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Identification of Hotspot Detection and Spatial Trends of Road Accidents using a GIS. A Case Study of Hyderabad

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Abstract: Road traffic accidents continue to be a major concern for sustainable urban safety and effective transportation management. Identifying crash hotspots with precision is essential for implementing focused safety interventions. In this study, a severity-weighted system was applied to evaluate crash hazard levels. A Geographic Information System (GIS)-based approach was adopted to analyze spatial patterns of road accidents in Hyderabad, with the primary objective of identifying high-risk locations. Using secondary data from 2021 to 2024, the research employed methods such as Kernel Density Estimation (KDE), Crash Hazard Level (CHL), and Predictive Accuracy Index (PAI) to examine accident frequency, severity, and spatial distribution. A total of 8,576 accident cases were analysed, classified according to factors such as time, location, accident type, and severity. KDE enabled the visualization of accident-prone areas, while CHL and PAI provided a quantitative framework for ranking hazardous zones and validating hotspot predictions. The analysis revealed an increasing trend in non-fatal accidents and highlighted traffic congestion as a major challenge for urban safety. Based on these findings, the study recommends targeted measures, including intersection redesign, enhanced road lighting, pedestrian safety improvements, awareness programs, and better emergency response systems. Overall, the GIS-based approach delivers valuable insights to support urban planners and policymakers in formulating data-driven strategies aimed at improving road safety in Hyderabad.

Keywords: Fractal analysis, road network efficiency, urban connectivity, Hyderabad RRR, GIS-based planning.

I. INTRODUCTION

Hyderabad plays a vital role as a rapidly growing urban center, where road traffic accidents present a complex challenge due to their association with engineering, geographical factors, and human behavior. Addressing such issues requires a systematic approach capable of automatically detecting statistically significant accident clusters. For effective traffic safety management, it is essential to identify accident-prone locations and analyze recurring patterns so that suitable measures can be implemented for each specific site. To meet this challenge, advanced technologies like Geographic Information Systems (GIS) provide powerful tools for data collection, spatial analysis, and visualization. In this study, GIS has been integrated with methods such as Kernel Density Estimation (KDE) and Crash Hazard Level (CHL) analysis to identify accident hotspots across Hyderabad. Using secondary data from 2021 to 2024, the study highlights spatial clusters of accidents in different regions of the city. These results are crucial for formulating targeted, evidence-based strategies to strengthen road safety and improve urban traffic management. Ultimately, the goal is to bridge the gap between data availability and practical application, providing planners and policymakers with meaningful insights for accident prevention, infrastructure development, and policy design supported by spatial evidence.

A. Objectives

The following are the specific objectives of the present study:

- 1) To identify major contribution factor to the severity of road accidents in Hyderabad. and Suggest effective countermeasures and improvement strategies for reducing accidents
- 2) To find out kernel density estimation based on department of traffic police station Accident data. And identify accident hot spots locations in Hyderabad city
- 3) To evaluate the severity of accidents using the Crash Hazard Level (CHL) method

- 4) To calculate the Predictive Accuracy Index (PAI) for assessing the reliability of hotspot identification
- 5) To develop detailed thematic maps showing accident-prone areas for better visualization and interpretation.

II. METHODOLOGY

A. Study Area And Data Preparation

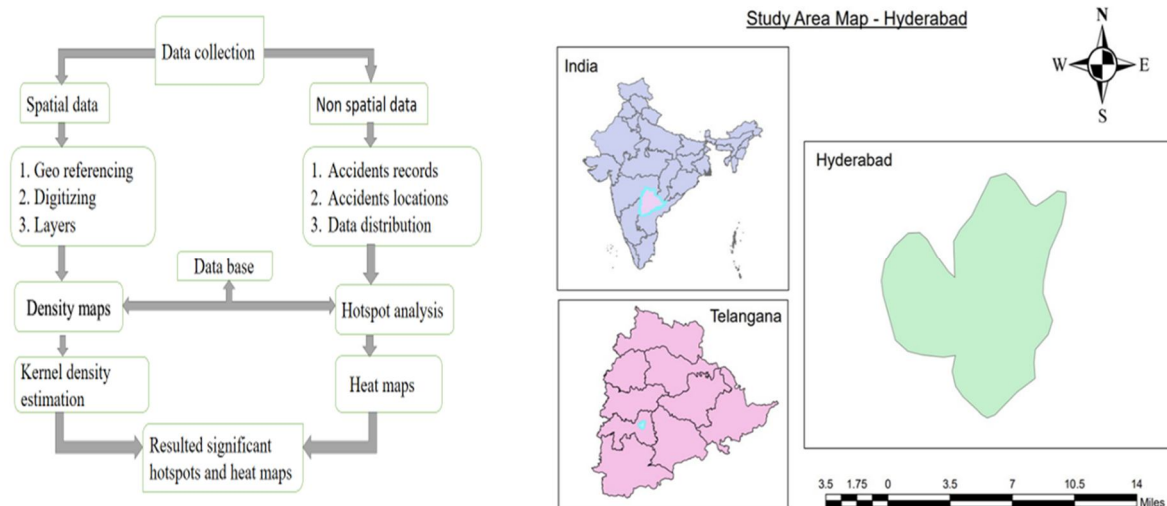


Fig.1 Study Area

B. Non-Spatial Data

Non-spatial data does not include geographical references such as coordinates, yet it remains valuable for identifying patterns, trends, and relationships. For example, it can provide insights into accident severity over time, the types of vehicles involved, or recurring causes. When spatial elements like GPS coordinates or location information are added, this data can be converted into spatial data, enabling advanced mapping and GIS-based analysis. In this study, the following non-spatial information was collected:

- 1) Date and time of the accident.
- 2) Number of persons injured or deceased.
- 3) Area where the accident occurred.
- 4) Type of vehicle involved.
- 5) Demographic details (age and gender).

C. Spatial Data

Spatial data refers to information intrinsically linked to a particular geographical location, depicting where features or events occur on the Earth's surface.

D. Geo-referencing

This is the process of connecting spatial data to actual geographic coordinates through mapping projections or reference systems. For instance, scanned maps or satellite imagery are aligned with latitude and longitude so they can be accurately used in GIS applications.

E. Digitizing

The conversion of paper maps or images into digital vector formats such as points, lines, and polygons. This allows the creation of editable and analysable layers, including features like roads, boundaries, or accident locations.

F. Layers

Spatial data is arranged into different layers, such as road networks, accident sites, or administrative boundaries. Each layer represents a specific theme, making it possible to combine and visualize multiple datasets in an integrated manner.

G. Purpose in Road Safety

In traffic accident studies, KDE is used to create a smooth surface that illustrates the distribution of crashes across a geographic area. This visualization helps researchers and traffic authorities to:

- Identify accident-prone zones.
- Compare accident intensity between different locations.
- Provide evidence-based support for targeted safety interventions.

H. Mathematical Formula

For a given set of n accident locations, the **Kernel Density Estimator** at a spatial point (x,y) is expressed as:

$$f(x,y) = \frac{1}{nh^2} \sum_{i=1}^n k\left(\frac{d_i}{h}\right)$$

Where:

$f(x,y)$ = estimated density at location (x,y)

n = number of observations (accident points)

h = bandwidth (kernel size), controlling the smoothness of the density surface

K = kernel function (determines the weight distribution around each point)

d_i = distance between location (x,y) and the i th accident location

I. Key Components of the Formula

1) Kernel Function(K)

The kernel function defines how accident influence decreases with distance. Common kernel types include:

- Gaussian Kernel (bell-shaped curve)
- Parabolic Kernel (parabolic shape)
- Uniform Kernel (equal influence within a fixed radius)
- In accident mapping, Gaussian kernels are often preferred because they generate smooth and realistic hotspot surfaces.

2) Bandwidth (h)

The bandwidth determines the degree of smoothing:

- A small bandwidth gives highly detailed maps but may introduce noise.
- A large bandwidth produces smoother surfaces but may obscure local variations.

Selecting an appropriate h is crucial for meaningful analysis.

3) Distance (d_i)

The Euclidean distance between the estimation location and an accident point influences the density value at (x,y) .

III. RESULTS AND DISCUSSION

Accident records collected from the Hyderabad Traffic Police for the years 2021 to 2024 show a total of 7,785 reported cases. Among these, 11% were fatal, 77% were non-fatal, and 12% resulted in property damage only. The overall accident rate increased by nearly 32% from 2021 to 2024, indicating a rising safety concern. Analysis further revealed that Mondays recorded the highest number of accidents. Two-wheelers and pedestrians were identified as the most common victims, while two-wheelers and four-wheelers were most often responsible for causing accidents. Gender-wise analysis (Fig. 6) shows that males were significantly more involved in crashes compared to females. Month trends (Fig. 4) highlight that accident occurrences peaked between October and December. From a spatial perspective, the variable at accident location i and its neighboring location j reflects the local clustering of accidents, with n representing the total number of accidents. Row-standardized weights were applied to quantify the spatial relationship between locations, ensuring that the influence of neighboring areas was appropriately scaled for accurate hotspot identification.

Table. 1 Number of road accidents from the department of traffic police station 2021 to 2024

Year	Fatal	Nonfatal	Property damage only	Overall accidents
2021	187	1461	132	1789
2022	143	1158	131	1432
2023	231	1876	285	2392
2024	219	2327	417	2963
Total	780	6822	964	8576



Fig.2 Year wise Accidents from 2021 to 2025

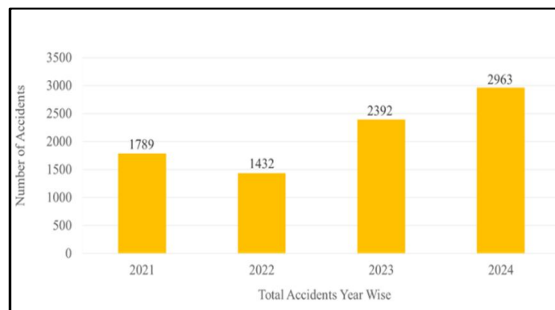


Fig.3 Total Accidents from 2021 to 2024 based on department of traffic police station



Fig.4 Accidents based on month from and pod from 2021 to 2024

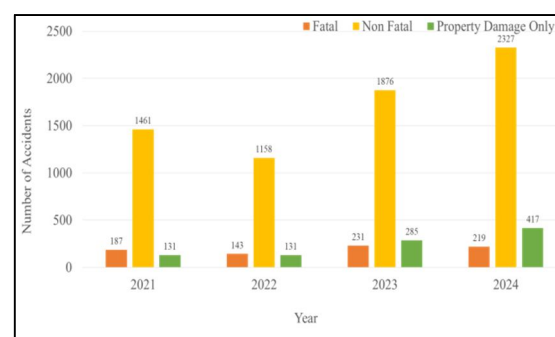


Fig.5 Accidents based on the fatal non-fatal month wise from 2021 to 2024

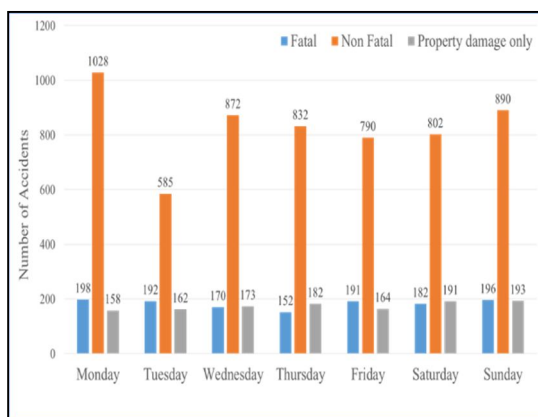


Fig.6 Day wise Accidents from 2021 to 2024

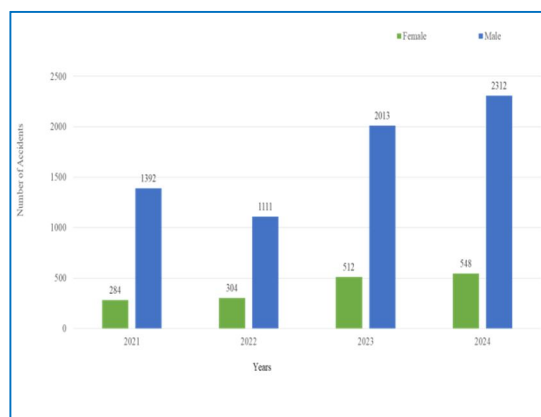


Fig.7 Accident based on gender from 2021 to 2024

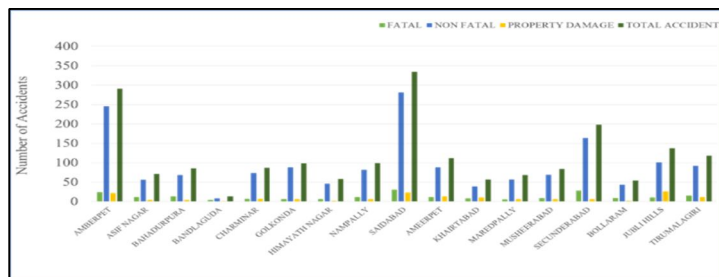


Fig. 8 Area wise Accident in 2021

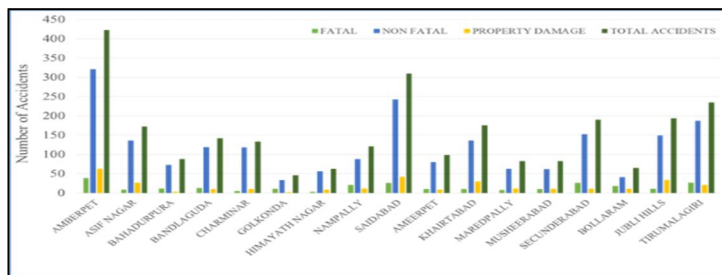


Fig.9 Area wise Accident in 2022

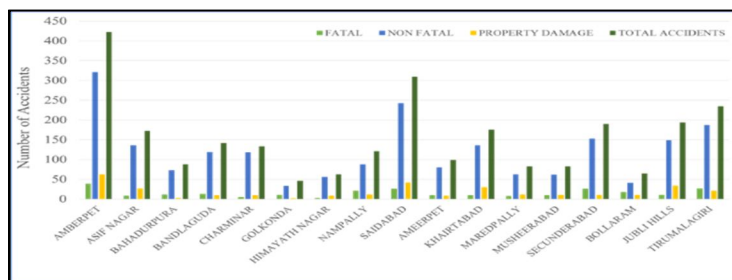


Fig.10 Area wise Accidents in 2023

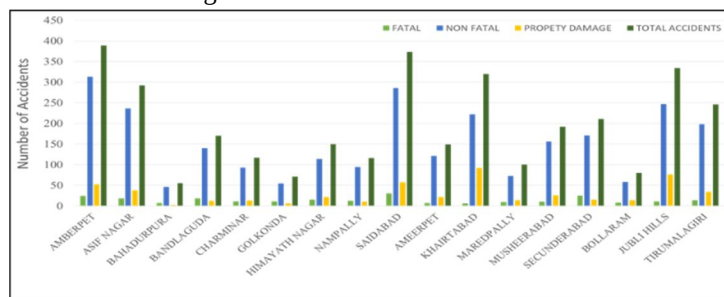


Fig.11 Area wise Accidents in 2024

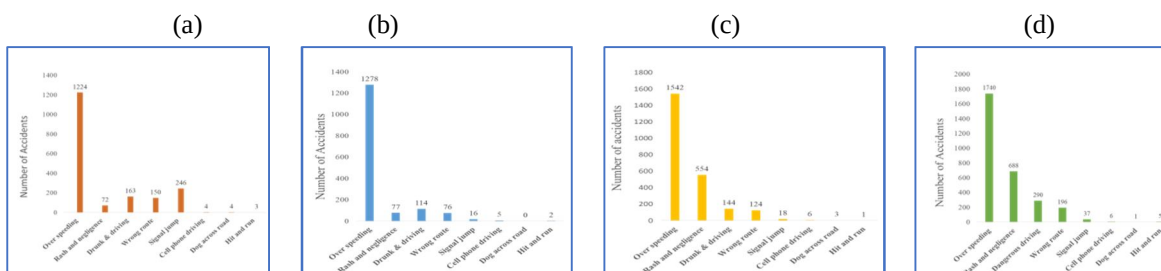


Fig.12 Causes of accidents in (a) 2021 (b) 2022 (c) 2023 & (d) 2024

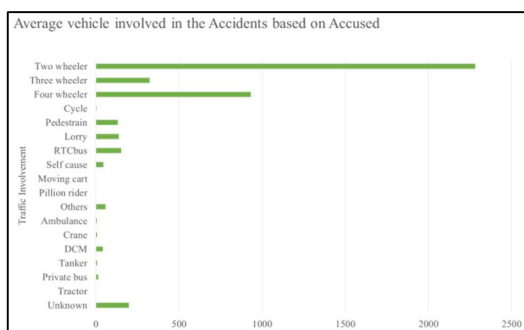


Fig.13 Average number of accidents based on accused

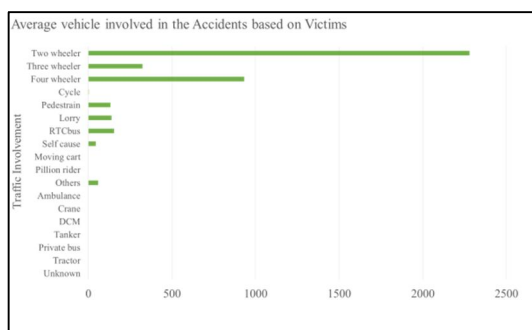


Fig.14 Average number of accidents victims

A. Crash Hazard Level (CHL)

The crash hazard level is an important measure used to evaluate the overall risk at accident-prone locations. It considers various factors that determine the severity of road crashes, helping authorities to identify and prioritize high-risk areas for targeted safety improvements. By assessing crash severity, this concept provides a structured way to guide decision-making in traffic safety management. Severity Index (SI).

To quantify the hazard level, the Severity Index (SI) is used as a weighted measure that combines crashes of different severities into a single value. This index makes it easier to compare accident locations or specific crash events, ensuring that areas with higher risks are given more attention.

Formula and Components

The Severity Index is calculated using the formula:

$$SI = L + 3S + 5D$$

L – Light Injury Crashes

These represent accidents where victims sustained minor injuries. As they are less severe, they are assigned the lowest weight of 1.

S – Serious Injury Crashes

These refer to accidents that caused major but non-fatal injuries. Since the severity is greater compared to minor injuries, they are weighted three times higher than L.

D – Fatal Crashes (Deaths)

Fatal accidents represent the most critical outcome, involving loss of life. To reflect their extreme impact, these crashes are weighted five times higher than L.

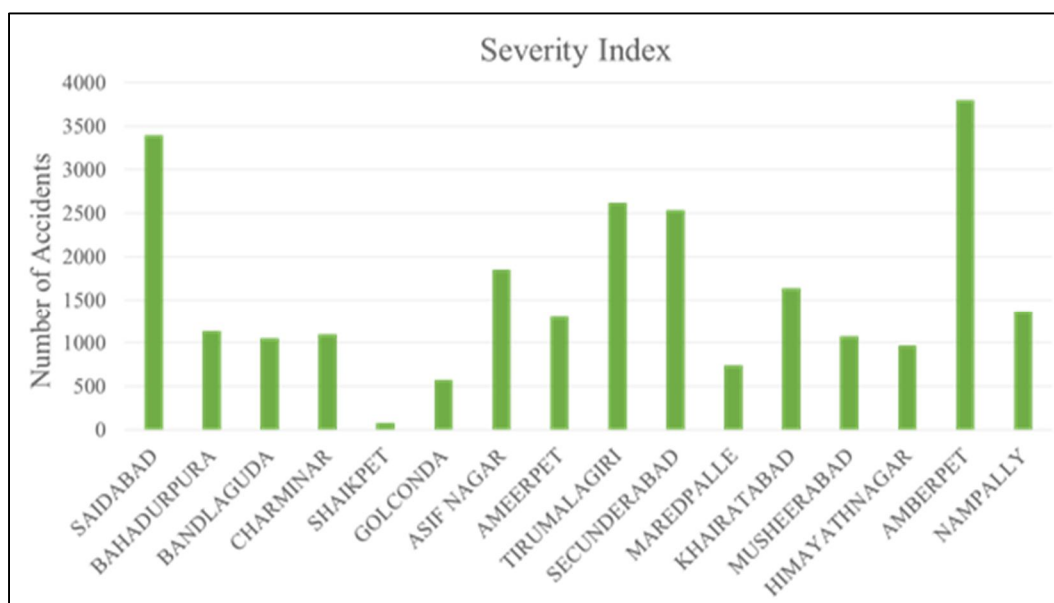


Fig.15 Based on area wise CRASH HAZARD LEVEL

The Kernel Density Estimation (KDE) analysis in ArcGIS generates a continuous raster surface that depicts the distribution and intensity of accident occurrences across the study area. This method estimates density by dispersing the impact of each accident point through a kernel function, producing a smooth surface with varying density values. Areas with high accident concentration are displayed in warmer shades such as red or yellow, highlighting critical hotspots where deaths, injuries, property damage, and overall accidents are clustered. Conversely, regions with lower accident frequency appear in cooler colors like blue, indicating relatively safer zones. The KDE output is particularly useful for detecting spatial patterns, accident clusters, and emerging trends, thereby supporting more informed decision-making for traffic management, safety planning, and preventive measures. Figure 10 presents the KDE results for different categories of accidents, offering a clear visualization of accident-prone areas within Hyderabad.

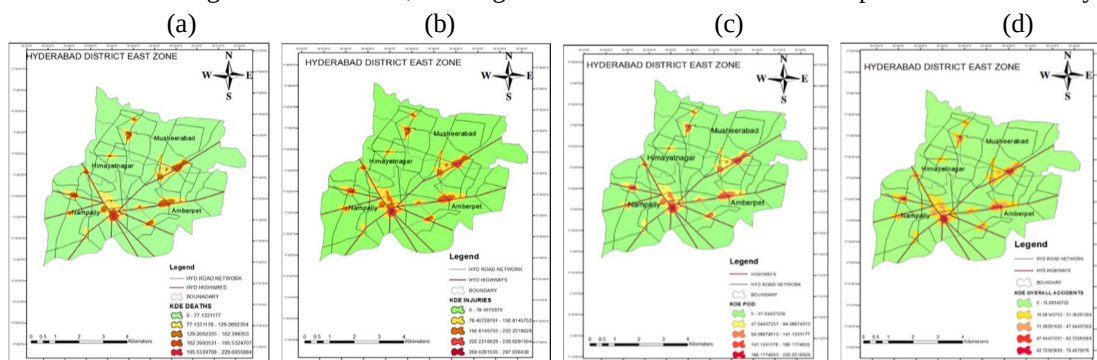


Fig.16 KDE of different category of accidents, Deaths(a), Injuries(b), Property damage only(c), and Overall accidents(d), in East zone.

Table.2 Ranking of hotspots in East zone.

SL NO	AREA	KDE DEATHS	KDE INJURIES	KDE PROPERTY DAMAGE ONLY	KDE OVERALL ACCIDENTS
1	MUSHEERABAD	229.66	259.62	235.22	78.49
2	AMBERPET	195.53	222.22	141.13	62.72
3	NAMPALLY	195.53	287.03	188.17	78.49
4	HIMAYATNAGAR	162.39	156.81	94.08	31.36

The table.2 comparison of accident severity across Musheerabad, Amberpet, Nampally, and Himayatnagar highlights variations in accident density. Musheerabad records the highest figures overall, with 229.66 KDE deaths, 259.62 injuries, and a POD of 235.22, making it the most critical hotspot. Nampally follows closely, showing the highest KDE injuries value of 287.03, along with a significant death score of 195.53. Amberpet also reports considerable accident levels, with 195.53 deaths and 222.22 injuries. In contrast, Himayatnagar shows comparatively lower accident densities, with 162.39 deaths and 156.81 injuries. Overall, Musheerabad and Nampally require priority interventions, while Amberpet and Himayatnagar still need preventive measures.

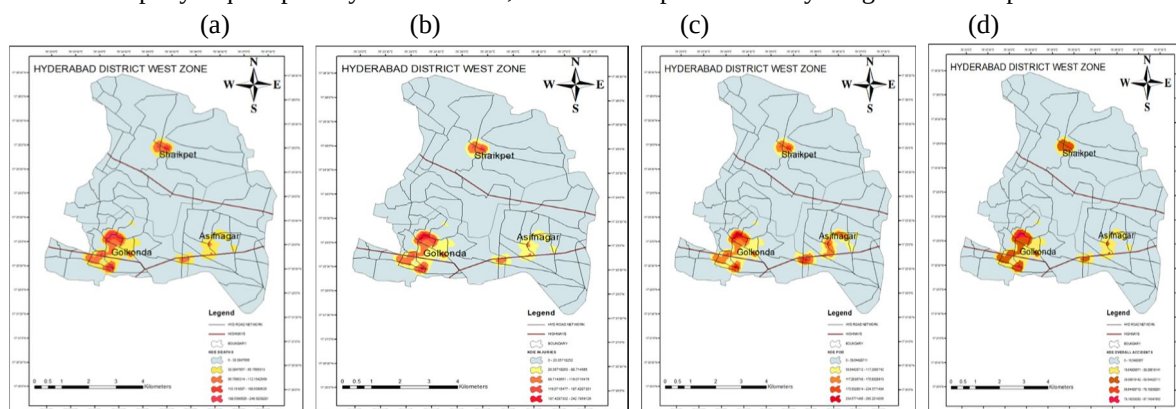


Fig. 17 KDE of different category of accidents, Deaths(a), Injuries(b), Property damage only(c), and Overall accidents(d), in West zone.

Table.3 Ranking of hotspots in West zone.

SL NO	AREA	KDE DEATHS	KDE INJURIES	KDE PROPERTY DAMAGE ONLY	KDE OVERALL ACCIDENTS
1	GOLCONDA	248.15	242.78	293.22	112.15
2	SHAIKPET	188.53	187.42	243.57	188.53
3	ASIFNAGAR	112.15	119.07	175.93	112.15

The table.3 analysis compares accident severity across three areas in Hyderabad’s West Zone—Golconda, Shaikpet, and Asifnagar—using Kernel Density Estimation (KDE) values. Golconda is the most accident-prone, with the highest figures for deaths (248.92), injuries (242.78), POD (293.22), and overall accidents (97.74), making it the most critical hotspot. Shaikpet follows, with significant fatal and non-fatal crashes, reflected in deaths (188.53), injuries (187.42), and a high POD of 234.57. Asifnagar, though less severe, still shows concerning values for deaths (112.15), injuries (119.07), and accidents (58.64). These findings suggest prioritizing Golconda and Shaikpet for urgent safety interventions.

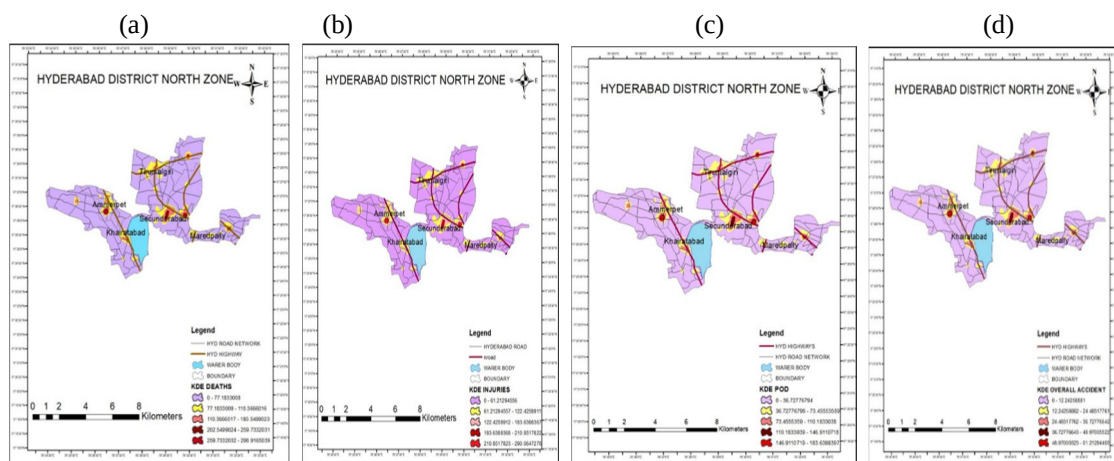


Fig.18 KDE of different category of accidents, Deaths(a), Injuries(b), Property damage only(c), and Overall accidents(d), in North zone.

SL NO	AREA	KDE DEATHS	KDE PROPERTY DAMAGE ONLY	KDE PROPERTY DAMAGE ONLY	KDE OVERALL ACCIDENTS
1	AMMERPET	298.91	210.06	183.63	61.21
2	SECUNDERABAD	298.91	290.06	146.91	61.21
3	MAREDPALLY	259.73	210.85	73.45	36.72
4	KHAIRATABAD	180.54	183.63	110.18	36.72
5	TIRUMALGIRI	110.36	122.42	146.91	24.48

Table.4 Ranking of hotspots in North zone.

The table.4 provides Kernel Density Estimation (KDE) values for accident analysis in five areas of Hyderabad’s North Zone: Ameerpet, Khairatabad, Tirumalgiri, Secunderabad, and Maredpally. Results show that Ameerpet and Secunderabad have the highest fatality scores (298.91), identifying them as severe accident hotspots, while Tirumalgiri records the lowest (110.36). Secunderabad also leads in injury cases (290.06), followed by Maredpally (210.85) and Ameerpet (210.06). Ameerpet shows the highest POD value (183.63), whereas Khairatabad and Maredpally are relatively lower. Overall accident density is greatest in Ameerpet and Secunderabad (61.21), with Tirumalgiri lowest (24.48). These findings emphasize prioritizing safety in Ameerpet and Secunderabad.

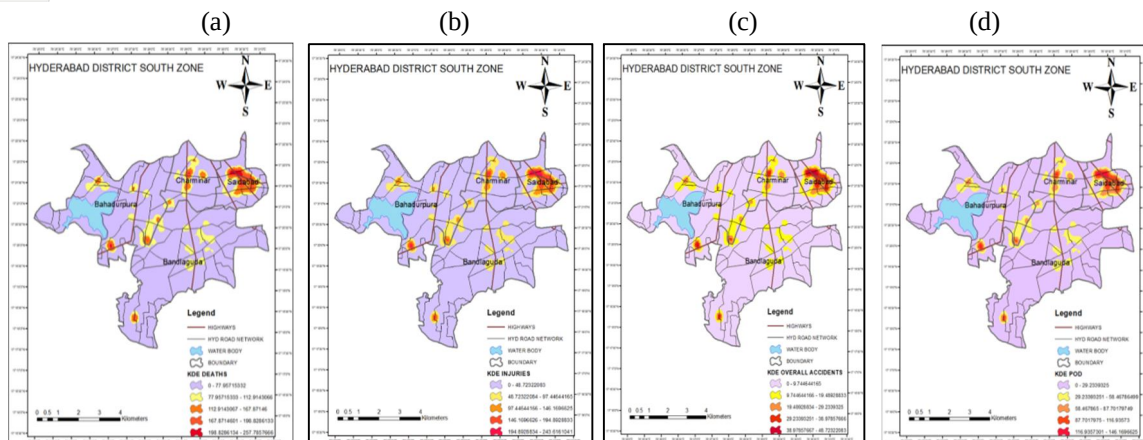


Fig.19 KDE of different category of accidents, Deaths(a), Injuries(b), Property damage only(c), and Overall accidents(d), in South zone.

Table.5 Ranking of hotspots in South zone.

SL NO	AREA	KDE DEATHS	KDE INJURIES	KDE PROPERTY DAMAGE ONLY	KDE OVERALL ACCIDENTS
1	SAIDABAD	389.78	243.61	146.16	48.97
2	BAHADURPURA	311.82	194.82	87.70	48.72
3	CHARMINAR	233.87	194.82	116.93	38.97
4	BANDLAGUDA	155.91	97.44	58.46	19.48

The table.5 shows Kernel Density Estimation (KDE) values for deaths, injuries, persons on duty (POD), and overall accidents across four major areas of Hyderabad's South Zone: Bahadurpura, Charminar, Saidabad, and Bandlaguda. Saidabad records the highest figures, with 389.78 deaths, 243.61 injuries, a POD of 146.16, and one of the highest overall accident densities (48.97). Bahadurpura follows with 311.82 deaths, 194.82 injuries, 87.70 POD, and a similar overall accident density (48.72). Charminar shows moderate accident levels (38.97) but higher POD (116.93). Bandlaguda reports the lowest values, marking it relatively safer. Overall, Saidabad and Bahadurpura emerge as the most critical hotspots.

B. Prediction Accuracy Index (PAI)

The Prediction Accuracy Index (PAI) is a statistical measure used to evaluate the effectiveness of methods in identifying accident-prone or hazardous locations. It compares the proportion of crashes captured within detected hotspots to the proportion of the total study area these hotspots cover. Mathematically, it is expressed as

$$PAI = (n/N) \div (m/M),$$

where n is crashes in hotspots, N is total crashes, m is hotspot area, and M is the total area. A higher PAI indicates that a small portion of the area contains a larger share of crashes, reflecting better hotspot detection and supporting targeted road safety planning.

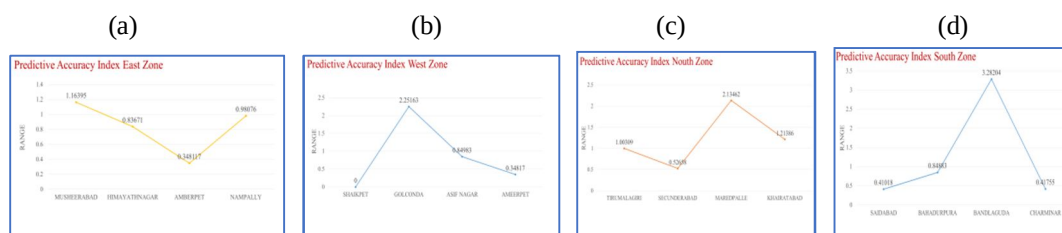


Fig.20 Predictive Accuracy Index Area Wise (a) East (b) West (c) North and (d) South Zones.

IV. CONCLUSION

The accident rate in Hyderabad consistently increased between 2021 and 2024. During this four-year period, the Department of Traffic Police recorded a total of 8,576 accidents. Among these cases, 12% were fatal, 77% were non-fatal, and 10% resulted in property damage only. Overall, the accident rate increased by 32% from 2021 to 2024, indicating a notable upward trend in road accidents. Kernel Density Estimation (KDE) successfully mapped accident-prone locations, showing high density at Bahadurpura (311.82) and low density at Tirumalgiri (110.36) for fatalities, high density at Secunderabad (290.06) and low density at Bandlaguda (97.44) for injury-related crashes, and high density at Golconda (293.22) and low density at Maredpally (73.45) for property-damage-only cases. Crash Hazard Level (CHL) provided a severity high ranking of accident area is Amberpet 3,796 and low ranking is Shaikpet 79, while Prediction Accuracy Index (PAI) validated hotspot predictions. Results highlighted that non-fatal accidents are 6,822 most frequent, but fatal are 780 and severe crashes remain a significant concern. The core challenge remains the **urban traffic congestion** and inability to widen the roads at Bandlaguda Charminar and Khairatabad due to dense built-up areas, making **targeted interventions** the best approach. Spatial models such as GIS and KDE proved vital in identifying patterns and making **data-driven decisions** for urban traffic safety.

V. RECOMMENDATIONS

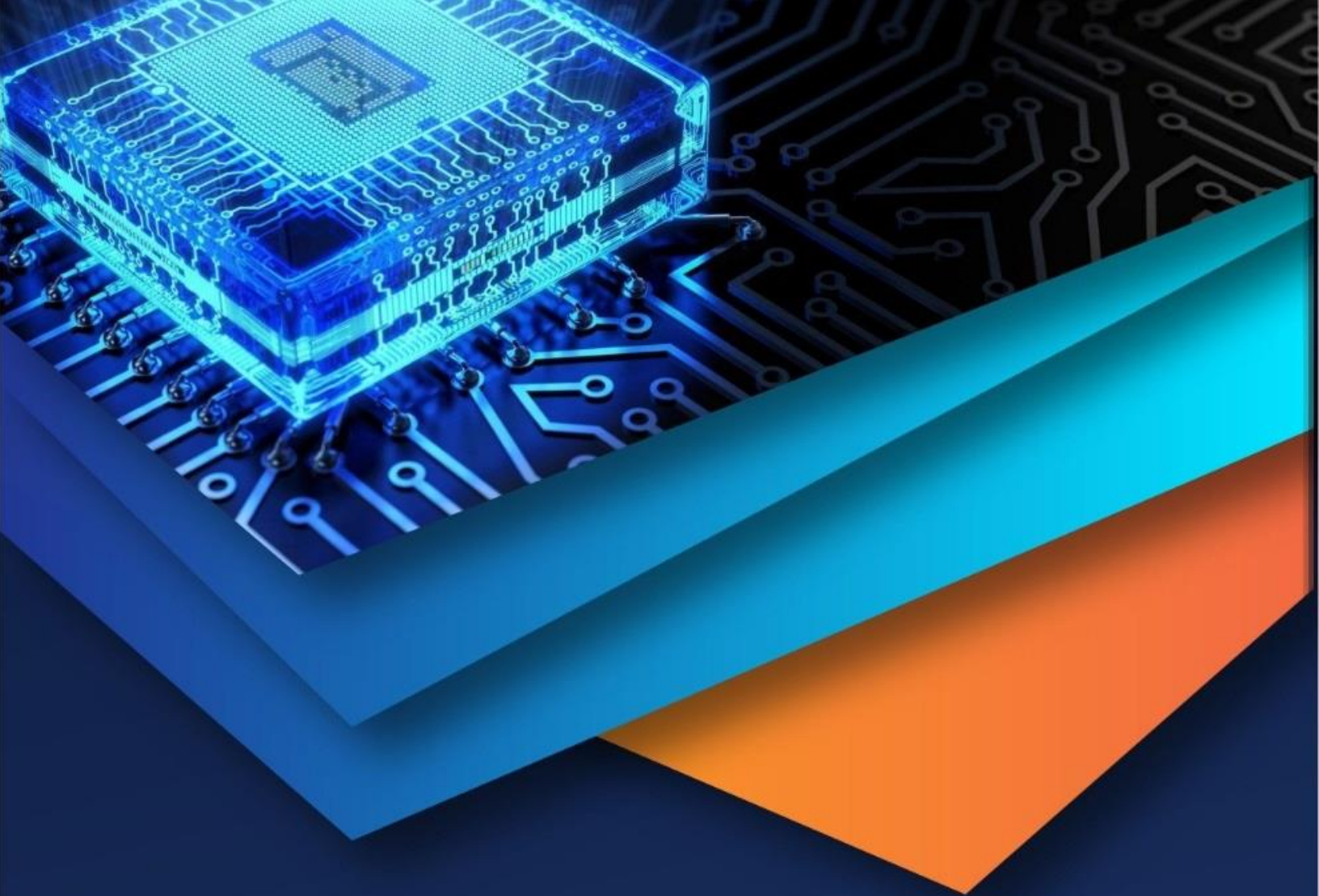
Redesign high-risk intersections in Secunderabad at Chilkalguda, improve street lighting at Ghmc areas, and develop pedestrian-friendly walkways at charminar. Introduce traffic calming measures in accident-prone areas to reduce speed and enhance safety. Strengthen emergency response and conduct targeted road safety awareness programs in vulnerable zones are Secunderabad Ameerpet and Saidabad.

V. ACKNOWLEDGMENT

I take this opportunity to express my heartfelt thanks and long felt a sense of gratitude to my guide Prof. P. SRAVANA, Professor of Civil Engineering, Jawaharlal Nehru Technological University College of Engineering, Science and Technology, Hyderabad for her excellent guidance in prosecuting this work. Her promptness, dedication has been constantly inspired me to better myself and aim higher. I profoundly thank her for sparing her precious time and for giving several suggestions at all stages of this work. I express my hearty gratitude to my parents for giving me the freedom and opportunity to pursue my own interests.

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