Traffic Congestion Prediction using Soft Computing Approach in Cognitive Internet of Vehicles

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ABSTRACT
Traffic congestion is a significant problem in urban cities, causing delays, fuel wastage, and adverse environmental effects. . In response to this challenge, Cognitive Internet of Vehicles (CIoV) has evolved as a revolutionary solution, utilizing advanced technologies to enhance traffic management systems. This paper proposes an approach for predicting traffic congestion by integrating multiple parameters, leveraging data from the Mobile Adaptive Routing Algorithm (MARA). Soft computing techniques, such as Support Vector Machine (SVM) and Artificial Neural Network (ANN), are used to develop an accurate and reliable predictive model. The experimental findings show that the model's high accuracy and reliability in traffic congestion prediction.The dataset generated through this approach proves to be a useful resource for urban planners, encouraging them to make informed decisions aimed at mitigating congestion. This predictive model offers a possible solution to the growing problem of urban traffic congestion by enhancing traffic management efficiency, promoting smoother traffic flow, and reducing environmental impact.

Keywords: Traffic congestion prediction, Machine learning, Soft computing approaches, Support Vector Machine (SVM), Artificial Neural Network (ANN)

1. INTRODUCTION

“Traffic congestion” refers to a condition when travel demand exceeds the existing road system capacity [1][2]. It has become a major urban transportation problem [3], [4], [5]. Over past few years, almost all the large and smart cities are suffering from this severe issue called “TRAFFIC”. This problem is continuously increasing because of industrialization and people are found to be wasting their timebecause of prolonged traffic congestion which hampers productivity, cost of fuel every single day in just travelling due to traffic issues, affecting the country’s economy directly or indirectly [6], [7].Modern traffic networks are complicated and dynamic, making traditional traffic management techniques difficult to handle. These approaches rely on historical data and simple models. This has prompted both governments and researchers to create sophisticated traffic prediction models and invest in Intelligent Transportation Systems (ITS).Therefore, a traffic prediction model is needed to take as preventive measures to avoid it [8], in addition to this country’s economy and pollution can also be reduced.

The Internet of Things (IoT) [9], [10], [11] is transforming traditional vehicular ad-hoc networks(VANETs) [12], [13] into the Internet of Vehicles (IoV) [14], [15], but challenges need to be addressed to enhance IoV's intelligence, leading to the development of the Cognitive Internet of Vehicles (CIoV) [16], [17].Although there have been a noticeable advancement in terms of automation and connectivity, still, it is not sufficient to reduce the road/traffic causalities to zero. Also, today’s one of the real world problem is formation of vehicular traffic congestion on roadswhich needs to be addressed properly. This could be realised with the advent of the CIoV, which strengthens the Internet of Vehicles (IoV) by utilizing soft computing and artificial intelligence approaches to make more intelligent, adaptive decisions.

A novel dataset was designed for this purposeusing traffic data from Mobile adaptive routing algorithm (MARA)which is a location-aided routing protocol designed to minimise data delivery delays in the CIoV where smart vehicles on road are considered as the nodes which communicate data with one another to exchange traffic-related information.MARA considers communicable nodes within the request zone and minimizes data delivery delay in Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication, ensuring uninterrupted connections and updating the corresponding route path. It discovers the shortest path, a novel road-aware routing strategy, and can improve routing performance in the CIoV by selecting a stable route [18]. Using soft computing techniques suchas support vector machine (SVM) [19] and artificial neural network (ANN) [20], extensive experiments are carried out on the developed benchmark demonstrated for an effective congestion predictionconsidering multiple parameters including vehicle speed, congestion levels, and end-to-end delay.

The primary goal of this paper is to develop a trained network using a soft computing approach to predict congestion for better traffic management.

The paper's structure is as follows: Section 2 presents a literature review of various soft computing approaches. Section 3 introduces a method for data collection and development of prediction model. Section 4 details experimental evaluation and a comparative analysis. Lastly, conclusions are outlined in section 5 and highlights possible directions for further research and development in section 6.

2. LITERATURE SURVEY

ShrideviJeevanKamble et al. [21] contributed to the field of traffic congestion prediction by implementing a machine learning (ML) approach utilizing GPS vehicle trajectory data to predict traffic speed and identify congestion. Their study employed a Gaussian process model in ML, leveraging three datasets: a training set, prediction set, and road sector data frame. The model was designed to predict traffic congestion based on multiple parameters, including hard delay constraints and vehicle speed data gathered from GPS-equipped vehicles. The authors evaluated traffic congestion by analyzing the average vehicle speed across different road sectors during three specific time slots. Their findings demonstrated that machine learning, particularly the Gaussian process, effectively provided real-time, future, and short-term traffic predictions using both live and historical data. This method provides insightful information for congestion management, leveraging the large amount of data generated by intelligent vehicles to improve traffic flow prediction and identification.

Sanaz Shaker Sepasgozaret al. [22] have made significant contributions to the field of VANETs by proposing a predictive model to the network traffic flow that integrates both V2V and V2R communication data. Their model, termed RF-GRU-NTP, combines machine learning and deep learning techniques to predict network traffic based on road traffic conditions. The investigation was divided into threephases: (1) network traffic prediction based on packet receiving data from V2R communication, where Random Forest (RF) was found to outperform other machine learning algorithms; (2) road traffic prediction using V2V data, where the Gated Recurrent Unit (GRU) algorithm achieved the highest accuracy for predicting traffic flow based on sender speed; and (3) a hybrid model that combined V2V and V2R data to improve prediction performance. Their work emphasizes the significance of "packet receive" and "receiver speed" as key features influencing network traffic flow and demonstrates the RF-GRU-NTP model's superiority over traditional algorithms like LSTM and Bi-LSTM. This research marks the first attempt to predict network traffic flow based on road traffic flow data, providing the groundwork for upcoming big data applications in VANETs.

CharalamposBratsas et al. [23] used Thessaloniki, Greece road network probe data to compare three machine learning models: a) Random Forestsb) Support Vector Regression and c) Multilayer Perceptron additionally to Multiple Linear Regression. The goal of the study was to predict traffic. Numerous tests clustered in three distinct types of scenarios were used to conduct the comparison. Using distinct randomly chosen dates and randomly chosen roads, the algorithms are tested in the first scenario. In the second scenario the algorithms are tested on randomly chosen roads at eight consecutive 15-minute periods, whereas an entire day is spent testing the algorithms on randomly chosen roads in the third scenario. The experimental results indicate that the Multilayer Perceptron model has the most near-zero errors and adapts better to circumstances with more variations than the Support Vector Regression model that works best at stable conditions with small variations.

Nadia Shamshad et al. [24] developed a traffic flow prediction system that combines machine learning techniqueswith real-time data from vehicle detection sensors and weather services. The system predicts traffic data in hourly intervals, ranging from 1 to 24 hours, using historical data from open-source platforms. The authors employed ANN for long-term traffic predictions and SVM for short-term predictions. Their findings revealed that shorter time intervals yielded more accurate predictions, with ANN excelling in long-term forecasting and SVM providing better short-term accuracy. The model also enables live traffic monitoring, identifying the most congested roads and considering environmental factors such as weather and accident records. This system offers valuable benefits to the public by providing real-time traffic updates, accident reports, and route suggestions based on traffic and weather conditions.

3. METHODOLOGY

This section describes the steps used to develop and assess the proposed traffic congestion prediction model, including data collecting, model development. The prediction model is built on two soft computing techniques: Support Vector Machine (SVM) and Artificial Neural Network (ANN).

3.1 Data collection

To predict traffic congestion, traffic data is collected using the node (vehicle) mobilityin Mobile adaptive routing algorithm (MARA) which is a location-aided routing protocol designed to minimise data delivery delays in the CIoV [18].We consider dataset with the parameters of traffic such as average velocity, average end-to-end delay, average packet delivery ratio, number of congestion state levels, total number of vehicles at the particular time, average distance, congestion probability and time (24hrs). The huge set of these datasets are employed to train the network using a soft computing approaches. The output of these approaches will be thevehicle traffic congestionprediction for the test dataset.

3.2 Development of prediction model:

In this section, the development of soft computing approaches to predict traffic congestion based on the pre-processed dataset is outlined. Both Support Vector Machines (SVM) and Artificial Neural Networks (ANN) are explored as potential methods for traffic prediction. The following subsections describe the specific steps taken to preprocess the data, build, train and evaluate the models.

3.2.1 Building and Training SVM and ANN Models:

- **Data Preprocessing**
- **Normalize the Data:** Scale the features to a uniform range (e.g., 0 to 1) to improve model performance.
- **Train-Test Split:** Divide the dataset into training and testing sets to evaluate the performance of the models**,** typically used 70-30 split.

3.2.2 Model Building with SVM

- Define the SVM Model: An SVM model is created using a Gaussian kernel function (RBF).
- Train the Model: The model was trained on the preprocessed training set using Error-Correcting Output Codes (ECOC) function for multi-class classification. The model also estimates posterior probabilities and is configured to differentiate betweencongestion levels (here, binary classification) based on traffic features.
- Evaluate the Model: The performance of the SVM model was assessed using the test dataset. The key performance metrics included accuracy, sensitivity, and specificity, providing a comprehensive evaluation of the model’s classification performance.

3.2.3 Model Building with ANN

- Define the ANN Architecture: A feedforward neural network is created. The network consists of an input layer, two hidden layers with 5 and 3 neurons respectively, and an output layer for binary classification (low vs. high congestion).
- Train the Model: The ANN was trained using backpropagation, mean squared error as the loss function, and an adaptive optimizer to minimize errors.
- Evaluate the Model: Similar to SVM, the ANN model performance is evaluated based on accuracy, sensitivity, and specificity using the test dataset.

4. Experimental Evaluation

For evaluating both the models, traffic data has been collected from MARA [6]. The 70% of data used as training data and the 30% of data used as testing data.To evaluate the performance to predict vehicle traffic congestion for the test dataset, it is necessary to assess performance metrics like sensitivity, specificity and accuracy.

- **Sensitivity**: Assesses the model’s ability to correctly identify congestion (true positives).
- **Specificity**: Evaluates the model's ability to accurately predict non-congestion conditions (true negatives).
- **Accuracy**: Measures the percentage of correctly predicted congestion levels.

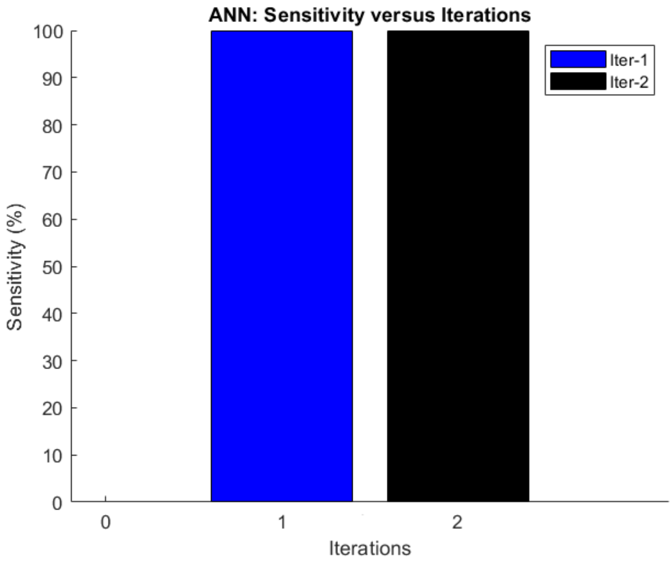

Fig 1: ANN sensitivity versus iterations

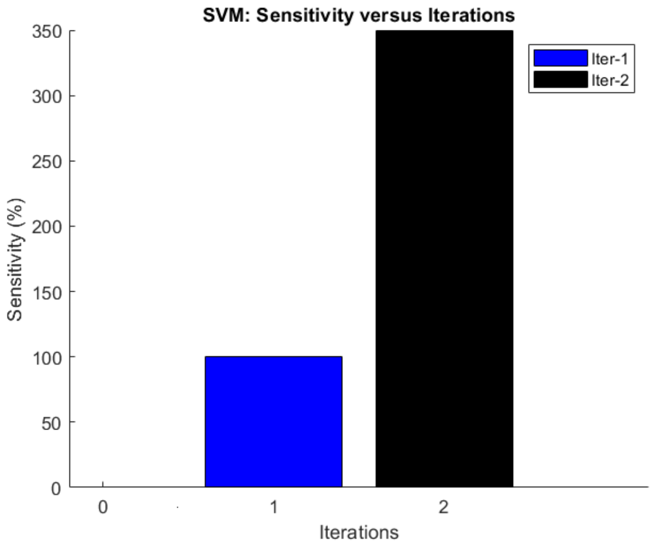

Fig 2: SVM sensitivity versus iterations

The figure 1 demonstrates the sensitivity of an ANN over two iterations (Iter-1 and Iter-2). The ANN achieves near-perfect sensitivity, reaching 100%, indicating its effectiveness in identifying true positives and accurately predicting traffic conditions based on the given dataset. This consistent performance suggests the ANN model is stable and robust for vehicle traffic prediction, avoiding false negatives.

The figure 2 shows the sensitivity results of a SVM over two iterations (Iter-1 and Iter-2). Iter-1 has a sensitivity of approximately 100%, similar to an ANN result. However, in Iter-2, the sensitivity spikes to over 300%, suggesting a highly skewed performance due to overfitting or excessive positive case classification. The SVM's performance varies between iterations, with the first showing effective traffic prediction. Further investigation is needed to understand this sensitivity spike and determine necessary adjustments in model tuning.

The sensitivity analysis for ANN and SVM in vehicle traffic prediction, reveals that ANN offers more stable performance across iterations, while SVM may suffer from overfitting in certain iterations. ANN is considered more reliable for consistent traffic prediction outcomes, while SVM may require careful adjustment to avoid overfitting in certain iterations.

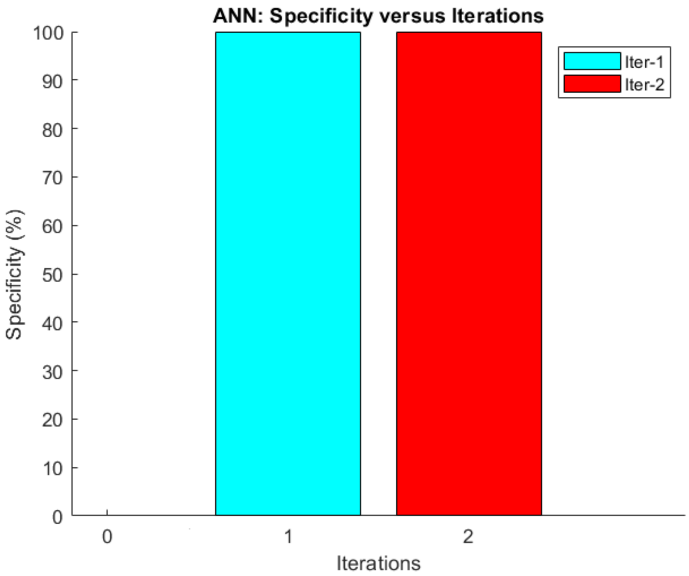

Fig 3: ANN specificity versus iterations

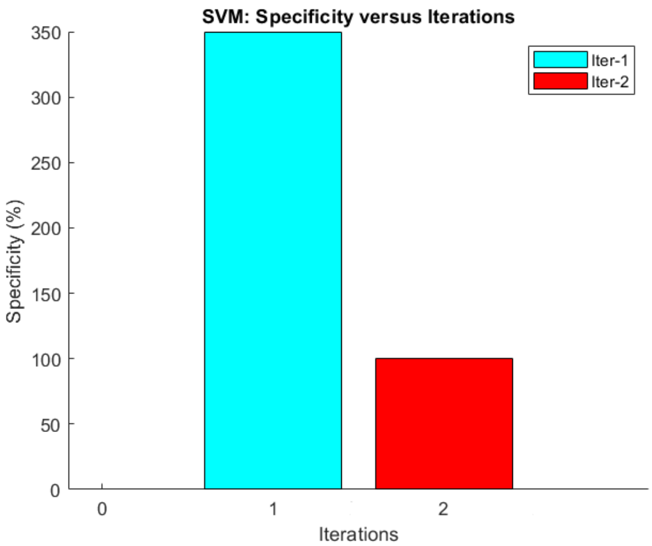

Fig 4: SVM specificity versus iterations

The figure 3 shows the specificity of an ANN model for vehicle traffic prediction, with Iter-1 and Iter-2 showing close to 100% specificity values, indicating high accuracy in predicting non-traffic scenarios. This consistency suggests the model maintains its ability to accurately identify non-traffic conditions, potentially showing stable performance with minimal overfitting or underfitting issues.

The figure 4 illustrates the specificity of a SVM model for vehicle traffic prediction over two iterations. The first iteration had a high specificity of over 350%, indicating overfitting on non-traffic scenarios. However, the second iteration shows a significant drop to below 100%, indicating a decrease in the model's ability to accurately predict non-traffic conditions, possibly due to adjustments made to reduce overfitting or changes in training data or model parameters.

The ANN model demonstrated high specificity in both iterations, indicating its reliability in avoiding false positives and ensuring accurate identification of non-traffic prediction. This suggests that the ANN model might be more robust than the SVM in handling different training scenarios or datasets for traffic prediction. However, the SVM model showed a significant drop in specificity between iterations, indicating variability in performance. Further analysis is needed to assess other performance metrics and overall prediction in traffic management applications.

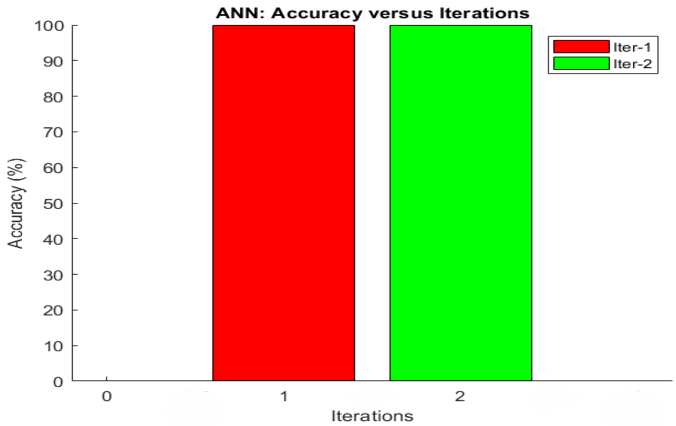

Fig 5: ANN accuracy versus iterations.

The figure 5 shows the accuracy of an ANN model over two iterations of the ANN training process. Both iterations show an accuracy of 100%, indicating that the model performed perfectly in both cases.

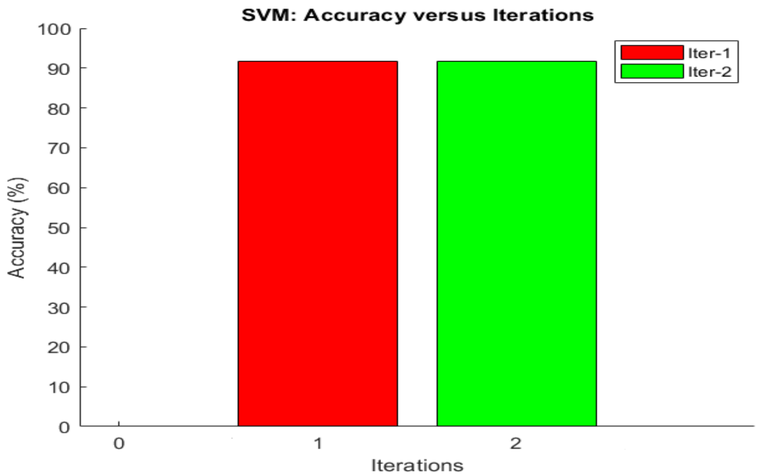

Fig 6: SVMaccuracy versus iterations.

The figure 6 shows the accuracy of an SVM model over two iterations of the SVM training process. Both iterations show an accuracy of 92%, indicating that the model performed perfectly in both cases.
The figure 7 shows the comparison of ANN and SVM accuracy. Both the models can effectively predict vehicle traffic congestion, although ANN's high accuracy, highlighting the model's robustness. By leveraging these soft computing approaches, traffic management systems can proactively address congestion, improving overall traffic flow and reducing delays.

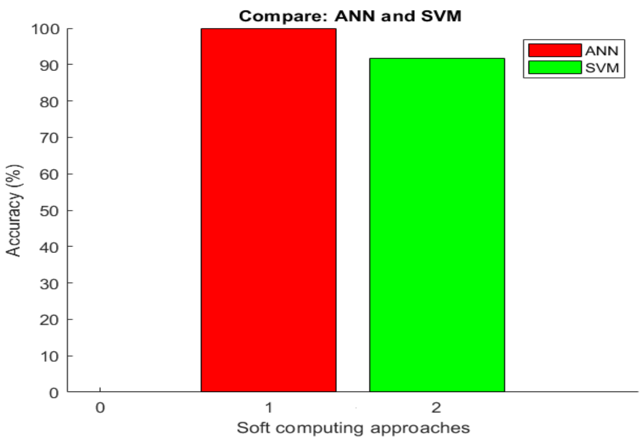

Fig 7: Compare ANN versus SVM accuracy.

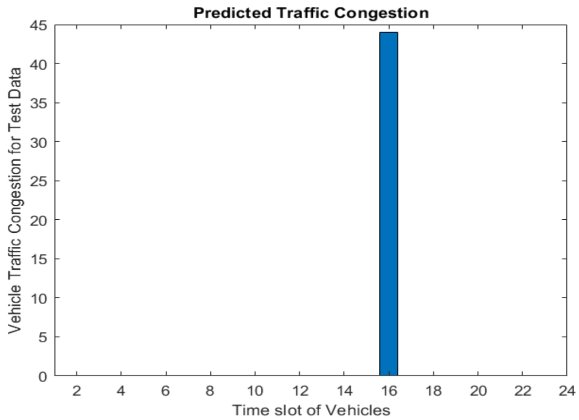

Fig 8: Prediction of vehicle traffic congestion for test data versus time.

Figure 8 shows predicted vehicle traffic congestion for test data specifically plotted against time slots over 24 hours. The traffic congestion is forecasted based on the number of vehicles data fed into the trained ANN model. Since, compared to the Support Vector Machine (SVM), ANN showed superior predictive performance, achieving higher accuracy in forecasting traffic congestion.

The ANN utilizes traffic datausede to train the network as inputs, processes them, and outputs predictions regarding vehicle congestion for specific time slots. The plot shows the number of vehicles predicted for a particular time slot. In the given example, the predicted vehicle congestion is recorded at time slot 16 hours, and the vehicle density is 44 vehicles which denotes the predicted vehicle traffic congestion for test data, reflecting how heavily congested a particular hour might be based on the ANN prediction.This approach is essential for traffic management systems because it can precisely forecast when traffic may maximum, allowing for immediate actions like changing traffic signals, implementing traffic control measures, or by providing drivers real-time information. This ultimately reduces delays and enhances road safety.

5. CONCLUSION

The model was evaluated on soft computing approach to predict traffic congestion using SVM and ANN models within the CIoV framework. By leveraging traffic data obtained from the MARA, our model effectively predicted congestion based on multiple parameters, including vehicle speed, congestion levels, and end-to-end delays.

The experimental evaluation demonstrated that both models performed well, but the ANN model exhibited superior stability, accuracy, and sensitivity across different iterations. The SVM model, while effective in certain scenarios, showed signs of overfitting.The ANN's ability to consistently predict traffic congestionhelps in making informed decisions for traffic management and control, leading to more efficient and safer transportation systems.

Overall, this work contributes to the growing field of intelligent transportation systems by offering a novel and effective solution for predicting traffic congestion. The proposed models can aid urban planners and traffic management authorities in making data-driven decisions to reduce congestion, optimize traffic flow, and minimize the environmental impact of urban transportation.

6. Future Scope

The proposed traffic congestion prediction models show promise but need further enhancement. Expanding the dataset with diverse traffic data, integrating real-time data from IoT sensors, traffic cameras, and vehicle detection systems, and incorporating environmental factors like weather conditions and accident data could improve accuracy and generalizability. Testing the models' scalability and deployment in real-world smart city applications could demonstrate their practical impact.

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