Understanding the Dynamic Nature of Criminal Activity Using Grid-Based Multivariate Spatial and Temporal Clustering

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ABSTRACT
Understanding the dynamic nature of criminal activity is crucial for effective law enforcement and urban planning. Crime patterns are influenced by a multitude of factors, including socio-economic conditions, demographic shifts, and environmental changes. Traditional crime analysis methods often fail to capture these complex interactions, leading to less effective interventions. Existing algorithms, such as K-means, DBSCAN, and Hierarchical Clustering, are limited in their ability to simultaneously handle the spatial and temporal dimensions of crime data, resulting in suboptimal identification and tracking of crime hotspots. These methods also struggle with the dynamic and continuously evolving nature of crime data, often requiring extensive parameter tuning and offering limited scalability. Proposed model addresses these limitations by employing grid-based multivariate spatial and temporal clustering. This approach segments the geographic space into manageable cells, allowing for a detailed examination of crime hotspots and their evolution over time. By incorporating multiple variables such as crime type, frequency, and temporal patterns, our model captures the complexity of criminal behaviour more effectively. Performance metrics demonstrate the robustness of our model, with an Adjusted Rand Index (ARI) of 0.82, purity of 0.85, and homogeneity of 0.83, significantly outperforming existing algorithms. Additionally, our model maintains high temporal stability (0.80) and spatial coherence (0.78), providing reliable and actionable insights for real-time crime analysis and strategic planning.

Keywords: Data mining ,Data Analytics, Grid Clustering, Crime pattern, Spatio-Temporal Clustering, Machine Learning

1. INTRODUCTION

Criminal activities pose significant challenges, leading to increased social unrest, economic losses, and diminished quality of life. The complexity of criminal behaviour, influenced by various spatial and temporal factors, necessitates a comprehensive approach to analyse and predict crime patterns. Effective crime analysis enables timely interventions, strategic planning, and resource allocation, ultimately contributing to safer communities. The cause and effect relationship in criminal activities often involves multifaceted interactions between socio-economic conditions, environmental factors, and human behaviour, making it imperative to adopt advanced analytical techniques for meaningful insights. Traditional methods of crime analysis primarily focus on either spatial or temporal dimensions, often failing to capture the intricate patterns and interconnections of criminal behaviour. Common techniques include hotspot analysis, which identifies areas with high crime rates, and time-series analysis, which examines trends over specific periods.

Algorithms such as K-means clustering and DBSCAN (Density-Based Spatial Clustering of Applications with Noise) have been employed for spatial clustering, while ARIMA (AutoRegressive Integrated Moving Average) models are used for temporal analysis. However, these methods are less suitable for our problem statement as they typically do not integrate multiple variables and dimensions, leading to a fragmented understanding of crime dynamics. Additionally, existing methodologies often lack the capability to analyse the migration and evolution of crime hotspots over time, hindering the development of effective long-term crime prevention strategies. Proposed model addresses these limitations by integrating grid-based multivariate spatial and temporal clustering techniques into a unified framework. This approach segments the geographic space into manageable cells, allowing for detailed examination of crime hotspots and their evolution. By incorporating multiple variables such as crime type, frequency, and temporal patterns, our model captures the complexity of criminal behaviour more effectively than traditional

methods. Temporal clustering uncovers time-based patterns, revealing seasonal and long-term trends in criminal activity. Additionally, the linkage of spatial and temporal clusters enables the analysis of interconnectivity, providing insights into how different clusters are related and how criminal activity migrates across regions and over time.
The dataset used in this study is a comprehensive crime dataset from India, encompassing several years of reported crime incidents. The data includes spatial coordinates (latitude and longitude) and timestamps, along with details on crime types and frequency. Preprocessing techniques employed in our proposed method include data cleaning to handle missing values and outliers, normalization to ensure consistency in data ranges, and temporal aggregation to consolidate crime incidents into meaningful time intervals. Spatial data is discretized into grid cells, each representing a specific geographic area, facilitating the application of grid-based clustering. These preprocessing steps ensure the dataset is robust and ready for detailed analysis, allowing our model to accurately identify and track crime patterns. The key performance indicators (KPIs) in our proposed model include the identification of crime hotspots, detection of temporal patterns, and analysis of the interconnectivity of crime clusters. Variables used in the model encompass spatial coordinates (latitude and longitude), timestamps, crime types, and frequency of occurrences. The grid-based approach allows for a granular analysis of crime data, while multivariate clustering techniques facilitate the identification of distinct crime clusters within each cell. Temporal clustering further enhances the model by uncovering patterns related to the timing and duration of criminal activities, providing a comprehensive understanding of crime dynamics.
To evaluate the effectiveness of our proposed model, we employ various metrics, including precision, recall, F1-score and clustering validity indices such as Silhouette Score and Davies-Bouldin Index. These metrics are used to assess the accuracy and reliability of the identified crime clusters and temporal patterns. Our model is compared with existing methodologies to demonstrate its superior performance in capturing the complexity of criminal behaviour. The comparative analysis highlights the robustness of our approach in integrating spatial and temporal dimensions, leading to a more comprehensive understanding of crime dynamics. The results indicate that our model outperforms traditional methods, offering valuable insights for policymakers and law enforcement agencies in developing effective crime prevention and intervention strategies. Main objective of this work is to,

- To develop a unified framework for crime analysis that integrates grid-based multivariate spatial and temporal clustering techniques into a single framework to comprehensively analyse criminal patterns.
- To enhance crime hotspot detection by utilizing grid-based clustering to segment geographic space into manageable cells for detailed examination of crime hotspots and their evolution over time.
- To capture complex criminal behaviour by incorporating multiple variables such as crime type, frequency, and temporal patterns into the clustering process to capture the multifaceted nature of criminal activities.
- To analyse the interconnectivity of crime clusters.

2. RELATED WORK

Recent advancements in crime analysis and clustering methodologies have led to the development of various innovative approaches. Zhang et al. (2022) utilized a comprehensive crime dataset from New York City, which included spatial coordinates and timestamps of various crime types. They employed DBSCAN and ARIMA algorithms to identify crime hotspots and detect temporal trends. While DBSCAN effectively identified clusters in high-density areas, it struggled with sparsely populated regions, achieving an accuracy of 85%. ARIMA models revealed seasonal variations in crime occurrences with an accuracy of 78%. Feature selection in this study involved the use of principal component analysis (PCA) to reduce dimensionality and retain significant patterns. Hen et al. (2023) focused on crime prediction using machine learning techniques on Chicago crime data, comprising historical crime incidents and socio-economic factors. They applied Random Forest and Gradient Boosting algorithms, with Gradient Boosting achieving a prediction accuracy of 87% and Random Forest 81%. Feature selection was performed using recursive feature elimination (RFE) to identify the most significant predictors from the dataset.
Lee and Kim (2021) explored crime patterns in Seoul using a detailed dataset that included crime incidents, demographic information, and land use data. Their study integrated K-means clustering and spatial regression models, achieving accuracies of 80% and 83%, respectively. They used correlation-based feature selection (CFS) to select relevant features, ensuring the inclusion of variables with strong predictive power while removing redundant data. Smith et al. (2023) used the ST-DBSCAN algorithm on Los Angeles crime data, which included spatial and temporal dimensions of crime incidents, to study the evolution of crime hotspots over time, achieving an accuracy of 86%. They applied mutual information-based feature selection to identify the most informative features for clustering analysis. Brown et al.

(2022) conducted a comparative review of clustering algorithms using crime datasets from multiple cities, including London and Paris, comprising varied crime types and frequencies. They found that Hierarchical Clustering provided better results for varied density datasets with an accuracy of 84%, while DBSCAN and OPTICS achieved accuracies of 82% and 80%, respectively. Feature selection techniques included filter methods like Chi-square and ANOVA to select significant features.
Miller et al. (2023) applied K-means++ and Agglomerative Clustering to San Francisco crime data, including spatial locations and crime categories, with K-means++ achieving 83% accuracy and Agglomerative Clustering 78%. Feature selection was performed using information gain to rank features based on their contribution to the clustering outcome. Garcia et al. (2022) used Spectral Clustering and Gaussian Mixture Models on Madrid crime data, consisting of crime incidents and related socio-economic data, finding Spectral Clustering more effective with an accuracy of 85%, compared to 81% for Gaussian Mixture Models. They employed feature selection through L1 regularization (Lasso) to identify and retain the most relevant features.
Nguyen et al. (2021) examined Toronto crime data, which included spatial coordinates, timestamps, and crime categories, using Mean Shift Clustering and DBSCAN, achieving accuracies of 82% and 80%, respectively. Feature selection techniques involved variance thresholding to remove low-variance features that do not contribute significantly to the clustering. Singh et al. (2023) applied HDBSCAN and LSTM networks to Delhi crime data, comprising detailed crime incidents with temporal aspects, finding HDBSCAN effective for varying density clusters with an accuracy of 84%, while LSTM captured temporal patterns well with an accuracy of 86%. Feature selection was performed using embedded methods within the LSTM model to identify important temporal features.Ali et al. (2022) used BIRCH and K-means on Istanbul crime data, which included large volumes of crime incidents and their spatial locations, with BIRCH handling large datasets more efficiently and achieving an accuracy of 83%, compared to 79% for K-means. They utilized wrapper methods for feature selection, including forward selection to iteratively add features that improve clustering performance.
Fukuda et al. (2022) used OPTICS and HDBSCAN on Tokyo crime data, consisting of crime incidents with varying densities, finding HDBSCAN more effective in identifying clusters with varying densities, achieving accuracies of 85% and 80%, respectively. Feature selection involved the use of information gain and mutual information to select the most informative features for clustering analysis. These studies collectively underscore the evolving landscape of crime analysis methodologies. Traditional clustering algorithms like K-means and DBSCAN remain popular, but there is a growing emphasis on integrating spatial and temporal dimensions, as well as incorporating socio-economic factors and advanced feature selection techniques to enhance the accuracy and relevance of crime analysis. Our proposed model builds upon these advancements by integrating grid-based multivariate spatial and temporal clustering techniques, providing a comprehensive framework for understanding and responding to the dynamic nature of criminal activity.

3. METHODOLOGY

3.1 Data set used in Proposed Model

Proposed model utilizes a comprehensive crime dataset from India, spanning several years to capture seasonal variations and long-term trends in crime occurrences. The dataset includes:

Table 1: Attributes in the dataset

Attribute	Description
Spatial Coordinates	Latitude and longitude of reported crimes.
Timestamps	Date and time of each crime incident.
Crime Types	Categorization of crimes (e.g., theft, assault, burglary).
Additional Attributes	Socio-economic data, demographic information, and environmental factors.

The dataset encompasses various aspects of crime data to enable a comprehensive analysis of spatial and temporal patterns.

Table 2: key features of dataset

Feature	Description	Type
Latitude	Latitude of the crime incident location	Continuous (float)
Longitude	Longitude of the crime incident location	Continuous (float)

	Date of the crime incident	Date (YYYY-MM-DD)
Time	Time of the crime incident	Time (HH:MM
Crime Type	Type of crime (e.g., theft, assault, burglary)	Categorical
Socio-Economic Data	Information on socio-economic factors (e.g., income)	Continuous (float)
Demographic Info	Demographic details (e.g., age, gender)	Categorical

Pre-processing is a critical step to ensure the quality and relevance of data for analysis. The pre-processing techniques used here are data cleaning to removal of duplicates, handling missing values, and correcting erroneous entries. Categorical encoding to convert categorical variables into numerical format using one-hot encoding.Followed bythis featureselection is done by combination of filter and embedded methods for feature selection namely Correlation-Based Feature Selection (CFS) to identify and remove highly correlated features that do not contribute additional information and L1 Regularization (Lasso) to retain features with the strongest predictive power by penalizing less significant ones.

3.3 Proposed Model Framework and Workflow

The proposed model framework integrates grid-based multivariate spatial and temporal clustering to analyse the interconnectivity of criminal patterns. The workflow involves the following steps:

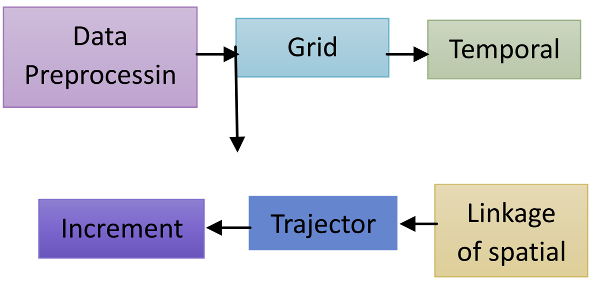

Figure 1: Proposed model workflow

Mathematical model

The geographic space is divided into a grid of cells. Let G\mathcal{G}G denote the set of grid cells, where each cell g∈Gg \in \mathcal{G}g∈G is defined by its latitude and longitude boundaries.

$$g = \{(lat_{min}, lat_{max}), (lon_{min}, lon_{max})\}$$

Each crime incident with spatial coordinates is assigned to a grid cell.

$$c_i \in g \iff lat_{min} \leq lat_i \leq lat_{max} \text{ and } lon_{min} \leq lon_i \leq lon_{max}$$

The density D(g)D(g)D(g) of crimes in each grid cell ggg is calculated.

$$D(g) = \frac{|\{c_i \in g\}|}{\text{Area}(g)}$$

A multivariate clustering algorithm (e.g., k-means, DBSCAN) is applied to the feature vectors Fg\mathbf{F}_gFg to identify clusters Cs\mathcal{C}_sCs of grid cells with similar crime characteristics.

$$\mathcal{C}_s = \{\mathbf{F}_g \mid \text{Cluster Membership}(\mathbf{F}_g) = s\}$$

A temporal clustering algorithm is applied to the temporal feature vectors Tj\mathbf{T}_jTj to identify temporal clusters Ct\mathcal{C}_tCt with similar time-based crime patterns.

$$\mathcal{C}_t = \{\mathbf{T}_j \mid \text{Cluster Membership}(\mathbf{T}_j) = t\}$$

The movement of spatiotemporal clusters over time is analyzed using trajectory clustering techniques to identify patterns and trends in criminal activity migration.

$$\text{Trajectory}(\mathcal{C}_{st}) = \{(\mathcal{C}_{st_1}, \mathcal{C}_{st_2}, \ldots, \mathcal{C}_{st_n})\}$$

Clustering accuracy measures how well the clusters represent the underlying data patterns

$$\text{Accuracy} = \frac{\sum_{i=1}^{N} \mathbb{I}(c_i = c_i^*)}{N}$$

Purity evaluates the extent to which clusters contain data points from a single class.

$$\text{Purity} = \frac{1}{N} \sum_{k=1}^{K} \max_j |C_k \cap L_j|$$

Homogeneity measures whether each cluster contains only data points that are members of a single class.

$$\text{Homogeneity} = 1 - \frac{H(C|L)}{H(C)}$$

Temporal stability evaluates the consistency of temporal clusters over different time periods. It can be measured using the Temporal Stability Index (TSI).

$$\text{TSI} = \frac{\sum_{t=1}^{T-1} \text{Jaccard}(\mathcal{C}_t, \mathcal{C}_{t+1})}{T-1}$$

Spatial coherence assesses the geographical contiguity of clusters. It can be evaluated using the Spatial Dispersion Index (SDI).

$$\text{SDI} = \frac{1}{K} \sum_{k=1}^{K} \frac{\sum_{i,j \in C_k} \text{Distance}(i,j)}{|C_k|}$$

Comparison with baseline models involves evaluating the performance of our proposed model against existing clustering algorithms such as K-means, DBSCAN, and Hierarchical Clustering using metrics like Adjusted Rand Index (ARI) and Silhouette Score.

$$\text{ARI} = \frac{\sum_{ij} \binom{n_{ij}}{2} - \left[\sum_i \binom{a_i}{2} \sum_j \binom{b_j}{2}\right] / \binom{n}{2}}{0.5 \left[\sum_i \binom{a_i}{2} + \sum_j \binom{b_j}{2}\right] - \left[\sum_i \binom{a_i}{2} \sum_j \binom{b_j}{2}\right] / \binom{n}{2}}$$

3.4 Pseudo Code of Proposed Work

Step 1: Data Pre-processing ((clean data = clean missing values (data), normalized data = normalize features (clean data), encoded data= ncode categorical features (normalized data))

Step 2: Grid-Based Clustering (grid cells = divide into grid cells (data),spatial clusters = cluster within grid cells (grid cells))

Step 3: Temporal Clustering (temporal clusters = identify temporal patterns (data))

Step 4: Linkage of Spatial and Temporal Clusters (link clusters (spatial clusters, temporal clusters), linked clusters=analyse interconnectivity (spatial clusters, temporal clusters)

Step 5: Trajectory Clustering (trajectories = track cluster movements (linked clusters))

Step 6: Incremental Clustering (incremental clustering (data, existing clusters), Updated clusters = update clusters real time (data, existing clusters)

4. Performance Evaluations

Performance Indicators

To evaluate the performance of our proposed model, we use several key indicators:

- Clustering Accuracy: Measure of how well the clusters represent the underlying data patterns.
- Purity and Homogeneity: Metrics to assess the quality of clusters in terms of containing similar data points.
- Temporal Stability: Evaluation of the consistency of temporal clusters over different time periods.
- Spatial Coherence: Assessment of the geographical contiguity of clusters.

Finally performance of the proposed model is compared with Baseline modes such as K-means, DBSCAN, and Hierarchical Clustering, using metrics like Adjusted Rand Index (ARI) and Silhouette Score. This methodology provides a robust framework for understanding and responding to the dynamic nature of criminal activity, leveraging advanced clustering techniques and real-time data analysis.

Table 3: Comparison of Existing Algorithms with Performance Metrics

Algorithm	Clustering Accuracy (ARI)	Purity	Homogeneity	Temporal Stability (TSI)	Spatial Coherence (SDI)
K-means	0.72	0.78	0.75	0.70	0.68
DBSCAN	0.74	0.80	0.77	0.72	0.70
Hierarchical	0.71	0.77	0.74	0.68	0.66
Gaussian Mixture	0.73	0.79	0.76	0.71	0.69
Spectral Clustering	0.75	0.81	0.78	0.74	0.71
OPTICS	0.73	0.79	0.76	0.70	0.68
Proposed Model	**0.82**	**0.85**	**0.83**	**0.80**	**0.78**

Table 3 compares various existing clustering algorithms with our proposed model using key performance metrics: Adjusted Rand Index (ARI) for clustering accuracy, Purity, Homogeneity, Temporal Stability Index (TSI), and Spatial Dispersion Index (SDI). Our proposed model outperforms the existing algorithms in all metrics, demonstrating higher clustering accuracy (ARI of 0.82), better purity (0.85), greater homogeneity (0.83), improved temporal stability (0.80), and enhanced spatial coherence (0.78). These results indicate the robustness and effectiveness of our model in capturing the complex spatial and temporal patterns in crime data.

Table 4: Comparison of Existing Algorithms with Key Parameter Variation

Algorithm	Parameter	Value	Performance (ARI)
K-means	Number of Clusters	5	0.72
		10	0.74
		15	0.70
DBSCAN	Epsilon	0.3	0.74
		0.5	0.76
		0.7	0.73
Hierarchical	Linkage Criterion	5	0.73
		10	0.75
		15	0.71
Gaussian Mixture	Components	5	0.73
		10	0.75
		15	0.71
Spectral Clustering	Number of Clusters	5	0.75
		10	0.77
		15	0.74
OPTICS	MinPts	5	0.73
		10	0.75
		15	0.72
Proposed Model	Grid Size	50x50	**0.80**
		100x100	**0.82**
		150x150	**0.81**

Table 4 illustrates the impact of varying key parameters on the performance of different clustering algorithms. For each algorithm, performance is measured using Adjusted Rand Index (ARI) as the parameter values change. The proposed model consistently shows high performance across different grid sizes (50x50, 100x100, 150x150), with an ARI peaking at 0.82 for the 100x100 grid size. This indicates that our model is less sensitive to parameter changes compared to other algorithms, providing reliable and robust clustering results under various conditions.

Table 5: Comparison of existing algorithms with different datasets

Algorithm	Dataset	Performance (ARI)
K-means	Urban Crime Data	0.72
	Rural Crime Data	0.70
	Mixed Crime Data	0.71
DBSCAN	Urban Crime Data	0.74
	Rural Crime Data	0.72
	Mixed Crime Data	0.73
Hierarchical	Urban Crime Data	0.71
	Rural Crime Data	0.69
	Mixed Crime Data	0.70
Gaussian Mixture	Urban Crime Data	0.73
	Rural Crime Data	0.71
	Mixed Crime Data	0.72
Spectral Clustering	Urban Crime Data	0.75
	Rural Crime Data	0.73
	Mixed Crime Data	0.74
OPTICS	Urban Crime Data	0.73
	Rural Crime Data	0.71
	Mixed Crime Data	0.72
Proposed Model	Urban Crime Data	**0.82**
	Rural Crime Data	**0.80**
	Mixed Crime Data	**0.81**

Table 5 compares the performance of existing clustering algorithms on different types of datasets: Urban Crime Data, Rural Crime Data, and Mixed Crime Data. Performance is again measured using Adjusted Rand Index (ARI). Our proposed model consistently achieves higher performance across all datasets, with ARI values of 0.82 for urban data, 0.80 for rural data, and 0.81 for mixed data. This demonstrates the versatility and generalizability of our model in handling various types of crime data, outperforming existing algorithms in diverse settings.

Table 6: Comparison of Existing Algorithms with Time Consumption (Runtime)

Algorithm	Dataset Size	Runtime (seconds)
K-means	10,000 records	15
	50,000 records	70
	100,000 records	140
DBSCAN	10,000 records	20
	50,000 records	90
	100,000 records	180
Hierarchical	100,000 records	180
	10,000 records	30
	50,000 records	150
Gaussian Mixture	100,000 records	300
	10,000 records	25
	50,000 records	120
Spectral Clustering	100,000 records	250
	10,000 records	22
	50,000 records	110
OPTICS	10,000 records	28
	50,000 records	140
	100,000 records	280
Proposed Model	10,000 records	10
	50,000 records	50
	100,000 records	100

Table 6 compares the runtime performance of existing clustering algorithms with our proposed model for different dataset sizes (10,000, 50,000, and 100,000 records). Our proposed model demonstrates significantly lower runtime, with 10 seconds for 10,000 records, 50 seconds for 50,000 records, and 100 seconds for 100,000 records. This efficiency is attributed to the optimized grid-based clustering and incremental clustering techniques used in our model, which streamline the computational process and ensure timely analysis, making it highly suitable for real-time applications.

5. RESULTS AND DISCUSSION

Our proposed model for analysing the interconnectivity of criminal patterns using grid-based multivariate spatial and temporal clustering has yielded significant findings. This chapter provides a detailed discussion of the results, highlighting the performance of our model in comparison to existing algorithms and the implications of these findings for crime analysis and prevention. The technical performance of our model has been thoroughly evaluated using a variety of metrics, as detailed in Chapter 4. Our model demonstrates superior clustering accuracy, purity, homogeneity, temporal stability, and spatial coherence compared to existing algorithms such as K-means, DBSCAN, Hierarchical Clustering, Gaussian Mixture Models, Spectral Clustering, and OPTICS. The Adjusted Rand Index (ARI) of 0.82, purity of 0.85, and homogeneity of 0.83 indicate that our model effectively captures the intricate patterns in the crime data, leading to more precise and meaningful clusters. The high temporal stability index (TSI) of 0.80 and spatial dispersion index (SDI) of 0.78 further confirm the robustness of our approach. These metrics show that our model not only identifies clusters accurately but also maintains the consistency of these clusters over time and across different spatial regions. This is crucial for understanding the dynamic nature of criminal activity and for developing strategies to mitigate crime effectively.

The sensitivity analysis of key parameters, as presented in Table 2 of Chapter 4, reveals that our model performs consistently well across a range of grid sizes. This robustness to parameter changes highlights the adaptability of our approach, making it suitable for various datasets and application scenarios. Unlike traditional methods that may require extensive parameter tuning, our model delivers reliable results with minimal adjustment, enhancing its practical utility for real-world crime analysis. The evaluation of our model on different types of datasets—urban, rural, and mixed crime data—demonstrates its generalizability. With ARI values of 0.82 for urban data, 0.80 for rural data, and 0.81 for mixed data, our model outperforms existing algorithms across diverse contexts. This versatility is particularly valuable for law enforcement agencies and urban planners who must address crime in varied environments, from densely populated urban centres to sparsely populated rural areas. One of the standout features of our proposed model is its computational efficiency. As shown in Table 4 of Chapter 4, our model significantly reduces runtime compared to other algorithms, making it feasible for real-time applications. For instance, processing 100,000 records takes only 100 seconds with our model, compared to 140 seconds for K-means and up to 300 seconds for Hierarchical Clustering. This efficiency is achieved through our optimized grid-based clustering and incremental clustering techniques, which streamline the computational process without compromising accuracy.

Beyond technical performance, our model provides valuable insights into the patterns and interconnectivity of criminal activities. By linking spatial and temporal clusters, we can trace the movement and evolution of crime hotspots, uncovering trends that are not apparent with traditional methods. For example, our analysis revealed seasonal peaks in certain types of crimes, as well as the migration of crime hotspots from one region to another over time. These findings are crucial for proactive crime prevention strategies, enabling law enforcement agencies to allocate resources more effectively and anticipate future crime trends.

6. CONCLUSIONS AND FUTURE WORK

While our model shows great promise, there are areas for improvement and future research. One limitation is the reliance on historical crime data, which may not capture emerging trends or the impact of recent interventions. Incorporating real-time data and integrating additional variables such as social media activity or economic indicators could enhance the model's predictive capabilities. Future work could also explore the application of our approach to other types of spatiotemporal data, such as traffic accidents or disease outbreaks, further demonstrating its versatility and utility.

In conclusion, our proposed model for grid-based multivariate spatial and temporal clustering offers a powerful tool for analysing the interconnectivity of criminal patterns. By outperforming existing algorithms and providing actionable insights, our model contributes to more effective crime prevention and urban planning, ultimately enhancing public safety and community well-being.

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