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Spatial Analysis of Urban Road Traffic Accidents Using GIS

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ABSTRACT: *Road traffic accidents are on the rise in urban areas globally, including Sri Lanka, leading to significant human and property losses. The Colombo Municipal Council (CMC) area in Sri Lanka witnesses a particularly high number of these accidents. This study aimed to analyze urban traffic accidents using GIS within complex urban networks. It employed a two-step approach, starting with a hot spot analysis based on accident times and types (fatal, non-grievous, and damage-only), using Kernel Density Estimation (KDE) and Nearest Neighbor Hierarchy (NNH) methods. Additionally, it created separate severity maps and compares the results visually, with KDE offering a comprehensive overview and NNH pinpointing high-accident areas. The KDE method was expected to benefit long-term traffic congestion reduction and safety enhancement. NNH's severity map provides immediate insights for road safety specialists. A mathematical approach involved calculating the Prediction Accuracy Index (PAI) for each method, revealing a notably higher value for NNH, making it a more suitable choice. In conclusion, this study recommended the Nearest Neighbor Hierarchy (NNH) method as superior for road safety analysis, offering important guidance for urban planning and accident prevention efforts*

KEYWORDS: urban traffic accidents, hot spot analysis, nearest neighborhood hierarchical and kernel density estimation, prediction accuracy index

INTRODUCTION

In recent years, urban traffic accidents have become a serious problem. A large number of lives are lost every day, and numerous serious and non-serious injuries occur worldwide on a daily basis. Furthermore, these accidents are having a severe impact on the world economy. The main reason for the increase in traffic accidents worldwide is the rapid growth of the world's population, driven by urbanization (World Health Organization, 2021). Consequently, even though the global traffic volume is increasing rapidly, the existing road infrastructure remains unchanged. Each year, the world loses approximately 1.35 million lives, and between 20 and 30 million people sustain fatal injuries. Approximately 3,700 people die every day worldwide due to accidents involving cars, buses, motorcycles, and pedestrians (World Health Organization, 2021). The death toll from HIV/AIDS isn't significantly higher than the fatalities resulting from traffic accidents. This has also contributed to the rise in traffic accidents (World Health Organization, 2021).

When compared with the rest of the world, urban road traffic accidents are also one of the major challenges facing Sri Lanka at present. Sri Lanka is still a developing country, and it also experiences substantial economic losses due to these traffic accidents. As a result, a significant portion of Sri Lanka's youth is exposed to accidents (The World Bank Annual Report, 2020). Furthermore, property damage is occurring at a high rate, making this a very serious situation nationwide. The highest number of traffic accidents in Sri Lanka occurs in the Colombo Municipal Council (CMC) area (The World Bank Annual Report, 2020). In fact, Colombo is the capital of Sri Lanka and has the highest population density, attracting a large number of people and vehicles for services. Therefore, this study aims to analyze traffic accidents in the CMC area.

Geographic Information System (GIS) technology has become a popular tool for visualizing accident data and analyzing hotspots (Deepthi, J.K. and Ganeshkumar, B., 2010). It can be employed for viewing, manipulating, and analyzing geospatial data. Additionally, it is faster and more efficient (Aghajani et al., 2017). Consequently, GIS is a crucial and comprehensive management tool for traffic safety (Khan, M. A. et al., 2018). Many agencies and researchers have reported using GIS for accident analysis, and this study also aims to utilize this technology.

Identifying hotspots is a systematic process for detecting road sections suffering from an unacceptably high risk of crashes. Therefore, the main objective of this study is to analyze urban traffic accidents using GIS in a complex urban network. Furthermore, the specific objectives are as follows:

-Identifying the highest-risk areas by creating a severity map using Kernel Density Estimation (KDE) and Nearest Neighbor Hierarchy (NNH) methods.

-Comparing the results using visual comparison methods and mathematical comparison methods.

LITERATURE/THEORETICAL UNDERPINNING

Hot spot analysis is a key tool in GIS for analyzing accident hazards by identifying hot spots through the creation of severity maps. Additionally, it can aid in making better decisions by revealing the relationship between spatial and attribute data (Shafabakhsh et al., 2017). Moreover, the traffic department pays more attention to accidents that result in serious casualties in actual traffic management. Thus, it is important to study the spatial distribution characteristics of areas with high accident severity.
Several GIS methods have been applied to road accident analysis over the last two decades. Many researchers have used the KDE method to identify road accident hot spots (Hashimoto et al., 2016; Thakali et al., 2015). KDE is an interpolation method used to locate hot spot areas. The approach is based on a point density function that is computed for each grid cell in the area (Prasannakumar et al., 2011).

In 2009, Anderson applied the KDE method using GIS in the City of Afyonkarahisar, Turkey, to find the spatial pattern of injury-related road accidents and identified high-density accident hot spots. In 2000, Banos and Huguenin-Richard used the KDE method to analyze traffic accidents and mapped them to investigate the distribution pattern of child pedestrian accidents. Additionally, in 2008, Erdogan et al. developed a traffic accident analysis approach to identify hot spots and the causes of accidents in Turkey using KDE. Furthermore, Blazquez and Cell in 2013 and Plug et al. in 2011 used KDE to observe the distribution pattern of traffic accidents spatially and temporally and highlighted that KDE is a valuable tool for studying the spatial pattern of crashes and identifying hot spots.

In the KDE method, Equation 1 is used for the estimation of kernel density. This involves placing a symmetrical surface over each point, evaluating the distance from the points to a reference location based on mathematical functions, and then summing the values for all the surfaces for that reference location. This procedure is repeated for successive points (Anderson, 2009).

$$f(x, y)=\sum_{i=1}^{n} \frac{1}{n\times 2\times \pi h^2} \times w_i \times K\left(\frac{d_i}{h}\right) \qquad 1$$

where
f(x,y) is the density estimate at the location (x,y);
n is the number of observations;
h is the bandwidth;
K is the kernel function and
d_i is the distance between the location (x, y) and the i^{th} observation;
W_i is the intensity of the observation.
For the crash count, W_i is unit, whereas this may vary when we consider different weights for different severities of crashes.

There are other geostatistical clustering methods that evaluate relative risk based on their degree of association with the surrounding areas. Examples of clustering methods widely used in road safety studies include K-means clustering, NNH clustering, Moran's I Index, and Getis-Ord Gi statistics (Thakali et al., 2015) NNH Clustering is a hot spot clustering method that is primarily used to detect accident hot spots.

In this method, outputs can be visualized in two different formats: Convex hull and ellipse, as shown in Figure 1. Convex hulls are polygons that fully cover all clustered points and are sensitive enough to identify the actual area where the hot spot occurs. Ellipse is more of a symbolic representation of the cluster (Levine, 1996). Additionally, there is an option to set a fixed search distance radius in the menus. CrimeStat and ArcMap are used as the GIS platforms for this hot spot clustering analysis. CrimeStat is a crime mapping software program developed by Ned Levine (Levine, 1996). It can be downloaded for free and is primarily used for analyzing point data.

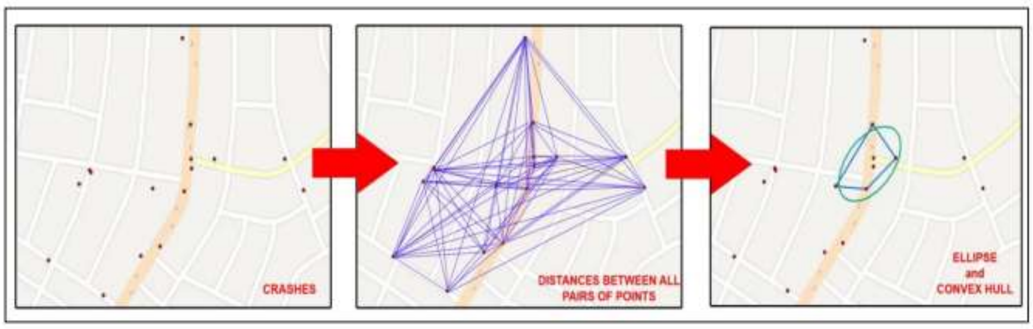

Figure 1: NNH clustering format
Source: (Aquil, M. M., & Faheem, M. I., 2021).

The Nearest Neighbor Index must be calculated before calculating the Nearest Neighbor Hierarchy. The following equation (2) is used for this. (Shariff, S.S. R. et al, 2018).

$$\text{Nearest Neighbor Index} = \frac{\text{AVG Nearest Neighbor}}{\text{Expected AVG Nearest Neighbor}} \qquad 2$$

Where:-

$$\text{Average Nearest Neighbor} = \frac{\text{Distance}}{\text{Number of Accidents}}$$

$$\text{Expected Average Nearest Neighbor} = \frac{1}{2}\sqrt{\frac{\text{Area}}{\text{Number of Point}}}$$

heories are developed to explain, predict, and comprehend phenomena, as well as to question and extend current knowledge within the constraints of crucial boundary assumptions in many cases. The theoretical framework introduces the theory that explains why the research problem under investigation occurs.

Two analysis methods have been used in this study, namely KDE and NNH (Levine, 2006 and 2009). These two methods are analyzed to obtain the appropriate severity map, graph, and to compare the results. The prediction accuracy index is calculated using the following Equation 3 (Shariff, S.S. R. et al, 2018).

$$\text{Prediction Accuracy Index (PAI)} = \frac{(n/N)\times 100}{(a/A)\times 100} \qquad 3$$

Where:-

n = the total number of accident found in that particular
N = the total number of accidents in the study area.
a = Equals to total area of hotspot.
A = Equals to the entire area in the study region.

Several research studies have been conducted to compare various hot spot procedures. The Prediction Accuracy Index (PAI), developed by Chainey et al. (2008), serves as a mechanism for evaluating the accuracy of different hot spot approaches. They assessed various approaches with respect to different types of crimes. In their study, the KDE hot spot technique yielded the best results when comparing several hot spot strategies in terms of crime prediction and technique measurement.
However, Levine (2008), in his analysis of their work, demonstrated that the convex hulls output of the NNH clustering algorithm outperformed the KDE technique. Both Prasannakumar V. et al. (2011) and Harirforoush, H. (2017) conducted studies that showed the NNH clustering algorithm's superiority over

KDE and other approaches in terms of prediction and PAI assessment (Prasannakumar V., 2011).

METHODOLOGY

2.1 Study Area

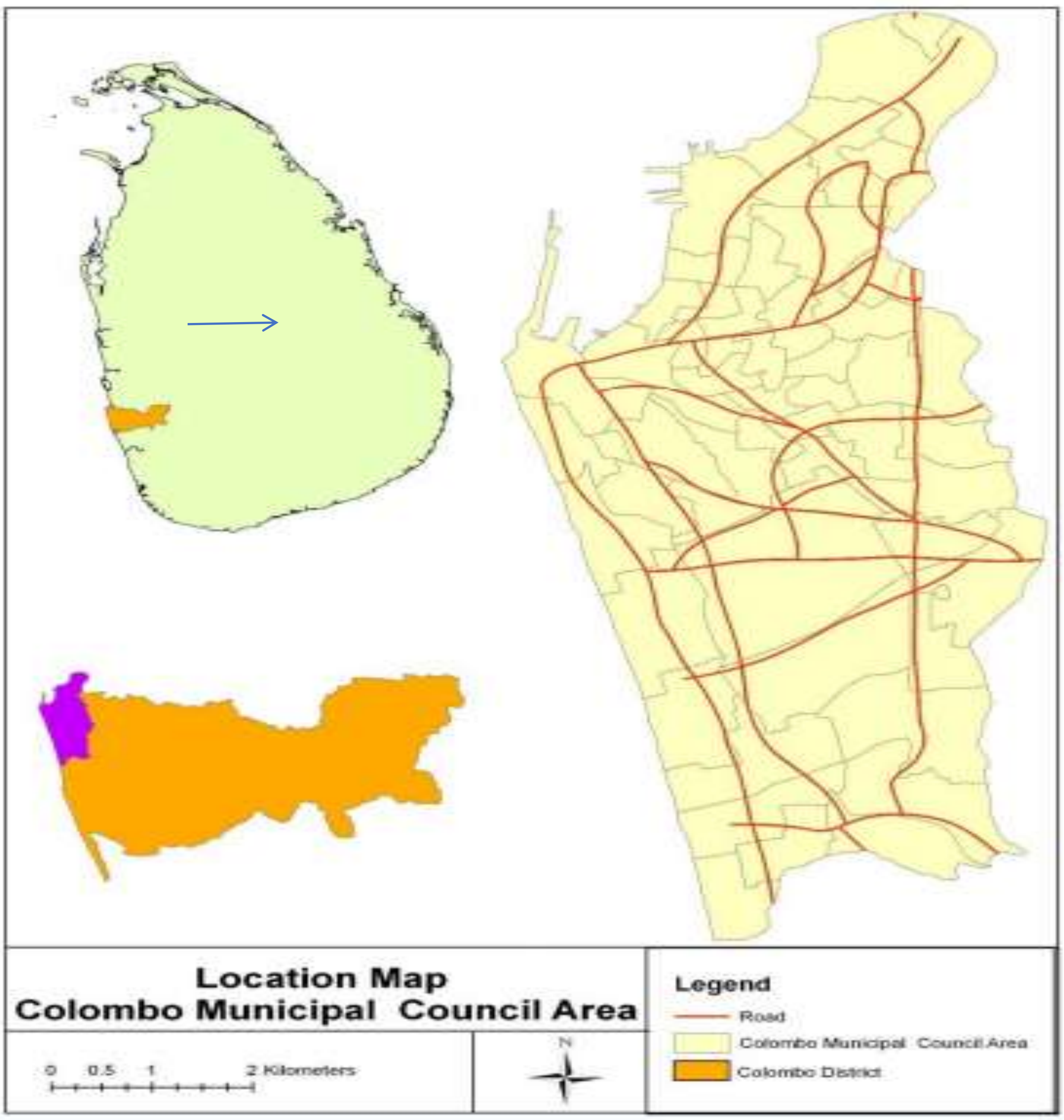

Figure 2: The Colombo Municipal Council Area Map

The study area selected for this research is the Colombo Municipal Council (CMC) area, as shown in Figure 2. Colombo is the capital of Sri Lanka, and the region covers an area of 37 square kilometers with a population of approximately 619,001 residents. An important aspect of this study is the significant population growth experienced by the CMC area over the past decade, leading to increased motorization and urban mobility levels. As a result, the highest number (9.7%) of traffic accidents per year has been reported within the Colombo municipal limits. Therefore, the CMC boundary has been chosen for the analysis of urban traffic accident

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METHOD

The methodology is presented as shown in figure

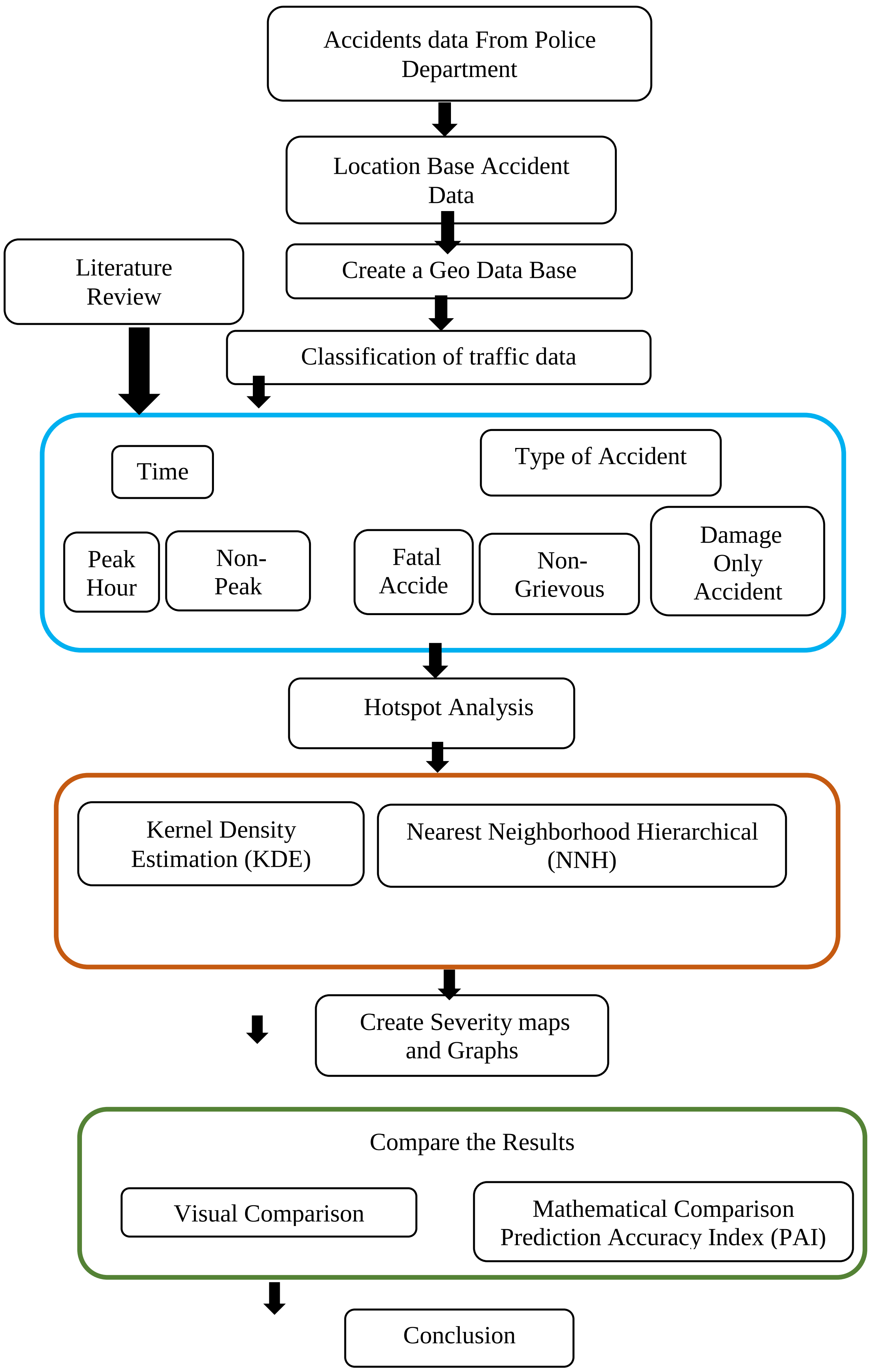

Figure 3: Methodology flow chart

The methodology of this study mainly consists of five (5) steps, including accident data collection, classification of accident data, hot spot analysis, creation of severity maps and graphs, and comparison of

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results and findings. The data were collected from the Colombo Police Headquarters within the CMC area for the year 2020. There are 23 police stations within the CMC area, and a total of 1124 sample data points were collected. This data included the date and time of the accident, as well as the type of accident, including fatal, non-grievous, and damage-only incidents. These accidents were further classified into peak hours and non-peak hours. Peak hours were defined as 6 to 10 in the morning, 11 to 2 in the afternoon, and 4 to 7 in the evening, corresponding to school and office start and end times, which are identified as rush hours. The rest of the time was categorized as non-peak hours. The road shapefile of the CMC area was obtained from the Survey Department.

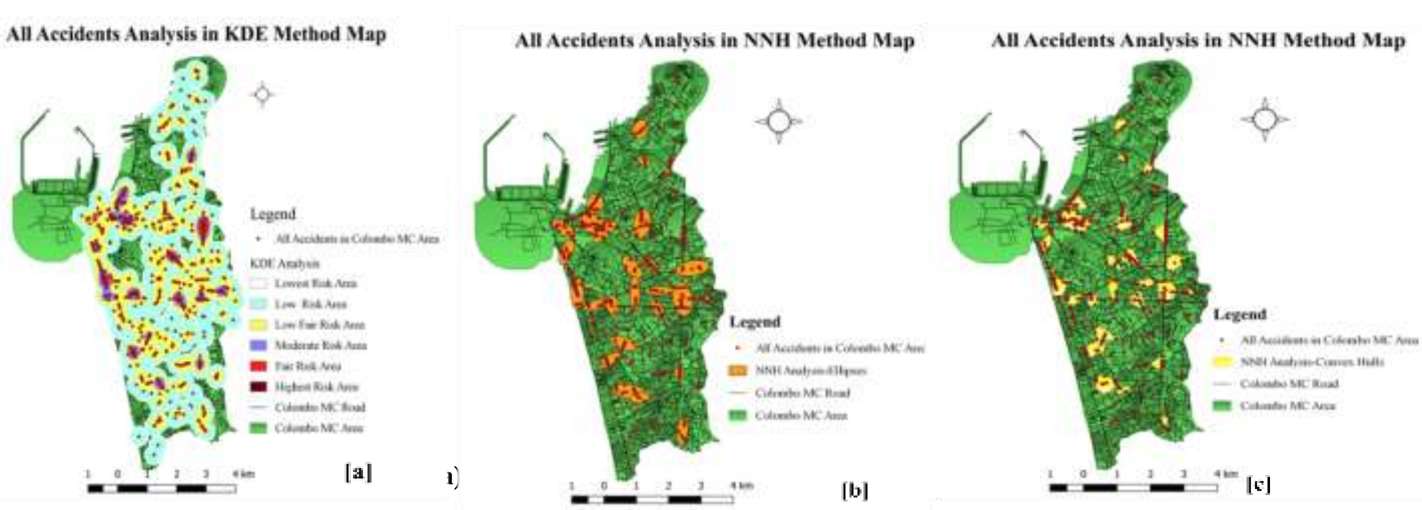
Hotspot analysis was employed to identify and provide the necessary information to assist decision-makers in making appropriate decisions to prevent and reduce traffic accidents. Hotspot analysis was conducted in two ways: using ARCGIS10 software to analyze KDE and CrimeStat software for NNH analysis. Finally, the results of the two estimation methods were compared using both visual and mathematical comparison methods. Graphic representations of accident data were utilized to provide a general understanding of the accident data. The PAI was used to compare the ability to capture hot spots between these different methods.

KDE Method

The two main parameters that affect the KDE are bandwidth and cell size. In this study, we considered a bandwidth value of 333m and a cell size of 0.00005 to estimate the density of all crash cases. Since the selection of the size is also a trade-off between computation time, sample size, and the information to retain, the output of KDE is presented in a raster format consisting of a grid of cells. As shown in Figure 4(a) (Severity map), a general distribution of all accidents is displayed using a color ramp map for easy understanding.

NNH Method

The NNH method considers two types of criteria for spatially mapping clusters of spatial point data: the threshold distance (d), which represents the Euclidean distance between each pair of data points and is used as a search radius value in the algorithm, and the second parameter, which is the minimum number of points required to form a cluster (n_{min}).
When using the NNH method in Crimestat software analysis, these parameters are set to d = 0.05 km and n_{min} = 10 accidents to create clusters. In this hotspot analysis, four (4) results are obtained in the form of ellipses and convex hulls. One of the ellipses is exceptionally large and is ignored because it does not lead to any meaningful conclusions. Consequently, the results from the convex hulls are also inconclusive. Therefore, meaningful conclusions can only be drawn from the remaining two results. The severity maps created using the NNH method are displayed in Figure 4(b) and Figure 4(c).



RESULTS AND DISCUSSION

All accident analysis in KDE and NNH method

In this study utilized the total number of vehicle accidents (1124) in CMC to identify hotspots.
The results of the KDE severity map showed that the lowest-risk and low-fair-risk areas were more

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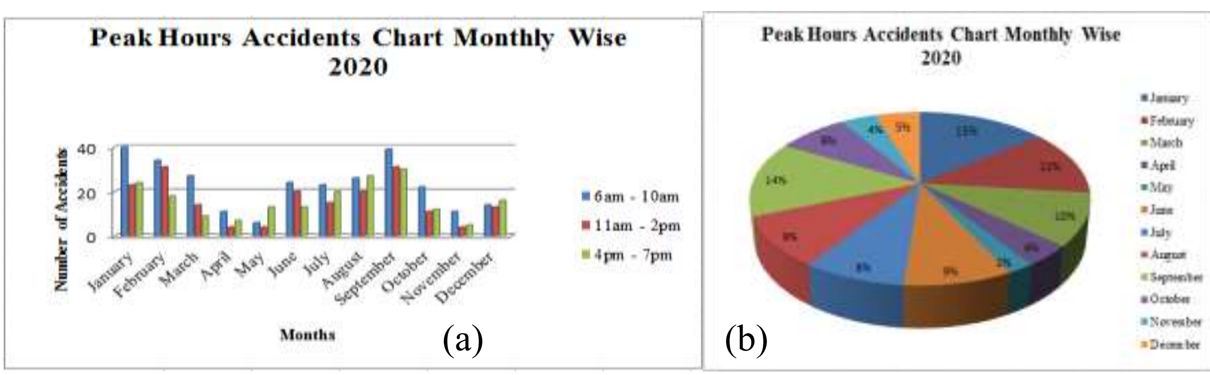
prevalent, while the moderate-risk and low-fair-risk areas were slightly less common. There was a very small portion of the highest-risk area, depicted in black, with a gradual decrease in risk represented by white. Further examination of the highest-risk area reveals that it was primarily located at intersections and road connections, where the impact of these accidents was minimal. No accidents have occurred outside of this region. In the NNH analysis, both severity maps were identical, but the method used to delineate the boundary of the danger zone differs. The NNH Method (Convex Hulls) generates a random-shaped cluster to represent the actual hotspot area, whereas the NNH Method (Ellipses) uses an ellipsoidal shape. Observing the distribution of accidents, it became evident that regions with a higher concentration of accident hotspot locations tend to cluster together. One advantage of this technique was its ability to identify small geographic areas with concentrated incidents. This can prove valuable for targeted interventions, whether through police deployment or community initiatives.

Peak Hours Traffic Accident Analysis

Secondly, this study also examined hotspot locations based on time. Accident data was categorized into time periods, distinguishing between peak hours and non-peak hours. In this context, peak hours generally refer to the time range between 6 a.m. and 7 p.m.. Specifically, peak hours encompass activities such as school hours, preschool operations, office and business start-up hours, which occur from 6 a.m. to 10 a.m. In this study, the time period between 6 a.m. and 10 a.m. was designated as the morning peak time. Subsequently, the period between 11 a.m. and 2 p.m. corresponded to the closing times of preschools and schools, as well as the rush hours for businesses. Additionally, the hours between 4 p.m. and 7 p.m. were recognized as busy hours due to office closures. In this context, pie charts and bar charts were initially generated using this data to provide a preliminary overview.



Graph 1: Distribution of peak hour's accidents

In Graph 1(a), the column bars represent different time ranges: rush hours were depicted in blue from 6 a.m. to 10 a.m., in red from 11 a.m. to 2 p.m., and in green from 4 p.m. to 7 p.m. It was evident that a significant number of traffic accidents occurred during the morning peak hours from 6 a.m. to 10 a.m., with similar accident frequencies observed during the time periods from 11 a.m. to 2 p.m. and from 4 p.m. to 7 p.m.. Graph 1(b) provides further insights, indicating that the highest number of accidents occurred in January, February, and September, while the average number of accidents took place in July, October, and December, with the lowest number of accidents recorded in May. These two charts collectively offer clear information about the peak hours and months during which the most accidents occurred. By conducting this analysis is over several years, it will be possible to identify the months with the highest number of accidents.

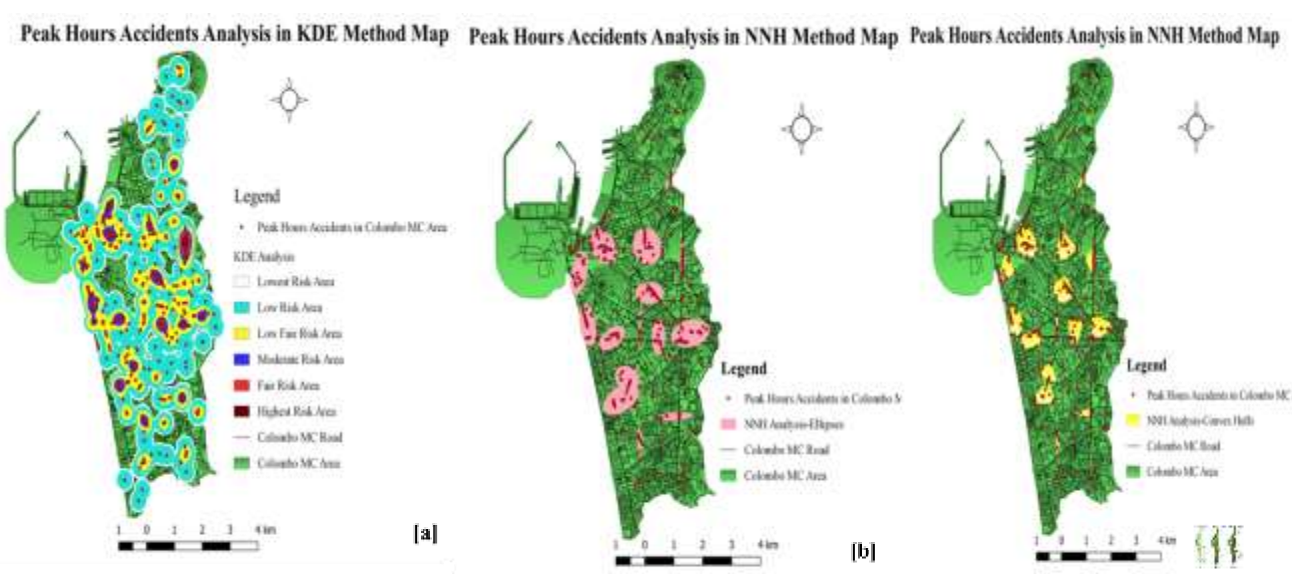
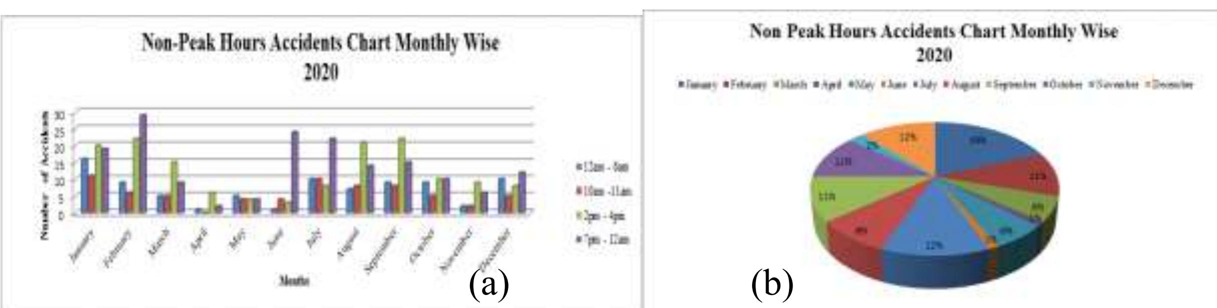


Figure 5: Severity map of KDE (a), NNH (Ellipse) (b) and NNH (Convex Hull) (c) Method for peak hour's accidents

It can be clearly observed that the regions with a high number of peak-hour accident hotspots are depicted in Figure 5(a), (b), and (c). The severity maps based on peak hours highlighted the same areas where more critical hotspots could be detected, enabling the identification of the highest-risk areas. These hotspots were predominantly situated at or near intersections or connection points on minor roads. Additionally, this information will be beneficial in gaining an understanding of the routes commonly traveled by drivers during these peak hours.

Non-Peak Hours Traffic Accident Analysis

In addition, non-peak hours were identified throughout the day. These included the period from midnight to dawn (12 am to 6 am), a relatively less busy time from 10 am to 11 am following the opening of schools and offices, the period after school hours when road activity increases from 2 pm to 4 pm, and nighttime hours, specifically from 7 pm to 12 am when road activity decreases after business hours and office closing time. Traffic accidents that occurred in the CMC area during these periods had been categorized, and bar charts and pie charts for each month had been prepared, as illustrated in Graph 2(a) and (b).



Graph 2: Distribution of Non- Peak hours accidents

The pie chart illustrated that the highest number of accidents occurred in January, while the average number of accidents took place in February, July, September, October, and December, with the lowest number of accidents occurring in April, June, and November. This provided an understanding of the accidents that occurred each month. Compared to peak hours, fewer hotspots were detected during non-peak hours.

Considering the KDE severity map, six risk areas had been designated. Among them, the highest-risk area has very low numbers, while the lowest-risk and fairly low-risk areas have significantly higher numbers of incidents. The moderate-risk area was depicted in Figure 6(a). This information allows for the identification of areas with the highest number of accidents, enabling the deployment of more police officers to those places during non-peak hours.

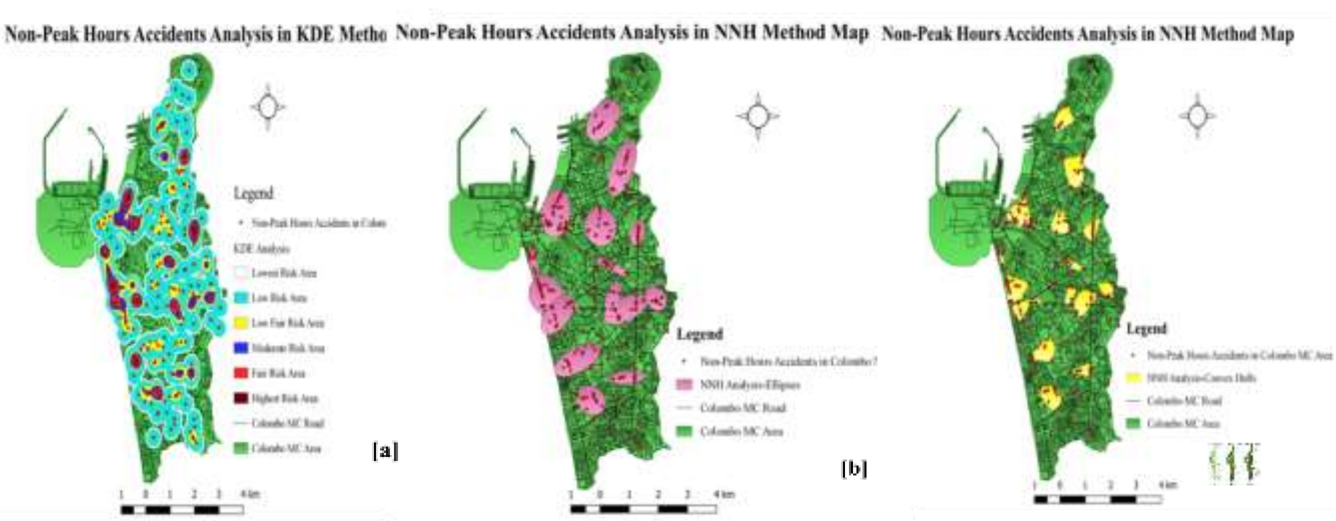
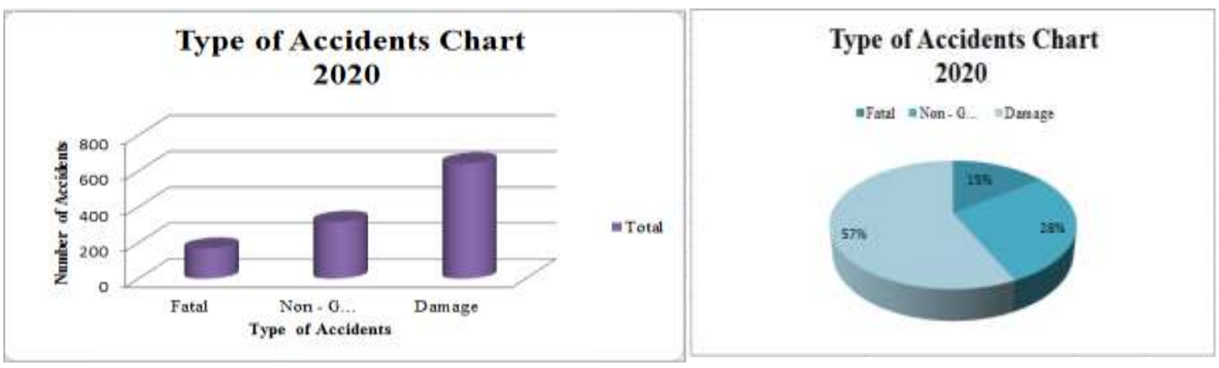


Figure 6: Severity map of KDE (a), NNH (Ellipse) (b) and NNH (Convex Hull) (c) Method for non-peak hour's accidents

By analyzing the NNH severity maps (Figure 6(b) and (c)), two results in the form of ellipses and convex hulls had been obtained. Based on these two results, the locations with the highest number of accidents during non-peak hours became evident. This method provides a direct and clearer visualization of accident hotspots compared to the KDE method, facilitating more precise planning when implementing remedies.

Types of Accident

Finally, all accident were categorized according to their type, including damage-only accidents, non-grievous accidents, and fatal accidents. Property damage only accidents were classified as damage only accidents. Non-grievous accidents encompass property damage and injuries, while fatal accidents involve both loss of life and property damage. Taking into account the total number of accidents that occurred in the year 2020, bar charts and pie charts had been created, as shown in Graph 3(a) and (b).



Graph 3: Distribution of accidents by type of accidents

Among the occurrence type of accidents, damage only accident had get high number within the CMC area. In pie chart showed that, fatal accidents had the lowest percentage as 15% and non-grievous accidents had the average percentage as 28%. Damage only accidents had the highest percentage as 57%. The main reason for the decrease in fatal accidents was the skill of the drivers and the main reason of increasing the damage only accidents was the carelessness of the drivers and pedestrians.

Figure 7: Severity map of KDE (a), NNH (Ellipse) (b) and NNH (Convex Hull) (c) Method Damage only accidents

In the above manner, damage only accidents had occurred 641 in the CMC area in 2020. These accidents had been analyzed by the KDE method and showed in the above figure 7 (a) and only a small number of highest risk areas could be seen. Compared to other analyses, the moderate risk area had increased. However in Figure 7 (b) and (c) suggested that it could be recognized that hot zone than the hot spots where they were particularly concentrated. Therefore it will more benefit to decision makers or town planners for their future plan. In addition to that, it can be useful for specific targeting, either by police deployment or community intervention.

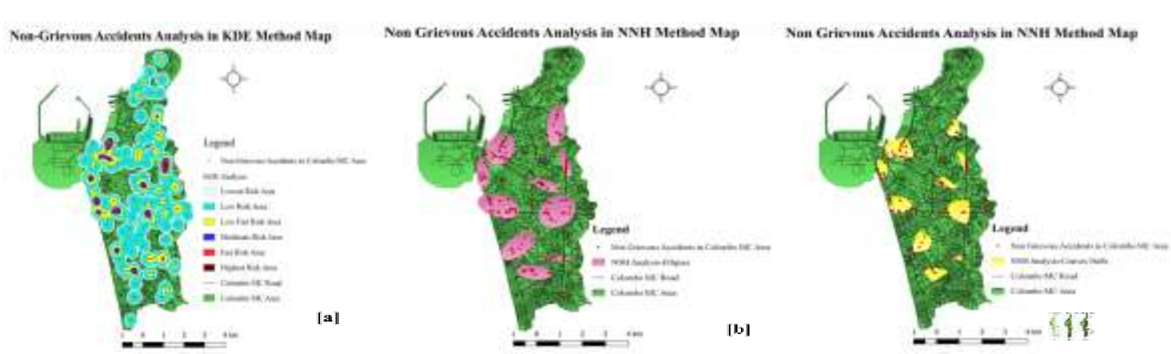


Figure 8: Severity map of KDE (a), NNH (Ellipse) (b) and NNH (Convex Hull) (c) Method Non- Grievous accidents

About 316 accidents had occurred in 2020 when classified as non-grievous. The number of accidents had been reduced by almost 50% compared to damage only accidents. Figure 8 (a) showed that how these accidents had been analyzed using the KDE method. Accordingly, it could be seen that the accident area had decreased from the damage only accident area and the highest risk area had gradually decreased. In addition, according to figure 8 (b) and figure 8 (c), it could be seen that the places where non-grievous accidents occurred can be identified and also solutions can be provided to reduce them.

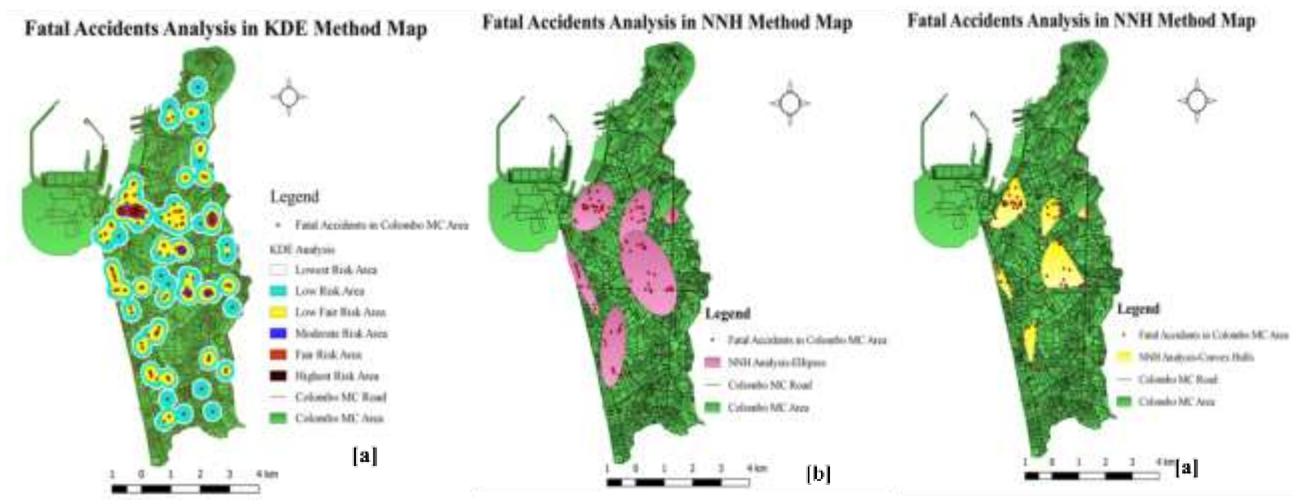


Figure 9: Severity map of KDE (a), NNH (Ellipse) (b) and NNH (Convex Hull) (c) Method for Fatal accidents

Fatal accidents had occurred very little but the impact of these accidents on the society is very high. In 2020, about 168 accidents of this type had occurred in the CMC area. Although the number of these accidents was very low considering the damage only accident and non-grievous accident, the damage caused by it was high. According to figure 9 (a), it showed that according to the KDE method, the limit had been reduced, where the low fair risk area and low high risk area were more and the highest risk area and fair risk area were very less. In the manner of figure 9 (b) and figure 9 (c), NNH method analysis, it was shown that the places where this type of accident had happened more. Compared with other types, it could be seen that there were very few places where these types of accidents have occurred. A clear understanding of the tactics can be applied to those places and to take appropriate measures.

Comparison of results

At the end the KDE method and NNH clustering method were compared using visual comparison and mathematical comparison method. By comparing these two methods, it was important to show what was the most suitable method for detecting hot spot in traffic accidents and the method used to analyze and evaluate them. Created severity maps were used to compare the visually. This could be achieved by aligning them parallel to one another, by superimposing them, by

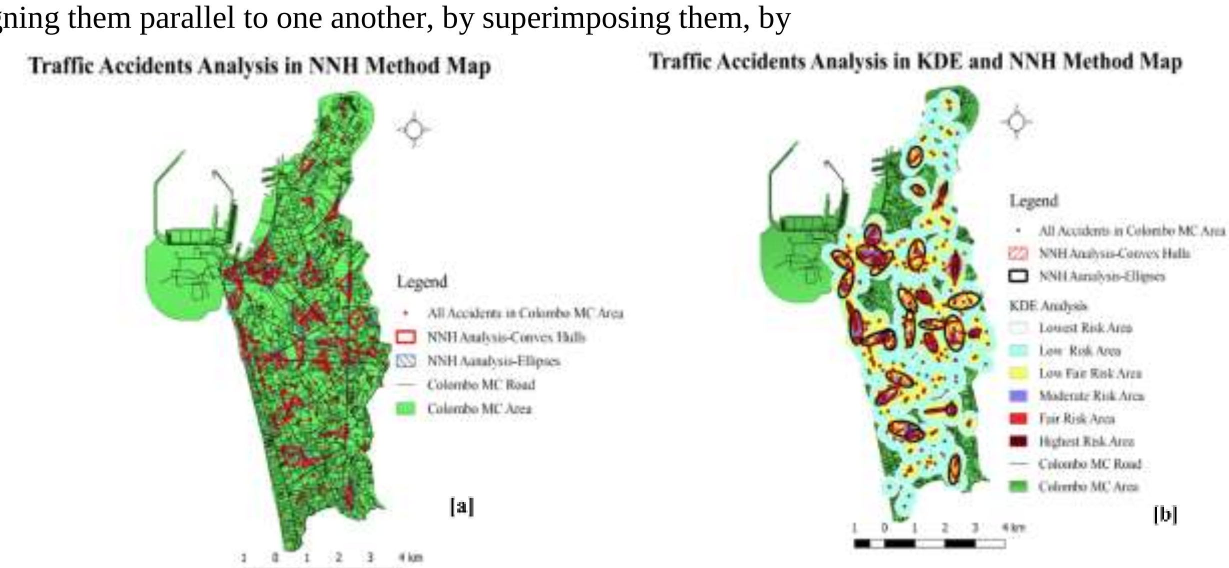


Figure 10: Convex Hulls and Ellipses Comparison Map (a) and KDE and NNH Method Comparison Map(b)alternating images, or by showing each image to a different eye. The findings of the NNH clustering analysis and the KDE analysis were compared by overlaying the maps produced by the two approaches to demonstrate how they differ visually. First of all, the two results given by NNH, ellipse and convex hulls, were compared.

According to the figure 10(a), when this NNH method was done with ellipses, it was seen how these ellipses collide with each other. But this did not happen when doing it through convex hulls. And here, when choosing convex hulls, it was an advantage to get the boundary obtained there on top of the accident data. No more space was added there. But in ellipse mode, all hotspot clusters were included in the ellipse. Nothing exists within its boundary. Therefore, from this point of view, it seemed that convex hulls were more appropriate than ellipse.

Next it was compared the result obtained by KDE and by NNH by referring figure 10 (b). When all these results were added to one map, it was easy to compare. If we needed to find the place where more accidents occur, it could be seen that the NNH method was more suitable for that. Here by KDE method all accidents should be taken and their separate risk areas should be represented. But the NNH method showed only where the highest number of accidents occur. Accordingly, it was clear that it was more appropriate to use the NNH method when applying color lights, police officers and other security measures to the places where the most accidents occur as an immediate solution.

Mathematical comparison of method

It was done in a mathematical way to compare and decide which method was more suitable. For this purpose, PAI values were calculated as shown in Table 1. PAI aids in comparing the effectiveness of collecting hot spots using various techniques. As previously indicated, PAI was based on the quantity of occurrences within the overall region, including hotspots and the research area. In other words, PAI assesses the approaches' capacity to capture hot spots while considering all the data and the entire study region. It was important to compare the findings and outputs of each method during the PAI calculation staged to understand and select the one that produced the highest rate of hot spot detection.

Table 1-Mathematical Comparison of Hot Spot Methods

Accident Type	Method	Area	Points	Density (n/A)	Hit Rate (n/N)*100	Percentage of Area	PAI
Hotspot of all accident	KDE	32.067	1124	35.052	100	66.992	1.493
	NNH ellipses	6.422	830	129.243	73.834	13.416	5.505
	NNH convex hulls	3.579	872	243.643	77.850	7.477	10.375
Peak hour accidents	KDE	28.311	635	22.429	100	50.145	1.995
	NNH ellipses	6.481	424	65.422	66.772	13.54	4.931
	NNH convex hulls	3.746	463	121.97	72.913	7.92	9.206
Non-peak hour accidents	KDE	28.411	467	16.437	100	59.354	1.685
	NNH ellipses	9.654	344	35.633	73.662	20.168	3.652

	NNH convex hulls	4.984	353	70.827	75.589	10.412	7.26
Damage only accidents	KDE	29.775	640	21.495	100	62.204	1.608
	NNH ellipses	7.661	430	56.128	67.188	16.005	4.198
	NNH convex hulls	3.835	460	119.948	71.875	8.012	8.971
Non-Grievous accidents	KDE	26.07	316	12.121	100	54.463	1.833
	NNH ellipses	9.899	223	225.28	70.57	20.68	3.412
	NNH convex hulls	4.708	223	473.66	70.57	9.836	7.175
Fatal accidents	KDE	17.474	168	9.614	100	36.505	2.739
	NNH ellipses	9.188	111	12.081	66.071	19.195	3.442
	NNH convex hulls	3.965	117	29.508	69.643	8.283	8.408

According to the results in Table 1, the calculated PAI values for all accident data sets, including peak-hour accidents, non-peak hour accidents, damage-only accidents, non-grievous accidents, and fatal accidents, were compared using two different methods: KDE and NNH. The KDE method yields very low values, while the NNH method produced the highest values, particularly in the convex hulls. Based on these results, it could be concluded that the NNH method was more suitable for identifying traffic accident hot spots.

CONCLUSION AND RECOMMENDATION

Conclusion

This study primarily focuses on the analysis of traffic accidents, classifying them into peak hours and non-peak hours. It reveals that a significant 59% of total accidents occur during peak hours, a period characterized by heavy traffic, increased carelessness, and subsequently, a rise in road accidents. Moreover, the study identifies that damage-only accidents are more prevalent, while fatal accidents are less frequent. This discrepancy can be attributed to the higher vehicle density in the CMC area, resulting in slower vehicle speeds and fewer fatal incidents.

The study establishes a systematic framework for hotspot analysis, employing GIS and Crimestat software, which utilize the KDE and NNH methods, respectively. Both methods reveal a concentration of accidents in the central part of the CMC area, particularly around intersections with three-way, four-way, and five-way junctions.

Furthermore, the research pinpoints specific accident-prone areas, including Dematagoda and Narahenpita along the Base Line road, as well as Borella, Pitakotuwa, Bambalapitiya, Kollupitiya roundabout, and Galle Face along the Galle road. These areas experience heightened accident rates due to the presence of numerous government and non-government offices, educational institutions, and commercial centers. Recommendations include the addition of more road signs and promoting alternative routes in these regions.

In comparing the two hotspot analysis methods, KDE and NNH, visual comparison indicates that KDE offers more comprehensive results, providing additional information. However, for pinpointing high-accident areas, the NNH method is deemed more suitable. Mathematical comparison, measured by the PAI value, favors the NNH method due to its higher accuracy. This study's findings can greatly assist decision-makers, town planners, and administrative officers in formulating road traffic accident prevention strategies within the CMC area, benefiting future planning efforts.

Recommendation

In the course of this study, a challenge emerged during data preparation due to inaccuracies in the real coordinates of accident data. Consequently, it became necessary to align this data with the actual road locations where the accidents occurred. The study primarily focused on the time and type of accidents, with a potential to yield valuable insights into the causes of these incidents and the development of solutions. Future research could enhance the study by considering additional factors, such as classifying accidents based on the age of the vehicle driver involved.

The analysis specifically examined data from the year 2020, but extending the study's timeframe to encompass five years could facilitate identifying monthly accident trends and proposing corresponding solutions. Furthermore, while the study centered on the CMC area, expanding the scope to cover all of Sri Lanka and analyzing accident data over multiple years could help pinpoint districts with the highest and lowest accident rates. This broader perspective would enable the formulation of targeted measures to reduce accidents in high-incidence areas.

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