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# A Comprehensive Literature Review of Traditional and Spatial Methods for Black Spot Identification in Road Crash Analysis

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## ABSTRACT

The desire to greatly reduce traffic accidents, enhance road safety, and remove black spots from junctions has led to an increased interest in researching the various black spot (BS) identification systems. Conventional and spatial Black spot detection systems are created using a variety of concepts and methodologies; however, as each approach has a unique input and output based on zones, area, size, and other factors, it might not be suitable for every situation. The next step in this research is to conduct a comprehensive literature review of various Black spot detection approaches and the technology tools that support them. The goal is to identify, evaluate, and assess the acceptability, feasibility, accuracy, and appropriateness of various scenarios and parameters. Through accounting for several types of inadvertent correlation between the location of the accident and traffic information, the research discovered multiple methods for Black spot identification, each based on unique ideas and a range of methods and instruments. According to the study, each BS identification method has particular advantages and disadvantages. The principal objectives of this review are to assess the principal methods for evaluating traffic accidents, identify black spots, and explore possible distinctions between traditional and spatial traffic data analysis. To execute the statistical outcomes of occurrences that are examined, both the conventional method and GIS are used. This review paper provides an overview of three basic GIS approaches, explains a traditional method for identifying traffic incidents, and provides some often-used accident analysis tools for traffic safety.

## 1. Introduction

Road traffic accidents are a major issue that leads to an increase in property losses, injuries, and fatalities. They can provide serious health, financial, and developmental difficulties for drivers. As of 2019, traffic accidents rank as the 12th most common cause of death overall and the leading cause of mortality for children and youth (ages 5 to 29). Compared to the 1.25 million road traffic deaths in 2010, there were an expected 1.19 million deaths in 2021, a 5% decrease. The European Region has had a 36% fall in deaths, the biggest drop since 2010. The number of deaths has stayed constant in the Region of the Americas, with a 16 percent drop reported in the Western Pacific Region, and a 2 percent decline in the South-East Asia Region. However, in 66 countries. there was a rise; 28 of these countries are in the African Region, which has seen a 17% rise in the number of deaths since 2010. Additionally, over 92% of road traffic deaths and injuries occur in low- and middle-income nations, while no low-income country has seen a decrease in the number of road traffic fatalities since 2020 (Organization 2023).

The previous studies stated that, the four important traffic components, which are road user characteristics, vehicle characteristics, the road and its components (traffic furniture), and environmental circumstances, have been identified as the leading causes of traffic crashes. According to the study by (Niezgoda, Tarnowski et al. 2015), it is difficult to identify the specific cause of road accidents because accidents are caused by a mix of multiple factors. For instance, the characteristics of the road user are the most dynamic and unpredictable of all the activities, which are inappropriate speed, using the right way, failure to maintain a proper lateral position, fatigue, drunken driving, and cell phone use while driving.

Several studies indicate that up to 72% of curve-related accidents are caused mainly by the use of inappropriate speed on the given geometrical element (Calvi 2018). so, it needs safety analysis to control such an accident. Road safety analysis is vital to find hazardous road segments and understand how the potential interaction between driving behavior, driver perceptions, and the road environment influences the safety of all road users (Cairney and McGann 2000).

This analysis has also been employed to save lives by understanding the causes of traffic crashes and coming up with safety mitigations. In addition, the aims of road safety analysis are to investigate pieces of information on black spot location and cause of the road crash needed by decision makers to apply suitable safety measures to eliminate and minimize the occurrence of traffic crashes and are necessary for national plans for traffic safety management (Li, Zhu et al. 2007). In general, if we want to decrease the number of traffic accidents, it should be necessary to determine where and when accidents occur frequently and the methods of determining the black spot area. An accident A black spot (often synonymously known as a crash hotspot) is a section of road or intersection where the frequency of occurrence of several types of road accidents or a particular type of road accident is comparatively higher than other similar sections on the road, which is taken into account in the critical value or standards. s. t.

### 1.1. The black spot of road crash

Black spots in road traffic crashes refer to locations with a higher concentration of accidents. Identifying these black spots is crucial for understanding the causes of accidents and implementing targeted safety measures. According to previous studies, (Hafeez and Kamal 2008) black spot was originally defined as a road location of limited with a high concentration of accidents. Additionally, the term Black spots is said to derive from the method that was originally used to identify hazardous sites.

The terms' hazardous location and high accident locations often used as synonym. Various methods, such as sorting, grouping, accident prediction, and machine learning algorithms, can be used to identify black spots. These methods analyze factors like road design, traffic volume, driver behavior, and infrastructure to determine the risk level of different road segments. A number of safety researchers utilize crash frequency (i.e., crashes per year) to rank the locations of black spots, while others use crash rate (i.e., crashes per vehicle-kilometers for segments and crashes per entering vehicle for intersections). More recently, ranking has also been based on the percentage of accident types that are thought to be treatable. Another aspect of diversity in practice is that rank might be based on the size (of either the frequency or the rate) or, more commonly, on the degree to which the frequency or rate exceeds minimal criteria or what is considered usual for such places. Studies have been conducted in different countries, including Greece (Karamanlis, Kokkalis et al. 2023, Karamanlis, Kokkalis et al. 2023), Morocco (Mbarek, Jiber et al. 2023), and China (Wang, Huang et al. 2023), to develop models for black spot identification. These models utilize algorithms like extreme learning machine, XGBoost, and hierarchical density-based spatial clustering to accurately identify black spots and analyze contributing factors. The results show that the proposed models have high recognition accuracy and can effectively identify black spots for further investigation and implementation of safety measures (Singh and Singh 2023). In some researcher showed that, there is no universally approved definition of Road Traffic Crash (RTC) hot spot identification (Loo and Anderson 2015). Black spot is locations that are generally classified after an assessment of the level of risk and the likelihood of a crash occurring at a location (Rokytová 2000).

The goal of black spot safety work is to increase road safety by modifying the environmental and geometric features of the trouble spots in the current road network. There is a propensity for traffic accidents in towns and cities to concentrate at particular locations, frequently at junctions. Inappropriate traffic control or road design may be partially to blame for a concentration of accidents at a particular location. In such situations, better traffic management or road design can prevent or lessen the clustering of incidents.

### 1.2. The Purpose of literature review

The objective of this literature review is to assess the key methods used to analyze road accidents and determine the black spot location, as well as to explore the possible differential between conventional and spatial traffic data analysis.

## 2. Traditional method for Black Spot identification

Traditional methods of black spot identification in road traffic accidents involve retrospective analysis of historical accident data and the identification of accident predictors after the accidents have occurred (Karamanlis, Kokkalis et al. 2023, Putter 2023). These methods analyze specific locations on road networks during set time periods to identify areas with a higher concentration of accidents, known as black spots (Wan, He et al. 2021). Factors such as road design, traffic volume, driver behavior, weather, and infrastructure are evaluated to uncover the underlying causes of increased collision rates (Karamanlis, Kokkalis et al. 2023). However, traditional methods face challenges such as limited data availability, data quality, and assessing contributing factors.

Most of the previous traditional method of traffic accident data analyses for determine the black spot location used mathematical statistical methods (Bargegol, Najafi Moghaddam Gilani et al. 2017, Liu and Sharma 2017). These methods mainly use accident frequency, accident rate and severity index to determine the location of accident hot spots (Sun, Wang et al. 2019). The Rate quality control Method in Turkey consists of calculating three different parameters for each road section. The three parameters are used to identify the hotspot areas such as, Accident rate, Accident frequency and Accident severity. Each of these values is compared with a critical value. If a certain road section shows higher values than the critical ones for all these three parameters, the section is considered to be a black spot. However, according to (Hauer 1996) stated that, some researchers rank locations by accident rate (accidents per vehicle-kilometers or per entering vehicles), some use accident frequency (accidents per km-year or accidents per year) and some use a combination of the accident rate and accident frequency (Mr. Kent Sjölinder and Mr. Hans Ek December 2001). Most statistical analyses are based on the assumption that the values of observations in each sample are independent of one another. In addition, the non-model-based methods for black spots identification are simple to use for traffic accident analysis, they tend to detect more sites with higher traffic volumes especially when we use the crash rate determination methods. And also (Geurts, Wets et al. 2006) non-model-based methods do not take into account systematic and random variation, so that potentially producing high numbers of false positives and false negatives (Cheng and Washington 2005). But, the strength of these non-model-based methods is that they are easy to use and understand the way to determine the area of the black spot values and compared the critical value.

The identification of such hazardous locations, there are different approaches are also used. Some of these methods include using manuals and guidelines which are limited to a specific standard of the countries and define their own criteria for the locations of the accident spot (Kowtanapanich 2007). Sliding Moving Window methods also have been proposed for traffic accident analysis. (Fathy and Siyal 1998) introduced a window-based image processing technique that measures traffic parameters, eliminating the need for a background frame. (Kwon, Park et al. 2012) compared the performance of three methods for identifying high collision concentration locations, including the Sliding Moving Window (SMW) method. (Jun 2008) used data mining technology to identify frequent factors leading to traffic accidents. (Ullah, Ullah et al. 2015) presented a novel method for automatic traffic accident detection, based on Smoothed Particles Hydrodynamics (SPH). These studies collectively highlight the potential of various methods, including the SMW method, for improving traffic accident analysis.

**Table 1.** Summary of traditional black spot identification methods applications

| Method | Description | Advantages | Disadvantages |
|---|---|---|---|
| Accident frequency method | It Ranks black spots based on the number of accidents that occurred. Suitable for similar sections with low traffic. | The process is simple to compute, and the results are simply clear. | Do not consider different road, severity, and traffic conditions. Traffic volume affects accuracy |
| Accident rate method | Consider the relation of road accidents number, volume, and road length. | Fully consider Traffic volume and road section. | Accident severity is not considered |
| Critical rate method | Consider the traffic volume of a section to check the crash rate to the critical crash rate | Helpful for BS prioritization and analyses different accident patterns. | As critical rate changes database should be updated |
| Sliding Window (SLW) Method | This method of network screening is identifying appropriate start and end points of Black Spot locations along the road segments containing homogeneous traffic and similar built-in environment attributes | use the sliding window for identifying black spot in high-speed roads | The method tends to overlook a hazardous location because the fixed section length can split continuous accidents into two different BS sections. In fact, the section length should be flexibly long enough to cover all continuous accidents of a BS section. |

**Summary:** Table 1 indicates that the traditional black spot analysis method is erroneous since there may be no relationship between any of the sections. The majority of the conventional analysis approach is disregarded by traffic factories. The traditional technique, known as WSI, is useful for locating the black areas when adequate secondary data is accessible. It is challenging to identify the black spot on each road segment since, in contrast to traditional hot spot location identification methods, the spatial analytic approaches do not call for the segmentation of roads. Generally speaking, with spatial analysis approaches, the location of each crash is all that is required. Similar to how the crash frequency method outperformed other traditional methods for identifying hot spots, it also had stronger theoretical justifications. Specifically, the crash frequency approach outperformed the crash rate approach. Given that many roadway authorities employ the crash rate technique, this result is extremely concerning. In actuality, the crash rate approach falsely implies a linear relationship between traffic volume and crash frequency, which is skewed towards low-volume venues. This is a concerning outcome because a lot of agencies employ this technique.

## 3. Spatial Methods for Black Spot Identification

Since then, the geographical information system has been used extensively in road traffic safety studies over the past five decades (Mohaymany, Shahri et al. 2013, Dereli and Erdogan 2017) GIS application varies from simple mapping and visualization roles to further advanced methods such as spatial statistical models and the analysis of large data methods. Nowadays, the precise and exact location of road traffic accidents and their attributes are stored in the GIS database.so that the GIS software allows us to gather spatial data, in which we can store, manipulate, analyze and visualize it with a simplest way. (Lloyd 2010, Loo and Anderson 2015). As to compare with traditional mathematical statistics, spatial statistics fully utilize in spatial data processing, graphic display and visual interface. Also, the distribution of traffic accidents can be visualized the location of crash occurred through GIS visualization technology. (Haji Mirza Aghasi 2017, Li, Abdel-Aty et al. 2020).

Furthermore, by using a variety of spatial analysis tools in GIS, scholars can explore the spatial distribution characteristics of traffic accidents and the spatial relationship between different traffic accidents from a variety of perspectives (Hu, Wu et al. 2020, Jiang, Yuen et al. 2020) Spatial analysis is the inspection of crash occurrence patterns by considering their relative locations or zones. Traffic crashes meet the main characteristics of spatial heterogeneity and spatial dependence of point data. Spatial dependence belongs to the influence of events at a location by neighboring events, while spatial heterogeneity happens when the spatial relationships among observed incidents and random parameters in the developed model are not established spatially (Dereli and Erdogan 2017).

Understanding of spatial and temporal crash patterns helps the safety specialists to detect the sections having a higher number of crashes, to compare with other similar locations. Hot spot identification methods employing geo-statistics have focused more on the occurrence of crashes than on crash severity, which is an important aspect of highway safety. Traffic accident black spot identification using GIS involves analyzing the geographical location and time-based occurrence of road accidents to pinpoint areas with a higher concentration of accidents, known as black spots (Wang, Huang et al. 2023). Various models and methods have been proposed for this purpose. One model integrates GIS-based processing with hierarchical density-based spatial clustering of applications with noise, and determines optimal clustering parameters based on a validation index (Ge, Dong et al. 2022). Another model combines adaptive kernel density estimation with the road risk index, achieving higher accuracy in identifying black spots compared to other methods (Karamanlis, Kokkalis et al. 2023).

Machine learning algorithms, such as logistic regression and clustering, have also been used to identify black spots and establish prediction models (Sisbreño, Sumilhig et al. 2023). These models utilize data from accident records and can effectively classify data sets and establish connections between factors and the severity of accidents (Karamanlis, Kokkalis et al. 2023).

The advantages of using GIS for analysis are can provide a more visual and intuitive understanding of the distribution of traffic accidents, to quickly form an overall grasp of the traffic safety situation in the region and developed a variety of spatial analysis tools, which can be used to excavate the spatial distribution characteristics of traffic accidents and the spatial relationship between different traffic accidents from multiple angles, which is difficult to be achieved by simple statistical analysis. Overall, the use of GIS tools in traffic accident black spot identification provides a cost-effective and efficient way to analyze and reduce road accidents.

### 3.1. GIS tools for traffic accident analysis

The essential purpose of the traffic accident analysis using GIS tools is to discover information required to help decision maker’s select appropriate safety measures to prevent and reduce crash occurrence (Li, Zhu et al. 2007) The geo statistical-based analysis using spatial units (density estimation method) (Sabel, Kingham et al. 2005, Erdogan, Yilmaz et al. 2008) or spatial arrangement of attribute values from each unit (spatial autocorrelation method). In general, geo statistical-based hot spot analysis requires less intense data and is more straightforward in application because of the uncomplicated mathematical calculations compared with traditional statistical hot spot analysis and it is a simple way of conducting hot spot analysis is to select areas by observing maps of where crashes occur (Thakali, Kwon et al. 2015).

It's crucial to thoroughly assess the data sources, methodology, and underlying assumptions of each GIS tool's study in order to resolve disparities in results. To evaluate the robustness and reliability of the results, sensitivity analysis, cross-tool comparison, and validation against ground truth data can be used. Furthermore, adding local expertise and expert judgment can offer insightful information on how to interpret data and identify significant areas of concern for focused interventions.

#### 3.1.1. Moran’s index (MI) statics

The Moran I statistic (Moran 1948) is likely the most often used way to evaluate spatial autocorrelation for planar-space areal data. Spatial autocorrelation is the tendency for a variable's value at one place to be associated with the values of the same variable at surrounding locations.

The degree of feature or spatial data concentration or dispersion is computed using this tool. It is important to remember that this analysis simultaneously observes the feature's position and attributes in order to assess the spatial feature distribution pattern. "What is the state (random, dispersed, or cluster) of the spatial feature distribution?" is addressed by the analysis's findings. Actually, this tool uses Z-Score and P-Value to compute the Moran Index (or statistic) and assess its significance. The statistical significance metrics, z-scores and p-values, reveal the distribution of traffic accidents. Since the Spatial Autocorrelation (Global Moran's I) tool is an inferential statistic, as table 2 illustrates, the analysis's findings must always be interpreted in light of its null hypothesis.

**Table 2** Interpretation of Global Moran's I

| | |
|---|---|
| The p-value is not statistically significant. | You cannot reject the null hypothesis. It is quite possible that the spatial distribution of feature values is the result of random spatial processes. The observed spatial pattern of feature values could very well be one of many, many possible versions of complete spatial randomness (CSR). |
| The p value is statistically significant, and the z-score is positive. | You may reject the null hypothesis. The spatial distribution of high values and/or low values in the dataset is more spatially clustered than would be expected if underlying spatial processes were random. |
| The p-value is statistically significant, and the z-score is negative. | You may reject the null hypothesis. The spatial distribution of high values and low values in the dataset is more spatially dispersed than would be expected if underlying spatial processes were random. A dispersed spatial pattern often reflects some type of competitive process—a feature with a high value repels other features with high values; similarly, a feature with a low value repels other features with low values. |

The Moran's Index (MI) statistics method is commonly used to identify congested roads and accident hotspots in urban areas. It involves calculating the traffic congestion index based on collected traffic indicator data and using the variation coefficient and Moran's Index to describe the spatial distribution of congestion in the road network (Feng, Bai et al. 2019). The improved Moran's I method is proposed to classify the spatial-temporal features of road traffic status, including homogeneous and heterogeneous congested and uncongested traffic (Chen, Wei et al. 2013, Cao, Liu et al. 2022). This method has been applied to analyze the spatial-temporal distribution and evolution of road traffic status using traffic flow data from urban expressways (Moons, Brijs et al. 2009) The results of these analyses can provide guidance for urban traffic control, traffic planning, and the optimization of parking space distribution on road sections.

The previous studies have utilized Moran's Index (MI) statistics in the identification of traffic accident black spots. (Pour, Moridpour et al. 2015, Sandhu, Singh et al. 2016) in GIS both employed MI in conjunction with other spatial analysis tools to identify these high-risk areas. (Moons, Brijs et al. 2008, Moons, Brijs et al. 2009), addressing issues such as the need for network adaptation and the distributional properties of the data. These studies collectively highlight the value of MI in traffic accident analysis and the need for its careful application. Local Moran's I is among the well-known local spatial autocorrelation approach used commonly in motor vehicle crash hot spot analysis (Mitra 2009). However, the family of Moran indices does not differentiate between hot or cold spots.

Furthermore, Global Moran's I, an index to measure global spatial autocorrelation in the entire study area. Given feature locations and attribute values associated with each feature, the index provides information on clustering patterns of features' attribute values in the study area. The local Moran's I approach carries a limitation in distinguishing between high- and low-valued clusters

### 3.1.2. Getis.Ord

The local Moran's I statistic is about the autocorrelation between a region and its neighborhood, But the local G statistic (Getis and Ord 1992) measures concentration of values of the target variable around a region. Because the statistics deal with different aspects of spatial association, it is often useful to apply both I and G statistics to the same data set (Getis and Ord 1992)
The Getis and Ord method can discern localized variation over the study area and pinpoint crash hot spots with statistical significance. Hotspot analysis using Getis-Ord is particularly useful for setting the needed actions for locations that have one or more clustering patterns such as traffic accidents, understanding the potential causes of that clustering, and visualizing the cluster locations and their geographic extent. The hot spot analysis tool in ArcMap uses the statistics and determines a significant red/blue spot based on neighbors' attribute values.

The previous studies have utilized GIS tools, including Getis-Ord Gi*, for identifying traffic accident black spots. (Mandloi and Gupta 2003, Sandhu, Singh et al. 2016) both used GIS to map and analyze accident data, with Sandhu specifically employing the Getis-Ord Gi* statistic. (Colak, Memisoglu et al. 2018) applied hot spot analysis based on network spatial weights to identify black spots, while (Harizi, Ouni et al. 2016) used the Getis-Ord statistic to detect and classify road accident black zones. These studies collectively demonstrate the effectiveness of GIS tools, particularly Getis-Ord Gi*, in identifying and analyzing traffic accident black spots.
In general, Getis-OrdGi* method can distinguish localized variation over the study area and pinpoint crash hot spots with statistical significance. Hotspot analysis using Getis-Ord is useful for: setting the needed actions for locations that have one or more clustering patterns such as traffic accidents, understanding the potential causes of that clustering and visualizing the cluster locations and their geographic extent.

### 3.2.3. Kernel Density estimation (KDE)

Kernel density estimation (KDE) is another hot spot analysis method along with the spatial autocorrelation method. It is a non-parametric estimation technique to represent density estimates from observed data (Läuter 1988). The major limitations of KDE's are the lack of statistical significance test in the analysis of traffic accident (Xie and Yan 2008, Anderson 2009). A range of studies have utilized GIS and Kernel Density Estimation (KDE) to identify traffic accident black spots. (Pour, Moridpour et al. 2015, Ge, Dong et al. 2022) both used KDE to analyze accident data and identify high-risk areas, with (Ge, Dong et al. 2022) further developing an adaptive KDE method for improved accuracy. (Sabel, Kingham et al. 2005, Sandhu, Singh et al. 2016) also employed KDE in conjunction with other techniques, such as Monte Carlo simulation and spatial statistics, to identify statistically significant clusters and critical analysis of black spot locations. These studies collectively demonstrate the effectiveness of KDE in GIS for traffic accident black spot identification.

Previous studies showed that conventional kernel density estimation (KDE) has been employed in several safety studies to detect the crash hazard regions (Pulugurtha, Krishnakumar et al. 2007, Anderson 2009) The idea behind density estimation is that the point pattern has a density at any location in the study region not just at the location where the event occurs or is displayed. This method estimates the accident density by counting the number of accidents in an area. This area is known as kernel. The total study area is divided by predetermined number of cells. Important criteria to estimate the most suitable density level is bandwidth or radius of the cell as shown in table 3.

Based on the previous studies, I suggested selecting the length of bandwidth affects output of hotspots. For instance, larger bandwidth shows hotspots area in larger form. Prior research suggested that a 50- to 200-m search bandwidth be used in urbanized areas while an 8 00-m bandwidth be used for rural areas for identification of crash density. (Steenberghen, Aerts et al. 2010). The following issues could arise from planar KDE's limitations: Agencies may not provide the additional attention required for the real high-risk locations because of two factors: (a) overestimation—some roads that do not have a high risk are shown to be risky—and (b) underestimation—many roads are shown as critical locations rather than the actual roadways that have a high crash risk.

Broadband is typically used as an input data to estimate detection zones in black spot analysis using the KDE approach. According to earlier research findings, the assessment of band width is also dependent on when traffic accident data is collected. The calculation of bandwidth length decreases as the data collection period increases because the accident cluster's dispersed data increases. in order for there to be a reciprocal relationship between the bandwidth and the time period.

**Table 3** Previous studies to determine the bandwidth

| Author and Publication Year | Road Traffic Accident Investigation | Taking into Account the AADT | Bandwidth Rate [m] | Study Area |
|---|---|---|---|---|
| Michal B. (2013) | Yes | No/Not defined | 100 | Urban |
| Saffet E. (2008) | Yes | No/Not defined | 500 | Highway |
| Zhixiao X. (2013) | Yes | No/Not defined | 100 | Urban |
| Tessa K. Anderson (2009) | Yes | No/Not defined | 200 | Urban |
| Álvaro B. (2019) | Yes | Yes, but at intervals | 50 | Urban |
| Lalita.t.(2015) | Yes | No/Not defined | 800 | Highway |

**Summary:** Spatial analysis with ArcGIS is generally more preferred than older methods because of: The spatial analysis spot/map technique has placed greater emphasis on the frequency of crashes than the severity of crashes. One of the shortcomings of the hot spot approach is its inability to differentiate between true positive and false positive sites, which is why the GIS methodology was developed. The researchers have been able to determine accident concentrations and examine the connections between accidents and contributory factors thanks to the analyses of GIS tools. Highway segmentation is not necessary for the applications of spatial analytic methodologies. The objective is to rapidly build an overall awareness of the traffic safety condition in the region by identifying hot spots through map visualization and intuitive comprehension of the distribution of traffic incidents.

## 4. Comparison of traditional and spatial black spot identification methods

A range of studies have compared traditional and spatial methods for identifying black spots on roads. (Ghadi and Török 2019) found that the sliding window method is more effective for high-speed roads, while the spatial autocorrelation method is better for low-speed roads. (Szénási, Felde et al. 2018) compared the sliding window method, 2D sliding window method, and DBSCAN method, considering factors such as accuracy and processing speed. (Szénási, Felde et al. 2020) further explored these methods, this time based on GPS coordinates, and found that the original sliding window and DBSCAN methods were the most effective. (Flahaut, Mouchart et al. 2003), A comparative approach compared the local spatial autocorrelation and kernel methods, finding that both have their own advantages and shortcomings. These studies collectively suggest that the choice of method should be based on road characteristics and the specific goals of the analysis.

The study identified various methods of Black spot identification based on different principles, and different techniques and tools employed by considering different types of accidental and traffic data. Most of the conventional analysis method (statistical analyses) are based on the assumption that the values of observations in each sample are independent of one another. for instance, Moran's Index measures the spatial dependence between the crash site and accident cluster site based on the spatial pattern and provides a powerful tool to study the occurrence of accidents in the given study area with in the short period of time. SLW method is more preferable for traffic data analysis applied on the link road which has the high speed but the spatial analysis like KDE is more preferable method to determine the black spot area on the intersection or crossing road in slow movement of traffic areas which has the lower speed.

## 5. Conclusion

The literature research demonstrated that several available variables and characteristics play a role in determining the degree of success and precision of an applied BS identification approach. Thus, the availability of the following characteristics must be taken into account when choosing the best approach for BS identification: region (Urban, NonUrban region), Type of Road (Highways, junctions), and Types of Data Available (Accident data, traffic data, road condition). This review article's objective was to investigate the GIS approaches and traditional strategies useful for ensuring road safety based on black spot analysis
.

In order to determine the study's potential practical applications, a comparison of several GIS methodologies is conducted with an emphasis on the geographic mechanism of crashes. To obtain accurate results, the majority of primary studies used Moran's I and GetisOrd; however, no study combined the use of GetisOrd and KDE approaches. The BS identification techniques make considerable use of GIS technology, particularly for accident density analysis. In order to investigate the spatial patterns of car crashes and ascertain whether they are randomly distributed, spatially concentrated, or dispersed, this research proposes a GIS approach. In order to analyze spatial patterns, create high-risk areas along highways, and cluster map car crash data, Moran's I and Getis-Ord Gi* statistics are used. Crash concentration maps, which display the road density of crashes, are produced using Kernel Density Estimation (KDE).

Similar to how the typical crash frequency method outperformed other conventional methods for identifying hot spots, it also had stronger theoretical justifications. Specifically, the crash frequency approach outperformed the crash rate approach. Given that many roadway authorities employ the crash rate technique, this result is extremely concerning. In actuality, the crash rate approach falsely implies a linear relationship between traffic volume and crash frequency, which is skewed towards low-volume venues. This is a concerning outcome because a lot of agencies employ this technique. But because each segment might not be connected to another, the traditional black spot analysis method is erroneous. The conventional method tends to overlook problematic places where the section lengths should be long enough to cover all continuous incidents that appear to be related to one another because the majority of the traditional analysis method ignores other traffic factories. The spatial analysis technique known as KDE is a more desirable method for identifying the black spot area on an intersection or crossing road in slow-moving traffic areas with a lower speed than the traditional black spot analysis method, such as the SLW method, which is better suited for traffic data analysis applied on link roads with high speeds. However, to overcome these challenges, machine learning algorithms have been used to effectively classify data sets and establish connections between factors and the severity of accidents. These algorithms include classification, regression, clustering, and dimensionality reduction.

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