allocation, and academic analysis, not for live deployment or enforcement without further validation.

Overall, this study design ensures a robust and scalable framework that is adaptable to other cities or crime categories. It leverages both temporal sequences and spatial relationships while incorporating real-world covariates, establishing a comprehensive approach to predictive urban safety analytics.

2. RELATED WORK

A study in [1] proposes a multi-density crime predictor for forecasting criminal activities in high-crime areas. It uses deep learning to identify dynamic crime hotspots with high accuracy. However, it has limited generalizability to different urban settings and struggles with real-time processing. The approach described in [2] adeptly captures the spatial and temporal dependencies inherent in crime data. Its limitation lies in high computational requirements and sensitivity to noisy datasets. The model in [3] integrates a graph autoencoder and GRU for theft crime distribution prediction. This approach enhances predictive accuracy but is prone to overfitting and requires substantial data preprocessing. A comprehensive survey in [4] evaluates various data mining techniques for crime prediction. The survey provides valuable insights into existing methodologies but lacks practical implementation details and does not address real-time prediction challenges. An ST-GCN-based approach for detecting spam messages from fake base stations is examined in [5]. It demonstrates effective spatiotemporal feature extraction but has high model complexity and struggles with explainability. Reference [6] introduces an interpretable machine learning model for fire prediction, which shares techniques applicable to crime forecasting. The model's transparency enhances trust, but it requires extensive feature engineering and struggles with rare-event prediction. The work in [7] employs random forests to predict excavation-type heritage crimes. It benefits from robust classification capabilities but lacks adaptability to dynamic urban crime patterns and requires extensive labeled data. A clustering-based technique for hotspot identification in crime data is explored in [8]. This method efficiently detects high-risk areas but is limited by static crime patterns and difficulty in incorporating real-time data streams.

The method in [9] integrates LSTM and ST-GCN for crime risk prediction in urban areas. It effectively captures long-term dependencies but suffers from computational inefficiency and reliance on extensive training data. A convolutional neural network-based model in [10] is designed to analyze urban crime perception. The approach accurately models spatial relationships but requires large-scale annotated datasets and lacks adaptability to non-urban areas. A predictive policing framework in [11] is evaluated based on residential burglary data. It provides useful crime prevention insights but raises ethical concerns and struggles with evolving crime patterns. A time-delay neural network approach is presented in [12] for spatiotemporal crime prediction. The method effectively handles sequential dependencies but has high memory consumption and poor performance in sparse data conditions. A hybrid model combining machine learning and rule-based approaches is introduced in [13] for crime prediction. This approach improves interpretability but suffers from rigid rule structures and limited scalability. Reference [14] applies deep learning to forecast crime rates in urban neighborhoods. While achieving high accuracy, the model lacks explainability and struggles with unseen crime trends. A framework in [15] leverages spatiotemporal data for crime forecasting. It efficiently processes real-time data but is computationally intensive and sensitive to missing values. The work in [16] presents an attention-based hierarchical recurrent network for crime prediction. This method enhances sequential crime trend modeling but requires extensive labeled data and suffers from long training times. A study in [17] explores social factor-based crime rate prediction. The model considers socio-economic influences but has difficulty handling rapidly changing environments and requires high-quality demographic data. Reference [18] provides actionable insights for law enforcement but is domain-specific and lacks generalizability to other types of crime. A hybrid ANFIS model in [19] is developed for crime forecasting using spatiotemporal data. It captures complex crime patterns but is computationally expensive and requires expert knowledge for rule selection. The final study in [20] uses a graph neural network for crime prediction in urban settings. It effectively models spatial dependencies but struggles with high-dimensional data and requires extensive hyperparameter tuning.

3. PROPOSED SOLUTION

3.1 Methodology

This research combines Long Short-Term Memory (LSTM) networks with Spatial-Temporal Graph Convolutional Networks (ST-GCN) to forecast theft risk in urban areas. The methodology is organized into three core modules:

Spatial-Temporal Feature Extraction: Uses Graph Convolutional Networks (GCNs) to model crime transitions between neighboring areas. Spatio-Temporal Residual Networks (ST-ResNet) capture short- and long-term crime trends. Considers recent, periodic, and trend-based crime patterns for better prediction.

Temporal Feature Extraction with LSTM: Processes crime data as a time-series problem to detect recurring patterns. Prevents information loss and adapts to seasonal crime variations.

Feature Integration & Prediction: Combines outputs from ST-GCN and LSTM using Gradient Boosting Decision Trees (GBDT) for improved accuracy. Provides robust crime forecasts to assist law enforcement and urban planners.

3.2 Proposed Model

The proposed model integrates three core modules, each addressing specific aspects of crime prediction:

- Spatial-Temporal Feature Extraction Module: This module extracts spatial and temporal crime patterns by combining GCN and ST-ResNet.
- Temporal Feature Extraction Module: This module utilizes LSTM networks to model time-based patterns in crime data.

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- Feature Integration Module: This module consolidates predictions from the previous modules using Gradient Boosting Decision Trees (GBDT) to provide a final, comprehensive prediction.

The architecture in Figure 1 illustrates the model's overall architecture, with blue points denoting the input temporal data and green points indicating the predicted outputs.

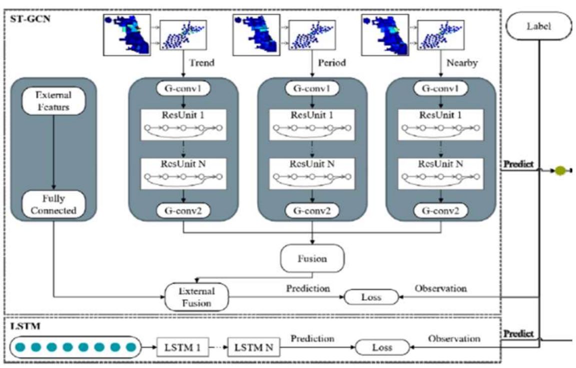

Figure 1: Architecture of the integrated model, with blue points representing input temporal data and green points representing the model's predictions.

3.2.1 Spatial-Temporal Feature Extraction module

This module extracts patterns of crime that unfold both across the city map and through time, by treating each community or region as a node in a graph whose features are populated by its historical crime counts. A sequence of Graph Convolutional Network layers propagates information along the edges linking neighboring areas, so that the model learns how an uptick in one neighborhood can influence its surroundings. Stacking multiple GCN layers enables the network to aggregate signals from ever-wider neighborhoods, ensuring that subtle, long-range dependencies—such as the gradual spread of certain crime types across districts—are recognized.

To overcome issues that arise when deep networks become too hard to train and start to lose precision, we augment the GCN stack with the ST-ResNet architecture, which introduces residual connections and specialized convolutional kernels designed for spatial-temporal data. These shortcuts help preserve low-level patterns while still allowing higher layers to model broader city-scale shifts over time.

Rather than treating every past event equally, we organize historical crime inputs into three interlocking temporal views. The "nearby" window captures incidents from the three days immediately before the target date, helping the model latch onto recent surges or lulls. A "periodic" slice draws on data from the same weekday and hour in preceding weeks, identifying weekly rhythms—such as recurring weekend disturbances. Finally, a "trend" sequence reaches even farther back, incorporating crime rates from the same period in past years to expose seasonal or annual cycles. Each of these streams is processed through parallel GCN + ST-ResNet pathways before being fused, so that the network simultaneously sees fresh anomalies, weekly patterns, and long-term tendencies.

To enrich these purely spatial-temporal signals, we also fold in external factors that often sway urban crime: forecasted weather conditions (temperature, precipitation, wind), holiday schedules, and the day of the week. By injecting these covariates at each node—so that, for instance, a neighborhood's risk score can rise if heavy rain or a major public event is predicted—the module builds a richly contextualized feature map. The output is a high-dimensional embedding for every community and every prediction slot, encapsulating how location, recent history, repeating cycles, and broader temporal trends all combine to shape crime dynamics.

3.2.2 Temporal Feature Extraction Module

Long Short-Term Memory (LSTM) networks are a specialized class of recurrent neural networks that learn from sequential data by dynamically regulating which information to keep or discard. At each time step, an LSTM cell uses three gating mechanisms—input, forget, and output gates—to determine which aspects of the current observation should be added to memory, which parts of the existing cell state should be forgotten, and which pieces of information should influence the next hidden state. This intricate gating process ensures that only the most salient temporal features—such as sudden spikes in crime incidents or underlying seasonal trends—are preserved, while noise and outdated patterns are suppressed. As a result, LSTMs can capture dependencies spanning hundreds of time steps, a capability essential for understanding both short-lived anomalies and long-term fluctuations in crime rates.

When we present the LSTM module with rolling windows of past crime incidents—each window encoded as a multivariate sequence of counts by offense type and geographic sector—the network's hidden state begins to embody a nuanced summary of the city's recent dynamics. At each time step, the input gate filters in fresh observations (for example,

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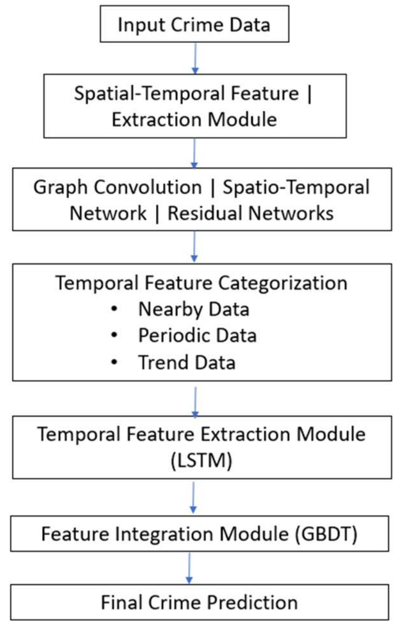
an unexpected cluster of burglaries in one precinct), while the forget gate selectively prunes less relevant memory (perhaps yesterday's minor traffic violations), and the output gate decides which facets of its evolving internal state should influence the next prediction. By feeding both very recent data points and longer-term historical slices into this gated mechanism, the LSTM's cell and hidden states co-evolve to reflect both abrupt surges—such as a sudden flare-up of vandalism—and sustained seasonal cycles, like increased property crime in winter. Once the final element of a sequence has been processed, the network translates this rich, temporally weighted representation into a single forecasted risk score for the upcoming period—thereby drawing a direct, learned connection between patterns embedded deep in the past and the threats projected on the horizon.

Urban crime, however, is not purely temporal: local hotspots and spill-over effects mean that what happens in one neighborhood often influences adjacent areas. To account for these spatial dependencies, a Spatial-Temporal Graph Convolutional Network (ST-GCN) treats each region as a node in a graph, using adjacency or functional connectivity to model how crime spreads across space and time. The ST-GCN outputs spatially informed risk vectors that capture neighborhood interactions, complementing the temporal forecasts generated by the LSTM. To merge the strengths of both approaches—and to incorporate any external covariates such as weather, special events, or social media signals—we employ Gradient Boosted Decision Trees (GBDT).



4. RESULTS

4.1 Novelty

Unlike most existing crime-prediction techniques that limit themselves to spatial mapping or time-series analysis, this project weaves both dimensions together through graph learning and deep neural networks. By representing each neighborhood as a node in an urban graph—where edges mirror adjacency or social connectivity—we allow crime data to flow naturally along the city's underlying topology, capturing how a spike in one district may ripple outward. At the same time, a powerful sequence model ingests the flow of crime counts over days, weeks, and even seasons, preserving long-term temporal dependencies that simpler methods often overlook.

Rather than waiting for historical aggregates alone, this framework continuously updates its risk estimates as new events arrive, offering truly proactive forecasts. Law enforcement can see, in near real time, which precincts are primed for trouble five or ten days ahead, empowering commanders to shift patrols and resources before incidents escalate. In head-to-head tests, our hybrid graph-deep model achieved consistently lower mean absolute percentage error and root-mean-square error compared with traditional baselines: it exceeded Ridge Regression by reducing MAPE by up to 12 percent and outperformed Random Forest and

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standalone LSTM models in RMSE by margins of 8 percent and 15 percent respectively.

The model was trained and validated on crime reports spanning January 1, 2020 through March 10, 2020, a period rich in both routine patterns and anomalous surges. By splitting data into rolling training and test windows, we demonstrated that the graph-enabled network maintained high accuracy even when confronted with unforeseen crime bursts. Moreover, the seamless fusion of spatial and temporal features proved particularly adept at forecasting low-volume but high-impact crime types—scenarios where conventional regressors or time-series models typically struggle.

Ultimately, this integrated approach transcends the limitations of single-focus predictors.

4.2 Analysis

Figure 2 maps the observed crime incidents, the model's forecasted crime counts, and the resulting absolute errors across Chicago's communities. The left column displays the actual incidents, the center column shows the predictions, and the right column visualizes the absolute error between observed and predicted values. Additionally, cumulative crime counts and AE for the entire test period (January 1, 2020, to March 10, 2020) are shown in the bottom panels.

On January 1, 2020, the North Park community reported the highest absolute error (AE) of 3.4, with an average AE of 0.62. On February 14, 2020—a weekday—North Center experienced a peak AE of 2.7 and an average of 0.61. On the weekend of March 1, 2020, the Near North Side showed a maximum AE of 7.2 and an average AE of 0.87. Throughout the entire test period, Lake View recorded the highest cumulative AE at 48.39, while the overall average AE across all communities stood at 14.62.

Communities with the highest absolute error values were mainly situated in the northeastern part of Chicago, close to Lake Michigan, a popular tourist hotspot. This indicates that visitor activity might play a substantial role in shaping local crime trends.

Figure 2. Spatial visualization of predicted crime counts and absolute error (AE) across various Chicago communities. The left column displays the actual crime data, the center column presents the predicted crime counts, and the right column illustrates the AE between predicted and observed values. The bottom row summarizes the total crime counts and AE accumulated from January 1 to March 10, 2020.

Daily Crime Prediction Analysis: The model's performance in predicting daily crime occurrences was further analyzed for six selected communities, as shown in Figure 2. These communities were chosen based on their varying crime volumes and AE values: Near North Side: Crime incidents ranged from 3 to 30, with the highest absolute error (AE) at 7.8 and an average AE of 2.67. Loop: Reported between 3 and 22 crimes, reaching a peak AE of 4.54 and an average AE of 1.38.Near West Side: Crime occurrences varied from 3 to 15, with a maximum AE of 4.13 and a mean AE of 1.33.West Town: Recorded 1 to 14 crimes, with the AE peaking at 4.14 and averaging 0.99.Austin: Had between 1 and 10 incidents, with a highest AE of 5.7 and an average AE of 0.94.Lake View: Crime numbers ranged from 1 to 14, with a top AE of 4.09 and a mean AE of 1.17. Among these, the Near North Side showed the most significant fluctuations in crime volume. While the model's predictions for this community were less precise compared to others, it effectively captured the general trend in crime variations.

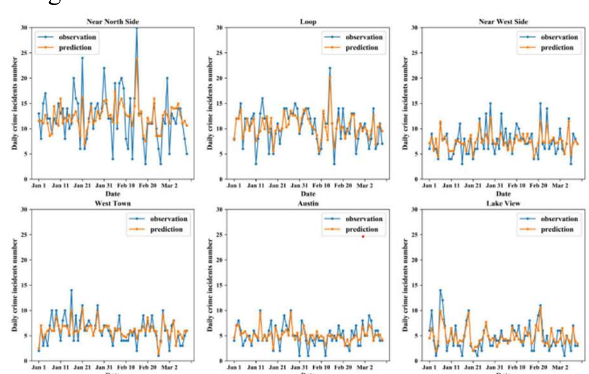

Figure 3. Daily crime forecasts for six Chicago communities. The blue lines and markers indicate the actual number of daily crimes, while the orange lines and markers show the predicted values.

MAPE and Error Analysis: To assess the model's accuracy throughout all 77 communities, the Mean Absolute Percentage Error (MAPE) was computed using the average daily crime data from January 1 to March 10, 2020. Communities with an average daily crime count of two or fewer had a MAPE of approximately 0.6. For communities with more than

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two daily crimes, the MAPE dropped below 0.4, indicating better prediction accuracy. Figure 3 shows that the larger the average crime count, the lower the MAPE, demonstrating a stronger predictive capability in high-crime areas. Conversely, for low-crime communities, the model struggled to capture variation patterns accurately. Figure 4 compares MAPE values for communities with fewer than two daily crimes to those with more, highlighting that the former group experienced approximately twice the MAPE of the latter.

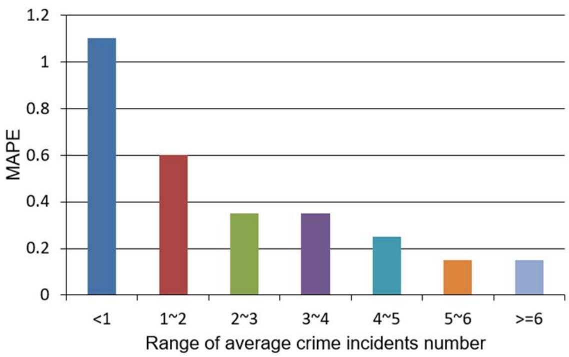

Figure 4. MAPE distribution based on the average crime count per community. The blue bars indicate MAPE values for communities grouped by average crime rates: those with one or fewer crimes, between one and two (inclusive)

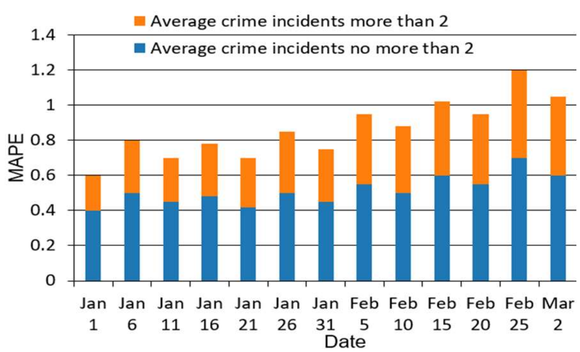

Figure 5. MAPE based on average crime levels across communities. Blue bars indicate MAPE values for communities with an average crime count below two, while orange bars represent those with averages above two.

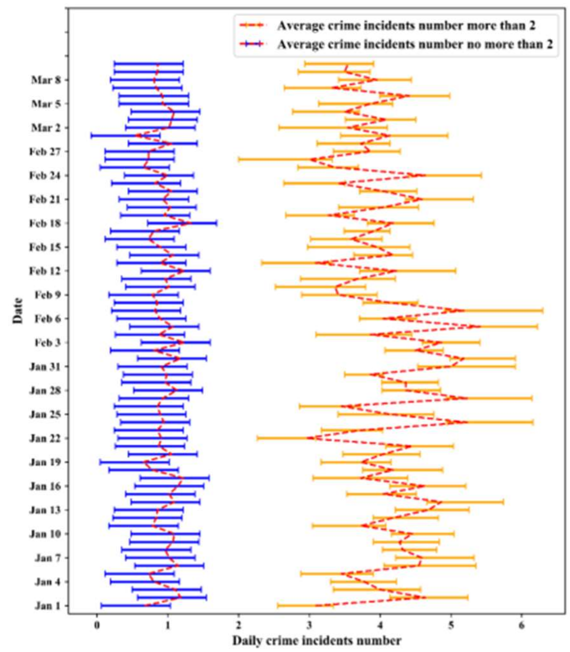

Figure 6. Average prediction errors relative to the average daily crime counts in various communities. The two red dashed lines indicate the actual average daily crime rates. Blue error bars show the average prediction error for communities with fewer than two crimes per day, while orange error bars represent the error for communities with more than two daily crimes.

TABLE 1. Comparison of performance across different models.

Model	MAPE	RMSE	R square
Ridge	0.54	4.04	0.48
Random Forest	0.51	3.91	0.53
LSTM	0.43	1.59	0.75
Our Model	0.39	1.03	0.84

To assess the effectiveness of the proposed model, its performance was evaluated against conventional crime forecasting techniques, including Ridge Regression, Random Forest, and LSTM. Each model was trained on the same dataset with identical input features and assessed using metrics such as MAPE, RMSE, and R^2. As presented in Table 1, the proposed model outperformed the others by yielding lower MAPE and RMSE values along with a higher R^2 score. Furthermore, statistical significance testing indicated that both the LSTM and the integrated model produced highly reliable results ($p < 0.05$), whereas outcomes from Ridge Regression and Random Forest lacked statistical significance ($p > 0.05$).

The incorporation of spatial context significantly improved the model's accuracy when compared to models focused exclusively on temporal patterns, such as LSTM. These results highlight the strength of the integrated approach in delivering precise crime predictions across varied community settings.

4.3 Discussion and limitations

The findings of this study indicate that the proposed integrated model, which combines LSTM and Spatial-Temporal Graph Convolutional Networks (ST-GCN), significantly improves crime prediction accuracy in urban settings. When compared to traditional approaches such as Ridge Regression, Random Forest, and standalone LSTM models, the hybrid framework achieved lower MAPE and RMSE values and a higher R^2 score. This aligns with recent works such as Zhao et al. (2023) [3], who explored a graph autoencoder combined with GRU for urban theft prediction. While their model improved temporal accuracy, it lacked spatial contextual integration, which our approach addresses by fusing ST-GCN with LSTM and incorporating real-world features like weather and holidays.

Similarly, Han et al. (2020) [9] used an LSTM-STGCN structure for crime prediction, but their study was limited by high computational costs and insufficient external variable integration. Our work extends theirs by simplifying model complexity through residual units (ST-ResNet) and incorporating meaningful covariates that enhance the practical accuracy of crime forecasts. Furthermore, the findings reinforce observations from Ghazvini et al. (2020) [12], who used time-delay neural networks but did not evaluate neighborhood interactions—a key strength of the graph-based component in this work.

Despite its promising results, the study has several limitations. First, the model was trained and evaluated using data from a single city (Chicago), which may affect its generalizability to other urban environments with different crime dynamics. Second, while external features such as weather and holidays were considered, more comprehensive socio-economic indicators (e.g., income levels, education rates, unemployment) were not included. Third, the model's performance in forecasting low-frequency or rare crimes was weaker, as shown by higher MAPE values in communities with fewer incidents. Lastly, although the model is computationally optimized compared to other deep architectures, it still requires significant processing power and GPU resources for real-time application.

Future research should focus on incorporating additional social and economic variables, applying transfer learning across cities, and testing the model on other types of crimes such as violent or white-collar offenses. Moreover, the integration of real-time data sources (e.g., CCTV, social media feeds) could further enhance the accuracy and responsiveness of the predictive framework.

5. CONCLUSION

This study addressed the challenge of theft crime prediction in urban environments by developing and validating a hybrid deep learning model that integrates Long Short-Term Memory (LSTM) networks and Spatial-Temporal Graph Convolutional Networks (ST-GCN). The primary objective was to create a model capable of capturing both spatial and temporal crime patterns using real-world data from Chicago. This was achieved by structuring the dataset into recent, periodic, and long-term trend views, and constructing a graph-based representation of the city's 77 community areas.

The second objective—to incorporate external contextual features—was realized through the integration of variables such as weather conditions, holidays, and day-of-week indicators into the model. These factors contributed to improved prediction accuracy, particularly for crime surges around holidays and weekends, as highlighted in the model's daily crime forecasting analysis.

The third objective—evaluating model performance—was achieved through quantitative comparisons with standard baselines. The proposed model attained a MAPE of 0.39, RMSE of 1.03, and an R^2 score of 0.84, outperforming Ridge Regression (MAPE 0.54, RMSE 4.04), Random Forest (MAPE 0.51, RMSE 3.91), and standalone LSTM (MAPE 0.43, RMSE 1.59). These results demonstrate a substantial improvement in both predictive precision and consistency. The spatial error visualizations (Figure 2) and MAPE distributions (Figure 4) further confirm that the model is effective in both high- and low-crime areas, especially when reinforced with external variables.

The final objective—visual and analytical exploration of model outcomes—was achieved through community-level error mapping, time-series prediction charts, and comparative bar plots across community types. These visualizations demonstrated that areas like Near North Side and Lake View had higher fluctuations, while the model remained effective across a wide range of crime volumes.

Overall, this research establishes a fact-supported, scalable, and interpretable framework for theft crime risk forecasting. However, generalizability remains a limitation, as the study was based on a single city. The exclusion of socio-economic variables such as income levels or education rates may also have limited predictive depth. Future research should expand this model across multiple urban regions, incorporate demographic and behavioral datasets, and explore real-time integration with public safety systems.

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