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Context-Aware Prediction Models for Dynamic Data Streams

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Abstract
Context-aware intelligence enhances predictive systems by integrating situational dependencies and temporal variability in complex environments. However, many methods inadequately address continuous streaming traffic dynamics and evolving contextual interactions in multiple scenarios. This research aims to develop a dynamic context-aware prediction model for streaming traffic data using a deep neural network to improve adaptive trajectory and flow prediction. Traffic data is aggregated from instant sensors, vehicular networks, and open traffic repositories, ensuring diversity in spatial–temporal patterns. Pre-processing employs Z-Score normalization for cleaning and standardizing the data. Feature extraction utilizes Linear Discrimination Analysis (LDA) to capture dominant mobility patterns. The model systematically acquires streaming inputs, performs sequential cleaning, extracts compact representations, and feeds them into a context-aware predictive engine. The proposed Vortex Algorithm-driven Dynamic Deep Neural Network (VA-DDNN) integrates Vortex Optimization for adaptive weight tuning and dynamic hyperparameter adjustment, enabling efficient convergence under fluctuating traffic conditions. The DDNN component models non-linear temporal dependencies, while the Vortex Algorithm enhances learning stability and avoids local minima during continuous updates. The model incorporates dynamic context modeling by capturing vehicle interactions, traffic density transitions, and environmental variations, enabling responsive prediction under streaming conditions. The Performance demonstrates improved prediction consistency, reduced latency, enhanced adaptability, and robustness across varying traffic scenarios with a precision of 97.4%, a recall of 92.5%, an F1-score of 94.8%, and a mAP of 92.10%. The method establishes an efficient model for the context-aware traffic prediction, supporting intelligent transportation systems with scalable and adaptive decision-making capabilities.

Keywords: Context-Aware Prediction, Traffic Data, Forecasting, Vortex Algorithm-driven Dynamic Deep Neural Network (VA-DDNN), Traffic flow prediction, Adaptive Traffic Modeling.

1. Introduction

Traffic flow analysis is one of the major challenges in Intelligent Transportation Systems (ITSs) and is receiving considerable attention because of its diverse application possibilities. Correct traffic flow allows traffic control systems to take preventive measures that decrease traffic and help commuters make appropriate decisions regarding the route selection [1]. Traffic congestion refers to the obstruction of vehicular or maritime traffic caused by increased traffic density within a specific region, resulting in reduced travel speeds, decreased operational efficiency, and diminished effectiveness of vehicle or vessel movement in congested areas. Travel time under the influence of external factors is identified as an area of road transportation and traffic flow modeling [2]. In the present era of advanced technology, an increasing number of devices are becoming interconnected and capable of seamless communication. Transportation systems, including automobiles and ships, can leverage this connectivity to enhance their operational efficiency and performance [3, 4]. Modern autonomous vehicles are equipped with sophisticated sensors that continuously monitor surrounding traffic conditions and support intelligent decision-making processes. The prediction of traffic flows by applying big data analytics is an important area in ITS a transportation networks characterized by their complexity and dynamism [5]. Data collected from vehicle sensors is applied to monitor driving behaviour to ensure that traffic safety is effectively managed, as well as to efficiently dispatch traffic. The issue of environmental sustainability is becoming a global concern, resulting in the quick adoption of Vehicles [6]. Together with context-aware computing and communications systems, these developments increase the capability of transportation systems to be adaptable to changing circumstances and providebetter solutions to mobility problems [7, 8].

Research Aim: This research aims to develop a context-aware traffic data stream forecasting model using Deep Neural Networks (DNNs) and adaptive traffic optimization techniques. The proposed dynamic spatiotemporal model captures interdependencies among traffic streams, improving prediction accuracy and adaptability to environmental changes.

Research Organization: Section 1 provides the research background. **Section 2** focuses on reviewing existing research. **Section 3** discusses the process of gathering data, pre-processing, and future extraction, as well as the proposed model. **Section 4** includes the results and discussion. **Section 5** presents the performance, constraints, and future work in the conclusion.

2. Related Work

The creation of a generic method for modelling the temporal evolution of such complex-aware networks to monitor traffic vehicles was investigated [9], utilizing Graph Neural Networks (GNN) to model the context-awareness for traffic flow resulting in an average precision increase from 7.52% to 0.05% when compared to the baseline. The temporal evolution of complex networks in traffic is one of the major challenges. The development of traffic flow prediction using a container-based micro service architecture that can decrease the risk and accident rates was explored [10]. Using the Open Worldwide Application Security Project (OWASP) for detecting any traffic attack, it successfully predicted the attacking traffic scenario with an accuracy rate of 92%. Most of the experimentations were carried out under a few static rules without considering analysis delay. The challenge of Internet of Drones (IoD), which affects navigation security and reliability in Drones for traffic context-aware detection, was discussed in [11], using Global Positioning System (GPS)-based detection for traffic flow detection with better execution time, high computational performance, low memory consumption, and high security. Challenges like this are extremely critical in the area of IoD since security and resource limitations in drones require security decisions to be transparent. Traffic trajectory compressions using context-aware predictions to counteract traffic attacks to maintain the traffic flow were examined [12]. Using the technique of Long Short-Term Memory (LSTM), which is effective in predicting the traffic situations, the outcome showed a Root Mean Square Error (RMSE) of 0.0047859 for predicting the trajectories. Due to an increase in the amount of data in the form of traffic trajectory, some problems arise in storing and processing the information. A traffic recovery model based on prediction through context-awareness to control traffic flows for emergency vehicles was analyzed [13], using the Reinforcement Learning (RL) method, which uses prediction for various conditions and not merely progressing from one phase to another. This result shows that approximately 80 of traffic flow are related to emergency events or other sudden actions. The implementation of a context-aware traffic detection model based on fuzzy logic to improve overall performance of traffic detection was conducted [14], using the assistance of the Vehicular Ad Hoc Network (VANET) technique that increases traffic efficiency and road safety to enhances passengers' comfort. The result shows a performance of 7.88%, while the detection rate of 16.46% for the consistency attack is one of the hardest attacks to tackle, where the attacker generates false paths for vehicles. A context-aware recommendation system with emotion-driven methods for shopping user experience, as well as decision-making to decrease the traffic flow, was investigated [15]. With the use of Large Language Models (LLMs), detecting context-aware traffic flow achieved a high accuracy and acceptable latency of 0.3267s. The limitations of the adaptability of the system are not the same depending on user behaviour patterns. Traffic flow decision-making through Context-aware tracking of high-order traffic using diverse visual experts was introduced in [16], where traffic flow is predicted using Farneback's method. The findings revealed that the traffic recovery and motion blur are involved (+0.091 and +0.057, respectively), and constraints considerably improve the robustness of traffic tracking. The idea of developing a light network for traffic sign recognition to mitigate heavy traffic through multi-scale context awareness was investigated [17]. In this process, the Multi-style Generative Network (MASG-Net) is used to predict traffic flows. The results showed mAP 90.8% while limiting vehicle terminal devices, demonstrating excellent detection accuracy and performance.

3. Methodology

Figure 1 illustrates the proposed adaptive traffic modelling and context-aware prediction model, which utilizes stream-based traffic data to enhance the prediction of traffic trajectories and flow patterns in dynamic traffic environments. Traffic data are collected from multiple sources, including sensing devices, vehicular networks, and open-access repositories, to ensure comprehensive spatiotemporal representation and data diversity. During the pre-processing stage, Z-score normalization is applied to clean and standardize the input traffic data, while Latent Dirichlet Allocation (LDA) is employed for feature extraction and dimensionality reduction. The proposed VA-DDNN model integrates adaptive weight tuning and hyperparameter optimization mechanisms to improve prediction accuracy, forecasting reliability, and overall traffic modelling performance.

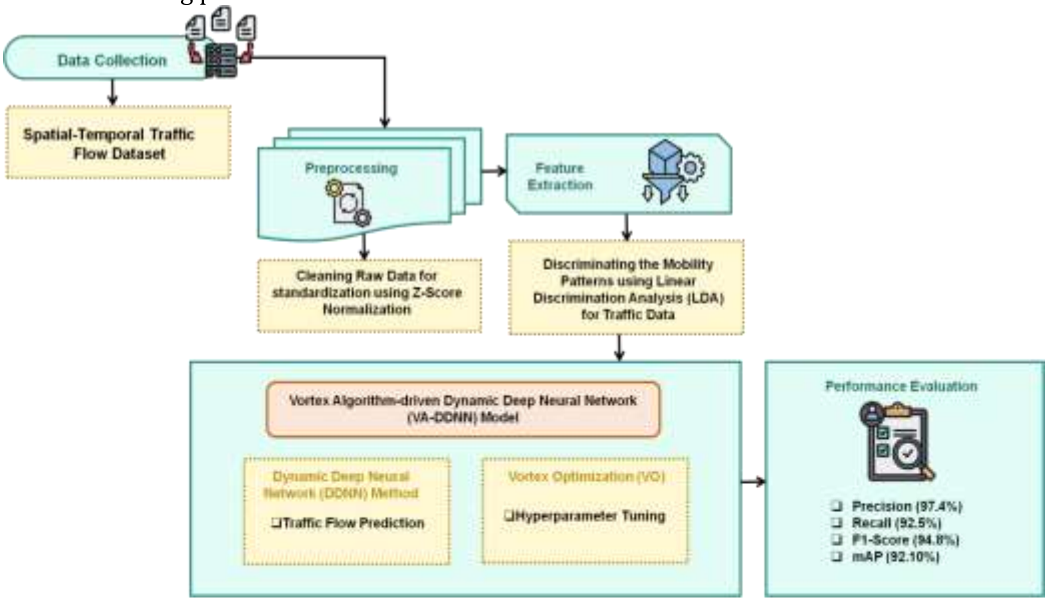

Figure 1: Methodology workflow for context-aware traffic flow prediction

3.1 Data Collection

The dataset used for analysis in this research comes from the Traffic Flow Forecasting Dataset, available on Kaggle at (https://www.kaggle.com/datasets/rabieelkharoua/traffic-flow-forecasting-dataset). The dataset is composed of 2,101 samples, with 47 traffic-related characteristics being considered for spatiotemporal traffic forecasting. The characteristics present in the dataset include historical traffic flow time series, day of the week, and hour of the day, road direction, number of lanes, and road names collected from 36 traffic sensor locations. To achieve the research objective of traffic context-aware prediction, the dataset is utilized to develop a model capable of predicting the behavior of dynamic streaming traffic in instant. Prior to model development, the dataset is separated into 20% testing data and 80% training data for performance evaluation.

3.2 Cleaning Raw Data for Standardization Using Z-Score Normalization

For context-aware traffic prediction with consistent and reliable traffic data input, raw data received from different sensors, vehicular networks, and traffic databases is cleansed and adjusted by applying the Z-Score technique. The method of the Z-Score method helps to eliminate the problem of scale variation between traffic data received from different sources, which is mathematically expressed in Equation (1).

$$X = \frac{z-v}{\sigma} \tag{1}$$

Where X is the normalized context-aware traffic feature value utilized for adaptive traffic modeling flow prediction, while z is the traffic data inputs in raw form such as traffic flow timeseries, weekday, time of day, road direction, and lane count, while v is the mean of all traffic cleaned data attributes recorded, and σ is the standard deviation for variation in the streaming traffic patterns required for accurate context-aware traffic prediction.

3.3 Discriminating the Mobility Patterns using Linear Discriminant Analysis (LDA) for Traffic Data

The LDA algorithm is used to extract features from streaming traffic data by finding dominant mobility patterns. LDA determines linear combinations of the features that can separate multiple classes of the traffic data, e.g., free-flowing, medium, and congested. The first step involves the computation of the mean vectors of the traffic categories, as shown in Equation (2).

$$\mu_l = \frac{1}{M_l}\sum_{m\in d_l} y_m \quad (2)$$

Where μ_l is the mean vector for the l^{th} traffic class indicating the traffic context-aware condition, M_l stands for the number of traffic samples belonging to the l traffic class, and $\Sigma_{m\epsilon d_l}$ shows the streaming traffic feature, and y_m represents the traffic flow time series, day of the week, time of day, road direction, and lane numbers. d_l denotes the set of samples belonging to the l^{th} traffic class, and evaluate the within-class traffic condition expressed in Equation (3 and 4).

$$R_x = \sum_{l=1}^{l}\sum_{m\epsilon d_l}(y_m - \mu_l)(y_m - \mu_l)^S \quad (3)$$

$$R_A = \sum_{k=1}^{l} M_l(\mu_l - \mu)(\mu_l - \mu)^S \quad (4)$$

R_x represents the within-class and scatter matrix measuring variations with similar traffic conditions, and $\Sigma_{l=1}^{l}$ traffic samples belonging to the l traffic class.$\Sigma_{m\epsilon d_l}$ shows the streaming traffic feature, and $y_m - \mu_l$ represents the traffic flow time series.S denotes the scatter matrix formulation resulting from multiplying feature difference vectors as part of the context-aware traffic flow prediction method, the between Scatter matrices of traffic states expressed in Equation (4). R_A denotes the between-class scatter matrix measuring separability between traffic states such as free-flow, medium, and congested traffic, and$\mu_l - \mu$ represents the overall mean vector of all traffic samples.$\Sigma_{k=1}^{l}$ refers to the traffic class/category, M_l stands for the number of traffic samples and the evaluation of eigenvalues and eigenvectors is represented in Equation (5).

$$R_x^{-1}T_A = \lambda_u \quad (5)$$

R_x^{-1} represents the within-class and scatter matrix measuring variations with similar traffic conditions, λ_u denotes the eigenvalue indicating the traffic feature for context-aware traffic flow prediction.T_A refers to the traffic transpose operation of the metrix eigenvector.

3.4 Context-Aware Traffic flow Prediction using the Vortex Algorithm-driven Dynamic Deep Neural Network (VA-DDNN) Model

VA-DDNN is developed by combining the concept of adaptive traffic modeling for deep learning with dynamic context awareness to make accurate predictions for context-aware traffic flow. The VA-DDNN model evaluates the sequences of the traffic data and identifies the non-linear spatial–temporal relationship through effective hidden representations. With VO-based adaptive parameter updates, the method becomes more accurate and converges faster to better prediction and forecasting solutions.

Dynamic Deep Neural Network (DDNN) Method forTraffic Flow Prediction: The DDNN method is utilized for the modeling of the nonlinear relationship that exists over time in the stream traffic dataset. The traffic data collected by each sensor is divided such that some are processed locally, whereas other parts are sent to the edge server for processing and traffic flow prediction. This procedure is mathematically expressed in Equation (6).

$$s_{pre} = nsc_{pre} \quad (6)$$

$$s_{local} - anksc_k + nsc_{pre} \quad (7)$$

Where s_{pre} represents the traffic flow processing time, nsc_{pre} refers to the computational cost of pre-processing in the traffic flow context-aware, and the time of traffic local data process forecasting is expressed in Equation (7). s_{local} denotes the local time of traffic data processing, $anksc_k$ refers to the local computational capacity with traffic data size, and the traffic data processing time shown in Equation (8).

$$s_{edge} = (1-b)nksc_f + (1+o)abknsc_f \quad (8)$$

s_{edge} represents the delay processing of the traffic flow edge server, $nksc_f$ denotes the current computational cost of traffic flow with traffic ratio processing o, and $abknsc_f$ refers to thetraffic data transmission with communicationb. The total delay of traffic data processing is expressed in Equation (9).

$$s = \max\{s_{local}, s_{edge}\} \quad (9)$$

Where s represents the total delays of the context-aware traffic flow, and$\max\{s_{local}, s_{edge}\}$ refers to the maximum traffic delay of the local data processing time and the traffic delay of the edge server processing time.

Hyperparameter Tuning with Vortex Optimization (VO): To improve the learning effectiveness of the DDNN method, the VO technique is used to tune the hyperparameters. This method is founded on the principles of vortex traffic flows seen in nature. To begin with, a group of particles containing hyperparameters that lead to better traffic flow predictions is randomly generated, and an update for the most traffic-fit one is as expressed in Equation (10).

$$Best_u^{(new)} = Best_u^{(current)} + (rand \times Best_u^{(current)}) \quad (10)$$

$\mathrm{Best}_u^{(\mathrm{new})}$ represents the new best hyperparameter velocity for improving the accuracy of context-awareness traffic flow prediction. $\mathrm{Best}_u^{(\mathrm{current})}$ denotes the best value of the current velocity, which shows the traffic direction of hyperparameter optimization. rand refers to the random number that provides variation during hyperparameter optimization. urepresents the velocity value, which determines the traffic vehicle speed of hyperparameter adjustment expressed in Equations(11 and 12).

$$\mathrm{particle\_j}_u^{\mathrm{new}} = \mathrm{particle\_j}_u^{(\mathrm{current})} + \left(\mathrm{rand}_u * \left(\mathrm{global}_u^{\mathrm{best}} / \mathrm{particle\_j}_u^{(\mathrm{current})}\right)\right) \tag{11}$$

$$\mathrm{particle\_j}_u^{(\mathrm{new})} = \mathrm{rand}_u * \mathrm{particle\_j}_u^{(\mathrm{current})} \tag{12}$$

$\mathrm{particle\_j}_u^{\mathrm{new}}$ represents the new velocity of the j^{th} particle for finding better hyperparameters for traffic prediction. $\mathrm{particle\_j}_u^{(\mathrm{current})}$ refers to the current traffic velocity of the j^{th} particle used for optimization. rand_u denotes the random variable that determines the adaptation to the traffic globally, the best solution found. $\mathrm{global}_u^{\mathrm{best}}$ represents the globally best traffic velocity from all velocities from the particles during the optimization process. j refers to the index of the j^{th} solution for the hyperparameter (i.e., particle). The best traffic position procedure is expressed in Equation (13).

$$\mathrm{particle\_j}_{\mathrm{position}}^{(\mathrm{new})} = \mathrm{particle\_j}_{\mathrm{position}}^{(\mathrm{current})} + \left(\mathrm{rand}_u * \left(\mathrm{particle\_j}_u^{(\mathrm{current})} * \left(\mathrm{global}_{\mathrm{position}}^{\mathrm{best}} - \mathrm{particle\_j}_{\mathrm{position}}^{(\mathrm{current})}\right)\right)\right) \tag{13}$$

$\mathrm{particle\_j}_{\mathrm{position}}^{(\mathrm{new})}$ represents the hyperparameter position used to enhance context-based traffic prediction. $\mathrm{particle\_j}_{\mathrm{position}}^{(\mathrm{current})}$ refers to the current hyperparameter traffic vehicle position of the j^{th} particle, and the$\mathrm{global}_{\mathrm{position}}^{\mathrm{best}}$ represents the best global hyperparameter position yielding minimal traffic prediction error. $(\mathrm{global}_{\mathrm{position}}^{\mathrm{best}} - \mathrm{particle\_j}_{\mathrm{position}}^{(\mathrm{current})})$ refers to the difference between the current particle position and the best global hyperparameter position.

Hyperparameter of Proposed VA-DDNN Method: The VA-DDNN-based architecture used for predicting traffic flow context-aware is set up with 80:20 ratios for training and testing. The DDNN structure comprises 4 hidden layers containing 64, 128, 256, and 128 neurons. The following parameters are considered: ReLU Activation, Softmax Output, 100 epochs, a batch size of 32, and a learning rate of 0.001. L2 regularization is done through the inclusion of a value of 0.0001, while the dropout rate is 0.3. The normal initialization is used to improve the stabilization of the VO algorithm. The population size is 30, and the number of iterations is 50 for minimizing validation loss. These hyperparameters enhance adaptive learning, stability, and robust context-aware traffic flow prediction performance.

4. Result and discussion

The proposed VA-DDNN model integrates spatial–temporal traffic patterns and context-aware attributes, including traffic flow sequence, weekday, time, road direction, and lane information, for accurate traffic prediction. VO-based hyperparameter optimization improves convergence stability, while DDNN captures complex temporal dependencies, resulting in enhanced mAP, precision, recall, F1-score, flexibility, and forecasting performance.

Experimental Setup: An efficient stream traffic processing, the proposed VA-DDNN context-aware traffic flow prediction system, is implemented in a high-performance computational platform. The hardware platform consists of an Intel Core i7/AMD Ryzen 7 processor with a speed of 3.2 GHz, 16 GB DDR4 RAM, NVIDIA RTX 3060 with 8 GB of memory, and a 512 GB SSD hard drive. Software-wise, it utilizes Python 3.10 programming language together with TensorFlow/Keras, Scikit-learn, NumPy, and Pandas libraries under Windows 11 and Ubuntu 22.04 LTS with CUDA 12.x. It ensures the scalable, stable and instant context-aware traffic flow prediction performance.

Exploratory Data Analysis: Figure 2(a) illustrates the probability density curve for a certain traffic variable from1 to 14 that characterizes typical traffic behavior, excess zeros, and abnormalities according to different scenarios. Figure 2(b) presents the cumulative significance of different network features of nodes (such as centrality measures) over the network indices for capturing multilayered spatial relationships. Figure 2(c) shows the high-dimensional spatial signatures for clustering different traffic categories (Low, Moderate, High, Extreme) using their underlying waveforms. Figure 2(d) depicts the time-series information about different traffic variables at each node in a sequential manner.

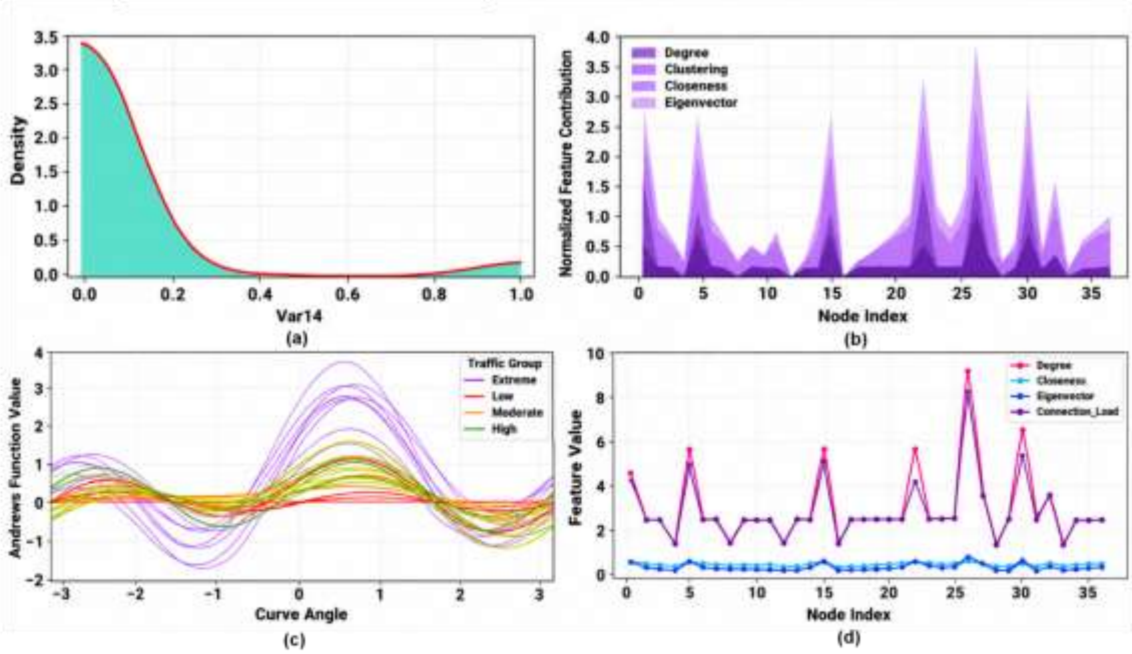

Figure 2: Investigative Data Analysis of (a) Overall Traffic Flow Distribution, (b) Normalization of Traffic Flow Network Features, (c) Signature of Traffic Flow Network, and (d) Node-wise Traffic Flow Features flow Context Predicting traffic movement using awareness

Evaluation Metrics: The effectiveness of the VA-DDNN model for the traffic flow forecasting algorithm based on context-aware analysis by employing precision, recall, F1-score, and mAP. Precision calculates the degree of accuracy of predictions made by estimating traffic flow through the prevention of false positive predictions, thus obtaining accurate estimations regardless of changes in traffic conditions. The recall measures the ability of the model to detect real traffic flow changes and congestion patterns. The F1-score combines precision and recall, providing a balanced measure for evaluating the reliability and detection capabilities of traffic predictions. Moreover, mAP calculates the prediction accuracy of the system for various road scenarios by taking an average of the precision obtained from various recall scores. All these metrics show the stability and reliability of the developed model under ITS systems.

Performance Evaluation: Table 1 and Figure 3 present the comparison of the existing and proposed methods, which involve YOLOv4-tiny, MobileNetV3, E-MobileNet, E-MobileNet + SPP, E-MobileNet + MDSPP, and MASG-Net. The YOLOv4-tiny [17] method achieves high traffic prediction accuracy, while the MobileNetV3* [17] method shows lower prediction accuracy. The E-mobilenet* [17] method achieved a high prediction accuracy compared to the YOLOv4-tiny. The E-mobilenet*+SPP [17] method shows the highest prediction value compared to all previous methods, and the E-mobilenet*+MDSPP [17] method shows the same prediction value as the previous one. The MASG-Net [17] method achieves the highest traffic prediction of all the previous methods. The proposed VA-DDNN method performs better, with improved performance and consistency, reduced latency, and a precision of 97.4%, a recall of 92.5%, an F1-score of 94.8%, a mAP of 92.10%.

Table 1: Comparison Analysis of Existing and Proposed Methods

Methods	Precision (%)	Recall (%)	F1-Score (%)	mAP (%)
YOLOv4-tiny [17]	91.7	74.2	82.0	80.2
MobileNetV3* [17]	89.6	72.4	80.1	78.9
E-mobilenet* [17]	93.6	83.3	88.2	85.4
E-mobilenet*+SPP [17]	94.1	83.8	88.7	86.5
E-mobilenet*+MDSPP [17]	94.5	87.7	91.0	89.8
MASG-Net [17]	95.1	90.3	92.6	90.8
VA-DDNN [Proposed]	97.4	92.5	94.8	92.10

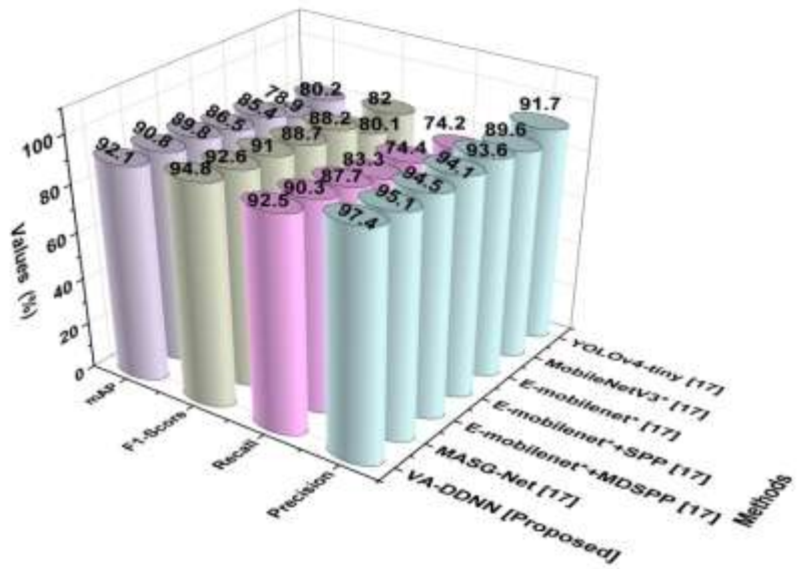

Figure 3: Performance Analysis of Existing and Proposed Methods for Context-Aware Model for Traffic Flow Prediction with Streaming Traffic Data

An ablation study was performed to assess the contribution of individual components within the proposed VA-DDNN model. As presented in Table 2, the baseline DDNN model achieved 90.8% precision, 85.4% recall, 87.2% F1-score, and a mAP of 86.1%. Incorporating Z-score normalization improved prediction performance by enhancing data consistency and reducing scale variations, resulting in a precision of 92.1%. The addition of LDA-based feature extraction further improved discriminative traffic pattern representation, increasing precision to 94.0% and mAP to 90.0%. Finally, integrating VO for adaptive hyperparameter tuning significantly enhanced convergence and learning stability, achieving the best performance with 97.4% precision, 92.5% recall, 94.8% F1-score, and 92.10% mAP, these results demonstrate the effectiveness of each component and validate the superiority of the complete VA-DDNN model.

Table 2: Ablation Analysis of the Proposed VA-DDNN model for Traffic Flow Prediction

Model Configuration	Precision (%)	Recall (%)	F1-Score (%)	mAP (%)
DDNN Only	90.8	85.4	87.2	86.1
DDNN + Z-Score Normalization	92.1	87.0	88.9	87.8
DDNN + Z-Score + LDA	94.0	89.2	91.1	90.0
VA-DDNN (Proposed)	97.4	92.5	94.8	92.10

Discussion: A traffic flow prediction method that can effectively process streaming data and adapt to the changing spatial-temporal dependencies. Current methods, including YOLOv4-tiny, MobileNetV3, E-MobileNet, E-MobileNet + SPP, E-MobileNet + MDSPP, and MASG-Net [17], achieve reasonable efficiency in predicting traffic flows and recognizing road signs. Nonetheless, the YOLOv4-tiny [17] method is characterized by weak context information extraction and poor precision in dealing with varying traffic flows. The MobileNetV3* [17] method is hampered by limited capability in extracting features associated with temporal dependencies, and the E-mobilenet* [17] method suffers from high latency. Although the E-MobileNet+SPP* [17] method lacks the capacity for adaptive streaming, while the E-MobileNet+MDSPP*[17] method increase model complexity, both methods fails to effectively deal with dynamic context changes. Although the MASG-Net [17] method provides increased mAP (90.8%), it suffers from static learning as well as decreased adaptability for continuously changing traffic patterns. The proposed VA-DDNN method addresses these problems in that it incorporates VO into DNN to achieve adaptive hyperparameter tuning, stable convergence, and robust context-aware traffic prediction with efficient performance.

5. Conclusion

Propose a predictive context-aware traffic flow model for traffic data streams using DNN to improve traffic flow prediction performance. Traffic data are obtained through the use of sensors, vehicular network technology, and traffic data archives. Data pre-processing is done using the Z-Score normalization technique, whereas LDA is used for extracting features through dominant mobility patterns. The proposed VA-DDNN architecture utilizes VO with DDNN for enabling adaptive learning and stable convergence under evolving traffic conditions. Although the model obtained a very high performance with a precision of 97.4%, a recall of 92.5%, an F1-score of 94.8%, and a mAP of 92.10%, its need for high computational power and scalability problems in large-scale urban networks remain limitations, and future research emphasizes the placement of the lightweight adaptation of the model to be run on the edge.

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