Intelligent Traffic Congestion Classification System using Artificial Neural Network

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ABSTRACT

Managing the ever increasing road traffic congestion due to enormous vehicular growth is a big concern all over the world. Tremendous air pollution, loss of valuable time and money are the common consequences of traffic congestion in urban areas. IoT based Intelligent Transportation System (ITS) can help in managing the road traffic congestion in an efficient way. Estimation and classification of the traffic congestion state of different road segments is one of the important aspects of intelligent traffic management. Traffic congestion state recognition of different road segments helps the traffic management authority to optimize the traffic regulation of a transportation system. The commuters can also decide their best possible route to the destination based on traffic congestion state of different road segments. This paper aims to estimate and classify the traffic congestion state of different road segments within a city by analyzing the road traffic data captured by in-road stationary sensors. The Artificial Neural Network (ANN) based system is used to classify traffic congestion states. Based on traffic congestion status, ITS will automatically update the traffic regulations like, changing the queue length in traffic signal, suggesting alternate routes. It also helps the government to device policies regarding construction of flyover/alternate route for better traffic management.

CCS CONCEPTS

• **Networks → Network services**; **Cloud computing**; • **Information systems → Information systems applications**; **Decision support systems**; *Expert systems*; *Data analytics*;

KEYWORDS

Intelligent transportation system; traffic congestion classification; artificial neural network; IoT; smart city

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1 INTRODUCTION

With the rapid development of information and communication technology (ICT), the concept of "smart city" emerges as a way to enhance urban management and environmental sustainability as well as increase standard of living of citizens [1]. Smart mobility is one of the important aspects in "smart city" [10]. Along with the population burst, enormous vehicular growth, socio-economical growth and rural to urban migration has imposed a very difficult challenge to the traffic management system especially in developing countries like India [15]. Population and economic growth leads to enormous vehicular growth in the streets of urban areas. The number of registered vehicles has increased from 0.3 million in 1951 to about 142 million in 2011 in India [14]. Almost every country throughout the world is facing problems in managing the transportation infrastructure and facilities [17]. So, ever increasing vehicular growth puts lots of pressure on transportation infrastructures whatever the country currently have. The streets of Indian urban areas are not able to accommodate the large number of vehicles and thus lead to traffic congestion. Increase in air pollution, loss of valuable time and money of the citizens are the common consequences of traffic congestion in the roads of urban areas. India experiences monetary loss of $6 billion a year due to traffic congestion according to World Bank study [14]. Also high traffic jam results in the increase in number of road accidents [4]. Hence a smart system is required for identification of traffic congestion state of a road to assists the users. IoT based Intelligent Transportation System can be used for monitoring and managing traffic congestion to achieve smooth mobility of traffic, reducing the travel time and air pollution as well enhance the road safety of commuters [15].

Identifying the traffic congestion status of the different road segment is one of the important tasks for the better management of traffic. Traffic congestion status identification over time series helps the traffic regulation authorities to make proper decisions regarding traffic rules and regulations of transportation system. A system needs to be devised which will monitor the traffic continuously by capturing the different parameters of traffic of a road segment and identifies the congestion status. Here,IoT plays a significant role in modern traffic management [11].

The aim of this paper is to present an intelligent traffic congestion status classification framework based on artificial neural network (ANN) [2]. The proposed system acquires real time traffic information and determines the traffic congestion status of different road segments using ANN technique. It will get the real time traffic information like traffic density and average speed of the vehicles from different road segments with the help of in-road stationary sensors and then infer the traffic congestion status using ANN technique. The traffic pattern will help the government/traffic regulatory bodies to make a proper decision regarding traffic rules and regulations and improvement in the area of traffic infrastructure.

The rest of the paper is organized as follows. Section 2 highlights related work on traffic data collection techniques and traffic congestion status estimation. In Section 3, the ANN based proposed system design for traffic congestion estimation and classification is described. Section 4 presents the simulation and result analysis of traffic congestion status identification. Finally, we conclude our paper in Section 5.

2 RELATED WORK

Due to the urbanization, the demand for good transportation system increases tremendously. Therefore, the number of vehicles in road also has risen day by day. There are a lot of research works have been done in different applications of smart traffic management system. Identifying traffic congestion on road is one of the important aspects of it.

In [18], the authors proposed a technique for aggregating floating car data (FCD) to reconstruct accurate traffic state. They determine traffic density and traffic flow with the help of traditional stationary devices like video camera, loop detector and FCD. An efficient and large scale traffic monitoring system is presented in [16], which deduce spatio-temporal traffic data by detecting cyclist, vehicles, pedestrian's etc. using radio-based Bluetooth/Wi-Fi technology. The traffic object equipped with Blue-tooth/Wi-Fi enable device, can detect all other traffic objects by their Bluetooth/Wi-Fi identification number. An object/vehicle is observed or detected by multiple other objects in different location and time and sends the information to the processing unit which reconstruct the traffic trajectory and estimates traffic situation.

In [19], authors proposed a technique to classify road traffic congestion level using decision tree algorithm. They consider vehicle velocity as a parameter to identify congestion level. They collect the road traffic data using GPS device. They used sliding window technique to generate moving pattern from vehicles velocity. They have used J48 decision tree algorithm to develop decision tree model to classify the congestion level. In [7], speed performance index was used to evaluate the road network traffic congestion states. Authors consider vehicle's speed as an important parameter to estimate traffic states. The speed performance index is calculated from vehicle's speed and based on index value, system classify the traffic congestion states. Coifman et al. [3] proposed a method which processes the data collected from automatic vehicle location system (AVL) to measure the travel time and average speed over the freeway and in turn it determines the traffic condition. In another study [13], traffic congestion estimation algorithm has been proposed where congestion features are extracted from MPEG video data and then use Gaussian Hidden Markov model to determine traffic congestion level. In [9], fuzzy logic rule has been used to estimate congestion level. Also in [8] fuzzy logic has been used to detect traffic congestion and a fuzzy based model is used for traffic control.

According to the above mentioned studies, some disadvantages are found in determining the traffic congestion states like: lack of congestion computational model, selection of traffic parameters to infer congestion states. In [9], vehicle velocity is only considered as a parameter to classify traffic congestion level. Similarly, in [8], authors only considers speed performance index as a measuring factor of congestion assessment. It also lacks proper computational technique. To overcome these short comings, this paper proposes an intelligent traffic congestion classification system based on ANN. The system considers two traffic parameters: traffic density and average speed to determine congestion states. It uses ANN model as computational technique to classify congestion levels.

3 PROPOSED SYSTEM

Intelligent traffic monitoring system is one of the important aspects of intelligent transportation system (ITS). It is the system which is administrated by government or transportation authority and can be used to monitor as well as analyze the traffic status of different road segments. The system basically collects the traffic data in real time and determines the congestion states for decision making and management of traffic in an efficient way. The proposed system classifies the traffic congestion states of road segments into three categories: High Congestion, Medium Congestion and Free Flow. Here, in-road stationary sensors capture the different traffic parameters like speed of vehicle, number of vehicle in road in real time and send it to the Artificial Neural Network based information processing unit, which determines traffic congestion states of road segments.

3.1 Overview of the System

The proposed system composed of components namely data collection unit, data transmission unit and information processing unit. These are described as follows.

3.1.1 Data Collection Unit. Traffic data is very important for decision making and precise traffic management planning. The proposed system uses in-road stationary sensors to monitor real time traffic. The sensors are deployed on the road at the both end of road segment. The sensors will capture the speed of vehicles, number of vehicles on the road by the stationary sensors.

3.1.2 Data Transmission Unit. The sensed traffic data need to be sent in periodic manner from field to remote data analysis unit. The local data collection unit will send the aggregated data through wireless or wired communication.

3.1.3 Information Processing Unit. The raw traffic data collected from the field are used to calculate average speed of the vehicles and traffic density of the road. These are analyzed to infer knowledge regarding traffic congestion states of different road segments so that regulatory authorities can make proper planning and decisions in timely manner.

The proposed system uses artificial neural network (ANN) in attempt to make the information processing unit intelligent. The unit receives the real time traffic data which are fed into ANN and it determines the traffic congestion status. The Figure 1 shows the overall design of intelligent traffic congestion classification system.

3.2 Traffic Parameters

The two main traffic parameters are used in the proposed system. These are namely i) traffic density and ii) average speed of vehicles

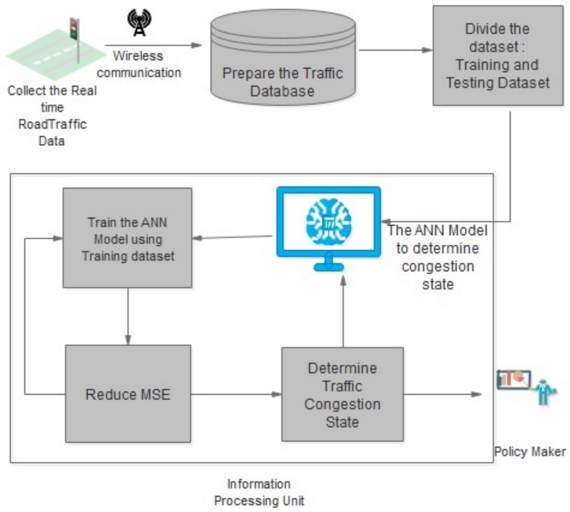

Figure 1: Intelligent Traffic Congestion Classification System.

of each road segment. These are defined as follows.

Traffic Density: Traffic Density is defined as the number of vehicles occupying a given length of a road segment. It can be expressed as:

$$d = \frac{n}{l} \tag{1}$$

where, n is the number of vehicles and l is the length of the road segment.

Average Speed: Average Speed (s_{avg}) is the sum of speed of all the vehicles divided by total number of vehicles.

where, Speed (s_i) is defined as the total distance travelled by the vehicle per unit time. Hence Average Speed can be expressed as:

$$s_{avg} = \frac{\sum_{i=1}^{n} s_i}{n}, \quad where \quad s_i = \frac{dis_i}{t} \tag{2}$$

where, dis_i is the distance travelled by i^{th} vehicle and t is the time period.

3.3 Traffic Congestion States Determination

ANN is an important branch in the field of artificial intelligence [2]. It is a good solution to make an information processing unit to become intelligent. Inspired by biological neural network, ANN based system was developed to solve different complex problems and can be used efficiently to categorize the congestion states. The ANN is composed of large number of elementary processing units called "neurons" and they are connected with each other with some weights. Each "neuron" takes input from source of information and produces output with the help of transfer function. Generally, ANN consists of three layers: i) input layer, ii) hidden layer and iii) output layer and each layer composed of several "neurons". Each layer is interconnected with some weights. In this work, fully connected multilayer perceptron (MLP) [5][6] is used.

Here, the input layer receives two traffic parameters i.e. traffic density and speed of vehicle along with road segment identification number as input to the neural network. This layer only passes the information from real world to the hidden layer, no computation is performed here.

Hidden layer consists of several neurons and it performs the computations on in-coming data and transfer the information to the output layer. An ANN may have any number of hidden layers, but here we consider only one hidden layer having five neurons.

Output layer is responsible for providing output to the outside world. As this work classifies the congestion states into three categories namely High congestion, Medium congestion and Free flow, the proposed ANN model have three neurons each corresponds to different congestion states. Figure 2 shows the proposed ANN model to classify congestion status. It has three inputs $I = I_1, I_2, I_3$ (I_1=Traffic Density, I_2= Average Speed and I_3= Road Segment Identification).

It is clear from the figure that each node of input layer is connected to every node of hidden layer with some weight. Also each node of hidden layer is connected to every node of output layer with some weight. The weighted matrix from input layer to hidden is represented by W_1 and weighted matrix from hidden layer to output layer is represented by W_2. Matrix W_1 and W_2 are shown as follows where $w^i_{j,k}$ represents the weight of the connection to the j^{th} neuron from k^{th} neuron in the i^{th} layer.

$$W^1 = \begin{bmatrix} w^1_{1,1} & w^1_{1,2} & w^1_{1,3} \\ w^1_{2,1} & w^1_{2,2} & w^1_{2,3} \\ w^1_{3,1} & w^1_{3,2} & w^1_{3,3} \\ w^1_{4,1} & w^1_{4,2} & w^1_{4,3} \\ w^1_{5,1} & w^1_{5,2} & w^1_{5,3} \end{bmatrix}$$

$$W^2 = \begin{bmatrix} w^2_{1,1} & w^2_{1,2} & w^2_{1,3} & w^2_{1,4} & w^2_{1,5} \\ w^2_{2,1} & w^2_{2,2} & w^2_{2,3} & w^2_{2,4} & w^2_{2,5} \\ w^2_{3,1} & w^2_{3,2} & w^2_{3,3} & w^2_{3,4} & w^2_{3,5} \end{bmatrix}$$

Every neuron (node) in the hidden layer processes the information based on input and bias using weighted sum method [5] and produces output based on activation function [5].

The weighted sum (n^1_1) at 1^{st} node in the hidden layer represented by :

$$n^1_1 = w^1_{1,1} * I_1 + w^1_{1,2} * I_2 + w^1_{1,3} * I_3 + b \tag{3}$$

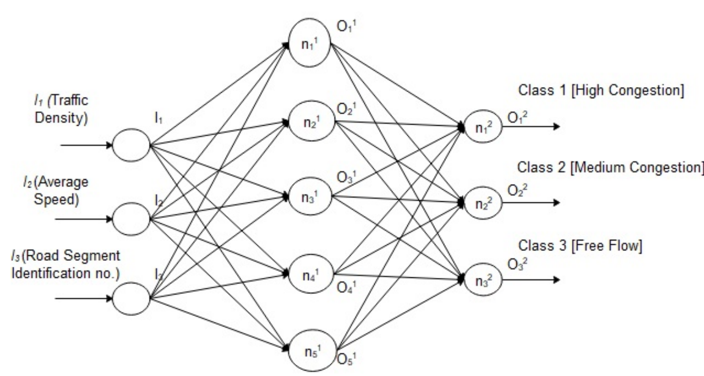

Figure 2: Artificial Neural Network Model.

Then the activation function is applied on the weighted sum (n_1^1) to produce the net output (O_1^1) at 1^{st} node in the hidden layer and can be represented by:

$$O_1^1 = f(n_1^1) \tag{4}$$

where f is activation function. This paper uses log sigmoid activation function [5] which maps the output in the range from 0 to 1 and is represented by :

$$f(n_1^1) = 1/(1 + e^{-n_1^1}) \tag{5}$$

Hence, weighted sum (n_1^1) at 1^{st} node in the hidden layer can be represented in dot product form:

$$n_1^1 = \sum_{k=1}^{m} w_{1,k}^1 i_k + b, \quad where \quad m = 3 \tag{6}$$

The weighted sum (n_1^1) is fed to log sigmoid activation function to get the net output (O_1^1) at the 1^{st} node in the hidden layer which can be represented in dot product form as follows:

$$O_1^1 = f(\sum_{k=1}^{m} w_{1,k}^1 i_k + b) \tag{7}$$

Likewise, net output $O_1^j, j = 5$ for all five node in the hidden layer can be calculated.

Now hidden layer output is fed into the node of output layer to calculate the final output for every node of output layer.

The weighted sum (n_1^2) at 1^{st} node (Class 1 node) in the output layer can be represented in dot product form:

$$n_1^2 = \sum_{k=1}^{m} w_{1,k}^2 O_k^1 + b, \quad where \quad m = 5 \tag{8}$$

Then weighted sum (n_1^2) is fed to log sigmoid activation function to get the net output O_1^2 of 1^{st} node (Class 1 node) in the output layer.

The net output O_1^2 at the 1^{st} node in the output layer can be represented in dot product form:

$$O_1^2 = f(\sum_{k=1}^{m} w_{1,k}^2 O_k^1 + b) \tag{9}$$

The neural network initializes the weights W^1 and W^2 with some random values. Hence the weights needs to be adjusted. Backpropagtion is a technique [5] in artificial neural network to adjust the weight of each nodes (neurons) of network by calculating the gradient of error function.

The error at node 1 of output layer (Class 1) is calculated using squared error [5] function E_{o1} represented by:

$$E_{o1} = 1/2(target - output)^2 \tag{10}$$

where, *target* is the actual output and *output* is the value which the node actually produce.

Similarly, error function E_{o2} and E_{o3} of node 2 (Class 2) and node 3 (Class 3) of output layer respectively should be calculated using Eq. 10.

Total error E_{total} of the network is represented by:

$$E_{total} = E_{o1} + E_{o2} + E_{o3} \tag{11}$$

Now the network will propagate backward to reduce the error by changing the values of weights. For that it needs to calculate the rate of change of error E_{total} with respect to change in weight represented by $\delta E_{total}/\delta w_{1,1}^2$:

$$\delta E_{total}/\delta w_{1,1}^2 = (\delta E_{total}/\delta O_1^2) \ * \ (\delta O_1^2/\delta n_1^2) \ * \ (\delta n_2^2/\delta w_{1,1}^2) \tag{12}$$

So, to adjust the weight $w_{1,1}^2$,$\delta E_{total}/\delta w_{1,1}^2$ is calculated and the weight$w_{1,1}^2$ is updated using following equations:

$$(w_{1,1}^2)^+ = w_{1,1}^2 - \epsilon * \delta E_{total}/\delta w_{1,1}^2 \tag{13}$$

Similarly, all other weights from hidden layer to output layer needs to be updated.

Also, the weights from input layer to hidden layer needs to be adjusted. To adjust the weight $w_{1,1}^1$, $\delta E_{total}/\delta w_{1,1}^1$ is calculated and the weight $w_{1,1}^1$ is updated by using following equ.:

$$\delta E_{total}/\delta w_{1,1}^1 = (\delta E_{total}/\delta O_1^1) \ * \ (\delta O_1^1/\delta n_1^1) \ * \ (\delta n_1^1/\delta w_{1,1}^1) \tag{14}$$

$$(w_{1,1}^1)^+ = w_{1,1}^1 - \epsilon * \delta E_{total}/\delta w_{1,1}^1 \tag{15}$$

Likewise, all other weights from input layer to hidden layer needs to be updated and this whole backpropagation process repeated five thousand times to minimize the error of the network. Once the neural network is designed, it needs to be trained with predefined or known traffic data set. The paper considers traffic density and average speed as input to the neural network and based on input neural network classifies the traffic congestion level. Why average speed along with density used as a input explained in result section. This paper considers three levels of congestion: high congestion, medium congestion and free flow.

4 SIMULATION AND RESULTS

To design and simulate the proposed artificial neural network based intelligent traffic congestion classification system, Python has been used.

The initial weights of connection between input layer nodes and hidden layer nodes are chosen randomly and the matrix is:

$$W^1 = \begin{bmatrix} -11.09 & -6.95 & -0.55 \\ 0.63 & 1.45 & -11.19 \\ -2.76 & -1.81 & 2.98 \\ 4.23 & 0.15 & 35.44 \\ 14.68 & -19.61 & -29.77 \end{bmatrix}$$

The initial weights of connection between hidden layer nodes and output layer nodes are also chosen randomly and the matrix is:

$$W^2 = \begin{bmatrix} -3.71 & -10.87 & 8.63 & -7.17 & 6.33 \\ 12.56 & -1.57 & 1.45 & -17.56 & 11.86 \\ -12.05 & -3.80 & 0.44 & -9.63 & -7.94 \end{bmatrix}$$

After training the proposed neural network five thousand times by backpropagation technique, the weights (W^1, W^2)are adjusted. The final weights of connection between input layer nodes and hidden layer nodes are represented by the matrix:

$$W^1 = \begin{bmatrix} 0.26 & -1.56 & -0.09 \\ 0.05 & -0.06 & 1.84 \\ -1.99 & 0.80 & 0.84 \\ 0.80 & 1.62 & 0.32 \\ 0.95 & -0.24 & -0.08 \end{bmatrix}$$

The final weights of connection between hidden layer nodes and output layer nodes are represented by the matrix:

$$W^2 = \begin{bmatrix} -0.73 & -0.40 & -0.04 & -1.47 & 1.47 \\ 0.08 & -1.08 & 1.11 & 1.27 & 0.67 \\ -1.66 & 0.67 & 0.46 & 1.31 & 0.44 \end{bmatrix}$$

The road traffic information is fed into the ANN. For the simulation, two traffic parameters: traffic density (I_1) and average traffic speed (I_2) have been considered. These two parameters along with road segment (RS) identification number is considered as input to the neural network. The sample traffic parameters shown in Table 1 are captured through survey conducted on different area within the kolkata city and human perception is being used to categorize the congestion level. Three road segments RS1, RS2 and RS3 are considered and 40 set of inputs for each road segments have been used.

Before the traffic parameters are fed into neural network, scaling is performed. Different road segment identification numbers (RS) are transformed into numeric value before feeding into the neural network. The neural network needs to be trained with some known traffic data set so that it can accurately classify the traffic congestion level of different road segments with respect to density and average speed of vehicles. As it is considered three congestion level high, medium and free flow, the proposed network have three output each corresponding to different congestion level. The output is encoded in numeric value ranging between zero and one with the help of sigmoid activation function mentioned in Eq. 5. The scaled parameters along with corresponding output is shown in Table 2.

The proposed neural network is trained with traffic data set mentioned in Table 2 for different types of road segments with varying lane width.

Once the network is trained, it can identify traffic congestion level of a road segment based on density and average speed. Some of the predicted traffic congestion level based on density and average speed is shown in Table 3. It shows that the proposed neural network model accurately classify the traffic congestion state. To justify the accuracy of the proposed system, field survey has been done on different road segments in Kolkata city. For example, if road traffic density is 340 vehicles/km and average speed 20 km/hr. of road segment 1 (RS1) (the scaled value is shown in Table 3, traffic density = 3.4 vehicles/km and average speed = 0.2 km/hr.), then proposed neural model categorizes it as a class 1 (high congestion) which perfectly matches with human observation (i.e. from field survey also it has been observed as high congestion in road segment (RS1) for the above mentioned scenario). Similarly, if road traffic density is 100 vehicles/km and average speed 80 km/hr. of road segment 1 (RS1), then proposed neural model categorizes it as a class 3 (free flow). As different road segments are of different types with varying lane width, therefore some road segments can become congested even when lesser number of vehicles is present in the road. In these cases also, the proposed ANN based model can classify the congestion states accurately. For example, in road segment 2 (RS2) which is narrower than RS1, if road traffic density is 155 vehicles/km and average speed 17 km/hr., then it categorize it as a class 1 (high congestion) despite of presence of lesser number of vehicles than RS1. The proposed ANN model identifies road segment 3 (RS3) as a high congestion states when it has 220 vehicles/km and average speed is 18 km/hr., which is also accurately matches with on field human observation. The congestion status in RS3 is identified as a medium congestion when it has 90 vehicles/km and average speed is 52 km/hr. as the scaled value shown in Table 3.

Table 1: Sample Traffic Parameters

Road Segment Identification	Traffic Parameter: Density (No. of cars/km)	Traffic Parameter: Avg. Speed (km/hr.)
RS1	380	12
RS1	350	18
RS1	320	23
RS1	300	28
RS1	270	39
RS1	255	42
RS1	248	48
RS1	210	55
RS1	190	60
RS1	150	72
RS1	130	78
RS1	90	82
RS1	60	90
.	.	.
.	.	.
RS2	180	12
RS2	150	18
RS2	120	25
RS2	100	35
RS2	80	42
RS2	70	47
RS2	62	53
RS2	48	70
RS2	10	90
.	.	.
.	.	.
RS3	250	16
RS3	230	16
RS3	180	27
RS3	120	43
RS3	100	50
RS3	65	75
RS3	50	77

The proposed system is compared with W. Pattara-atikom et al. [12] with respect to human observation to evaluate the accuracy of the system. The comparison has been done on the dataset shown in Table 1. In [12], the authors considered only vehicle velocity to estimate traffic congestion. They used two threshold values β

Table 2: Sample Training Data Set

Training Data Set					
Road Segment Identity	Scaled Traffic Parameter		Output		
	Density (No. of Car/km)	Avg. Speed (km/hr.)	Class1	Class2	Class3
1	3.8	0.12	1	0	0
1	3.2	0.23	1	0	0
1	2.7	0.39	1	0	0
1	2.55	0.42	0	1	0
1	2.1	0.55	0	1	0
1	1.9	0.60	0	0	1
1	1.3	0.78	0	0	1
1	0.6	0.90	0	0	1
.	.	.	.	.	.
.	.	.	.	.	.
2	1.8	0.12	1	0	0
2	1.2	0.25	1	0	0
2	1.0	0.35	1	0	0
2	0.8	0.42	0	1	0
2	0.62	0.53	0	1	0
2	0.30	0.70	0	0	1
2	0.10	0.90	0	0	1
.	.	.	.	.	.
.	.	.	.	.	.
3	2.50	0.16	1	0	0
3	2.30	0.16	1	0	0
3	1.80	0.27	1	0	0
3	1.20	0.43	0	1	0
3	1.00	0.50	0	1	0
3	0.65	0.75	0	0	1
3	0.50	0.77	0	0	1

and γ to classify the congestion levels into three categories: red, yellow and green which correspond to high congestion, medium congestion and free flow levels respectively. If average velocity is less than β km/hr, then the system classify it as a red level i.e. high congestion while it classifies as a yellow level if the average velocity is between β km/hr and γ km/hr, and when the average velocity is greater than γ, the system classify the road segment as green level i.e. free flow. However the system does not always classify the traffic congestion levels accurately. Only vehicle velocity cannot be considered as a measure to classify congestion levels. This is because velocity may be less than threshold value β not due to congestion but due to bad road condition or weather condition (like heavy rainfall, fog etc). The intelligent traffic congestion classification system presented in this paper considers traffic density and average speed to overcome the above mentioned problem presented in [12]. Thus, the proposed work classifies the congestion level accurately. Figure 3 shows the comparison between the proposed system and W. Pattara-atikom et al. system in terms of accurate classification of congestion level. It uses the users' observations for classifying congestion level and it is shown in the figure as the reference line. High congestion is represented by 1 while medium congestion and free flow is represented by 2 and 3 respectively in the comparison graph.

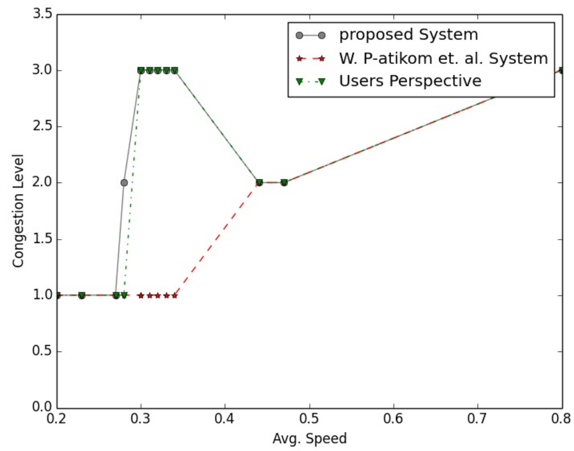

Figure 3: Performance analysis with respect to average speed and congestion level.

Table 3: Sample Traffic Congestion State Prediction

Training Data Set					
Road Segment Identity	Scaled Traffic Parameter		Output		
	Density (No. of Car/km)	Avg. Speed (km/hr.)	Class1	Class2	Class3
1	3.40	0.20	9.99e-01	3.12e-05	6.08e-04
1	3.0	0.23	9.99e-01	5.48e-05	5.85e-04
1	2.9	0.27	9.99e-01	6.60e-05	4.99e-04
1	2.55	0.44	5.15e-03	9.93e-01	2.09e-03
1	2.5	0.47	2.04e-04	9.98e-01	8.62e-04
1	1.0	0.80	3.62e-10	1.11e-03	9.98e-01
1	0.5	0.34	2.04e-06	1.14e-01	8.90e-01
1	0.48	0.33	2.78e-06	1.91e-01	8.08e-1
1	0.4	0.31	4.03e-06	2.95e-01	6.86e-01
1	0.39	0.32	2.32e-06	1.23e-01	8.77e-01
1	0.38	0.3	5.77e-06	4.34e-01	5.24e-01
1	0.35	0.3	4.56e-06	3.19e-01	6.51e-01
1	0.35	0.28	6.08e-5	8.78e-01	3.23e-01
2	1.35	0.17	9.99e-01	3.21e-05	5.88e-04
2	0.68	0.48	4.03e-05	9.99e-01	1.22e-03
2	0.25	0.78	3.99e-10	1.11e-03	9.98e-01
3	2.20	0.18	9.99e-01	6.55e-04	6.77e-08
3	2.00	0.19	9.98e-01	3.09e-03	8.47e-08
3	0.90	0.52	1.74e-01	8.08e-01	3.17e-08
3	0.60	0.72	5.56e-06	3.65e-02	9.52e-01

The graph shown in Figure 3 is drawn according to traffic data presented in Table 3. The paper sets the value of β with 35 km/hr. and value of γ with 55km/hr. Based on these threshold values, whenever the average speed is below 35km/hr. the W. Pattara-atikom et al. system always classified the road segments as a highly congested road. But it does not always reflect the actual scenario for example during adverse weather conditions (such as during heavy rainfall, fog) or due to poor road condition the aver-age vehicular speed might be decreased irrespective of the number of vehicles present in the road. For the data sets of table 3: (1, 0.5, .34), (1, 0.48, .33), (1, 0.4, .31),(1, 0.39, .32), (1, 0.38, .3), (1, 0.35, .3),(1, 0.35, .28), W. Pattara-atikom et. al. system wrongly classifies the congestion level as a high congestion level. But the proposed system classifies the congestion level accurately for the above mention data sets as indicate in Table 3. The proposed ANN based system classifies the congestion level as free flow even when the average speed is less than threshold value (35km/hr.) taking into account the value of traffic density as well which almost matches with the result obtained from field survey.

5 CONCLUSION

This paper proposes an intelligent traffic congestion state classification system based on artificial neural network model (ANN). Here we consider two road traffic parameters: traffic density and speed as measures to classify traffic congestion states and three congestion levels: high congestion, medium congestion and free flow. ANN model is designed to determine the traffic congestion status. After training the neural network, it determines the congestion status of road segments. From the result it is seen that the proposed system accurately classifies the congestion status for different types of road segments with varying lane width provided the model is perfectly trained with adequate traffic data sets. Based on traffic congestion status, ITS will automatically update the traffic regulations like, changing the queue length in traffic signal, suggesting alternate routes. It also helps the government to device policies regarding construction of flyover/alternate route for better traffic management.

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