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Traffic Flow Prediction Based on VANET Data by Combining Artificial Neural Network and Genetic Algorithm

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Abstract

In many developing countries, predicting traffic flow is one of the solutions to prevent congestion on highways and routes, and the intelligent transportation system is considered one of the solutions to problems related to transportation and traffic. Knowledge of the predicted situation for traffic flow is essential in traffic management and informing passengers. This research presents a short-term intelligent transportation traffic flow forecasting model, which first examines how traffic forecasting can improve the performance of intelligent transportation system applications. Then the method and basic concepts of traffic flow forecasting are introduced, and the two main categories of forecasting, statistical models and machine learning-based forecasting methods (supervised and unsupervised) are discussed. Finally, a method based on machine learning using a genetic algorithm is Presented. The prediction was used as a powerful method for the mathematical modeling of traffic data in the proposed genetic algorithm method to select important traffic data features and neural networks for classification. The simulation and results presented in this research show a 3 percent improvement in traffic flow prediction with the proposed method, which uses SVM as a classifier in the primary method, and the simulation of this method has output a value of 93.6, But the suggested method has an output of 96.6

Keyword: Traffic Flow Prediction, Vanet Data, Artificial Neural Network, Genetic Algorithm.

1. *Introduction*

One of the critical issues in the transportation system that can be solved with the help of the intelligent transportation system is the management and identification of traffic congestion on urban and suburban roads. Vehicle ad hoc networks are presented as a generation of networks to improve driving safety and comfort. These networks provide the connection between mobile hosts (vehicles). Vehicles in these networks can share information in a short range using wireless protocol (Hajian, S.R., 2015; Singh, G., Chakrabarty, N., & Gupta, K., 2014). With the help of using MANETs in the transportation system and making the system smarter, vehicles and roads can be equipped with facilities that allow vehicles to know the position of the road ahead and the status of vehicles moving on the same route. Find and prevent them from entering crowded areas and getting involved in traffic. In this way, on the roads, installing the necessary infrastructure around the road, such as cameras. By equipping cars with new technologies such as global positioning systems and sensors, it is possible to establish communication between moving vehicles to exchange traffic information and be aware of the condition of the road ahead, allowing drivers to make intelligent decisions and refrain from Entering crowded areas. Many methods have been proposed to detect congestion in road traffic using VANETs, each with limitations. Currently, road traffic management systems are based on a centralized strategy that uses various technologies, such as cameras and sensors, to obtain information about traffic conditions. The data is analyzed in the data processing center, where decisions are made and communicated to operational services and drivers through panels and displays on the road. Most congestion detection algorithms are designed to identify areas with high traffic congestion and low speeds. Each vehicle receives and broadcasts information such as position and speed and processes information from other vehicles in the network. The development of a traffic congestion detection system significantly impacts the economy, environment, and society, and in general, it allows for spending less time in traffic (Hajian, S.R., 2015; Singh, G., Chakrabarty, N., & Gupta, K., 2014).

One of the critical technologies for intelligent transportation systems is VANET, which tries to make the environment safer and better transportation by using wireless communication. Traffic flow prediction with high accuracy is an essential issue in current transportation systems. It can help to have the best route planning, better choice in choosing a more significant route for passengers, and reduce traffic flow (Hajian, S.R., 2015). Determining where and when traffic occurs is a promising solution for transportation management. However, the new view of network traffic flow is that the traffic on the road can affect the network traffic. According to V2V communication in VANET, vehicles can send packets to each other to predict road traffic. With the increase in vehicles and traffic on the roads, the number of sent packets increases, leading to network traffic. Previous studies have worked on road and network traffic separately and are reviewed. However, most of them independently addressed the traffic problem on the road or network. At the same time, there is a need to explore the relationship between road and network traffic parameters and the goal of network traffic prediction.

Intelligent methods through machine learning (ML) techniques are optimal solutions that can solve traffic forecasting problems to predict traffic flow. Some computational approaches, such as Bayesian modeling, fuzzy logic, hybrid modeling, neural networks (NN), and statistical modeling, most of them, especially neural networks, are promising solutions to improve the prediction accuracy in data traffic flow. A significant point that should be considered in all these cases is the accuracy of the forecast. Machine learning techniques are divided into three types: unsupervised learning (training is based on unlabeled data), supervised learning (training is based on labeled data), and reinforcement learning (learns from the performance of the learning agent). In addition, some types of ML schemes, such as transfer learning and online learning, are classified by these three types of ML schemes (Sepasgozar, S. S., & Pierre, S., 2022).

Traffic flow prediction plays a vital role in controlling traffic flow and preventing traffic from happening. The city is a complex system that consists of multiple and interdependent subsystems, of which the traffic system is one of its essential subsystems. Studies show that this is the cornerstone of the world economy (Transportation and Economy Report, 2021). It has also been announced as one of the main dimensions of a smart city (Rizwan, P., Suresh, K., & Babu, M. R., 2016, October). Therefore, active traffic management is a must. In most countries, traffic is managed through fixed time signals, while in large cities of some developed countries, traffic is managed through central control systems. Today, different control methods, such as traffic lights, variable news signs, and highway entrance timings, require predicting traffic conditions. The parameters involved in solving the traffic problem include wide vehicles and street width, traffic light function, and the number and conditions of entry and exit routes, which need proper control and use.

2. Related Works

In 2018, Zhang et al. proposed a model based on deep belief networks (DBN) for traffic flow prediction. In addition, they use the Fletcher-Reeves conjugate gradient algorithm to optimize the fine-tuning of model parameters. Since the traffic flow has various characteristics at different times, including weekdays, weekends, days, and nights, the meta-parameters of the model must adapt to time. Therefore, they use a genetic algorithm to find the optimal meta-parameters of DBN models for different times. Data sets from the Caltrans performance measurement system were used to evaluate the performance of their models. Experimental results show that the proposed model performs better at different times (Zhang, Y., & Huang, G., 2018).

In 2018, Du et al. proposed a multimodal hybrid deep learning method for short-term traffic flow prediction, which can jointly and adaptively capture the spatiotemporal correlation and long-term interdependence features of multimodal traffic data by an auxiliary multimodal deep learning architecture. The basic module consists of one-dimensional convolutional neural networks (1D CNN) and recurrent units (GRU), To learn Due to the highly nonlinear characteristics of multimodal traffic data. The first is used to capture local trend characteristics, and the second is used to capture long-term dependencies. Then, they designed a hybrid multimodal deep learning framework to integrate the feature-sharing representation of traffic data from different modalities by several attentional CNN-GRU modules. The results showed that the proposed multimodal deep learning model could handle complex nonlinear urban traffic flow prediction satisfactorily and effectively (Du, S., Li, T., Gong, X., & Horng, S. J., 2018).

In 2019, Han et al. proposed a model that uses a convolutional neural network to extract spatial features and short-term memory to extract temporal features of traffic flow. The connected parallel structure of the convolutional neural network and short-term memory reflects a compelling performance in traffic flow prediction. The Shanghai Inner Ring Elevated Road dataset is used to predict 591 sensors in 6 months, To apply the parallel spatiotemporal deep learning network in the prediction of large datasets. Experimental results confirm that the overall performance of our parallel spatiotemporal deep learning network outperforms other state-of-the-art methods (Han, D., Chen, J., & Sun, J., 2019).

In 2021, Li et al. proposed a model aimed at spatiotemporal correlation and evolution characteristics of traffic flow data, the Conv-BiLSTM module including a convolutional neural network (CNN) and a two-way short-term memory (BiLSTM) considering the spatiotemporal characteristics. They gave. First, the obtained traffic speed data based on spatiotemporal features are constructed into a three-dimensional matrix as input to the prediction network module. After CNN extracts spatial features, temporal features and alignment features are extracted by BiLSTM, followed by prediction results as output. Prediction and evaluation experiments on highway traffic data in Shanghai prove that the traffic congestion situation predicted by this method is mainly consistent with the actual situation. The results show that the proposed method is more efficient for predicting traffic congestion than conventional and advanced methods (Li, T., Ni, A., Zhang, C., Xiao, G., & Gao, L., 2020).

In 2021, Qasimpour and colleagues designed a system to collect traffic data needed for research. In the next step, the collected traffic data was called, and using the actions that were done for its standardization and normalization, the error rate was calculated using test and training data. Then traffic data analysis was done using a primary neural network and wavelet, and the error rate was calculated. The results show that calculations using wavelet transforms are suitable; the error values using test and training data were 22% due to the smaller number of inputs. In other words, the level of desirability was about 22%. In the last stage, the collected traffic data were optimized using optimization algorithms, and the best point with the least possible error was calculated for each optimization algorithm (Ghasempoor, Z., & Behzadi, S., 2021).

In 2022, Ghazlan and his colleagues presented a paper titled "Network Traffic Prediction Model Considering Road Traffic Parameters Using Artificial Intelligence Methods in VANET." They believe that vehicular ad hoc networks (VANETs) are built on vehicles that are intelligent and capable of vehicle-to-vehicle (V2V) and vehicle-to-roadside (V2R) communications. In this paper, a model for predicting network traffic is proposed considering the parameters that can lead to the occurrence of road traffic. The proposed model integrates a Random Forest-Gated Network Traffic Prediction (RF-GRU-NTP) algorithm to simultaneously predict traffic flow based on road and network traffic. This model has three phases: network traffic prediction based on V2R communication, road traffic prediction based on V2V communication, and network traffic prediction considering road traffic based on V2V and V2R communication. The proposed hybriimplemented in the third phase selects essential features from the combined data set (including V2V and V2R communications using random forest (RF) machine learning algorithms and deep learning algorithms to predict network traffic flow. It is applied where the Gated Recurrent Unit (GRU) algorithm gives the best results. The simulation results show that the proposed RF-GRU-NTP model has better performance in execution time and prediction errors than other algorithms used for network traffic prediction (Sepasgozar, S. S., & Pierre, S., 2022).

In 2022, Medina-Salgado and his colleagues presented an article titled "Review: Urban Traffic Flow Prediction Techniques." They believe that in recent decades, transportation infrastructure development has made significant progress. However, traffic problems continue to expand due to the increase in population in urban areas that require these means of transportation. This has led to an increase in congestion control problems that directly impact citizens: air pollution, fuel consumption, traffic violations, noise pollution, accidents, and loss of time. In Latin America, the haphazard growth of cities increases distances and routes, and the number of cars and motorcycles increases rapidly, adding to the problem. In this sense, intelligent transportation systems are an alternative to improve the traffic environment; they combine the Internet of Things and intelligent algorithms to collect data from multiple sources and process information to improve the efficiency of transportation flow, respectively. However, the processing and modeling of traffic data is challenging due to the complexity of road networks, the space-time dependence between them, and the heterogeneous traffic patterns. In this review, (1) intelligent techniques used to analyze mobility data in predicting traffic flow in urban areas are grouped; likewise, (2) the results of the implementation of said techniques are shown, in addition, (3) The procedures performed are described and analyzed to understand the advantages and limitations of these intelligent techniques. According to the above, (4) the datasets used in the literature and available for use are shown; in addition, (5) the measurable results of the accuracy of different techniques were compared, highlighting the advantages and limitations, which allowed (6) related challenges are identified and from there, (7) a general classification is proposed in which the knowledge obtained in this traffic flow study is converged from a computational approach (Medina-Salgado, B., Sanchez-DelaCruz, E., Pozos-Parra, P., & Sierra, J. E., 2022).

3. The Proposed Method

When traffic congestion occurs, the corresponding recovery time required is not affected by the traffic control strategies but only by the scaling laws related to the degree of congestion. Whereas, due to the physical limitations of traffic infrastructure capacity, reactive approaches can only try to maintain the system equilibrium in the face of traffic flow fluctuations. Whenever traffic volume fluctuates beyond the physical limit of the traffic infrastructure's capacity, reactive methods cannot do anything in this field, and traffic congestion occurs. On the contrary, by extracting and analyzing the feature information in the traffic flow information recorded by ITS, the preventive method can predict the future traffic volume in a certain period and formulate the appropriate traffic control plan (such as deviating measures). Adjusting the traffic lanes and increasing the input of public transport capacity at a particular time.) to reduce the traffic flow in the expected period as much as possible, so the possibility of traffic congestion can be eliminated (Medina-Salgado, B., Sanchez-DelaCruz, E., Pozos-Parra, P., & Sierra, J. E., 2022).

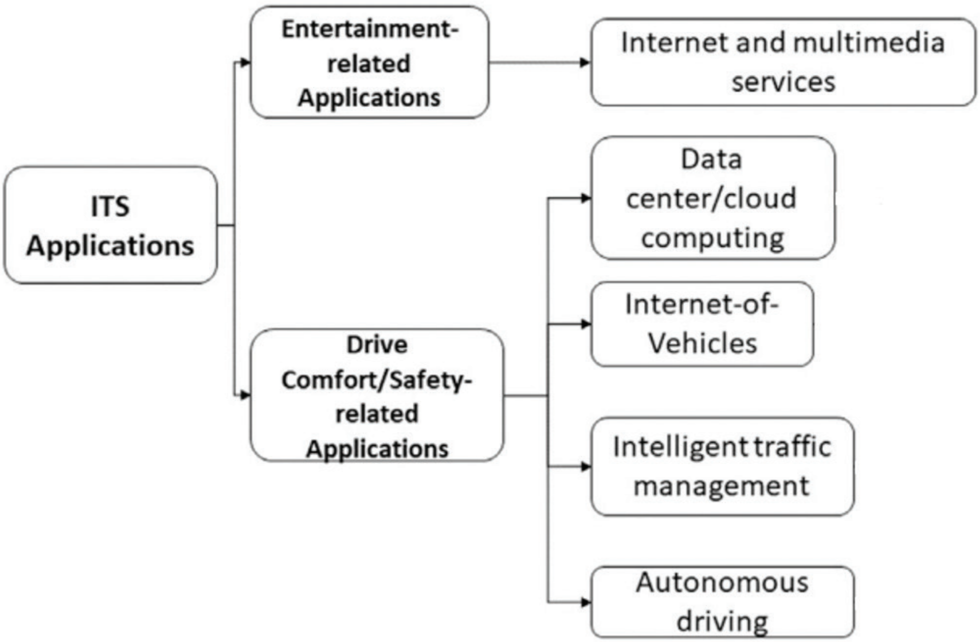

Fig. 1: An illustration of the classification of applications related to ITS

Before we discuss specific approaches, we describe existing ITS-related applications and their corresponding research directions in this section. We then detail the features of the proactive approach and how the traffic forecasting approach, as the core of such methods, can further enhance the performance of the ITS.

In Fig. 1, we provide a taxonomy of existing ITS-related applications. Currently, ITS-related applications are divided into two main categories. The first is entertainment applications. Its primary purpose is to provide Internet access services (e.g., multimedia data streaming.) to passengers in the vehicle or other participants in the transportation system to enhance their travel comfort level. For such applications, the relevant research focuses on improving the reliability and efficiency of data transmission, e.g., reducing packet loss ratio and data transmission latency. The second category of applications is the focus of current research, i.e., driving safety and comfort-related applications.

Typically, the primary design goal of vehicular networks is to ensure the reliable transmission of traffic management information and traffic safety information within the transportation system. The main challenge is to overcome the negative impact of the highly dynamic topology of vehicular networks on data transmission. To achieve this design goal., existing research efforts are mainly focused on the design of routing protocols. To face this challenge, data dissemination methods and SDN-enabled VANET delivery schemes (Boukerche, A., Tao, Y., & Sun, P., 2020). The flowchart of the proposed method is shown in figure 2.

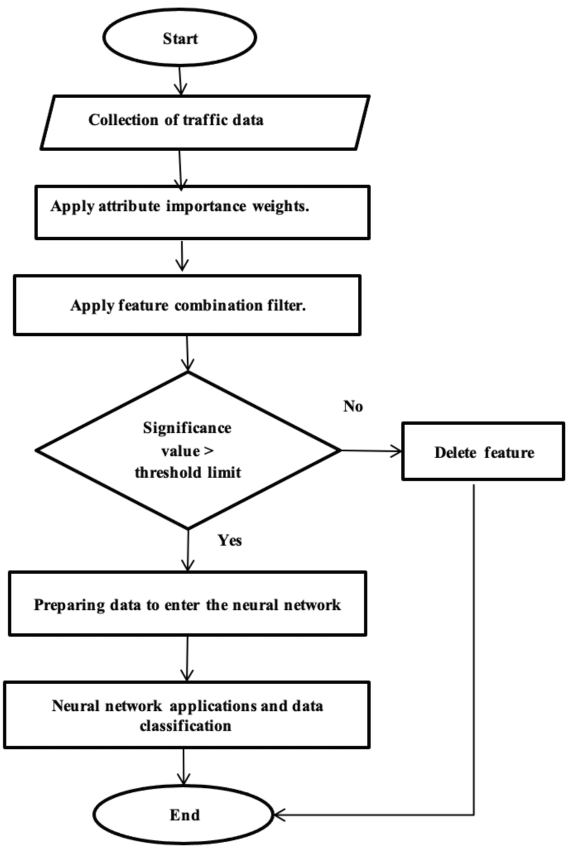

Fig. 2: Flowchart of the proposed method

Based on the above flowchart, traffic data was first collected at the beginning of the stage. Vanet-related data is collected and analyzed as usable traffic data. After data collection, weights are assigned to the parameters in the next step, and a threshold value is also considered. If the feature is greater than the limit, it enters the following steps, and if the feature is not greater than the limit, the feature is removed and not be combined with other features. Neural networks act as a classifier and output extraction on data.

The proposed method provides a model for predicting short-term traffic flow. To provide a more comprehensive overview of the role of traffic prediction in ITS systems, firstly, how traffic prediction can improve the performance of relevant ITS applications is discussed. Then, the general forecasting method and some basic concepts of traffic flow forecasting are introduced. Accordingly, two main forecasting categories were discussed, namely statistical models and ML-based forecasting methods. Supervised and unsupervised learning methods were introduced for the machine learning category. Moreover, a method based on machine learning using algorithm and genetics was presented, which considers the role of genetic algorithm in combining feature and neural networks for classification and prediction work.

Genetic algorithm: Genetic algorithm is an optimization method inspired by living nature that can be used in classifications as a numerical method, direct and random search.

Objective function: The objective function used in this method is based on the minimization of the set, and because this function is used as a combiner of features, it has tried to minimize each fitness function, which ultimately causes the maximum number of cases to be selected.

$$\text{Cost=Min(F)} \tag{1}$$

As it is clear from the above function, the purpose of the cost function is to minimize each fitness-related feature. Fitness function: The fitness of chromosome F, which is a function of all introduced fitness parameters, is defined as follows:

$$F = \sum_i \alpha(w_i, f_i), \forall\, f_i \ \in \{X, M\} \tag{2}$$

The initial fitness parameters are assigned arbitrary weights w_i. After the best-fit chromosome is evaluated for each generation, the weights for the fitness parameters are updated as follows:

$$w_i = w_{i-1} + c_i \times \Delta f_i \tag{3}$$

Here Δf represents the change in the value of the fitness parameter, $\Delta f_i = f_i - f_{i-1}$ and $c_i = \frac{1}{1+e^{-f_{i-1}}}$. After each generation, the best suitable chromosome is evaluated to evaluate the improvement in the fitness parameters of different features and values of each feature.

The value of each f in the proposed method is the volume with X and the permeability value with M. Considering that the goal of maximum throughput is the volume required for passage and the amount of time required for this passage, two necessary parameters are used in this context.

```
CostFunction=@(x) MinOne(x);
function z=MinOne(w,x,m)
z=sum(w*(x.^2+m));
end
for i=1:nPop
pop(i).Cost=CostFunction(pop(i).w ,pop(i).Position, pop(i).M);
end
Costs=[pop.Cost];
[Costs, SortOrder]=sort(Costs);
pop=pop(SortOrder);
```

Based on the above code snippet, each of the population gives two parameters of their fitness function (volume X and transit time M) to the goal of cost minimization, which is the goal function for calculation, and this function calculates and stores it, and finally for Sorting and filtering it. Applying a filter for feature combination: Using the genetic algorithm described in the previous section, each feature of the requests receives a weight between 0-1 after normalization. A threshold value is applied to reduce the dimension and combine the practical features for the next stage's input. β is considered. All features with a weight higher than this threshold value be included as input to the next step and be used in classification, and other features be removed from the set as irrelevant features or noise features (Knoblich, G., Butterfill, S., & Sebanz, N., 2011).

Artificial neural: network Although artificial neural networks are not comparable to the natural nervous system, they have learning ability, generalization ability, parallel processing, and robustness that are distinguished in some applications such as pattern separation, control, and generally wherever learning is needed.

Artificial neural networks are trained to distinguish between input patterns to provide the corresponding desired response to each input in the output. In many applications, artificial neural networks are required to determine the class or group to which the pattern belongs and recognize the input pattern. The number of patterns an artificial neural network can distinguish from each other is called the resolution of that network. Artificial neural networks' superiority over conventional methods is evident when the number of patterns available for classification is large. Therefore, this feature of artificial neural networks is used in applying pattern recognition (Li, X., Chen, F., Sun, D., & Tao, M., 2015).

4. Simulation and Results

recent technologies such as connected cars and autonomous vehicles have been widely explored by researchers worldwide, To improve the current transportation conditions. Due to recent advances in automotive, computer vision, and cognitive technologies, autonomous vehicles have attracted extensive attention from academia and industry. Autonomous vehicles are defined as computer-controlled artificial intelligence agents that can monitor, make decisions, and manage themselves entirely without human intervention. These intelligent vehicles behave autonomously, supporting tasks such as sensing the neighborhood environment, planning the shortest and safest route/travel route, speed control, driverless driving, and navigation without human intervention. Reduction of human errors, the number of accidents, traffic congestion, fuel consumption, and efficient parking are some of the critical benefits of self-driving vehicles. Also, the demand for physical road signals, traffic police, and car insurance decreases with self-driving vehicles. In this chapter, we test the method mentioned in the previous chapter and show the results of different evaluation stages.

Dataset: The vision of a smart city, in which services are provided to improve citizens' daily lives, is realized through several intelligent city use cases or scenarios that increasingly contribute to this vision. Imaginative city scenarios show great diversity in many fields. The 101 scenarios of the CityPulse EU FP7 project show this. The number of users and data sources, coverage of spatiotemporal scenarios, security, network, and data processing capabilities are a few factors that differ in different scenarios. Consider when architecting the Smart City Framework (SCF), i.e., the hardware and software infrastructure to support the above scenarios.

On the other hand, existing SCFs need a set of measurable criteria to evaluate against the requirements of future smart city scenarios. The datasets used in the simulation are available for download at the D address. They are available in raw format or semantically annotated using the Pulse City Information Model. Vehicle traffic data sets have been observed between two points for a certain period in 6 months (449 observations). Data are available in raw (CSV) format and semantically annotated using the Pulse City Information Model.

Evaluation: The system used in the evaluation has an Intel Pentium T4400 @2.2 GHz processor, 3.0 GB RAM, 320 GB hard disk, and a Windows Ten operating system. Matlab and Weka software has been used to simulate the method presented in the previous chapter. After loading the database, its statistical results are shown in code.

```
data =
        x: [30x1255 double]
        t: [1x1255 double]
       nx: 30
       nt: 1
  nSample: 1255
```

The data used has 1255 samples, the data part of its features is loaded in x, and the class part is loaded in t. Also, the number of samples in the database is shown in nSample. Genetics in the proposed method causes the combination of features. This improves the model and the efficiency of the method and increases productivity. In the genetic algorithm used in the proposed method, two practical inputs on the fitness function are used for the appropriate selection; the two inputs of this function are the throughput values assigned to the traffic areas and the number of items passed through that intersection at that time. The number of passages in Neighboring passages and the number of the first generation have been set equal to the number of devices at that time, and the maximum repetition has been considered 50. A view of an implementation of the genetic algorithm is shown in Figure 3.

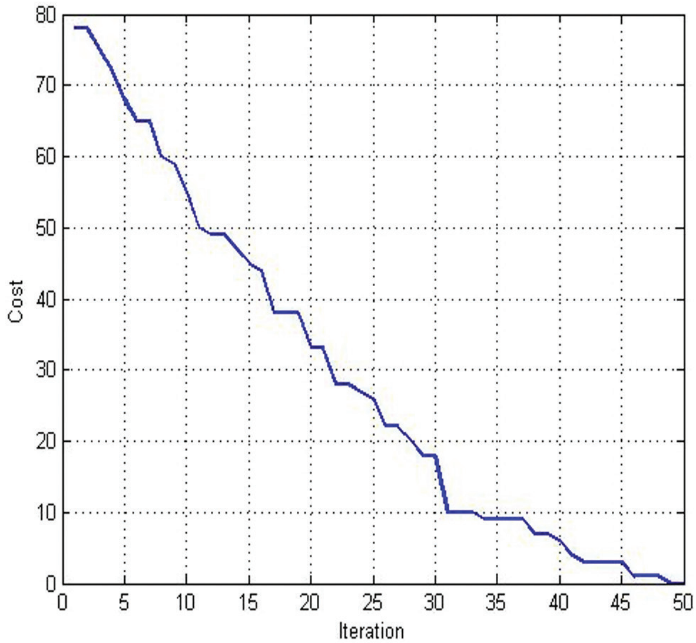

Fig. 3: An example of the implementation of the genetic algorithm of the proposed method

As shown in Figure 2-4, the cost function in this algorithm is reduced in each iteration so that the minimum cost is extracted and used with maximum efficiency. For this purpose, the resulting values are shown in 50 iterations according to the considered parameters. Care must be taken in choosing the number of repetitions because if the number of repetitions is high, it requires high computing power. If the number is high, the desired minimization will be achieved. The number of 50 selected in the proposed method was obtained heuristically and with many trials and errors. We implement the proposed method on the introduced data set and extract its results. The number of rounds to perform the method is set to 50. The output diagram of the genetic algorithm method is shown in Figure 4.

As shown in Figure 4, initially, the value of the function cost in the genetic algorithm of the proposed method was higher than 0.7, which reduced the considered repetitions of this value, and the best cost obtained after 50 repetitions were about 0.2. have been.

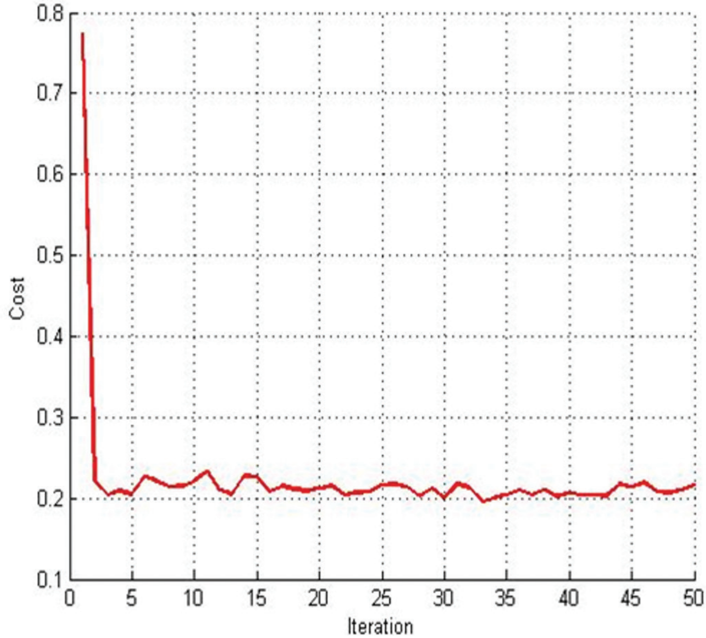

Fig. 4: Cost change chart of the proposed genetic algorithm in the considered scenario

The genetic algorithm used in the proposed method is of binary type and produces a string of zero and one in the output, which is used as a combination of features. An example of this generated output is shown in Figure 5.

```
Columns 1 through 16
  0   0   1   1   0   0   0   0   0   1   0   0   1   1   1   1
 Columns 17 through 30
  0    1   0   0   1   0   1   0   1   1   1   1   1   0
```

Fig. 5: An example of a pattern generated by a genetic algorithm as a combination of features

In the evaluation phase, we run different classification algorithms on the data set, and this is due to the comparison of the proposed method with standard classification algorithms. For this purpose, various criteria are examined, which include:

Accuracy: Accuracy refers to a measure of how well a model's predictions match the modeled reality. The classification accuracy of the test data can be calculated by dividing the number of correctly classified objects by the total number of objects (Lakshmi, K., Visalakshi, N. K., Shanthi, S., & Parvathavarthini, S., 2017; Tatbul, N., Lee, T. J., Zdonik, S., Alam, M., & Gottschlich, J., 2018).

$$Accuracy = \frac{TN+TP}{TN+FN+TP+FP} \quad (4)$$

Table.1.Class assigned by the model

Negative	Positive		
FN Rate : It represents the number of records whose real category is positive, and the classification algorithm has mistakenly recognized their category as unfavorable.	TP Rate : It represents the number of records whose real category is positive, and the classification algorithm correctly recognizes their category as positive.:	Positive	Real class
TN Rate : It indicates the number of records whose real category is harmful, and the classification algorithm has correctly recognized their category as unfavorable.	FP Rate : It represents the number of records whose actual category is harmful, and the category classification algorithm mistakenly recognized them as positive.	Negative	

Precision and Recall: Precision and Recall are practical criteria in information retrieval that determine the suitability of the documents retrieved by the system to the user's needs. These criteria are defined as follows.

$$Recall = \frac{TP}{FN+TP} \quad (5)$$

$$Precision = \frac{TP}{FP+TP} \quad (6)$$

F-measure: IAcombined measure can be used to evaluate recovery efficiency. Instead of these two measures, The F-Measure parameter combines Recall and Precision (Lakshmi, K., Visalakshi, N. K., Shanthi, S., & Parvathavarthini, S., 2017; Tatbul, N., Lee, T. J., Zdonik, S., Alam, M., & Gottschlich, J., 2018).

$$F - Measure = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (7)$$

An accuracy test using the K-Fold method with K=10 was used in all experiments. In this type of validation, the data is divided into K subsets. From these K subsets, each time, one is used for validation, and another K-1 is used for training. This procedure is repeated K times, and all data are used precisely once for training and once for validation. Finally, the average result of these K validation times is chosen as a final estimate. K-nearest neighbor, J48, SMO, Decision Table, algorithm based on Bayes theory, and Bagging are used for evaluation (Lakshmi, K., Visalakshi, N. K., Shanthi, S., & Parvathavarthini, S., 2017; Tatbul, N., Lee, T. J., Zdonik, S., Alam, M., & Gottschlich, J., 2018).

Table.2. Comparison of different categories with each other

J48	DecisionTable	Bagging	KNN=5	KNN=3	SMO	NaiveBayes	
95.8752	93.2429	95.884	95.305	96.0109	93.804	92.9806	Accuracy

0.959	0.932	0.959	0.953	0.96	0.938	0.93	TP Rate
0.045	0.075	0.045	0.051	0.043	0.066	0.076	FP Rate
0.959	0.933	0.959	0.953	0.96	0.938	0.93	Precision
0.959	0.932	0.959	0.953	0.96	0.938	0.93	Recall
0.959	0.932	0.959	0.953	0.96	0.938	0.93	F-Mea-sure

As shown in Table 2, the KNN method with K=3 has shown the highest output accuracy at 96%. Regarding output accuracy, the Bagging algorithm, J48, and KNN with K=5 are in the following categories. Based on Bayes's theory, the algorithm's results have shown the lowest output for this operation. Also, in this table, the rate of TP and FP is shown. The highest TP is related to KNN with K=3, and the highest FP is related to the Bayesian algorithm. The values of the three criteria, Precision, Recall, and F-Measure, are equal for all algorithms, and the highest value is related to KNN with K=3.

After preparing the data, enter the input into the artificial neural network to perform

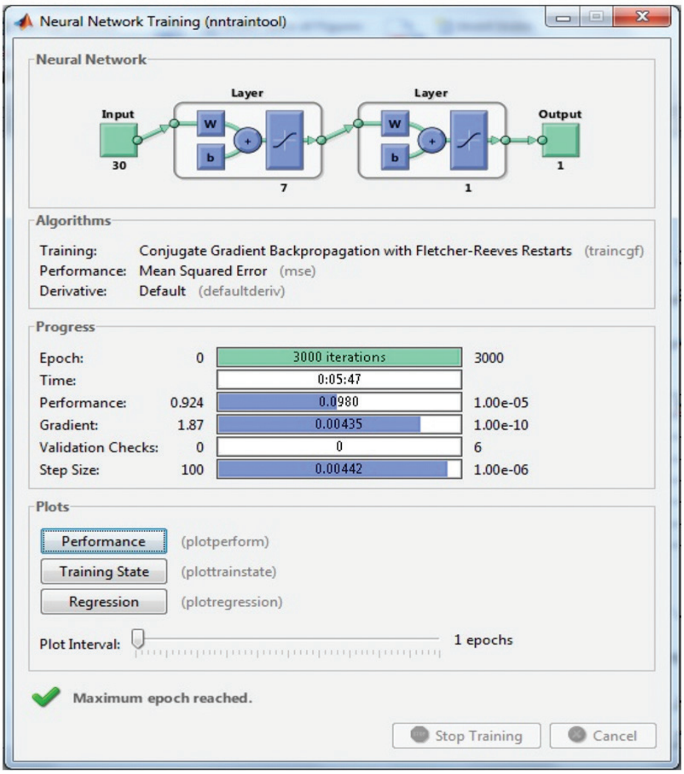

Fig. 6: Artificial neural network simulation environment in Matlab

the diagnosis. Multiple hidden layers can be used to create MLP neural network. The number of these hidden layers can affect the accuracy of the method. Of course, it should be noted that the number of these layers affects the network's training time, so you should choose the correct number. In the proposed method, we use a hidden layer. The number of input layer neurons equals the number of features, and the number of output layers equals

Meanwhile, the number of neurons in the hidden layer can be different, so we have tested different numbers for the proposed method to achieve the desired result. In Figure 6, you can see an example of network training time in the simulated environment. In Figure 7-4, you can see the comparison chart of the proposed method with different data sets with different numbers of neurons in the hidden layer.

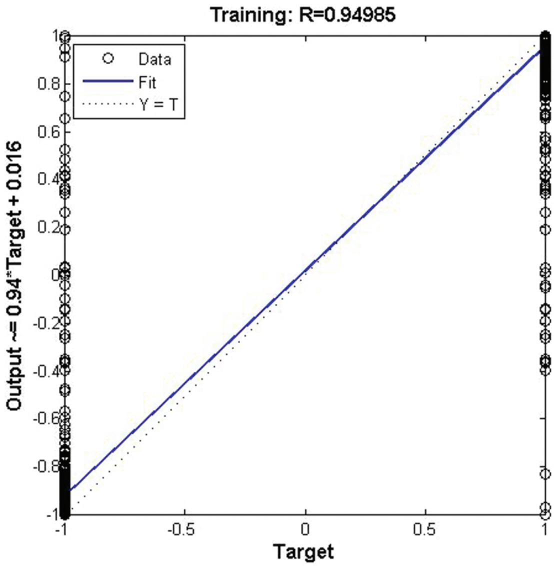

Fig. 7: Regression diagram of neural network training in Matlab

As you can see in figure8, the proposed method has shown the best result in the number of neurons, 7 neurons in the hidden layer. In this evaluation, the maximum number of iterations is set to 3000, and the training function used for the artificial neural network is traingdm. Also, the transfer functions from the input layer to the tension hidden layer and from the hidden layer to the output layer are considered transit functions. However, the proposed method has shown better output accuracy with different numbers of hidden layer neurons. According to the accuracy obtained for the proposed method, we suggest the number of 7 neurons in the hidden layer. In the following evaluation, we have examined the transfer functions between the layers, considering that the values in the adjusted class are 1 and -1; for this reason, the transit function must be included in the transfer function of the hidden layer to the output

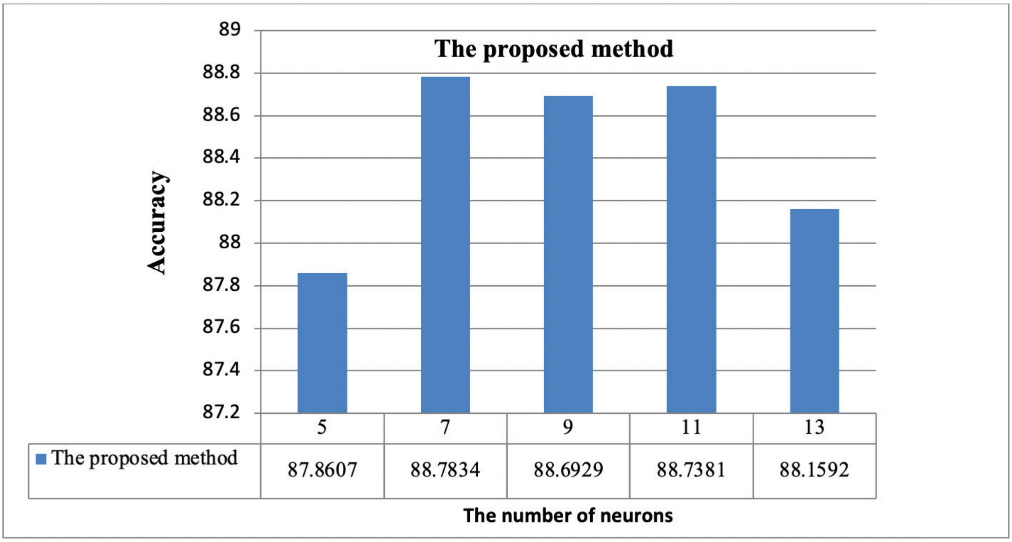

Fig. 8: Comparison of the number of neurons used in the hidden layer

layer because the function transit maps value to numbers between -1 and 1. The logs function maps the output numbers to values between 1 and 0, the linear function can produce any number, and only the tansig function can produce values between -1 and 1. In this way, three choices remain for the transfer functions between the layers, displayed in Figure 9.

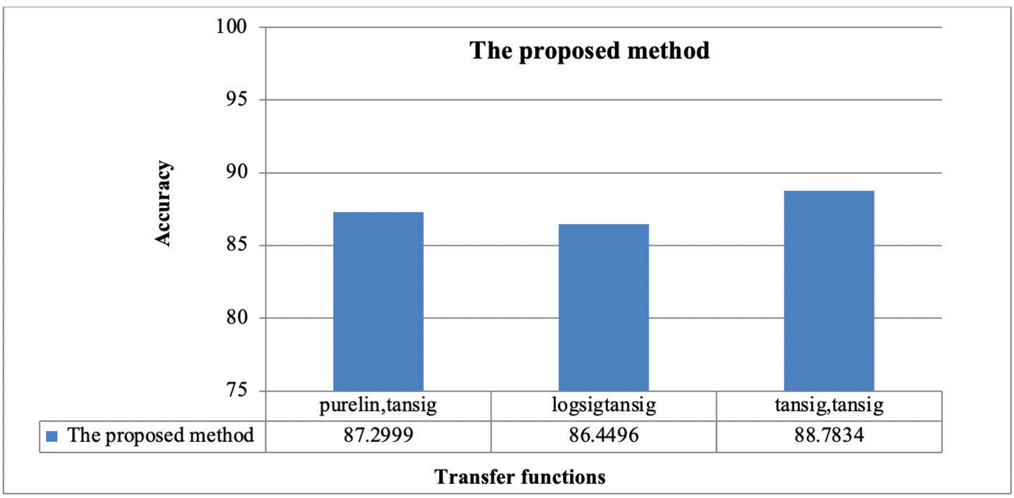

Fig. 9: Evaluation of the proposed method in terms of transfer functions between layers

The best output is obtained in the combination of tansig and tansig in the proposed method. In this combination, the transfer function of the input layer to the hidden layer is tansig, and the transfer function from the hidden layer to the output layer is the tansig function. In this combination, the tansig function transfers from the input layer to the hidden layer, and the tansig function transfers from the hidden layer to the output layer. For the proposed method, tansig and tansig functions are suggested for selecting functions between layers.

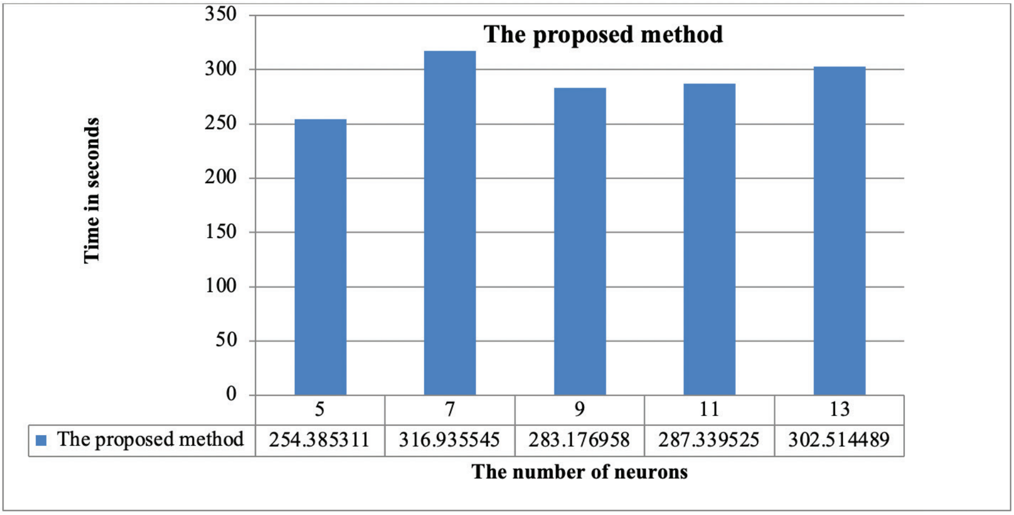

Fig. 10: Training time of different methods versus the number of different hidden layer neurons

One of the evaluations is the time used in network training. This time is directly related to the number of neurons used in the hidden layer, and also, the number of features used in the data set can reduce or increase the amount of time used in training. In choosing the number of neurons of the hidden layer, the most accuracy should be done. The number of suitable neurons for the hidden layer is considered in the proposed method 7, and also Figure 10 shows that the best time is obtained in the number of 5 hidden layer neurons.

As it is apparent in the figure, the best training time in the number of different neurons goes back to the number of 5 neurons in the hidden layer. Also, the last time in 5 neurons for the hidden layer is allocated to the proposed method. Different training functions can be used to train the network. All functions use backpropagation to minimize the difference between the target and obtained values. In backpropagation training, if a difference is observed in the output, the neurons' weights are changed to a certain amount, and this change is repeated until the minimum difference is reached. The types of functions that can be used in the training of the multilayer artificial neural network are shown in Table 3.

Table.3.Algorithms that can be used in network training

Description	Function name	Row
Slope reduction batch training	Traingd	1
Slope reduction batch training with Momentum, which has a faster convergence than the previous one	Traingdm	2
Training with variable learning speed	Traingda	3
As before, with an additional parameter	Traingdx	4
Elastic post-release training	Trainrp	5
Fletcher-Reeves gradient algorithms	Traincgf	6
Polak-Ribirere gradient algorithm	Traincgp	7
A powell-Beale restarts gradient algorithm	Traincgb	8
Scaled slope algorithm	Trainscg	9
Quasi-Newton Algorithm (Linear Search Procedure for Sib-Tom Algorithm) Space and Big Computing	Trainbfg	10
Quasi-Newton Algorithm (Linear Search Procedure for Sib-Tom Algorithm) Space and Big Computing	Trainoss	11
The Levenbery-Marqwardt quasi-Newton algorithm tries to reduce the computations.	Trainlm	12

The widely used training functions were used in the proposed neural network. To achieve the best type of training function and the accuracy obtained in the data set with the compared method are shown in Figure 11.

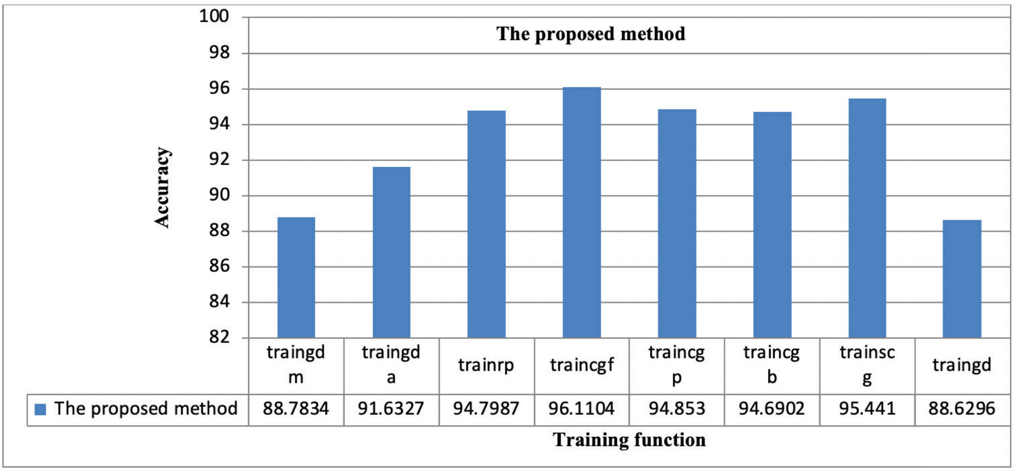

Fig. 11: Evaluation of different training functions

The figure shows that the proposed method in the traincgf training function has shown the best result. For the proposed method, the traincgf function is suggested as the training function. The following evaluation is the maximum number of repetitions of the training algorithm on the data set, which can also affect the accuracy of the displayed output. The values obtained in this evaluation are shown in Figure 12.

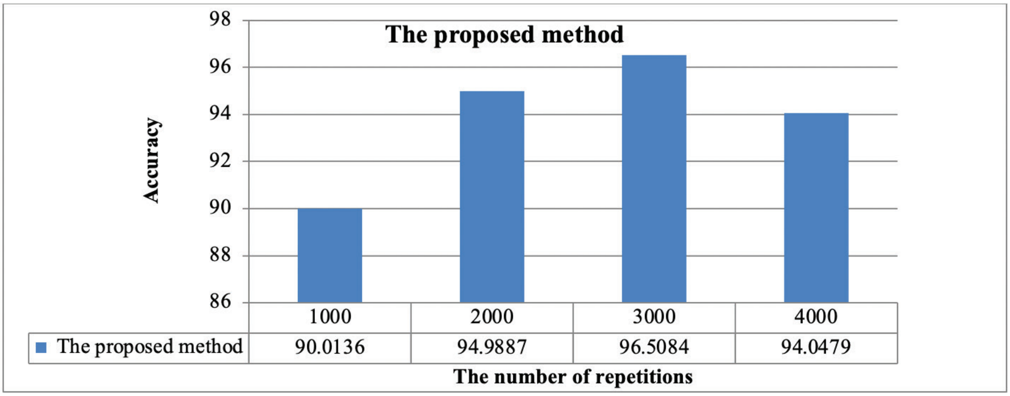

Fig. 12: Accuracy obtained with the different maximum number of iterations

As shown in the figure, the proposed method has shown the best output in the maximum repetition of 3000. The proposed method, 3000, is suggested as the appropriate value for the maximum number of repetitions. Figure 13 compares the proposed method with the primary method based on accuracy criteria. The basic method used the SVM method as a classifier, and based on the simulation, this method gave an output value of 93.6. However, the proposed method has an output value of 96.6, which according to this comparison, is a 3% improvement achieved in the proposed method.

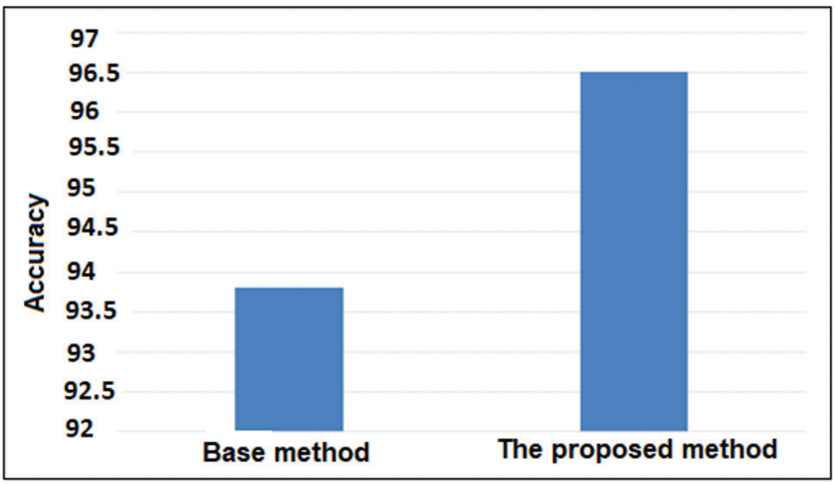

Fig. 13: Comparison of the proposed method with the base method (Boukerche, A., Tao, Y., & Sun, P., 2020)

Conclusion

In the proposed method, artificial neural networks are used as a powerful method for the mathematical modeling of traffic data. ANNs provide functions such as self-learning, self-organization, and pattern recognition. They can also perform nonlinear approximations between input and output spaces. Being a non-parametric approach, they do not make any assumptions about the data distribution. In addition, the parallel structure of artificial neural networks makes them useful for implementation on parallel computers. The idea of predicting traffic information using a neural network and genetic algorithm was exploited in the proposed method.

After a comprehensive review of the use of different architectures in traffic flow prediction, we now discuss the challenges that remain unsolved during the implementation of traffic flow prediction models; Most studies for traffic flow forecasting use RMSE and MAE to measure the performance of the proposed models. However, these two criteria only succeed when the input data sets differ entirely. Hence, defining appropriate criteria for evaluating traffic flow prediction models is still an open issue. In addition, from the above comparison, most studies predict traffic flow for short-term forecasting. The long-term forecast horizon is considered another challenge while predicting traffic flow. An immense value than the prediction horizon can reduce costs and provide better ITS management. However, with the increase in the size of the horizon, the prediction accuracy decreases. However, recent studies prove that long-term forecasting is possible using data-driven approaches and can provide more accurate results. Another challenge for traffic flow forecasting is the presence of unusual factors such as accidents, weather, and scheduled events. For example, if rainfall intensity increases, both velocity and flow decrease. There is also the possibility of error due to uncertainty in complex factors such as employment trends, holidays, and availability of alternative routes. Considering such unusual factors when designing DL architectures can significantly improve prediction accuracy. Also, due to the dynamic nature of traffic data, traffic flow sometimes follows different patterns on the same day. Therefore, the forecasting technique should be able to model the traffic flow in different periods. Several recent researchers have addressed unusual factors in their studies. Weather information is widely considered, but roadwork needs to be more integrated.

Besides, consideration of reduced visibility due to fog is rarely used. Furthermore, only a few studies have considered the impact of demand and capacity for work zones. Furthermore, only a few studies have considered the impact of demand and capacity for work zones. Traffic forecasting can be a factor in controlling the flow of car traffic, which we tried to do based on vanet traffic data using a neural network and genetic algorithm. For future research, it is suggested to use other evolutionary algorithms to select and combine features. Also, evolutionary algorithms are presented in combination for the mentioned purpose, and the results are analyzed.

References

Boukerche, A., Tao, Y., & Sun, P. (2020). Artificial intelligence-based vehicular traffic flow prediction methods for supporting intelligent transportation systems. *Computer networks, 182,* 107484.

Du, S., Li, T., Gong, X., & Horng, S. J. (2018). A hybrid method for traffic flow forecasting using multimodal deep learning. arXiv preprint arXiv:1803.02099.

Ghasempoor, Z., & Behzadi, S. (2021). Traffic Modeling and Prediction Using Basic Neural Network and Wavelet Neural Network Along with Traffic Optimization Using Genetic Algorithm, Particle Swarm, and Colonial Competition*. Journal of Geomatics Science and Technology, 10*(3), 147-163.

Hajian, S.R. (2015). A review of technology-based methods in identifying road traffic congestion in vehicular networks*. The Second National Conference Of New Achievements in Electricity and Computers, Esfarain,* 2015.

Han, D., Chen, J., & Sun, J. (2019). A parallel spatiotemporal deep learning network for highway traffic flow forecasting. *International Journal of Distributed Sensor Networks, 15*(2), 1550147719832792.

Knoblich, G., Butterfill, S., & Sebanz, N. (2011). Psychological research on joint action: theory and data. *Psychology of learning and motivation, 54,* 59-101.

Lakshmi, K., Visalakshi, N. K., Shanthi, S., & Parvathavarthini, S. (2017). Clustering Categorical Data using k-modes based on Cuckoo Search Optimization Algoriothm. *Ictact journal on Soft Computing, 8*(1).

Li, T., Ni, A., Zhang, C., Xiao, G., & Gao, L. (2020). Short-term traffic congestion prediction with Conv–BiLSTM considering spatio-temporal features. *IET Intelligent Transport Systems, 14*(14), 1978-1986.

Li, X., Chen, F., Sun, D., & Tao, M. (2015). Predicting menopausal symptoms with artificial neural network. *Expert Systems with Applications, 42*(22), 8698-8706.

Medina-Salgado, B., Sanchez-DelaCruz, E., Pozos-Parra, P., & Sierra, J. E. (2022). Urban traffic flow prediction techniques: A review. *Sustainable Computing: Informatics and Systems, 35,* 100739.

Rizwan, P., Suresh, K., & Babu, M. R. (2016, October). Real-time smart traffic management system for smart cities by using Internet of Things and big data. In *2016 international conference on emerging technological trends (ICETT)* (pp. 1-7). IEEE.

Sepasgozar, S. S., & Pierre, S. (2022). Network traffic prediction model considering road traffic parameters using artificial intelligence methods in VANET. *IEEE Access, 10,* 8227-8242.

Singh, G., Chakrabarty, N., & Gupta, K. (2014). Traffic congestion detection and management using vehicular ad-hoc networks (VANETs) in India. *International Journal of Advanced Computer Technology (IJACT), 3,* 24.

Tatbul, N., Lee, T. J., Zdonik, S., Alam, M., & Gottschlich, J. (2018). Precision and recall for time series. *Advances in neural information processing systems,* 31.

Transportation and Economy Report (2021). http://www.michiganmobility.org/slrtp/

Zhang, Y., & Huang, G. (2018). Traffic flow prediction model based on deep belief network and genetic algorithm. *IET Intelligent Transport Systems, 12*(6), 533-541.

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