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Vehicle Safety Improvement through Deep Learning and Mobile Sensing

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Abstract—Information about vehicle safety, such as the driving safety status and the road safety index, is of great importance to protect humans and support safe driving route planning. Despite some research on driving safety analysis, the accuracy and granularity of driving safety assessment are both very limited. And the problem of precisely and dynamically predicting road safety index throughout a city has not been sufficiently studied and remains open. With the proliferation of sensor-equipped vehicles and smart devices, a huge amount of mobile sensing data provide an opportunity to conduct vehicle safety analysis. In this paper, we first discuss the mobile sensing data collection in VANET and then identify two main challenging issues in vehicle safety analysis in VANET, i.e., driving safety analysis and road safety analysis. In each issue, we review and classify the state-of-the-art vehicle safety analysis techniques into different categories. For each category, a short description is given followed by the limitation discussion. Furthermore, in order to improve the vehicle safety, we propose a new deep learning framework (DeepRSI) to conduct real-time road safety index prediction from the data mining point of view. Specially, the proposed framework considers the spatio-temporal relationship of vehicle GPS trajectories and external environment factors. The evaluation results demonstrate the advantages of our proposed scheme over other methods by utilizing mobile sensing data collected in VANET.

1 Introduction

In modern society, cars and other private vehicles are widely used by many people. A crucial problem that each person has to face everyday is the increasing number of accidents occurred on the road. Consequently, the expense and related dangers are also recognised as a serious problem. Unfortunately, this transportation safety problem continues to worsen because of population growth and the increasing number of vehicles in urban areas. According to the report from World Health Organization[1], each year approximately 1.25 million people die of road traffic injuries around the world, which means one person is killed every 25 seconds. If the current trend continues, road accidents are predicted to increase by 65% and become the fifth major cause of death by 2030.

With the high demand for reducing road accidents and improving traffic safety, various kinds of sensors have been equipped with many newly manufactured vehicles. And the high speed mobile communication networks have accelerated the proliferation of sensor-equipped smart devices such as smartphones and wearable devices. These abundant mobile sensors provide an enormous opportunity to collect a huge amount of mobile sensing data to conduct vehicle safety analysis in vehicular ad hoc networks (VANET).

Accurate vehicle safety analysis can be applied in autonomous driving system. With large amount of sensing data and many advanced data analysis techniques, autonomous driving is very promising to achieve lower accident rate than human driving. To realize the autonomous driving, two kinds of information should be analyzed in real time, i.e., the driving safety and road safety information. The driving safety information include the driver's driving behaviors and the vehicles surroundings. The road safety information include the road safety level about various accidents.

Some studies have been conducted to survey the state of the art of vehicle safety analysis in VANET by analyzing its challenges and comparing recent approaches. In [1], Liu et al. introduce the architecture of in-vehicle networks, the controller area network (CAN) frame format and the vulnerabilities of in-vehicle networks. Then the authors make a summary on the methodologies that have been used in the experimental studies, present a general procedure that can be followed to attack in-vehicle networks, and introduce some existing experimental studies. Considering that the intrinsic vulnerabilities of the CAN bus and the available interfaces make in-vehicle networks vulnerable, the authors propose the corresponding countermeasures to enhance in-vehicle network security. In addition, some challenges and future directions are also presented. In [2], Khan et al. present a brief review of different mobile phone sensing systems which can be utilized to improve the vehicle safety and conduct intelligent driver assistance. The authors categorize all the urban sensing systems into two broader categories, such as participatory and opportunistic sensing systems. In each category of systems, three sub-classes are further identified, including personal, social and public sensing systems. Moreover, the authors also briefly introduce the area of application of each system.

Compared to these existing studies, in this article, our emphasis is on the comprehensive taxonomy and comparison of different vehicle safety analysis techniques. We first discuss the mobile sensing data collection in VANET and then identify two main challenging issues in vehicle safety analysis, i.e., *driving safety analysis* and *road safety analysis*. For each issue, many techniques are investigated and classified into different categories, as shown in Table 1. For each category, a short description is given followed by the limitation discussion. Furthermore, for the road safety analysis, existing works mainly leverage mathematical models and images analysis techniques to assess and predict the road safety. However, model-based works often need empirical assumptions and parameters, and image-based methods only focus

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1. http://www.who.int/violence_injury_prevention/road_safety_status/report/

TABLE 1: Different vehicle safety analysis techniques in VANET.

Issues	Techniques		Examples
Driving safety analysis	Analyzing driving behavior	Dynamic Time Warping	[3]
		Naive Bayes classifier	[4]
		Inertial sensing data comparison	[5]
	Detecting vehicle's surroundings	Vehicle detection	[6]
		Pedestrian detection	[7]
		Traffic sign and lane detection	[8]
Road safety analysis	Mathematical model	Analysis of Covariance model	[9]
		Linear model and thresholding	[10]
		Empirical Bayes model	[11]
	Image analysis	Support Vector Regression	[12]
		Support vector machine	[13]
		Convolutional neural networks	[14]

on extracting relationships between images and road safety, which cannot achieve high prediction accuracy. Thus, we further propose a *new deep learning framework (DeepRSI)* to predict the real-time road safety index with multi-domain urban data from the data mining point of view. Specially, the complex spatio-temporal relationship between vehicle GPS trajectories and safety index is analyzed. We also consider some external environment factors (e.g., weather condition and event), which influence the road safety index. The evaluation results demonstrate that our proposed scheme can achieve better performance than other methods by utilizing mobile sensing data collected in VANET.

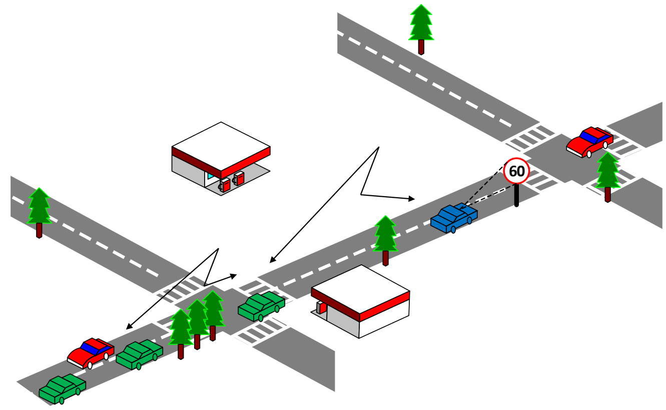


Fig. 1: An example of recognized traffic sign transmission between various vehicles in VANET.

2 Vehicle safety analysis in VANET

2.1 Mobile sensing data collection

With the proliferation of sensors, the sources of mobile sensing data in VANET can be divided into two categories: one is the smart device such as smartphone and wearable device. These smart devices are usually equipped with many sensors, including GPS, accelerometer, magnetic field, and gyroscope. The collected mobile sensing data can be preliminarily analyzed by the smart device or transmitted to the cloud through the wireless communication networks for further mining. The other one is the vehicle, which is assembled much more sensors (the average amount reaches 70 to 100) than the smart device. According to the application domain, we can divide these sensors into four categories: safety, diagnostics, convenience, and environment monitoring. Because vehicles have more computational power than smart devices, complex data analysis can be conducted locally. Moreover, vehicles are able to communicate with other vehicles, infrastructures, and mobile devices in VANET to exchange data and derived information. Thus, with these vast amounts of mobile sensing data collected in VANET, various services and applications can be provided.

2.2 Challenges in vehicle safety analysis

During the various services and applications in VANET, vehicle safety analysis is the most crucial. The philosophy of vehicle safety analysis is to obtain various safety information of vehicles and roads to prevent potential accidents and improve transportation safety. The obtained safety-related information is shared and transmitted between various vehicles in VANET. Fig. 1 gives an example of recognized traffic sign transmission. Vehicle safety analysis needs to address many challenges in the future before it becomes successful, which include data collection, computation accuracy, system dynamic, and so on. In this article, we identify two main challenging issues in vehicle safety analysis system: *driving safety analysis* and *road safety analysis*.

In driving safety analysis, driving behaviors of a driver will be analyzed to detect aggressive driving style and vehicle's surroundings will be detected to conduct intelligent driver assistance. How to accurately detect driving style with limited data collection and precisely recognize vehicles surroundings without extra specialized device are crucial to the success of driving safety analysis.

In road safety analysis, we analyze the effect on the road safety from external environments, including road geometry, traffic flow, weather, and human behavior. Through predicting the fine-grained safety level of road in a city, emergency mechanisms (e.g., sending warnings and conducting traffic controls) could be launched in advance and less traffic accidents may occur. How to dynamically and accurately analyze the effect of external factors to predict the safety level of road with high granularity are enormous challenges to the practical application of the road safety analysis.

2.3 Driving safety analysis

Over the past decade, there has been significant research effort dedicated to the development of driving safety analysis system, which is intended to enhance transportation safety and prevent accidents. Several systems have been proposed to improve the driving safety from two aspects: analyzing driving behavior [3], [4], [5], and detecting vehicle's surroundings [6], [7], [8].

With the wide adoption of smartphones and development of sensing technology, the driving style can be measured more objectively. Aggressive driving, a particular type of driving style, has been reported to be a influential factor of accidents by the American Automobile Association (AAA) Foundation for Traffic Safety[2]. By understanding an individual's driving behavior, a system can timely remind the driver to change aggressive driving styles to reduce the risk of an accident. Johnson et al. [3] study the problem of detecting and recognizing potentially aggressive driving behavior in a mobile, effective, and inexpensive way. MIROAD [3], a driver monitoring system, is developed by utilizing the Dynamic Time Warping algorithm and fusing multiple smartphone based sensor data into a single classifier. Hong et al. [4] seek to understand and model aggressive driving style by applying a machine learning technique (i.e., Naive Bayes classifier) on a number of driving-related features. To obtain an objective measurement of driving style, the authors also construct a lightweight in-vehicle sensing platform based on drivers own smartphones. Considering the effect of phone use on the driving safety, Wang et al. [5] explore a low-infrastructure approach that senses vehicle dynamics to determine whether the phone is used by the driver or passenger. The location of smartphone is inferred by comparing the centripetal acceleration measured from smartphone with the acceleration measured at a reference point inside the vehicle. In [5], a data calibration algorithm is also proposed to mitigate the noise of sensor readings and unpredictable geometries, such as different size of turns, driving speed, and driving styles. However, considering privacy protection and energy consumption in smartphone, drivers may refuse smartphones to collect data, which will limit the extensive adoption of these systems.

Besides analyzing driving behavior, many works develop various intelligent driver assistance systems to detect vehicle's surroundings to promote driving safety. Satzoda et al. [6] propose VeDAS, a multipart-based vehicle detection algorithm, to detect vehicles from fully and partially visible rear views by employing Haar-like features. A modified active learning framework is proposed to train the Adaboost classifiers. Then, the detected parts from the classifiers are associated by using a novel iterative window search algorithm and a symmetry-based regression model to extract fully visible vehicles. Jeong et al. [7] leverage the far-infrared camera to detect sudden pedestrian crossing (SPC) at night for supporting the intelligent driver assistance system. Multiple pedestrians are detected based on cascade random forest with low dimensional Haar-like and OCS-LBPs features. The system infers the SPC based on the likelihood and spatiotemporal features of each pedestrian, such as the overlapping ratio and the direction and magnitude of the pedestrians movement. Considering the spatial structures in visual signals, Li et al. [8] extend the framework of deep neural networks to conduct traffic sign and lane detection. A multitask deep convolutional network is proposed to detect the presence of the target and the geometric attributes of the target. Then the authors adopt a recurrent neuron layer to detect traffic sign and lane, although their spatial structures may be hard to explicitly define. However, these existing systems normally need expensive cameras and extra specialized devices equipped in vehicles to detect surroundings.

2. https://www.aaafoundation.org/aggressive-driving-research-update

2.4 Road safety analysis

Although analyzing the driving safety of a driver is an effective way to reduce accidents and improve the transportation safety, it fails to consider the effect from external environments. Road safety analysis, on the other hand, analyzes and predicts the safety of each road in a city, which can support safe route planning and transportation safety control. It is another crucial aspect in vehicle safety analysis. Previous road safety analysis can assess the safety index of each road in a city and make some prediction based on various mathematical models [9], [10], [11] or image analysis [12], [13], [14].

Some methods develop various models to describe and predict road safety index from factors like street geometry, traffic flow and human behavior, based on a number of empirical assumptions and parameters. Traunmueller et al. [9] investigate the relationship between the safety perceptions and characteristics of the built environment to understand the impact of place-familiarity, visual properties of environment and the presence of people. In Streetwise [9], based on the assumption that most users would provide a correct contribution, the problem of environment safety assessment is approached by utilizing an Analysis of Covariance model on crowdsourced data to detect significant factors that affect road safety. uSafe [10] proposes a platform to inform citizens about the safety of urban environments based on user-generated content reported via mobile devices. Based on the proposed model with empirical parameters, the direct participation of the citizens are extracted, and then the safety in urban environment is assessed. Especially, the anonymity and privacy protection are also considered in the proposed system. Different customizable protection mechanisms are designed and corresponding effectiveness is ensured through an empirical model. Elvik et al. [11] study the predictive performance of road safety estimation through the empirical Bayes model. The road safety is analyzed and predicted from the accident record of an entity and the expected accident frequency of similar entities determined by another empirical model named Safety Performance Function. In [11], five versions of empirical Bayes estimate of road safety are proposed and their prediction performances are compared on historical data collected in Norway. However, in these model-based works, empirical assumptions and parameters might not be applicable to all urban environments.

In addition, some methods study the relationship between visual elements and city attributes to predict road safety based on image analysis. Streetscore [12] is a scene understanding algorithm based on support vector regression to predict the perceived road safety from streetscapes. The authors create a perceptive road safety map for a city by collecting training data from an online survey with contributions from more than 7000 volunteers. Arietta et al. [13] present a method to learn the relationships between visual elements and city attributes such as crime rates, theft rates and danger perception from street-level images of a city. Effective features are automatically extracted from images and fed into support vector machine classifier. Unlike most scene analysis focusing on identifying objects directly present in a scene, Khosla et al. [14] propose to look beyond the immediately visible elements of an urban scene to predict potential crime rate for an area. Through training crime data and images collected from Google street view, the authors utilize the convolutional neural network to analyze and predict the safety of a road from an urban scene. However, these image-based methods focus on extracting

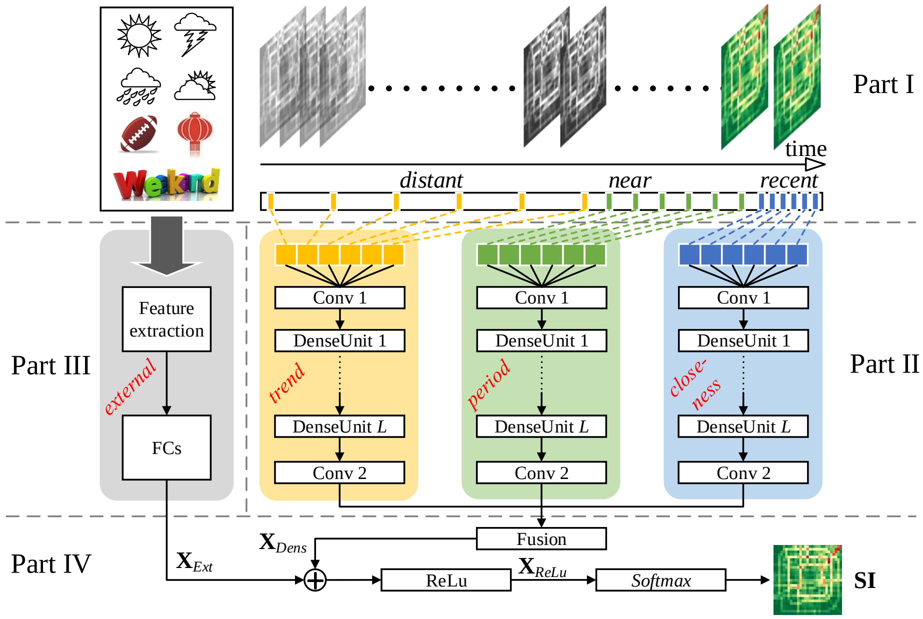


Fig. 2: Illustration of the proposed deep learning framework to predict the real-time road safety index.

relationships between images and perceptive road safety, which cannot achieve high fine granularity or prediction accuracy. Different from existing efforts, we propose a new method to analyze multiple cross-domain factors to accurately infer the road safety index of a city from the data mining point of view.

3 A NEW DEEP LEARNING FRAMEWORK TO CONDUCT ROAD SAFETY ANALYSIS

In this section, in order to conduct road safety analysis, we propose a *new deep learning framework (DeepRSI)* to predict the real-time road safety index based on the deep dense convolutional network [15]. The designed architecture is comprised of four major parts, as shown in Fig. 2.

3.1 Multiple cross-domain data collection

In part I, we collect and preprocess a large amount of multiple historical cross-domain urban data from authoritative official organizations in the New York City[3,4]. These data include urban map, weather data, holiday event data, GPS trajectories generated by over 13,000 taxis, and accident event records. These taxis in VANET are equipped with GPS which can be viewed as a large number of mobile sensors measuring the travelling speed on the road. The trajectory data can also provide the pick-up and drop-off locations in each trip. As shown in Fig. 3, we divide the city into disjointed grids. Each grid has a unique road safety index to be inferred. Vehicle GPS trajectories are preprocessed and derived into traffic flow in each grid and each time slot in the form of a matrix.

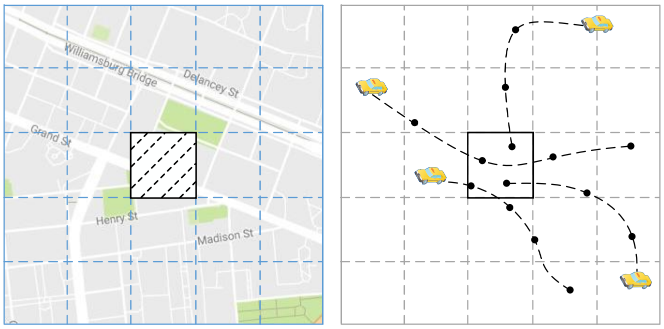
3.2 Deep spatio-temporal dense network structure

Deep learning is a technique to learn representations of data with multiple levels of abstraction by utilizing various computational models that are composed of multiple processing layers. The technique can discover intricate structure in large data sets by using the backpropagation algorithm to indicate how a machine should change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer.

In part II of DeepRSI, we design a novel deep spatio-temporal dense network structure to analyse the spatio-temporal pattern of vehicle traffic flow in each region of a city. This deep spatio-temporal dense network framework utilizes dense convolutional unit to collectively model spatial and temporal dependencies of vehicle traffic flows between any two regions in a city. For *temporal* dependencies, we first divide the time axis into three segments, i.e., recent time, near time and distant history. The vehicle traffic flow matrices of time intervals in each segment are then fed into three corresponding temporal components to model three temporal properties: *closeness*, *period* and *trend*, respectively. For *spatial* dependencies, we design a sequence of dense convolutional units in each temporal component to model the spatial properties of vehicle traffic. Thus, three spatio-temporal components are generated, which have the uniform network structure consisting of 2 convolutional layers and L dense convolutional units. Such new proposed deep spatio-temporal dense network structure can collectively capture the spatial and temporal dependencies of vehicle traffic flows between nearby and distant regions in a city.

In part III, we also concern some external factors, such as weather condition and event, which will influence the road safety index. For example, the heavy rain and snow will make roads very slippery and the heavy fog will decrease the visibility. Some holidays (such as Chinese Spring Festival) can significantly lead to traffic congestion. All these factors will easily cause serious traffic accidents. Thus, in our system, we mainly consider weather, holiday event, and metadata (i.e. day of the week and weekend). Then, we feed these external factors into a two-layer fully-connected neural network. The first layer can be viewed as an embedding layer for each sub-factor followed by an activation, and the second layer is used to map low to high dimensions that have the same shape as $\mathbf{X}_{Dens}$. The output of the external component

3. https://data.cityofnewyork.us/
4. http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml



(a) Grid. (b) Vehicle trajectories.

Fig. 3: Illustration of the grid and vehicle GPS trajectories.

is denoted as $\mathbf{X}_{Ext}$ with the parameters θ_{Ext}.

3.3 Real-time road safety index prediction to improve vehicle safety

In our system, the road safety index (SI) is a number used to communicate to the public how safe an area is. As the SI increases, traffic accidents will occur with a decreasing possibility. The SI values are divided into several ranges, and each range is assigned with a descriptor. We calculate the safety index as follows:

$$SI = (1 - R_a) * 100, \tag{1}$$

where R_a is the traffic accident rate per 100,000 inhabitants and has been normalized.

In part IV, we fuse these four components and add a classification output layer to generate a complete network architecture. The different regions are all affected by closeness, period and trend, but the degrees of influence may be various. Thus, we first dynamically aggregate the outputs of the three spatio-temporal components with a proposed parametric-matrix-based fusion method, as follows:

$$\mathbf{X}_{Dens} = \mathbf{W}_c \circ \mathbf{X}_c^{(L+2)} + \mathbf{W}_p \circ \mathbf{X}_p^{(L+2)} + \mathbf{W}_q \circ \mathbf{X}_q^{(L+2)}, \tag{2}$$

where $\circ$ is Hadamard product, $\mathbf{X}_c^{(L+2)}$, $\mathbf{X}_p^{(L+2)}$ and $\mathbf{X}_q^{(L+2)}$ are the outputs of the three spatio-temporal components, $\mathbf{W}_c$, $\mathbf{W}_p$ and $\mathbf{W}_q$ are the learnable parameters that adjust the degrees affected by closeness, period and trend, respectively. Furthermore, we combine the spatio-temporal aggregation with the external component to predict the final road safety index in each and every region, as follows:

$$\mathbf{X}_{ReLu} = ReLu(\mathbf{X}_{Dens} + \mathbf{X}_{Ext}), \tag{3}$$

where $\mathbf{X}_{ReLu}$ is the final aggregation of four components, $ReLu$ is a rectified linear unit that is simply the half-wave rectifier $f(z) = max(z, 0)$, which can yield a faster convergence than the standard logistic function and tanh function in a deep network. Finally, with a softmax classification layer being added as the output layer, the whole deep network can be trained to predict the real-time road safety index **SI** in each region of a city.

4 Experiment Results

We carry out experiments of road safety index prediction on an Intel core i7 machine with 32GB RAM and NVIDIA TITAN X graphics card. A large amount of multiple historical cross-domain

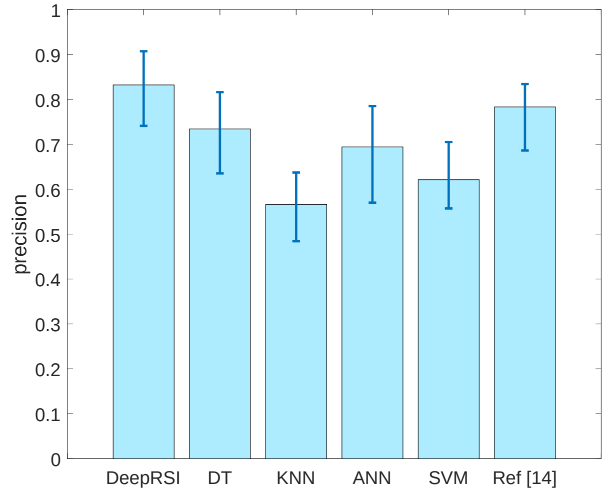


Fig. 4: Precision of different methods for road safety index prediction.

urban data (more than 200G) are collected from authoritative official organizations in the New York City. The total distance of all vehicle trips reaches 216 million kilometers, and the amount of accessing points is over 78 million. Because taxis contribute about 30 percent of traffic flow in the New York City[5], the data is big enough to represent the traffic patterns there. In this article, about two-thirds of data are used to train our models, and the other part are used as the ground truth to compare the performance of our methods. The whole city is divided into disjointed grids with the granularity of $200m \times 200m$. Each grid has a unique road safety index label to be inferred.

We measure our method by two performance metrics: precision and recall. The precision for a category in road safety indexes is defined as the ratio of the number of correctly predicting a road safety index to the total number of instances classified into this category. And the recall for a category in road safety indexes is defined as the ratio of the number of correctly predicting a road safety index to the total number of instances that actually belong to this category. The results also compare our proposed method DeepRSI with other data analysis models, including decision tree (DT), k-nearest neighbors (KNN), artificial neural network (ANN), support vector machine (SVM), and image based deep learning method [14].

As shown in Fig. 4, DeepRSI outperforms other methods in term of mean precision. The mean precision of all categories in DeepRSI can reach 83.2% with the highest precision 90.7% and lowest precision 74.1% for one category. When we apply the DT algorithm to infer the road safety index, the mean precision of all categories is 73.4%. When the KNN algorithm is utilized to infer the road safety index, the mean precision of all categories is 56.6%. And the mean precision of all categories can achieve 69.4%, when the road safety index is inferred by the ANN algorithm. When we apply the SVM algorithm to conduct the road safety index inference, the mean precision of all categories is 62.1%. Moreover, image based deep learning method [14] can achieve 78.3% mean precision of safety index prediction.

As illustrated in Fig. 5, DeepRSI can achieve better performance other methods in term of mean recall. The mean recall of all

5. www.sciencedirect.com/science/article/pii/S0965856408001900

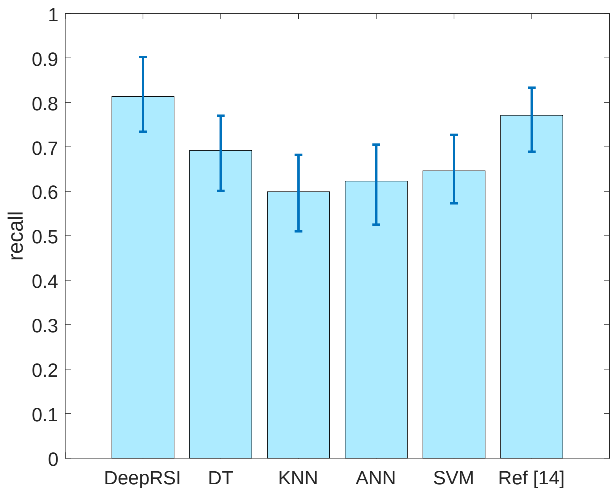


Fig. 5: Recall of different methods for road safety index prediction.

categories in DeepRSI can reach 81.3% with the highest precision 90.2% and lowest precision 73.4% for one category. And when the road safety index is predicted by DT, KNN, ANN, SVM, and image based deep learning method [14], the mean recall of all categories can reach 69.2%, 59.9%, 62.3%, 64.6%, and 77.1%, respectively.

5 Conclusion

In this paper, we discuss many challenges and approaches in vehicle safety analysis in VANET. Compared to other existing studies, our emphasis is on the comprehensive taxonomy and comparison of different vehicle safety analysis techniques. We first discuss the mobile sensing data collection in VANET and then identify two main challenging issues in vehicle safety analysis, i.e., driving safety analysis and road safety analysis. In each issue, we review and classify many the state-of-the-art vehicle safety analysis techniques into different categories. For each category, a short description is given followed by the limitation discussion. Furthermore, in order to improve the vehicle safety, we propose a new deep learning framework (DeepRSI) to conduct real-time road safety index prediction from the data mining point of view. The proposed framework considers the spatio-temporal relationship of vehicle GPS trajectories and external environment factors. The preliminary results demonstrate the effectiveness of our proposed scheme by utilizing mobile sensing data collected in VANET.

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