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Spatial Analysis for the Classification of Prone Roads Traffic Accidents: A Systematic Literature Review

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ABSTRACT

Identifying prone road traffic accidents (PRTA) has been based on the total number of accidents data. Determining road names that have not been appropriately approved makes the data biased. Many researchers have reviewed many factors, spatial methods of analysis, and ways to improve past traffic strategies. The searching method with a systematic literature review (SLR) was conducted on seven publishers of the traffic accident classification database. They are ACM Digital Library, IEEE e-Xplore, ScienceDirect, Springer, Sage, Taylor & Francis, and Wiley, then produced 189 major relevant studies to the findings of this study. SLR is used to find the most relevant journals, research topics, trends in the field, multi-criteria spatial dataset parameters, estimation methods, trends, the best methods currently, proposed improvement methods, and the most commonly used efforts to determine in a collection of road traffic accidents. The study results obtained that multi-criteria spatial data were developed in different spatial analyses. The SLR mapping results found gaps for hybrid two types of classification methods on multi-criteria decision making (MCDM) and Spatial Multi-level Classification. The consistency test of many methods is done by the Consistency Test Method (MCT), the value of Precision-Recall Accuracy (ARC), and Site Consistency Test (SCT).

Key words : spatial analysis, spatial data modeling, prone road traffic accident, hybrid methods, multi-criteria spatial analysis, SLR.

1. INTRODUCTION

The number of traffic accidents based on statistical data series is one indicator of the main factors determining PRTA classification. Data on the number of accidents that can be accessed publicly do not contain complete information on the accident road. The detailed data is still private in Government Agencies. Things that become indicators of the main factors, if not detailed in the spatial analysis modeling process, will result in biased decisions when used as a policy to reduce the number of traffic accidents. The main factors of traffic accidents are the lack of interchanges along roads, inappropriate and nonstandard horizontal curves along roads, traffic of smugglers roads [1], and road horizontal alignment conditions [2]. Other factors are the function of road geometry, the environment, and traffic conditions [3]. Real-time traffic and weather data are also factors that affect road accidents [4]. Road geometric construction design [5], poorly functioning road infrastructure, environmental conditions, roadway signals, congestion, human factors, and lack of safety while driving are also critical determinants of road accidents [6].

The number of accidents resulting in death continues to increase each year. In 2004 the road traffic was ranked 9th. The World Health Organization (WHO) estimates that 2030 road traffic will advance to the 5th rank [7]. On the World Health Day (WHD) dated April 7, 2004, WHO made the theme "Road Safety is No Accident". Data collected by WHO recorded every 1.25 million people per year deaths due to road accident, ≥ 20 million people injured in a road accident. 75% of casualties occur in developing countries, with 32% occurring in motorcyclists. WHO estimates that between the years 2000 to 2020, the number will increase by 60% if transportation systems are not improved by setting up traffic systems to achieve safe roads [8]. WHO has published its report on the "Global Status Report on Road Safety 2015", in which deaths from road accidents rank first with the highest number of deaths occurring in some developing countries such as Indonesia. It can be predicted and prevented by applying a transportation system that can warn against accident-prone areas [7].

Previous research reviewed methods for predicting RTA using modified C4.5 algorithm [9], autoregressive integrated moving average [10], hot spot analysis (Getis-OrdGi*) [11][12]. The methods to explain RTA factors, among others, a machine learning approach [13], accident modification factors [14], factor analysis [15], minimum uniform crash criteria [16], the simple crash ratio of a reference group [17], minimum uniform crash criteria [16], critical crash rate method [18], extremely severe crash [19], the simple crash ratio of a reference group [17], critical crash rate method [18], yearly multiplier [17], and extremely severe crash [19].

The Systematic Literature Review (SLR) is used to identify, evaluate, and assess in interpreting the results of studies that have been carried out. The purpose of SLR is to answer the research topic, problem statement, and advanced research that could be done in software engineering [20][21]. The initial step in the SLR is a review of the research question (RQ), identify the methods used to answer the RQ, identify as much literature relevant to the RQ, documenting all search results to make it easier to find out how full of reviews that have been conducted on the RQ [22].

The SLR results in the spatial analysis for the PRTA classification mostly use the artificial intelligence (AI) hybrid method two types of classification methods on MCDM (AHP method, Fuzzy AHP method, TOPSIS, WSM, and WPM) and Spatial Multi-level Classification (Artificial Neural networks, Extreme learning machines, k-nearest neighbors, Naive Bayes, Decision trees). The SLR will provide an overview of the topic of the study of the PRTA classification that has been published in several publisher databases. The SLR current state focuses on the type of road network, the multi-criteria spatial dataset used, the AI method used for spatial modeling, and the spatial analysis method used to advance the consistency of results between the field and search results data. The SLR results will be used as a reference for further research. Among other things, it analyzes multi-criteria parameters that affect the results in the road traffic classification category. Directs to evaluate newly proposed models using hybrid classification methods on MCDM and spatial multi-level to PRTA classification.

The proposed model using hybrid classification methods on MCDM and spatial multi-level classification is used in this study to process the determinant parameter data in the PRTA classification that include road conditions, traffic volume, accident rate [23] [24] [25]. Spatial datasets based on (i) arterial road networks (speed scheme, V/C ratio, the width of the road, number of lanes, road shoulder, median strip, horizontal alignment, vertical alignment, road conditions, and vehicle type), (ii) collector road networks (speed scheme, V/C ratio, the width of the road, number of lanes, median strip, horizontal alignment, vertical alignment, road conditions, and vehicle type), and (iii) local road networks (speed scheme, V/C ratio, the width of the road, road conditions, average daily traffic volume (ADT), and adjustment the size of the city).

The PRTA classification results can be used as a reference for conducting road safety audits, minimizing accident rates on the road, and ensuring no deaths. It helps policymakers make decision-making processes in road management following the Global Plan for the Decade of Action for Road Safety year 2011-2020 WHO for pillar one and pillar 2.

2. RESEARCH METHODOLOGY

The systematic literature review (SLR) was conducted to map the PRTA classification on the type of road network. In this paper, three stages of SLR, planning research topics, implement SLR research, and the SLR report, as shown in Figure 1.

Planning research topics with processes that identify the need for research on SLR topics, develop a review of the protocol to research issues, and evaluate review protocols on a research topic. The SLR stage implementation with process research for primary research topics, select primary studies (PS) in research topics, extract data from PS, assess the quality of PS, and synchronize the multi-parameter criteria. Reporting the results SLR with process disseminate results.

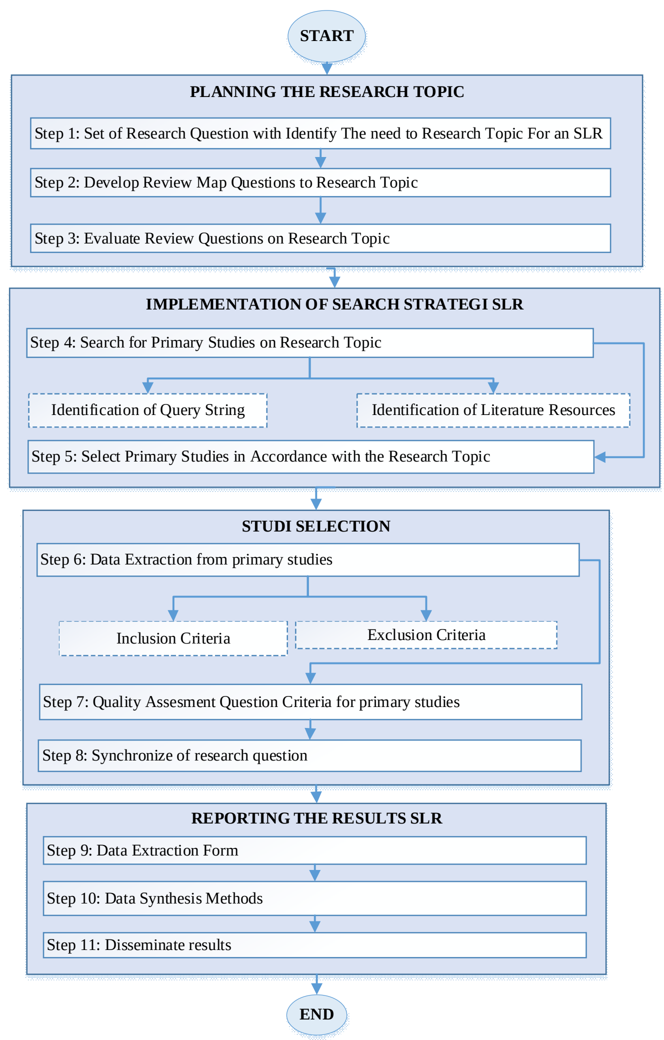

Figure 1: Systematic Literature Review Steps

2.1 Search Strategy

The material used in SLR activities is the search process on popular digital library databases. This activity aims to collect material on the topic under study to produce a broad literature review coverage. Searching on digital library databases (Journal, conference, symposium, and book chapter) are limited to the publication from January 2013 to September 2018. Keyword search is used to focus on the title, keyword, and abstract. Here is a list of digital library databases used in searching the SLR materials: ACM Digital Library, IEEE eXplore, Science Direct, Springer, Sage, Taylor & Francis, and Wiley.

Keyword search used in the SLR material search process was developed from PICOC [26] [27] [28], namely by identifying the keyword search such as:

- Knowing the population and the intervention of the research topic
- The RQ that have been defined
- Search the title, abstraction, and the relevant keyword terms (synonyms, antonyms, and alternative spelling)
- Using Boolean search 'AND$_s$' dan 'OR$_s$'. (roads traffic accident OR accident rate OR safety-critical system OR road safety analysis OR the location of traffic accident OR PRTA OR black spots OR black sites OR black zone OR black area OR trouble spot) AND (Multi-criteria OR classification OR spatial analysis OR spatial data modeling)

2.2 Study Selection

Study selection is made by applying inclusion and exclusion criteria, which serves to review the abstract and the title of a paper on the SLR activities and decide whether the paper being taken follows the search process based on the topic suitability [29]. The article was obtained from various digital library sources, then calculated to identify an appropriate theme that fit the research topic by choosing a search strategy, developing a search process, evaluating the results, and doing the inclusion and exclusion criteria [28].

Study selection to choose the feasibility of the primary study (PS) with inclusion and exclusion criteria concerning the relevance of the article according to research topics, place of publication, the period making the article, evaluation of papers on the subject which is becoming a trend for further research, restrictions on the use of language in the article referenced.

A. *Inclusion Criteria (Primary studies)*

Studies on articles that contain some term keyword PRTA classification discussing the problem, objectives, mathematical models, datasets multi-criteria parameter, methods, and results achieved. Studies in an article published in journals and conferences international in the English Language, published in January 2011 to September 2018, if there is a publication with same study the will be used the complete version and in the year the new

B. *Exclusion Criteria (Secondary Studies)*

The study did not focus on discussing the article with the context, objectives, or research to multi-criteria parameter dataset, mathematical modeling, classification methods in the field of research topics the PRTA classification manifestly missing, non-peer-reviewed publications, articles Page ≤ 3 pieces. Grey literature (papers without bibliographic information, date/type paper, volume and issue numbers were excluded), and Publications Articles that do not include the full text, in the search engines (www.google.co.id) the contacting authors.

Storage and processing of the results of the search process using software article Mendeley. Figure 2 excludes primary studies based on the title and abstract and the exclusion of PS based on the full text, the number of articles that have been obtained at this stage of the process of finding articles with select primary studies by the research topic. Papers that do not conform to SLR activity research topics are not included for inclusion/calculation; the result SLR only refers to the article, which has some similarities according to research topics studied.

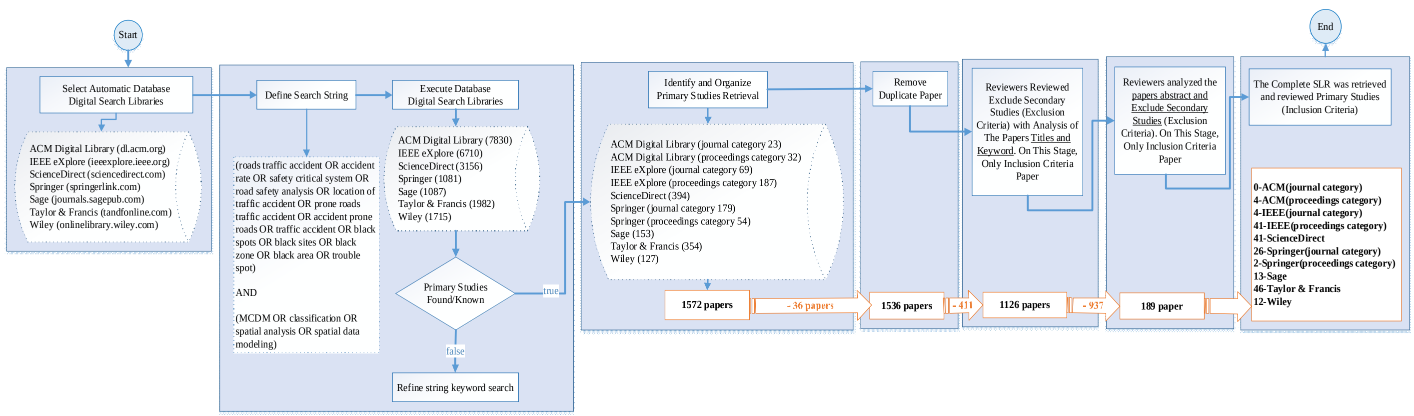

Figure 2: Search and Selection Paper of Primary Studies

2.3 Data Extraction and Synthesis Phase

Data extraction is used to collect data on the SLR process with "?" Primary Inclusion Criteria Study paper categories. This process to answer the RQ is described in Table-1. The synthesis phase is used to normalize the terms used in the PRTA classification by using the term commonly used, including:

- Multi-criteria Spatial Dataset that is used as input to the model to be built.
- Mathematical modeling is using to determine the PRTA classification.
- The relationship between mathematical modeling and the multi-criteria parameter dataset is determined by civil engineering and computer science expertise.

Table 1: The Data Extraction Properties

Property	Description
Study identifier on Publication Papers (Researcher, Year, Title, and Country)	**RQ1, RQ2.** How to identify articles in the paper using keywords which correspond to the research topic (spatial analysis or spatial data modeling for roads traffic accident, accident rate, location of traffic accident, road safety analysis, black spots, black sites, black zone, black area, trouble spot, accident-prone roads, prone-roads traffic accident)? Journal publication.
Paper Database resource; Type of Papers; Application context; Type research on papers; Contributions of the publication; Research Trends and Topics	**RQ3.** ACM Digital Library, IEEE eXplore, ScienceDirect, Springer, Sage, Taylor & Francis, Wiley; Journal, conference, symposium, and book chapter; government and academic; inductive and deductive approach (research, experience, position or concept paper; evaluation research papers, validation research papers, solution proposal papers, and opinion papers; how does the activity can use for the identification of research topics and trend in the field of GIS to the prone-roads traffic accident classification? Trends and topic research Researchers.
Dataset Multi-Criteria Parameter to PRTA classification	**RQ4.** How do management to comparison the Dataset Multi-Criteria Parameter use to determine the prone-roads traffic accident classification? Spatial Datasets roads traffic accident classification.
Mathematics Model to PRTA classification	**RQ4, RQ5.** What are mathematic model shapes used as input the dataset Multi-Criteria Parameter to determine prone-roads traffic accident classification? Analysis of spatial or spatial data modeling to roads traffic accident classification.
PRTA classification methods	**RQ6, RQ7, RQ8.** What methods are most widely used for prone-roads traffic accident classification, and How do we identify the application of MCDM methods to determine Prone-roads traffic accident classification? Validation methods to roads traffic accident classification; Metrics used to measure estimation accuracy, precision, and recall methods comparison.

2.4 Study Quality Assessment and Data Synthesis

The Study Quality Assessment is critical in assessing the quality of the primary studies undertaken at this selection study stage through inclusion or exclusion criteria. Giving the detailed data statements on the inclusion or exclusion criteria, measure the quality of the PS result by determining the strength of the conclusions describe, as a reference to the importance of individual studies when the result is being synthesized and instructions on advanced research recommendations/ future work [27]. The Study Quality Assessment can be realized if the PS minimizes bias (Systematic error) and maximize internal and external validity (Generalizability and Applicability) [27].

The quality assessment was done by evaluating the credibility of the paper, paper completeness, and relevance of the PS were selected to provide an overview of Quartile (Q1-Q4) in the selected PS. Ranked at each given paper quality scores by category as suggested [27] [30] [31] [28], that is poor quality (score= 0), partially quality (score= 0,5), and excellent quality (score=1). All paper documents obtained in the process will be evaluated by a device, which classifies paper into the category of the PS [30], that is:

- Evaluation of Research Papers (ERP), paper implement and evaluate the use of a technique of problem-solving methods.
- The Validation Research Papers (VRP) uses a case study to evaluate an engineering problem-solving method.
- The Solution Proposal Papers (SPP) contains a new method to provide solutions to a problem.
- Opinion Papers (OP), the paper outlines the strengths and weaknesses of the comparison in using a method.

The Data Synthesis is used to collect evidence from primary studies (Inclusion Criteria) and was selected to answer the RQ of accumulating evidence and qualitative of quantitative data. Descriptive / narrative of synthesis data obtained from the results of studies (homogeneous/heterogeneous) on the intervention, population, context, sample sizes, outcomes, study quality, tabulated in a table to describe the differences and similarities with the review question [27]. The Quantitative data synthesis. The Data Synthesis by using a table, pie chart, bar chart based on RQ.

2.5 Threats to Validity

Threats to validity are used to perform analytical studies related to the research topic of the PRTA classification based on the multi-criteria parameter with MCDM methods. The article search in the journal is not based on a reading of the manual of topics on all titles so that it is not aware of any bias in the selection of research topics.

SLR will conduct a study on the results of a conference paper or paper that is published in the journal by a research topic, the PRTA classification. The research topics are selected based on strategy SLR that has been done by (a) reviewing the various databases of the digital library, (b) create a keyword search with Boolean ANDs and ORs and (c) make the Study Quality Assessment (QA) Criteria through the inclusion and exclusion criteria.

The RQ is determined to determine the feasibility study was taken on a research topic, but it is possible the study SLR is not going well because not all of the databases of digital libraries in the extraction of items (title, abstract, and keywords). SLR of the reference, all the studies were extracted following topics the proposed research to identify studies missed during the search at the beginning [32]. To overcome this, then the threats to validity are grouped into four categories, that is construct, internal, external, and conclusion [33].

Concept Validity Threats. Major construction on Validity Concept that determines a keyword search of the most commonly used of the research topics are taken [33], this section there are five taxonomic concepts built to get the keyword search that is commonly used is (1)"accident roads", (2)"multi-criteria parameter", (3)"spatial analysis or spatial data modeling", (4), and (5)"MCDM method". The first concept is all words that contain the term "accident roads" and all the words that contain a synonym for "accident roads" ("roads traffic accident", "accident rate", "location of traffic accident", "road safety analysis", "black spots", "black sites", "black zone", "black area", "trouble spot", "accident-prone roads", "prone-roads traffic accident") been associated with the field research topics of accident roads. The second concept is related to the word "multi-criteria parameter" contained in all the synonyms "accident roads" that are used to detect the parameter criteria used to determine the "accident roads". The concept of the third, fourth and fifth are all words in the search database that contains the word "spatial analysis", "mathematics modeling", "classification", and "MCDM methods" are synchronized with the synonyms of the word "accident roads". A complementary manual search of the SLR is not done; this threat can be overcome by entering the keyword search. This threat is to be addressed by entering the keyword search commonly used in the digital library database.

Internal Validity Threats. The primary purpose of conducting SLR on the study was to reduce the internal validity threats [28]. Threats to the internal validity occur because the conclusions are subjective on the activities of the SLR in the choice of articles of paper and extraction of data to the contents of the paper. This can happen if the SLR on paper main does not clearly describe the research topics taken [31]. To overcome these threats because of lack of understanding in the knowledge content of articles of paper, the writer who is currently pursuing a Ph.D. is controlled by the promoter in determining papers selected as a premier study.

External Validity Threats. External validity is the SLR result determination overall, representing a review of the main research topics were taken [31]. The SLR ability to identify valid literature produced on an issue entire contents, research if literature made invalid, then the idea is poured on a research topic, not by the generated content [34].

Conclusion Validity Threats. To produce a valid conclusion validity, all articles of the paper refer to research topics taken. In certain circumstances, where some research in making conclusion validity did not include all reviews (excluded review paper) should be included (Included review paper) in the review to produce conclusion validity for certain conditions [31], because it does not all the contents of articles of paper related to the main study can be identified [27]. To overcome conclusion validity threats, need to be designed study selection with the inclusion and exclusion criteria.

3. RESULT AND DISCUSSION

In this mind map SLR in Figure 10, 189 major study papers through SLR were used to analyze spatial datasets, spatial analysis through mathematical modeling, and methods used for the PRTA classification. SLR distribution is carried out from January 2013 to September 2018. This topic shows the research direction on the main research topics. The spatial analysis to SLR studies found that Spatial data analysis using the MCDM method approach from SLR primary studied only focuses on road safety subject [35] [36] [37]. Figure 3 is the distribution of the number of papers included in the PS category to be used as reference research material (2018=43 papers; 2017=49 papers; 2016=30 papers; 2015=20 papers; 2014=24 papers; 2013=23 papers).

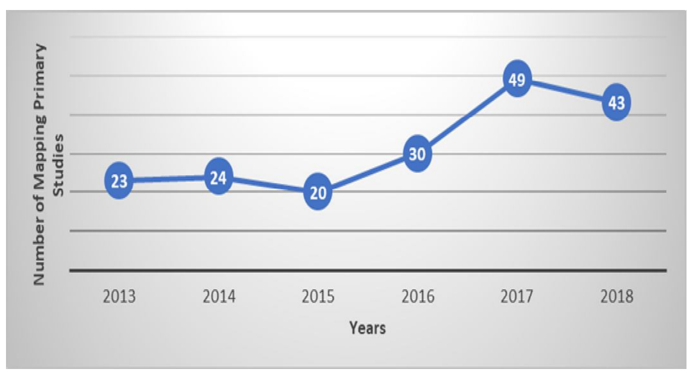

Figure 3: The Number of PS SLR

The amount of paper distribution in each publisher in the Scopus journal and proceeding was in Figure 4, 142 papers (75%) published in journals, and 47 papers (25%) published in the proceedings.

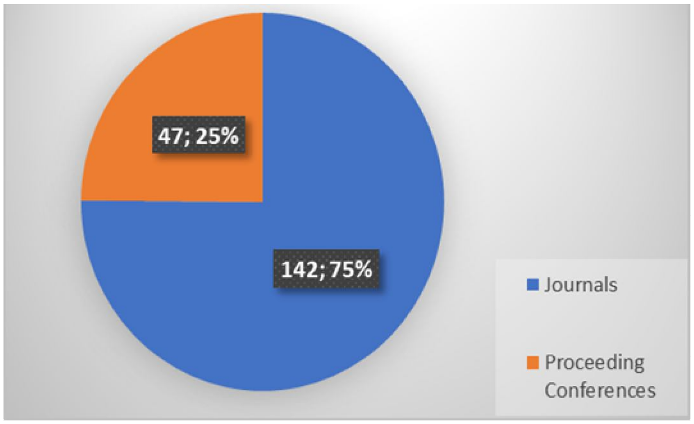

Figure 4: The Number of Mapping PS

A brief overview of the primary studies is shown in Figure 5, which shows that this study is still a trending topic in several Scopus indexed journal publishers distributions. The highest value is on the publisher Taylor & Francis. Publisher IEEE Digital Explore contributes to the highest number of importance on the conference results in Figure 6.

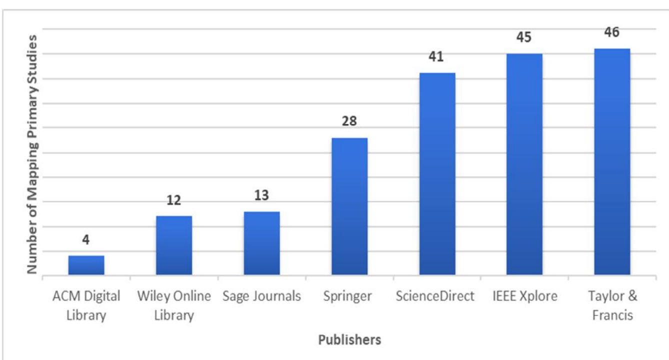

Figure 5: The Distribution PS in Scopus Journal

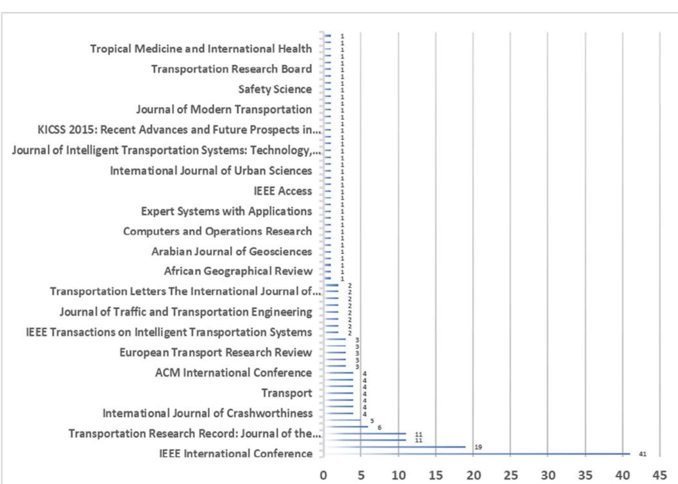

Figure 6: Distribution of Name of the Journal to PS

3.1 Research Topics Field

Figure 7 is the distribution of research topic models in the PS of spatial analysis for the most used type of classification with a value of 29% papers, followed by the second order for the classification method of 27% model clustering. Others use predictive, statistical, regression, probability, distribution, estimation, forecasting, dan optimization models. In this study, researchers improve using classification categories.

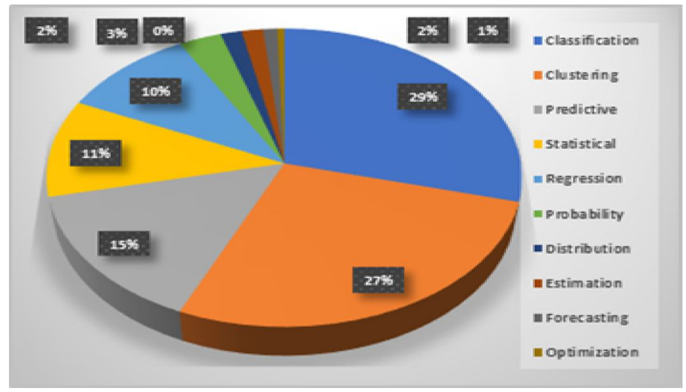

Figure 7: Dissemination of Research Model in PS

3.2 Methods Used

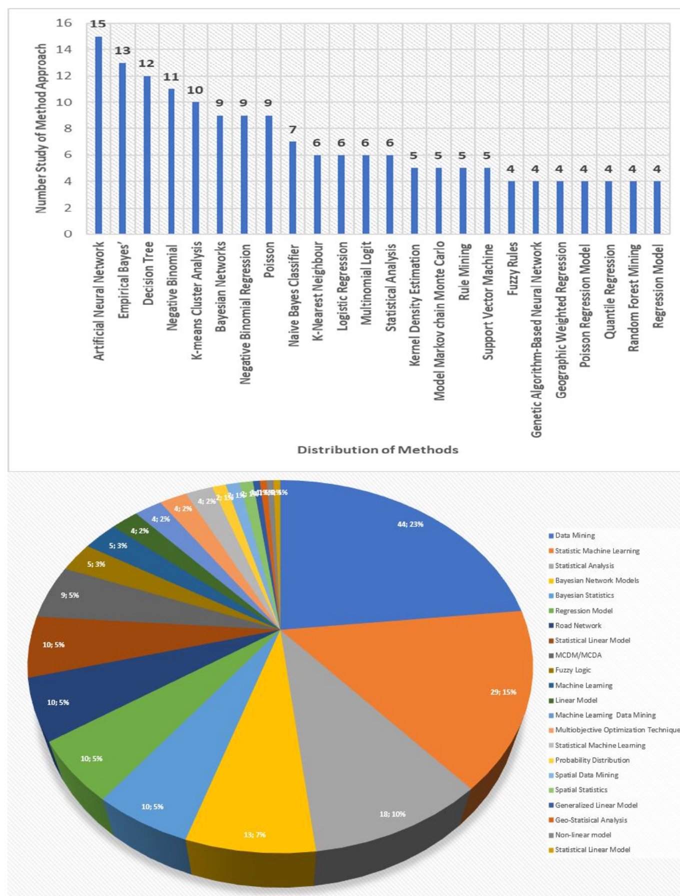

Figure 8: Number Study of Method Approach

The summary of the state-of-the-art methods obtained from SLR of the PS, presented in Figure 8 and Appendix. The Artificial Neural Network (ANN) method has the highest rating of methods that are often used in SLR in primary studies. The Empirical Bayes method and decision tree in data mining are also widely used in the clustering category in spatial data modeling of accident-prone areas. In this study, the authors conducted a hybrid MCDM method with ANN, test the consistency of the method from the model produced with the Method Consistency Test (MCT), the value of Precision Recall Accuracy (ARC) and Site Consistency Test (SCT).

3.3 Spatial Datasets

Based on the previous SLR, the authors present a list of spatial datasets and methods used as targets in the development of this study. Spatial datasets are used to describe the needs of spatial data in the form of multi-criteria parameters. In the GIS field research, the need for spatial data and data attributes is essential, but it will be an obstacle if data acquisition is a private agency.

The amount of use of data properties in GIS. Private data types are most widely used in developing GIS applications for modeling spatial data. The PS has obtained a value of 96% in previous studies that used private data types, while only 4% used public data types, as shown in Figure 9.

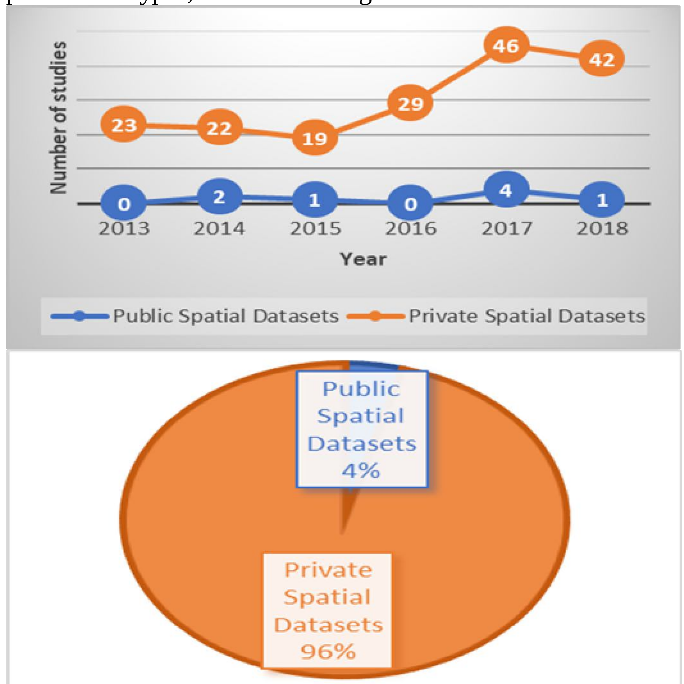

Figure 9: Number of Mapping Criteria Type Datasets

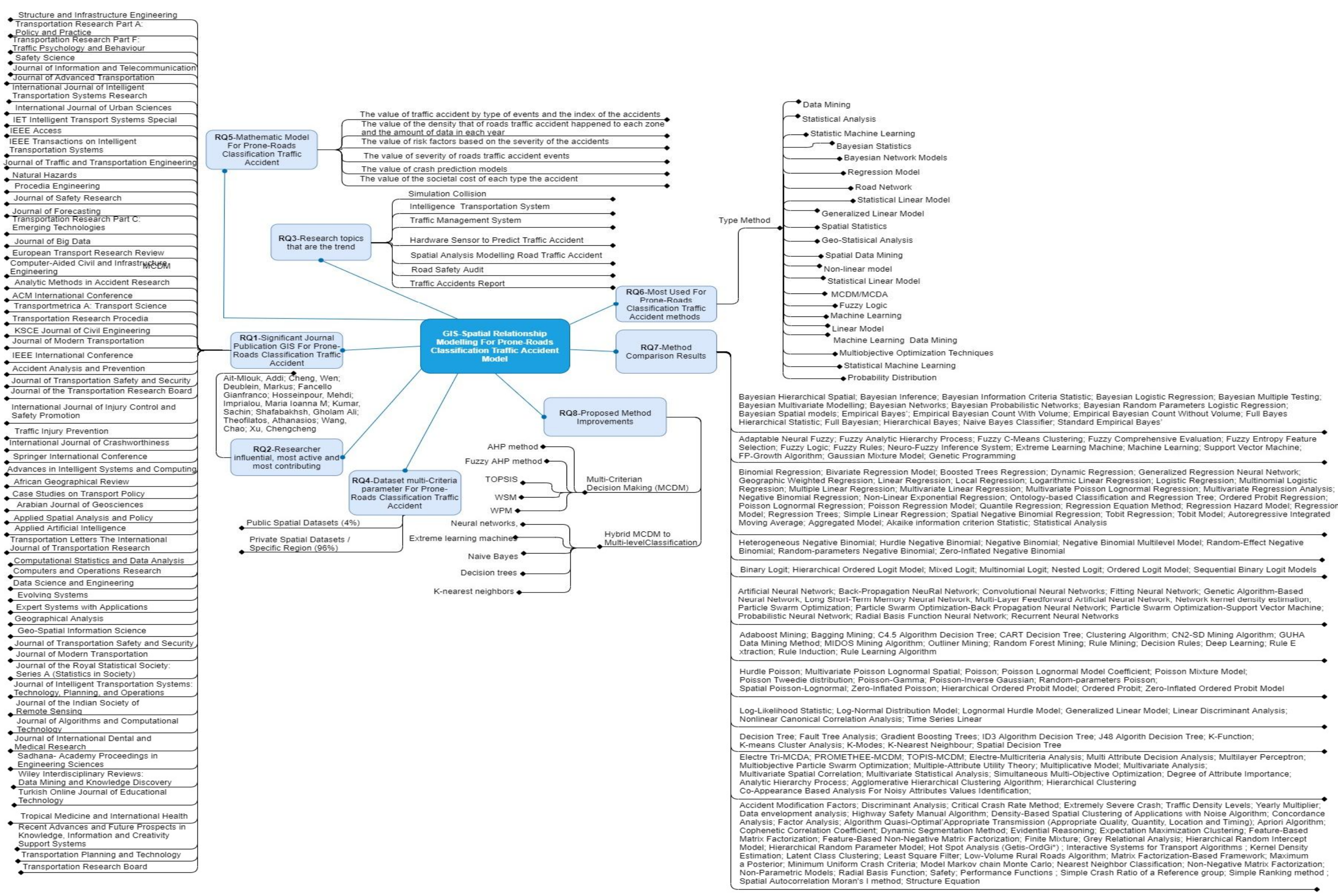

Figure 10: Mind Map of the SLR

3.4 Proposed Method Improvements

This paper uses an Inductive Qualitative Approach in the modeling of PRTA to identify the findings of science during the research process. They propose a PRTA classification using multiple criteria parameters (data series), make the modeling of PRTA classification by calculating (1) the value of traffic accident by type of events and the index of the accidents, (2) the value of the density that of roads traffic accident happened to each zone and the amount of data in each year, (3) the value of risk factors based on the severity of the accidents, (4) the value of severity of roads traffic accident events, (5) the value of crash prediction models using data series, and (6) the value of the societal cost of each type the accident, and (7)the test result is using SCT, MCT, and APR.

The SLRs that have been carried out in this study, there is no topic on the PRTA Classification proposed using two types of classification methods on MCDM (AHP method, Fuzzy AHP method, TOPSIS, WSM, and WPM) and Spatial Multi-level Classification (Neural networks, Extreme learning machines, k-nearest neighbours, Naive Bayes, Decision trees). The results of the best methods through APR measurement will be a reference in decision making in road management.

3.5 Implications for Research

The most crucial thing in developing spatial analysis modeling for the PRTA classification is to have a significant analysis between the data in the field and the resulting spatial analysis. Testing to obtain substantial results needs to be done with MCT, ARC, or SCT (depending on the dataset's behavior). Based on the review through SLR, different evaluation results were obtained between each paper discussion; this depends on the multi-criteria datasets of the parameters and the type of model used.

Many researchers have developed models through hybrid methods with methods that have the same characteristics. The results of this SLR review several models used for the PRTA classification, where the models with classification types using ANN are most widely used in the 2013-2018 study period.

3.6 Limitations of This Review

The study on SLR is carried out with several limitations relating to the lack of validity of search terms, the publisher period, and the publisher database's selection. This paper reviews the needs of the multi-criteria parameter datasets, types of models, and methods used for spatial analysis. Referring to the SLR results, it will be used to find out how valid the results of the classification are given because this relates to the spatial datasets, both private and public, and models and methods.

4. CONCLUSION AND FUTURE WORKS

The SLRs study that has been conducted on 189 papers as the PS, there is no topic on the PRTA classification in the arterial road, collector road, local road, road pavement, and road geometry categories using two types of classification methods on MCDM (AHP method, Fuzzy AHP method, TOPSIS, WSM, and WPM) hybrid Multi-level Classification (Neural networks, Extreme learning machines, K-nearest neighbors, Naive Bayes, Decision trees). The best methods through APR measurement will be a reference in decision making in road management.

Existing research is still limited to one type of road used as an object (specific region), and 96 % is used Private Spatial Datasets and in this study, using an Inductive Qualitative Approach in the modeling of PRTA to identify the findings of science that is done during the research process.

APPENDIX

Table 2. the Distribution of Method to Road Traffic Accident

Authors	Methods Used
[38] [39]	Agglomerative Hierarchical Clustering Algorithm
[40]	Density-Based Spatial Clustering
[41] [42]	Expectation Maximization Clustering
[43]	Fuzzy C-Means Clustering
[44]	Hierarchical Clustering
[40] [45] [46] [47] [48] [49] [50] [51] [52]	K-means Cluster Analysis
[53] [54]	K-Modes Clustering Algorithm
[53]	Latent Class Clustering
[18] [55] [56]	Network kernel density estimation
[57] [58] [59] [60]	Kernel Density Estimation
[61]	Traffic Density Levels
[62]	Fuzzy Analytic Hierarchy Process
[63]	Fuzzy Comprehensive Evaluation
[64]	Fuzzy Entropy Feature Selection
[40] [65]	Neuro-Fuzzy Inference System
[66]	Adaptable Neural Fuzzy
[49] [67] [68]	Fuzzy Logic
[69] [70] [71] [67] [72]	Fuzzy Rules
[73] [74] [75] [76] [77] [78] [79] [80] [81] [82] [83] [84] [85]	Artificial Neural Network
[86]	Back-Propagation Neural Network
[61]	Convolutional Neural Networks
[82]	Fitting Neural Network
[82]	Generalized Regression Neural Network
[87] [88] [89] [85]	Genetic Algorithm-Based Neural Network
[61] [71]	Genetic Programming
[90] [91] [92]	Long Short-Term Memory Neural Network
[82]	Multi-Layer Feedforward Artificial Neural Network
[93]	Multiobjective Particle Swarm Optimization
[94]	Particle Swarm Optimization
[76]	Particle Swarm Optimization-Back Propagation Neural Network
[74]	Probabilistic Neural Network
[86] [74]	Radial Basis Function Neural Network
[61]	Recurrent Neural Networks

Authors	Methods Used
[37]	Simultaneous Multi-Objective Optimization
[94] [95] [96] [87] [97]	Support Vector Machine
[98] [99]	Hierarchical Ordered Logit Model
[100]	Sequential Binary Logit Models
[101] [61]	Mixed Logit
[102] [103]	Nested Logit
[104] [95] [100] [105] [103] [106]	Multinomial Logit
[107] [103] [108]	Binary Logit
[100] [109]	Ordered Logit Model
[110]	Akaike information criterion Statistic
[111] [112] [113] [114] [115]	Bayesian Hierarchical Spatial
[116] [99] [117]	Bayesian Inference
[118] [110]	Bayesian Information Criteria Statistic
[101] [4]	Bayesian Logistic Regression
[119]	Bayesian Multiple Testing
[113]	Bayesian Multivariate Modelling
[120] [76] [121] [122] [123] [88] [114] [117]	Bayesian Networks
[124] [125]	Bayesian Probabilistic Networks
[52] [126] [52] [126]	Bayesian Random Parameters Logistic Regression
[127] [128] [129]	Bayesian Spatial models
[130]	Binomial Regression
[128]	Bivariate Regression Model
[131]	Boosted Trees Regression
[83]	Dynamic Regression
[132]	Empirical Bayesian Count Without Volume and With Volume
[112] [133]	Full Bayes Hierarchical Statistic
[134]	Full Bayesian
[135]	Gaussian Mixture Model
[136] [137]	Generalized Linear Model
[3]	Heterogeneous Negative Binomial
[124] [138]	Hierarchical Bayes
[98]	Hierarchical Ordered Probit Model
[3] [139]	Hurdle Negative Binomial
[3] [139]	Hurdle Poisson
[87]	Linear Discriminant Analysis
[140] [141] [142]	Linear Regression
[143]	Local Regression
[140]	Logarithmic Linear Regression
[144] [145] [146] [147] [148] [149]	Logistic Regression
[150] [110]	Log-Likelihood Statistic
[133] [108] [110]	Log-Normal Distribution Model
[151]	Matrix Factorization-Based Framework, Feature-Based Matrix Factorization, Non-Negative Matrix Factorization, Feature-Based Non-Negative Matrix Factorization
[12]	Multinomial Logistic Regression
[152] [153]	Multiple Linear Regression
[79]	Multivariate Analysis
[154]	Multivariate Linear Regression
[155]	Multivariate Poisson Lognormal Regression
[124] [156]	Multivariate Regression Analysis
[155] [133]	Multivariate Spatial Correlation
[157] [92]	Multivariate Statistical Analysis
[41] [158]	Multivariate-Poisson-lognormal-spatial
[136] [159] [80] [3] [86] [160] [65] [139] [138] [161] [153]	Negative Binomial
[115] [162]	Negative Binomial Multilevel Model
[75] [163] [164] [115] [162] [165] [72] [166] [138]	Negative Binomial Regression
[95] [126]	Nonlinear Canonical Correlation Analysis
[65]	Non-Linear Exponential Regression
[78] [103][75]	Ordered Probit Regression
[150] [136] [75] [3] [133] [65]	Poisson

Authors	Methods Used
[139] [161] [153]	
[167] [134]	Poisson Lognormal Regression
[146]	Poisson Mixture Model
[163] [14] [166] [168]	Poisson Regression Model
[169]	Poisson Tweedie distribution
[111] [137]	Poisson-Gamma
[137]	Poisson-Inverse Gaussian
[170] [138] [72]	Quantile Regression
[115]	Random-Effect Negative Binomial
[97]	Random-parameters Negative Binomial
[97]	Random-parameters Poisson
[140] [171]	Regression Equation Method
[118]	Regression Hazard Model
[73] [107] [14] [118]	Regression Model
[38] [87]	Regression Trees
[172]	Simple Linear Regression
[173] [138]	Spatial Poisson-Lognormal
[174] [175] [176] [177] [12] [178]	Statistical Analysis
[108][97]	Tobit Regression
[11][12]	Spatial Autocorrelation (Moran's I method)
[3]	Zero-Inflated Negative Binomial
[98]	Zero-Inflated Ordered Probit Model
[3]	Zero-Inflated Poisson
[179]	Ontology-based Classification and Regression Tree
[180] [181] [76] [46] [48] [87]	K-Nearest Neighbour
[45]	Standard Empirical Bayes'
[17] [45] [169] [182] [163] [183] [130] [184] [138] [72] [125] [171] [185] [43]	Empirical Bayes'
[186] [187] [66] [188] [127] [47] [189] [190]	Naive Bayes Classifier
[124] [138]	Hierarchical Bayes
[190]	Adaboost and bagging Mining
[37] [191]	Analytic Hierarchy Process
[192] [190] [193][9]	C4.5 Algorithm Decision Tree
[188] [193] [194]	CART Decision Tree
[87] [195]	CN2-SD Mining Algorithm
[187] [189] [81] [192] [88] [196] [197] [193] [194] [198] [110] [198]	Decision Tree
[199]	Degree of Attribute Importance
[200] [201]	Electre-Multicriteria Analysis
[19]	Fault Tree Analysis
[186]	Gradient Boosting Trees
[202]	GUHA Data Mining Method
[188] [194]	ID3 Algorithm Decision Tree
[188]	J48 Algorith Decision Tree
[195]	MIDOS Mining Algorithm
[203]	Multi Attribute Decision Analysis
[24][25]	Multiple-Attribute Utility Theory
[204]	Outliner Mining
[35] [36]	Promethee-MCDM
[95] [4] [190]	Random Forest Mining
[94] [189]	Rule Extraction
[201] [50] [15] [130] [54] [205] [206]	Rule Mining
[185]	Simple Ranking method
[35]	TOPIS-MCDM

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REFERENCES

[1] M. Keymanesh, H. Ziari, S. Roudini, and A. N. Ahangar, "**Identification and Prioritization of 'Black Spots' without Using Accident Information**," *Model. Simul. Eng.*, vol. 2017, 2017.

[2] J. Ambros and V. Valentová, "**Identification of road horizontal alignment inconsistencies – a pilot study from the czech republic**," *Balt. J. Road Bridg. Eng.*, vol. 11, no. 1, pp. 62–69, 2016.

[3] M. Hosseinpour, A. Shukri Yahaya, A. Farhan Sadullah, N. Ismail, and S. M. Reza Ghadiri, "**Evaluating the effects of road geometry, environment, and traffic volume on rollover crashes**," *Transport*, vol. 31, no. 2, pp. 221–232, 2016.

[4] A. Theofilatos and G. Yannis, "**Investigation of powered 2-wheeler accident involvement in urban arterials by considering real-time traffic and weather data**," *Traffic Inj. Prev.*, vol. 18, no. 3, pp. 293–298, 2017.

[5] M. I. Sameen and B. Pradhan, "**Assessment of the effects of expressway geometric design features on the frequency of accident crash rates using high-resolution laser scanning data and GIS**," *Geomatics, Nat. Hazards Risk*, vol. 8, no. 2, pp. 733–747, 2017.

[6] M. Holozadah, "**Road safety audits: Why, when, where and how**," *J. Public Work. Infrastruct.*, vol. 2, no. 3, pp. 254–274, 2010.

[7] World Health Organization, "**Saving Millions of lives: Decade of action for road safety 2011-2020**," *WHO Publ.*, vol. 11, pp. 5–7, 2011.

[8] World Health Organization, "**Road Safety Is No Accident**," 2004.

[9] J. S. Mapa, A. M. Sison, and R. P. Medina, "**Road Traffic Accident Case Status Prediction Integrating a Modified C4.5 Algorithm**," *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 8, no. 5, pp. 2622–2625, 2019.

[10] C. C. Ihueze and U. O. Onwurah, "**Road traffic accidents prediction modelling: An analysis of Anambra State, Nigeria**," *Accid. Anal. Prev.*, vol. 112, no. July, pp. 21–29, 2018.

[11] M. A. Aghajani, R. S. Dezfoulian, A. R. Arjroody, and M. Rezaei, "**Applying GIS to Identify the Spatial and Temporal Patterns of Road Accidents Using Spatial Statistics (case study: Ilam Province, Iran)**," in *Transportation Research Procedia*, 2017, vol. 25C, pp. 2131–2143.

[12] U. R. R. Manepalli and G. H. Bham, "**Identification of Crash-Contributing Factors Effects of Spatial Autocorrelation and Sample Data Size**," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2386, no. 1, pp. 179–188, 2013.

[13] T. Ketha and S. S. Imambi, "**Analysis of Road Accidents to Indentify Major Causes and Influencing Factors of Accidents – A Machine Learning Approach**," *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 8, no. 6, pp. 3492–3497, 2019.

[14] F. Russo, M. Busiello, S. Biancardo, and G. Dell'Acqua, "**Assessing Transferability of Highway Safety Manual Crash Prediction Models to Data from Italy**," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2433, no. 1, pp. 129–135, 2014.

[15] J. Wang and Y. Ohsawa, "**Evaluating model of traffic accident rate on urban data**," in *Federated Conference on Computer Science and Information Systems*, 2016, vol. 8, pp. 181–186.

[16] K. M. Derdus, V. Gavole, and O. Member, "**A Mobile Solution for Road Accident Data Collection**," in *Proceedings of the 2nd Pan African International Conference on Science, Computing and Telecommunications (PACT 2014)*, 2014, pp. 115–120.

[17] Y. Choi, S. Kho, K. Jang, and D. Kim, "**Evaluating Time Trend Correction Approaches Associated with Empirical Bayes Before-after Study for Road Safety**," *KSCE J. Civ. Eng.*, vol. 22, no. 11, pp. 4593–4601, 2018.

[18] H. Harirforoush and L. Bellalite, "**A new integrated GIS-based analysis to detect hotspots: A case study of the city of Sherbrooke**," *Accid. Anal. Prev.*, no. August, pp. 1–13, 2016.

[19] Y. D. & W. W. Chengcheng Xu, Chen Wang and To, "**Investigation of extremely severe traffic crashes using fault tree analysis**," *Int. J. Transp. Res.*, vol. 12, no. 3, pp. 1–8, 2020.

[20] B. Kitchenham, "**Procedures for performing systematic reviews,**" *Keele, UK, Keele Univ.*, vol. 33, no. TR/SE-0401, p. 28, 2004.

[21] Y. E. L. Mokaddem and F. Jawab, "**Researches and applications of intelligent transportations systems in urban area: Systematic literature review**," *ARPN J. Eng. Appl. Sci.*, vol. 14, no. 3, pp. 639–652, 2019.

[22] D. Budgen and P. Brereton, "P**erforming systematic literature reviews in software engineering**," *Int. Conf. Soft. Engin.*, p. 1051, 2006.

[23] T. Sipos, "**Spatial statistical analysis of the traffic accidents**," *Period. Polytech. Transp. Eng.*, vol. 45, no. 2, pp. 101–105, 2017.

[24] A. V. Vitianingsih and D. Cahyono, "**Geographical Information System for mapping accident-prone roads and development of new road using Multi-Attribute Utility method**," in *Proceedings - 2016 2nd International Conference on Science and Technology-Computer, ICST 2016*, 2017, pp. 66–70.

[25] A. V. Vitianingsih, D. Cahyono, and A. Choiron, "**Web-GIS Application using Multi-Attribute Utility Theory to Classify Accident-Prone Roads**," *J. Telecommun. Electron. Comput. Eng.*, vol. 10, no. 2–3, pp. 83–89, 2018.

[26] M. Petticrew and H. Roberts, ***Systematic Reviews in the Social Sciences**: A Practical Guide*. 2008.

[27] B. Kitchenham and S. Charters, "**Guidelines for performing Systematic Literature Reviews in Software Engineering**," *Engineering*, vol. 2, p. 1051, 2007.

[28] J. Vilela, J. Castro, L. E. G. Martins, and T. Gorschek, "**Integration between requirements engineering and safety analysis: A systematic literature review**," *J. Syst.*

Softw., vol. 125, pp. 68–92, 2017.

[29] K. Petersen, S. Vakkalanka, and L. Kuzniarz, "**Guidelines for conducting systematic mapping studies in software engineering: An update**," *Inf. Softw. Technol.*, vol. 64, pp. 1–18, 2015.

[30] S. Tiwari and A. Gupta, "**A systematic literature review of use case specifications research," in *Information and Software Technology***, 2015, vol. 67, no. June, pp. 128–158.

[31] D. Dermeval *et al.*, "**Applications of ontologies in requirements engineering: a systematic review of the literature**," *Requir. Eng.*, vol. 21, no. 4, pp. 405–437, 2016.

[32] P. Achimugu, A. Selamat, R. Ibrahim, and M. N. R. Mahrin, "**A systematic literature review of software requirements prioritization research**," *Inf. Softw. Technol.*, vol. 56, no. 6, pp. 568–585, 2014.

[33] C. Wohlin, P. Runeson, M. Höst, M. C. Ohlsson, B. Regnell, and A. et al. Wesslén, "**Experimentation in software engineering**," *Exp. Softw. Eng.*, vol. 9783642290, pp. 1–236, 2012.

[34] M. Gasparic and A. Janes, "**What recommendation systems for software engineering recommend: A systematic literature review**," *J. Syst. Softw.*, vol. 113, pp. 101–113, 2016.

[35] M. Rosić, D. Pešić, D. Kukić, B. Antić, and M. Božović, "**Method for selection of optimal road safety composite index with examples from DEA and TOPSIS method**," *Accid. Anal. Prev.*, vol. 98, no. January, pp. 277–286, 2017.

[36] A. Ait-Mlouk, T. Agouti, and F. Gharnati, "**Mining and prioritization of association rules for big data: multi-criteria decision analysis approach**," *J. Big Data*, vol. 4, no. 1, pp. 1–21, 2017.

[37] H. Pilko, S. Mandžuka, and D. Barić, "**Urban single-lane roundabouts: A new analytical approach using multi-criteria and simultaneous multi-objective optimization of geometry design, efficiency and safety**," *Transp. Res. Part C Emerg. Technol.*, vol. 80, no. July, pp. 257–271, 2017.

[38] M. A. Raihan, M. Hossain, and T. Hasan, "**Data mining in road crash analysis: the context of developing countries**," *Int. J. Inj. Contr. Saf. Promot.*, vol. 25, no. 1, pp. 41–52, 2018.

[39] S. Kumar and D. Toshniwal, "**A novel framework to analyze road accident time series data**," *J. Big Data*, vol. 3, no. 1, pp. 1–11, 2016.

[40] A. Almjewail, A. Almjewail, S. Alsenaydi, and H. Alsudairy, "**Analysis of Traffic Accident in Riyadh**," *5th Int. Symp. Data Min. Appl.*, vol. 753, no. Part of the Advances in Intelligent Systems and Computing, pp. 12–25, 2018.

[41] C. Han, H. Huang, J. Lee, and J. Wang, "**Investigating varying effect of road-level factors on crash frequency across regions: A Bayesian hierarchical random parameter modeling approach**," *Anal. Methods Accid. Res.*, vol. 20, no. Desember, pp. 81–91, 2018.

[42] F. M. Nafie Ali and A. A. Mohamed Hamed, "**Usage Apriori and clustering algorithms in WEKA tools to mining dataset of traffic accidents**," *J. Inf. Telecommun.*, vol. 2, no. 3, pp. 231–245, 2018.

[43] R. Bandyopadhyaya and S. Mitra, "**Fuzzy Cluster–Based Method of Hotspot Detection with Limited Information**," *J. Transp. Saf. Secur.*, vol. 7, no. 4, pp. 307–323, 2015.

[44] S. Kumar and D. Toshniwal, "**Analysis of hourly road accident counts using hierarchical clustering and cophenetic correlation coefficient (CPCC)**," *J. Big Data*, vol. 3, no. 1, pp. 1–11, 2016.

[45] A. S. Lee, W. H. Lin, G. S. Gill, and W. Cheng, "**An enhanced empirical bayesian method for identifying road hotspots and predicting number of crashes**," *Journal of Transportation Safety and Security*, vol. 0, no. 0, Taylor & Francis, pp. 1–17, 2018.

[46] M. G. Kaur and E. Harpreet Kaur, "**Prediction of the Cause of Accident and Accident Prone Location on Roads Using Data Mining Techniques**," in *2017 8th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, 2017, pp. 1–7.

[47] L. Li, S. Shrestha, and G. Hu, "**Analysis of Road Traffic Fatal Accidents Using Data Mining Techniques," in *IEEE 15th International Conference on Software Engineering Research, Management and Applications (SERA)***, 2017, pp. 363–370.

[48] G. A. Shafabakhsh, A. Famili, and M. S. Bahadori, "**GIS-based spatial analysis of urban traffic accidents: Case study in Mashhad, Iran**," *J. Traffic Transp. Eng.*, vol. 4, no. 3, pp. 290–299, 2017.

[49] Y. S. Murat and Z. Cakici, "**An Integration of Different Computing Approaches in Traffic Safety Analysis**," in *Transportation Research Procedia*, 2017, vol. 22, pp. 265–274.

[50] S. Kumar and D. Toshniwal, "**A data mining approach to characterize road accident locations**," *J. Mod. Transp.*, vol. 24, no. 1, pp. 62–72, 2016.

[51] S. An, T. Zhang, X. Zhang, and J. Wang, "**Evolution of Traffic Flow Analysis under Accidents on Highways Using Temporal Data Mining**," in *Intelligent Systems Design and Engineering Applications (ISDEA), 2014 Fifth International Conference on*, 2014, pp. 454–457.

[52] S. H. Park and Y. G. Ha, "**Large imbalance data classification based on MapReduce for traffic accident prediction**," in *Proceedings - 2014 8th International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing, IMIS 2014*, 2014, pp. 45–49.

[53] S. Kumar, D. Toshniwal, and M. Parida, "**A comparative analysis of heterogeneity in road accident data using data mining techniques**," *Evol. Syst.*, vol. 8, no. 2, pp. 147–155, 2017.

[54] S. Kumar and D. Toshniwal, "**Analysing Road Accident Data Using Association Rule Mining**," in *2015 International Conference on Computing, Communication and Security (ICCCS)*, 2015, pp. 1–6.

[55] A. S. Mohaymany, M. Shahri, and B. Mirbagheri, "**GIS-based method for detecting high-crash-risk road segments using network kernel density estimation**," *Geo-Spatial Inf. Sci.*, vol. 16, no. 2, pp. 113–119, 2013.

[56] T. Bao and W. Han, "**Traffic accident prediction based on time series linear mode**," in *IEEE Conference Anthology, ANTHOLOGY 2013*, 2014, pp. 2–4.

[57] J. M. Su, Y. M. Wang, C. hung Chang, and P. J. Wu, "**Application of a Geographic Information System to Analyze Traffic Accidents Using Nantou County, Taiwan, as an Example**," *Journal of the Indian Society of Remote Sensing*, no. November, Springer India, pp. 1–11, 2018.

[58] S. S. Vemulapalli *et al.*, "**GIS-based Spatial and Temporal Analysis of Aging-Involved Accidents: a Case Study of Three Counties in Florida**," *Appl. Spat. Anal. Policy*, vol. 10, no. 4, pp. 537–563, 2017.

[59] G. A. Shafabakhsh, A. Famili, and M. S. Bahadori, "**GIS-based spatial analysis of urban traffic accidents: Case study in Mashhad, Iran**," *J. Traffic Transp. Eng. (English Ed.*, vol. 4, no. 3, pp. 290–299, 2017.

[60] L. Thakali, T. J. Kwon, and L. Fu, "**Identification of crash hotspots using kernel density estimation and kriging methods: a comparison**," *J. Mod. Transp.*, vol. 23, no. 2, pp. 93–106, 2015.

[61] M. I. Sameen, B. Pradhan, H. Z. M. Shafri, and H. Bin Hamid, "**Applications of Deep Learning in Severity Prediction of Traffic Accidents**," in *Global Civil Engineering Conference:GCEC 2017*, 2018, vol. 8, pp. 793–808.

[62] I. Radojković, P. Milosavljevic, G. Janaćković, and M. Grozdanović, "**The key risk indicators of road traffic crashes in Serbia, Niš region**," *Int. J. Inj. Contr. Saf. Promot.*, vol. 7300, no. May, pp. 1–7, 2018.

[63] Y. Liu, X. Huang, J. Duan, and H. Zhang, "**The assessment of traffic accident risk based on grey relational analysis and fuzzy comprehensive evaluation method**," *Nat. Hazards*, vol. 88, no. 3, pp. 1409–1422, 2017.

[64] E. I. Vlahogianni and M. G. Karlaftis, "**Fuzzy-entropy neural network freeway incident duration modeling with single and competing uncertainties**," *Comput. Civ. Infrastruct. Eng.*, vol. 28, no. 6, pp. 420–433, 2013.

[65] M. Hosseinpour, A. S. Yahaya, S. M. Ghadiri, and J. Prasetijo, "**Application of Adaptive Neuro-fuzzy Inference System for road accident prediction**," *KSCE J. Civ. Eng.*, vol. 17, no. 7, pp. 1761–1772, 2013.

[66] R. S. and K. M. K. M. Prasad, "**Providing cluster categorization of heuristics technique for increasing accuracy in severe categorization of road accidents**," in *2017 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 2017*, pp. 1152–1159.

[67] M. Driss, T. Saint-Gerand, A. BenSaïd, K. Benabdeli, and M. A. Hamadouche, "**A fuzzy logic model for identifying spatial degrees of exposure to the risk of road accidents (Case study of the Wilaya of Mascara, Northwest of Algeria)**," in *2013 International Conference on Advanced Logistics and Transport, ICALT 2013*, 2013, pp. 69–74.

[68] M. M. Imprialou, M. Quddus, and D. E. Pitfield, "**High accuracy crash mapping using fuzzy logic**," *Transp. Res. Part C Emerg. Technol.*, vol. 42, no. May, pp. 107–120, 2014.

[69] Y. Ye *et al.*, "**Geographically Weighted Regression Model For Urban Traffic Black-Spot Analysis**," in *IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, 2017, pp. 4866–4869.

[70] A. M. Wahaballa and M. Gaber, "**Sensitivity of Traffic Accidents Mitigation Policies Based on Fuzzy Modeling : A Case Study**," in *IEEE 20th International Conference on Intelligent Transportation Systems (ITSC) Sensitivity*, 2017, pp. 1712–1717.

[71] P. Krömer, T. Beshah, D. Ejigu, V. Snášel, J. Platoš, and A. Abraham, "**Mining traffic accident features by evolutionary fuzzy rules**," in *Proceedings of the 2013 IEEE Symposium on Computational Intelligence in Vehicles and Transportation Systems, CIVTS*, 2013, pp. 38–43.

[72] S. Washington, M. M. Haque, J. Oh, and D. Lee, "**Applying quantile regression for modeling equivalent property damage only crashes to identify accident blackspots**," *Accid. Anal. Prev.*, vol. 66, no. May, pp. 136–146, 2014.

[73] Y. Lee, C. H. Wei, and K. C. Chao, "**Evaluating the Effects of Highway Traffic Accidents in the Development of a Vehicle Accident Queue Length Estimation Model**," *Int. J. Intell. Transp. Syst. Res.*, vol. 16, no. 1, pp. 26–38, 2018.

[74] H. Behbahani and A. Mohamadian, "**Forecasting accident frequency of an urban road network : A comparison of four artificial neural network techniques**," *J. Forecast.*, vol. 37, no. 7, pp. 767–780, 2018.

[75] F. Galatioto, M. Catalano, N. Shaikh, E. Mccormick, and R. Johnston, "**Advanced accident prediction models and impacts assessment**," *IET Intell. Transp. Syst. Spec.*, vol. 12, no. 9, pp. 1131–1141, 2018.

[76] X. Gu, T. Li, Y. Wang, L. Zhang, Y. Wang, and J. Yao, "**Traffic fatalities prediction using support vector machine with hybrid particle swarm optimization**," *J. Algorithms Comput. Technol.*, vol. 12, no. 1, pp. 20–29, 2018.

[77] L. Wenqi, L. Dongyu, and Y. Menghua, "**A Model of Traffic Accident Prediction Based on Convolutional Neural Network**," in *2nd IEEE International Conference on Intelligent Transportation Engineering (ICITE)*, 2017, pp. 198–202.

[78] S. Alkheder, M. Taamneh, and S. Taamneh, "**Severity Prediction of Traffic Accident Using an Artificial Neural Network**," *J. Forecast.*, vol. 36, no. 1, pp. 100–108, 2017.

[79] M. De Luca, "**A comparison between prediction power of artificial neural networks and multivariate analysis in road safety management**," *Transport*, vol. 32, no. 4, pp. 379–385, 2017.

[80] F. T. Kibar, F. Celik, and F. Wegman, "**Analyzing Truck Accident Data on the Interurban Road Ankara-Aksaray-Eregli in Turkey : Comparing the Negative Binomial Regression and the Artificial Neural Networks Models Abstract**," *J. Transp. Saf. Secur.*, vol. 9962, no. August, pp. 1–25, 2017.

[81] S. H. A. Hashmienejad and S. M. H. Hasheminejad, "**Traffic accident severity prediction using a novel multi-objective genetic algorithm**," *Int. J. Crashworthiness*, vol. 22, no. 4, pp. 425–440, 2017.

[82] A. Can Yilmaz, C. Aci, and K. Aydin, "**Traffic accident reconstruction and an approach for prediction of fault rates using artificial neural networks: A case study in Turkey**," *Traffic Inj. Prev.*, vol. 17, no. 6, pp. 585–589, 2016.

[83] B. Dadashova, B. Arenas-Ramírez, J. Mira-Mcwilliams, and F. Aparicio-Izquierdo, "**Methodological development for selection of significant predictors explaining fatal road accidents**," *Accid. Anal. Prev.*, vol. 90, no. May, pp. 82–94, 2016.

[84] R. Deb and A. W. C. Liew, "**Incorrect attribute value detection for traffic accident data**," in *Proceedings of the International Joint Conference on Neural Networks*, 2015, pp. 1–7.

[85] S. A. Jafari, S. Jahandideh, M. Jahandideh, and E. B. Asadabadi, "**Prediction of road traffic death rate using neural networks optimised by genetic algorithm**," *Int. J. Inj. Contr. Saf. Promot.*, vol. 22, no. 2, pp. 153–157, 2015.

[86] H. Huang, Q. Zeng, X. Pei, S. C. Wong, and P. Xu, "**Predicting crash frequency using an optimised radial basis function neural network model**," *Transp. A Transp. Sci.*, vol. 12, no. 4, pp. 330–345, 2016.

[87] G. G. Faisal, S. M. Zakaria, G. F. Najmuldeen, and I. M. Al-Ani, "**Extracting grey relational systems from incomplete road traffic accidents data: the case of Gauteng Province in South Africa**," *J. Int. Dent. Med. Res.*, vol. 9, no. 1, pp. 70–74, 2016.

[88] Y. Castro and Y. J. Kim, "**Data mining on road safety: Factor assessment on vehicle accidents using classification models**," *Int. J. Crashworthiness*, vol. 21, no. 2, pp. 104–111, 2016.

[89] H. Park, A. Haghani, and X. Zhang, "**Interpretation of Bayesian neural networks for predicting the duration of detected incidents**," *J. Intell. Transp. Syst. Technol. Planning, Oper.*, vol. 20, no. 4, pp. 385–400, 2016.

[90] Z. Yuan, X. Zhou, and T. Yang, "**Hetero-ConvLSTM : A Deep Learning Approach to Traffic Accident Prediction on Heterogeneous Spatio-Temporal Data**," in *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 2018, pp. 984–992.

[91] P. A. Nandurge and N. V Dharwadkar, "**Analyzing road accident data using machine learning paradigms**," in *2017 International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*, 2017, pp. 604–610.

[92] Q. Yuan, X. Li, C. Wang, and Y. Li, "**Cluster and Factor Analysis on Data of Fatal Traffic Crashes in China**," in *4th International Conference on Transportation Information and Safety (ICTIS)*, 2013, pp. 211–224.

[93] C. Qiu, C. Wang, B. Fang, and X. Zuo, "**A multiobjective particle swarm optimization-based partial classification for accident severity analysis**," *Appl. Artif. Intell.*, vol. 28, no. 6, pp. 555–576, 2014.

[94] S. Sarkar, S. Vinay, R. Raj, J. Maiti, and P. Mitra, "**Application of optimized machine learning techniques for prediction of occupational accidents**," *Comput. Oper. Res.*, no. Available online 7 March 2018, pp. 1–38, 2018.

[95] A. Iranitalab and A. Khattak, "**Comparison of four statistical and machine learning methods for crash severity prediction**," *Accid. Anal. Prev.*, vol. 108, no. February, pp. 27–36, 2017.

[96] J. You, J. Wang, and J. Guo, "**Real-time crash prediction on freeways using data mining and emerging techniques**," *J. Mod. Transp.*, vol. 25, no. 2, pp. 116–123, 2017.

[97] C. Caliendo, M. L. De Guglielmo, and M. Guida, "**Comparison and analysis of road tunnel traffic accident frequencies and rates using random-parameter models**," *J. Transp. Saf. Secur.*, vol. 8, no. 2, pp. 177–195, 2016.

[98] G. Fountas and P. C. Anastasopoulos, "**Analysis of accident injury-severity outcomes: The zero-inflated hierarchical ordered probit model with correlated disturbances**," *Anal. Methods Accid. Res.*, vol. 20, no. September, pp. 30–45, 2018.

[99] C. Chen, G. Zhang, H. Huang, J. Wang, and R. A. Tarefder, "**Examining driver injury severity outcomes in rural non-interstate roadway crashes using a hierarchical ordered logit model**," *Accid. Anal. Prev.*, vol. 96, no. November, pp. 79–87, 2016.

[100] T. Usman, L. Fu, and L. F. Miranda-Moreno, "**Injury severity analysis: Comparison of multilevel logistic regression models and effects of collision data aggregation**," *J. Mod. Transp.*, vol. 24, no. 1, pp. 73–87, 2016.

[101] A. Theofilatos, "**Incorporating real-time traffic and weather data to explore road accident likelihood and severity in urban arterials**," *J. Safety Res.*, vol. 61, no. June, pp. 9–21, 2017.

[102] H. Razi-Ardakani, A. Mahmoudzadeh, and M. Kermanshah, "**A Nested Logit analysis of the influence of distraction on types of vehicle crashes**," *Eur. Transp. Res. Rev.*, vol. 10, no. 2, p. 44, 2018.

[103] M. Kamruzzaman, M. Haque, and S. Washington, "**Analysis of Traffic Injury Severity in Dhaka, Bangladesh**," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2451, no. 1, pp. 121–130, 2014.

[104] L. Bu, F. Wang, and H. Gong, "**Spatial and factor analysis of vehicle crashes in Mississippi state**," *Natural Hazards*, no. September, Springer Netherlands, pp. 1–22, 2018.

[105] H. Manner and L. Wünsch-Ziegler, "**Analyzing the severity of accidents on the German Autobahn**," *Accid. Anal. Prev.*, vol. 57, no. August, pp. 40–48, 2013.

[106] A. K. Çelik and E. Oktay, "**A multinomial logit analysis of risk factors influencing road traffic injury severities in the Erzurum and Kars Provinces of Turkey**," *Accid. Anal. Prev.*, vol. 72, no. November, pp. 66–77, 2014.

[107] Ö. Kaygisiz, M. Senbil, and A. Yildiz, "**Influence of**

urban built environment on traffic accidents: The case of Eskisehir (Turkey)," *Case Stud. Transp. Policy*, vol. 5, no. 2, pp. 306–313, 2017.

[108] J. W. Lu Ma, Xuedong Yan, "**Modeling traffic crash rates of road segments through a lognormal hurdle framework with flexible scale parameter**," *Turkish Online J. Educ. Technol.*, vol. 49, no. 8, pp. 928–940, 2015.

[109] C. G. Prato, T. K. Rasmussen, and S. Kaplan, "**Risk Factors Associated with Crash Severity on Low-Volume Rural Roads in Denmark**," *J. Transp. Saf. Secur.*, vol. 6, no. 1, pp. 1–20, 2014.

[110] J. Weng, W. Qiao, X. Qu, and X. Yan, "**Cluster-based lognormal distribution model for accident duration**," *Transp. A Transp. Sci.*, vol. 11, no. 4, pp. 345–363, 2015.

[111] S. A. Alarifi, M. A. Abdel-aty, J. Lee, and X. Wang, "**Exploring the Effect of Different Neighboring Structures on Spatial Hierarchical Joint Crash Frequency Models**," *Transp. Res. Rec.*, pp. 1–13, 2018.

[112] D. Morris, A. Antoniades, and C. C. Took, "**On making sense of neural networks in road analysis**," in *Proceedings of the International Joint Conference on Neural Networks*, 2017, pp. 4416–4421.

[113] M. Boulieri, Areti, Liverani, Silvia and de Hoogh, Kees and Blangiardo, "**A space–time multivariate Bayesian model to analyse road traffic accidents by severit**y," *J. R. Stat. Soc. Ser. A (Statistics Soc.*, vol. 180, no. 1, pp. 119–139, 2017.

[114] A. Gregoriades and K. C. Mouskos, "**Black spots identification through a Bayesian Networks quantification of accident risk index**," *Transp. Res. Part C Emerg. Technol.*, vol. 28, no. March, pp. 28–43, 2013.

[115] C. Wang, M. A. Quddus, and S. G. Ison, "**The effect of traffic and road characteristics on road safety: A review and future research direction**," *Saf. Sci.*, vol. 57, no. August, pp. 264–275, 2013.

[116] P. Xu, H. Huang, N. Dong, and S. C. Wong, "**Revisiting crash spatial heterogeneity: A Bayesian spatially varying coefficients approach**," *Accid. Anal. Prev.*, vol. 98, pp. 330–337, 2017.

[117] J. Zhao and W. Deng, "**The use of Bayesian network in analysis of urban intersection crashes in China**," *Transport*, vol. 30, no. 4, pp. 411–420, 2015.

[118] R. L. and M. G. Guo and M. G. Ruimin Li, "**Competing risks analysis on traffic accident duration time**," *J. Adv. Transp.*, vol. 49, no. 3, pp. 402–415, 2015.

[119] M. Nešić, K. Lipovac, M. Vujanić, and D. Jovanović, "**Roadside public survey approach in black spot identification on rural roads: case study**," *Transport*, vol. 31, no. 2, pp. 271–281, 2016.

[120] G. Pettet, S. Nannapaneni, B. Stadnick, A. Dubey, and G. Biswas, "**Incident analysis and prediction using clustering and Bayesian network**," in *2017 IEEE SmartWorld Ubiquitous Intelligence and Computing, Advanced and Trusted Computed, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People and Smart City Innovation, SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI 2017* **-** , 2018, pp. 1–8.

[121] Z. Grande, E. Castillo, E. Mora, and H. K. Lo, "**Highway and Road Probabilistic Safety Assessment Based on Bayesian Network Models**," *Comput. Civ. Infrastruct. Eng.*, vol. 32, no. 5, pp. 379–396, 2017.

[122] E. Castillo, Z. Grande, E. Mora, X. Xu, and H. K. Lo, "**Proactive, Backward Analysis and Learning in Road Probabilistic Bayesian Network Models**," *Comput. Civ. Infrastruct. Eng.*, vol. 32, no. 10, pp. 820–835, 2017.

[123] A. Karimnezhad and F. Moradi, "**Road accident data analysis using Bayesian networks**," *Transp. Lett.*, vol. 9, no. 1, pp. 12–19, 2017.

[124] M. Deublein, M. Schubert, B. T. Adey, J. Köhler, and M. H. Faber, "**Prediction of road accidents: A Bayesian hierarchical approach**," *Accid. Anal. Prev.*, vol. 51, no. March, pp. 274–291, 2013.

[125] M. Deublein, M. Schubert, and B. T. Adey, "**Prediction of road accidents: comparison of two Bayesian methods**," *Struct. Infrastruct. Eng.*, vol. 10, no. 11, pp. 1394–1416, 2014.

[126] C. Xu, W. Wang, P. Liu, and F. Zhang, "**Development of a Real-Time Crash Risk Prediction Model Incorporating the Various Crash Mechanisms Across Different Traffic States**," *Traffic Inj. Prev.*, vol. 16, no. 1, pp. 28–35, 2015.

[127] L. Rapant, "**Markov Chain Model Approach for Traffic Incident Length Prediction**," in *Proceedings of the 2017 International Conference on E-Society, E-Education and E-Technology*, 2017, pp. 63–67.

[128] C. Dong, D. B. Clarke, S. S. Nambisan, and B. Huang, "**Analyzing injury crashes using random-parameter bivariate regression models**," *Transp. A Transp. Sci.*, vol. 12, no. 9, pp. 794–810, 2016.

[129] N. Dong, H. Huang, P. Xu, Z. Ding, and D. Wang, "**Evaluating Spatial-Proximity Structures in Crash Prediction Models at the Level of Traffic Analysis Zones**," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2432, no. 1, pp. 46–52, 2014.

[130] R. McCarthy, G. W. Flintsch, S. W. Katicha, K. K. McGhee, and A. Medina-Flintsch, "**New Approach for Managing Pavement Friction and Reducing Road Crashes**," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2591, no. 1, pp. 23–32, 2016.

[131] G. Narasimhan, B. G. Ephrem, S. Cheriyan, and N. Balasupramanian, "**Predictive analytics of road accidents in Oman using machine learning approach**," in *2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies, ICICICT 2017*, 2018, pp. 1058–1065.

[132] W. Cheng, G. S. Gill, L. Loera, X. Wang, and J. H. Wang, "**Evaluation of the impact of traffic volume on site ranking**," *J. Transp. Saf. Secur.*, vol. 10, no. 5, pp. 491–505, 2018.

[133] J. Aguero-Valverde, "**Multivariate spatial models of excess crash frequency at area level: Case of Costa Rica**," *Accid. Anal. Prev.*, vol. 59, no. October, pp. 365–373, 2013.

[134] S. Barua, K. El-Basyouny, and M. T. Islam, "**A Full Bayesian multivariate count data model of collision severity with spatial correlation**," *Anal. Methods Accid. Res.*, vol. 3–4, no. October, pp. 28–43, 2014.

[135] A. Mansourkhaki, A. Karimpour, and H. S. Yazdi, "**Introducing prior knowledge for a hybrid accident prediction model**," *KSCE J. Civ. Eng.*, vol. 21, no. 5, pp. 1912–1918, 2017.

[136] F. P. Fancello Gianfranco, Soddu Stefano, "**An accident prediction model for urban road networks**," *J. Transp. Saf. Secur.*, vol. 10, no. 4, pp. 387–405, 2018.

[137] L. Zha, D. Lord, and Y. Zou, "**The Poisson inverse Gaussian (PIG) generalized linear regression model for analyzing motor vehicle crash data**," *J. Transp. Saf. Secur.*, vol. 8, no. 1, pp. 18–35, 2016.

[138] M. Quddus, "**Exploring the Relationship Between Average Speed, Speed Variation, and Accident Rates Using Spatial Statistical Models and GIS**," *J. Transp. Saf. Secur.*, vol. 5, no. 1, pp. 27–45, 2013.

[139] M. H. Pour, J. Prasetijo, A. S. Yahaya, and S. M. R. Ghadiri, "**A Comparative Study of Count Models: Application to Pedestrian-Vehicle Crashes Along Malaysia Federal Roads**," *Traffic Inj. Prev.*, vol. 14, no. 6, pp. 630–638, 2013.

[140] R. Tian, L. Li, M. Chen, Y. Chen, and G. J. Witt, "**Studying the effects of driver distraction and traffic density on the probability of crash and near-crash events in naturalistic driving environment**," *IEEE Trans. Intell. Transp. Syst.*, vol. 14, no. 3, pp. 1547–1555, 2013.

[141] T. Osayomi, "**Regional determinants of road traffic accidents in Nigeria: identifying risk areas in need of intervention**," *African Geogr. Rev.*, vol. 32, no. 1, pp. 88–99, 2013.

[142] G. Athipathi; S. Nagan; T. Baskaran, "**Development of Accident Prediction Model High Speed Corridors in India**," in *Global Conference on Communication Technologies (GCCT)*, 2015, pp. 72–77.

[143] X. Liu and J. C. Xia, "**Locally analysing the risk factors for fatal single vehicle crashes hot spots in Western Australia**," *Int. J. Crashworthiness*, vol. 20, no. 6, pp. 524–534, 2015.

[144] M. Aron and R. Billot, "**Advanced Concepts, Methodologies and Technologies for Transportation and Logistics**," *Adv. Intell. Syst. Comput.*, vol. 572, no. 1, pp. 309–333, 2018.

[145] D. Potoglou, F. Carlucci, A. Cirà, and M. Restaino, "**Factors associated with urban non-fatal road-accident severity**," *Int. J. Inj. Contr. Saf. Promot.*, vol. 25, no. 3, pp. 303–310, 2018.

[146] R. E. Avelar, K. Dixon, and S. Ashraf, "**A Comparative Analysis on Performance of Severe Crash Prediction Methods**," *Transp. Res. Rec.*, pp. 1–11, 2018.

[147] S. Gargoum, Y. Li, K. El-basyouny, and A. Kim, "**Factors Affecting Classification of Road Segments into High- and Low-Speed Collision Regimes**," *Transp. Res. Rec.*, vol. 2659, no. 1, pp. 98–105, 2017.

[148] T. Lu, Z. Dunyao, Y. Lixin, and Z. Pan, "**The traffic accident hotspot prediction: Based on the logistic regression method**," in *2015 International Conference on Transportation Information and Safety (ICTIS)*, 2015, pp. 107–110.

[149] M. Karacasu, B. Ergül, and A. A. Yavuz, "**Estimating the causes of traffic accidents using logistic regression and discriminant analysis**," *Int. J. Inj. Contr. Saf. Promot.*, vol. 21, no. 4, pp. 305–312, 2014.

[150] P. Songpatanasilp and T. Horanont, "**Modeling Traffic Accidents Occurrences Based on Land Use and Road Factors Using Geographically Weighted Regression Models**," *KICSS 2015 Recent Adv. Futur. Prospect. Knowledge, Inf. Creat. Support Syst.*, vol. 685, no. Part of the Lecture Advances in Intelligent Systems and Computing, pp. 220–232, 2018.

[151] K. Moriya, S. Matsushima, and K. Yamanishi, "**Traffic Risk Mining From Heterogeneous Road Statistics**," *IEEE Transactions on Intelligent Transportation Systems*, IEEE, pp. 1–14, 2018.

[152] H. Cai, D. Zhu, and L. Yan, "**Using multi-regression to analyze and predict road traffic safety level in China**," in *ICTIS 2015 - 3rd International Conference on Transportation Information and Safety, Proceedings*, 2015, pp. 363–369.

[153] T. H. Beak, J. K. Lim, and B. H. Park, "**Relations between operational method and traffic accident of circular intersection in Korea**," *KSCE J. Civ. Eng.*, vol. 19, no. 4, pp. 1097–1107, 2015.

[154] D. C. Watson, A. Al-kaisy, and N. D. Anderson, "**Examining the effect of speed, roadside features, and roadway geometry on crash experience along a rural corridor**," *J. Mod. Transp.*, vol. 22, no. 2, pp. 84–95, 2014.

[155] M. I. M. Imprialou, M. Quddus, D. E. Pitfield, and D. Lord, "**Re-visiting crash-speed relationships: A new perspective in crash modelling**," *Accid. Anal. Prev.*, vol. 86, no. January, pp. 173–185, 2016.

[156] L. K. Lloyd and J. J. Forster, "**Modelling trends in road accident frequency - Bayesian inference for rates with uncertain exposure**," *Comput. Stat. Data Anal.*, vol. 73, pp. 189–204, 2014.

[157] M. Vaniš and K. Urbaniec, "**Employing Bayesian Networks and conditional probability functions for determining dependences in road traffic accidents data**," in *2017 Smart Cities Symposium Prague, SCSP 2017 - IEEE Proceedings*, 2017, pp. 1–5.

[158] M. Hosseinpour, S. Sahebi, Z. H. Zamzuri, A. S. Yahaya, and N. Ismail, "**Predicting crash frequency for multi-vehicle collision types using multivariate Poisson-lognormal spatial model: A comparative analysis**," *Accid. Anal. Prev.*, vol. 118, no. March, pp. 277–288, 2018.

[159] W. L. Soro and D. Wayoro, "**A mixed effects negative binomial analysis of road mortality determinants in Sub-Saharan African countries**," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 52, no. January, pp. 120–126, 2018.

[160] J. Kamla, T. Parry, and A. Dawson, "**Roundabout**

Accident Prediction Model Random-Parameter Negative Binomial Approach," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2585, no. 2, pp. 11–19, 2016.

[161] G. B. C, "**Risk maps generation for road accidents**," in *IEEE 79th Vehicular Technology Conference (VTC Spring),* 2014, pp. 1–5.

[162] A. Sukhai and A. P. Jones, "**Understanding geographical variations in road traffic fatalities in South Africa**," *South African Geogr. J.*, vol. 95, no. 2, pp. 187–204, 2013.

[163] M. A. Dereli and S. Erdogan, "**A new model for determining the traffic accident black spots using GIS-aided spatial statistical methods**," *Transp. Res. Part A Policy Pract.*, vol. 103, no. September, pp. 106–117, 2017.

[164] I. Omer, V. Gitelman, Y. Rofè, Y. Lerman, N. Kaplan, and E. Doveh, "**Evaluating Crash Risk in Urban Areas Based on Vehicle and Pedestrian Modeling**," *Geogr. Anal.*, vol. 49, no. 4, pp. 387–408, 2017.

[165] Y. Ouyang and I. Bejleri, "**A GIS-Based Community Level Method to Evaluate the Influence of Built Environment on Traffic Crashes**," *Transp. Res. Board*, vol. 2432, no. 1, pp. 124–132, 2014.

[166] J. Oh and D. Park, "**Analysis on crash reduction factors for road segment safety**," *Int. J. Urban Sci.*, vol. 18, no. 3, pp. 396–403, 2014.

[167] R. Goel, "**Modelling of road traffic fatalities in India**," *Accid. Anal. Prev.*, vol. 112, no. October, pp. 105–115, 2018.

[168] V. R. Mohan, R. Sarkar, V. J. Abraham, V. Balraj, and E. N. Naumova, "**Differential patterns, trends and hotspots of road traffic injuries on different road networks in Vellore district, southern India**," *Trop. Med. Int. Heal.*, vol. 20, no. 3, pp. 293–303, 2015.

[169] M. P. Sánchez González, F. Escribano Sotos, and Á. Tejada Ponce, "**Impact of provincial characteristics on the number of traffic accident victims on interurban roads in Spain**," *Accid. Anal. Prev.*, vol. 118, no. October, pp. 178–189, 2018.

[170] A. J. Khattak, J. Liu, B. Wali, X. Li, and M. Ng, "**Modeling Traffic Incident Duration Using Quantile Regression**," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2554, no. 1, pp. 139–148, 2016.

[171] K. Van Raemdonck and C. Macharis, "**The Road Accident Analyzer: A Tool to Identify High-Risk Road Locations**," *J. Transp. Saf. Secur.*, vol. 6, no. 2, pp. 130–151, 2014.

[172] A. Tolón-Becerra, X. Lastra-Bravo, and I. Flores-Parra, "**National and Regional Analysis of Road Accidents in Spain**," *Traffic Inj. Prev.*, vol. 14, no. 5, pp. 486–495, 2013.

[173] Q. Cai, M. Abdel-Aty, J. Lee, and N. Eluru, "**Comparative analysis of zonal systems for macro-level crash modeling**," *J. Safety Res.*, vol. 61, no. June, pp. 157–166, 2017.

[174] H. E. Colak, T. Memisoglu, Y. S. Erbas, and S. Bediroglu, "**Hot spot analysis based on network spatial weights to determine spatial statistics of traffic accidents in Rize**, Turkey," *Arab. J. Geosci.*, vol. 11, no. 151, pp. 1–11, 2018.

[175] Y. Darma, M. R. Karim, and S. Abdullah, "**An analysis of Malaysia road traffic death distribution by road environment**," *Sadhana - Acad. Proc. Eng. Sci.*, vol. 49, no. 9, pp. 1605–1615, 2017.

[176] X. N. Chen Lei, "**Analyzing Method of Traffic Accident Causation through Experts Method and Statistics Analysis**," in *Fifth Conference on Measuring Technology and Mechatronics Automation*, 2013, pp. 272–275.

[177] E. Ertunc, T. Cay, and O. Mutluoglu, "**Intersection road accident analysis using geographical information systems: Antalya (Turkey) example**," in *AICT 2013 - 7th International Conference on Application of Information and Communication Technologies, Conference Proceedings*, 2013, pp. 1–5.

[178] C. Wang, M. Quddus, and S. Ison, "**A spatio-temporal analysis of the impact of congestion on traffic safety on major roads in the UK**," *Transp. A Transp. Sci.*, vol. 9, no. 2, pp. 124–148, 2013.

[179] M. Effati and A. Sadeghi-Niaraki, "**A semantic-based classification and regression tree approach for modelling complex spatial rules in motor vehicle crashes domain**," *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, vol. 5, no. 4, pp. 181–194, 2015.

[180] S. Wang, R. Li, and M. Guo, "**Application of nonparametric regression in predicting traffic incident duration**," *Transport*, vol. 33, no. 1, pp. 22–31, 2018.

[181] M. Kibanov, M. Becker, M. Atzmueller, and A. Hotho, "**Adaptive kNN Using Expected Accuracy for Classification of Geo-Spatial Data**," in *Proceedings of the 33rd Annual ACM Symposium on Applied Computing Pages 857-865*, 2018, pp. 857–865.

[182] M. S. Satu, S. A, F. H, A. Tania, and D. Farid, "**Mining Traffic Accident Data o f N5 National Highway in Bangladesh Employing D ecision Trees**," in *2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC)*, 2017, pp. 722–725.

[183] W. Cheng, G. S. Gill, T. Sakrani, M. Dasu, and J. Zhou, "**Predicting motorcycle crash injury severity using weather data and alternative Bayesian multivariate crash frequency models**," *Accid. Anal. Prev.*, vol. 108, no. August, pp. 172–180, 2017.

[184] A. Borsos, S. Cafiso, C. D'Agostino, and D. Miletics, "**Comparison of Italian and Hungarian Black Spot Ranking**," in *Transportation Research Procedia*, 2016, vol. 14, pp. 2148–2157.

[185] S. Da Costa, X. Qu, and P. M. Parajuli, "**A Crash Severity-Based Black Spot Identification Model**," *J. Transp. Saf. Secur.*, vol. 7, no. 3, pp. 268–277, 2015.

[186] L. Garcí, E. Puertas, and J. F. Andres, "**Traffic Accidents Classification and Injury Severity Prediction**," in *2018 3rd IEEE International Conference on Intelligent Transportation Engineering (ICITE)*, 2018, pp. 52–57.

[187] I. N. L. O. S. Baños, J. R. Asor, and G. M. B. Catedrilla, "**A Study On The Road Accidents Using Data**

Investigation And Visualization," in *International Conference on Information and Communications Technology (ICOIACT)*, 2018, pp. 96–101.

[188] T. K. Bahiru, D. Kumar Singh, and E. A. Tessfaw, "**Comparative Study on Data Mining Classification Algorithms for Predicting Road Traffic Accident Severity**," in *2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT)*, 2018, pp. 1655–1660.

[189] M. Taamneh, S. Alkheder, and S. Taamneh, "**Data-mining techniques for traffic accident modeling and prediction in the United Arab Emirates**," *J. Transp. Saf. Secur.*, vol. 9, no. 2, pp. 146–166, 2017.

[190] H. Al Najada and I. Mahgoub, "**Big vehicular traffic Data mining: Towards accident and congestion prevention**," in *International Wireless Communications and Mobile Computing Conference, IWCMC 2016*, 2016, pp. 256–261.

[191] J. Xi, Z. Zhao, W. Li, and Q. Wang, "**A Traffic Accident Causation Analysis Method Based on AHP-Apriori**," in *Procedia Engineering*, 2016, vol. 137, pp. 680–687.

[192] G. Tao, H. Song, J. Liu, J. Zou, and Y. Chen, "**A traffic accident morphology diagnostic model based on a rough set decision tree**," *Transp. Plan. Technol.*, vol. 39, no. 8, pp. 751–758, 2016.

[193] X.-F. Zhang and L. Fan, "**A Decision Tree Approach for Traffic Accident Analysis of Saskatchewan Highways**," in *26th IEEE Canadian Conference Of Electrical And Computer Engineering (CCECE)*, 2013, pp. 1–4.

[194] B. Ghimire, S. Bhattacharjee, S. K. Ghosh, and P. Campus, "**Analysis of Spatial Autocorrelation for Traffic Accident Data based on Spatial Decision Tree**," in *2013 Fourth International Conference on Computing for Geospatial Research and Application*, 2013, pp. 111–115.

[195] J. Kim and K. R. Ryu, "**Mining traffic accident data by subgroup discovery using combinatorial targets**," in *Proceedings of IEEE/ACS International Conference on Computer Systems and Applications, AICCSA*, 2016, pp. 1–6.

[196] A. Jain, G. Ahuja, Anuranjana, and D. Mehrotra, "**Data mining approach to analyse the road accidents in India**," in *2016 5th International Conference on Reliability, Infocom Technologies and Optimization, ICRITO 2016: Trends and Future Directions*, 2016, pp. 175–179.

[197] I. Al-Turaiki, M. Aloumi, N. Aloumi, and K. Alghamdi, "**Modeling traffic accidents in Saudi Arabia using classification techniques**," in *4th Saudi International Conference on Information Technology (Big Data Analysis) (KACSTIT)*, 2016, pp. 1–5.

[198] J. Abellán, G. López, and J. De Oña, "**Analysis of traffic accident severity using Decision Rules via Decision Trees**," *Expert Syst. Appl.*, vol. 40, no. 15, pp. 6047–6054, 2013.

[199] T. Gang, H. S. Song, Y. G. Yan, and M. Jafari, "**Cause analysis of traffic accidents based on degrees of attribute importance of rough set**," in *Proceedings - 2015 IEEE 12th International Conference on Ubiquitous Intelligence and Computing, 2015 IEEE 12th International Conference on Advanced and Trusted Computing, 2015 IEEE 15th International Conference on Scalable Computing and Communications, 20*, 2016, pp. 1665–1669.

[200] G. Fancello, M. Carta, and P. Fadda, "**A decision support system for road safety analysis**," in *Transportation Research Procedia*, 2015, vol. 5, pp. 201–210.

[201] A. Ait-Mlouk, F. Gharnati, and T. Agouti, "**An improved approach for association rule mining using a multi-criteria decision support system: a case study in road safety**," *Eur. Transp. Res. Rev.*, vol. 9:40, no. September, pp. 1–13, 2017.

[202] E. Turunen, "Using GUHA Data Mining Method in Analyzing Road Traffic Accidents Occurred in the Years 2004–2008 in Finland," *Data Sci. Eng.*, vol. 2, no. 3, pp. 224–231, 2017.

[203] A. A. Rassafi, S. S. Ganji, and H. Pourkhani, "**Road safety assessment under uncertainty using a Multi Attribute Decision Analysis based on Dempster–Shafer theory**," *KSCE J. Civ. Eng.*, vol. 22, no. 8, pp. 3137–3152, 2017.

[204] Z. Zhao and W. Wang, "**Traffic Detection Algorithm Based on Outlier Mining**," in *Proceedings of 2018 International Conference on Big Data Technologies*, 2018, no. 37, pp. 40–43.

[205] L. Lin, Q. Wang, and A. Sadek, "**Data Mining and Complex Network Algorithms for Traffic Accident Analysis**," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2460, no. 1, pp. 128–136, 2014.

[206] J. M. Manasa, S. Bhattacharjee, S. K. Ghosh, and S. Mitra, "**Spatial Decision Tree for Accident Data Analysis**," in *2014 9th International Conference on Industrial and Information Systems (ICIIS)*, 2014, pp. 1–5.