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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.

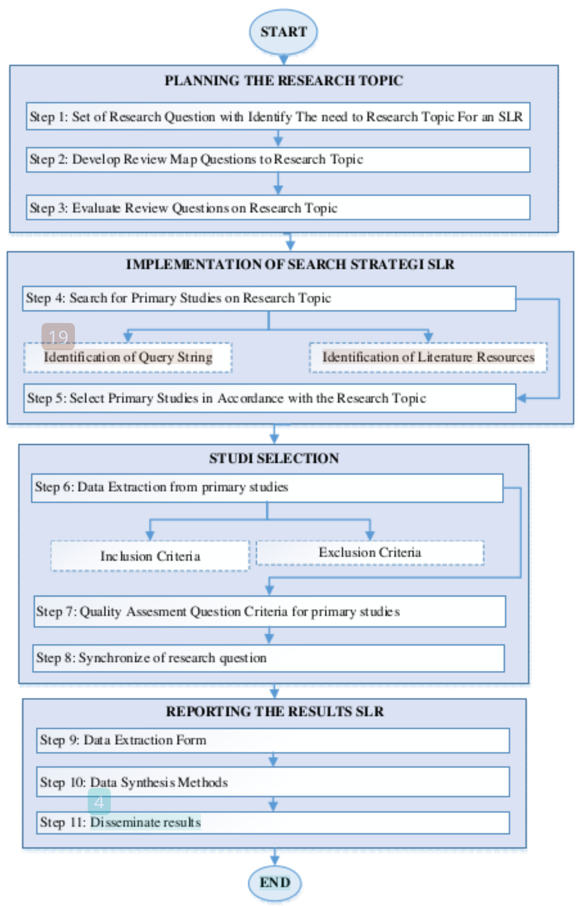

Figure 1: Systematic Literature Review Steps

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 $\leq$ 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.

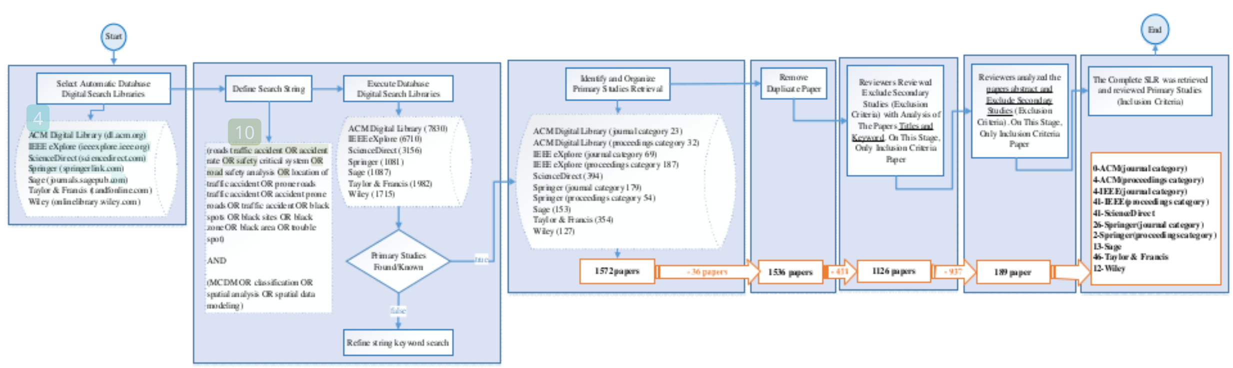

Figure 2: Search and Selection Paper of Primary Studies

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).

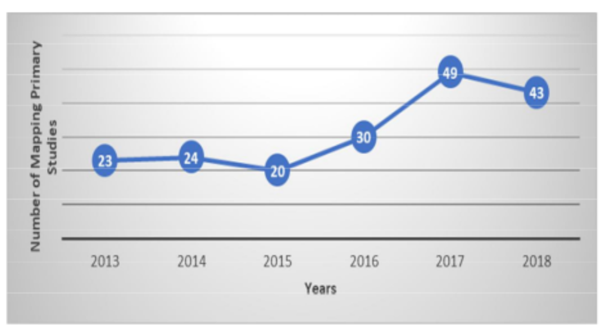

Figure 3: The Number of PS SLR

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.

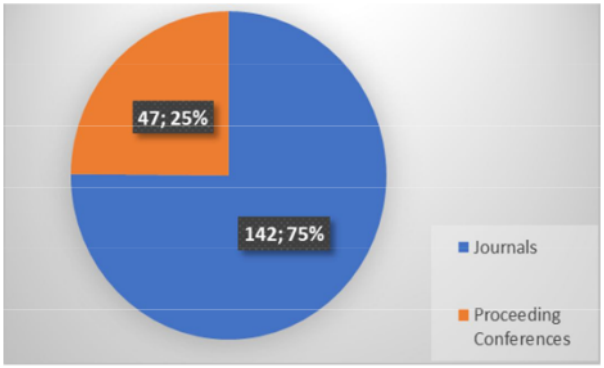

Figure 4: The Number of Mapping PS

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.

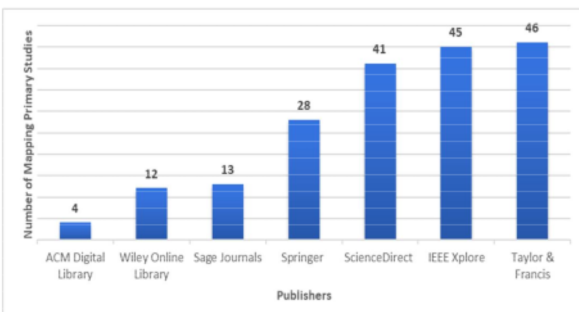

Figure 5: The Distribution PS in Scopus Journal

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.

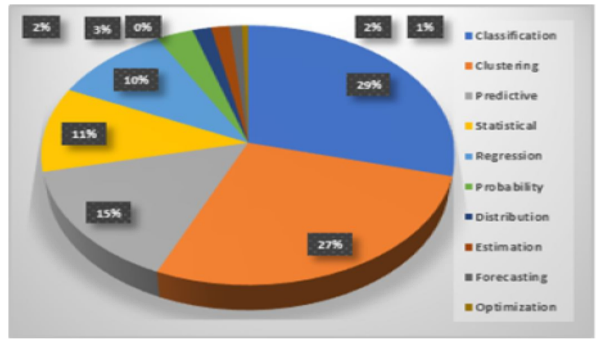

Figure 7: Dissemination of Research Model in PS

3.2 Methods Used

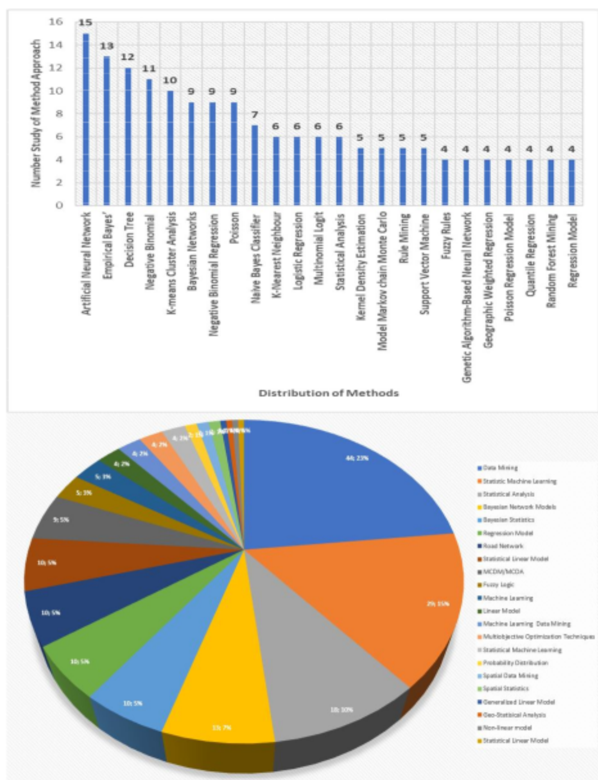

Figure 8: Number Study of Method Approach

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.

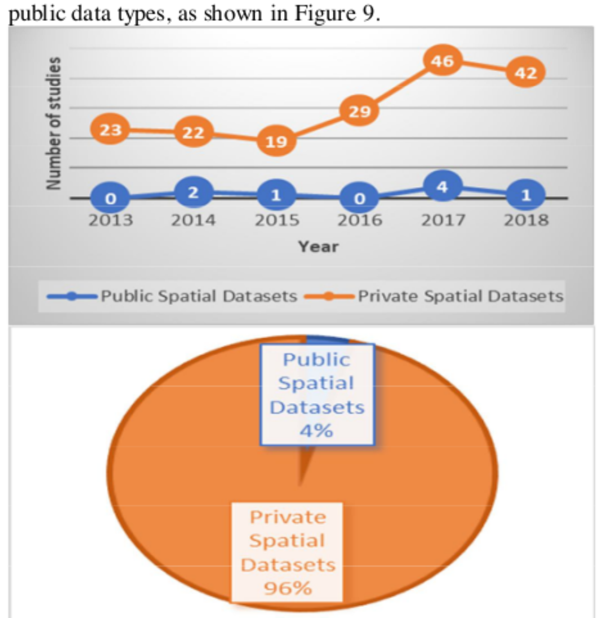

Figure 9: Number of Mapping Criteria Type Datasets

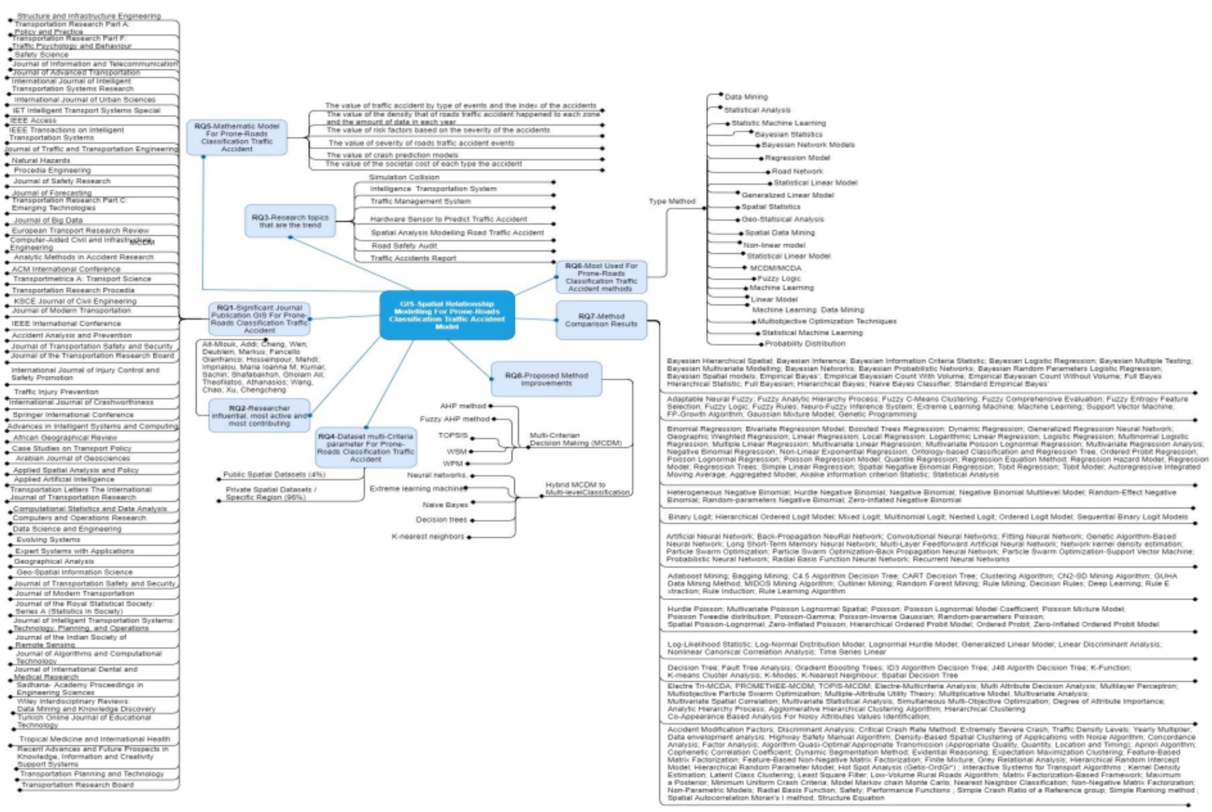

Figure 10: Mind Map of the SLR

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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PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9

PAGE 10

PAGE 11

PAGE 12

PAGE 13

PAGE 14

PAGE 15

PAGE 16

PAGE 17