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COMPREHENSIVE EVALUATION OF REGIONAL ROAD TRANSPORT SAFETY SERVICE LEVEL

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Abstract. Ensuring road transport safety is a critical imperative for regional development and public welfare. This abstract outline a comprehensive evaluation framework designed to assess the service level of regional road transport safety. The proposed methodology integrates diverse parameters, encompassing infrastructure, technology, policy, and human factors, to provide a holistic understanding of the safety landscape. Using real-time data integration and powerful analytics, the assessment system combines quantitative and qualitative indicators. Technology aspects of infrastructure evaluations centre on the effectiveness of automated transportation systems and their influence on accident reduction; architecture evaluations also cover the layout of roads, advertising, and maintenance requirements. Policy evaluation is examining current laws and the ways in which they are enforced while considering how they affect the behaviour of drivers and public safety. The proposed method uses DCNN method for intelligent road transport safety. Using DCNN algorithms to monitor and regulate traffic congestion in smart cities represents a significant leap in the use of deep learning in traffic management.

Key words: road safety, transport system, intelligent transportation, deep convolutional neural network

1. Introduction. the ever-changing field of public welfare and regional development, road transportation safety is essential to long-term growth. Highways are the veins that connect people, promoting trade, social exchanges, and overall economic growth in the area. Nonetheless, given the growing intricacy of transit systems and the spike in automobile traffic, it is now crucial to prioritize the security of motorists.

This study recognizes the complexity of this important domain and sets out to thoroughly assess the service's level of regional transportation security. The aim is to create a solid foundation that surpasses conventional measurements by adopting a comprehensive strategy that incorporates multiple aspects like infrastructure, technological advances, regulations, and human behavior [31, 17].

As we examine this assessment further, it becomes clear that transportation security is a collection of interrelated issues rather than a single problem. The infrastructure is the physical foundation of safety and includes everything from roadway layout to upkeep requirements. At the same time, the introduction of state-of-the-art technologies—like smart transportation systems—is essential to enhancing safety precautions. Road usage policies are equally significant because they affect driver conduct as well as security results. Human factors emphasize the crucial role that individuals play in this safety equation. These factors include driver instruction, public understanding, and new developments like driver-assistance structures [15, 16].

The perception module builds an image of the driving environment using data from multiple sensors, while the positioning module estimates the exact location of the vehicle [1, 3]. As of right now, the preparation module is involved; its primary responsibility is to decide how to navigate the EV by using safer localization as well as cartography. All of this is made possible solely by the way one perceives data. Furthermore, the vehicle management system regulates the suspension, stopping, and speed systems [32]. Consequently, when considering every element on the road—pedestrians, cyclists, other cars, etc.—the process becomes somewhat complicated. As a result, the communications section is essential to autonomous electric cars because it enables the car to handle these issues when being driven on public roads. This kind of interaction is often referred to as

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"vehicle-to-everything" (V2X) communication, which includes "vehicle-to-vehicle," "vehicle-to-infrastructure," "vehicle-to-pedestrian," and "vehicle-to-network" (V2N) communication [23, 28].

Existing research issues are, It is a big problem to ensure the high quality and integrity of data generated by Internet of Vehicles (IoV) devices. The dependability of this data directly affects the accuracy of traffic projections and management choices. The need for real-time processing of enormous volumes of data in order to make timely traffic management choices is a significant difficulty. Processing delays might result in inefficient and ineffective traffic control. Managing processing and storage resources gets increasingly difficult as the scale of the urban environment and the number of IoV devices grows.

The ability of two automobiles to interact with one another, or interaction between vehicles, has so far been noted and examined in research [6, 13]. By informing other side automobiles of one another, this reduces collisions and permits road leaving at nominal rates of speed and acceleration [29]. Alternatively, the vehicle can connect to the facilities by sticking out of the road via V2I interaction, which disseminates data extensively [21]. Any relevant data regarding safe distances from cars nearby, limits on speed, security, obstacles, and unintentional alerts can be found among the sophisticated offerings, and it also aids in lane monitoring [14].

The main contribution of the proposed method is given below:

1. DCNNs are used to analyze photos of highways, advertising, and intersections to assess the security of roadways.
2. This aids in the detection of possible risks and the evaluation of the built environment's general safety.
3. Traffic management system optimization is aided by DCNNs. Through traffic pattern evaluation and congestion identification, the network can rapidly modify traffic signals, thereby enhancing overall road security and effectiveness.

Remaining sections of this paper are structured as follows: Section 2 discusses about the related research works, Section 3 describes the Intelligent Transport System, Road Safety and Deep Learning methods, Section 4 discusses about the experimented results and comparison and Section 6 concludes the proposed optimization method with future work.

2. Related Works. Through V2N, which integrates automobile equipment used by users, the server that offers central oversight and information on congestion, highways, and other amenities is linked [22]. Because of this, the implementation of V2X communication in combination with currently available vehicle-sensing abilities forms the foundation for intricate applications meant to improve vehicle traffic, customer entertainment, supplier offerings, and roadway security [26, 27].

The information obtained from actual contact is eventually what will determine whether such systems succeed when put into practice in a real-world setting [10]. For example, robot vision uses trajectory analysis to track automobiles in each jurisdiction [9] and the processing of images to monitor the back cars [5]. Historical data is also used to determine the optimal control parameters for optimizing the efficiency of fuel and minimizing fuel consumption [18]. Utilizing data collected by in-car sensors to analyze driver actions regardless of whether the vehicle is entirely autonomous reduces the likelihood of drunk or drowsy operating [11].

Research on communication via V2X has been done in the past, with an emphasis on safety and connection [20, 8, 4]. Additionally, reviews that focus on different facets of the self-driving car have been published. The author [30] described the current state of the art for linked cars, outlining applications, challenges, and needs for vehicle data. The idea that half of the issues are resolved by cooperative traffic management and communication between transportation infrastructures was supported in [33].In their research, they include strategies for intersections that are signalized but concentrate on non-signalized intersections. A comprehensive review of automated passing was released in [2].

Additionally, several research donations centered on cloud computing can be found [7, 25, 12]. The authors of these research papers have examined cloud-based vehicular calculating and its application to mobile online computing and transportation networks. In addition to the interaction system design, one can also find more information about privacy, safety concerns, and hot-button issues like apps in the cloud and their development. The challenges associated with car cloud networks were covered in [24]. Finally, comparable talks about vehicle cloud options, such as visitor designs, offerings, and apps that can enable vehicle clouds in an increasingly dynamic environment, may be observed [19].

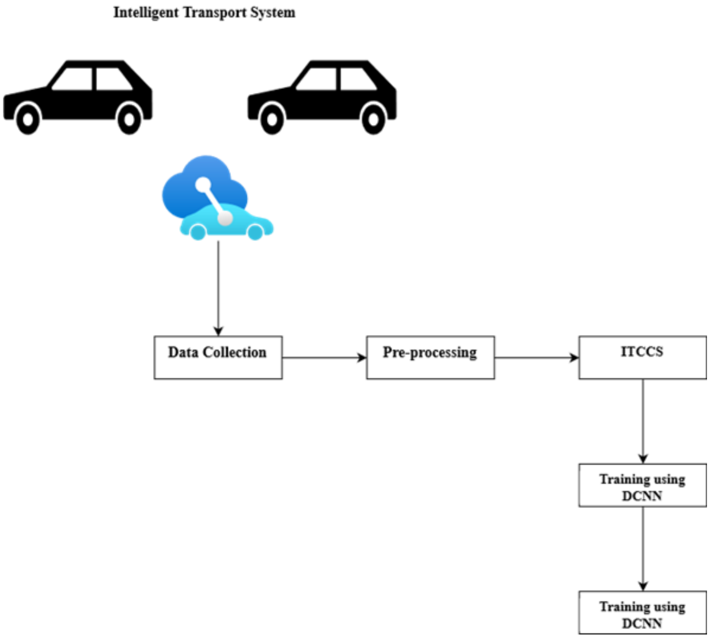

Fig. 3.1: Architecture Diagram of Proposed Method

3. Proposed Methodology. In this study, deep learning techniques are used to monitor and control traffic congestion in smart cities using an intelligent traffic congestion control system (ITCCS). This study suggests an ITCCS-VN that makes use of DCNN methods. A detailed view of the proposed ITCCS-VN, where data is gathered using IoV-enabled devices, is shown in Fig 3.1. With the help of this system, signals can be sent and current can be sent to another junction from one junction. Then, after data is received from detectors, the preprocessing, training, efficiency, and verification stages are applied to these sensing values in the sensory layer.

It is a difficult task to ensure road safety during traffic congestion; it calls for a mix of infrastructure upgrades, traffic control techniques, and increased driver awareness. The application, network, and communication layers together make up the IOV layers, which offer a thorough framework for putting safety precautions in place. Vehicles can share information in real time thanks to vehicle-to-vehicle communication. This communication can improve overall situational awareness during traffic by transmitting vital information like sudden braking, lane changes, or potential hazards on the road.

Optimized traffic flow is made possible by the interaction of cars with infrastructure, such as traffic lights and road signs. By dynamically adjusting signal timings in response to traffic levels, traffic management systems can lower the risk of accidents.

Vehicle to Infrastructure (V2I) information exchange and broadcasting are made possible by VN for vehicles. With the aid of VN, it is thus possible to collect sensory data from wireless communication vehicles rather than expensive cellular communication. First, V2V or V2I communication can be used to gather data from roadside base stations. In order to track and route traffic congestion even more, the base station (server) can then send the data it has gathered straight to the data center.

A proposed model is also shown in Fig. 3.1. In this model, preliminary processing, instruction, and performance layers are applied to the congested roadway data that the VN senses. Following the efficiency layer, the computing edge receives the output. To further anticipate if there is traffic congestion, the learned data is imported from edge computing during the validation phase.

There are stages within each step. The dataset is gathered in the first phase from a variety of traffic control sensors that are deployed across several VNs. A prelabelled VN dataset is chosen to put the suggested research model into practice. There are 2282 instances and 515 features in this dataset; 514 of the attributes are independent, and one is dependent on the output class. Preprocessing is the next layer, where moving averages and normalization are used to reduce the noise in the data. Following that, the preprocessed data are split into datasets for 70% training and 30% testing. Following this procedure, the testing dataset is stored in edge computing, while the training data are sent to the training layer.

Using DCNN, a classification procedure is carried out in the training layer to forecast traffic congestion. Every neuron, including f(x)= sigmoid(x) in the hidden layer, has an activation function. The input and hidden layer sigmoid functions of the suggested ITCCS-VN can be represented as.

By using a VN architecture to provide a secure communication mechanism between nodes, the proposed techniques significantly improve performance by mitigating noisy data through a preprocessing layer and by incorporating fused DL techniques to achieve higher accuracy, higher execution capacity, and more robust decision-making.

3.1. DCNN. The application of Deep Convolutional Neural Networks (DCNNs) in road safety is no exception to their impressive performance in a variety of computer vision tasks. DCNNs are highly effective at acquiring hierarchical representations for visual data, which makes them suitable for tasks like semantic segmentation, image classification, and object detection. The following are some ways that DCNNs can be used to improve traffic safety:

People walking, cars, bikes, and obstructions are just a few of the things in the road environment that can be detected and recognized by DCNNs. This feature makes it possible to detect hazards in real time and to send out alerts or take appropriate action. Road infrastructure evaluation is made possible by the application of DCNNs to image analysis. This entails recognizing lane markers, traffic signs, and other items that are essential for safe navigation. It is possible to mark any disparities or deterioration for maintenance. DCNNs can analyze traffic patterns and spotting irregularities like abrupt speed changes or unpredictable behavior. This data is useful for anticipating possible safety problems and putting preventative measures in place.

The integration of DCNNs with in-car cameras facilitates the real-time observation of driver conduct. This involves spotting indicators of inattentiveness, sleepiness, or reckless behavior so that structures can react quickly with alerts or interventions. DCNNs can be used to evaluate historical data and forecast areas that may be prone to accidents based on a variety of variables, including traffic volume, meteorological conditions, and previous occurrences. This makes it easier to take preventative action against accidents. Using real-time imagery from roadside cameras, DCNNs can identify dangerous situations like debris, low visibility, and slick roads. Subsequently, alerts that are generated automatically can notify officials and drivers.

Real-time analysis of traffic flow and congestion by DCNNs can aid in adaptive traffic management. By using this data, traffic signal timings can be optimized, traffic jams can be avoided, and the general safety of roads can be raised. Due to its ability to recognize and anticipate the movements of cyclists and pedestrians, DCNNs can be extremely helpful in maintaining their safety. This is especially crucial in shared road areas and at junctions. Events like incidents and road closures can be identified by DCNNs. Emergency response services can receive this information and use it to make timely, focused interventions. Road safety can be better understood by combining DCNNs with context-dependent data and data from other sensors, like radar or LiDAR. This multimodal data fusion improves safety assessments' precision and dependability.

The input layer, convolution layer, pooling layer, fully connected layer, and output layer are the five fundamental parts of the architecture. Many convolution and pooling layers may be present in a real CNN model. Here is a thorough explanation of each component.

We start by defining a few variables as follows:

n: the number of convolution and pooling layers; m: the number of samples;

hj: hj is the feature image of layer j, j = 1, 2, …, n, and h0 is the input sample xi; xi: xi is the sample i, i = 1, 2, …, m;

bj is the bias of layer j, j = 1, 2, …, n; yi is the output of sample i, i = 1, 2,…, m; wj is the convolution kernel of layer j, j = 1, 2,…, n.

The Deep CNN method is used in this smart road safety technique to distinguish between images with and without defects. Recently, a range of 2D and 3D databases have been used for Deep Convolutional Neural Network (DCNN) research [30]. AlexNet, ResNet, Mini-VGGNet, and SqueezeNet are examples of state-of-the-

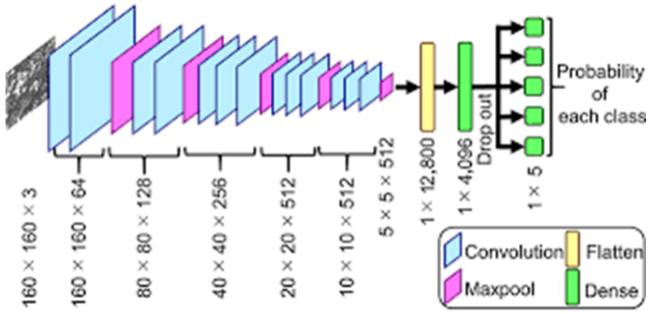

Fig. 3.2: Structure of DCNN

art DL networks for tasks like medical imaging, food processing, and fruit disease detection. This study uses the AlexNet architecture as a basis model to extract the feature maps from the input data. Equation (3.1) illustrates how it makes use of minimal convolutional procedures and 2D kernels.

$$AO_{nm}^{xy} = f(\sum_{ch=0}^{Ch_{m-1}} \sum_{rw=0}^{Rw_{m-1}} Ke_{nm}^{cr} AO_{n-1}^{(x+ch)(y+rw)} + bi_{nm}) \tag{3.1}$$

Layers and Feature Maps: The number of layers (n), the number of feature mappings (m), the biases (bi), and the kernels ([Kenmcr]) are all important components in the DCNN architecture. Ch and Rw reflect the kernel's height and width, which are important in feature extraction via convolutional methods.

The activation function (f (.)) is the ReLu (Rectified Linear Unit) function, which is noted for its effectiveness in non-linear transformations in neural networks.

Focus on Defect diagnosis: The DCNN is specifically designed to highlight the faulty region of pictures, which is critical for applications such as road safety, traffic congestion analysis, and fruit disease diagnosis. This is accomplished by focusing the fully connected feature map to the FC-layer (Fully Connected layer) largely on feature extraction from the faulty or sick region.

DCNN Structure: As illustrated in figure 2 of the cited material, the general structure of the DCNN is designed to maximize the process of discriminating between faulty and non-defective pictures, enabling efficient and accurate analysis.

The outputs attribute at [x, y] is represented by ?AO?_nm∧xy, the layers by n, the number of feature maps by m, the bias by bi, and the amount of the kernel at (c, r) for the mth feature map by ?Ke?_nm∧cr, where Ch and Rw are the kernel's whole height and breadth. Finally, the activation function (ReLu in this case) is indicated by f (.). As seen in Figure 4.3, the defective portion usually has a smaller proportion than the apple overall. As a result, we restricted a fully linked feature map to the FC-layer (completely connected) for road safety traffic congetion and initially concentrated on the feature extraction of the illness region. In figure 3.2 shows the structure of DCNN.

The first convolution layer (1D convolution 1) employs 32 convolution kernels, each measuring 5 pixels, with a stride of 1 and valid padding. The output signal z(n) can be generated by convolving the input signal x(n) with the convolution kernel w(n) of size l when it is received by a 1D convolution layer. This can be done as follows

$$z\left(n\right) = x\left(n\right) \times w\left(n\right) = \sum_{m=0}^{l-1} x\left(m\right).w(n-m) \tag{3.2}$$

$$z_t^l = \sigma(b_t^l + \sum_j z_j^{l-1} \times w_{i,j}^t) \tag{3.3}$$

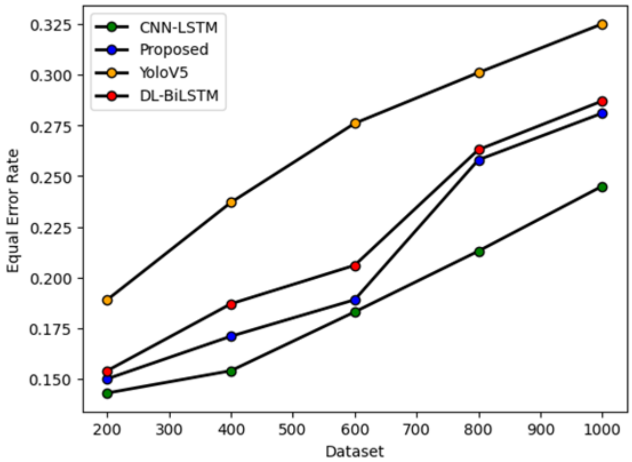

Fig. 4.1: Evaluation of Equal Error Rate

This input, represented as a 1D vector, is processed through the first convolution layer (1D convolution 1) to yield 32 distinct learned features. The convolved feature can be expressed as follows:

The lth layer's z_t∧l represents the ith feature, the (l-1)th layer's z_j∧(t-1) represents the jth feature, and w_(i,j)∧t indicates the kernel associated with the jth feature.

This DCNN approach can be useful in identifying road problems, traffic patterns, and possible risks in the context of smart road safety, contributing to more effective traffic management and road safety measures. Such technology can considerably improve road maintenance methods and overall traffic safety by precisely identifying and evaluating faults.

When scaled up, the complexity of DCNN algorithms may provide issues in terms of processing resources and energy usage. A fundamental problem remains ensuring that the system reacts efficiently to continually changing traffic circumstances and unanticipated incidents. Another problem is ensuring interoperability across different IoV devices and platforms from diverse vendors.

4. Result Analysis. Devices and programs. A machine featuring an i7-7500U CPU running at 2.9 GHz and an NVIDIA GeForce GTX 940MX GPU with 4 GB RAM was used to conduct the experiments. The code used makes use of Python 3.7.5 and the TensorFlow 2.0.0 library.

The parameter metrics used for road safety are Accuracy, Recall, Equal Error Rate (EER) and AUC. The proposed method DCNN is compared with existing methods such as CNN-LSTM ,DL-BiLSTM and Yolov5.

Equal Error Rate: The definition of EER is as follows. Where n is the total number of frames from the video being considered for anomaly detection, F P stands for false positive, and F N for false negative. A lower EER value suggests that the model is more adept at identifying anomalies.

$$EER = \frac{FP + FN}{n} \tag{4.1}$$

The point at which the false acceptance rate (FAR) and the false rejection rate (FRR) are equal is measured by the Equal Error Rate (EER), a metric that is frequently used in biometric and signal detection applications. The EER can be modified for use in the context of road safety to assess how well a system—like a smart bus system or predictive model—performs in differentiating between safe and unsafe roadways. In figure 4.1 shows the Equal Error rate of Proposed method. The proposed method achieves lower equal error rate compared with exiting methods.

Assessing the effectiveness of models or systems intended to boost road safety and enhance service delivery is a necessary step in evaluating the accuracy of road safety and service level. In figure 4.2 shows the evaluation of Accuracy.

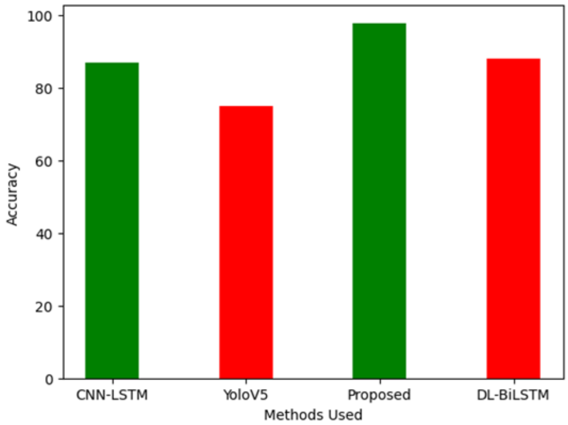

Fig. 4.2: Accuracy

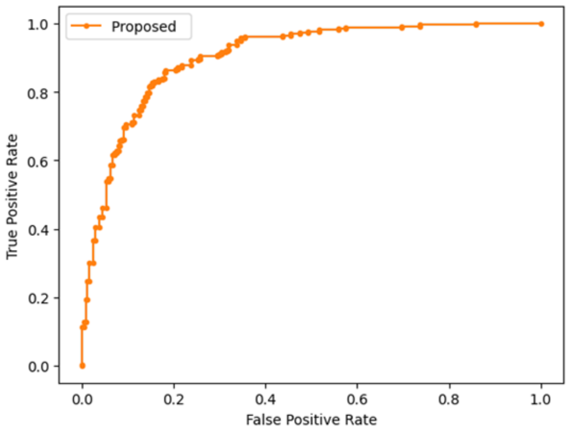

Fig. 4.3: AUC curve

The process of evaluating the precision of traffic safety measures entails determining how well systems or models are intended to improve road safety work. In the setting of automobile safety, accuracy usually refers to the degree to which a system can recognize, and forecast occurrences or circumstances related to safety. The proposed method achieves better result compared with existing methods.

When evaluating the effectiveness of binary classification models, such as those employed in applications related to road safety, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is a helpful statistic. A model's capacity to discern between positive and negative classes across a range of classification thresholds is represented graphically by the ROC curve.

A comprehensive understanding of a model's capacity to distinguish between safe and unsafe circumstances is offered by the AUC-ROC analysis. It is a useful tool for comparing various models or iterations and evaluating the overall effectiveness of road safety models. In figure 4.3 shows the evaluation of AUC curve.

Recall, sometimes referred to as Sensitivity or True Positive Rate, is an important performance indicator for assessing how well a road safety model works. It calculates the percentage of real-world successes (traffic safety incidents) that the model accurately recognizes. A high recall is preferable in the context of road safety because it means that the model is successfully capturing a significant percentage of true positive cases, reducing the amount of safety-related events that go unnoticed. In figure 4.4 shows the evaluation of Recall. The proposed

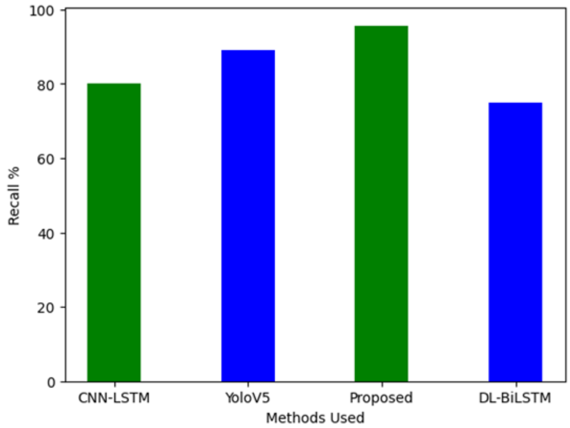

Fig. 4.4: Evaluation of Recall

method achieves better recall compared with the exiting methods.

Limitation to be considered by proposed models are: The efficacy of ITCCS-VN is strongly reliant on the accuracy and dependability of data collected from IoV devices. Incorrect or inadequate data might result in incorrect traffic projections and management choices. Scaling this technology for bigger, more complicated metropolitan contexts may bring difficulties. As the number of IoV devices and data points grows, the system's processing capabilities may need to be more resilient and efficient. Real-time data processing is crucial in traffic management. Any processing delays can result in obsolete information, potentially resulting in ineffective traffic control.

5. Conclusion. For the benefit of the general public and regional development, road transport safety must be ensured. The comprehensive evaluation framework intended to gauge the quality of service provided by regional road transport safety is outlined in this abstract. The suggested approach combines a number of variables, including infrastructure, technology, policy, and human factors, to give a comprehensive picture of the state of safety. The assessment system integrates quantitative and qualitative indicators through real-time data integration and robust analytics. Infrastructure assessments' technological components focus on automated transportation systems' efficiency and impact on lowering accident rates; assessments of architecture address road design, advertising, and upkeep needs. A vehicular network, or VN, is a type of self-organizing, service-oriented, multifunctional communication network that facilitates message exchange between vehicles and roadside infrastructure. When there is a lot of traffic, the load that the vehicles are creating may be more than the road can handle, which results in traffic congestion.

This study suggested a fusion-based ITCCS-VN that assembled data from an IoV-enabled VN using machine learning techniques and then intelligently assessed it to forecast and manage traffic congestion. Examining existing laws and the manner in which they are implemented while taking into account the impact on driver behavior and public safety is known as policy evaluation. The suggested technique for intelligent road transport safety makes use of the DCNN method.

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