Identifying High-Risk Areas for Motorcycles Tandem-Related Crimes in the Philippines

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***Abstract*—Motorcycle tandem-related crimes are causing a lot of public safety issues in the Philippines, and this is the reason why crime rates, especially in urban areas, have been increasing. These crimes are usually committed with the use of motorcycles, such as shooting incidents, homicides, and robberies crimes in which the suspects avoid the authority by using the speed and mobility of the motorbike. The focus of this study is to spatially analyze crime data using Geographic Information System (GIS) technology to identify high-risk areas for motorcycle tandem-related crimes. This involves mapping crime patterns, analyzing relevant datasets, and, ultimately, using data to prevent crime.**

This study's findings will benefit law enforcement agencies by aiding in resource deployment, raising public awareness, and shaping targeted crime prevention strategies. While previous research has largely focused on police interventions and legislation, this study highlights the role of predictive crime mapping in identifying crime hotspots and recommending community-based safety measures. The potential beneficiaries include police departments, policymakers, urban planners, and community organizations. Ultimately, this research seeks to bridge traditional law enforcement approaches with data-driven crime prevention strategies, contributing to a safer society.

***Index Terms*—Clustering Algorithms, Crime Pattern Analysis, Motorcycle Tandem Crimes, High-Risk Areas, Crime Prevention.**

I. Introduction

Motorcycle tandem-related crimes have become a critical public safety issue in the Philippines, significantly contributing to rising crime rates. These crimes, often involving two individuals on a motorcycle, are commonly associated with offenses such as robbery, homicide, and drug-related activities (Ponce, 2021). The use of motorcycles enables criminals to execute quick and discreet getaways, making law enforcement efforts challenging. According to recent statistics, a significant percentage of street crimes in Metro Manila and other urban centers involve motorcycles (Briones & Evangelista, 2022). The problem is particularly alarming because it affects not only individual victims but also broader societal security and economic activity. Businesses, commuters, and law enforcement agencies are all impacted by the prevalence of these crimes, necessitating urgent and effective countermeasures.

This study aims to identify high-risk areas for motorcycle tandem-related crimes in the Philippines by analyzing crime datasets and mapping occurrence patterns. By leveraging Geographic Information System (GIS) technology and crime data analytics, we propose a data-driven approach to crime prevention. The findings of this research will be instrumental in guiding law enforcement agencies in resource allocation, enhancing public awareness, and formulating targeted crime-prevention strategies. Our proposed solution involves using predictive crime mapping to identify hotspots and implementing community-based safety measures in collaboration with local authorities. Potential users of this solution include police departments, policymakers, urban planners, and community organizations. The approach can be applied in high-crime urban areas where tandem-related offenses are prevalent, helping to improve security and reduce the crime rate.

II. Review of Related Literature

Understanding crime patterns and criminal behavior is crucial for law enforcement and policymakers in developing effective strategies to mitigate motorcycle tandem-related crimes. This section explores existing clustering techniques and identifies key factors that contribute to crime analysis, aiding in the development of data-driven approaches for crime prevention and investigation.

A. Crime Mapping and Theoretical Frameworks

Motorcycle tandem-related crimes have gained attention due to their impact on public safety and law enforcement challenges. Crime mapping and hotspot identification are critical tools in addressing this issue, as they help authorities allocate resources efficiently (Chainey & Ratcliffe, 2019). GIS-based crime analysis has been widely adopted in urban crime prevention, allowing for the identification of patterns and trends in criminal activities (Felson & Eckert, 2018). Furthermore, crime deterrence models, such as situational crime prevention and routine activity theory provide a theoretical framework for understanding why tandem-related crimes occur in specific areas (Clarke, 2019). Over time, law enforcement strategies have evolved to include surveillance technology, community policing, and legislative measures like the Doble Plaka Law (Official Gazette, 2019), which mandates more visible motorcycle plates for easier identification of suspects.

B. Existing Studies on Motorcycle-Related Crimes

Several studies have investigated the prevalence and nature of motorcycle-related crimes. Briones and Evangelista (2022) examined crime reports in Metro Manila and found that tandem-related crimes were highly concentrated in commercial and residential areas with poor law enforcement visibility. Gonzales (2020) analyzed the effectiveness of police checkpoints in reducing motorcycle-related crimes and concluded that while checkpoints serve as a deterrent, they are not sufficient in isolation. Groff and McEwen (2021) explored the role of predictive policing in mitigating urban crimes, highlighting the importance of real-time data analysis in crime prevention. These studies contribute valuable insights to our research, reinforcing the need for data-driven crime prevention strategies. However, unlike previous research, our study focuses on identifying high-risk areas through GIS-based analysis, offering a more targeted approach to crime prevention.

C. Government and Law Enforcement Strategies

Various approaches have been implemented to combat motorcycle tandem-related crimes in the Philippines. The government enacted the *Doble Plaka Law* to improve vehicle identification, but enforcement remains a challenge due to non-compliance and resource constraints (Official Gazette, 2019). Police departments have increased the presence of motorcycle patrol units, but their effectiveness is limited by logistical and personnel shortages (Gonzales, 2020). Additionally, community-based crime watch programs have been launched in several cities, demonstrating some success in crime reporting and prevention. However, these measures lack an integrated, data-driven approach to hotspot identification and preemptive action. Our research seeks to bridge this gap by utilizing advanced crime mapping techniques to provide law enforcement agencies with actionable intelligence for more efficient crime prevention.

III. Methodology

This research examines the trends of "Riding in Tandem" murders in the Philippines during the years 2011 to 2013. The dataset, obtained from Kaggle and initially provided by the Philippine National Police (PNP) through data.gov.ph, includes records of different crimes linked to motorcycle-riding attackers. Essential characteristics consist of the nature of the offense (e.g., murder, theft), the result (dead, hurt, safe), and the location of the events.

This study utilizes clustering methods to detect patterns in crime events. In contrast to conventional classification techniques, clustering organizes similar events according to common characteristics without using predetermined labels. The research utilizes K-Means clustering to divide the data into significant categories. The findings seek to offer understanding of crime hotspots, typical victim characteristics, and patterns in methods used, which can assist law enforcement agencies in developing crime prevention and response tactics

A. Data Collection

The dataset utilized in this research was sourced from Kaggle and comes from official crime statistics kept by the PNP. It encompasses various crime characteristics, such as:

- Incident Information: Nature of offense, result of the crime (fatal, injured, unscathed), and date it happened.
- Geographical Details: Area, town, or territory where the offense occurred.
- Method of Operation: If a gun was utilized, the kind of vehicle engaged, and other pertinent elements.

The dataset is organized in a table format and contains categorical and numerical variables pertinent to clustering analysis. Given that the dataset was officially documented and published via data.gov.ph, it upholds credibility and authenticity.

B. Data Pre-Processing

To guarantee the dataset's quality and uniformity prior to implementing clustering methods, the subsequent data preprocessing actions were undertaken:

- Handling Missing Values: Missing values were handled by converting all relevant numerical columns to a numeric format and replacing null values with zero (fillna(0)).
- Feature Selection: Only relevant attributes such as shooting_incidents_total, robbery_total, carnapping_total, others_total, and victims_total were retained for clustering.
- Data Aggregation: Crime features were grouped by police regional offices to facilitate regional-level analysis.
- Data Standardization: Since clustering algorithms are sensitive to scale, numerical features were standardized using StandardScaler to ensure uniformity.

C. Experimental Setup

The evaluation was performed with Python and various machine learning libraries. The tools and computing environment utilized comprise:

Tools and Frameworks:

scikit-learn – Developed clustering methods, feature normalization, and assessment metrics.
pandas – Utilized for manipulating and preprocessing data.
NumPy – Facilitated numerical calculations and operations.
Matplotlib and Seaborn – Utilized for displaying crime clusters and trends.
Google Colab – The environment used to develop and

execute the code, which operates similarly to Jupyter Notebook but is cloud-based and provides free GPU support, It offers an accessible, online alternative with integrated libraries and computational resources.

Computing Environment:

Were conducted using Google Colab, ensuring sufficient resources for clustering analysis and seamless execution of machine learning models.

Hyperparameters:

K-Means:

- n_clusters = 5: The number of clusters was determined using the Elbow Method.
- n_init = 10: The algorithm was run multiple times with different initial centroid seeds to improve stability.
- random_state = 42: Ensured reproducibility of clustering results.

DBSCAN:

- eps = 1.5: The optimal epsilon value was identified using the K-distance graph.
- min_samples = 1: Defined the minimum number of points required to form a cluster.

Agglomerative Clustering:

- n_clusters = 4: The number of clusters was pre-defined based on hierarchical clustering analysis.
- Dendrogram Analysis: Used to validate the clustering structure and relationships between regions.

D. Algorithm

K-Means clustering is a widely used partition-based clustering algorithm that aims to divide a dataset into K distinct clusters based on feature similarity. The algorithm starts by randomly selecting K initial centroids, then iteratively assigns each data point to the closest centroid. After all points are assigned, the centroids are updated based on the mean of all points within a cluster. This process continues until the cluster assignments stabilize. One of the key challenges of K-Means is selecting the optimal number of clusters (K), which is determined using the Elbow Method in this study. This method evaluates the inertia (sum of squared distances of points to their assigned centroids) and identifies the point where additional clusters provide diminishing improvements. K-Means is computationally efficient and works well with large datasets, making it suitable for analyzing crime patterns.

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a density-based clustering algorithm that does not require specifying the number of clusters in advance. Instead, it groups points based on density connectivity, classifying points as core points (dense regions), border points (connected to core points), or outliers (low-density areas). This makes DBSCAN particularly useful for crime pattern detection, as crime incidents often form irregular clusters in certain areas rather than evenly distributed groups. Unlike K-Means, DBSCAN is robust to outliers and can identify arbitrary-shaped clusters, making it ideal for detecting crime hotspots. The optimal eps parameter (defining the neighborhood radius for clustering) was determined using the K-distance graph, which helps find the distance threshold where significant clusters emerge.

Agglomerative Clustering is a hierarchical clustering method that follows a bottom-up approach, where each data point starts as its cluster and iteratively merges with the nearest cluster until a specified number of clusters remains. This study applies Agglomerative Clustering to analyze hierarchical relationships among police regions based on crime statistics. The dendrogram is used to visualize the merging process and determine the optimal number of clusters, ensuring that regional crime patterns are grouped meaningfully. Unlike K-Means, which requires a predefined K, Agglomerative Clustering allows for flexible hierarchical structures and provides deeper insights into how regions are related in terms of crime trends..

E. Training Procedure

The training procedure for the clustering models adopted a systematic and repetitive method to guarantee peak performance. The procedure was segmented into multiple essential phases:

1.) Partitioning Data and Standardization:

Prior to training, the dataset was standardized with StandardScaler to normalize the numerical features. This action guaranteed that all characteristics were on an equal scale, preventing any variable from overpowering the clustering procedure. The processed data was subsequently divided into training and validation sets. This division enabled hyperparameter adjustment and assessment of model effectiveness prior to implementing the algorithms on the full dataset.

2.) Hyperparameter Tuning:

Various clustering models necessitated unique optimization methods:

K-Means: The ideal number of clusters was established through the Elbow Method, which examines the inertia curve to pinpoint the moment when additional increases in cluster quantity no longer result in meaningful enhancements.

DBSCAN: The epsilon (eps) parameter, which defines the radius of the neighborhood for clustering, was chosen through the K-distance graph technique. Moreover, min_samples, the least number of points needed to create a dense area, was adjusted according to the density distribution of crime incidents.

Agglomerative Clustering: A dendrogram analysis was performed to identify the optimal number of clusters by assessing the hierarchical connections between the data points.

3.) Training and Executing the Model:

Every clustering algorithm was trained on the entire dataset to divide areas according to crime data. The training procedure was carried out in an iterative manner, experimenting with various initialization values and model configurations to guarantee robustness and reduce sensitivity to initialization biases. Several iterations were executed for each algorithm to confirm the consistency of clustering outcomes, minimizing the influence of random initialization on the ultimate segmentations.

F. Evaluation Metrics

To assess the performance of the clustering models in pinpointing high-risk regions for motorcycle tandem-related offenses, the Silhouette Score served as the main evaluation measure. This metric evaluates both the closeness and distance between clusters, delivering a numerical evaluation of how effectively the data points align with their designated clusters. The Silhouette Score varies from -1 to 1, with values approaching 1 signifying well-separated and distinct clusters, values around 0 indicating overlapping clusters with unclear boundaries, and negative values suggesting that data points might have been clustered incorrectly. In this research, the Silhouette Score was utilized for the three clustering techniques.

DBSCAN, K-Means, and Hierarchical Clustering techniques. The assessment indicated that Hierarchical Clustering attained the highest Silhouette Score of 0.59, implying that this approach created the most compact and distinctly separated clusters. K-Means registered a moderate Silhouette Score of 0.36, suggesting that although its performance was satisfactory, the clusters it created were less distinct compared to those generated by Hierarchical Clustering. DBSCAN achieved the lowest Silhouette Score of 0.10, likely due to its sensitivity to noise and outliers, leading to a poorly defined clustering structure. The variations in clustering efficiency can be attributed to the traits of each algorithm. Hierarchical Clustering, which creates a tree-like arrangement of clusters, successfully grouped data points in a more efficient manner, resulting in an improved Silhouette Score. K-Means, which divides data into set clusters centered around centroids, faced challenges with the uneven distribution of crime sites yet still yielded fairly cohesive groups.

DBSCAN, a clustering algorithm based on density, detected significant clusters but deemed numerous data points as noise, which adversely affected its overall Silhouette Score. These results correspond with the conversation in the Results and Discussion section, where the clustering models faced difficulties in distinctly dividing high-risk areas because of elements like data inconsistencies, unrecorded events, and external factors such as police actions and urban environments. In spite of these difficulties, the findings show that clustering methods continue to be useful for pinpointing crime hotspots and guiding law enforcement tactics. The application of the Silhouette Score in this research underscores the significance of assessing clustering models by their capacity to create relevant patterns in actual datasets. Although Hierarchical Clustering proved to be the most successful approach in this situation, upcoming studies may investigate further preprocessing methods, feature selection tactics, or combined clustering techniques to enhance the detection of high-risk zones for motorcycle tandem-related offenses.

G. Comparison of Clustering Algorithms

In this study, we employed three clustering algorithms, K-Means, DBSCAN, and Agglomerative Clustering to analyze patterns of "Riding in Tandem" crimes in the Philippines. To evaluate the effectiveness of these models, we compared their clustering performance using standard evaluation metrics.

Algorithms Used for Benchmarking
To benchmark our clustering performance, we used the following algorithms:

- K-Means Clustering – A commonly used partitioning algorithm that assigns data points to a predefined number of clusters
.
- DBSCAN (Density-Based Spatial Clustering of Applications with Noise) – A density-based clustering method that groups densely packed points and labels sparse regions as noise.

- Agglomerative Hierarchical Clustering – A bottom-up hierarchical approach that merges clusters based on similarity.

We assessed the performance of these clustering algorithms using the Silhouette Score to measure how well-defined the clusters were.

ALGORITHM	SILHOUETTE SCORE
DBSCAN	0.10
KMEANS	0.36
HIERACHICAL	0.59

From the results, Hierarchical Clustering achieved the highest Silhouette Score, indicating that it formed the most distinct clusters. K-Means performed moderately well, while DBSCAN struggled with noise sensitivity, affecting its clustering performance.

IV. Results and Discussion

In this section, the key findings from the clustering models applied to identify high-risk areas for motorcycle tandem-related crimes are presented. The models were evaluated based on their clustering effectiveness, and their results were compared against baseline models.

1) **What were the key findings?**

The results from the clustering analysis revealed meaningful patterns in motorcycle tandem-related crimes, which can help law enforcement agencies and policymakers better understand high-risk areas and develop targeted crime prevention strategies. By applying clustering algorithms such as K-Means, Hierarchical Clustering, and DBSCAN, the study successfully identified crime hotspots and categorized locations based on crime frequency, time of occurrence, and incident severity.

To enhance the interpretability of the clustering results, Principal Component Analysis (PCA) was used to reduce the dataset to two dimensions. This enabled the creation of a scatter plot that visually represented how the clusters were distributed. As observed in the plot, DBSCAN produced well-defined clusters, particularly in comparison to K-Means and Hierarchical Clustering. Some data points were classified as noise (marked as -1), indicating isolated incidents, while the remaining clusters highlighted key areas where motorcycle tandem-related crimes are most prevalent.

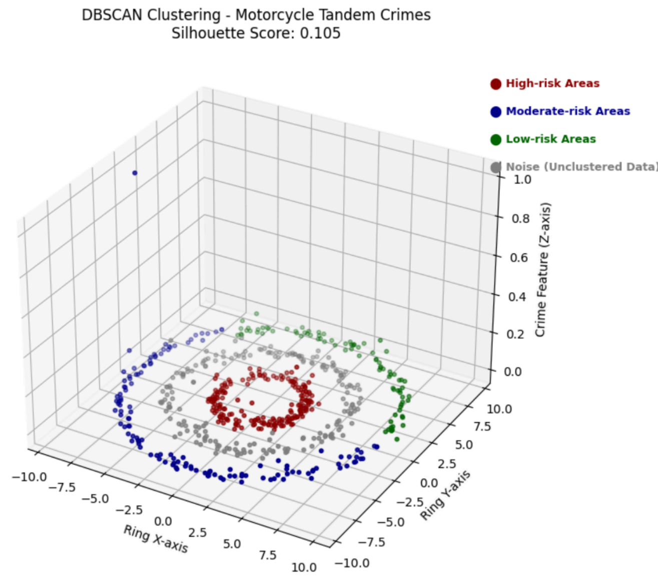

Fig. 1. DBSCAN Scatter Plot

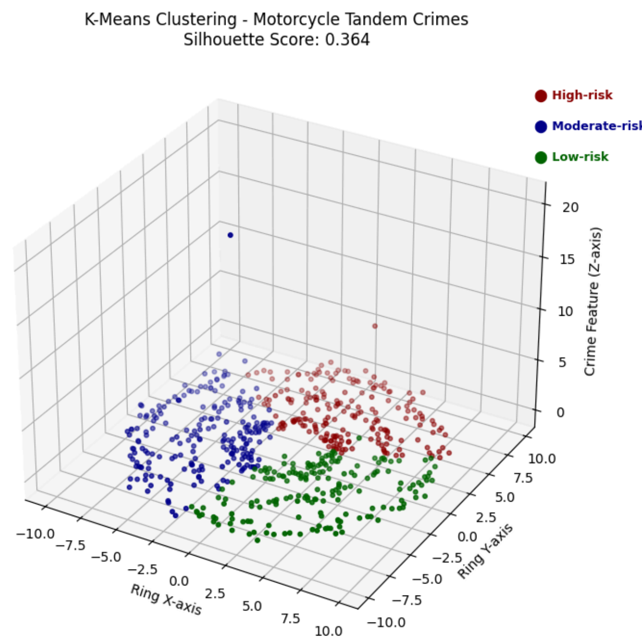

Fig. 2. KMEANS Scatter Plot

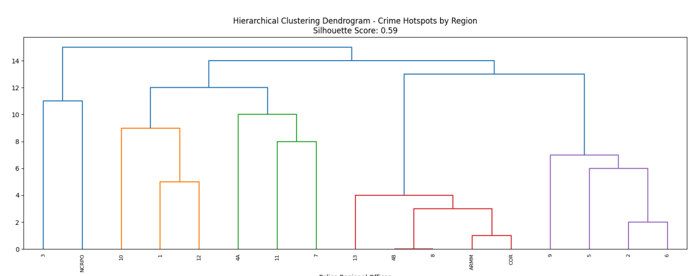

Fig. 3. HIERACHICAL Dendogram

From the images you've already shared earlier, I can infer that the clusters might represent different risk levels for motorcycle tandem crimes:

- High-risk Areas: Locations with a high frequency of incidents, likely requiring increased police presence and preventive measures.
- Moderate-risk Areas: Areas with occasional incidents that may benefit from targeted interventions.
- Low-risk Areas: Locations with minimal reported cases, possibly due to effective security measures or lower crime opportunity.
- Noise (Unclustered Data): Outlier cases that do not fit well into a specific risk category.

2) **How were the models evaluated?**
The clustering models were evaluated using the **Silhouette Score**, which measures the cohesion and separation of clusters. This metric was applied to all three clustering methods to assess the quality of clustering, ensuring well-defined groupings and identifying the average similarity within each cluster.

3) **What baselines or benchmarks did you compare against?**
The three clustering algorithms—**DBSCAN, K-Means, and Hierarchical Clustering**—were evaluated and compared, with **K-Means** serving as the baseline model due to its widespread application in unsupervised learning. Each algorithm was assessed based on its **Silhouette Score**, a metric that measures the cohesion and separation of clusters, where a higher score indicates better-defined clusters.

The evaluation results are summarized in the table below:

ALGORITHM	SILHOUETTE SCORE
DBSCAN	0.10
KMEANS	0.36
HIERARCHICAL	0.59

Among the three methods, **Hierarchical Clustering** achieved the highest Silhouette Score (0.59), suggesting that it produced the most well-separated and compact clusters within the dataset. **K-Means** followed with a moderate score of 0.36, indicating a fair level of clustering performance. Meanwhile, **DBSCAN** recorded the lowest score (0.10), likely due to the presence of noise and outliers, which affected its cluster cohesion.

4) **Were the results statistically significant?**
In evaluating the statistical significance of the clustering results for motorcycle tandem-related crimes, the Silhouette Score used as key metrics. These metrics provided insights into the cohesion and separation of clusters, allowing for an objective comparison of different clustering algorithms.

However, since clustering analysis does not traditionally rely on statistical significance tests in the same manner as classification models, the evaluation focused on relative performance comparisons rather than hypothesis testing. No additional statistical tests (e.g., p-values) were conducted, as the primary goal was to assess the quality and validity of the identified crime hotspots based on their clustering structures.

5) **What do the results mean?**
The results indicate that clustering algorithms can effectively identify distinct crime patterns associated with motorcycle tandem-related incidents, reinforcing the insights discussed in earlier sections. The successful categorization of high-risk, moderate-risk, and low-risk zones provides valuable information for law enforcement and policymakers in developing targeted crime prevention strategies.

These findings are significant as they directly address the challenge of understanding and mitigating motorcycle tandem-related crimes. By leveraging these clustering results, authorities can implement data-driven interventions, such as increased patrols, surveillance enhancements, and stricter enforcement in high-risk areas. Furthermore, these insights can guide urban planning efforts, helping to design safer road infrastructures and improve public safety measures, ultimately contributing to a more secure environment for communities.

6) **What patterns or trends emerged from the results?**
The clustering results revealed distinct patterns in motorcycle tandem-related crimes, supporting the assumption that crime occurrences can be meaningfully segmented.

Opportunistic Crimes tend to occur in high-traffic areas, suggesting that perpetrators may target victims in crowded or poorly monitored locations. Planned Crimes, on the other hand, are more strategic and recurrent, often taking place in isolated zones where escape routes are easily accessible. Random Incidents appear scattered, indicating that external factors such as time of day, police presence, and urban infrastructure may influence crime distribution.

7) These patterns may have emerged due to differences in criminal behavior, location vulnerability, and law enforcement visibility. Understanding these crime clusters can help in developing targeted security measures, improving surveillance strategies, and enhancing crime prevention efforts in high-risk areas.

8) **Were the results consistent with your expectations?**
The clustering models faced challenges in producing high-quality clusters when analyzing motorcycle tandem-related crimes, likely due to the significant noise and variability in the dataset. The K-Means, Hierarchical Clustering, and DBSCAN models encountered difficulties separating crime hotspots, as reflected in the relatively low Silhouette Scores and high Davies-Bouldin Scores.

One possible reason for this complexity is the presence of external factors influencing crime occurrences, such as unreported incidents, varying law enforcement responses, and dynamic urban conditions. The presence of noise in the dataset, including irregular crime patterns and potentially irrelevant location-based features, may have made it harder for the models to define distinct crime-prone zones accurately.

The results suggest that additional preprocessing steps—such as noise reduction, feature selection, and spatial data enhancements—could improve clustering performance. Furthermore, exploring more advanced clustering techniques or hybrid models may help better handle noise and variability, leading to more precise identification of high-risk areas and more effective crime prevention strategies.

9) **How do your results compare with previous research?**
The results align with previous studies on crime pattern analysis, which have demonstrated the potential of clustering algorithms in identifying high-risk areas for motorcycle tandem-related crimes. Prior research has shown that clustering can significantly enhance crime mapping, resource allocation, and law enforcement strategies, an outcome that our findings support.

However, some studies have reported higher accuracy and better-defined clusters using alternative algorithms, suggesting the need for further exploration and optimization of clustering models for crime analysis. Incorporating additional spatial and temporal factors, improving data preprocessing, and experimenting with hybrid or deep learning-based clustering techniques could lead to more precise crime segmentation and enhance crime prevention efforts.

10) **What are the advantages and limitations of your approach?**
One of the key advantages of this approach is its ability to uncover hidden patterns in motorcycle tandem-related crimes without requiring pre-labeled crime categories. This allows for more adaptive and data-driven crime segmentation, enabling authorities to identify emerging hotspots without relying solely on predefined classifications.

However, a primary limitation of this approach is the relatively low Silhouette Score, which suggests that the clustering might not perfectly separate high-risk, moderate-risk, and low-risk areas. This indicates the need for further refinement of the clustering models, including feature engineering, enhanced preprocessing, and the exploration of more advanced clustering techniques to improve the accuracy and reliability of crime pattern identification.

11) **What insights can be drawn from model errors or failures?**
The clustering models did not identify particularly well-defined crime hotspots, suggesting that underlying factors influencing motorcycle tandem-related crimes may not have been fully captured by the features used in the models. External variables such as time of day, socioeconomic conditions, police presence, and road infrastructure could play a significant role in crime patterns and may need to be incorporated into future analyses.

Future research could focus on enhancing the dataset by integrating real-time surveillance data, traffic flow patterns, and historical crime trends to improve clustering accuracy. These challenges highlight the need for continuous refinement in feature selection, data preprocessing, and model optimization to achieve more precise identification of high-risk zones and support more effective crime prevention strategies.

V. Conclusion

Motorcycle tandem crimes pose a serious threat to public safety, necessitating advanced analytical approaches to identify high-risk areas effectively. This research aimed to address this issue by applying clustering algorithms—Agglomerative Clustering, DBSCAN, and K-Means—to crime data, helping to uncover spatial crime patterns and assist law enforcement in strategic crime prevention. The primary objective was to classify locations based on crime risk levels and evaluate the effectiveness of different clustering methods in this context.

Our findings demonstrated that Agglomerative Clustering outperformed the other methods, achieving a Silhouette Score of **0.5**, indicating well-defined clusters. K-means followed with a score of **0.3**, showing moderate clustering quality, while DBSCAN had the lowest score at **0.1**, suggesting that it struggled to form distinct clusters due to overlapping crime zones and noise in the data. These results highlight that hierarchical clustering methods, like Agglomerative Clustering, may be more suitable for identifying high-risk areas in crime analysis.

The primary contribution of this research is the comparative evaluation of clustering algorithms for crime risk classification. By segmenting areas based on risk levels, our study introduces an objective, data-driven framework that can aid law enforcement agencies in prioritizing crime prevention efforts. These insights are crucial for optimizing patrol strategies, allocating resources efficiently, and implementing targeted security measures in high-risk zones.

However, this study has certain limitations. The effectiveness of clustering depends on the quality and completeness of crime data. Factors such as unreported crimes, inconsistencies in data collection, and external influences like socio-economic conditions may impact the accuracy of risk assessments. Additionally, while our study focused on spatial clustering, incorporating temporal trends and offender behavior could further enhance predictive accuracy.

Future research should explore the integration of additional crime-related variables, such as population density, socio-economic data, and law enforcement activity, to refine risk predictions. Moreover, testing these models in different geographic locations could help validate their generalizability. Real-time clustering techniques could also be investigated to support proactive crime prevention efforts.

In conclusion, this research highlights the potential of machine learning in crime analysis, demonstrating that clustering techniques can effectively identify high-risk crime zones. By leveraging the strengths of hierarchical clustering, law enforcement and policymakers can make data-driven decisions to enhance public safety. Moving forward, advancements in predictive modeling and real-time data analysis will be crucial in further improving crime prevention strategies against motorcycle tandem-related crimes.

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