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Research Article

A Fuzzy Wavelet Neural Network (FWNN) and Hybrid Optimization Machine Learning Technique for Traffic Flow Prediction

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ABSTRACT

Traffic go with the flow forecasting is essential in urban planning and management, optimizing transportation structures and resource allocation. However, accurately predicting visitors glide is tough because of its inherent complexity, nonlinearity, and diverse uncertain factors. The trouble declaration underscores the issue in as it should be forecasting site visitors flow, mainly in urban environments characterized through dynamic and complex site visitor's styles. In the existing paintings there are numerous traditional devices getting to know models used for visitors flow prediction, however those conventional strategies show off barriers in reaching excessive prediction accuracy. Therefore, the proposed work targets to put into effect hybrid optimization techniques for correct prediction in shipping machine. Here fuzzy wavelet neural community (FWNN) is used to address complicated nonlinear structures with uncertain conditions and hybrid optimization method called hybrid firefly and particle swarm optimization (HFO-PSO) which combines the exploration and exploitation talents of firefly and this fusion allows the version to capture intricate visitor's styles efficiently and optimize the prediction technique, improving accuracy and efficiency. Moreover, the prediction performance of the proposed model is established and compared by means of the usage of distinct measures.

1. INTRODUCTION

Traffic glide prediction is a essential area of look at within transportation structures, especially in urban environments wherein increasing vehicular quantity poses vast demanding situations to green mobility. Over the past decades, several studies efforts were dedicated to developing accurate fashions for predicting site visitors congestion, aiming to alleviate associated troubles which includes extended journey times, environmental pollution, and usual city congestion [1]. Traditional techniques for traffic congestion prediction regularly rely upon statistical tactics and simplistic gadget gaining knowledge of strategies. However, those methods generally tend to conflict with the complexity and variability of real-world visitor's styles, specially whilst faced with dynamic external factors which includes weather conditions, unique events, or street incidents.

Traffic congestion offers a myriad of troubles that impact both people and society at huge. One of the most evident problems is the tremendous boom in travel instances throughout top hours, leading to delays and frustration among commuters. This now not most effective influences individuals seeking to reach their locations however also disrupts deliver chains and logistics, ultimately impacting companies and the economic system. Moreover, congestion contributes to environmental degradation via multiplied vehicle emissions [2]. The slow-transferring or idling visitors feature of congested regions ends in higher degrees of air pollutants, posing fitness dangers to residents and contributing to weather change.

The dependency on non-public vehicles also ends in better fuel consumption and carbon emissions, exacerbating environmental concerns. In addition to environmental and monetary influences, site visitors congestion has social effects. It can contribute to heightened pressure stages among commuters, affecting basic well-being and great of life. Congestion

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additionally will increase the chance of avenue injuries, in particular rear-give up collisions and fender-benders in prevent-and-go traffic conditions, posing dangers to both drivers and pedestrians [3]. Furthermore, it limits the effectiveness of public transportation systems. Buses and trains regularly get stuck inside the same traffic jams as non-public cars, resulting in unreliable schedules and reduced elegance of public transit options [4]. This perpetuates the cycle of vehicle dependency and congestion. Traffic congestion is a complicated difficulty with a long way-reaching results on urban lifestyles. It influences journey times, air nice, public health, financial productiveness, and overall city livability. Addressing congestion calls for holistic techniques that prioritize sustainable transportation options, efficient urban planning, and progressive era solutions to create towns wherein mobility is green, equitable, and environmentally responsible.

Traditional methods for traffic congestion prediction frequently depend upon statistical techniques and simplistic device gaining knowledge of techniques. However, these processes tend to conflict with the complexity and variability of real-global site visitor's patterns, specially whilst confronted with dynamic external elements such as climate conditions, special occasions, or street incidents. As a end result, the accuracy and reliability of such models under real-time situations are frequently constrained. To deal with those demanding situations, latest research have increasingly became to superior deep getting to know techniques, that have proven promise in shooting the elaborate patterns inherent in traffic statistics. Deep studying architectures, in particular the ones incorporating recurrent neural networks (RNNs) and interest mechanisms, have emerged as effective gear for modeling the nonlinear and dynamic nature of traffic drift [5]. One splendid approach is the integration of Bidirectional Long Short-Term Memory (Bi-LSTM) networks with attention mechanisms [6]. Bi-LSTM networks are well-desirable for shooting temporal dependencies in site visitors records by processing statistics in both forward and backward directions.

The targets of this studies embody the development and implementation of advanced predictive models for site visitors waft, aimed at addressing critical challenges in transportation control and concrete planning. The primary aim is to layout and installation deep learning techniques that accurately forecast visitors waft in real-time, benefiting both avenue vacationers and governing government.

The observe makes a specialty of leveraging the Fuzzy Wavelet Neural Network (FWNN) greater with a Hybrid Feedforward (FF) and Particle Swarm Optimization (PSO) set of rules. This version structure is adapted to seize the complex, nonlinear styles inherent in site visitors drift statistics, thereby improving prediction accuracy over conventional strategies. The authentic contributions of this paper are as follows:

Chapter 1 presents an extensive creation to the studies on visitor's congestion prediction, highlighting its objectives, demanding situations, and background. It ambitions to cope with the urgent need for accurate site visitors forecasting to beautify transportation performance and urban planning. Chapter 2 is a complete literature assessment that synthesizes previous research in site visitors' prediction. It explores various methodologies, algorithms, and models employed in the discipline, offering a vital analysis in their strengths, weaknesses, and contributions. Chapter 3 introduces fuzzy wavelet neural community (FWNN) is used to handle complex nonlinear structures with unsure situations and hybrid optimization approach called hybrid firefly and particle swarm optimization (HFO-PSO) which mixes the exploration and exploitation abilities of firefly and this fusion permits the model to capture complicated site visitors Also, the overall performance and comparative evaluation of the FWNN and HFO-PSO technique is established and as compared the use of distinctive measures in Section four. Finally, the general paper is concluded with the findings, effects, and destiny scope in Section 5.

2. RELATED WORKS

This section presents the literature assessment of the existing paintings associated with network visitors float prediction and forecasting the use of device learning fashions. Also, it investigates the blessings and downsides of each model in line with its forecasting operations and prediction results

Traffic congestion has profound economic implications that increase beyond mere inconvenience, affecting people, organizations, and broader monetary structures. One of the most extremely good influences is lost productiveness [7]. When commuters and people spend immoderate time stuck in traffic, it translates into lost hours that could had been applied for more efficient activities. This decrease in performance without delay affects financial output and might result in lower standard productivity tiers inside a location. Moreover, traffic congestion consequences in extended expenses for organizations. Transportation and logistics companies face demanding situations in assembly delivery schedules, leading to higher operational expenses [8].

Neural networks, specifically deep getting to know models, have shown full-size promise in predicting site visitors congestion by means of learning complicated styles from full-size quantities of historical site visitor's statistics. These models can method diverse inputs, such as visitors volume, velocity, climate conditions, or even social activities, to forecast visitor’s conditions with excessive accuracy. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are typically used architectures on this domain [9]. CNNs excel at shooting spatial dependencies via analyzing visitors waft as snap shots or grids, at the same time as RNNs, especially Long Short-Term Memory (LSTM) networks, are adept at dealing with temporal dependencies, making them appropriate for time-collection visitors records [10]. The integration of those networks allows for a comprehensive understanding of ways visitors evolves over the years and area, imparting sturdy congestion predictions that can usefully resource in actual-time traffic control and making plans.

However, neural community-primarily based visitors prediction systems have first rate boundaries. Firstly, they require enormous categorized datasets for education, which may be challenging and steeply-priced to acquire. Moreover, the models are computationally in depth, necessitating extensive hardware assets and know-how in device studying for proper implementation and preservation [11]. Additionally, those models may additionally conflict with generalization when exposed to unforeseen visitor’s styles or incidents, together with unexpected avenue closures or natural screw ups, as they heavily depend upon ancient records. Lastly, the black-container nature of neural networks way that the interpretability of predictions is often restricted, making it tough for site visitor’s authorities to recognize and trust the decision-making method of these AI systems fully [12].

Big data analytics has emerged as a transformative innovation in traffic management by using harnessing massive datasets to perceive visitor’s styles and are expecting congestion [13]. This generation gives vast blessings by using empowering authorities to proactively manipulate site visitors and allocate resources efficiently. By analyzing historical and real-time site visitor’s records, inclusive of vehicle actions, journey instances, and road situations, predictive fashions can be advanced to expect congestion hotspots and optimize visitors’ drift. The number one gain of massive facts analytics in visitors control is its potential to allow proactive interventions. By figuring out styles and tendencies from large datasets, visitor’s authorities can put into effect focused measures inclusive of adjusting sign timings, deploying traffic manage personnel, or redirecting visitors to alleviate congestion earlier than it escalates. This proactive method no longer handiest improves visitors waft but additionally enhances typical road protection and reduces travel times for commuters.

However, the effectiveness of massive records analytics in traffic management is contingent upon the supply and great of statistics [15]. Accurate and complete datasets are vital for constructing reliable predictive fashions. Challenges may additionally rise up when statistics resources are constrained or when unforeseen occasions or behavioral changes effect traffic styles unpredictably. Additionally, the a hit implementation of huge data analytics requires strong infrastructure for statistics collection, garage, processing, and evaluation, which may be high priced and useful resource intensive.

3. PROPOSED WORK

In the world of urban transportation research, predicting visitors waft as it should be is paramount for powerful site visitors management and concrete planning. This calls for harnessing a numerous variety of statistics assets, such as site visitors float data, weather conditions, or even cultural factors that affect using behaviors. In a latest study focusing on the city of Denmark, a comprehensive approach become hired to tackle this complex problem.

Firstly, a wealth of statistics become gathered and curated. Real-time traffic drift data provided insights into the movement and volume of motors across distinct parts of the town. These records turned into complemented through climate data, capturing variables along with temperature, precipitation, and wind pace, which play important roles in determining traffic styles and congestion levels. Additionally, cultural facts, which include local activities, holidays, or social behaviors, had been included to account for precise contextual factors influencing traffic dynamics in Denmark.

Next, to construct a predictive version, a choice of relevant capabilities (x1, x2, ..., xn) become cautiously chosen from the accrued datasets. These functions fashioned the idea for education the fuzzy wavelet neural community (FWNN), a sophisticated version that excels in capturing nonlinear relationships and patterns inside complicated datasets. The FWNN integrates factors of fuzzy good judgment for dealing with uncertainty, wavelet evaluation for sign processing, and neural networks for studying tricky styles inside the records.

To optimize the overall performance of the FWNN, a hybrid optimization technique known as hybrid firefly and particle swarm optimization (HFO-PSO) became implemented. This innovative approach mixed the exploration abilities of firefly algorithms with the swarm intelligence of particle swarm optimization. The purpose turned into to quality-song the parameters of the FWNN to maximize its predictive accuracy whilst minimizing computational costs. Once the version was trained and optimized, it underwent rigorous evaluation. Predicted site visitors flow values generated by using the FWNN were as compared in opposition to actual observed values the use of the imply rectangular mistakes (MSE) as a loss characteristic. The MSE quantified the average squared difference among anticipated and actual traffic glide values, supplying a clean degree of prediction accuracy.

Furthermore, the studies included a section of first-class-tuning and validation. The version's overall performance become confirmed using strategies like pass-validation to make certain its robustness and generalizability across distinct situations and time periods. Any adjustments or refinements to the model were made based totally on these validation consequences, aiming to beautify its effectiveness in real-global traffic prediction applications.

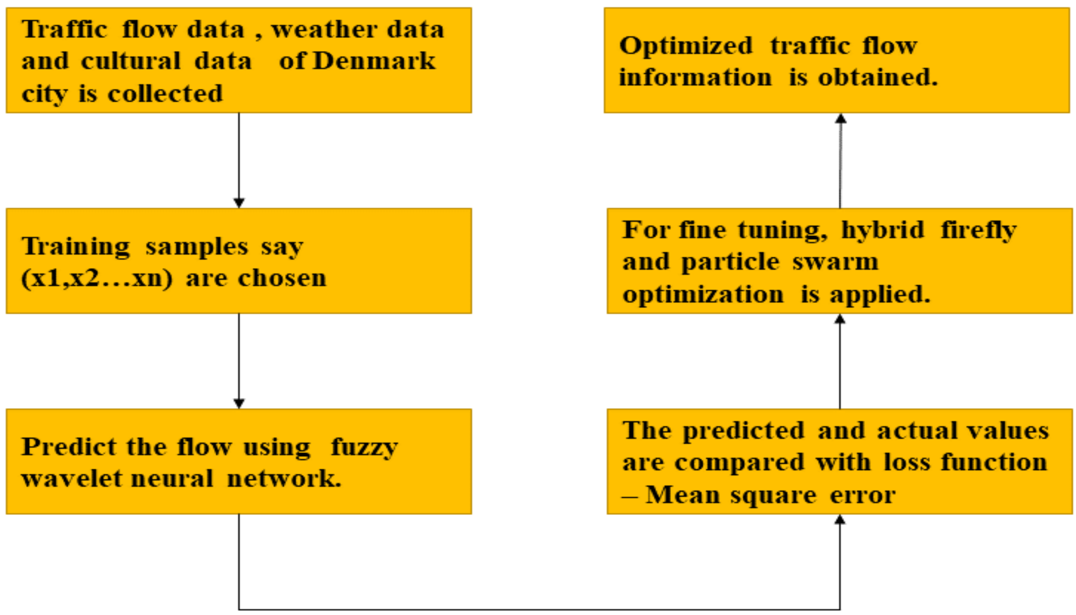

Fig.1. Overall architecture Proposed work

3.1 Algorithmic Framework

Algorithm 1 takes historical visitors and weather statistics as input. By studying styles and correlations within this records, it predicts site visitors waft for the subsequent 30 and 60 mins. The procedure includes using machine learning strategies to understand how variables which includes time of day, traffic volume, and weather conditions impact visitors. Once trained, the model outputs visitors flow forecasts for the desired destiny intervals, assisting in powerful visitors management and planning.

Algorithm 1-Traffic flow prediction Algorithm.

Step 1: Training samples are chosen
Step 2: Predict traffic flow with fuzzy wavelet neural network
Step 3: Predicted value is compared with actual value using loss function
Step 4: For fine tuning, firefly optimization and particle swarm optimization is used.
Step 5: Optimized traffic information is retrieved

3.2 Flowchart of FWNN and HFFPSO algorithm

The below Fig 2 describes the process of predicting traffic congestion using a Fuzzy Wavelet Neural Network (FWNN) optimized by a Hybrid Fast-Fuzzy Particle Swarm Optimization (HFFPSO) algorithm involves a systematic workflow.

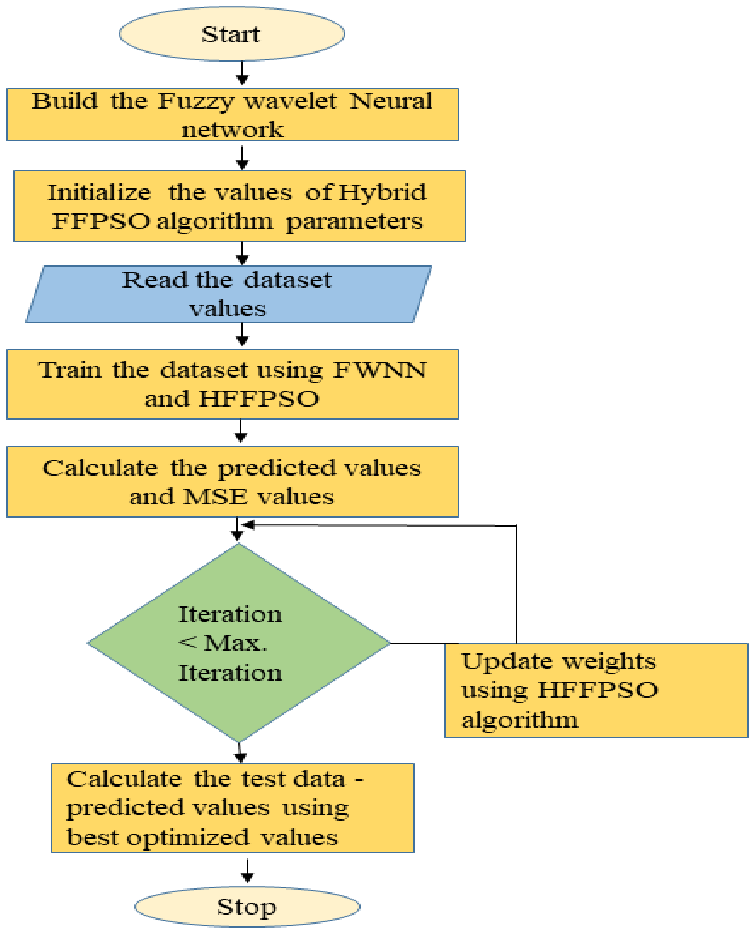

Fig .2. Flowchart of FWNN and HFFPSO algorithm

Initially, the FWNN is built, leveraging the combined strengths of fuzzy logic, wavelet transforms, and neural networks. Fuzzy logic enables coping with uncertainty, wavelet transforms system non-desk bound signals effectively, and neural networks provide robust sample popularity skills.

This included version forms a powerful tool for traffic prediction. The HFFPSO algorithm parameters are then initialized. HFFPSO combines Particle Swarm Optimization (PSO) with fuzzy logic, improving global seek competencies and convergence pace. The site visitor's dataset is then read, comprising variables which include visitors quantity, pace, and climate situations. Training commences using FWNN and HFFPSO. The set of rules iteratively adjusts version weights and parameters to minimize prediction mistakes, comparing performance thru predicted values and Mean Squared Error (MSE) calculations. Throughout iterations, if the current iteration matter is much less than the most, FWNN weights and parameters are continually refined with the aid of HFFPSO. The final optimized version is implemented to test facts for assessment. This systematic technique supplies correct site visitors congestion predictions, vital for effective site visitors management and concrete making plans.

3.3 Wavelet transform in signal analysis

Wavelet transform is a powerful mathematical tool used extensively in signal analysis across various fields, including traffic congestion prediction. This method involves the decomposition of a signal into wavelets, which are functions derived from a mother wavelet through dilation and translation operations. The application of wavelet analysis offers unique advantages in understanding and processing time-series data.

3.3.1. Components of Wavelet Transform

Wavelet analysis begins with selecting a suitable mother wavelet, such as Haar, Meyer, Coiflet, Daubechies, or Morlet wavelet, each possessing distinct characteristics tailored to specific applications. The chosen mother wavelet serves as the basis for constructing a family of wavelet functions used in the analysis. Wavelets can be represented in the following form:

$$\psi_{a,b} = |a|^{-\frac{1}{2}}\psi\left(\frac{x-b}{a}\right), (a, b \in R, a \neq 0) \qquad (1)$$

$\psi(x)$ is the mother wavelet function, and aa and bb are parameters controlling the dilation and translation of the wavelet, respectively. The expression $|a|^{-\frac{1}{2}}$ accounts for the scaling factor necessary for wavelet analysis. The mother wavelet function $\psi(x) \in L^2(R)$ (the space of square-integrable functions) and satisfies the condition:

$$c_{\psi} = \int_0^{+\infty} \frac{|\psi(w)|^2}{w} dw < +\infty \qquad (2)$$

This condition ensures that the Fourier transform $\psi(w)$ of $\psi(x)$ is well-behaved, facilitating efficient signal representation in the frequency domain. The function $f(x)$ representing the signal to be analyzed (e.g., traffic data), can be reconstructed from its wavelet coefficients $W\,f(a,b)$ using the inverse wavelet transform:

$$f(x) = \frac{1}{c_{\psi}} \iint W\,f(a,b)|a|^{-\frac{1}{2}}\psi\left(\frac{x-b}{a}\right)\frac{1}{a^2} dadb \qquad (3)$$

Here, $W\,f(a,b)$are the wavelet coefficients that capture the signal's details at different scales and positions in the time-frequency domain. The term c_{ψ} is a normalization factor related to the mother wavelet, ensuring proper scaling and reconstruction of the signal. Wavelet transform enables the examination of traffic data at multiple resolutions, from broad trends to fine details, providing a comprehensive understanding of congestion dynamics. Wavelet coefficients highlight significant features in the traffic signal, facilitating the extraction of relevant information for predictive modeling. Wavelet analysis can detect sudden changes or irregularities in traffic patterns, aiding in early congestion prediction and management strategies.

3.4 Fuzzy Wavelet Neural Network

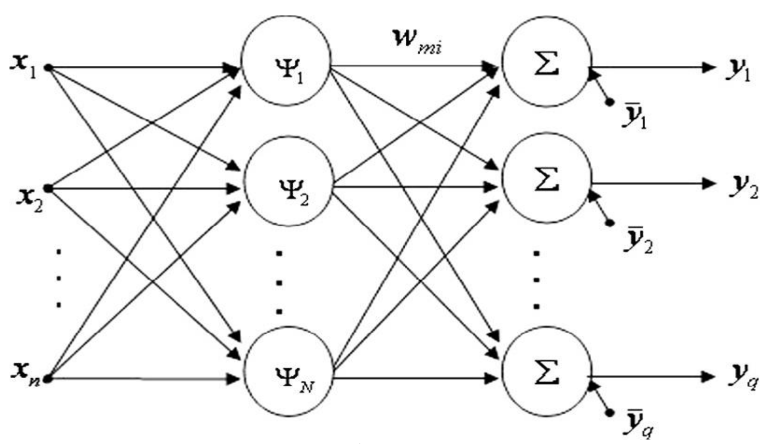

Fig.3. Structure of wavelet neural network

A wavelet neural network (WNN) integrates the advantageous properties of wavelet transforms and artificial neural networks to model complex functions efficiently. The structure of a WNN begins with an input layer comprising several nodes , $x_1, x_2, \ldots\ldots x_n$representing the input variables. Each of these input nodes is connected to a hidden layer consisting of wavelet nodes, denoted as $\Psi_1, \Psi_2, \ldots\ldots\Psi_n$. These wavelet nodes serve as activation functions, where each Ψ_i is a wavelet function. Wavelets are mathematical functions that can efficiently localize information in both time and frequency domains, which is particularly useful for capturing localized features in data.

The wavelet transforms in the hidden layer techniques the inputs via scaling and translating the mom wavelet characteristic, which lets in the network to investigate records at numerous ranges of decision. This multi-decision functionality is a key energy of WNNs, making them appropriate for tasks related to non-stationary alerts or features with localized irregularities. The outputs from the wavelet nodes are then aggregated and surpassed via a summation node, represented via Σ. This summation node plays a linear aggregate of the wavelet-transformed indicators, correctly integrating the information extracted with the aid of the wavelets.

The end result of this summation is fed into the output layer, which includes nodes y_1,y_2,….y_n. These output nodes provide the final predictions or classifications based totally on the processed input alerts. The schooling of a WNN involves adjusting the parameters of the wavelet functions (which includes scale and translation) and the weights of the summation node to minimize the error between the predicted and real outputs. This is normally executed through backpropagation algorithms tailored to address the wavelet foundation capabilities. Overall, the combination of wavelet transforms with neural networks inside the WNN structure leverages the strengths of both strategies, presenting a powerful tool for approximating complex, non-linear features with high precision and adaptability.

3.5 Firefly Algorithm

Fireflies, the winged beetles regarded for his or her bioluminescent capability to provide mild and blink at night, have stimulated researchers to expand optimization algorithms primarily based on their conduct. The Firefly Algorithm (FA) is a nature-inspired optimization approach that leverages the herbal conduct of fireflies to remedy complex actual-life problems, consisting of site visitors congestion prediction. This algorithm is grounded in three number one assumptions: fireflies are unisex and are drawn to each different regardless of gender; the brightness of a firefly is a crucial thing in its elegance to others; and whilst fireflies have the identical brightness, they flow randomly.

3.6 Hybrid Firefly-Particle Swarm Optimization (hippos) Model

The search capabilities of the firefly set of rules (FA) and the particle swarm optimization (PSO) algorithm thru a hybrid version known as FFPSO (Firefly and Particle Swarm Optimization). This hybrid model leverages the strengths of each algorithm: the short convergence of PSO for exploration (nearby search) and the exceptional-tuning talents of FA for exploitation (global search). This hybrid technique is in particular useful in packages like visitors congestion prediction, in which correct and timely predictions are crucial for powerful traffic management and making plans.

In traffic congestion prediction, the FFPSO algorithm can successfully deal with the complexities of actual-time data and dynamic site visitor's patterns. The algorithm follows the same steps as the FA with the important thing distinction being in how the placement vector is updated. In FFPSO, the space among particles is calculated using the Cartesian distance formula. For the particle pp and the modern position xx, the distances r_px and r_gx are calculated as follows:

$$r_{px} = \sqrt{\sum_{k=1}^{d}(pbest_{i,j}} - x_{i,j})^2 \quad (4)$$

$$r_{gx} = \sqrt{\sum_{k=1}^{d}(gbest_{i,j}} - x_{i,j})^2 \quad (5)$$

r_{px} is the distance between the personal best position $pbestpbest$ and the current position xx. r_{gx} is the distance between the global best position $gbestgbest$ and the current position xx. d is the dimension of the search space. $pbest_{i,j}$ and $gbest_{i,j}$ are the j-th components of the personal best and global best positions of the i-th particle, respectively. $x_{i,j}$is the j-th component of the current position of the i-th particle. The position vectors x_i of the FFPSO are then updated using the following equation, which includes a random mutation component:

$$x_i(t+1) = \omega . x_i(t) + \mathrm{C1}.\, e^{-r^2{}_{px}}\left(pbest_i - x_i(t)\right) + \mathrm{C2}.\, e^{-r^2{}_{gx}}\left(gbest_i - x_i(t)\right) + \boldsymbol{\alpha}\left(\gamma - \frac{1}{2}\right) \quad (6)$$

C1and C2are constants that manage the influence of the non-public great and global quality positions, respectively. α is a random mutation time period that allows in fending off nearby optima and exploring new regions of the hunt space. This equation efficaciously combines the exploitation potential of FA with the exploration capability of PSO, making the FFPSO model relatively appropriate for predicting traffic congestion. The capacity to balance local and global search enables the model to evolve to the ever-converting visitor's conditions and offer correct congestion forecasts, which are critical for optimizing traffic glide and decreasing delays.

4. RESULTS AND DISSCUSSION

4.1 Dataset Description

In this work, the City Pulse dataset, which includes avenue site visitors and weather records accumulated from Aarhus, Denmark, from February 2014 to June 2014, is applied. The dataset contains 449 commentary points of automobile site visitors information observed among two points for set periods over six months. Several base fashions, inclusive of Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Autoencoder, are hired for predicting site visitors congestion.

$$MSE = 1/n \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (7)$$

During the training process, Mean Square Error (MSE) is used as the loss function, with Model Checkpoint technology implemented to save the optimized model, and Early Stopping technology to prevent overfitting by terminating training at the appropriate time.

$$MSE = 1/n \sum_{i=1}^{n} |y_i - \hat{y}_i| \qquad (8)$$

$$RMSE = \sqrt{1/n \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \qquad (9)$$

$$MAPE = 1/n \sum_{i=1}^{n} |y_i - \hat{y}_i| \times 100 \qquad (10)$$

For evaluating prediction performance, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are used as metrics. These blunders metrics are calculated the use of the following formulas: RMSE, which measures the square root of the average squared variations among predicted and actual values; MAE, which computes the average absolute variations between anticipated and actual values; and MAPE, which expresses prediction accuracy as a percent by averaging the absolute percent differences among predicted and actual values.

4.2 Comparative Analysis

TABLE I. TRAFFIC PREDICTION PERFORMANCE

Models	**Flow in next 30 mins**		
	RMSE	**MAPE**	**MAE**
LSTM	9.72	9.81	3.56
Auto encoder	8.53	9.23	3.21
CNN	8.32	8.42	3.16
RNN	8.11	8.62	3.22
Fuzzy Wavelet NN and Hybrid Firefly & PSO algorithm	8.20	8.14	3.09

Table I display Fuzzy Wavelet NN mixed with the Hybrid Firefly & PSO algorithm excels in traffic congestion prediction, accomplishing the bottom errors (RMSE: 8.20, MAPE: 8.14, MAE: 3.09). This version effectively captures both temporal and spatial styles, supplying advanced accuracy. The fuzzy approach integrates fuzzy good judgment's capability to address uncertainty with wavelet transformation's efficiency in processing time-series data. The hybrid optimization set of rules (Firefly & PSO) similarly refines the model via enhancing convergence speed and accuracy. This mixture showcases the energy of hybrid tactics, making it a standout choice for precise quick-time period visitors flow prediction.

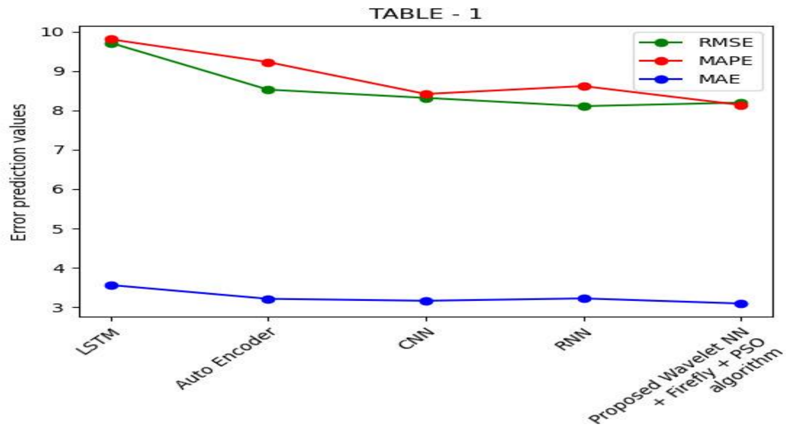

Fig.4. Error prediction values Vs Models – Flow in 30 minutes

Figure 4 illustrates the performance of various prediction fashions based on error metrics (RMSE, MAPE, MAE). Each model is represented on the x-axis, whilst the y-axis indicates the mistake values, with lower values indicating better accuracy. The graph famous distinct performance patterns: the Fuzzy Wavelet NN with Hybrid Firefly & PSO set of rules stands out with the lowest blunders values throughout all metrics, demonstrating superior accuracy in traffic drift prediction. Traditional RNNs additionally carry out well, outperforming LSTM, Autoencoder, and CNN fashions. This visualization highlights the effectiveness of hybrid fashions in accomplishing precise short-time period site visitors glide predictions.

TABLE II. TRAFFIC PREDICTION MODEL EVALUATION

Models	**Flow in next 60 mins**		
	RMSE	**MAE**	MAPE
LSTM	6.87	5.92	6.96
Auto encoder	6.46	5.69	6.95
CNN	6.44	5.66	6.95
RNN	6.32	5.67	6.93
Proposed Wavelet NN + Firefly + PSO algorithm	6.25	5.23	6.91

Table 2 compares different site visitors prediction fashions based on their overall performance metrics over a 60-minute forecasting horizon. The proposed hybrid version, which combines Wavelet Neural Network with Firefly and PSO algorithm, achieves the first-class outcomes with the lowest RMSE, MAE, and MAPE values. Among the individual neural community fashions (LSTM, Autoencoder, CNN, RNN), the RNN model plays slightly better in RMSE and MAE. Overall, these findings propose that the hybrid approach holds promise for enhancing the accuracy of visitors go with the flow prediction compared to conventional neural community architectures.

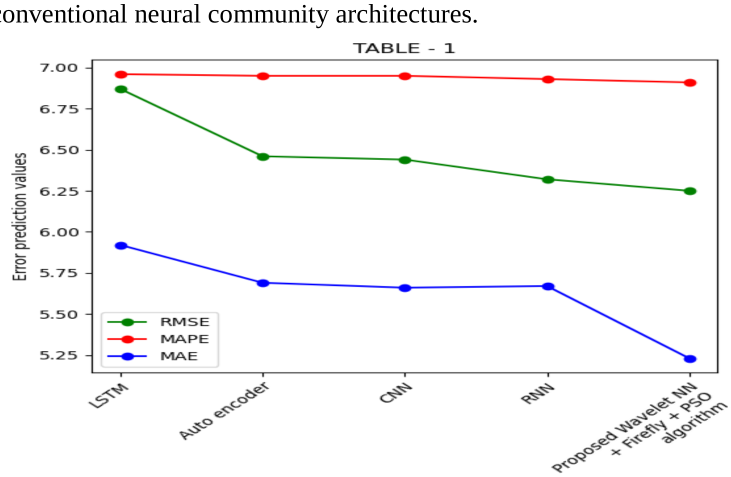

Fig .5. Error prediction values Vs Models – Flow in 60 minutes

Figure 5 illustrates error prediction values as opposed to extraordinary fashions for visitors flow over a 60-minute duration. The effects show that the proposed hybrid model combining Wavelet Neural Network with Firefly and PSO algorithm outperforms different man or woman neural network models (LSTM, Autoencoder, CNN, RNN) in terms of accuracy. This hybrid version indicates the lowest error values (RMSE, MAE, MAPE), indicating advanced overall performance in predicting traffic glide. Specifically, it achieves a first-rate reduction in prediction errors as compared to standard neural community architectures, highlighting its potential for reinforcing traffic prediction accuracy in actual-world scenarios.

TABLE III. ACCURACY OF MODELS

Models	Accuracy(in %)
LSTM	73
Auto encoder	80
CNN	74
RNN	76
Proposed Wavelet NN + Firefly + PSO algorithm	85

Table III show accuracy chances of various fashions for visitors congestion prediction offer precious insights into their performance. Among the man or woman models, the Autoencoder demonstrates the best accuracy at 80%, observed carefully through the RNN at 76%, LSTM at 73%, and CNN at 74%. Notably, the proposed hybrid version combining Wavelet Neural Network with Firefly and PSO set of rules achieves the highest accuracy of 85%. This shows that the hybrid approach appreciably complements prediction competencies, probable because of its capability to capture complicated patterns and optimize parameters efficaciously. Higher accuracy in congestion prediction is crucial for actual-time traffic management and can cause more dependable and efficient transportation structures.

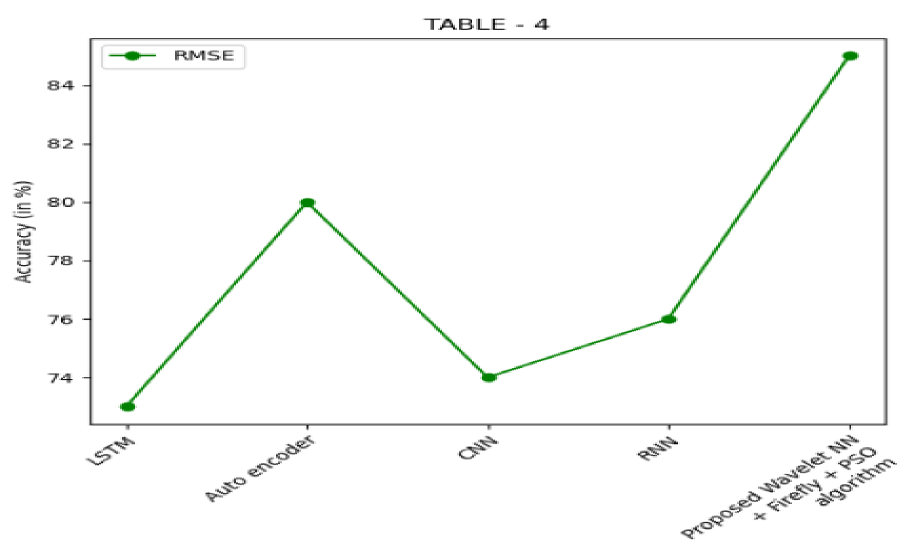

Fig .6. Accuracy of Proposed Model

Figure 6 highlights the predictive accuracy of both conventional and proposed strategies for traffic prediction. The proposed fuzzy wavelet neural network combined with the hybrid Firefly and PSO algorithm achieves an impressive accuracy of 85%, surpassing conventional methods which includes LSTM, autoencoder, CNN, and RNN. These conventional techniques fall brief in turning in the favored effects compared to the hybrid model. The findings underscore the effectiveness of integrating fuzzy common sense, wavelet neural networks, and optimization algorithms for enhancing traffic prediction accuracy, that is critical for reinforcing site visitors management and optimizing transportation systems.

TABLE IV. TRAINING TIME OF EXISTING AND PROPOSED METHOD

Models	Training Time (in seconds)
LSTM	127
Autoencoder	110
CNN	136
RNN	124
Fuzzy Wavelet NN and Hybrid Firefly & PSO algorithm	134

Table IV shows the training times (in seconds) for specific fashions used in visitors congestion prediction. The consequences display that the Autoencoder version has the shortest schooling time at 110 seconds, observed closely by means of the LSTM and RNN fashions at 127 and 124 seconds, respectively. The CNN version requires barely greater time at 136 seconds. Notably, the Fuzzy Wavelet Neural Network blended with the Firefly and Particle Swarm Optimization (PSO) set of rules famous a schooling time of 134 seconds. These education time metrics offer insights into the computational efficiency of each model, that is crucial for real-time traffic congestion prediction programs.

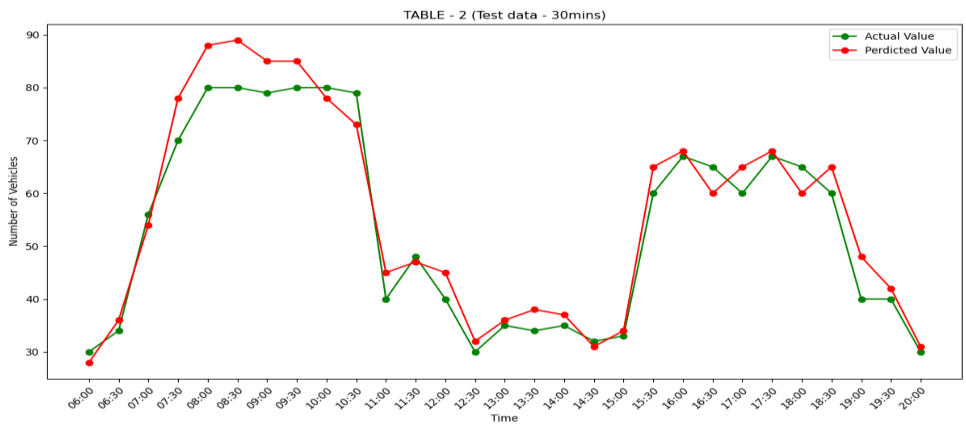

Fig .7. Difference between actual and predicted values of Test data- 30 minutes prediction

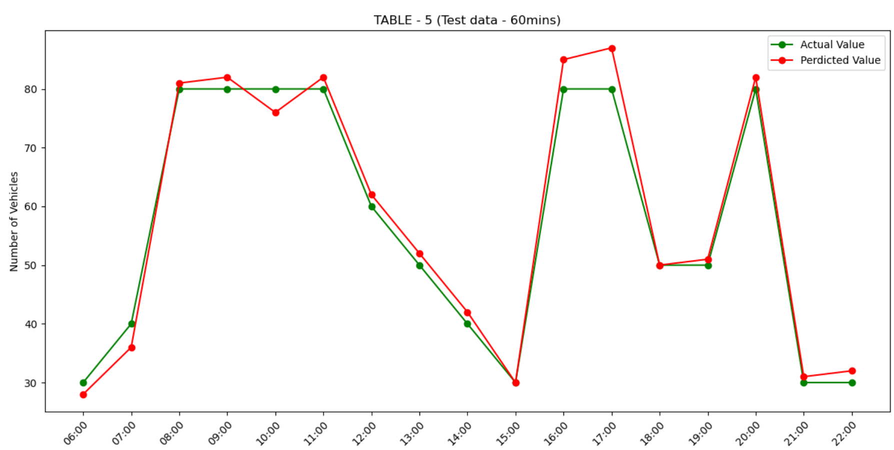

Fig .8. Difference between actual and predicted values of Test data- 60 minutes prediction

Figure 7 and figure 8 evaluating real and anticipated values for 30-minute and 60-minute predictions can provide precious insights into site visitors congestion forecasting. These comparisons illustrate how as it should be a predictive version can assume site visitor’s conditions at distinct future intervals. In the 30-minute prediction, if the differences among real and predicted values are small, it suggests that the version is powerful in brief-time period traffic forecasting. This may be especially beneficial for fast site visitors control decisions, inclusive of adjusting signal timings or informing drivers approximately brief-time period delays. Accurate short-term predictions help in mitigating on the spot congestion and improving site visitor’s drift. On the alternative hand, the 60-minute prediction provides insights into the version's functionality for longer-term forecasts. While commonly much less correct than brief-time period predictions, effective 60-minute forecasts are essential for proactive traffic control techniques. These would possibly encompass rerouting site visitors, making plans roadwork schedules, or issuing tour advisories to save you congestion buildup. If the version continues affordable accuracy at 60 mins, it could assist in strategic planning and lowering traffic congestion over an extended horizon.

5. CONCLUSION

The comprehensive study on traffic flow prediction successfully addresses the complex challenges of forecasting vehicle movements within transportation networks. The core innovation of this research lies in the development of the Fuzzy Wavelet Neural Network (FWNN) model. This sophisticated six-layer architecture effectively captures and analyzes the nonlinear and time-varying patterns inherent in traffic flow data. The FWNN model leverages fuzzy logic to manage uncertainty and wavelet analysis for robust feature extraction from time-series data. The results demonstrate that the FWNN optimized with HFPSO significantly improves traffic congestion prediction performance, offering reliable short-term and long-term forecasts. This approach surpasses traditional models in capturing the complex dynamics of traffic flow, making it highly effective for traffic management and congestion mitigation. The integration of advanced computational techniques in this research highlights its potential in providing superior prediction accuracy and efficiency in traffic congestion forecasting.

Conflicts Of Interest

The paper states that the author has no financial or non-financial interests that could be perceived as influencing the research or its interpretation.

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