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Research Paper

Classification of traffic accidents' factors using TrafficRiskClassifier

Wei Sun [a,*], Lili Nurliyana Abdullah [a,*], Fatimah binti Khalid [a], Puteri Suhaiza binti Sulaiman [a]

[a] Department of Multimedia, Faculty of Computer Science and Information Technology, Universiti Putra Malaysia, Serdang, Malaysia

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ABSTRACT

The TrafficRiskClassifier model introduced in this study adopts an innovative approach that incorporates migration learning, image classification, and self-supervised learning, aiming to significantly improve the accuracy and efficiency of traffic accident risk analysis. Compared with traditional traffic safety analysis techniques, this model focuses on utilizing contextual information and situational data of traffic accidents to achieve a higher level of risk classification accuracy. The core of this approach is to deeply mine and analyze the detailed information in the accident environment, to provide more scientific and effective support for traffic accident risk prevention and response. Initially, by integrating migration learning with image classification techniques, the model proficiently extracts pivotal features from intricate traffic scenarios and formulates initial assessments of accident risks. Subsequently, self-supervised learning is incorporated in this study, augmenting the model's capability to comprehend and categorize accident imagery. The TrafficRiskClassifier model exhibits a generalization ability of 91.82%, 85.16%, and 80.92% on individual classification tasks, respectively, signifying its robust learning capacity and proficiency in managing unseen data. Furthermore, the TrafficRiskClassifier model delineates a functional nexus between accident risk and variables such as weather, road conditions, and personal factors, employing a polynomial regression approach. This methodology not only amplifies the predictive precision of the model but also renders it versatile across diverse scenarios. Through the analysis of various polynomial functions, the model achieves enhanced accuracy in classifying disparate risk levels. The outcomes demonstrate that the TrafficRiskClassifier model can efficaciously amalgamate contextual information within traffic scenarios, thereby achieving more precise classification of traffic accident risks, and consequently serving as an invaluable instrument for urban traffic safety management.

1. Introduction

Globally, traffic accidents have escalated into a significant public health issue, resulting in an extensive number of fatalities and injuries annually. As per the Global Status Report on Road Safety 2018 by the World Health Organization (WHO), approximately 1.35 million individuals perish in road accidents worldwide annually, with traffic-related injuries emerging as

* Corresponding authors.
E-mail addresses: gs66334@student.upm.edu.my (W. Sun), liyana@upm.edu.my (L.N. Abdullah), fatimahk@upm.edu.my (F.binti Khalid), psuhaiza@upm.edu.my (P.S.b. Sulaiman).

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the primary cause of mortality among individuals aged 5 to 29 years (World Health Organization, 2018). Consequently, the prevention and diminution of traffic accidents on an international scale represent an imperative necessity.

During our investigation into the effects of urbanization on traffic accidents, it was discerned that human factors are crucial in influencing traffic accident occurrences in numerous countries and regions. Data collected form World Health Organization (WHO) indicate that approximately 10% of road traffic deaths are related to drink driving; this corresponds to self-reported rates of 16–21% of people admitting to drink driving in a survey conducted by the European Survey Research Association (ESRA). The same self-reports reveal that nearly 50% of drivers across 48 countries report exceeding the speed limit outside built-up areas (World Health Organization, 2023). Speeding, drink-driving, driver fatigue, distracted driving, and non-use of safety belts, child restraints and helmets are among the key behaviours contributing to road injury and death (World Health Organization, 2021). Vulnerable road users such as pedestrians, cyclists, moped riders, and motorcyclists are particularly at high risk of severe or fatal injury when motor vehicles collide with them because of their lack of protection (Economic and Social Commission for Asia and the Pacific, 2020). Specifically in Morocco, human factors are identified as one of the primary reasons behind the nation's roads ranking among the most perilous globally. A survey in Sudan revealed that individual factors contributed to 60.6% of traffic accidents, with suboptimal road conditions (45.5%), animal-related factors (5.6%), and vehicle scarcity (1.4%) following suit (Deme, 2019). The Czech In-depth Accident Study (CzIDAS) indicates that distraction constitutes a factor in 40% of the analyzed accidents. Distractions may originate from diverse causes, encompassing attention overload (35%), distracted driving (19%), and monotonous driving (13%) (Bucsuházy et al., 2020). Furthermore, the likelihood of road traffic accidents is directly correlated with environmental factors such as rainfall, extreme low temperatures, fog, and hot weather conditions. The incident rates of accidents are 34%, 25%, 21%, and 20% respectively, attributable to fog, rain, temperature variances, and additional weather-related factors (Hammad et al., 2019). From a geographical standpoint, the proportion of fatal traffic collisions is notably higher in rural regions (66%) as compared to urban areas (34%). Accidents predominantly occur on straight roads, succeeded by curved roads, intersections, and Y/T intersections, which witness the highest rates of traffic fatalities. The minimal incidence of traffic fatalities was observed at roundabouts and overpasses (Darma et al., 2017). This paragraph accentuates the impact of human factors, environmental conditions, and geographical location on the rates of traffic accidents, factors that are especially critical in the context of urbanization. Urbanization directly influences road use patterns and traffic flow, thereby significantly impacting traffic safety.

However, challenges remain in the realm of traffic safety research. The issue of data lack in traffic accident studies is a persistent concern (Fiorentini & Losa, 2020; Parsa et al., 2019; Zhang et al., 2023), as is the need for greater interpretability and transparency in traffic safety risk analysis (Adadi & Berrada, 2018; Coeckelbergh, 2020; Gilpin et al., 2019). Additionally, while much research has focused on local attributes of traffic accidents, there is a growing recognition of the importance of incorporating contextual information from the entire scene for a more explicit and classification (Hu et al., 2023; Kumar et al., 2020; Panda et al., 2022).

The TrafficRiskClassifier model introduced in this study adopts an innovative approach that incorporates migration learning, image classification, and self-supervised learning, aiming to significantly improve the accuracy and efficiency of traffic accident risk analysis. This model successfully addresses the shortcomings of traditional traffic risk analysis methods by combining multiple hybrids learning strategies such as migration learning, image classification and self-supervised learning. Compared with previous traffic safety analysis techniques, this model especially emphasizes the use of contextual information and situational data of traffic accidents to improve the accuracy of risk classification. Its core advantage lies in the in-depth mining and analysis of detailed information in the accident context, which provides a more scientific and effective method for preventing and responding to traffic accident risks. The incorporation of transfer learning and image classification techniques enables the TrafficRiskClassifier to extract key features from intricate traffic scenarios, facilitating an initial risk assessment. This assessment is further refined using self-supervised learning, which allows the model to better categorize and understand accident imagery. Moreover, the application of polynomial regression in this model allows for an intricate examination of the relationship between accident risk and various factors such as weather conditions, road quality, and personal attributes. This approach not only enhances the predictive accuracy of the TrafficRiskClassifier but also affords it the versatility to adapt to diverse scenarios. Through comparative analysis of various polynomial functions, the model achieves a remarkable level of accuracy in classifying different levels of risk.

Next, Chapter 2 is a literature review that reviews previous studies in the relevant field. Chapter 3 describes in detail the research methodology used in this study. Chapter 4 presents the results of the study and its discussion. Chapter 5 summarizes the main findings of the study while pointing out limitations and directions for improvement in future work.

2. Literature review

Within the scholarly discourse on traffic accident severity classification, accidents are typically categorized into three distinct types: “fatal”, “serious”, and “minor”. Fatal crashes, defined as accidents resulting in the death of one or more individuals, have a profound global impact. Research underscores this, noting that on average, 1.35 million people perish annually in traffic accidents (Ahmed et al., 2023; Chand et al., 2021). Serious accidents refer to incidents that culminate in substantial injuries, albeit non-fatal in nature. The severity of these accidents is typically assessed based on the quantity of individuals injured and the extent of direct property damage incurred (Jianfeng et al., 2019). Minor accidents are characterized by less severe injuries, and while the direct discourse on such incidents is limited, ancillary research implicitly addresses these minor injuries through the analysis of various accident types and their influence on overall accident severity (Z. Yang et al., 2022b). These classifications offer a foundational framework for comprehending the diverse severities of injuries sustained in traffic accidents.

An review of the literature pertaining to factors influencing traffic accidents reveals that meteorological conditions, roadway conditions, and individual factors are integral in determining the frequency and severity of traffic accidents. Meteorological conditions exert a substantial impact on traffic accidents, with varying weather conditions influencing different types of accidents in distinct manners, for instance, snowy conditions predominantly affect cycling accidents, whereas daylight glare significantly elevates the risk of multi-vehicle collisions on highways (Becker et al., 2022; Drosu et al., 2020; Edwards, 1998; Lio et al., 2019; Xing et al., 2019). Roadway conditions, encompassing aspects such as traffic congestion and the state of the pavement, play a pivotal role in the incidence of accidents. Research has elucidated an inverse correlation between traffic congestion and the frequency of accidents, while the condition of the road surface is also found to significantly influence the occurrence of accidents (Ahmed et al., 2023; Mkwata & Chong, 2022; Retallack & Ostendorf, 2019). Individual factors, particularly those encompassing driver error and fatigue, exert a profound impact on the incidence of road accidents. While existing research has delved into the relationship between personal factors and traffic accidents, a notable research gap remains regarding the precise assessment of the impact of personal factors, particularly in relation to drivers' psychological and physiological states on accidents (Gopalakrishnan, 2012; Paramasivan et al., 2022; Wang et al., 2014).

Conventional traffic accident data analysis methodologies are utilized in road safety research, encompassing a broad spectrum of aspects ranging from road condition analysis to driving behaviour assessment and the development of collision warning systems. Plain Bayesian classifiers have gained prominence in applications such as pavement detection and the safety assessment of driving behaviour (Tijani et al., 2022; F.-J. Yang, 2018; L. Yang et al., 2022a). Logistic regression has been used to analyse accident severity and driving behaviour (Ashqar et al., 2021; Eboli et al., 2020; Otte et al., 2018), whereas linear regression has played an important role in studies on the relationship between economic dynamics, road design improvements and traffic safety (Aldala'in et al., 2020; Hauer, 2015; Ranadive et al., 2023). KNN algorithms have shown their clustering and classification capabilities in accident prediction and case retrieval (X. Dong & Lu, 2019; Hatti, 2022). K-mean clustering and auto coders have been used to extract hidden information from traffic accident data and to performing accident hotspot identification (Anderson, 2009; Priyanka & Jayakarthik, 2020, 2020; Puspitasari et al., 2020). Transfer learning and transformer techniques have shown potential in traffic accident risk prediction and detection (Hajri & Fradi, 2022; Kang et al., 2022; Liu et al., 2023; Saleh et al., 2022; Sohail et al., 2023; Tamagusko et al., 2022).

Existing research in traffic accident analysis focuses on three main areas: traffic accident prediction, real-time traffic behavior analysis, and driver fatigue and distraction detection. Research in traffic accident prediction is mainly aimed at understanding the factors that lead to accidents and applying various machine learning models to make predictions, especially on highways and arterial roads (Ahmed et al., 2023; Silva et al., 2020; Z. Yang et al., 2022b). In terms of real-time traffic behavior analysis, the application of advanced technologies is not limited to linking vehicle data to assess traffic safety in real time and analyzing the driving behavior of city bus drivers (Mussah & Adu-Gyamfi, 2022; Sohail et al., 2023). Further research extends to real-time accident prediction and real-time conflict prediction models that use real-time data to predict scenarios and behavioral patterns that may lead to accidents. For example, Formosa et al. demonstrated the significant predictive performance of deep neural networks in identifying high-risk situations by predicting potential traffic conflicts through deep learning (Formosa et al., 2020). Zhang et al. developed a real-time model for predicting pedestrian conflicts at signalized intersections using machine learning with the aim of improving traffic management (Zhang and Abdel-Aty, 2022). Katrakazas et al. proposed a method for detecting conflict-prone traffic conditions in real-time to enhance the predictive capability of collision prevention (Katrakazas et al., 2017). Hossain et al. provided a review of real-time crash prediction models, discussing the design paths and requisites for these models, emphasizing the enhancement of predictive capabilities (Hossain et al., 2019). Finally, Zheng and Sayed introduced a new method for predicting real-time crash risk at signalized intersections using traffic conflict data, highlighting the importance of transferability of real-time crash pre-diction models (Zheng and Sayed, 2020). The Theofilatos et al. study compares for the first time the performance of ML and DL models in predicting real-time traffic and weather da-ta combined with historical crash data on the Attica Toll Road in Greece. It is emphasized that the DL model outperforms the other models in terms of performance metrics such as accuracy, sensitivity, specificity, and area under the curve (AUC), demonstrating the potential and advantages of the DL model in dealing with such problems (Theofilatos et al., 2019). Also, Orsini et al. used the Real-Time Conflict Prediction Model (RTConfPM), which predicts motor vehicle tailgating conflicts based on time-to-collision (TTC) values recorded by radar sensors, and compared the performance of multiple classifiers, including KNN, NB, DA, DT, and SVM. It is emphasized that KNN and SVM significantly outperform the other models in terms of recall metrics, illustrating the effectiveness and application potential of different ML classifiers in real-time conflict prediction (Orsini et al., 2021). The importance of these findings is that they provide the first performance comparison between machine learning and deep learning approaches in real-time collision/conflict prediction modeling. On the other hand, research in the field of driver fatigue and distraction detection focuses on the development of effective detection methods and systems, including the use of machine learning techniques for the identification of (B.-T. Dong et al., 2022; Kashevnik et al., 2021; Koay et al., 2022). These studies reveal the multifaceted and complex nature of road safety research, while identifying limitations of current research and providing perspectives for future research directions.

Research in contextual information analysis of traffic accidents focuses on understanding personality and behavioural traits in traffic accidents, utilising nationwide traffic accident datasets, and applying advanced technologies such as the Internet of Vehicles (IoV) and Artificial Intelligence (AI) for accident prediction and prevention. Research has shown that driver personality and behavioural patterns have a significant impact on traffic safety (Aswad et al., 2015; Legree et al., 2003; Moosavi et al., 2019; Sümer, 2003; Zhu et al., 2017). In addition, the use of metadata and *meta*-features is becoming increasingly important in crash analysis, as these techniques can improve the accuracy and efficiency of crash detection, understand the relationship between driving behaviour and crash risk, and perform long-term trend analysis (Af Wåhlberg et al., 2017; Barraclough et al., 2016; Selmoune et al., 2019; Yong-Kul Ki et al., 2006). Collectively, these studies underscore the significance of comprehending contextual factors in traffic accidents and exemplify the implementation of sophisticated techniques such as artificial intelligence, machine learning, and contextaware systems in exhaustive traffic accident analysis. Finally, while current research methodologies have made significant strides in traffic safety analysis, there is an ongoing need to refine these approaches.

3. Research methodology

The primary objective of this research is to develop a sophisticated traffic accident risk classification model, termed TrafficRiskClassifier. This model is dedicated to extracting salient features influencing traffic accidents and employs a combination of self-supervised learning and deep learning within a transfer learning framework. The fundamental aim of this study is to categorize the risk level of traffic accidents through the TrafficRiskClassifier model, integrating the analysis of both visual data and textual reports related to traffic incidents.

3.1. Basic models introduction

In this section, the concepts underlying the TrafficRiskClassifier model are introduced, including transfer learning, self-supervised learning, multimodal data fusion, and self-attention mechanisms. These concepts as Table 1 are key to understanding and implementing the TrafficRiskClassifier model.

3.2. Research methodology

In this section, the research process of the TrafficRiskClassifier model is described in detail, as shown in Fig. 1. The model construction is divided into several key steps, including data preprocessing, feature extraction, model architecture design, training and optimization.

3.3. Data collection and preprocess

Data collection is the first step in building the TrafficRiskClassifier model, which involves obtaining multimodal data about traffic accidents from multiple sources. The following as Fig. 2 is the detailed data collection process.

3.4. Feature extraction

Feature extraction is a key step in building the TrafficRiskClassifier model, which involves extracting useful information from multimodal data. The following is the detailed process of visual and textual feature extraction:

3.4.1. Visual feature extraction

- Using Convolutional Neural Networks: It automatically extracts features from an image using convolutional layers, eliminating the need to encode these features manually (Al-Saffar et al., 2017).
- Pre-processing: Image data is usually pre-processed before feature extraction, including resizing to 224*224 and normalising to 64 pixels.
- Convolutional Layers: Each convolutional layer uses a set of learnable filters to capture specific patterns in the image.
- Pooling Layer: After the convolutional layers, a pooling layer is used to reduce the spatial dimensionality of the feature map, which helps to reduce the amount of computation and increase the efficiency of feature extraction.

Table 1
Basic concept of technology.

Technique	Concepts
Transfer Learning (Weiss et al., 2016)	In the case of traffic accident risk classification, using pre-trained deep learning models and adapting them to the analysis of traffic accident data.
Self-Supervised Learning (Jaiswal et al., 2020)	This is a form of unsupervised learning in which the model uses part of its input data to predict the rest. In traffic accident risk classification, this helps the model to learn from unlabeled traffic accident data.
Multimodal Data Fusion (Gao et al., 2020)	This involves combining different types of data, such as images and text, to gain a more comprehensive understanding of the accident scene.

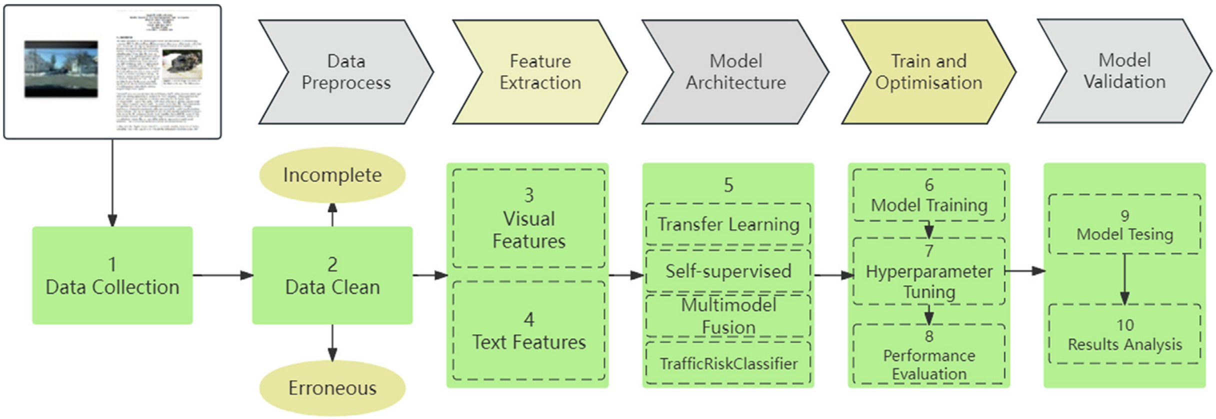
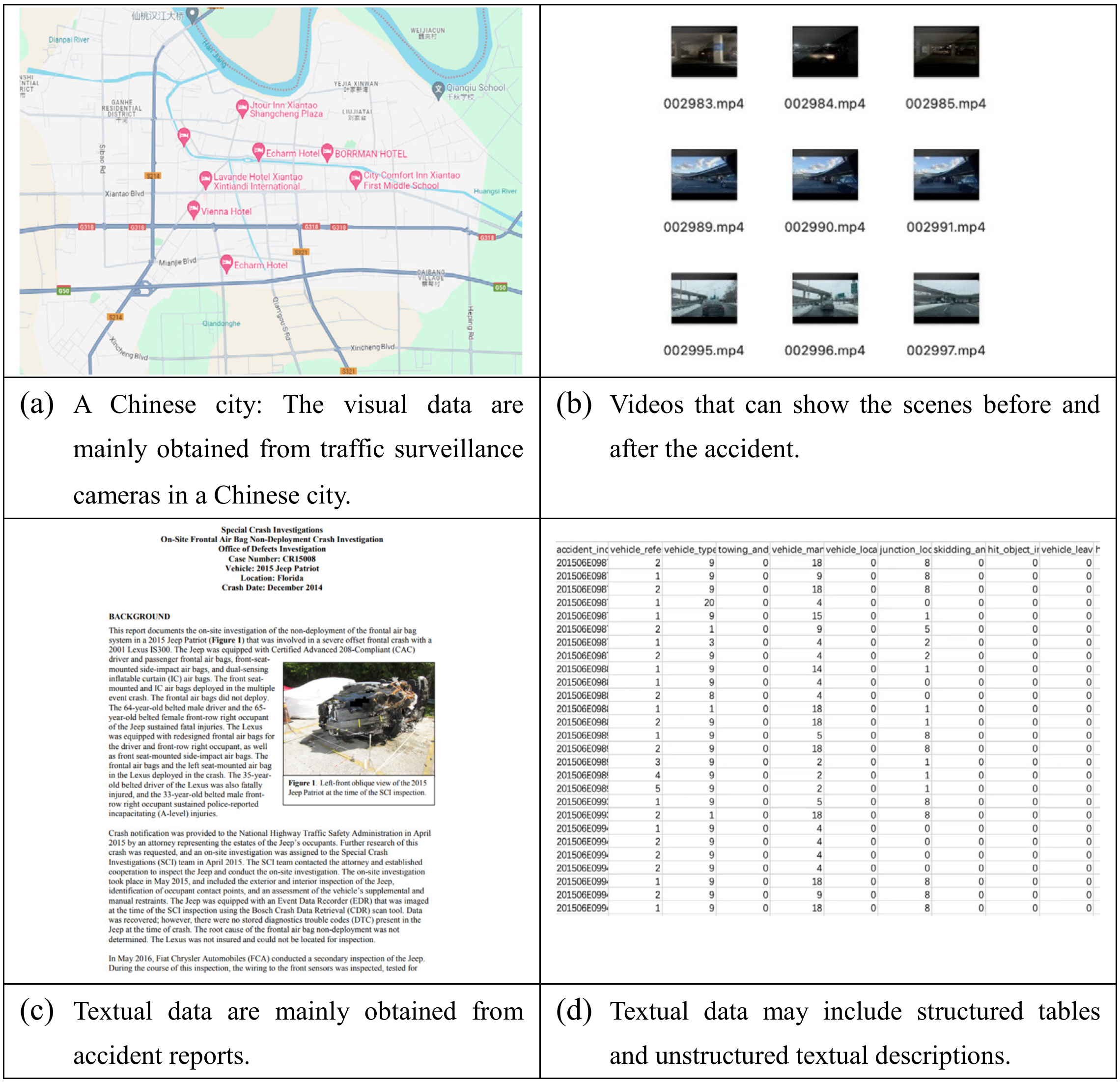


Fig. 1. Flow chart of TrafficRiskClassifier.



(a) A Chinese city: The visual data are mainly obtained from traffic surveillance cameras in a Chinese city.

(b) Videos that can show the scenes before and after the accident.

(c) Textual data are mainly obtained from accident reports.

(d) Textual data may include structured tables and unstructured textual descriptions.

Fig. 2. Data collection and preprocess.

- Feature Vectors: After a series of convolution and pooling layers, the image is converted into one-dimensional feature vectors that capture key information about the image for subsequent classification tasks.

3.4.2. Text feature extraction

- Feature fusion: Combining manually filtered text features with image feature vectors as Table 2 so that the model can take both types of information into account.
- Feature encoding: The text classification results are hot-coded as Table 3 and fed into the classification model together with the image features.

3.5. Model architecture design

The model design proposed in this study, shown in Fig. 3, is overall divided into three key parts to deal with the specific problem of traffic accident classification. First, the model is based on the VGG16 architecture, which is widely used in image classification algorithms, for basic training of images from different traffic accident scenarios. This step exploits the powerful feature extraction capabilities of VGG16 for visual tasks and specializes the model through a finetuning process to adapt it to the specific needs of traffic accident classification.

The second part involves a self-supervised learning technique that generates new image data by learning the original data collected in the study. Subsequently, a migration learning approach is used to perform further learning based on the weights, parameters, and features of the trained base model to enhance the model's ability to understand and classify the new image data.

The third part focuses on the fusion of text data extracted from traffic accident reports and establishes the functional equation between the contextual information of traffic accidents and different traffic categories and factors by constructing a polynomial regression model. This process not only extracts textual features, but also trains the model to accurately portray the complex relationships between different traffic accident categories.

The final stage is multimodal feature fusion, which combines the visual features extracted through the VGG16 model with the textual features obtained through the polynomial regression method. This merging process is realized through a concatenation operation that generates a feature representation containing both visual and textual information. After the multimodal feature fusion, the classifier's task is to make the final classification decision based on these fused features to achieve accurate classification and prediction of traffic accident risks. With such a detailed and systematic methodology, the model is able to effectively combine features from different data sources, providing a new, multidimensional solution for traffic accident classification.

3.6. Train and optimization

Following the model architecture design in this study, the subsequent step focuses on the training and optimization of the developed model. This phase is crucial as it involves finetuning the model parameters to ensure optimal performance in classifying traffic accidents.

3.6.1. Training procedure

Table 2
Define variable.

Items	Features	Label
Individual	Drinking	1
	Normal	2
	Operating	3
	Talking	4
	Texting	5
Road	Dry	1
	Ice	2
	Snowy	3
	Wet	4
Weather	Cloudy	1
	Overcast	2
	Rainy	3
	Snowy	4
	Sunny	5

Table 3
Severity level.

Items	Levels	Label
Severity	Fatal	1
	Serious	2
	Light	3

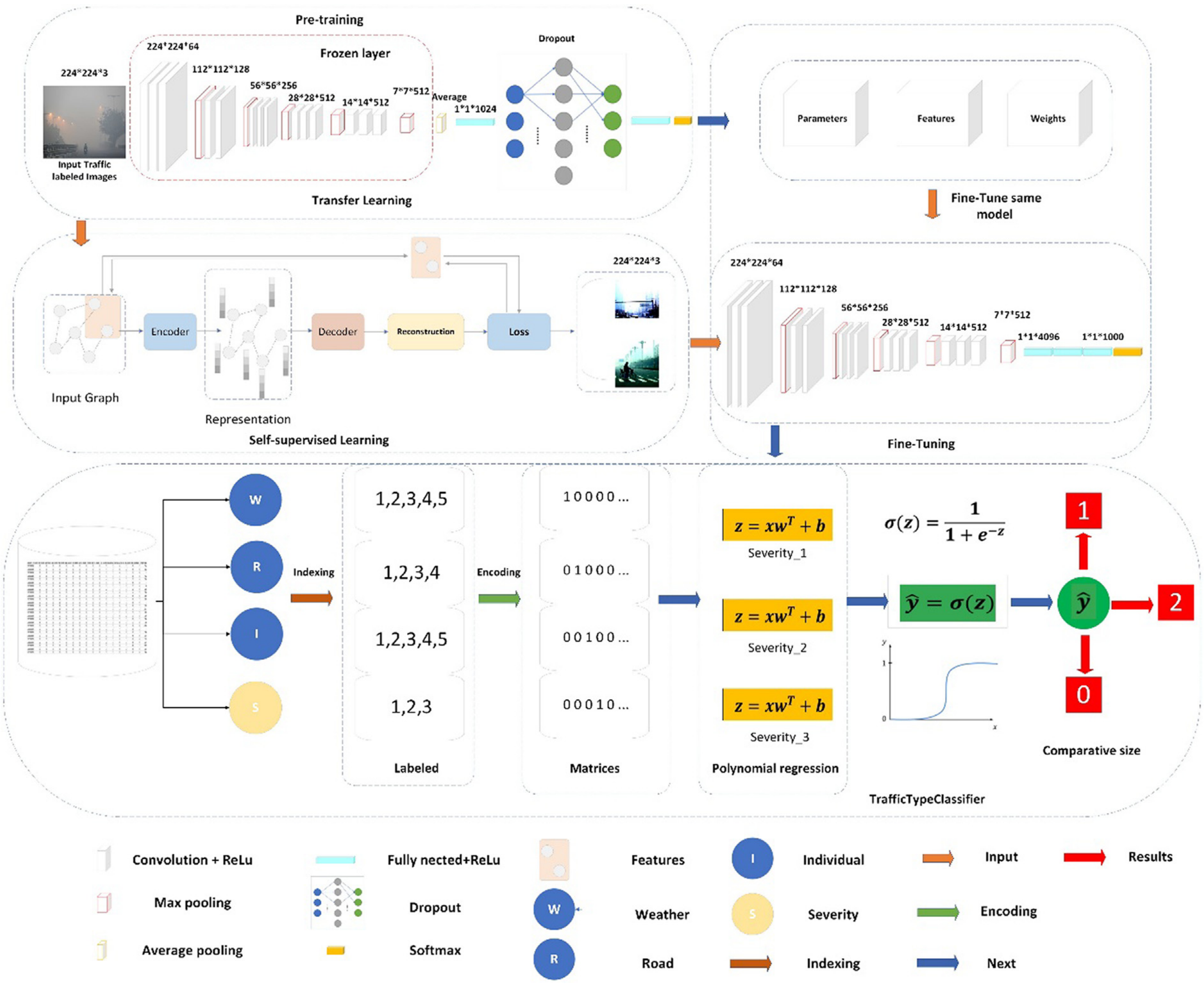


Fig. 3. An overview of the TrafficRiskClassifier.

- Data Preparation: The data set is divided into training, validation, and testing sets. The training set is used for learning the model parameters, the validation set for tuning the hyperparameters, and the testing set for evaluating the model's performance.
- Model Training: The VGG16 part of the model, pre-trained on a large image dataset, undergoes finetuning with the traffic accident image data. For the textual data, the polynomial regression method extracts textual features, which are then used to train the model to understand the relationship between text data and traffic accident categories.
- Fusion and Classifier Training: The multimodal feature fusion combines visual and textual features. The concatenated features are then fed into a series of fully connected layers.

$$F(x) = \begin{cases} F(severity\_1) \\ F(severity\_2) \\ F(severity\_3) \end{cases} \quad (1)$$

$$F(severity) = \text{intercept} + \sum(coefficient \times feature) \tag{2}$$

*The value of F(x) is based on the comparison of the size of the three severity function relationships.

3.6.2. Optimization strategies

Hyperparameter Tuning: Hyperparameters such as learning rate, batch size, and the number of epochs is adjusted based on the performance on the validation set. And regularization techniques like dropout and weight decay are employed to prevent overfitting as Table 4.

Loss Function: Crossentropy loss for classification tasks, is chosen to measure the difference between the predicted and actual labels. The crossentropy loss function measures the difference between two probability distributions and is used to measure the difference between the distribution of actual labels and the probability distribution predicted by the model.

$$\text{Loss} = \sum_{c=1}^{M} y_{o,c} log(p_{o,c}) \tag{3}$$

* 1. M is the total number of categories. 2. $y_{o,c}$ is an indicator. If the category c is an observation o's true category, then 1, otherwise 0. 3. $p_{o,c}$ is the probability that observation o is predicted to be of category c by the model.

In order to assess the generalization ability of the model and reduce the risk of overfitting, the study uses 5 k-fold cross-validation technique, where the dataset is randomly divided into k subsets, and each time, one of the subsets is selected as the test set and the rest as the training set, and k times of training and testing are carried out to ensure that the assessment results are stable and reliable. In this way, the performance of the model on different data subsets can be assessed, and thus the model parameters can be optimized.

Optimizer Selection: In terms of choosing an optimizer, this paper employs the Adam optimizer to minimize the loss function. The key advantage of the Adam optimizer is that it adaptively adjusts the learning rate for each parameter by considering the second-order moment estimates (variances) of the gradient. This approach is particularly helpful in coping with the different learning rate requirements that different parameters may have. Adam reduces the bias of the model in the early stages of training by correcting the first and second-order moment estimates, allowing the algorithm to perform parameter updates more efficiently at the beginning of training. These properties make Adam a popular choice for optimizing the parameters of neural networks, as it typically converges faster and is less sensitive to the choice of initial learning rate.

Compute the first-order moment estimate of the gradient:

$$m_t = \beta_1 \times m_{t-1} + (1 - \beta_1) \times g_t \tag{4}$$

Compute the second-order moment estimate of the gradient:

$$v_t = \beta_2 \times v_{t-1} + (1 - \beta_2) \times g_t^2 \tag{5}$$

Corrections to the estimates of first-order moments and second-order moments:

$$\widehat{m}_t = \frac{m_t}{1 - \beta_1^t} \tag{6}$$

$$\widehat{v}_t = \frac{v_t}{1 - \beta_2^t} \tag{7}$$

Updating parameters:

$$\theta_{t+1} = \theta_t - \frac{\mu}{\sqrt{\widehat{v}_t} + \varepsilon} \times \widehat{m}_t \tag{8}$$

* 1. g_t is the gradient at time step t; 2. m_t is the first order moment estimate of the gradient; 3. v_t is the second order moment estimate of the gradient; 4. β_1 and β_2 is the decay rate; 5. μ is the learning rate; 6. ε is a very small number in case the denominator is zero; 7. θ_t is the learning rate at time step t of the parameter.

Table 4
Hyperparameter tuning setting.

Hyperparameter	Setting
Learning Rate	Start with 0.0001, use learning rate decay strategy to reduce to 0.1 every 20 epochs.
Batch Size	Select 32 as the batch size.
Training Rounds	Set to 100 epochs and use the Early Stop strategy.
Dropout	Use a dropout rate of 0.5 for fully connected layers close to the output layer.
Weight Decay	Set to 1e-4 to avoid overfitting.

3.7. Evaluation Metrics

Metrics such as accuracy, and F1-score are used to evaluate the model's performance on the validation and test sets. In the evaluation of models, "Adaptability" and "Generalizability" are two key concepts that describe the ability of a model to be applied in different environments and to perform on unseen data, respectively.

Accuracy is the number of correct predictions as a proportion of the total number of predictions and is applicable to assessing overall model performance.

$$Accuracy = \frac{TruePositives(TP) + TrueNegatives(TN)}{TotalPredictions} \tag{9}$$

The F1 score is the reconciled mean of precision and recall, and is a composite of precision and recall, particularly applicable to those cases where the categories are unbalanced.

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{10}$$

Mean Squared Error (MSE):

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(y_i - y_i)^2 \tag{11}$$

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - y_i)^2} \tag{12}$$

Mean Absolute Error (MAE):

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|(y_i - y_i)| \tag{13}$$

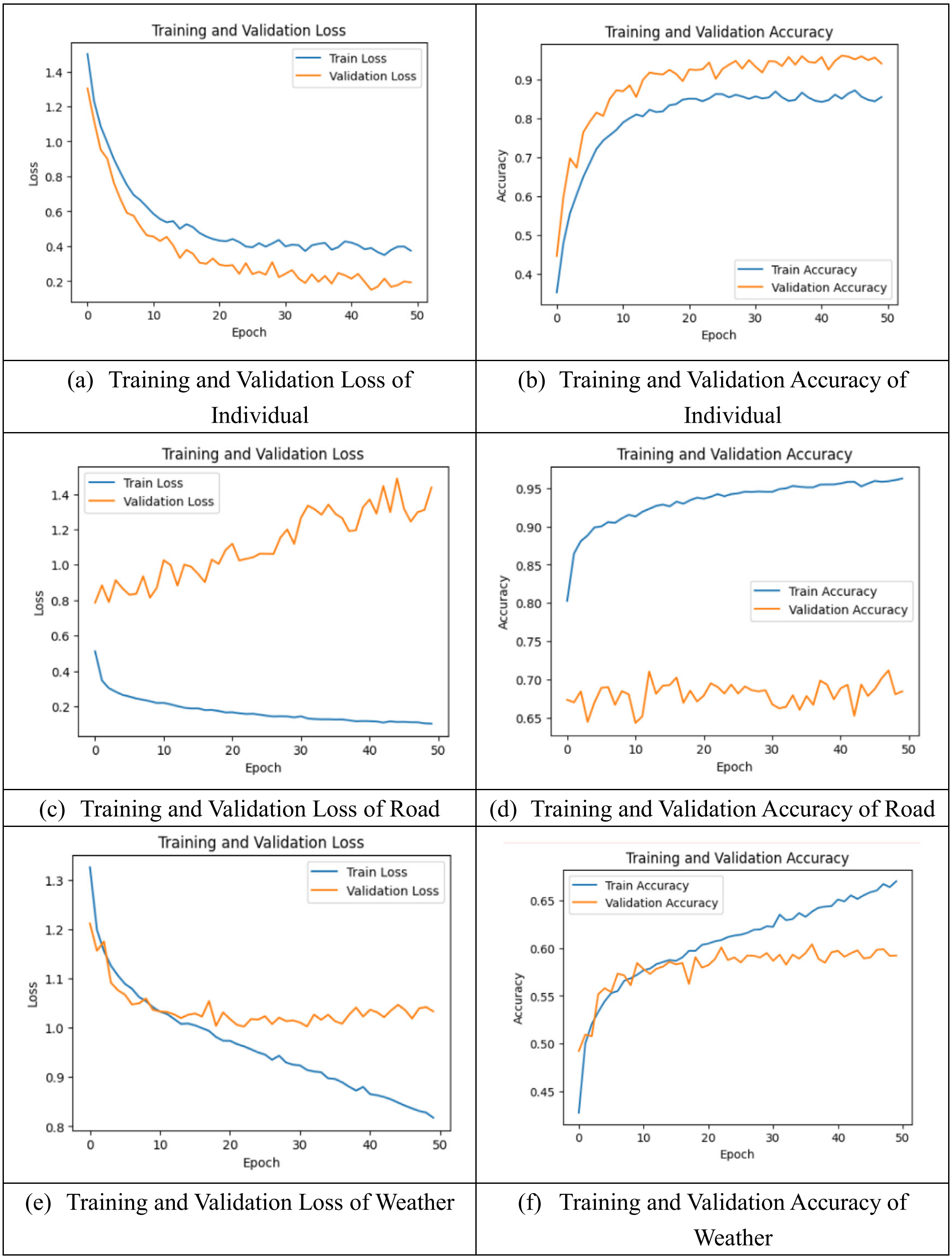
Coefficient of Determination (R-squared):

$$R^2 = 1 - \frac{\sum_i (y_i - y_i)^2}{\sum_i (y_i - y_i)^2} \tag{14}$$

4. Results and discussion

The purpose of this study is to improve the accuracy of traffic accident classification by analyzing contextual and situational data from current traffic. In the research methodology, the study chose personal factors, roadway factors, and weather factors as the objects of study, and based on traffic accident reports as well as videos in the city, the study delves into their relationship with the types of risk of traffic accidents and classifies the traffic accident scenarios. The following are the experimental results of the study's proposed methodology.

In the proposed TrafficRiskClassifier model of the study, the model is trained and evaluated for different influencing factors using the separation model approach. In Fig. 4a, the model over 50 training cycles shows that both the training loss and the validation loss gradually decrease with increasing cycles. Ideally, both should decrease and converge, indicating that the model is learning and able to generalize well to unseen data. Fig. 4b shows the increase in accuracy over the training period. We expect the accuracy to increase over time and that the validation accuracy should closely follow the training accuracy, indicating that the model is not overfitting the training data. The comparison of training and validation losses in Fig. 4c shows a clear difference. The training loss continues to decrease while the validation loss rises, indicating that the model is overfitting the training data and not generalizing well to the validation data. The training and validation accuracy comparison in Fig. 4d presents a similar problem: the training accuracy is high and continues to improve, while the validation accuracy is low and does not improve significantly, further reinforcing the signs of overfitting. The training and validation loss comparison in Fig. 4e shows the training loss (blue curve) continues to decrease as the training period increases, which shows that the model's fitting effect on the training data is gradually improving. Validation loss (orange curve) drops rapidly in the first few epochs, then levels off and even rises with slight fluctuations. This indicates that after an initial improvement in the model's performance on unseen validation data, it begins to stagnate or even slightly overfit. Finally, the Fig. 4f has both training and validation accuracies improving over time, but there is a gap between the two, suggesting some degree of overfitting of the model. In general, the TrafficRiskClassifier model shows varying degrees of performance and generalization ability under different experimental settings. In some cases, the model performed well on the training data and poorly on the validation data, clearly indicating overfitting.



(a) Training and Validation Loss of Individual

(b) Training and Validation Accuracy of Individual

(c) Training and Validation Loss of Road

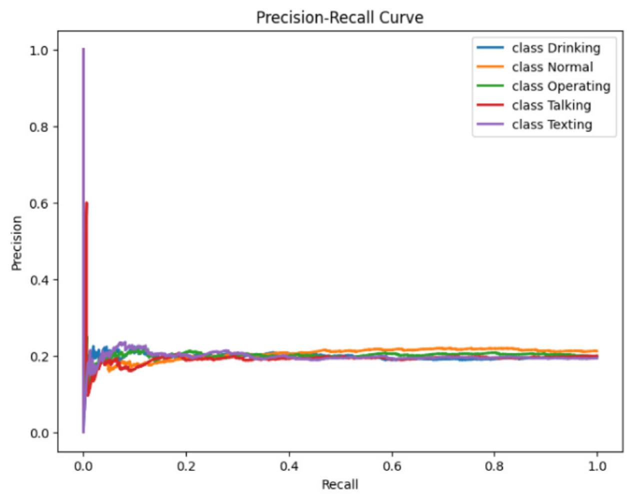
(d) Training and Validation Accuracy of Road

(e) Training and Validation Loss of Weather

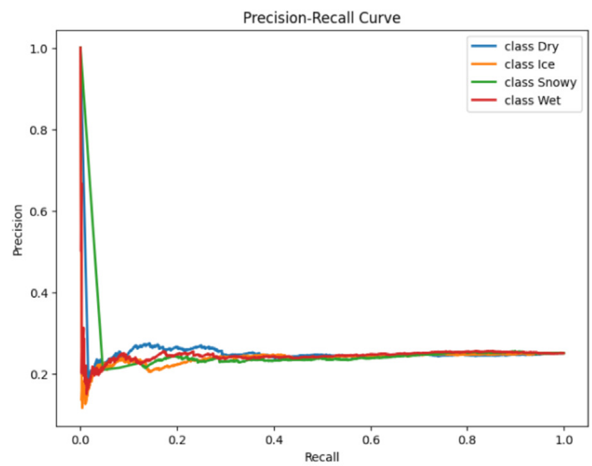
(f) Training and Validation Accuracy of Weather

Fig. 4. Loss and accuracy of different factors.

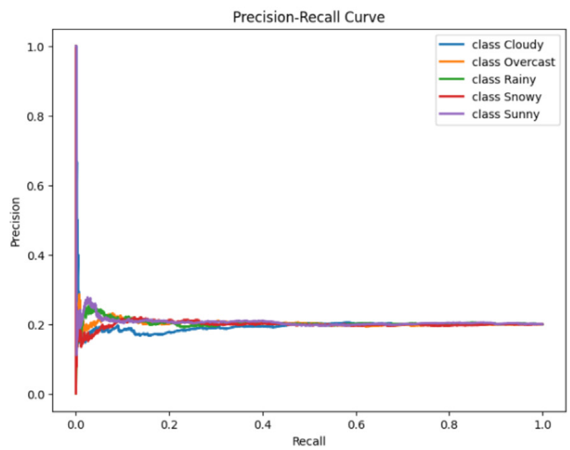
Fig. 5a (Categorization of Personal Behavior) shows the PR curves for the categories "Normal", "Texting", "Drinking", " Talking" and "Eating". It can be observed that the "Normal" category has a very high precision rate when the recall is high, indicating that the model performs well in normal behavior classification. The curves for the other categories have high precision in regions with low recall, but the precision drops rapidly as the recall increases. Fig. 5b (Weather conditions catego-



(a) PR of Individual



(b) PR of Road



(c) PR of Weather

Fig. 5. Precision-Recall line of different factors.

rization) shows the P-ratio of the four categories "Dry", "Ice", "Snow", and "Wet " PR curves for the four categories. In this figure, the PR curve for the category "Dry" performs the best, showing high precision and high recall. The PR curves for the other categories have lower precision at high recall, but still maintain some degree of precision. Fig. 5c (Road Condition Classification) reflects the results of the "Clear", "Overcast", "Rainy", " Snowy" and "Foggy". The precision rate of the "Clear" category stays high when the recall rate is high, while the precision rates of the other categories drop significantly when the recall rate increases. In review, the TrafficRiskClassifier model performs well in identifying "Normal" behaviors in personal behavior classification, while the precision rate of identifying other behaviors decreases at high recall rates. In weather condition classification, the accuracy of recognizing "Dry" weather is high, while the accuracy of recognizing other weather conditions decreases with increasing recall. In road condition classification, the model recognizes "Clear" condition with high precision and recall, while the precision for other conditions decreases with increasing recall.

In the personal behavior classification task as shown in Table 5, the confusion matrix indicates that the model has high accuracy in recognizing the five categories "Drinking", "Normal", "Operating", "Talking" and "Texting" with high accuracy. For the "Drinking" behavior, the model correctly identified 417 cases, and only 38 cases were misclassified, showing high recognition ability. For the "Normal" state, the model performed the best, correctly classifying 442 cases and only 27 cases were misclassified. The categories "Operating", "Talking" and "Texting" also perform well, with 429, 418 and 401 cases correctly categorized, respectively. The three categories of "Talking" and "Texting" also performed very well, with 429, 418 and 401 correctly categorized respectively. The main trend of misclassification is the tendency to misclassify behaviors as "Normal", which may be due to the prevalence of "Normal" data or the model's tendency to be conservative in identifying non-specific behaviors.

In the road condition categorization task as shown in Table 6, the model shows a high level of confusion in distinguishing the four categories "Dry", "Ice", "Snowy" and "Wet". The model shows high classification accuracy in distinguishing the four categories "Dry", "Ice", "Snowy" and "Wet". Especially for the categories "Dry" and "Snowy", the model correctly identified 831 and 801 cases, respectively, with very few misclassifications. For the categories "Wet" and "Ice", the model also performs well, correctly classifying 808 and 417 cases. The misclassification cases are fewer and more evenly distributed, showing no significant bias.

In the weather condition categorization task as shown in Table 7, the models were not able to categorize the weather conditions in "Cloudy", "Overcast", "Rainy", "Snowy" and "Sunny" are also recognized with high accuracy. Among them, the "Cloudy" and "Sunny" states were particularly accurately recognized, with 895 and 589 cases correctly classified, respectively. The model is also quite accurate in recognizing the "Overcast", "Rainy" and "Snowy" states. The misclassified cases are more scattered, indicating that the model's ability to recognize different weather conditions is relatively balanced.

Table 8 shows the performance of traditional approaches on different performance metrics, including single multi-task models (e.g., VGG16, VGG19, ResNet50, ResNet101, InceptionV3, MobileNet, EfficientNet) and segmentation models (e.g., ResNet50), as well as our proposed TrafficRiskClassifier model. In the comparative accuracy analysis, among the traditional single multi-task models, VGG16 and MobileNet perform better on the individual classification task, with accuracies of 71.88% and 72.81%, respectively. However, these models have lower accuracy on road and weather classification tasks. In addition, the segmentation model ResNet50 performed well on all tasks, especially on the individual and road classification tasks with accuracies of 88.62% and 87.06%, respectively. Finally the TrafficRiskClassifier model achieves 92.6% accuracy on the personal classification task when using the "Normal" setting and also shows excellent performance on the road and weather classification.

In terms of computation time, traditional models such as VGG19 and ResNet101 have long computation times, which may limit their use in real-time applications. However, the TrafficRiskClassifier model has a significantly reduced computation time in the "Normal" setting, which increases the usability of the model in real-time or resource-constrained environments. In terms of model size factor, traditional models such as VGG19 and ResNet101 are large in terms of model size, which increases the storage and memory requirements. However, the TrafficRiskClassifier model significantly reduces the model size, which makes it more suitable for mobile devices or embedded systems.

MobileNet and the segmentation model ResNet50 show high adaptability when it comes to achieving adaptability for small datasets, 77.43% and 86.73%, respectively. The TrafficRiskClassifier model in the study also shows high adaptability under the "Normal" setting, which indicates that the model can effectively adapt to different data distributions.

Finally, when confronted with the generalizability of the models, the segmentation model ResNet50 demonstrated 89.91% generalizability on the individual classification task, while MobileNet also demonstrated high generalizability (78.34%) on

Table 5
Individual Confusion Matrix.

Actual	Predict				
	Drinking	Normal	Operating	Talking	Texting
Drinking	**417**	20	8	6	4
Normal	9	**442**	4	13	1
Operating	3	16	**429**	8	0
Talking	8	17	11	**418**	9
Texting	1	10	0	1	**401**

Table 6
Road Confusion Matrix.

Actual	Predict			
	Dry	Ice	Snowy	Wet
Dry	**831**	4	5	2
Ice	7	**417**	6	0
Snowy	3	6	**801**	4
Wet	10	7	3	**808**

Table 7
Weather Confusion Matrix.

Actual	Predict				
	Cloudy	Overcast	Rainy	Snowy	Sunny
Cloudy	**895**	9	4	6	6
Overcast	1	**539**	6	9	5
Rainy	9	4	**526**	16	9
Snowy	12	2	2	**543**	4
Sunny	6	6	1	7	**589**

Table 8
Performance values obtained for traditional methods.

Performance Measures			Accuracy (%)	Time (s)	Size (MB)	Adaptability (%)	Generalizability (%)
Single multi-task model	VGG16	Individual	71.88	1175.5	169.7	51.18	66.21
		Road	66.94			48.12	71.43
		Weather	62.69			26.43	68.67
	VGG19	Individual	61.88	1282.7	230.49	48.75	56.43
		Road	68.21			24.31	68.73
		Weather	63.71			19.43	62.36
	ResNet50	Individual	16.25	1086.3	273.87	28.31	15.24
		Road	53.44			29.81	52.32
		Weather	6.56			19.75	6.78
	ResNet101	Individual	54.38	1101.4	492.5	50.93	55.16
		Road	7.5			36.37	9.76
		Weather	21.24			21.18	7.8
	InceptionV3	Individual	69.45	1036.1	254	6825	62.54
		Road	62.5			69.06	73.65
		Weather	64.06			68.5	71.24
	MobileNet	Individual	72.81	971.8	39.1	77.43	78.34
		Road	9.38			9.66	7.67
		Weather	8.44			6.56	7.23
	EfficientNet	Individual	10.94	1029.1	49.4	46.68	9.56
		Road	6.25			51.49	2.76
		Weather	7.19			20.99	6.89
Split model	VGG16	Individual	20.03	677.1	174.6	19.87	19.26
		Road	25.02	873.4	174.5	24.78	25.11
		Weather	47.57	1091.2	174.6	45.54	46.45
	ResNet50	Individual	88.62	632.52	294.51	86.73	89.91
		Road	87.06	864.27	294.5	85.45	78.67
		Weather	59.91	1062.2	294.5	57.87	50.82
TrafficRiskClassifier	No transfer	Individual	52.69	68.83	0.43	51.27	49.26
		Road	27.69	63.89	0.43	25.34	29.45
		Weather	24.75	82.97	0.44	23.51	27.71
	Normal	Individual	92.6	389.72	58.17	85.36	91.82
		Road	95.26	355.31	58.16	93.72	85.16
		Weather	81.62	475.88	58.17	80.17	80.92

the individual classification task. The proposed TrafficRiskClassifier model shows 91.82% generalization ability on the individual classification task under the “Normal” setting, which indicates that the model has good learning ability and can handle unseen data.

In this study, a 5-fold crossvalidation method was used to evaluate the performance of three different models (Individual, Road, and Weather) in TrafficRiskClassifier as shown in Table 9. The Individual model showed high stability in the five tests, with an average accuracy of 89.73%, and the fluctuation of its accuracy ranged from 88.79% to 90.81%, this result shows that

Table 9
Performance values obtained for 5 k-fold cross-validation in TrafficRiskClassifier.

Accuracy	Individual	Road	Weather
1st	88.79%	91.10%	80.69%
2nd	90.81%	91.48%	79.69%
3rd	88.80%	93.80%	85.44%
4th	88.79%	92.90%	82.06%
5th	90.21%	95.55%	82.64%
Average	89.73%	94.93%	82.51%

the model has good adaptability and generalization ability to different data distributions. Meanwhile, the Road model has the highest average accuracy of 94.93% among all the models, and exhibits the lowest volatility, with accuracy varying from 91.10% to 95.55%, demonstrating excellent performance and high stability. In contrast, the Weather model has an average accuracy of 82.51%, which is the lowest of the three models, but the fluctuation in accuracy from 79.69% to 85.44% demonstrates its improved performance and some generalization ability achieved through the crossvalidation process.

For the traffic accident risk class severity_1 (fatal risk), a polynomial regression model reveals the predictive contribution of different weather conditions, road surface conditions, and individual behavioral characteristics to this risk class as Table 10. The functional relationships of the model show that the primary and higher order terms of certain features, as well as the interaction terms between the features, are significantly associated with the fatal risk class.

For example, the positive coefficient of weather_5 (representing sunny weather) indicates that sunny weather is positively associated with a higher lethal risk class, while the negative coefficient of weather_3 (representing rainy weather) indicates that rainy weather is associated with a lower lethal risk class. This may be related to the fact that people drive faster or more adventurously in sunny weather, whereas rainy weather may cause drivers to be more cautious. In addition, the positive interaction term coefficient for weather_1 road_1 emphasizes the possibility that specific weather conditions together with specific road surface conditions may influence the risk rating. For severity_2 (severe risk) and severity_3 (slight risk), we observe significant effects of different combinations of features. For example, weather_4 presents a positive coefficient in predicting the severity risk level, which may imply that a particular weather condition is associated with an increase in crash severity. On the other hand, the feature presents a negative coefficient for minor risk levels, which may indicate that the same weather condition exhibits different patterns of influence at different risk levels. The influence of different factors, such as the interaction between weather and road surface condition, shows the importance of their joint effect on the accident risk level. For example, the negative interaction term coefficient of weather_2 road_3 may indicate that a certain pavement condition may reduce the severity of accidents in each weather.

In the Fatal model as Table 11, an accuracy of 0.987 indicates that the model performs very well in predicting fatal risk. This means that in almost all cases the model correctly distinguishes between fatal and non-fatal risks. In the Serious model, an accuracy of 0.862 is satisfactory but indicates that there is room for improvement. This indicates that the model is accurate in most cases when identifying serious risks, but there is still a percentage of false positives. In the Light model, the accuracy of 0.849 is relatively low, especially when compared to predictions of serious and fatal risks. This could mean that minor risks are not characterized enough with serious or fatal risks.

A lower MSE on Fatal indicates a lower prediction error in the prediction of fatal risk. Whereas the MSE values for Serious & Light: are 0.1186 and 0.1277 respectively, these values are relatively high, especially when compared to the fatal risk category. This indicates greater error in predicting Serious and Light risks. The RMSE value for Fatal is 0.1130, which further confirms that there is less error in the prediction of fatal risk. Serious & Light have RMSE values of 0.3443 and 0.3574 respectively, these values are higher indicating greater instability and error in prediction. The value of MAE for Fatal is 0.0253 which indicates a small average error in fatal risk prediction. The MAE values for Serious & Light are 0.2369 and 0.2551, respectively, and these higher values indicate a larger average error in predicting serious and minor risks. The R-squared values for all three traffic accident risk models are very close to zero.

Table 10
Significant characterization of coefficient heatmap of TrafficRiskClassifier.

Severity level	Characteristics	Coefficient	Correlation Explanation
Fatal	weather_5	Positive	Positive correlation to high-risk category
Fatal	weather_3	Negative	Negative correlation to low-risk category
Fatal	weather_1 and road_1	Positive	Interaction term emphasizes the combined effect of specific weather and road surface
Serious	weather_4	Positive	Positive correlation to higher risk category
Light	weather_4	Negative	Negative correlation to lower risk category
Fatal/Light	weather_2 and road_3	Negative	A particular road surface condition may mitigate accident severity for a given set of weather conditions

Table 11
Performance values obtained for classification methods.

Performance Measures		Accuracy	MSE	RMSE	MAE	R-squared
TrafficRiskClassifier	Fatal	0.987	0.0127	0.1130	0.0253	0.0004
	Serious	0.862	0.1186	0.3443	0.2369	0.0007
	Light	0.849	0.1277	0.3574	0.2551	0.0009

The TrafficRiskClassifier model performs well in predicting fatal risks, but its accuracy in predicting severe and minor risks needs to be improved. In the prediction of fatal risk, the model's errors (MSE, RMSE, and MAE) are all relatively low, indicating that the model's predictions are relatively accurate and stable in this category. In the prediction of severe and minor risks, the error metrics are high, indicating that the model's predictions are less accurate and stable on these categories.

5. Conclusion

In this study, this research successfully developed a traffic accident risk classification model called TrafficRiskClassifier, which employs an innovative combination of transfer learning, image classification, and self-supervised learning to effectively utilize video, text, and image data of urban traffic accidents. Through detailed analysis and application of advanced machine learning techniques, this study not only improves the accuracy of traffic accident risk identification, but also provides new perspectives and tools for future traffic safety management and accident prevention. The models perform well on the individual classification task, where the TrafficRiskClassifier model demonstrates 91.82%, 85.16%, and 80.92% generalization ability, respectively. In contrast, other traditional models such as ResNet50 and MobileNet, while also demonstrating good generalization ability, were slightly less accurate than the TrafficRiskClassifier.This result suggests that the TrafficRiskClassifier model has a significant advantage in dealing with unseen data and is able to more accurately predict and classify traffic accident risks. In addition, by adopting the K-fold cross-validation technique, we further validate the stability and generalization ability of the model, which strengthens the effectiveness of the model as a tool for predicting and classifying the risk of future traffic accidents. Although the TrafficRiskClassifier model demonstrated high accuracy and stability in the prediction of fatal risks, there were limitations in the prediction of severe and minor risks. The high error of the model on these categories suggests that further optimization of the model is needed in future work to improve its prediction ability on all types of risk levels.

Accurate classification and prediction of traffic accident risks is essential in current transportation system management and safety assessment. This not only helps to identify high-risk traffic scenarios, but also can provide a scientific basis for transportation planning, road design, and the implementation of safety measures. The model developed in this study demonstrates a high degree of accuracy and efficiency by integrating multimodal data and employing advanced data analysis techniques, especially in handling complex nonlinear relationships and fusing multiple types of data. This enables us to classify traffic accident risks more accurately and thus identify potential risk factors and risk scenarios more effectively.

Overall, the TrafficRiskClassifier model proposed in this study has made significant progress in classifying traffic accident risks. Future research should focus on further optimizing the model structure and algorithms to improve the prediction accuracy for serious and minor accident risks. A major limitation of this study is that it did not adequately address the unbalanced categorization of the data. Although this study adopted other strategies to improve the overall accuracy of the model, resampling techniques such as SMOTE were not employed to directly target the under-sampling of a few classes. In previous research, significant improvements in the model's ability to handle unbalanced data have been demonstrated through the application of resampling techniques, particularly in real-time collision/conflict prediction models. Future work will consider the use of such techniques to improve the model's prediction accuracy for minority classes, thereby further enhancing the model's generalization ability and utility. In addition, consideration should be given to applying the model to a wider range of traffic scenarios and conditions to verify its effectiveness and applicability in different environments. Through continuous iteration and improvement, TrafficRiskClassifier is expected to become an important tool for improving urban traffic safety and reducing traffic accidents.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Wei Sun: Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Project administration, Methodology, Investigation, Data curation. **Lili Nurliyana Abdullah:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Fatimah binti Khalid:** Methodology, Investigation, Conceptualization. **Puteri Suhaiza binti Sulaiman:** Methodology, Investigation, Data curation, Conceptualization.

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