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Article

A Neuro-Fuzzy Approach to Road Traffic Congestion Prediction

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Abstract: The fast-paced growth of artificial intelligence applications provides unparalleled opportunities to improve the efficiency of various systems. Such as the transportation sector faces many obstacles following the implementation and integration of different vehicular and environmental aspects worldwide. Traffic congestion is among the major issues in this regard which demands serious attention due to the rapid growth in the number of vehicles on the road. To address this overwhelming problem, in this article, a cloud-based intelligent road traffic congestion prediction model is proposed that is empowered with a hybrid Neuro-Fuzzy approach. The aim of the study is to reduce the delay in the queues, the vehicles experience at different road junctions across the city. The proposed model also intended to help the automated traffic control systems by minimizing the congestion particularly in a smart city environment where observational data is obtained from various implanted Internet of Things (IoT) sensors across the road. After due preprocessing over the cloud server, the proposed approach makes use of this data by incorporating the neuro-fuzzy engine. Consequently, it possesses a high level of accuracy by means of intelligent decision making with minimum error rate. Simulation results reveal the accuracy of the proposed model as 98.72% during the validation phase in contrast to the highest accuracies achieved by state-of-the-art techniques in the literature such as 90.6%, 95.84%, 97.56% and 98.03%, respectively. As far as the training phase analysis is concerned, the proposed scheme exhibits 99.214% accuracy. The proposed prediction model is a potential contribution towards smart cities environment.

Keywords: Neuro-fuzzy; machine learning; congestion prediction; AI; cloud computing; smart cities

1 Introduction

The management of road traffic is amongst the major problems considered in most of the big cities around the globe. Especially, in peak hours, most of the roads can be observed congested with a large number of vehicle queues for an indefinite period. This problem is not limited to the under-developing countries but evident in the developed countries as well. Among the several reasons for this overwhelmingly increasing traffic are necessity and affordability of automobiles and progressive commuting for the jobs and work-related activities. The congestion in the different road junctions creates several issues related to environment pollution, mental health, increase in fuel consumption as well as the financial issues [1]. Governments and agencies employ different ways to minimize the delays that occur during driving. For instance, building flyovers and underpasses, ring-shaped roads, one-way roads, segregating the city metros from the general traffic. Moreover, introducing the restriction and rescheduling of the heavy-duty traffic in the city and automating the system of traffic signals [2].

Many researchers figured out the levels of congestion over the road junctions with the help of information from the spatial and temporal traffic flow [3] by using the technique of fuzzy logic to examine the continuous and discrete level of traffic congestion patterns [4]. Moreover, Hidden Markov models (HMM) have been investigated to calculate five distinct traffic congestion statuses by intelligently examining traffic videos and imagery. The velocity and volume of the vehicles on the roan in a particular scene are used as an input to the designed fuzzy inference system (FIS) in many road traffic scenarios to estimate and generalize the road congestion [5]. Although, the mentioned techniques were promising in terms of adequately guessing the congestion but still there is a lot of room for improvement in terms of prediction accuracy especially when it comes to real time environments. In this paper, a neuro-fuzzy model has been developed, which is an amalgamation of the fuzzy system (FS) and neural network (NN). The proposed model is capable of learning and drawing the member function's boundaries for the fuzzy system with the help of a neural network. This results in a set of dynamic fuzzy membership functions that encompass the accurate distribution of the involved fuzzy variables pertaining the provided examples. Further, in this research, cloud based intelligent road traffic congestion prediction empowered with hybrid neuro fuzzy technique is proposed. The core contributions of the article are enumerated as follows:

a) Formulation of an optimization problem where the main objective is to minimize the miss-rate and improve the accuracy for optimum decision-making for road traffic congestion.
b) For better approximation of the traffic congestion, Fuzzy Logic empowered NN has been proposed. This is mainly because the fuzzy logic covers the missing part of knowledge with adequate approximation of its membership function duly learnt from the NN trained over appropriate number of examples.
c) Proposed Cloud empowered hybrid neuro-fuzzy based proposed model is compared with various state of art algorithms and methods. Simulation results shown that Proposed hybrid

neuro-fuzzy based proposed model exhibits far better results as compared to state of the art algorithms.

The remaining paper is organized as follows. The literature review is presented in Section 2; whereas the Section 3 describes the hybrid neuro-fuzzy based proposed model. Section 4 validates the proposed model by the simulation results. Finally, the conclusion of the paper is presented in Section 5.

2 Literature Review

The concept of a smart city is expressed as a combination of enormous information with computerized frameworks, and the distributed Internet of Things (IoT) based sensory [6,7] with inherent cloud computing facilities to process the induced big data [8]. The idea of cognitive computing is to gain from procuring information with people to enhance the user experience and pervasiveness. As an example, the Google makes an intelligent use of customers feedback and suggestions to provide a better experience ubiquitously. That involves intelligent and complex user's behavior analysis and prediction based on the past experiences. The classification and prediction are based on the past traits of the user, his/her likes/dislikes and their activities over the network or web. Mainly these activities include web usage, network usage and shopping trends etc. [9,10]. These technologies set a roadmap towards a fully operational knowledge base community, referred to as smart environments including smart homes, smart campuses, smart clinics (telemedicine solutions), smart classrooms and what not [11,12]. Nowadays the term smart city is the most prevalent among the modern technological revolutions. The most recent analysis of the World Health Organization (WHO) assumes that, by 2050, 70% of the population will live in urban areas. Essentially, counting on the similar smart projects in the everyday life. Whereas the smart traffic control is among the most emerging areas of the smart cities.

According to [13], mainly probabilistic and AI based models have been investigated for traffic congestion prediction in the literature over the recent years. The AI based mainly comprises ANN, regression models, decision trees and SVM based algorithms. Similarly, convolutional neural network (CNN), long-short-term memory (LSTM) and extreme learning machine (ELM) models were investigated under deep learning paradigm. As far as the probabilistic models are concerned, they become complex with increase in number of factors on the road traffic like weather, number of vehicles etc. However, deep learning methods outsmart them and hence are more popular in the recent years of study. A study in [14] was conducted for the road traffic congestion prediction based on estimated time of arrival (ETA) and certain human factors. The social media, Google maps including online traffic management web portals for a selected city, weather APIs and local events were the main data sources. After due pre-processing, the authors built the model based on ETA segregated as weekends and weekdays and investigated various ML algorithms like random forest (RF), XGBoost, KNN, GradientBoost (GB) etc. and achieved the accuracies as 92%, 91%, 91% and 83%, respectively.

Rani et al. in [15] proposed a neural network followed by fuzzy inference system approach for traffic delay prediction. In this approach, the delay coefficients were predicted based on the environmental factors incurred during the road traffic in an urban city. The scheme exhibits accuracies as 91.265% and 90.6 during training and validation phases respectively. The smart city projects investigate the most recent innovation to improve urban lifestyles. In the urban areas, smart city technologies likewise increase the presentation and provides the individuals prevalent with higher facilities [16]. Urban cities, around the globe are being revolutionized to smart cities with the help of Information and Communication Technology (ICT). The IoT interfaces comprising of heterogeneous type of gadgets, wearables, autos, unmanned air vehicles (UAVs) as well as different stuff in cooperation and trade the information through equipment, application programming interfaces (APIs), sensors, actuators, and combinations of several open-ended systems [17].

In [18], authors proposed a machine learning approach for avoidance of road traffic congestion. Two approaches were investigated in this regard. Firstly, the curve fitting technique was used to minimize the error rate and improve the accuracy of the overall system. Second approach was using the time series approach. Both schemes exhibit the accuracies of 95.84% and 97.56%, respectively for the road traffic congestion prediction. The techniques were promising in terms of accuracy but with an inherent cost of complexity was encompassed. Strategies for information and calculations of AI ought to be set up to get data and learning to diminish. Although processing and capacity procedures have as of late progressed, most information scientific methodologies exploit inspecting systems that are time-proficient, however, they ignore a major number of information that can contain critical data [19]. Planning and evolution are of the greatest impact in the IoT and demands an ideal trusted agreement layer known as middleware [20]. For sake of secure and consistent interoperability among applications, Machine-to-Machine, and existing web-based services without human intervention. This type of electronic data interchange (EDI) mechanism results in timely and hassle-free system [21]. Siddiqui et al. [22] proposed a deep learning neural network (DLNN) based road traffic congestion control approach. The scheme exhibits a significant accuracy of 98.03% but for a specific dataset. Moreover, the suitability of the scheme for a real-life environment like smart city was neither stated nor its alignment or configuration with the smart city architecture was explained. A study in [23] proposed an innovative and promising learning algorithm for vehicle re-identification as a potential support to traffic management systems by involving unique feature.

In [24], authors proposed a real-time approach for small object detection (RSOD) that could potentially help the UAV based smart traffic monitoring system by means of enhanced surveillance. RSOD outperforms YOLOv3 for the Visdrone-DET2018 and UAVDT datasets with an improvement in mean Average Precision (mAP) of 3.4% and 5.1%, respectively. Several AI, Machine Learning (ML) and soft-computing approaches like Neural Network [18], Fuzzy system [25–27], Swarm Intelligence [28] and Evolutionary Computing [29] like Genetic Algorithm [30,31], Differential Evolution (DE) [32,33], are strong candidate solutions in the field of the smart cities [34], engineering and wireless communication systems [35–37] and healthcare [38,39] etc.

Based on the brief literature review, authors conclude the research gap and motivation regarding study that there is a dire need for a comprehensive traffic road congestion prediction approach for the smart cities. Because, due to involvement of several factors, probabilistic models or too complex to design. Then among AI models, a lightweight model is demanded to encompass the ideology of IoTs, fog and cloud computing paradigm as a layered approach which precisely explains and projects the data flow from sensors to the cloud layer where the proposed neuro-fuzzy engine is deployed for real time analysis and provisioning of the road traffic congestion prediction with enhanced accuracy and reduced error rate.

3 Proposed Cloud-based Intelligent Traffic Congestion System Model

Proposed work introduces the energy efficient model for the smart cities. This section elaborates the way neural network with fuzzy system together help in congestion prediction to facilitate the smart cities population. In this regard, the general context of artificial intelligence in smart cities is presented in Fig. 1 along with the Proposed Hybrid Neuro-Fuzzy based Smart City Infrastructure Integration Model. It consists of four main intelligence attention levels named as facilities of smart city and IoT, neuro-fuzzy component, Fog computing & cloud computing.

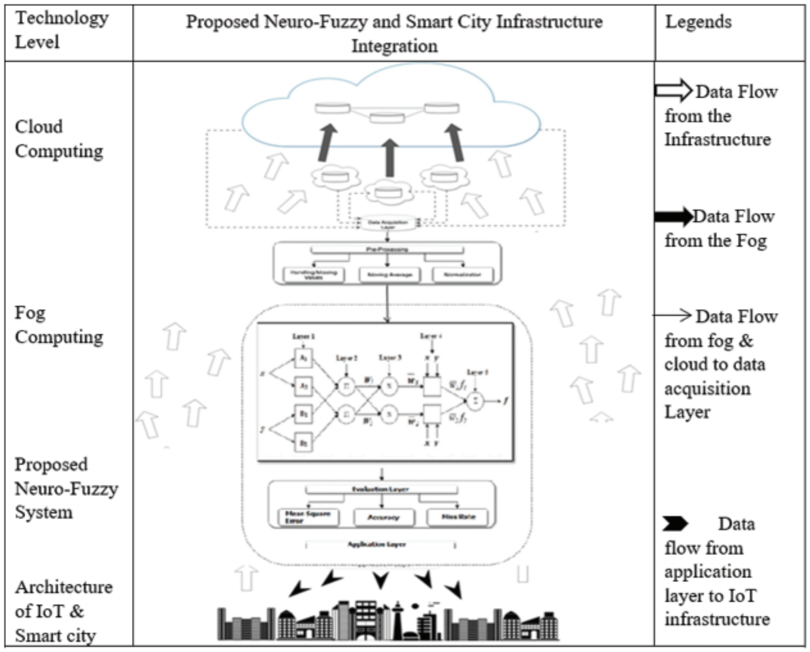

Figure 1: Proposed hybrid neuro-fuzzy and smart city infrastructure integration model

The proposed neuro-fuzzy approach presented in Fig. 1 depicts the hierarchical structure of a smart city where the intelligent software control is implemented in coordination with cloud and fog computing for the necessary analytics. The unique facts can, then, be transferred to the cloud or fog layer. The operational analytical agent of the neuro-fuzzy approach at that time provides a proper reaction based on estimates for the traffic. The analysis of the Fog-driven approach supports local activities in predefined conditions; however, the analysis of a cloud-driven approach can cover larger geographical area with different states. The surroundings of the sensors are detected by the laid diverse sensory IoT network. However, the information sources for the end-user, the proposed learning model is required. The model of neuro-fuzzy can be used at the stage of cloud computing, tools, and methodologies and it can be integrated with semantics and ontologies to gather around the information [40,41].

3.1 Working Methodology

The proposed traffic congestion prediction model is shown in Fig. 2. Proposed Model is divided into four sub-layers named: sensors layer, object layer, preprocessing layer and application layer. The application layer further divided into sublayers. The sensor layer contains various types of IoT enabled sensors that collect data from the environment as an input also known as the acquisition layer. Data received through IoT enabled sensors is forwarded to the object layer through the wireless link.

Due to the channel state information (CSI) at the wireless link, received data at the object layer may contain some missing values and noise [42–44] that is precisely known as the raw data. After collecting the raw data, the preprocessing layer is activated. In this layer, handling the missing values and mitigating the noise using the moving average method and normalization take place, respectively. In the application layer, the proposed hybrid neuro-fuzzy approach has been used to predict road traffic congestion. The application layer further divided into three sub-layers named as

Fuzzy Inference System (FIS), Prediction Layer & Performance evaluation layer. Knowledgebase of the Fuzzy Inference system layer is updated using the Adaptive Backpropagation Neural Network system. The output of the FIS layer is used in the Prediction layer to predict the traffic congestion, consequently.

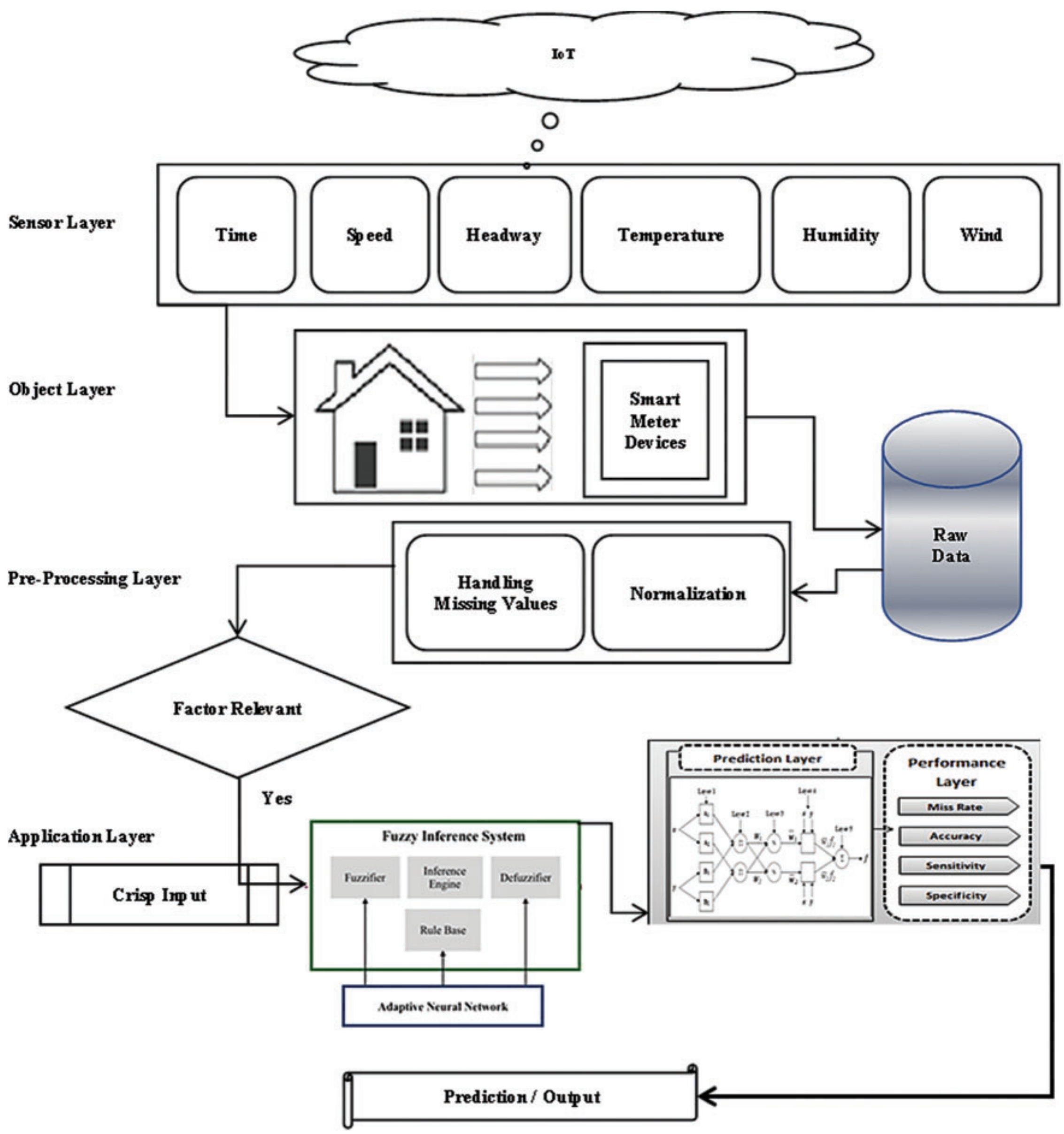

Figure 2: Proposed hybrid neuro-fuzzy empowered traffic congestion model in smart cities

In addition to the prediction layer, the hidden layer initializes the weights of the input layer and updates its weights by using a mathematical technique (explained subsequently) of calculating the weights (except the first hidden layer), and finally uses the least mean square (LMS) technique to calculate weights for the overall output layer of the network. The test and error method are used to fine-tune the hidden layers ideally along with the adequate number of neurons considered in the hidden layers in contrast to the activation function. These outcomes of the network as used to adjust the boundaries of the fuzzy membership functions that strengthens the proposed neuro-fuzzy model. The mathematical modeling for adjusting the bounds of trim membership functions based on the outcome of activation function is given in Tab. 1. Triangular membership functions are used in the modeling due to their appropriateness to the real-life applications rather than Gaussian membership functions that exhibits more complexity while aggregating the fuzzy values.

Table 1: Mathematical membership function used in the proposed hybrid neuro-fuzzy system

Variables	Membership Function (MF)
Queue (Q) $= \mu_Q(q)$ **(Trimmf)**	$\mu_{Q,Zero}(q) = \left\{ \frac{2-q}{2}, 0 \le q \le 2 \right\}$
	$\mu_{Q,veryfew}(q) = \left\{ \begin{array}{l} \frac{q}{2}, 0 \le q \le 2 \\ \frac{4-q}{2}, 2 \le q \le 4 \end{array} \right\}$
	$\mu_{Q,few}(q) = \left\{ \begin{array}{l} \frac{q-2}{2}, 2 \le q \le 4 \\ \frac{6-q}{2}, 4 \le q \le 6 \end{array} \right\}$
	$\mu_{Q,medium}(q) = \left\{ \begin{array}{l} \frac{q-4}{2}, 4 \le q \le 6 \\ \frac{8-q}{2}, 6 \le q \le 8 \end{array} \right\}$
	$\mu_{Q,high}(q) = \left\{ \frac{q-6}{2}, 6 \le q \le 8 \right\}$
Arrival (A) $= \mu_A(a)$ **(Trimmf)**	
	$\mu_{A,Zero}(a) = \left\{ \frac{2-a}{2}, 0 \le a \le 2 \right\}$
	—
	$\mu_{A,veryfew}(a) = \left\{ \begin{array}{l} \frac{a}{2}, 0 \le a \le 2 \\ \frac{4-a}{2}, 2 \le a \le 4 \end{array} \right\}$
	$\mu_{A,few}(a) = \left\{ \begin{array}{l} \frac{a-2}{2}, 2 \le a \le 4 \\ \frac{6-a}{2}, 4 \le a \le 6 \end{array} \right\}$
	$\mu_{A,medium}(a) = \left\{ \begin{array}{l} \frac{a-4}{2}, 4 \le a \le 6 \\ \frac{8-a}{2}, 6 \le a \le 8 \end{array} \right\}$

(Continued)

Table 1: Continued

Variables	Membership Function (MF)
	$\mu_{A,large}(a) = \left\{ \frac{a-6}{2}, 6 \leq a \leq 8 \right\}$ —-
Time (T) $= (\mu_T(t))$ **(Trimmf)**	$\mu_{T,None}(t) = \left\{ \frac{20-t}{20}, 0 \leq t \leq 20 \right\}$ $\mu_{T,veryshort}(t) = \left\{ \begin{array}{l} \frac{t}{20}, 0 \leq t \leq 20 \\ \frac{40-t}{20}, 20 \leq t \leq 40 \end{array} \right\}$ $\mu_{T,short}(t) = \left\{ \begin{array}{l} \frac{t-20}{20}, 20 \leq t \leq 40 \\ \frac{60-t}{20}, 40 \leq t \leq 60 \end{array} \right\}$ $\mu_{T,medium}(t) = \left\{ \begin{array}{l} \frac{t-40}{20}, 40 \leq t \leq 60 \\ \frac{80-t}{20}, 60 \leq t \leq 80 \end{array} \right\}$ $\mu_{T,high}(t) = \left\{ \frac{t-60}{20}, 60 \leq t \leq 80 \right\}$

3.2 Hybrid Neuro-Fuzzy System

The proposed hybrid Neuro-Fuzzy system combines the strengths of both the neural networks and fuzzy systems like separately investigated in [35–37]. In the proposed hybrid neuro-fuzzy system, the neural network is applied to build the rule-base/knowledgebase which is further used in the prediction layer. Fig. 3 shows the proposed architecture which is used in the prediction layer for traffic congestion. It consists of five distinct layers; each layer has its own functionality. Where, x and y represent the crisp input values the obtained from IoT and processed. These values are then mapped to corresponding fuzzy values after passing through the fuzzifiers like Queue (Q) and Arrival (A) which are shown in Tab. 1. Further the A_i and B_i shows the linguistic labels related to node function. Here "W" represents the optimum learned weights that are used for intelligent prediction of traffic congestion.

Mathematical membership functions used in proposed hybrid Neuro-Fuzzy Architecture are shown in Tab. 1, which are further used in the neural network-based knowledge base. In the proposed hybrid Neuro-Fuzzy system, adaptive backpropagation neural network is used to create the intelligent & adaptive knowledge of the FIS. Based on the disseminated and induced knowledge, the proposed prediction model predicts the road traffic congestion accurately.

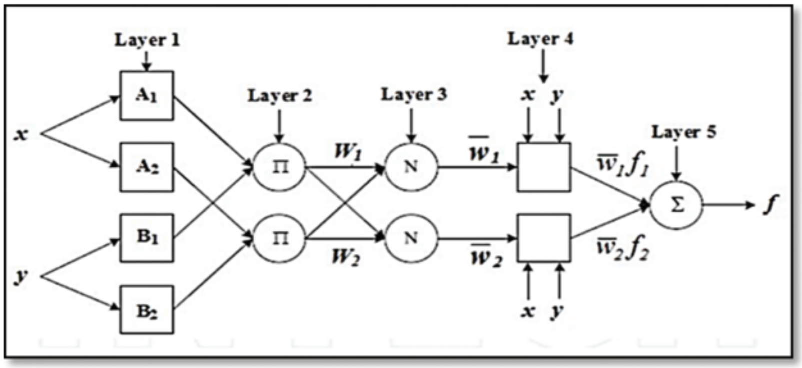

Figure 3: The proposed architecture used in prediction layer

Eq. (1) represents the net of the hidden layer (ψ_j) of the neural network. Where r_I represents the inputs as shown in Tab. 1 and ω_{ij} represents the weights between input and hidden layer.

$$\psi_j = b_1 + \sum_{i=1}^{m} (\omega_{ij} * r_i) \tag{1}$$

$$\acute{\omega}_j = \frac{1}{1 + e^{-\psi_j}} \text{ where } j = 1, 2, 3 \ldots n \tag{2}$$

Here, $\acute{\omega}_j$ in Eq. (2) represents the output of the hidden layer. Input is shown in Eq. (3) from the given output layer.

$$\psi_k = b_2 + \sum_{j=1}^{n} (\upsilon_{jk} * \acute{\omega}_j) \tag{3}$$

Output layer activation function is shown in Eq. (4)

$$\acute{\omega}_k = \frac{1}{1 + e^{-\psi_k}} \text{ wherek} = 1, 2, 3 \ldots r \tag{4}$$

Error in backpropagation written as Eq. (5)

$$E = \frac{1}{2} \sum_k (\tau_k - \acute{\omega}_k)^2 \tag{5}$$

where τ_k represents the output of desired and out_k showed the output of calculated.

$$\Delta\upsilon_{j,k} = -\epsilon \frac{\partial E}{\partial \nu_{j,k}} \tag{6}$$

Eq. (6) can be written as after apply chain rule:

$$\Delta\upsilon_{j,k} = -\epsilon \frac{\partial E}{\partial \acute{\omega}_k} \times \frac{\partial \acute{\omega}_k}{\partial \psi_k} \times \frac{\partial \psi_k}{\partial \nu_{j,k}} \tag{7}$$

After substituting the values in Eq. (7), the value of weight changed can be obtained as shown in Eq. (8)

$$\Delta\upsilon_{j,k} = \epsilon\left(\tau_k - \acute{\omega}_k\right) \times \acute{\omega}_k\left(1 - \acute{\omega}_k\right) \times \left(\acute{\omega}_j\right)$$

$$\Delta\upsilon_{j,k} = \epsilon\xi_k\acute{\omega}_j \tag{8}$$

where

$$\xi_k = \left(\tau_k - \acute{\omega}_k\right) \times \acute{\omega}_k\left(1 - \acute{\omega}_k\right)$$

$$\omega_{I,j} \propto -\left[\sum_k \frac{\partial E}{\partial\acute{\omega}_k} \times \frac{\partial\acute{\omega}_k}{\partial\psi_k} \times \frac{\partial\psi_k}{\partial\acute{\omega}_j}\right] \times \frac{\partial\acute{\omega}_j}{\partial\psi_j} \times \frac{\partial\psi_j}{\partial\omega_{I,j}}$$

$$\Delta\omega_{I,j} = -\epsilon\left[\sum_k \frac{\partial E}{\partial\acute{\omega}_k} \times \frac{\partial\acute{\omega}_k}{\partial\psi_k} \times \frac{\partial\psi_k}{\partial\acute{\omega}_j}\right] \times \frac{\partial\acute{\omega}_j}{\partial\psi_j} \times \frac{\partial\psi_j}{\partial\omega_{I,j}}$$

$$\Delta\omega_{I,j} = \epsilon\left[\sum_k \left(\tau_k - \acute{\omega}_k\right) \times \acute{\omega}_k\left(1 - \acute{\omega}_k\right) \times \left(\nu_{j,k}\right)\right] \times \acute{\omega}_k\left(1 - \acute{\omega}_k\right) \times \alpha_i$$

$$\Delta\omega_{I,j} = \epsilon\left[\sum_k \xi_k\left(\nu_{j,k}\right)\right] \times \acute{\omega}_j\left(1 - \acute{\omega}_j\right) \times \alpha_i$$

$$\Delta\omega_{I,j} = \epsilon\xi_j\alpha_i \tag{9}$$

where,

$$\xi_j = \left[\sum_k \xi_k\left(\nu_{j,k}\right)\right] \times \acute{\omega}_j(1 - \acute{\omega}_j)$$

The layer of output as well as hidden written in Eq. (10) which updating the weight and bias between them.

$$\nu^{+}_{j,k} = \nu_{j,k} + \lambda_F\Delta\upsilon_{j,k} \tag{10}$$

Eq. (11) shows the input and hidden layer bias and weight updating.

$$\omega^{+}_{I,j} = \omega_{I,j} + \lambda_F\Delta\omega_{I,j} \tag{11}$$

λ_F is the learning rate of the proposed system. The convergence of the proposed system depends upon the care-full selection of λ_F. After that Prediction layer predicts the traffic congestion. In the performance evaluation layer, we evaluate the performance of the prediction layer in terms of accuracy, miss rate, sensitivity, specificity, etc.

4 Simulation and Results

MATLAB 2019a is used for simulation purpose, different statistical performance metrics [45,46] are used in this research to evaluate the performance of the proposed system model in both training and validation phases, respectively. Eqs. (12)–(19) show the parameters derived from the formulas.

$$\text{Miss rate} = \frac{\left(\frac{O_y}{T_N} + \frac{O_N}{T_y}\right)}{T_N + T_y} \tag{12}$$

$$\text{Accuracy} = \frac{\left(\frac{O_N}{T_N} + \frac{O_y}{T_y}\right)}{T_N + T_y} \tag{13}$$

$$\text{Sensitivity} = T_{Cy}/\left(T_{Cy} + F_{CN}\right) \tag{14}$$

$$\text{Specificity} = T_{CN}/\left(T_{CN} + F_{Cy}\right) \tag{15}$$

$$\text{Negative prediction value (NPV)} = \frac{\frac{O_y}{T_y}}{\left(\frac{O_y}{T_y} + \frac{O_N}{T_y}\right)} \tag{16}$$

$$\text{Positive prediction value (PPV)} = \frac{\frac{O_N}{T_N}}{\left(\frac{O_N}{T_N} + \frac{O_y}{T_N}\right)} \tag{17}$$

$$\text{False positive ratio (FPR)} = 1 - \text{specificity} \tag{18}$$

$$\text{False negative ratio (FNR)} = 1 - \text{sensitivity} \tag{19}$$

The proposed system model calculates the predicted output as negative (N) and positive (y). The resultant output shows the value of the negative (N) and positive (Y) existence of congestion. Tab. 2 shows the performance of the proposed Hybrid Neuro-Fuzzy System Model during training. In which 616 samples are taken as total which is further divided into 316 positives and 300 negative samples. It is clearly shown that 310 samples are estimated correctly in which congestion not found, whereas 06 samples are wrongly estimated as negative in which congestion found, but congestion does not exist. Similarly, 295 samples are correctly estimated as negative in which congestion found and 05 samples are estimated wrongly in which congestion not found, but congestion exists.

Table 2: Training of the proposed hybrid neuro-fuzzy system model

Proposed model (Sample data used in training is 70%)			
Total samples (N = 616)		Result (O_N, O_y)	
Input	Expected output (T_N, T_y)	O_N (Not Congestion) Positive	O_y (Congestion) Negative
	$T_N = 316$ (Positive)	310	06
	$T_y = 300$ (Negative)	05	295

Validation results are presented in Tab. 3 in which 264 samples are taken in total that are further divided into 144 and 120 positives negative samples, respectively. From the simulation experiments, it is observed that 140 samples are estimated correctly, and congestion was not found whereas 4 samples are wrongly estimated as negative in which congestion found, but congestion does not exist. Similarly, 2 samples are wrongly estimated as congestion not found, but, congestion exists, whereas 118 samples are correctly estimated as negative in which congestion found, respectively.

Table 3: Validation of the proposed hybrid neuro-fuzzy system model

Proposed model (Sample data used in validation is 30%)			
Total samples (N = 264)		Result (O_N, O_y)	
Input	Expected output (T_N, T_y)	O_N (Not Congestion) Positive	O_y (Congestion) Negative
	T_N= 144 (Positive)	140	04
	T_y = 120 (Negative)	02	118

Table 4: Performance evaluation of proposed hybrid neuro-fuzzy system model during validation & training using different statistical measures

	Miss rate	Accuracy	Sensitivity	Specificity	PPV	NPV	FPR	FNR
Training	0.786%	99.21%	99.41%	99.01%	99.10%	99.33%	98.01%	98.41%
Validation	1.27%	97.2%	99.59%	97.72%	98.22%	99.33%	96.72%	98.59%

The performance of the proposed hybrid neuro-fuzzy empowered model during training and validation by using different statistical metrics is shown in Tab. 4. It is clearly shown that the proposed system during training produces 99.21% and 0.786% accuracy and miss rates, respectively. During validation, the proposed system produces 98.72% and 1.272% accuracy and miss rates, respectively. Tab. 4 also shows system model performance in terms of sensitivity, specificity, during training & validation phase. It clearly shows that the proposed system during training gives 99.41% and 99.01% sensitivity and specificity, respectively. And during validation proposed system gives 99.59% and 97.72% sensitivity and specificity, respectively. Also, some more statistical measures are added to predict the values such as false positive, false negative, as well as positive and negative prediction values gives the result during training 98.01%, 98.41%, 99.10%, and 99.33%. Further, during validation, the proposed system gives 96.72%, 98.59%, 98.22%, and 99.33%, respectively.

The comparison of the proposed system model using neuro-fuzzy results with previous literature approaches presented in Tab. 5. It clearly observed from Tab. 5, proposed system model empowered with neuro-fuzzy exhibits 99.214% and 98.728% accuracy during training and validation phases, respectively which is significantly superior to the earlier methods proposed by Rani et al. (2018) [15], Ata et al. (2019) [18] and Siddiqui et al. (2021) [22]. The evaluation of the proposed system model provides better accuracy in validation phase by 8%, 1.2% and 0.7% as compared [15,18] and [22], respectively. The scheme possesses an affordable complexity and is compatible with real-time smart city environment. Because the once the proposed neuro-fuzzy system is learnt, it is like plug and play component.

Table 5: Comparison of performance measure of proposed hybrid neuro-fuzzy during validation & training with previously published methods

Literature		Performance during training		Performance during validation	
		Accuracy (%)	Miss rate (%)	Accuracy (%)	Miss Rate (%)
Rani et al. (2018) [15]		91.265	8.732	90.6	9.4
Ata et al. (2019) [18]	Fitting model	96.2	3.8	95.84	4.16
	Time series model	98.15	1.85	97.56	2.44
Siddiqui et al. (2021) [22]	DNN	98.95	1.05	98.03	1.97
Proposed hybrid neuro-fuzzy model		99.214	0.786	98.728	1.272

5 Conclusion

Modeling, simulation, and analysis of the intelligent traffic congestion points prediction in the smart cities is a challenging task. In this research, a similar model for the prediction of traffic congestion has been proposed to improve the accuracy. The proposed cloud-based hybrid neuro-fuzzy empowered model forecasts the congestion point in the different junctions of road. Neural network has been trained over the dataset examples to optimize the fuzzy membership functions for better approximation and reasoning. The inputs come from various IoT sensors implanted on the roadside in a smart city scenario and after due preprocessing over the cloud server, fetched into the proposed system. Simulation results have shown that the accuracy of the proposed model is 99.214% and 98.728% during the training and validation phases, respectively. It also observed that the proposed model possesses more accurate results as compared to previously published state-of-the-art road traffic congestion approaches in the literature.

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