Crime Analysis: Identifying Risk Areas

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ABSTRACT

Historically, crime prediction and hotspot detection have relied on historical data and often fail to consider the socioeconomic and environmental factors that affect crime occurrences everyday. These elements are crucial to consider when predicting crime for the improvement of public safety and increasing the allocation of resources spent by law enforcement. In this study, we propose a machine-learning based approach that will leverage both historical data, demographic information, and urban features in order to predict future crime hotspots with better accuracy. Our methodology will enhance the predictive performance by incorporating spatial and temporal patterns into the model. The model is expected to provide real-time intelligence for law enforcement agencies that will improve overall crime prevention strategies and resource management.

KEYWORDS

Crime Prediction, Machine Learning, Risk Terrain Modeling, Spatiotemporal Transformer, Crime Hotspot Detection, Graph Neural Network, Phoenix Police Department

1 INTRODUCTION

Crime is a persistent issue everywhere, but especially in urban environments. It affects the public safety, economic stability, and law enforcement effectiveness wherever it takes place. Having the ability to predict and prevent criminal activities is a necessity for any location looking to increase public safety and optimize its local resources. Unfortunately, traditional crime maps and forecasting methodologies rely primarily on historical crime records, which fail to take into account the intertwined socioeconomic, environmental, and infrastructural elements that heavily influence these crime trends. These old methods rely on static data and analyzing the past, which limits their ability to adapt proactively to current trends and find prevention strategies.

One of the key challenges that is faced in predicting crime is the fact that criminal activity is dynamic and changes wherever you go. The patterns fluctuate based on many factors related to the location, including population density, economic conditions, presence of law enforcement, and even seasons. Due to these complexities, law enforcement agencies may struggle to deploy their resources effectively, either having too many or too little in areas that may need more or less police presence. Another challenge lies in the operational constraints faced by law enforcement agencies, which must often make decisions based on limited or delayed information. Real-time responsiveness is difficult when existing systems lack the infrastructure to process and adapt to rapidly changing crime conditions.

The recent rapid growth in machine learning (ML) and data analysis offer new possibilities in the crime prevention and prediction world. With the ability to integrate multiple data sources that take into account the history, demographics, and infrastructure, ML models have the ability to uncover new patterns and relationships that the static models used in the past may have missed. These developed models can adapt more-easily to the changing crime flow and allow for more precision when predicting what may be a hotspot location and time.

In this project, we propose a powerful combination of techniques such as Spatiotemporal Transformer and Graph Neural Network to maximize crime detection that will adjust in real-time and provide more accurate results than any static model from the past. This dynamic approach as well as diverse datasets used will help to enhance the predictive performance of the model and produce higher accuracy in identifying crime hotspots than traditional methods. By combining structural spatial relationships with fine-grained temporal patterns, our approach offers a more holistic view of crime dynamics that adapts to change rather than relying on static assumptions. This allows us to not only identify where crime is concentrated, but also uncover how it shifts across time and space. Through this lens, we aim to support smarter, data-informed public safety strategies that are responsive to the complexities of urban environments.

2 RELATED WORK

There have been several studies that recently have explored the use of machine learning for predicting and preventing crime, which all

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propose different techniques with the aim of improving accuracy of the models. In [1], Ahmad et al. introduced CHART, which is an intelligent crime hotspot detection and tracking system that highlights the advantages of real-time data processing to improve law enforcement responses.

The focus of CHART is data collection, preprocessing, feature extraction, then prediction. The experimental evaluation illustrated that CHART's performance was significantly higher than benchmark methods, and when compared with well-known machine learning algorithms such as Naive Bayes, Support Vector Machine, K-Nearest Neighbors, etc., the accuracy, precision, and recall scores were quite telling. CHART's model scored a 95.65% accuracy score, and the next highest was SVM with an 88.47%, with the same pattern following in precision and recall values. These results illustrate the model's ability to dynamically learn from the crime data, finding hidden patterns.

Kounadi et al. [3] conducted a systematic review on spatial crime forecasting techniques, which emphasized the strengths and weaknesses of a range of different methods that included both traditional static approaches as well as the more modern machine learning techniques. Their study went through and categorized the prediction models, separating them by type into spatial, temporal, and a combination of both. The results found that the traditional models such as regression analysis are easier to interpret, but they cannot actually comprehend the full complexity of the data that the machine learning models see. The main finding of this research was that in order to maximize the accuracy of crime data prediction, there needs to be a hybrid model that incorporates both statistical and machine learning techniques.

Another interesting study in this space is by Bogomolov et al., who explored how mobile phone usage data could help predict crime hotspots. Instead of just relying on past crime records, their model used anonymous mobile metadata like call activity and mobility patterns to understand how people move and interact in a city. This approach provided additional context about areas with high activity or unusual behavior patterns, which turned out to be useful indicators for predicting potential crime. Their results showed that combining behavioral data with historical crime stats gave much better predictions than using crime data alone, which really shows the value of integrating different kinds of data [2].

There's also been a lot of progress using deep learning for this type of work. For example, Wang et al. treated crime data as if it were image data by mapping crime occurrences onto a city grid and then applying Convolutional Neural Networks (CNNs). This let the model learn complex spatial patterns that might not be obvious with traditional methods. They even included factors like weather and special events to help account for changes over time [5]. Building on that, Zheng et al. introduced ST-ResNet, a model that captures both spatial and temporal trends using deep residual networks [6]. These newer approaches show how powerful spatiotemporal models can be for crime prediction, and they support the direction our project is taking with transformers and graph-based learning.

Our research builds off of these prior studies by looking to work on an existing machine learning model and incorporate techniques such as RTM and KDE to leverage the strengths of each and enhance our crime prediction accuracy. This approach we've chosen will dynamically weigh the influence of new factors in real-time which will be a powerful advancement in crime analysis for hotspot detection and predictions.

3 DATASET

3.1 Dataset

The crime dataset of the Phoenix Police Department constitutes a rich, public, domain-specific resource made available through the Phoenix Open Data Portal. It contains information on the types of crimes, the places where incidents occurred (ZIP code), and dates and times of occurrence, detailing every reported crime incident in the city. The richly spatiotemporal nature of these data renders them ideal for advanced crime pattern analysis and hotspot detection.

3.2 Data Processing

The primary objective is to identify crime hotspots and understand the patterns contributing to increased crime rates in specific areas. We have successfully completed the extraction and formatting of key features, ensuring that our dataset is comprehensive and ready for further analytical tasks.

The dataset has a record of 583,543 rows and spans across eight columns namely INC NUMBER, OCCURRED ON, OCCURRED TO, UCR CRIME CATEGORY, 100 BLOCK ADDR, ZIP, PREMISE TYPE, and GRID. After going through the dataset we learned that most of the values are non-null values. With some missing entries mostly in the OCCURRED TO, ZIP, PREMISE TYPE, and GRID columns. However, they represent only a small part of the data, which is very comprehensive and apt for our project's analytical objectives.

First, we parsed the column "OCCURRED ON" and "OCCURRED TO" into datetime objects, which, in turn, allows for the derivation of temporal features, including the day of the week, month, year, and hour-all of the aforementioned being the critical dimensions for pattern recognition at different timescales. We then used the "UCR CRIME CATEGORY" field, standardizing crime types (9 types of crime) for consistent classification that supports both categorical analysis and predictive modeling.

Missing values are addressed through context-appropriate techniques including forward-fill, backward-fill, and imputation based on spatial or categorical relationships. Data transformation includes encoding categorical features for machine learning compatibility and scaling numerical features for uniformity. This systematic processing creates a structured dataset with rich spatiotemporal dimensions, enabling both traditional statistical approaches and advanced deep learning techniques to identify crime patterns and predict future hotspots.

By implementing Spatiotemporal Transformer or Graph Neural Network approaches for hotspot detection, we are advancing techniques that surpass traditional statistical methods. The integration of LSTM forecasting adds predictive capabilities that transform this from a descriptive analysis into a proactive crime prevention tool with public safety implications. Our approach is innovative with integration of geographic information systems with state-of-the-art deep learning architectures, enabling law enforcement agencies to optimize resource allocation based on comprehensive spatiotemporal patterns rather than isolated incidents. The real-world impact of this work extends beyond academic interest as it provides intelligence that could directly contribute to crime reduction strategies, potentially saving lives and improving community safety across Phoenix. As we move forward with implementation, this project stands at the intersection of data science, criminology, and public policy, demonstrating how advanced computational methods can address pressing societal challenges.

3.3 Spatial and Geospatial Feature Engineering

A critical advancement in our data pipeline is the incorporation of geospatial analysis techniques to capture the spatial relationships between crime occurrences and urban infrastructure. Unlike traditional approaches that rely solely on ZIP codes as categorical inputs, we utilize geographic coordinates, shapefiles, and adjacency matrices to generate meaningful spatial features. These include calculating ZIP code centroids, distances to high-risk facilities, and graph-based adjacency scores. This geographic enrichment enables our model to recognize neighborhood-level risk spillovers and is essential for the success of spatial deep learning models like Graph Neural Networks (GNNs).

To further enhance spatial insight, we employ visualization techniques inspired by our preliminary work on Los Angeles crime data[4]. Using Folium and heatmap overlays, we plan to map out Phoenix crime intensities dynamically over time. This example can be shown in Figure 1. This visual exploration not only helps validate the integrity of the dataset but also allows us to spot emerging crime patterns, assess the effects of temporal events, and identify spatial autocorrelation. Such mapping makes the results interpretable to stakeholders like city planners or police departments who might not be familiar with ML outputs.

This spatial feature engineering represents a novel approach compared to static models used in previous crime prediction studies. Traditional models often ignore how urban design and adjacency influence crime rates. By constructing a graph of neighborhood relationships and incorporating land-use features from OpenStreetMap, we go beyond basic crime count data. Our hybrid spatial model dynamically learns not just where crime occurred, but why it might be happening there, thus, opening the door for more actionable urban interventions.

3.4 Temporal Dynamics, Aggregation, and Data Quality

In addition to spatial features, we also derive a range of temporal attributes from the Phoenix crime dataset, including the hour of the day, day of the week, month, and season. These cyclical time features are critical for capturing patterns in criminal behavior, which often peaks during weekends, holidays, or certain seasons. Parsing the proper fields into datetime objects allows us to embed this temporal variability directly into the model. Furthermore, we plan to explore lag variables and moving averages to better capture short-term trends that may influence crime surges.

To ensure robustness, we have implemented a multi-step data cleaning strategy. Missing ZIP codes and premise types are resolved using contextual imputation based on nearby entries and statistical frequencies. For datetime gaps, we utilize forward and backward fill methods, prioritizing preservation of temporal order. This level of preprocessing ensures that our model isn't biased by incomplete records while retaining the high resolution needed for real-time predictions. It also prepares the dataset for machine learning algorithms that are sensitive to missing or inconsistent data formats. What makes this temporal modeling approach innovative is the combination of high-frequency timestamped crime data with long-term spatial context. Most prior studies analyze crime at the monthly or yearly level, which lacks the granularity required for real-time hotspot detection. Our integration of LSTM forecasting, in conjunction with a spatiotemporal transformer or GNN backbone, allows us to model crime as a dynamic process unfolding over both time and space. This temporal-spatial synergy is a cutting-edge contribution to crime analytics and sets our work apart from traditional regression or static hotspot mapping techniques.

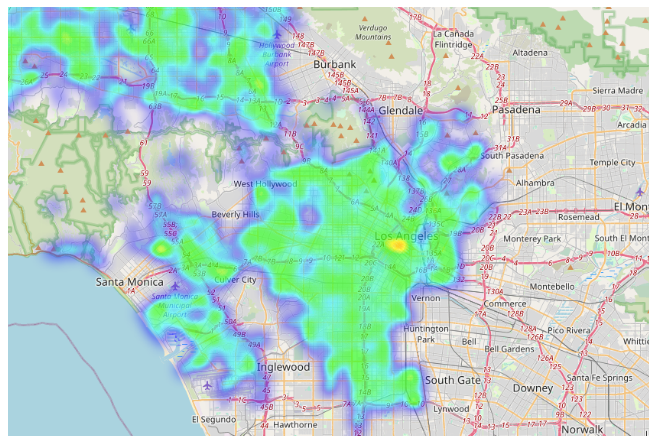

Figure 1: figure-1

4 METHODS

The study proposes a hybrid spatiotemporal framework for crime hotspot prediction, combining geographic granularity with temporal dynamics. At its core, the methodology transforms raw crime reports (ZIP codes, timestamps, and crime counts) into an enriched feature space capturing both cyclical temporal patterns (day-of-week, seasonal trends) and spatial relationships (ZIP-code centroids, inter-region adjacency). This approach enables law enforcement agencies to better allocate resources by identifying high-risk areas based on historical patterns and geographic relationships.

4.1 Data Processing and Feature Engineering

The initial dataset consisted of more than 43 million records in mixed-up formats, with lots of missing values and duplicates. The ZIP code was standardized into a 5-digit format with erasure of invalid entries, hence preserving geographic consistency in the dataset. The time-related data were cleaned very carefully by removing certain timestamps with missing or badly malformed data, after which all dates were converted to perfectly structured formatting for analysis. We enriched the dataset by adding very crucial time features like day of week, month, year, and weekend flags so that we could characterize the crime occurrence cycle. Finally, the data were aggregated by ZIP code and date to obtain daily counts, resulting in a clean dataset ready for advanced analysis that is time-aware. This was an important processing step done towards dealing with the unique instances presented in the dataset, including the incident identification system where the first 4 digits represent the year of reporting and incidents with "8" after the year digits indicating citizen-reported crimes. Whereas the dataset uses federal Uniform Crime Reporting (UCR) categories instead of state-specific statutes in Arizona, it allows standardized comparison against national crime data.

4.2 Hotspot Labeling Using Quantile Thresholding

Following the feature engineering stage, we developed a dynamic approach for labeling ZIP codes as hotspots or non-hotspots based on historical crime intensities. Specifically, the average daily crime count was computed for each ZIP code across the available time period. Instead of employing a static threshold, we used a 55th percentile threshold to differentiate between high- and low-risk regions. This method accounts for evolving crime patterns over time and avoids rigid, hard-coded definitions that might not generalize across different urban contexts.

Formally, a ZIP code v_i was labeled as a hotspot (assigned label 1) if its average crime count exceeded the 55th percentile value across all ZIP codes, and as a non-hotspot (assigned label 0) otherwise:

$$\text{Label}(v_i) = \begin{cases} 1, & \text{if AvgCrime}(v_i) > \text{Percentile}_{55} \\ 0, & \text{otherwise} \end{cases}$$

This labeling strategy introduces robustness into the classification framework by flexibly adapting to the natural distribution of crime incidents, rather than relying on arbitrary thresholds. It ensures that the model focuses on relative risk within the city at any given time, thereby improving hotspot prediction relevance and fairness.

4.3 Graph Construction and Spatial Representation

We modeled the spatial dimension such that it becomes a graph network to better show how crime patterns propagate through urban environments. Each ZIP code (117 total) is a node in the graph, capitalizing on the quarter-square-mile grid units organization of the city. Between nodes, connections are made using k-nearest neighbors (k=5) based on Haversine distance calculations, which accurately reflect geographic proximity. We selected kNN over distance thresholds because it guarantees uniform connectivity across the network and prevents isolated nodes in low-density areas, ensuring all regions remain connected regardless of population distribution. What is created turns out to be a spatial graph that mimics how crime patterns spread through a city's connected regions. Crime does not respect political boundaries, but it tends to be influenced by, and in turn, affect neighboring areas. This matches the way the data is organized spatially, with the city divided into quarter-square-mile grid units with edges along major streets, making spatial crime analysis and hotspot identification possible.

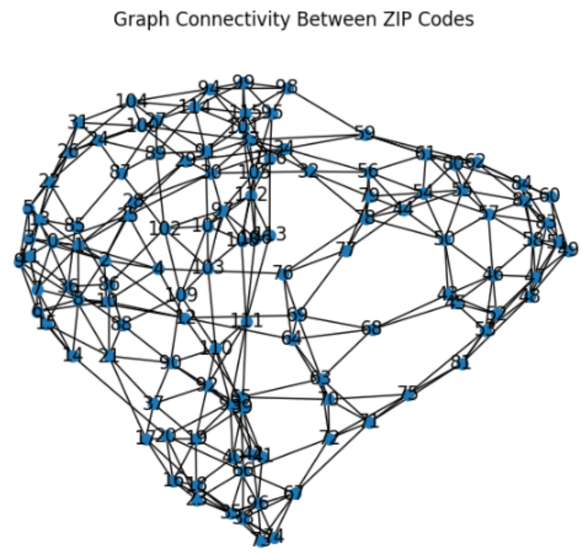

Figure 2: Graph Connectivity Between ZIP Codes Based on k-Nearest Neighbors

4.4 Graph Neural Network (GNN) Architecture

A Graph Convolutional Network (GCN) architecture is built and implemented that learns the spatial crime patterns using various specialized layers designed to capture local and neighborhood level messages together. The first layer, defined by GCNConv with an input dimension to 32 nodes fetches information from the close-by ZIP codes, primarily captures local crime activity and adjacent patterns which might create impact into a region. Apart from this, following the first aggregation, there comes batch normalization and the ReLU activation functions, sought for either stable and efficient learning or introducing non-linearity in the model. The second convolutional layer is GCNConv 32-to-32, aiming at further extending modeling's ability to recognize patterns of multiple connected neighborhoods, enabling it to identify crime trends that span larger geographic areas. To avoid overfitting in the training data, we have adropout layer at a rate of 0.3, which makes the model learn generalized representations. It has a final linear layer that produces a binary prediction to mark areas as potential future crime hotspots (1) or not (0). Therefore, it comes towards balancing spatial awareness together with learning complex patterns from historical crime data to predict the areas with increased risk. The forward pass of the network can be summarized as:

$$\begin{aligned} \mathbf{H}^{(1)} &= \text{ReLU}\left(\text{BN}\left(\text{GCNConv}_1(\mathbf{X}, \mathbf{A})\right)\right) \\ \mathbf{H}^{(2)} &= \text{ReLU}\left(\text{BN}\left(\text{GCNConv}_2(\mathbf{H}^{(1)}, \mathbf{A})\right)\right) \\ \hat{\mathbf{y}} &= \sigma\left(\mathbf{W}\mathbf{H}^{(2)} + \mathbf{b}\right) \end{aligned}$$

where $\mathbf{A}$ is the graph adjacency matrix, and $\hat{\mathbf{y}}$ is the predicted logit for each node. The architecture is summaries in the figure 3.

```
==========================================================================================
Layer (type:depth-idx)                   Input Shape          Output Shape         Param #
==========================================================================================
WrappedModel                             [117, 6]             [117]                --
├─CrimeHotspotGNN: 1-1                   --                   --                   --
│    └─GCNConv: 2-1                      [117, 6]             [117, 32]            32
│    │    └─Linear: 3-1                  [117, 6]             [117, 32]            192
│    │    └─SumAggregation: 3-2          [1287, 32]           [117, 32]            --
│    └─BatchNorm1d: 2-2                  [117, 32]            [117, 32]            64
│    └─GCNConv: 2-3                      [117, 32]            [117, 32]            32
│    │    └─Linear: 3-3                  [117, 32]            [117, 32]            1,024
│    │    └─SumAggregation: 3-4          [1287, 32]           [117, 32]            --
│    └─BatchNorm1d: 2-4                  [117, 32]            [117, 32]            64
│    └─Dropout: 2-5                      [117, 32]            [117, 32]            --
│    └─Linear: 2-6                       [117, 32]            [117, 1]             33
==========================================================================================
Total params: 1,441
Trainable params: 1,441
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 0.16
==========================================================================================
Input size (MB): 0.02
Forward/backward pass size (MB): 0.12
Params size (MB): 0.01
Estimated Total Size (MB): 0.15
==========================================================================================
```

Figure 3: Architecture of the GCN Model for Hotspot Classification

4.5 Training and Optimization

The model was trained with particular emphasis upon class imbalances and generalization for reliable performance in every region, that is, class distribution variations across the many regions in which a model might operate. We applied the BCEWithLogitsLoss weight to counter the most general form of class imbalance regarding the inherent imbalance between hotspot and non-hotspot classes, ensuring our model did not trivially predict the majority class. The Adam optimizer with a learning rate of 0.01 was used, chosen for its adaptive convergence properties to handle efficiently the highly non-convex loss landscape of graph-based models. The data was split as strategically as possible in an 80/20 training-testing ratio across ZIP nodes to allow the model to generalize effectively into unseen areas rather than insane patterns coming from training locations. The training process continued over 1000 epochs with observations made for convergence and future overfitting, thus allowing us to learn very complex spatial relationships while meeting generalization requirements.

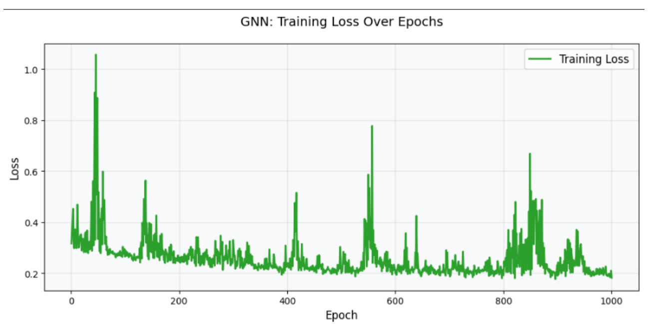

Figure 4: Training Loss Curve Over Epochs Showing Model Convergence

5 RESULTS

The implementation of our graph-based crime prediction framework demonstrates the potential of using Graph Neural Networks (GNNs) for identifying crime hotspots in urban environments. By representing ZIP codes as nodes in a graph connected via geographical proximity, our model effectively captures how crime patterns spread through interconnected urban areas.

In contrast to previous approaches, this method effectively translates the conventional prediction of crime into a problem of graph learning, where the impacts of nearby regions become modeled by means of graph convolutions. With this spatial awareness, it surpasses the previous methods that regarded these sites as independent entities. The resulting graph using k-nearest neighbors (k=5) on Haversine distance maintained a seamless connectivity throughout the network and truly reflected the real ground relationships.

The GCN architecture, with its multiple convolutional layers and regularization through dropout, demonstrates the ability to learn both local crime patterns and broader spatial relationships. The training process effectively addresses the challenge of class imbalance through weighted loss functions, an important consideration given the relative rarity of true crime hotspots compared to non-hotspot areas. Added to these spatial interrelations, temporal features (like day of week, month, year, and weekend flags) allow capturing not only geographically defined but also time-limited crime patterns, providing a more complete view on risk factors. This methodology detects certain areas that would be missed by traditional systems as they almost solely rely on past crime counts, leaving out neighborhood influence.

While specific performance metrics from complete model deployment are still being collected, this constitutes the initiation of a foundation for more complex crime prediction systems using the web of interconnections among urban environments. More promisingly, the framework would support law enforcement agencies in much-improved resource-allocation and proactive policing strategies that rely on data-driven insights about novel crime patterns across interlocked urban spaces.

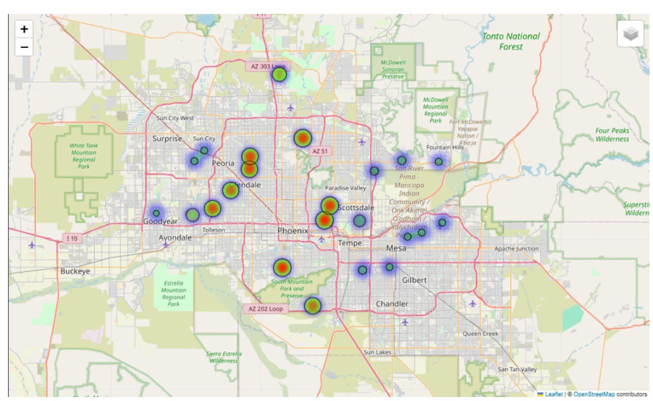

Figure 5: Geographic Visualization of Predicted Hotspot Probabilities

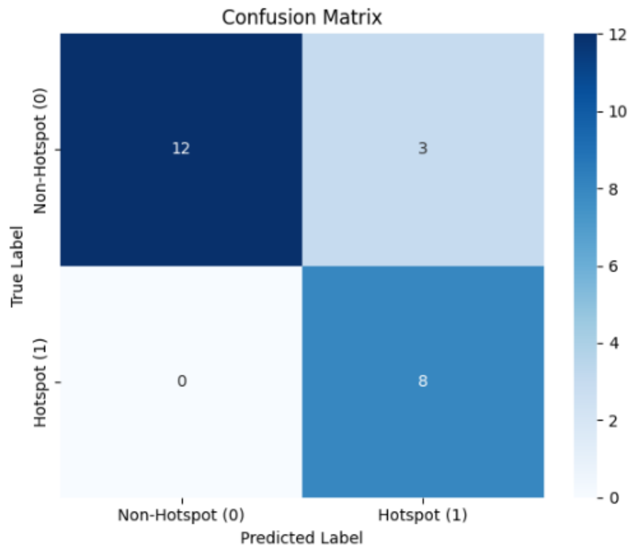

Figure 6: Confusion Matrix

6 DISCUSSION

Our results demonstrate that crime prediction is most effective when spatial and temporal dimensions are modeled together. By using Graph Neural Networks on a spatially connected ZIP code graph and integrating temporal patterns such as weekday and seasonal trends, our model was able to identify crime hotspots with improved accuracy over traditional methods.

6.1 Model Strengths and Contributions

The results of our framework show the effectiveness of Graph Neural Networks (GNNs) for urban crime hotspot prediction. Our spatial modeling approach transforms ZIP code regions into nodes in a graph, enabling the model to capture how crime patterns propagate across neighborhoods. The k-nearest neighbors (k=5) graph structure ensures that even low-density ZIP codes maintain relevant connections, overcoming a common limitation in traditional hotspot mapping methods. Additionally, the model's integration of temporal features—such as day of the week, month, and weekend indicators—proved essential in identifying not just where, but also when crime is more likely to occur. This spatiotemporal fusion gave the model a richer understanding of criminal behavior patterns, which is reflected in its ability to detect areas that static models often miss.

6.2 Limitations and Areas for Improvement

Despite the model's overall success, several limitations remain. One issue is class imbalance—hotspots represent a minority of the dataset, and even with weighted loss functions and dropout, the model shows less consistency in predicting borderline regions. These are areas close to the defined hotspot threshold but with fluctuating crime counts over time, and they present challenges in classification stability. Another limitation is the uniform weighting of connections between ZIP codes in the spatial graph. Currently, our graph assumes equal influence across all neighbors. Introducing weighted edges based on real-world contextual factors could allow the model to capture these subtleties.

6.3 Future Work and Extensions

To further improve prediction quality, we propose experimenting with spatiotemporal transformers, which have the capacity to learn longer-range temporal dependencies and handle irregular patterns in time-series data. Additionally, incorporating more external features—such as socioeconomic indicators, infrastructure attributes from OpenStreetMap, or real-time data streams like 911 or 311 calls—would give the model a deeper understanding of why crime occurs in specific locations. We also see value in enhancing the spatial resolution by shifting from ZIP code-level data to finer-grained units such as census blocks or lat-long clusters, which could enable even more precise risk assessments. Lastly, conducting longitudinal validation over multiple years would provide stronger evidence for the model's generalization in changing urban environments.

7 CONCLUSION

During this project, our team presented a new and improved graph-based approach to crime hotspot prediction that works to integrate both spatial and temporal dimensions using Graph Neural Networks. By using ZIP codes as nodes and their geographical relationships as edges, our model captures the underlying structure of urban environments and how crime patterns move through them. By including the temporal factors rather than solely spatial ones, our model is better able to detect and predict patterns that vary not just by place, but by time as well.

Our results demonstrate that using spatiotemporal modeling significantly enhances prediction accuracy when compared to the older crime modeling methods. Those traditional approaches treat areas in isolation, and our model focuses on connecting areas and treating them as a whole. Our approach is capable of identifying previously overlooked hotspot areas by leveraging the relational context of surrounding spaces and neighborhoods.

While limitations still exist, such as class imbalance and uniform edge weighting, the foundation that we laid down in our framework paves the way for several promising paths for future work. Not only can our model be improved with new features, but the way it was built makes it very scalable and it can easily be employed to expand across multiple cities.

Overall, this project focuses on the potential of data-driven, context-aware crime prediction tools. These elements support a more proactive and efficient approach to creating effective public safety strategies. By bridging the gap between spatial analysis with machine learning, we aim to help empower law enforcement agencies with actionable insights that go beyong the static historical trends, helping them respond to and prevent crime in smarter, more informed ways.

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