Deep Learning for Security in Digital Twins of Cooperative Intelligent Transportation Systems

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***Abstract*—The purpose is to solve the security problems of the Cooperative Intelligent Transportation System (CITS) Digital Twins (DTs) in the Deep Learning (DL) environment. The DL algorithm is improved; the Convolutional Neural Network (CNN) is combined with Support Vector Regression (SVR); the DTs technology is introduced. Eventually, a CITS DTs model is constructed based on CNN-SVR, whose security performance and effect are analyzed through simulation experiments. Compared with other algorithms, the security prediction accuracy of the proposed algorithm reaches 90.43%. Besides, the proposed algorithm outperforms other algorithms regarding Precision, Recall, and F1. The data transmission performances of the proposed algorithm and other algorithms are compared. The proposed algorithm can ensure that emergency messages can be responded to in time, with a delay of less than 1.8s. Meanwhile, it can better adapt to the road environment, maintain high data transmission speed, and provide reasonable path planning for vehicles so that vehicles can reach their destinations faster. The impacts of different factors on the transportation network are analyzed further. Results suggest that under path guidance, as the Market Penetration Rate (MPR), Following Rate (FR), and Congestion Level (CL) increase, the guidance strategy's effects become more apparent. When MPR ranges between 40% ∼ 80% and the congestion is level III, the ATT decreases the fastest, and the improvement effect of the guidance strategy is more apparent. The proposed DL algorithm model can lower the data transmission delay of the system, increase the prediction accuracy, and reasonably changes the paths to suppress the sprawl of traffic congestions, providing an experimental reference for developing and improving urban transportation.**

***Index Terms*—Intelligent collaboration algorithm, intelligent transportation system, convolutional neural network, deep learning, digital twins.**

I. Introduction

IN THE 21st century, the living standards of people have been significantly improved with the accelerated growth of the social economy. During the promotion process of urban intelligentization, the means of transportation also become diversified. Urbanization has provided great convenience to people's material, spiritual, and cultural life; however, the explosive growth of urban population and transportation has become the primary factor in traffic congestion in many large cities worldwide. The lousy traffic conditions not only cause many inconveniences to people but also affect social security, disrupt social order, and bring significant losses to the economic development of the cities [1], [2]. According to statistics released by relevant departments, China's annual direct economic losses due to traffic accidents and traffic congestion account for about 2% of the annual Gross Domestic Production (GDP); in addition, the indirect economic losses, such as environmental pollution and the opportunity cost of people's time lost due to congestion on travel, cannot be estimated accurately. Therefore, improving urban transportation and investigating security performance have become the research focuses of this field. However, performances of Intelligent Transportation System (ITS) are not perfect at present, while Digital Twins (DTs) may be a solution to this problem. DTs can consistently reproduce the objects involved in the transportation field in physical space as digital models in virtual space in all time and space. The real intelligent transportation can be researched and controlled by observing, analyzing, deducing, and operating DTs. Systems of DTs are not simple numbers of ITS but multi-level, multi-scale, multi-temporal, and multi-domain comprehensive models formed based on networked perception and information acquisition via intelligent processing, reproducing the real-world ITS and other relevant objects perfectly in the virtual space [3].

Under the fast iteration of science and technology, the application fields of promising technologies, such as Big Data (BD), Fifth-Generation (5G) communication technology, Internet of Things (IoT), cloud computing, and Artificial Intelligence (AI) are becoming increasingly broader. The process of intelligence is accelerating, and the application of intelligence in the transportation field is also increasing. Intelligent Transportation System (ITS) incorporates lots of state-of-the-art technologies, such as Deep Learning (DL) and BD [4]. ITS can collect real-time traffic data, offers travel services on a large-scale, and monitor the transportation status in real-time, such as the operating time of vehicles, and driving speed records of vehicles. Hence, ITS can provide a comprehensive and objective response to the real-time speed and faults of the vehicles and understand road conditions and other information clearly.

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Congestion frequently occurs in transportation. Intelligent collaboration is a critical content in the AI field, whose primary purpose is enabling multi-agents to have productive collaboration capabilities. Research on intelligent collaboration algorithms has brought new challenges to AI, modern optimization, and machine learning theories. The core of intelligent collaboration is that multi-agents can achieve the best overall performance through efficient collaborative controls [5]. Applying intelligent collaboration to vehicle transportation can effectively optimize and coordinate traffic conditions and clear and guide congested road conditions. In the field of intelligence, the intelligent algorithms for autonomous extraction of DL data features will result in notable consequences when applied to path planning and road condition prediction, reducing various security accidents on the road [6].

In summary, rational planning and security investigation on paths in the transportation field has crucial economic value and social significance under the rapid development of computer technology and the social economy. Innovatively, a CITS DTs model based on CNN-SVR is constructed by improving the DL algorithm and introducing DTs. Besides, effective traffic guidance and evacuation strategies are formulated. The DL algorithm is improved to construct a CITS model. Furthermore, the system model is simulated to analyze its performance, presenting an investigational basis for future transportation evolution.

II. Related Work

A. Research Status of ITS

Under the blooming science and technology, ITS has been increasingly applied in actual social life since it was proposed in the 1960s. As of now, many scholars have analyzed and researched this technology. To recognize the streets in ITS, Dinh *et al.* (2017) introduced a new robust road geometry model extraction method. Finally, they found that the proposed method showed the correct path geometry. Using motion data was a sustainable method to extract the vanishing points without being affected by other side effects [7]. Iqbal *et al.* put forward a cloud computing-based field data processing and intelligent decision-making framework for ITS. They trained Artificial Neural Networks (ANNs) to deal with traffic jams. The simulation found that this framework could process data in real-time according to priority, which provided the fastest path for intelligent monitoring and enhanced the intelligent data transmission [8]. Eini *et al.* proposed a Distributed Model Predictive Control (DMPC) method for the Urban Transportation Network (UTN) system. Consequently, they found that the proposed DMPC algorithm could consider the traffic demand and interference prediction and meet all constraints throughout the entire time range simultaneously [9]. Jaleel *et al.* introduced Collaborative Adaptive Edge Signaling (CASE) as a new multi-agent RL method to control the phase and timing of traffic signals. Meanwhile, they transplanted the controller to the most advanced edge learning platform for performance comparisons. The results confirmed that transplanting this controller to a general-purpose Graphics Processing Unit (GPU)-based platform could accomplish better real-time performance and increase the calculation time by eight times [10].

B. Application of DL

As cities keep growing, the convenience of transportation plays a significant role. However, traffic congestion occurs frequently in cities, causing significant obstacles to the economic development of cities. Therefore, many scholars have researched the prediction of urban traffic conditions. Zhao *et al.* put forward a new traffic prediction model based on Long Short Term Memory (LSTM) networks. After comparing with other representative prediction models, they verified that the proposed model had better performance [11]. Akilan *et al.* designed a 3D-CNN and Long Short Term Memory (LSTM) pipeline model for applications in intelligent transportation and video surveillance [12]. Zhao *et al.* predicted the traffic conditions using the ensemble learning of the LSTM network, the Non-Negative Constraint Theory (NNCT) weighted integration, and the Population Extremum Optimization (PEO) algorithms. Simulations found that the commonly used performance indicators and three statistical tests were better than the other six commonly used traffic prediction models [13]. Sun *et al.* recommended an adaptive DL-assisted Digital Pre-Distortion (DL-DPD) model using optimized deep Recurrent Neural Network (RNN). The experimental results proved the effectiveness of the adaptive DL-DPD and revealed that the online system switched sub-DPD modules more frequently than anticipated [14].

In summary, the above analyses can reveal that most works have only predicted traffic conditions and processed data. Nevertheless, DL is not employed to investigate the security issues in ITS. Therefore, using DL algorithm and DTs to research the security issues in ITS DTs is of great significance to developing defense mechanisms in the transportation field.

III. Construction and Performance Analysis of the DL-Based CITS DTs Model

A. ITS Composition and Problems

ITS is a comprehensive transportation management system formed by integrating modern information technology, communication technology, sensor technology, and other intelligent technologies based on an almost comprehensive traditional transportation system. The core feature of ITS is the organic integration of intelligent technology and traditional transportation industry systems. It uses modern communication technology and intelligent analysis methods, such as BD, cloud computing, and AI, to perceive and optimizes the traffic conditions simultaneously. It can relieve urban road congestion, maximize the efficiency of urban road utilization, and ensure traveling safety [15], [16]. Commonly, ITS comprises a traffic information collection and management system, intelligent transportation system, and Electronic Toll Collection (ETC) system, as displayed in Figure 1.

In ITS, the traffic information collection and management system displays real-time traffic conditions to intelligent traffic command centers in various regions via sensors and devices installed on roads, vehicles, stations, and other places. After

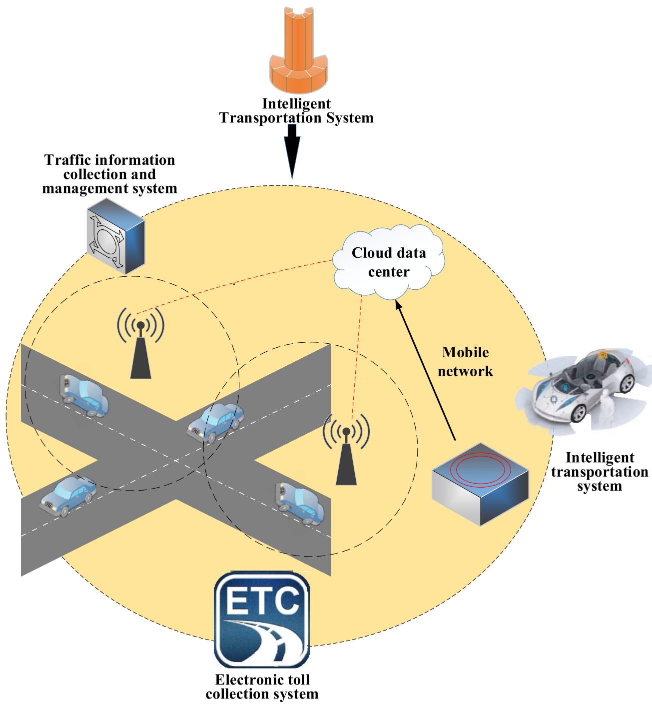

Fig. 1. A schematic diagram of ITS composition.

the sensor information is collected, each command center organizes and publishes the data information and utilizes signal lights for dynamic adjustment and control. In this way, vehicles can avoid congested road sections, and ultimately, the efficient operation of urban transportation networks can be ensured. The intelligent transportation system uses the background information center to match the capacity resources to the demands, thereby improving the efficiency of road transportation. Examples include expertly matching goods and vehicles, reducing empty trucks, and dispatching buses intelligently. The ETC system allows users to purchase ETC devices and toll cards. When passing the toll station, the reading device on the lane establishes real-time communication with the card on the vehicles, and the toll is deducted from the user's toll card [17].

However, ITS also has some problems. The first is the insufficient utilization of traffic information. The transportation system has the characteristics of large traffic volume, complicated road networks, and three-dimensional road surfaces. Nevertheless, it also has weaknesses such as more data but less effect, strong single point and weak global, and massive dormant data. Secondly, the transportation infrastructure is not perfect. The transportation infrastructure shortage hinders ITS construction goals. In the meantime, the management is backward due to the low utilization rate of current transportation facilities. Finally, the core key technology of ITS is lacking. At present, most key technologies and equipment depend on imports, such as wireless communication technology, perception technology, control technology, wireless video technology, and relevant equipment, requiring continuous payment of high costs. Therefore, research on ITS and its security performance has exceptional significance in promoting the development of China's transportation industry.

B. Application Analysis of DL in Intelligent Transportation

Accurate and fast real-time traffic flow prediction and security assurance are crucial links in ITS development, the foundation for traffic control and guidance. As one of the AI technologies, DL has achieved results beyond other methods in different fields and ushered in a new wave in the history of neural network development. Applying DL technology to solve practical problems has become a vital technique. Among various DL models, Convolutional Neural Network (CNN) is the fastest-growing and best-performing feed-forward neural network model. Its most significant advantage is that it has the characteristics of local connection and weight sharing. Loads of neurons in CNN follow a particular organization and react to overlapping areas in the visual field [18], [19]. In addition, the Support Vector Regression (SVR) also has broad application prospects. SVR can solve nonlinear problems while avoiding neural network structure selection and solving high-dimensional problems. Therefore, CNN and SVR are combined herein to accomplish real-time traffic flow prediction and security assurance.

In CNN, the first operation parameter becomes the input, the second parameter (function w) is named the kernel function, and the output is sometimes referred to as the feature map. Usually, CNN will perform convolution operations in multiple dimensions. If a two-dimensional matrix I the input, a two-dimensional kernel K is adopted:

$$S(i,j)=(I\cdot K)(i,j)=\sum_{m}\sum_{n} I(m,n)\,K(i-m,j-n) \quad (1)$$

In (1), $i, j, m,$ and n are all fixed parameters, referring to the dimension and order of the matrix. Convolution can be exchanged and equivalently written as the following equation:

$$S(i,j)=(I\cdot K)(i,j)=\sum_{m}\sum_{n} I(i-m,j-n)K(m,n) \quad (2)$$

The exchangeability feature of the convolution operation is because the kernel input is flipped, the input index is increasing, and the kernel index is decreasing. The only purpose of the kernel flip is exchangeability. Although the exchangeability is very useful during the proofing process, it is not an influential property in neural networks. In contrast, many neural network libraries will have a correlation function called cross-correlation, almost the same as the convolution operation but cannot flip the kernel:

$$S(i,j)=(I\cdot K)(i,j)=\sum_{m}\sum_{n} I(i+m,j+n)K(m,n) \quad (3)$$

Any neural network that uses matrix multiplication but does not depend on the unique properties of the matrix structure is suitable for convolution operations and does not require significant modifications. To process large-scale input more effectively, a typical CNN usually employs three crucial ideas: sparse interaction, parameter sharing, and equivariant representation to improve machine learning systems.

Support Vector Machine (SVM) is a linear classifier that applies to binary classification operations and regression problems. In the latter case, it is called SVR [20]. Assuming that the following training dataset is given:

$$T = \{(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)\} \quad (4)$$

$$\begin{cases} x_i = (x_{i1}, x_{i2}, \ldots, x_{id})^T \in \chi = R^n \\ y_i \in \gamma = R \end{cases} \quad (5)$$

In dataset (4), the values of x_i and y_i are given in equation (5), and $i = 1, 2, \ldots, N$. The sample (x_i, y_i) is often calculated according to the difference between model output $f(x_i)$ and the actual value y_i, and the loss is zero only when $f(x_i) = y_i$. SVR is described in mathematical language as follows:

$$\min_{w,b} \frac{1}{2} \|w\|_2^2 + C \sum_{i=1}^{N} L_\varepsilon (f(x_i) - y_i) \quad (6)$$

In (6), $C \geq 0$ stand for the penalty parameter, L_ε refers to the loss function, which is defined as follows:

$$L_\varepsilon(z) = \begin{cases} 0 & if|z| \leq \varepsilon \\ |z| - \xi & else \end{cases} \quad (7)$$

In (7), ξ stands for the slack variable.

C. Construction of CITS DTs Model Based on CNN-SVR

At present, technologies such as intelligent perception, network transmission, and AI keep advancing quickly. Under this background, the edge-cutting DTs ITS can implement the ITS functions of the corresponding real physical space in the virtual space. Regarding the traffic environment in the physical space, vehicle turn signals, tail lights, horns, and various traffic signs and markings can only transmit extremely limited information, making it challenging for humans to concentrate for a long time, respond quickly, and deal with emergencies rationally. DTs of ITS can be constructed by improving traffic emergencies continuously, and the development goal of "zero accidents and zero congestion" can be eventually achieved.

1) Construction of CNN-SVR Algorithm: According to the fundamental characteristics of CNN and SVR, the designed CNN model adopts a single hidden layer structure, considering gradient diffusion and calculation. The hidden layer includes a Conv layer and a Mean pooling layer, which are connected correspondingly. All nodes of the Mean pooling layer are expanded into a feature vector and establish a full connection to the output node. Then the vector is input to the SVR for the final prediction of traffic flow. The model structure is presented in Figure 2, where w refers to the convolution kernel, and *pool* refers to the mean sampling factor.

The Conv layer calculates through convolution operation, including multiple convolution planes. Assuming that $h_{1,a}$ and $w^{1,a}$ are the a-th convolution plane and convolution kernel in this layer, respectively, the excitation function is *ReLu*, and the bias is b, then the following equation stands:

$$h_{1,a} = \mathrm{Re}Lu\left(x \cdot w^{1,a} + b^{1,a}\right) \quad (8)$$

Assuming that the sizes of x and $w^{1,a}$ are respectively $M \times N$ and $m \times n$, and $M \geq m$, $N \geq n$. Then all the elements of their

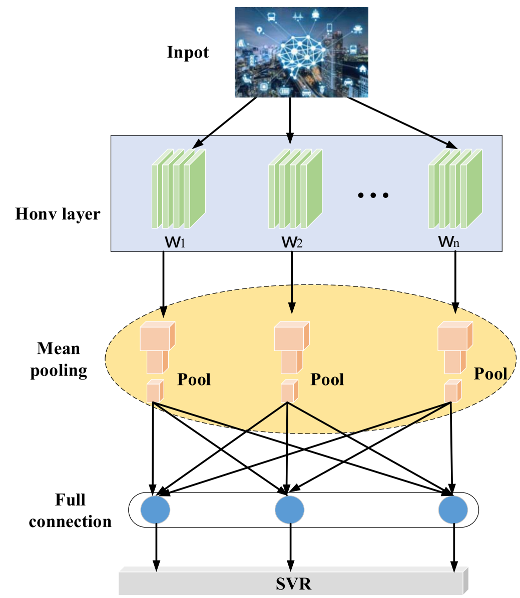

Fig. 2. The prediction process based on CNN-SVR.

convolution C are as follows:

$$C_{ij} = \sum_{s=1}^{m} \sum_{i=1}^{n} x_{i+m-s, j+n-i} \cdot w_{st}^{1,a}, \quad 1 \leq i \leq M - m + 1, \; 1 \leq j \leq N - n + 1 \quad (9)$$

The Conv layer H_1 comprises all convolution planes $h_{1,a}$.

As for the structure of the down-sampling layer, if $h_{1,a}$ is blocked non-overlappingly, and the size of each block is $\lambda \times \tau$, then the *ij*-th block will be expressed as:

$$G_{\lambda\tau}^{A}(i, j) = (a_{st})_{\lambda \times \tau} \quad (10)$$

The values of s and t are calculated as follows:

$$\begin{cases} (i-1) \cdot \lambda + 1 \leq s \leq i \cdot \lambda \\ (j-1) \cdot \tau + 1 \leq t \leq j \cdot \tau \end{cases} \quad (11)$$

The down-sampling of $G_{\lambda\tau}^{A}(i, j)$ is average pooling, and the expression is:

$$down\left(G_{\lambda\tau}^{A}(i, j)\right) = \frac{1}{\lambda \times \tau} \sum_{s=(i-1)\cdot\lambda+1}^{i\cdot\lambda} \sum_{t=(j-1)\cdot\tau+1}^{j\cdot\tau} a_{st} \quad (12)$$

This layer is the down-sampling calculation of the base layer of the volume. If $h_{2,a}$ refers to the a-th sampling plane of this layer, then:

$$h_{2,a} = g\left(\beta_2 down_{\lambda_2\tau_2}(h_{1,a}) + \gamma_2\right) \quad (13)$$

In (13), β_2 takes 1, the bias γ_2 takes 0, and the matrix g stands for the constant linear function. Here, $g(x) = x$. The down-sampling layer H_2 consists of all the sampling planes $h_{2,a}$.

The full connection layer is a regular feed-forward network whose excitation function is *ReLu*. Thus, the following equation stands:

$$H_3 = ReLu\left(w^3 H_2 + b^3\right) \quad (14)$$

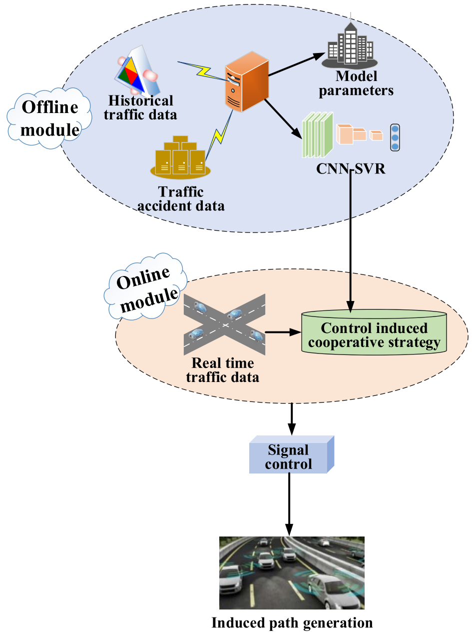

Fig. 3. A schematic diagram of CITS DTs model based on CNN-SVR.

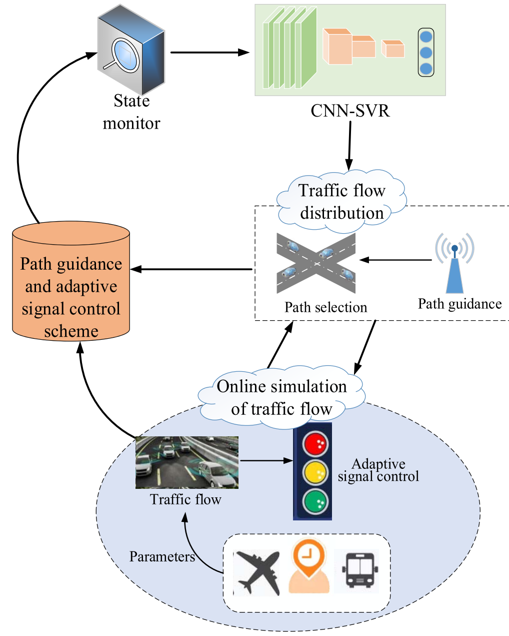

Fig. 4. The flowchart of online ITS DTs collaboration strategy.

The output of the full connection layer is H_3.

In the output layer, the linear ε-*SVR* serves as the model output, whose objective function is:

$$\begin{cases} \min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*) \\ s.t.\ f(x_i) - y_i \le \varepsilon + \xi_i \\ y_i - f(x_i) \le \varepsilon + \xi_i^* \\ \xi \ge 0,\ \xi_i^* \ge 0,\ i = 1, 2, \ldots, N \end{cases} \tag{15}$$

2) The CITS DTs Model Based on CNN-SVR: Here, the improved CNN-SVR algorithm discussed above is adopted to construct a CITS DTs model, which solves the problems of traffic distribution and signal control by establishing online and offline modules in the virtual space. The CITS DTs model based on CNN-SVR is exhibited in Figure 3.

In this model, an offline training --online real-time control and guidance coordination strategy is established. Regional control is adopted for the sudden traffic congestion in virtual space [21]. The offline module uses the constructed CNN-SVR algorithm for DL on the inherent characteristics of numerous historical traffic flow parameter data and emergency message data. The memory and time occupied during the learning process are wholly accomplished by the offline module. The online module is optimized by simultaneously optimizing the signal setting and path guidance in the same iterative process. Due to the comprehensive offline training process of the model, an ideal coordination scheme can be obtained in one iteration, which effectively reduces the computational burden. Given road network information and demand variables that change with time, the proposed algorithm can solve the traffic distribution and signal control problems. The detailed online collaboration strategy is explained in Figure 4 below.

Start
Set up every 2s be a sampling point n,
If $v_n - \mu_n < \sigma_n$
then n=n+1
Otherwise, $SL^i = n$,. $SL^i \leftarrow$ Stage duration
$v_n \leftarrow$ Prediction speed of time n
$\sigma_n \leftarrow$ Velocity mean square error of stage $[i, n]$
$\mu_n \leftarrow$ Average speed
SL is determined,
$SL = I \cdot \Delta$
Integer $I \leftarrow$ Interval length, Rounding calculation
$\Delta \leftarrow$ Interval number
end

Fig. 5. Process of the guidance cooperative prediction algorithm.

In the proposed CNN-SVR-based online module of the CITS DTs coordination strategy, the traffic flow distribution scheme is based on an adaptive signal control scheme [22], and the traffic signal is set based on the predicted dynamic traffic flow information. The complicated online iterative process is shifted to offline considering the trend of path selection under future traffic conditions, fully utilizing the massive traffic data and continually learning the internal connections between data. Significantly, the data features of sudden congestion caused by emergencies can train an intelligent trafficDTs model that can apply to online real-time prediction. In the model's guidance cooperative strategy, the process of the guidance cooperative prediction algorithm is demonstrated in Figure 5 below.

The traffic guidance strategy aims to guide the paths dynamically by providing travelers with road information.

The time that the vehicle travels on the road is expressed as the following three parts: the road segment travel time T_t^s, the time T_t^c through the intersection, and the queuing delay time T_t^d. Thus, the total travel time T_i is:

$$T_i = T_t^s + T_t^c + T_t^d \tag{16}$$

Equation (16) also proves that the dynamic travel time prediction consists of the three components on the right side of the equation. According to the driving sequence of the vehicles, the time T_t^c and the delay time T_t^d to pass the intersection are re-predicted on the premise that the first part of the prediction is completed. Suppose that the vehicle starts to enter road section i at time t_0. In that case, the travel time T_i is predicted as:

$$T_i(t_0) = T_t^s(t_0) + T_t^d\left(t_0 + T_t^s(t_0)\right) + T_t^c\left(t_0 + T_t^d\left(t_0 + T_t^s(t_0)\right)\right) \tag{17}$$

To simplify the description, suppose that:

$$t_1 = T_t^s(t_0) \tag{18}$$

$$t_2 = T_t^d\left(t_0 + T_t^s(t_0)\right) = T_t^d(t_0 + t_1) \tag{19}$$

$$t_3 = T_t^c\left(t_0 + T_t^s(t_0) + T_t^d\left(t_0 + T_t^s(t_0)\right)\right) = T_t^c(t_0 + t_1 + t_2) \tag{20}$$

The travel time of the road segment is the time from the upstream intersection to the downstream intersection to wait in line for the end of the convoy. Hence:

$$t_1 = \left(L_i - L_i^q(t)\right)/\overline{V}_i \tag{21}$$

In (21), L_i refers to the length of road section i, $\overline{V}_i$ describes the average velocity of vehicles on road section i, and $L_i^q(t)$ refers to the queue length on road section i at time t. On this basis, the queue length at t_1 is obtained:

$$L_i^q(t) = L_i - \overline{V}_i/t_1 \tag{22}$$

With the continuous advancement of traffic flow, vehicles on road section i will leave the downstream intersection. Suppose no vehicles on the road that stop in midway; that is, all vehicles entering the road from the upstream intersection exit from the downstream intersection in turn. In that case, another expression of the queue length of the vehicles at time t_1 can be obtained, namely:

$$L_i^q(t) = N_i(t_0) \cdot \overline{I}/m_i - \mu_i \overline{I} \lambda_i t_1 \tag{23}$$

In (23), λ_i refers to the green signal ratio at the downstream intersection of road section i, $N_i(t)$ refers to the total number of vehicles on road section i at time t, I refers to the average vehicle length, which is assumed to be a constant here, and m_i refers to the number of lanes. Solving the equations (22) and (23) together can obtain the expression of the travel time of the road section, as follows:

$$t_1 = \left(m_i L_i - N_i(t_0) \cdot \overline{I}\right) / \left(m_i\left(\overline{V}_i - \lambda_i \mu_i \overline{I}\right)\right) \tag{24}$$

$$L_i^q(t) = L_i - \overline{V}_i \frac{m_i L_i - N_i(t_0) \cdot \overline{I}}{m_i\left(\overline{V}_i - \lambda_i \mu_i \overline{I}\right)} \tag{25}$$

Suppose the saturation queue length of the signal period C is L_0. In that case, the arrival flow rate when the saturation is 1.0 is denoted as $L_0 = xgS/3600$. If it reaches flow $q > L_0$, a super-saturation delay will appear, that is, two or more stops. For the case where the average saturation during time T is x_i, that is, when $x_i \le 1.0$, $\lambda_i \le L_0$; when $x_i > 1.0$, $\lambda_i > L_0$, and $0 \le 3600/S = g/L_0$. Thus, the total stopping delay is:

$$D_{i,L_0} = \sum_{j=1}^{L_0} \max\left[r - \frac{jC}{L_0+1} + (j-1)t_0, 0\right] \tag{26}$$

Vehicles arrive at $C/(L_0+1), 2C/(L_0+1), \ldots, L_0C/(L_0+1), 2C/3$, respectively. Further, when the saturation reaches x_i, the total delay of vehicles during period C can be expressed as:

$$D = p_{i,1}D_{i,1} + p_{i,2}D_{i,2} + \cdots + p_{i,q}D_{i,q} + \cdots + p_{i,q_c}D_{i,q_c} = \sum_{j=1}^{q_c} p_{i,j}D_{i,j} \tag{27}$$

Then, the average delay of vehicles can be obtained as the following equation:

$$t_2 = \frac{D}{\lambda_i} = \frac{1}{\lambda}\sum_{j=1}^{q_c} p_{i,j}D_{i,j} \tag{28}$$

The average time for each vehicle to pass through the intersection *cT.* is:

$$t_3 = C_i\lambda_i/\mu_i + \beta \tag{29}$$

In (29), $C_i\lambda_i/\mu_i$ refers to the basic time for vehicles to pass through the intersection, β is a floating parameter that describes the different time it takes for the vehicle to turn in different directions, C_i refers to the signal cycle of the downstream intersection of road section i, and μ_i denotes the maximum capacity of a single lane per unit time at a downstream intersection. Hence, the travel time of the vehicle through the road section i is:

$$t_i = t_{1i} + t_{2i} + t_{3i} \tag{30}$$

D. Simulation Analysis

The proposed CITS system DTs model is predicted and analyzed on the Veins online simulation platform to verify its effectiveness. The IEEE 802.11 MAC protocol is adopted. During experiments, the vehicles are indeed covered in the transmission range of wireless signals. However, the signal transmission may fail due to various factors. Relevant experimental data are obtained by simulating the constructed system model. The security performance of the proposed algorithm is analyzed and compared with some classic DL algorithms, including CNN, LSTM [23], RNN [24], Multi-Layer Perceptron (MLP) [25], and DNN [26]. During simulation experiments, the hyperparameters are set as follows: 20 iterations, 1,000 seconds of simulation, 0.002 learning rate, and 128 batch size. The experimental environment is configured from software and hardware. As for software, the operating system is Linux 64bit, the Python version is 3.6.1, the simulation platform is Veins, and the development platform is PyCharm. As for hardware, the Central Processing

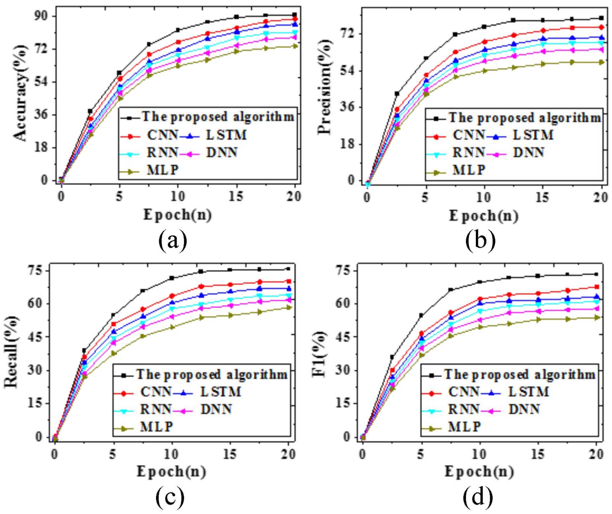

Fig. 6. Comparison of the accuracy curves of different learning algorithms.

Unit (CPU) is Intel Core i7-7700@4.2GHz 8 Cores, the internal memory is Kingston DDR4 2400MHz 16G, and the Graphics Processing Unit (GPU) is NVIDIA GeForce 1060 8G.

The state of the transportation system is analyzed from a variety of factors. The system's security prediction performance is analyzed in terms of accuracy, precision, recall, and F1 values. The system's data transmission performance is analyzed as per vehicle density changes and vehicle time changes in the transportation system. Meanwhile, the following three variables, Market Penetration Rate (MPR) [27], Congestion Level (CL) [28], Average Velocity (AV) [29], Average Traveling Time (ATT) [30], Average Delay (AD) [31], Average Pollutant Emission (APE) [32], and Following Rate (FR) [33], are employed as influencing factors to analyze the security impact of the system in the transportation field.

IV. Results and Discussions

A. Algorithm Security Performances

The proposed algorithm is compared with several classic DL algorithms. Its security prediction performance is analyzed from the Accuracy, Precision, Recall, and F1 values. The results are presented in Figure 6.

In Figure 6, the proposed algorithm is compared with several classic DL algorithms from the perspectives of Accuracy, Precision, Recall, and F1. Apparently, the security prediction accuracy of the proposed algorithm reaches 90.43%. Compared with other classic DL algorithms, the accuracy is improved by at least 2.1%. Furthermore, the accuracy difference with the MLP algorithm even exceeds 20%. In the meantime, the Precision, Recall, and F1 values of the proposed algorithm are the highest, which is at least 3% different from other DL algorithms. Hence, compared with other classic DL algorithms, the security prediction accuracy of the constructed CITS DTs model based on CNN-SVR is better.

B. Data Transmission Performances of Algorithms

The proposed algorithm and other classic algorithms are analyzed from the perspective of vehicle density changes and vehicle time changes in the transportation system. The results are shown in Figure 7 ∼ Figure 9.

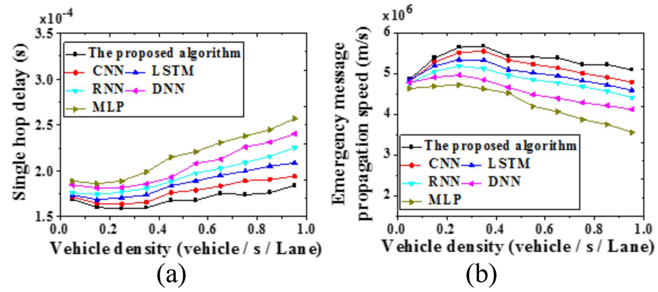

Fig. 7. Vehicle density changes under different algorithms (a. Relationship with single-hop delay; b. Relationship with message propagation speed).

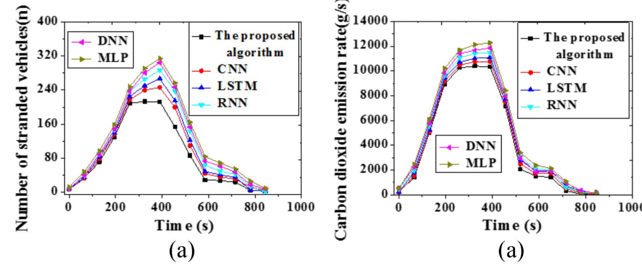

Fig. 8. Changes in the number of stranded vehicles and carbon dioxide emissions over time under different algorithms (a. Number of stranded vehicles; b. Carbon dioxide emissions).

The changes in message transmission delay with vehicle density under different algorithms are analyzed, as shown in Figure 7a. Compared with other classic DL algorithms, as the traffic volume continues to increase, the proposed algorithm can maintain a low single-hop transmission delay for the emergency messages under more lanes and dense vehicles, which is perpetually less than 1.8s. The single-hop delay of other classic DL algorithms will increase significantly. Thus, the proposed algorithm can respond to emergency messages in time. The changes in message propagation speed with vehicle density under different algorithms are analyzed, as shown in Figure 7b. Compared with other classic DL algorithms, as the traffic volume continues to increase, emergency messages in the proposed CNN-SVR CITS algorithm can be spread faster. However, the message propagation speed of other classic algorithms decreases as the vehicle density increases. Therefore, the CITS DTs model based on CNN-SVR can better adapt to the road environment and maintain high data transmission speed.

Furthermore, changes in the number of stranded vehicles and carbon dioxide emissions over time under different algorithms are analyzed, and the results are illustrated in Figure 8. The proposed algorithm enables vehicles to reach their destination earlier and leave city roads as soon as possible. At the beginning of the experiment, due to the low vehicle production rate and the small number of vehicles on urban roads, vehicles exert less impacts on the road driving state. At this time, the number of vehicles and the changes in carbon dioxide emissions of the six algorithms are basically the same.

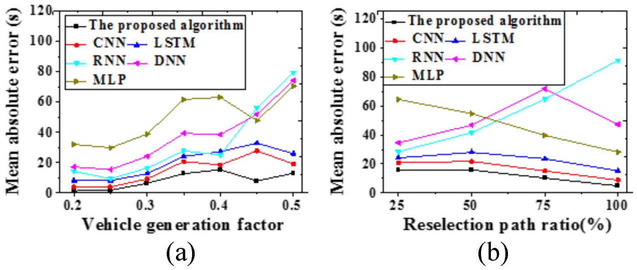

Fig. 9. Reselected path proportion and MAE of vehicle generation coefficient (a. MAE of vehicle generation coefficient; b. MAE of reselected path proportion).

However, overtime, the number of vehicles on urban roads has gradually increased, and the vehicle dissipation capabilities of the six algorithms have begun to change significantly. The number of stranded vehicles and carbon dioxide emissions of the proposed algorithm are lower. The proposed algorithm can provide reasonable path planning for vehicles, allowing vehicles to reach their destinations faster and leave the urban road network sooner. Hence, the number of stranded vehicles is the least.

The security prediction errors of each algorithm are further compared, and the results are presented in Figure 9 above. In Figure 8a, as traffic density increases, the proposed algorithm can adapt to various traffic conditions well, and its prediction error does not increase significantly; in contrast, the prediction errors of RNN, DNN and MLP increase significantly. In Figure 8b, as the number of vehicles reselecting the path increases, the error of the prediction models based on historical data increases rapidly. However, the error of the proposed algorithm remains changed. Therefore, the proposed CNN-SVR algorithm can accurately update road information and simultaneously use queues to reflect changes in traveling time of vehicles before and after; thus, it can provide relatively stable prediction accuracy.

C. Impacts of Different Factors on Traffic Security

When analyzing the collaborative induction performance of CITS, SGR, AV, ATT, AD, and APE serve as the influencing factors to study the impacts of the CNN-SVR CITS DTs model on the transportation network under different conditions. Results are explained as follows:

The improvement ratios of SGR, AV, ATT, AD, and APE of the proposed algorithm under different FRs are analyzed, as shown in Table I.

As shown in Table I, SGR shows an increasing trend as FR goes uptrend. AV increases with FR, indicating that as the number of drivers with a follower behavior increases, the efficiency of traffic operation will also increase significantly. When other factors are constant, with the increase in FR, the number of vehicles with follower behavior among vehicles without communication equipment will increase. Therefore, more vehicles will follow the vehicles under the guidance and choose unobstructed detours, so that the average road network traveling velocity increases. Regarding the relationship between FR and ATT, as FR goes up, ATT decreases because more vehicles will receive guidance among vehicles without

TABLE I
RELATIONSHIPS OF DIFFERENT FRs TO VARIOUS INDICATORS

Evaluation indicators		FR(%)			
		0	10	20	40
SGR	Mean (%)	50.78	63.62	69.41	71.53
	Improvement rate (%)	0.14	0.18	0.21	0.23
AV	Mean (m/s)	10.46	11.37	11.52	11.43
	Improvement rate (%)	21.68	27.76	29.87	33.68
ATT	Mean (s)	256.94	242.16	235.68	222.01
	Improvement rate (%)	21.08	27.64	28.67	32.06
AD	Mean (s)	191.04	172.65	168.87	156.49
	Improvement rate (%)	27.86	34.27	35.89	40.62
APE	Mean (g)	72.69	68.73	64.95	62.01
	Improvement rate (%)	19.26	25.53	26.62	29.68

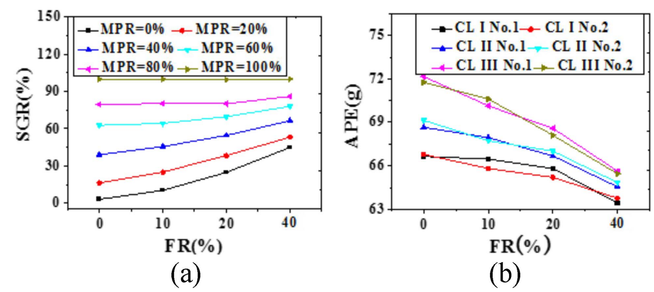

Fig. 10. Relationships of FR to SGR and APE (a. Relationship to SGR; b. Relationship to APE).

communication equipment as FR increases, the number of vehicles choosing detour paths with shorter traveling time increases, and the average travel time decreases significantly. With the increase in FR, AD presents a decreasing trend because when other factors are fixed, the number of vehicles with follower behaviors among vehicles without communication equipment increases. Consequently, the total number of vehicles subject to guidance increases, and the average delay decreases accordingly. As the FR increases, the APE will decrease, indicating that the higher the congestion level, the more obvious the improvement effect of the path guidance strategy on the environment. Relationships of vehicles' FR to Strategy Guidance Rate (SGR) and Air Pollutant Emissions (APE) are displayed in Figure 10.

According to Figure 9a, as FR increases, SGR also increases. When the value of MPR is small, the increasing trend of SGR is more apparent. Because in CITS, if the number of vehicles is fixed, under the same FR, the sum of guided vehicles among vehicles not equipped with CITS communication device and vehicles equipped with CITS communication device goes up with MPR, making the overall SGR mount up. Under a small MPR, vehicles not equipped with CITS communication device occupy the majority. As FR mounts up, guided vehicles among vehicles not equipped with CITS communication device are more, making SGR

TABLE II

RELATIONSHIPS WITH VARIOUS INDICATORS UNDER DIFFERENT CL (LEVELS)

Evaluation indicators		CL (levels)		
		Level I	Level II	Level III
SGR	Mean (%)	62.76	63.15	63.62
	Improvement rate (%)	0.17	0.22	0.09
AV	Mean (m/s)	11.17	10.89	10.54
	Improvement rate (%)	12.62	30.06	42.18
ATT	Mean (s)	228.67	239.52	246.69
	Improvement rate (%)	16.05	28.32	33.24
AD	Mean (s)	162.17	173.65	182.93
	Improvement rate (%)	21.04	34.57	41.69
APE	Mean (g)	65.08	68.72	69.84
	Improvement rate (%)	11.26	24.23	35.61

present an explicit up-going trend. According to Figure 10b, as FR increases, APE decreases. As FR increases from 0%→10%→20%→40%, APE decreases successively. The higher the CL, the more apparent the effect of increasing FR on reducing APE. When CL is level I, FR from 0%→40% reduces APE by about 4.51%; when CL is level II, FR from 0%→40% reduces APE by about 5.63%; when CL is level III, FR decreases from 0%→40% reduces APE by about 9.50%. These data shows that the higher the CL, the more apparent the improvement effect of the path guidance strategy on the environment.

The improvement ratios of SGR, AV, ATT, AD, and APE of the proposed algorithm under different CLs are analyzed, as shown in Table II.

Table II suggests that the increase in CL exerts almost no influences on the improvement ratio of SGR. However, it can significantly affect the improvement ratios of AV, ATT, AD, and APE. The reason is that the vehicle path selection is affected by different path impedance factors. For AV, ATT, AD, and APE, as the level of CL increases, the proposed algorithm shows a clearer increasing trend in the improvement ratio than those without guidance strategies. This result reveals that the route guidance strategy based on vehicle-road coordination can better improve the evaluation indicators under higher traffic demands. Influences of different factors on the ATT under different CL (levels) are analyzed, and the results are shown in Figure 11.

According to Figure 10a, as FR goes up, ATT declines, and the rate of decrease gets increasingly faster. The reason is that as FR keeps increasing, guided vehicles among the vehicles not equipped with CITS communication device occupy the majority, and vehicles selecting the detour path that takes shorter time get more so that ATT decreases sharply. Figure 10b illustrates the changes in ATT with MPR under varied CLs. As MPR goes up, ATT gently decreases; nevertheless, when MPR increases to above 60%, the decreasing speed of ATT gets reduced because an extra high MPR can reduce ATT.

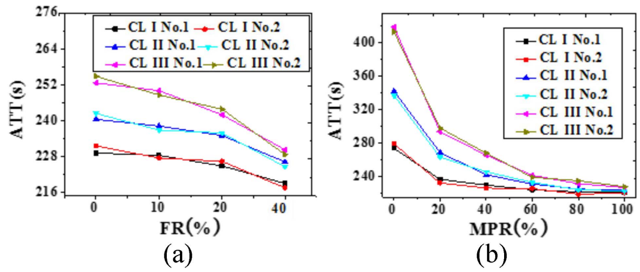

Fig. 11. Impacts of different factors on average traveling time (a. FR; b. MPR).

However, when MPR increases to a specified level, the number of vehicles selecting the roundabout path will boost, resulting in congestion shifting and decelerated ATT reduction. Hence, comprehensively weighing the equipment cost and congestion is necessary for actual applications. When MPR ranges from 40% to 80% and CL takes level III, ATT is reduced the fastest, and the gain is the maximum. Therefore, as MPR, FR, and CL increase, the path guidance strategy of the CITS model based on CNN-SVR has more noticeable improvement effects and achieves more incredible economic benefits.

V. CONCLUSION

The DL algorithm is applied to the intelligent transportation field; moreover, a CITS DTs model is built based on the SVR algorithm, and its path guidance strategies are proposed. Furthermore, the constructed system model is simulated to analyze its performance. Results suggest that the constructed model can increase the accuracy of security prediction, reaching 90.43%. Besides, it can formulate a practical guidance strategy while planning a reasonable path, providing a probing reference for developing ITS. Still, some shortcomings are found in the proposed algorithm. Only simulation experiments are run. In addition, no detailed analysis has been made on the complicated road factors, such as road intersections encountered in actual traffic conditions. Therefore, the system for the real-life transportation network will be further improved and tested in the following work, in an effort to contribute a well-founded developmental remark about the intelligent transportation industry.

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