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A LITERATURE SURVEY OF CRASH INJURY SEVERITY PREDICTION

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Abstract: Accurate prediction of the severity of road traffic accident injuries provides a foundation for accident prevention, emergency resource allocation, and response planning. As a result, the selection of traffic accident injury severity prediction models has garnered significant attention from both authorities and researchers. This paper aims to provide a comprehensive review of the research progress on traffic accident severity prediction models. It begins by reviewing relevant datasets and features used in severity prediction. Next, it summarizes various approaches and models in traffic accident severity prediction, including traditional statistical models and machine learning techniques. A comparative analysis of these models is then conducted. Finally, the paper discusses the key challenges in current research and explores future development trends, offering theoretical guidance for both researchers and practitioners.
Keywords: Traffic accidents; Road traffic injuries; Prediction models

1 INTRODUCTION

According to the Global Status Report on Road Safety 2023 by the World Health Organization (WHO, 2023)[1], annual global road traffic fatalities have decreased to 1. 19 million, indicating initial progress in safety interventions. However, road accidents remain the leading cause of death for individuals aged 5-29 years, with vulnerable road users such as pedestrians, cyclists, and motorcyclists accounting for over half of global fatalities, particularly in low-income regions. To achieve the United Nations Sustainable Development Goal (SDG) of halving road traffic injuries and deaths by 2030, targeted strategies are urgently required. Traffic accident causation involves multi-faceted factors, including road design, environmental conditions, infrastructure quality, and driver behavior. Existing studies face critical limitations in model adaptability, data integration, and real-time responsiveness, necessitating systematic review and innovative advancements.

Traditional statistical models [2-4](eg. logistic regression, ARIMA) excel in interpretability but struggle to capture complex spatio-temporal relationships and nonlinear patterns. Machine learning methods[5-7] (eg. random forests, support vector machines) enhance prediction accuracy through data-driven approaches but rely heavily on manual feature engineering and exhibit limited generalization. Deep learning techniques[8-11] (eg. CNNs, LSTMs) demonstrate superior capabilities in automated feature extraction and spatio-temporal modeling[13-14], yet their high data dependency and poor explainability hinder practical deployment. Recent advancements in graph neural networks[12] (GNNs) and sparse spatio-temporal dynamic hypergraph learning (SSTDHL) improve predictive performance via heterogeneous data fusion, though computational complexity and real-time adaptability remain challenges. Current research predominantly focuses on isolated models or localized factors, lacking comprehensive comparisons of model performance, systematic exploration of data-driven paradigms, and strategies for multimodal fusion[15-16].

This study addresses three critical questions through a systematic review of 95 articles published between 2001 and 2024:

• Key Influencing Factors: What are the core driving factors of traffic accident severity, and how do they exhibit heterogeneity across regions and cultures?

• Model Performance Comparison: Why do prediction models (statistical, machine learning, deep learning, and graph networks) differ in accuracy, stability, and applicable scenarios?

• Optimization Pathways: How can predictive performance be enhanced through data-driven model selection, multi-modal fusion, and real-time dynamic modeling?

The methodology integrates multi-platform data (Google Scholar, Web of Science, etc.) and keyword-based searches (eg. “traffic accident prediction”, “injury severity”, “predictive models”). Comparative analyses focus on algorithmic frameworks, evaluation metrics (eg. accuracy, F1-score, AUC), and practical applications, while emphasizing model interpretability and real-time decision support.

This study presents the first comprehensive synthesis of multi-dimensional influencing factors and model evolution pathways for traffic accident severity prediction. A novel ”data-algorithm-scenario” adaptation framework is proposed to advance intelligent transportation systems. The paper is structured as follows: Section 2 analyzes severity classification criteria and key influencing factors; Section 3 evaluates model performance and limitations; Section 4 discusses optimization strategies and future directions; and Section 5 concludes with policy recommendations. By integrating emerging algorithms and multi-source data, this research provides a scientific foundation and actionable insights for reducing traffic casualties and optimizing urban planning.

2 ANALYSIS OF INFLUENCING FACTORS

2. 1 Traffic Accident Severity Classification

As per the classification criteria for human injury severity promulgated by the Ministry of Justice of the People's Republic of China, human injuries are categorized into three tiers: minor, moderate, and severe[17]. In prior research, Kashani[18] delineates minor injury accidents and fatal or severe injury accidents based on the severity of injuries sustained by the most affected passengers, aligning with the two-tiered severity scale.

2. 2 Key Factors Affecting the Severity of the Accident

Kashani [19] has conducted an analysis to pinpoint the primary factors contributing to the severity of traffic accidents, considering a comprehensive set of 19 variables. These variables encompass demographic and behavioral aspects of drivers (such as age and gender), roadway characteristics (including pavement width, lane width, shoulder width, road type, road markings, sight distance, and safety barriers), accident-specific details (pertaining to time, day, month, crew size, number of injured individuals, cause, and type of accident), vehicular information (type of vehicle involved), and ambient conditions (lighting and atmospheric factors).

Haq[20] posits that the severity of traffic accidents is significantly influenced by a multitude of factors, which include the specific location of the accident, the state of the road surface, prevailing weather conditions, vehicular speed at the time of the incident, the adequacy of safety infrastructure, and temporal elements such as the time of day, with particular emphasis on night-time occurrences.

In research on traffic accident prediction, models usually identify the following key influencing factors:

• Road user vulnerability:Pedestrians and non-motorised drivers are more likely to be seriously injured in traffic accidents.
• Environmental factors:Such as weather conditions and road surface conditions, which have a significant impact on the occurrence of crashes and severity of injuries.
• Traffic infrastructure:Including road design, traffic signals and signs, are critical to preventing crashes.
• Time of day factors:The frequency and gravity of collisions tend to escalate during the morning and evening rush hours. Recognizing these patterns is essential for crafting strategic traffic policies and safety initiatives.
• Road conditions:These include pavement conditions, road design, lane widths, shoulder conditions, etc. , which may affect driver safety.
• Traffic flow:Traffic accidents are particularly influenced by vehicular density and circulation patterns, with a heightened effect observed during periods of peak congestion.
• Weather conditions:Rain, snow, fog, temperature and other weather factors may reduce visibility and increase roadway slippage, thereby increasing the risk of accidents.
• Light conditions:Driving at night or in low light conditions may obstruct a driver's vision, increasing the likelihood of an accident.
• Driver characteristics:Including age, gender, driving experience, driving behaviour (eg. speeding, drink driving, disobeying traffic rules), etc.
• Vehicle characteristics:Vehicle type, size, weight, braking system and other vehicle-related factors can also affect the occurrence and severity of an accident.
• Traffic signals and signs: The setting, visibility and functional status of traffic signals guide driver behaviour.
• Road user behaviour:This includes the behaviour of pedestrians, cyclists and other road users whose actions can be unpredictable and increase the risk of accidents.
• Emergencies: Emergencies such as vehicle breakdowns and animals crossing the road may cause drivers to react suddenly, increasing the likelihood of accidents.
• Socio-economic factors:The socio-economic status of residents may affect their choice of transport mode and the likelihood of complying with traffic rules.

Incorporating these variables within traffic accident predictive models enhances the precision and dependability of forecasts. Such an analysis facilitates a deeper comprehension of the causal factors behind accidents, thereby informing the development of preventative strategies.

Variability exists in the focus of influencing factors across traffic accident prediction studies, which is contingent upon multiple factors such as research objectives, data accessibility, geographic context, and cultural disparities. Below are some specific examples, along with their representation in different studies and corresponding references:

Some Depending on the purpose of the study, Studies may focus on specific crash types or specific prediction tasks (eg. short-term prediction, long-term trend analysis, etc.). For example, some studies may focus on identifying high-risk driving behaviours, while others may be more concerned with the impact of road design on crashes[21]. Some of them are also due to the limitation of dataset characteristics. Different datasets may contain different characteristics such as weather conditions, traffic flow, road type, etc. , which may affect which factors the researcher chooses to analyse[22]. Some of them are in the consideration of the research methodology. The choice of research methodology also affects the influences considered. For example, deep learning methods may automatically extract features, whereas traditional statistical methods may require manual selection and design of features[23]. Some of this is due to different choices of geographic location. Traffic patterns and causes of accidents may vary from one area to another, and this may influence the influences that researchers focus on. For example, studies in urban areas may focus more on traffic congestion, while rural areas may focus more on road conditions and wildlife presence[24]. Some of them are due to cultural differences. Driving culture and behaviour in different regions may affect the pattern of traffic accidents, and researchers may take these factors into account to improve the accuracy of the model[25]. Others are due to factors that are unique or less commonly studied in research. Some studies may explore such unique or less studied factors as drivers psychological states, microenvironmental characteristics of the road (eg. roadside vegetation, noise levels), and so on [26].

In summary, most articles consider road user vulnerability, traffic flow, road conditions, weather conditions, lighting conditions, driver characteristics, vehicle characteristics, traffic signals and signs, time factors, socio-economic factors, urban planning, and transport policies as common influencing factors, but each article may choose to focus on specific influencing factors based on its research objectives, dataset characteristics, research methodology, and geographic location, among other factors. In addition, some studies may also explore other unique or less studied factors to provide new insights or improve the performance of predictive models.

3 MODEL EVALUATION METRICS

Numerous scholars utilize a variety of evaluative criteria and metrics to assess the performance of models. Precision[27], a pivotal metric, reflects the proportion of accurate predictive outcomes. Sensitivity[28], also known as the true positive rate, indicates the model's capability to accurately identify cases of severe injury. Specificity[29] measures the model's accuracy in distinguishing non- serious or non-injurious events. The F-score [30], serving as the harmonic mean of precision and recall, provides a comprehensive assessment of the model's overall efficacy. Lastly, the Area Under the Curve (AUC)[31], specifically the region under the Receiver Operating Characteristic (ROC) curve, quantifies the model's ability to differentiate between various outcome categories.

Castro and Kim[32] conducted an in-depth analysis of 81, 960 traffic incidents in the UK from 2010 to 2012, focusing on the predictive accuracy of accident severity. They leveraged an array of machine learning techniques, such as Bayesian networks, decision trees, and multi-layer perceptrons, for their predictive modeling. In their quest for a holistic model performance assessment, they relied on a suite of indicators beyond mere accuracy, incorporating precision, recall, and the F-measure as critical benchmarks.

In an effort to shed light on the efficacy of various methodologies and identify those with superior performance in the realm of crash injury severity prediction, we embark on a comparative analysis of 96 scholarly articles spanning from 2001 to 2024, addressing two pivotal research inquiries. Our primary objective is to juxtapose the efficacy of diverse algorithms, thereby discerning the most effective approaches for predicting crash severity. For each study under review, we delineate the spectrum of predictive models deployed, along with their respective algorithmic frameworks and distinguishing characteristics. Concluding our analysis, we synthesize a concise overview of the prevalent and impactful methodologies gleaned from the extensive examination of over 20 studies. This synthesis aims to distill the essence of the most efficacious strategies in the field, fostering a deeper comprehension of their predictive capabilities.

4 DIFFERENT TYPES OF PREDICTIVE MODELS FOR ROAD CRASH INJURY SEVERITY PREDICTION

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4.1 Different Types of Predictive Modelling

Among the 96 scrutinized studies, a plethora of modeling techniques for forecasting traffic accidents have been identified, categorizable into several key paradigms: traditional Statistical Models, advanced Machine Learning Techniques, cutting-edge Deep Learning Approaches, Graph Neural Networks (GNNs), Spatio-Temporal Models, Hybrid Models that integrate various methodologies, Multi-Modal Forecasting which leverages diverse data streams, Multi-Process Information Fusion that amalgamates information from multiple sources, Real-Time and Dynamic Graph Structures that adapt to instantaneous data fluctuations, and more. This diverse array of models reflects the evolving landscape of traffic accident prediction, each bringing unique insights and strategies to the forefront of research. These model types do have some crossover and overlap, but they can be categorised based on their main characteristics and application scenarios. Below are the broad categories into which these models are classified along with their corresponding data characteristics and problems addressed:

4.1.1 Traditional statistical methods

Problem Solving: prediction, classification, regression, etc.

Data Types: Usually applied to structured data, such as tabular data.

Traditional statistical methods usually include autoregressive moving average model(ARMA)[33], Linear Regression, autoregressive integral sliding average model (ARIMA)[34], seasonal autoregressive moving average model (SARIMA)[35], multivariate autoregressive moving average (VAR)[36], Logistic Regression, Negative Binomial Regression Model[37], etc.

4.1.2 Machine learning methods

Solve problems: a wide range of prediction and classification tasks, including non-linear problems. Data Types: Applicable to all types of data, including structured, semi-structured, and unstruc- tured data. Algorithmic model:Random Forest handles nonlinear relationships well but can be computationally expensive[38]. Support Vector Regression (SVR) is effective in regression tasks but may not capture temporal dynamics as effectively[39]. Knearest neighbor (KNN) is Simple to implement but may suffer from the curse of dimensionality[40].

4.1.3 Deep learning methods

CNNs is excellent at capturing spatial features but may not fully capture temporal dynamics[41]. Problem solving:CNNs are particularly adept at handling a spectrum of advanced tasks, including but not limited to image recognition, speech processing, and natural language understanding, showcasing their versatility in various domains.

Data Types:CNNs are renowned for their prowess in managing data with grid-like structures, predominantly images and videos, and to some extent, audio. This capability renders CNNs in- dispensable in domains requiring the extraction of grid-like features for predictive analytics, particularly where high-dimensional, spatially-rich data is concerned[42].

4.1.4 Hybrid prediction models

Problem solving:Combining the strengths of different models to improve performance [43].

Data types:The versatility of Hybrid Prediction Models is evident in their ability to accommodate a broad spectrum of data types, contingent upon the specific models integrated within the hybrid system. This flexibility allows them to tackle complex problems that may require the simultaneous analysis of structured data, such as tabular statistics, and unstructured data, like text and images, or even time-series data that necessitates the understanding of temporal dynamics.

Algorithmic model:LSTMCNN Combines the strengths of both LSTM and CNN but can be complex and computationally intensive.

4.1.5 Graph learning methods

Problem solving:Social network analysis, recommender systems, bioinformatics, etc [44].

Data type:graph-structured data, including nodes and edges. Algorithmic model:STGCN Captures spatiotemporal dependencies through graph convolution but may be limited by fixed graph structures.

4.1.6 Sparse Spatio Temporal Dynamic Hypergraph Learning (SSTDHL)

Problem solving: Traffic flow prediction, weather prediction, etc [45].

Data Type: Data with spatial and temporal dimensions. Algorithmic model:A novel framework that addresses the issue of sparse data and captures higherorder dependencies.

4.1.7 Fourier Enhanced Heterogeneous Graph Learning (FEHGCARN)

Algorithmic model: Integrates Fourier transformation and heterogeneous graph learning to capture complex spatiotemporal relationships [46].

Traditional statistical methods are easy to implement and understand but may lack the ability to capture complex spatiotemporal dynamics[47]. Machine learning methods are versatile and can capture nonlinear relationships but may require extensive feature engineering and parameter tuning[48]. Deep learning methods, especially CNNs and RNNs, can automatically learn complex features but can be datahungry and may not generalize well to new situations[49]. Hybrid models combine the strengths of different approaches but can be challenging to design and optimize. Graph learning methods, including SSTDHL and FEHGCARN, can capture complex interactions in data but may require careful graph construction and are computationally intensive. It's important to note that the choice of model often depends on the specific characteristics of the dataset and the prediction task at hand. Newer models like SSTDHL and FEHGCARN show promise in addressing some of the limitations of traditional models, but they may also introduce new challenges related to computational complexity and the need for largescale training data.

In this curated selection of studies, the models range from traditional statistical analyses to cutting-edge machine learning and deep learning algorithms. Each model represents a unique strategy in capturing the complexities of traffic accident data, with some focusing on spatial and temporal dynamics, while others emphasize the integration of multimodal data streams. The researchers involved have contributed significantly to the advancement of predictive modeling by applying these models to real-world traffic scenarios, thereby providing valuable insights into accident causation and prevention. In this curated selection of studies, the models range from traditional statistical analyses to cutting-edge machine learning and deep learning algorithms. Each model represents a unique strategy in capturing the complexities of traffic accident data, with some focusing on spatial and temporal dynamics, while others emphasize the integration of multimodal data streams. The researchers involved have contributed significantly to the advancement of predictive modeling by applying these models to real-world traffic scenarios, thereby providing valuable insights into accident causation and prevention (Table 1-2).

Table 1 The Road Traffic Accident Prediction Models

Model Type	Algorithms	Author
Statistical Models	1. Autoregressive Integrated Moving Average (ARIMA) 2. Negative Binomial Regression 3. Logistic Regression Models	P. B. Kumar et al. (2022)[50] Sarkar et al. (2020) [51] Al-Ghamdi et al. (2001)[52]

Machine Learning Techniques	1. Support Vector Machine (SVM) 2. Decision Trees 3. Random Forest 4. K-Nearest Neighbors (KNN) 5. Neural Networks	Li, Z. et al. (2021)[53] A, Mahdi Rezapour et al. (2013) [54] Yang et al. (2023)[56] Zhang et al. (2020) [57] J. Wang et al. (2019) [28]
Deep Learning Approaches	1. Convolutional Neural Networks (CNNs) 2. Long Short-Term Memory (LSTM) Networks 3. Hybrid Models (CNN-LSTM)	F. Milletari et al. (2024)[58] M. I. Khan et al. (2024) [59] M. M. Kunt et al. (2011) [60]
Graph Neural Networks (GNNs)	1. Graph Convolutional Networks (GCNs) 2. Graph Attention Networks (GATs)	H. Wang et al. (2022)[61] M. Shi et al. (2023)[62]
Spatio-Temporal Models	1. Spatio-Temporal Graph Convo- lutional Networks (STGCNs) 2. Dynamic Spatio-Temporal Graph CNNs 3. Hybrid Models (eg. RNN-GCN) 4. Spatial-Temporal Graph Neural Networks (STGNNs)	Y. Zhang et al. (2022)[63] X. Zhang et al. (2021) [64] H. Zhu et al. (2020)[65] Jia et al. (2024)[66]
Hybrid Models	1. HetGAT (Heterogeneous Graph Attention Network)	Jin et al. (2021)[67]
Multi-Modal Forecasting	1. GAMCN (Graph and Atten- tive Multi-Path Convolutional Net- work)	J. Qi et al. (2022)[68]
Multi-Process Information Fusion	1. Bi-GRCN (Bidirectional-Graph Recurrent Convolu- tional Network) 2. Hybrid Models (eg. RNN-GCN)	H. Zhu et al. (2022)[69] H. Zhu et al. (2020)[65]
Multi-Modal Forecasting	1. GAMCN (Graph and Atten- tive Multi-Path Convolutional Net- work)	J. Qi et al. (2022)[70]

Table 2 The Road Traffic Accident Prediction Models

Model Type	Algorithms	Author
Multi-Process In- formation Fusion	1. Bi-GRCN (Bidirectional-Graph Recurrent Convolutional Network) 2. STGC-GNNs (Spatial-Temporal Granger Causality Graph Neural Networks)	W. Jiang et al. (2022) [69] S. He et al. (2023)[71]
Real-Time and Dynamic Graph Structures	1. TL-DCRNN (Transfer Learning with Diffu- sion Convolutional Recurrent Neural Network)	Zhang et al. (2020) [72]
	2. DetectorNet	H. Li et al. (2021) [73]

Each model type has its unique advantages and limitations, and the most appropriate model is usually chosen based on the nature of the problem and the characteristics of the data. For example, a spatio- temporal model might be chosen if the problem involves complex spatial and temporal dependencies, or a graph neural network might be chosen if the data is characterised by a graph structure. Multimodal prediction and multiprocess information fusion, on the other hand, focus on integrating different types of information to improve the accuracy and robustness of predictions.

According to the latest research, better performing models usually have the following characteris- tics. Integrate multiple data sources, that high-performing predictive models in traffic accident analysis share several distinguishing traits. These models excel by amalgamating data from diverse sources, including traffic flow, velocity, and meteorological data, which allows for a more holistic and precise depiction of the traffic ecosystem. This multifaceted data integration enhances the predictive accuracy of models by providing a richer context for analysis. Advanced models adeptly account for spatio-temporal dependencies, capturing the intricate dynamics of traffic flow and the interplay between different geographic locales. They leverage deep learning techniques, with a particular emphasis on hybrid models that integrate Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Graph Neural Networks (GNNs). These models are particularly effective due to their advanced feature extraction and sequential modeling capabilities, which are crucial for understanding complex traffic patterns. Furthermore, these models are designed to be adaptive and real-time, equipping them to swiftly respond to unpredictable events such as accidents and roadworks. They utilize dynamic graph structures that facilitate the incorporation of real-time traffic data, enabling timely interventions and adjustments. Lastly, these models are not only performant on specific datasets but also possess explanatory and generalization capabilities. They offer insights into the rationale behind their predic- tions, enhancing their transparency and trustworthiness to decision-makers. Moreover, their ability to generalize across various regions makes them versatile tools for traffic management and safety initiatives globally. This convergence of data integration, deep learning, adaptability, and explanatory power positions these models at the forefront of traffic accident prediction, offering innovative solutions for urban planning and traffic governance.

4.2 Traditional Statistical Models

Traditional statistical models are suitable for processing various types of data and informa- tion, suitable for data processing with small amount of data and simple relationship between vari- ables, usually based on strict mathematical theories, the models are relatively simple and easy to under- stand and interpret. However, it is difficult to extend to high-dimensional feature space and is suitable for use in the limited environment of the theater. Traditional statistical models are widely used in data analysis and inference, and in traffic accident prediction, regression modeling is the most commonly used technique to identify risk factors associated with the severity of road traffic accidents[52, 65, 74-76]. Followed by cluster analysis models(eg. latent class cluster analysis)[77]. With the development of technology, machine learning models have emerged. In practical applications, traditional statistical mod- els are combined with machine learning models to make full use of the interpretability of traditional statistical models and the powerful predictive ability of machine learning models to adapt to different scenarios and meet the characteristics of multidimensional data(eg. latent class clus-tering analysis)[78].

4.3 Machine Learning Models

Compared to traditional statistical models, machine learning models are based on data-driven approaches that do not require strict assumptions about the distribution of the data or the relationship between the variables, and the models are complex enough to capture non-linear relationships and features of high-dimensional data. Machine learning methods are able to handle more complex functions and therefore can provide accurate predictive models [79].

Over the years, machine learning methods have been widely used in traffic accident prediction, among which Random Forest is an integrated learning method, in traffic accident prediction, Random Forest can be used to identify multiple factors that lead to accidents, such as weather conditions, traffic flow, and type of roadway. Zhang[80]concluded that Random Forest has the highest overall prediction accuracy, and serious collisions also had the highest prediction accuracy, followed by K-nearestneighbors. Singh[81] modeled injury severity of crashes using Multinomial Logit, Decision Trees, and Random Forests, and class balancing using Synthetic Minority Oversampling (SMOTE) and Stochastic Class Balancing. Among the three models, the Random Forest model has the best performance.

Support Vector Machine (SVM), can be used to categorize traffic accident data and predict whether an accident will occur or not. Li[82] developed two models, Support Vector Machine (SVM) and Ordered Probit, and the correct prediction rate of the SVM model was percent of 48. 8 and the correct prediction rate of Ordered Probit model is percent of 44. 0. Thus, the Support Vector Machine model performs better in predicting the severity of collision damage.

The K-Nearest Neighbors (KNN) algorithm is a straightforward machine learning method classified as instance-based learning. It classifies new data points based on the categories of their closest matches in the training set, using distance metrics like Euclidean or Manhattan distance to define ”closeness. ” In traffic accident analysis, KNN can predict accident severity by identifying patterns in historical data. For instance, Beshah and Hill[83] utilized KNN alongside decision trees and Naive Bayes to forecast injury severity in Ethiopian traffic accidents. Their analysis of over 18, 000 accidents demonstrated the high predictive accuracy of these algorithms, with KNN outperforming the others, as indicated by the highest AUC score, suggesting its strong discriminative power for this dataset. Bayesian networks[83, 84], which visually represent variables’ conditional probabilities, facilitate the analysis of complex factor interactions. In traffic accident analysis, these networks model accidents as outcome variables, examining factors like weather and rule adherence. Nodes and directed edges illustrate factor relationships and dependencies. Juan[85]combined Latent Class Clustering to homogenize data with Bayesian Networks to pinpoint severe accident causes. This approach helped identify key variables for predicting serious accidents, with a focus on accident types and visibility distances. In summary, Bayesian networks provide a powerful framework for modeling and analyzing the complex relationships between traffic accidents and various factors. With this model, we can not only identify and understand the key drivers of accidents but also predict and prevent future accidents, thereby improving road safety.

4.4 Deep Learning Models

In addition, there are deep learning techniques, particularly graph neural networks (GNNs), and the processing of spatio-temporal data. They utilise complex network structures to learn patterns in traffic data and make predictions. These models perform well because they are not only able to handle complex spatio-temporal data, but also adapt to the dynamics of the traffic system, while providing a certain degree of interpretability, which contributes to the development of traffic planning and intelligent transport systems. HetGAT (Heterogeneous Graph Attention Network), this model combines Heterogeneous Graph Attention Networks and Time-Expanded Convolutional Networks for modelling the multiscale temporal contextual effects of traffic flow, effectively integrating spatio-temporal factors and improving prediction accuracy[86]. STGC-GNNs leverage spatial-temporal causality to model traffic flow dependencies, ideal for forecasting up to 60 minutes ahead[71]. The Bi-GRCN merges graph convolutions with bidirectional LSTMs to enhance traffic prediction by considering past and future data[69]. ETGCN enhances speed prediction accuracy through integrated graph structures that capture spatial correlations alongside temporal dynamics[87]. SST-DHL employs hypergraph learning with cyclic units to process spatio-temporal data, enhancing model interpretability and prediction precision, especially in sparse datasets[88]. Hybrid models, such as LSTM-CNN, harness the strengths of different neural architectures to analyze both spatial and temporal aspects of traffic data[89]. However, these models tend to focus more on tasks within the sametransportation mode, with less consideration given to the interactionof traffic feature information across different modes.

4.5 Model Comparison

In the comparison of accuracy, stability and generalization ability in traffic accident prediction, the models for predicting the influencing factors of traffic accident severity have their own advantages. In many studies, in terms of accuracy, Random Forest[90-92] stands out for its high accuracy. It improves the accuracy of prediction by constructing multiple decision trees and taking their average prediction results.

Kenny Santos [93] noted that Random Forest outperformed other methods in 70 percent ctiveness. Support Vector Machine (SVM) followed closely, with a 53 percent success rate and recognized for its proficiency in handling nonlinear challenges by utilizing kernel functions to map data into higher dimensions for optimal hyperplane detection. Regarding stability, Bayesian Networks and K-Nearest Neighbors (KNN) excelled; Bayesian Networks, with their probabilistic graphical model framework, maintained robust performance under minor data fluctuations, achieving top results in 67 percent of cases. KNN, attributed to its straightforward approach and swift adaptation to new data, secured the best outcome in 40 percent of applications.

5 DISCUSSION

This paper presents a summary of the key factors influencing traffic crash severity as well as a comparative study of different analytical approaches to traffic crash injury severity prediction through a comprehensive analysis of many academic papers published between 2001 and 2024. The study reveals the strengths and limitations of prevalent models for forecasting the severity of injuries in traffic accidents, along with their suitable use cases, summarized as follows:

• Random forest, with high accuracy and stability, performs best in most studies, especially when there are complex interactions between variables. Especially in the evaluation of feature importance, it can evaluate the impact of each feature on the prediction results. But its interpretability is poor. As an integrated model, its decision-making process is not transparent enough and difficult to explain; It takes a long time and more computing resources to build and train the model. It is suitable for large-scale data sets that require high accuracy prediction.

• The support vector machine algorithm is adept at identifying the most effective hyperplane in a high-dimensional context, making it well-suited for classifying data with intricate boundary definitions. However, the kernel function and parameters need to be selected reasonably, which is sensitive to parameters. It is suitable for scenarios where there are nonlinear relationships in the data set and good generalization ability is required.

• Bayesian networks articulate the probabilistic interconnections among variables, offering valuable decision support. Nonetheless, they require substantial data to accurately estimate these probabilities within the model. They are particularly useful for predictive tasks where the expression of variable probability relationships is essential.

• K-nearest neighbors, without training, use data directly when predicting. For unbalanced datasets, performance may degrade. It is suitable for small-scale datasets or occasions requiring rapid prototyping development.

• Artificial neural networks, nonlinear modeling, can capture complex nonlinear relationships in data, and through learning, the network can adapt to changes in data. However, in order to obtain good performance, it needs a lot of data for training. It is suitable for scenes with complex patterns and a large amount of data, and requires a strong learning ability of the model.

In terms of model selection and application, this paper makes the following recommendations:

• Data-driven model selection. The most appropriate model is selected based on the characteristics of the dataset and the needs of the prediction task. For example, spatio-temporal models may be a better choice for data with significant spatio-temporal dependencies. For example, STGCN (Spatial-Temporal Graph Convolutional Network) is able to capture both spatial and temporal dependencies of traffic data [94].

• Model integration leverages the complementary advantages of various models, such as the synergy between deep learning and machine learning. This approach involves employing deep learning for feature extraction, followed by training machine learning models like SVMs or random forests on these extracted features to bolster predictive accuracy. For instance, CNNs can be utilized to identify key features, which are subsequently used to refine the performance of conventional machine learning algorithms [95].

• Adaptability&Real-time. Developing adaptable and real-time models is crucial for responding swiftly to unforeseen incidents like traffic accidents. These models, which may incorporate dynamic graph structures, are designed to adjust to fluctuations in live traffic data. For example, dynamic graph convolutional networks can modify their structure in response to real-time traffic flow and events, enhancing their predictive capabilities and responsiveness[95].

• Explanatory properties. Selection or development of models with some explanatory power to help decision makers understand the logic behind the predictions and increase the credibility and acceptance of the models. For example, Bayesian networks, as probabilistic graphical models, can provide explanations of conditional dependencies between variables[32].

The severity of traffic accidents is shaped by numerous interrelated factors, which collectively determine the probability and extent of an incident. Investigators must take into account a range of elements such as traffic flow, road conditions, and weather when modeling accident severity. The selection of an appropriate predictive model hinges on these diverse influencing factors, necessitating a tailored approach based on their specific attributes. For the researcher, the study of influencing factors is somewhat dependent on the data set. Different datasets may contain different features and information. For example, some datasets may contain detailed weather information, while others may contain more comprehensive road design parameters, and thus the researcher needs to select and adapt the model according to the characteristics of the available datasets. At the same time, traffic patterns, driver behaviour and road infrastructure may differ significantly from one region to another due to geographical and cultural differences. For example, factors influencing traffic crashes may differ between urban and rural areas, requiring targeted analysis and modelling.

Future research in predicting the severity of traffic accident injuries could focus on advancing deep learning models. This includes investigating sophisticated network architectures like CNNs and RNNs for analyzing spatial and temporal data characteristics, crucial for deciphering traffic accident patterns. Additionally, combining ensemble learning with deep learning could enhance model precision and stability. Furthermore, developing a multi-task learning framework to forecast injury severity alongside related metrics like accident likelihood and duration may bolster the model's ability to generalize across various scenarios.

6 CONCLUSIONS

This paper identifies key factors in traffic accident severity and evaluates statistical prediction models. It analyzes model strengths and weaknesses to guide the choice of the most suitable model for predicting accident severity. Choosing the right model is essential for traffic accident prevention, as it enables precise predictions and preemptive measures by traffic management, thereby reducing accidents and injury severity. Precise forecasting of high-risk zones and times aids in optimizing traffic monitoring and enforcement, enhancing resource efficiency and road safety policy development.

In traffic accident prediction studies, the selection of influencing factors is based on data avail- ability, theoretical support, geographic location characteristics, cultural differences, model capture capa- bilities, and practical implications for traffic safety management. Key factors typically include traffic volume and density, road and infrastructure conditions, weather and lighting conditions, driver charac- teristics, vehicle characteristics, time factors, socio-economic factors, and urban planning and transport policies. The comprehensive consideration of these factors helps to construct more accurate and practical prediction models, which can provide a scientific basis for traffic planning and management and enhance road safety.

In the future, we will continue to explore new data sources and algorithms to further improve the performance of our predictive models. At the same time, we will also focus on the explanatory and real-time nature of the models to ensure that they are not only accurate, but also able to provide timely insights to decision makers. Through these efforts, we expect to be able to make a greater contribution to reducing traffic accidents and improving road safety, as well as laying a solid foundation for the development of intelligent transport systems.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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