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Research paper

Privacy-Preserving Mechanism for Vehicle-To-Everything (V2X) Technologies: Hybridization of Deep Learning with Optimization Algorithms for Secure Smart Transportation in Dubai

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Abstract

The progress of artificial intelligence (AI) and Internet of Things (IoT) technologies has resulted in a steady upsurge in the intellect and network abilities of vehicles. As an outcome, the IoT-based vehicle-to-everything (V2X) interaction methods are also recognized as the Internet of Vehicles (IoV). The IoV has garnered significant attention from both industry and academia. Whereas an inter-vehicular system links an automobile to exterior devices utilizing the technology of V2X. To reduce accidents of smart vehicles and detect malicious assaults in vehicular systems, numerous scholars have performed machine learning (ML)-based techniques for intrusion detection in IoT environments. In this study, we focus on the design and implementation of Privacy-Preserving Vehicle-to-Everything Technologies using Hybrid Deep Learning and Optimization Algorithms (PPV2XT-HDLOA) for Smart Transportation in Dubai. The presented PPV2XT-HDLOA model enhances V2X transportation by leveraging advanced data-driven techniques to optimize vehicle communication. To achieve this, the PPV2XT-HDLOA model applies the z-score normalization approach for data normalization to ensure data uniformity and enhance model convergence. To reduce dimensionality, the reptile search algorithm (RSA) can be employed to recognize the most relevant features. For the classification process, the hybrid deep learning model combining bidirectional temporal convolutional networks and bidirectional gated recurrent units (BiTCN-BiGRU) technique is exploited. Finally, the hyperparameter tuning of the BiTCN-BiGRU technique is carried out using the mountain gazelle optimization (MGO) algorithm to achieve optimal fine-tuning of parameters, ensuring superior classification performance. To demonstrate the better solution of the PPV2XT-HDLOA technique, a wide range of simulations have been tested, and the outcomes are inspected under several measures. The comparison investigation reported the improvement of the PPV2XT-HDLOA technique under various metrics.

***Keywords**: Vehicle-to-Everything; Internet of Vehicles; Traffic Systems; Artificial Intelligence; Network Security; Privacy-Preserving*

1. Introduction

Autonomous driving is the most transformative technology of the 21st century, giving the possibility to revolutionize transportation methods by enhancing efficacy, accessibility, and safety [1]. Latest improvements in perception methods, planning models, and decision-making structures have driven significant growth. Nevertheless, despite these strides, single-vehicle autonomous methods face substantial restrictions, specifically in dynamic, occluded, and complex settings [2]. Challenges like blind spots, inadequate sensor range, and obstacles confine a vehicle's capability to recognize its setting fully, resulting in possible security hazards in situations with dense traffic, urban settings, or opposing weather conditions [3]. Thus vehicle-to-everything (V2X) communication method, named the Internet of Vehicles (IoV), became a prominent interest of either industry or academia. V2X communication has become a favorable model to overcome these restrictions [4]. By allowing infrastructure, vehicles, and other related agents to fuse and share sensor data, V2X methods improve situational awareness by increasing the sensor coverage of individual vehicles [5]. This ability enables independent methods to predict occluded risks, coordinate movements effectively, and create informed decisions in complicated situations [6]. Therefore, V2X-based cooperative perception gives a favorable method to address the essential task of single-vehicle autonomy, specifically in surroundings with obstructed views, challenging weather conditions, or dense traffic.

With the fast development in the number of vehicles in the IoV and more complicated system settings, the growth of system threats is presented by significant security conflicts to the IoV, and its communication and data security are facing considerable attacks [7]. Once a vehicle is hacked, it will endanger the reliability and safety of the vehicle, leading to casualties or traffic accidents. The IoV intrusion detection approaches are generally separated into 2 types, namely Deep Learning (DL) and Machine Learning (ML) [8]. Conventional ML physically removes aspects utilizing support vector machines (SVM), decision trees (DT), and more, categorizing attack and normal data

samples [9]. These models have certain flaws, like long processing time and lower detection performance while dealing with multi-dimensional and massive intrusion detection data of the IoV. Mining the intrusion data sample across DL may attain hidden features, thus recognizing network intrusion data [10]. Nevertheless, the higher false-positive rate is the major concern of these DL-based intrusion detection methods for the IoV.
This paper focuses on the design and implementation of Privacy-Preserving Vehicle-to-Everything Technologies using Hybrid Deep Learning and Optimization Algorithms (PPV2XT-HDLOA) for Smart Transportation in Dubai. To accomplish that, the PPV2XT-HDLOA model applies the z-score normalization approach for data normalization. To reduce dimensionality, the reptile search algorithm (RSA) can be employed. For the classification process, the hybrid DL model combining bidirectional temporal convolutional networks and bidirectional gated recurrent units (BiTCN-BiGRU) technique is exploited. Finally, the hyperparameter tuning of the BiTCN-BiGRU has been carried out using the mountain gazelle optimization (MGO) algorithm to achieve optimal fine-tuning of parameters. To demonstrate the greater solution of the PPV2XT-HDLOA technique, a wide range of simulations has been tested, and the outcomes are inspected under several measures.
Key Features and Importance of the PPV2XT-HDLOA Model for Dubai

- The PPV2XT-HDLOA model uses z-score normalization for consistent data in real-time vehicle communication. Dubai's fast-paced, digital transportation system requires standardized data processing to increase reaction speed and dependability. 2. RSA-Based Feature Selection
- The model efficiently identifies relevant data features, filtering out unnecessary information and enabling Dubai's transportation network to process the most important real-time insights. This would improve predictive traffic management, making metropolitan infrastructure more flexible.
- The BiTCN-BiGRU hybrid deep learning model improves traffic pattern, vehicle behavior, and network interaction categorization, informing autonomous vehicle decision-making. Such a methodology will greatly enhance AI-driven transportation solutions in Dubai, where self-driving taxis and smart roads are being integrated.
- The Mountain Gazelle Optimization (MGO) technique optimizes deep learning models for optimum efficiency. V2X-enabled cars will analyze information quickly, communicate better, and respond quickly to traffic changes in Dubai, decreasing accidents and improving urban transportation.

2. Related Works

Restrepo and Vander Peterson [11] developed an innovative multi-level sensor collaboration structure that incorporates drone-based sensing and V2X communication to improve tunnel-centric navigation. By utilizing a V2X-enabled framework for real-world data exchange and drones for aerial vision, the projected structure guarantees collision-free navigation and strong situational awareness. The multi-level structure integrates vehicular data, drone imagery, and ground-based sensors, utilizing advanced sensor fusion models like DL techniques and Kalman filters. Chen et al. [12] introduce an innovative RL approach called RL4V2X for motion-controlling and decision-making of independent driving. This model contains GRU, CNN, and 3 gate networks. Kokare et al. [13] developed a RIS-aided simultaneous wireless information and power transfer (SWIPT) method for V2X systems, which can employ either the SWIPT mechanisms or the advantage of RIS to improve the performance of the network. Then, the overview of the present work and the DRL structure for RIS-SWIPT-assisted 6G method is presented. Eventually, this chapter emphasizes a few investigation opportunities and challenges for RIS-SWIPT systems for 6G methods, which can be addressed by utilizing DRL approaches.
Raslan et al. [14] developed a novel incorporation of Advanced Driver Assistance Systems (ADAS) with V2X communication technology focused on improving road safety. In cases of driver drowsiness, this method utilizes an alarm system to alert the driver, followed by controlled vehicle stops if needed, while concurrently notifying nearby vehicles through the V2X system. Likewise, possible collisions and emergency messages are quickly dispatched to pre-defined contacts, assisting in quick emergency response efforts. In addition, this method employs outside cameras for precise recognition of traffic signals and gives real-world alerts to drivers related to lane departures. Saleem et al. [15] projected a neural receiver intended to optimize Bit Error Rate (BER) for vehicle-to-network (V2N) uplink situations in a 6G system. This method trains several neural receivers by altering their trainable parameters and utilizing the finest fit technique as a proposal for large-scale employment. The presented neural receiver gets a signal in the frequency area at the base station (BS) as input and creates an optimum log-likelihood ratio (LLR) at the output. It measures the channel depending on the received signal, and matches and demodulates the higher-order modulated signal.
Xu et al. [16] project V2X-ViTs, a strong cooperative perception structure with V2X communication utilizing an innovative vision Transformer method. Initially, this method developed V2X-ViTv1, comprising holistic attention modules. Particularly, V2X-ViTv1 contains alternating layers of multi-scale window self-attention and heterogeneous multi-agent self-attention that take per-agent spatial and inter-agent interaction relationships. These major modules are intended in a unified Transformer structure to control common V2X tasks, comprising asynchronous data sharing, pose errors, and heterogeneity of V2X modules. Then, an advanced framework, V2X-ViTv2, is projected.
In the existing research [17], Vision 2050 of the UAE in Intelligent Mobility aims to transform the transportation landscape by integrating advanced technologies such as autonomous vehicles (AVs), the Internet of Things (IoT), and intelligent transportation channels (ITCs). This vision aligns with the broader goals of sustainable urban development and environmental stewardship, addressing challenges like traffic congestion, pollution, and urbanization. The UAE's strategic approach involves leveraging these technologies to enhance liveability and ecological sustainability while ensuring safety and efficiency in transportation systems. The following sections delve into the key components of this vision. Majji KC, Baskaran, et al. [18], the authors of the paper, discuss the integration of artificial intelligence analytics in the UAE automotive industry, highlighting the role of virtual assistants. The authors explore how AI can enhance decision-making processes, improve customer interactions, and streamline operations within the automotive sector. The study emphasizes the potential for AI to transform traditional practices and offers insights into the future of automotive technologies in the region.
Ajel, et. al. [19], in this doctoral dissertation, the author examines the investment landscape for electric cars in the Gulf region, addressing both opportunities and challenges for market expansion. The research delves into the economic implications of electric vehicle adoption, regulatory frameworks, and consumer attitudes. The findings suggest that while there is significant potential for growth, several barriers must be overcome to facilitate widespread adoption of electric vehicles in the Gulf area. Patil et al. [20] - This paper presents a protocol for Level 4 autonomy in self-driving cars specifically tailored for the UAE context. The authors discuss the technical and regulatory aspects of implementing autonomous vehicles, including safety protocols, infrastructure requirements, and public acceptance. The study

contributes to the understanding of how autonomous driving technology can be adapted to the unique challenges and opportunities present in the UAE.

ElGhanam et al. [21] - This conference paper explores machine learning techniques for predicting electric vehicle charging demand in the UAE using origin-destination data. The authors provide a comprehensive analysis of the factors influencing charging behavior and propose a model that can help optimize charging station placements and improve grid management. The study underscores the importance of data-driven approaches in addressing the growing demand for electric vehicle infrastructure. Singh et al. [22] - This chapter discusses the integration of Internet of Things (IoT) technologies in autonomous vehicles, highlighting the concept of intelligent mobility. The authors explore the synergies between IoT and autonomous driving, focusing on how connected vehicles can enhance safety, efficiency, and user experience. The paper contributes to the discourse on smart transportation systems and their potential impact on urban mobility.

Saad et al. [23] introduce a knowledge-empowered Distributed Multi-Agent Deep Reinforcement Learning (K-MADRL). According to traffic flow information, LSTM is utilized to implement Unmanned Internet of Aerial Agents (UIAAs) to gather vehicle state information. UIAAs collect vehicle state knowledge and train the local DRL methods. The trained policy is sent to the vehicles through System Synchronization Blocks (SSB) for distributed execution.

The literature review highlights the inadequacies of current UAE legislation in regulating artificial intelligence as a subject of commercial transactions, emphasizing the need for specific provisions to address the unique characteristics and risks associated with AI products. It discusses the balance that must be struck between protecting consumer interests and fostering innovation in the AI sector. These reviews summarize the key themes and contributions of each paper, providing a foundation for further exploration of the topics discussed. The identified research gaps are given below. Despite the latest investigations like Chen et al. [12] and Xu et al. [16], which help to further the development of V2X communication and cooperative perception, there are still considerable limitations. The concept suggested by Chen et al. (2024) is the RL4V2X, which can boost autonomous driving decisions, yet this model cannot experience stable communication when the V2X links are not available, resulting in poor model accuracy. Likewise, Xu et al. (2024) proposed V2X-ViTv2, which is a Transformer-based cooperative perception system, but it has constraints in computational complexity and the absence of privacy-preserving algorithms, preventing its application in large-scale smart city networks. The current frameworks tend to overlay communication reliability and perception accuracy, but not many combine the preservation of privacy with the hybrid deep learning optimization. In addition, most of the previous studies are based on simulation-based testing without relation to the city-specific structures, like the smart mobility agenda of Dubai Vision 2050.

The proposed PPV2XT-HDLOA framework addresses these gaps through:

- Detection of privacy-preserving feature extraction with RSA.
- Hybrid BiTCN-BiGRU classification, which incorporates the concept of bidirectional temporal and sequential dependencies to enhance the detection of abnormal behaviors by the vehicles.
- Adaptive parameter tuning using the MGO algorithm to achieve optimum computation efficiency at the same time exhibiting scalability.
- Applicability The solution should be contextually aligned with the Dubai-based AI-driven transportation projects, which imply its applicability to actual implementation in high-density vehicular networks.

2.1 Research Gaps and Comparative Analysis.

Even though several recent research as Chen et al. [12] and Xu et al. [16], have contributed greatly to the development of V2X communication and cooperative perception, there are still several significant challenges. Chen et al. (2024) proposed an RL-based theory (RL4V2X) of self-driving, which, however, is less effective in the case of intermittent communication between V2X and is also not equipped with privacy-saving mechanisms. Xu et al. (2024) developed the V2X-ViTv2 that improves perception with the help of Transformer architectures, but has disadvantages in terms of high computational costs and is incapable of supporting large vehicular networks in real time. Moreover, most of the previous studies focus on the accuracy and latency gains, yet they do not consider the privacy, flexibility, and efficiency requirements of the new smart transportation system, like the Dubai Vision 2050. The proposed PPV2XT-HDLOA framework fills these gaps with the Reptile Search Algorithm (RSA) used to select the features, the BiTCN-BiGRU hybrid deep learning used to perform the efficient classification, and the Mountain Gazelle Optimization (MGO) used to make the adaptive parameter adjustments. This integration is accurate in detection and privacy-preserving, and enables real-time vehicular systems to be computationally feasible. In addition, by revealing itself to AI-based and privacy-conscious V2X infrastructures, PPV2XT-HDLOA will directly contribute to smart mobility goals at the global and regional level. Saleem et al. (2025) and Saad et al. (2025) are two recent publications that point to the shift to 6G-capable vehicular communication and distributed AI, which supports the topicality of the proposed model.

3. The Proposed Model

In this paper, we focus on the design and implementation of the PPV2XT-HDLOA model for Smart Transportation in Dubai. The presented PPV2XT-HDLOA model enhances V2X transportation by leveraging advanced data-driven techniques to optimize vehicle communication. It contains various kinds of stages involved as data normalization, dimensionality reduction, hybrid classification, and parameter selection process. Fig. 1 determines the entire flow of the PPV2XT-HDLOA system. Global smart cities like Singapore, Seoul, and major U.S. metropolitan regions are investing heavily in V2X technology to construct connected, intelligent, and cyber-secure transportation networks. The US has started many V2X pilot projects employing AI-driven models to enhance traffic flow, safety, and emergency response. Self-driving vehicles in South Korea can communicate with urban infrastructure in real time using 5G-powered V2X technologies, establishing a new benchmark for smart mobility. Dubai must immediately embrace powerful AI-powered V2X models like PPV2XT-HDLOA before competitor cities adopt them to remain a transportation innovation leader. This framework will put Dubai at the forefront of transportation innovation, supporting its 2026 air taxi aspirations and long-term smart city aims with a secure, AI-enhanced, and ultra-efficient vehicle communication system. As Dubai's leadership pushes toward autonomous, seamless mobility, AI-driven V2X models will unleash safer, quicker, and smarter transportation alternatives for residents and tourists.

3.1 Stage I: Z-score Normalization

Primarily, the PPV2XT-HDLOA model applies the z-score normalization approach for data normalization to ensure data uniformity and enhance model convergence. Min-max is dependent upon the maximum and minimum values of un-normalized data applied in re-scaling [24]. The higher and lower bounds were well-defined linearly by the min-max standardization technique, and the data were rescaled between 0 and 1 or from −1 to 1. To make sure that data scaling is consistent and the learning process is stable, each feature is normalized using the z-score method shown in Equation (1). This transformation makes the input variables have a mean of zero and a variance of one, which speeds up the convergence of deep learning models. Eq. (1) displays the mathematical formulation of this normalization:

$$x'_{i,n} = \frac{x_{i,n}-(x_i)}{(x_i)-(x_i)}(nmax - nmin) + nmin \quad (1)$$

In this case, x is the value of the input feature, μ is the mean of the feature, and σ is the standard deviation. This normalization process gets rid of bias caused by different variable sizes and makes sure that the model is trained in a balanced way. Here, min and max Indicate the minimum and maximum values of the characteristic. i, correspondingly. Likewise, the upper and lower bounds are denoted as $nmin$ and $nmax$, respectively.

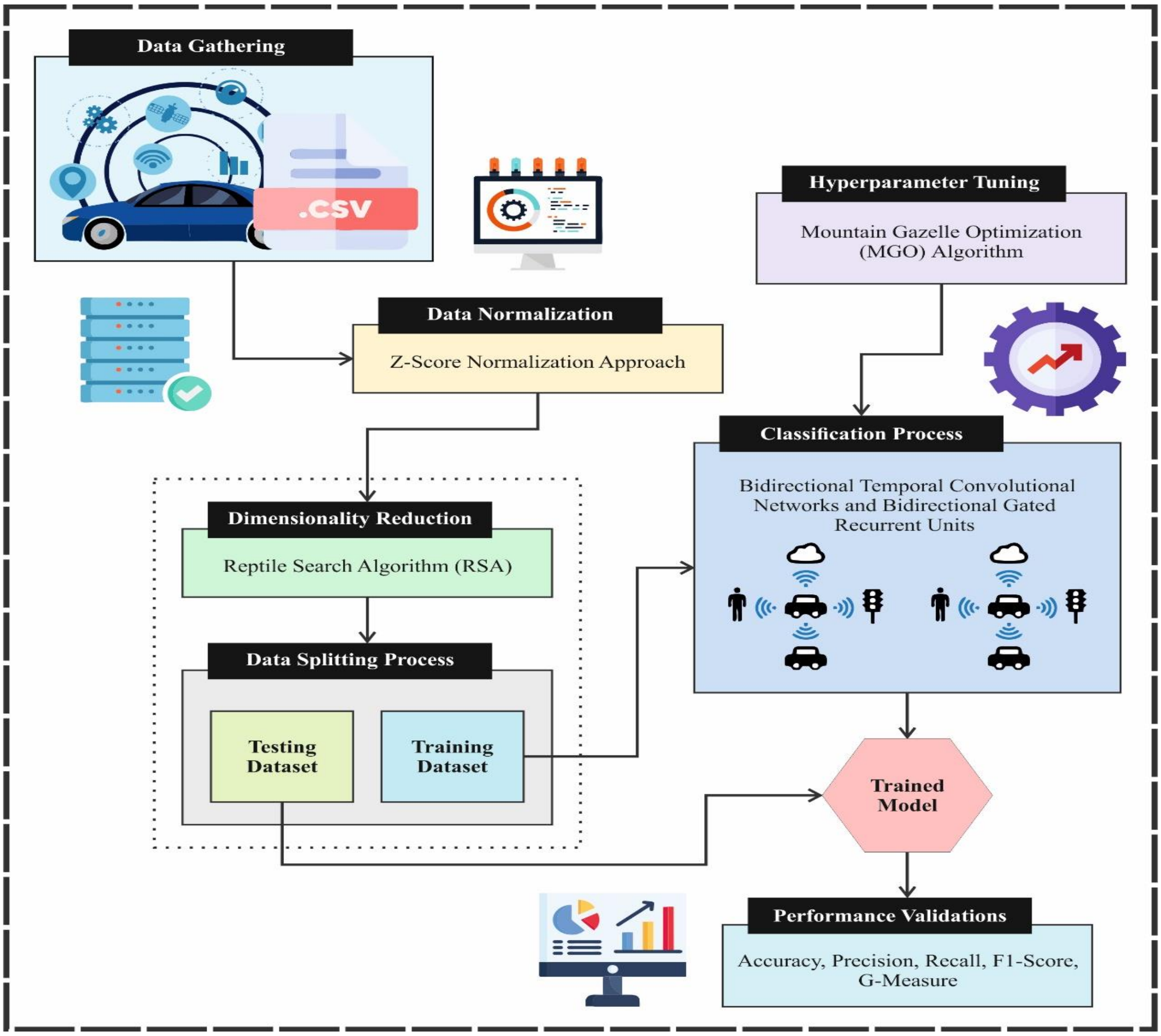

Fig. 1: Overall flow of PPV2XT-HDLOA system

3.2 Stage II: Dimensionality Reduction using RSA

To reduce dimensionality, the RSA can be employed to recognize the most relevant features. The RSA is proposed to depend upon the crocodiles' hunting behaviors naturally [25]. The exploitation and exploration search devices were done depending upon 4 kinds of crocodiles' actions, such as belly walking, hunting coordination, high walking, and hunting cooperation. In RSA, the initial stage produces the early locations of every individual in the search space by utilizing Eq. (2). The Reptile Search Algorithm (RSA) is used to choose features after normalization. RSA emulates the hunting strategy of reptiles by balancing exploration and exploitation phases to determine optimal feature subsets. The following math equations explain how it moves and hunts.

$$X_{ij} = rand \times (ub_j - lb_j) + lb_j, j = 1,2, \ldots, D \quad (2)$$

In these equations, X stands for the candidate solution vector, α stands for the adaptive coefficient that controls how much exploration is done, and β stands for the hunting behavior. By updating these parameters over and over, RSA can get closer to the most useful feature subset. Here, $rand$ signifies the randomly generated amount among 0 and 1, lb_j and ub_j Represent the lower and upper bounds. D Represents the size of an optimizer issue. X_{ij} indicates the generated location of ith individual in jth Dimension.

Encircling stage (Exploration)

In this stage, crocodiles will enclose the quarry in the searching space. The belly and high walking of crocodiles were arithmetically demonstrated to comprehend this objective. The iteration count is employed as the foundation for the walking method. The computation was exposed in Eqs. (3) and (4).

$$X_{(i,j)}(t+1) = Best_j(t) - \eta_{(i,j)}(r) \times \beta - R_{(ij)}(r) \times rand, if\ t \le T/4 \quad (3)$$

$$X_{(i,j)}(t+1) = Best_j(t) \times X_{r1,j} \times ES(t) \times rand, if\ t \le T/2\ and\ t > T/4 \quad (4)$$

While $Best_j(t)$ Denotes the present best location within the population. t Means the current number of iterations, and T Refers to the maximum count of iterations. $\eta_{(i,j)}(t)$ Denotes a hunting operator that is defined utilizing Eq. (5). β Refers to a value of constant value that indicates the exploration accuracy and is fixed at 0.005. $R_{(i,j)}(t)$ Denotes a decrease function that is intended to utilize Eq. (6). r_1 refers to a randomly generated integer among $[1, N]$. $ES(t)$ Means a probability ratio named evolutionary sense that lies within the range of [−2, 2], which can be gained by utilizing Eq. (7).

$$\eta_{(i,j)} = Best_j(t) \times P_{(i,j)} \quad (5)$$

$$R_{(i,j)} = \frac{Best_j(t) - X_{r_2 j}}{Best_j(t) + \varepsilon} \quad (6)$$

$$ES(t) = 2 \times r_3 \times \left(1 - \frac{t}{T}\right) \quad (7)$$

While ε Represents a very small positive number. r_2 refers to a randomly produced integer among $[1, N]$. r_3 It is set as —l or 1 at random. $P_{(i,j)}$ Indicates a percentage difference between the present and best positions, which is computed utilizing Eqs. (8) and (9).

$$P_{(i,j)} = \alpha + \frac{X_{(i,j)} - M(x_i)}{Best_j(t) \times (ub_j - lb_j) + \varepsilon} \quad (8)$$

$$M(x_i) = \frac{1}{D} \sum_{j=1}^{D} X_{(i,j)} \quad (9)$$

Here, α Denotes a sensitive parameter that is similar to β And fixed as 0.1.
Hunting stage (Exploitation)
In this stage, crocodiles do the local exploration by utilizing hunting cooperation and coordination. If $t \le 3T/4$ and $t > T/2$ThenHunting coordination is employed. Or else, the hunting cooperation might be employed if $t \le T$ and $t > 3T/4$. These dual actions are demonstrated in Eqs. (10) and (11).

$$X_{(i,j)}(t+1) = Best_j(t) \times P_{(i,j)}(t) \times rand, if\ t \le 3T/4\ and\ t > T/2 \quad (10)$$

$$X_{(i,j)}(t+1) = Best_j(t) - \eta_{(i,j)}(r) \times \varepsilon - R_{(i,j)}(r) \times rand, if\ t \le T\ and\ t > 3T/4 \quad (11)$$

The fitness function (FF) denotes the accuracy of classification and the chosen nominated features. It exploits the classifier accuracy and diminishes the dimensionality of the chosen feature. Accordingly, the below-mentioned FF has been deployed to assess a discrete solution, as exposed in Eq. (12).

$$Fitness = \alpha * \ ErrorRate + (1 - \alpha) * \frac{\#SF}{\#All\_F} \quad (12)$$

While $ErrorRate$ Means the classification rate of error utilizing the preferred features. $ErrorRate$ It was intended as the ratio of incorrect categories to the number of classifications made between 0 and 1. $\#SF$ signifies the quantity of preferred features and $\#All\_F$ Means the total number of attributes in the database. α It is exploited to control the prominence of classification excellence and sub-set length.

3.3 Stage III: Classification using BiTCN-BiGRU

For the classification process, the hybrid DL model combining the BiTCN-BiGRU technique is exploited. The conventional TCN utilizes forward convolution on the sequence of input, removing only forward features and forgetting the backward hidden information [26]. Nevertheless, the BiGRU and the BiTCN create a hybrid DL component. The Bi-TCN lengthens the appropriate regions of the convolution kernel by utilizing the lengthy convolution architecture. Bi-directional branches are added based on the TCN, the residual connection architecture is calculated, recursive stacking and dilated causal convolution are presented, and a Bi-TCN is made.
Causal convolution normally fails to access upcoming data due to its unidirectional architecture. The causality feature of causal convolution guarantees that the sequence of output is. $y = (y_1, y_2, \dots, y_t)$ is produced as the sequence of input $x = (x_1, x_2, \dots, x_t)$ Pass over the network, with all outputs at some specified time, relying only on the inputs previous to the present time point. To successfully seize long-range dependences in the sequence, causal convolution requires seeing ahead and reverting to historical information that usually needs more hidden layers (HLs). Hence, BiTCN uses dilated convolutions to attain a greater receptive area with smaller layers, while maintaining the feature mapping sizes. Whereas k denotes convolution kernel size, d Signifies the dilation factor that develops exponentially afterward all layers of convolution of the input sequence.
In consideration of information in either forward or reverse directions, the Bi-TCN enhances its ability to remove hidden features from the sequence, unlike the conventional TCN. Additionally, the BiGRU contains dual GRUs in opposite directions: one GRU examines the data in the forward direction succeeding the time series, and the other GRU manages the data from the reverse direction. While x_t Denote the input of the time step. t, h_t Represents the output of the combined dual HLs. With this bi-directional architecture, more complete time series information is hence gained to predict, which enhances its part in the complete model output and the modeling ability of hybrid methods for the sea-level height data. The rise in BiTCN's receptive area can result in problems like slower convergence and gradient explosion. To deal with these challenges and avoid vanishing gradients, the BiTCN method combines residual blocks that additionally enable quicker convergence.

This model presents the primary feature extraction from the sea-level height data utilizing the BiTCN residual block. This stage captures the fundamental spatial features from the input sequences. Bi-GRU has been applied to remove extracted feature information from extracted data sequences and take the temporal dependencies. The fully connected (FC) layer then maps these extracted features into the 1D space. Fig. 2 depicts the infrastructure of the BiTCN-BiGRU technique.

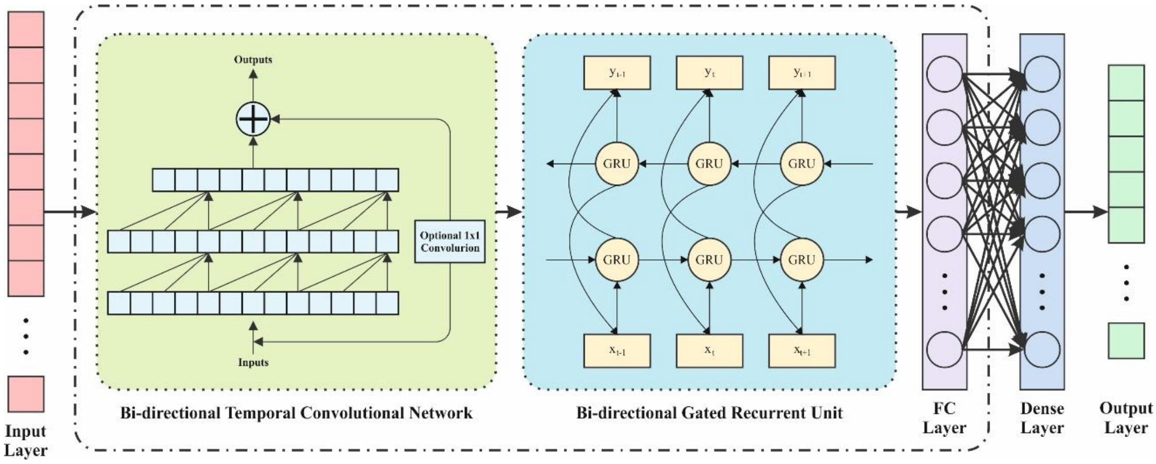

Fig. 2: Architecture of BiTCN-BiGRU

3.4 Stage IV: Parameter Optimizer Process

Finally, the parameter tuning of the BiTCN-BiGRU has been carried out using the MGO algorithm to achieve optimal fine-tuning of parameters, ensuring superior classification performance. The MGO technique is a newly developed metaheuristic technique [27-29]. This technique takes stimulation from mountain gazelle groups and social behavior, and the optimizer procedure depends upon the four features of gazelles' survival, such as bachelor male herds, maternity herds, territory solitary males, and migration to hunt for food. The mathematical calculation of these phases is explained below:

Territory Solitary Males (TSM)

The male mountain gazelles begin in single areas based on attaining maturity and acquiring power. Adult males violently protect these areas and are involved in fights against them for the territory of females. In the meantime, younger males effort to inhabit these areas or appeal to females. Whereas adult males concentrate on defending their recognized surroundings. The Temporal Convolutional Network (TCN) component captures long-range temporal dependencies in sequential V2X data. Its convolutional operation across multiple dilated layers is formulated as follows: The mathematical method of representing the adult male land is assumed as follows:

$$TSM = male_{gazelle} - |\phi_1 * V_c - \phi_2 * X(t) * G| * Cof_r \quad (13)$$

$$V_c = X_n * \lfloor a_1 \rfloor + POP * \lceil a_2 \rceil, \quad n = \left\{\left\lceil \frac{N}{3} \right\rceil \ldots.. N\right\} \quad (14)$$

$$G = N_1(D) * \exp\left(2 - iter * \left(\frac{2}{iter_{\max}}\right)\right) \quad (15)$$

$$Cof_r = \begin{cases} (b+1) + a_3 \\ b * N_2(D) \\ a_3(D) \\ N_3(D) * N_4(D)^2 * cos\left((a_4 * 2) * N(D)\right) \end{cases} \quad (16)$$

$$b = -1 + iter * \left(\frac{-1}{iter_{\max}}\right) \quad (17)$$

In the above expression, x_t stands for the input sequence, f stands for the filter size, and d stands for the dilation rate, which controls how long each convolution lasts. This structure makes it easy to handle time-dependent data for vehicle communications. Here, $male_{gazelle}$ signifies the male location vector; ϕ_1 and ϕ_2 are generated randomly within the range of 1 or 2; V_c signifies the coefficient vector; Cof_r Refers to an arbitrarily chosen coefficient vector, which is upgraded in every iteration and increases the hunting ability. $X(t)$ represents the initial location of the gazelle; X_n refers to a randomly generated solution in nth range, POP refers to an average amount of population, while $\left\lceil \frac{N}{3} \right\rceil$ is chosen at random; N means the total amount of gazelles; a_1, a_2, a_3 and a_4 are arbitrarily chosen values within the range of 0 to 1; N_1 signifies the randomly produced number; N_2, N_3, and N_4 mean the sizes of the problem and are nominated numbers at random; $iter$ and $iter_{\max}$ represents the present and maximum count of iterations, correspondingly.

Maternity Herds (MH)

This one generally plays an essential part in the mountain gazelle's life cycle. While these kinds of packs give birth to dense male gazelles. Also, the male gazelles play a vital part in the gazelle's delivery, and young males try to own females. This action was expressed below in the mathematical formulation:

$$MH = \left(V_c + Cof_{1,r}\right) + \left(\phi_3 * male_{gazelle} - \phi_4 * X_{rand}\right) * Cof_{2,r} \quad (18)$$

While, ϕ_3 and ϕ_4 are arbitrarily produced numbers 1 or 2; $Cof_{1,r}$ and $Cof_{2,r}$ are chosen coefficient vectors at random; X_{rand} represents the chosen location vector at random of a gazelle.

Bachelor of Male Herds (BMH)

Generally, the male gazelles develop and inclined to create lands and try to control female gazelles. At that time, young male gazelles arrive in a struggle with adult males for land and control of females, which frequently results in significant violence. This behavior is mathematically demonstrated below:

$$BMH = (X(t) - F) + (\phi_5 * male_{gazelle} - \phi_6 * V_c) * Cof_r \tag{19}$$

$$F = (|X(t)| + |male_{gazelle}|) * (2 * a_5 - 1) \tag{20}$$

Here, $X(t)$ signifies the location vector of the gazelle in pare present iteration; ϕ_5 and ϕ_6 are selected numbers at random from 1 or 2; a_5 refers to a random number within the range of 0 to 1.

Migration in Search of Food (MSF)

In the hunt for food, the mountain gazelles cover huge distances and are always on the lookout for novel resources. They were recognized for their inspiring running velocity and great jumping aptitude. As an outcome, they frequently move to abundant distances to discover food and travel. The following formulation was employed for expressing this behavior:

$$MSP = (ub - lb) * a_6 + lb \tag{21}$$

Here, lb and ub are the lower and upper limits of the optimization issue; a_6 represents a produced number at random within the interval from 0 to 1.

The MGO system originates an FF to achieve enhanced outcomes of classification. It defines a positive number to represent the better candidate solution. Here, the decrease of the classifier error rate is measured as the FF The Mountain Gazelle Optimization (MGO) algorithm is used to fine-tune the hyperparameters of the BiTCN-BiGRU network. MGO imitates how gazelles look for food when they move across landscapes. The mathematical model below shows what happens during the exploration phase, as assumed in Eq. (22).

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{no.of\ misclassified\ samples}{Total\ no.of\ samples} * 100 \tag{22}$$

In these equations, X stands for the position of the gazelle, r_1 and r_2 are random numbers that affect the direction and step size, and F(X) stands for the fitness function that shows how well the classification works. To reduce classification error, the algorithm updates the position vectors repeatedly. The last fitness function (Eq. 22) is meant to lower the model's overall error rate.

4. Performance Validation

This article studies the performance of the PPV2XT-HDLOA technique on the CIC-ToN-IoT dataset [30] from Kaggle. The dataset consists of 119957 samples under nine classes defined in Table 1. It contains 42 features, and 31 of them are selected.

Table 1: Details of Database

Classes	No. of Samples
“Normal”	78369
“MiTM”	336
“DoS”	5440
“DDoS”	5987
“Password”	6016
“Injection”	5867
“XSS”	5951
“Ransomware”	5976
“Backdoor”	6015
Total Samples	**119957**

Fig. 3 displays the classifier performances of the PPV2XT-HDLOA model on the test dataset. Figs. 3a-3b represents the confusion matrix through precise identification and classification of all 9 dissimilar classes on a 70%TRASE and 30%TESSE. Fig. 3c presents the PR outcome, which shows higher performance over 9 classes. Eventually, Fig. 3d demonstrates the ROC study, which illustrates capable solutions with great ROC values for 9 different classes.

In Table 2 and Fig. 4, a brief global classification performance of the PPV2XT-HDLOA methodology is portrayed for 70%TRASE and 30%TESSE. The performances imply that the PPV2XT-HDLOA method can efficaciously identify the samples. With 70%TRASE, the PPV2XT-HDLOA model gains average $accu_y$ of 99.23%, $prec_n$ of 91.07%, $reca_l$ of 84.37%, $F1_{score}$ of 85.54%, and $G_{measure}$ of 86.46%, respectively. In addition, with 30%TESSE, the PPV2XT-HDLOA system reaches average $accu_y$ of 99.24%, $prec_n$ of 92.07%, $reca_l$ of 84.52%, $F1_{score}$ of 85.74%, and $G_{measure}$ of 86.80%, correspondingly. Parameters optimized with the help of MGO are then transferred to the PPV2XT-HDLOA model, and performance is tested with the CIC-ToN-IoT data. The results below demonstrate the classification accuracy, precision and recall of the model in various V2X attack categories.

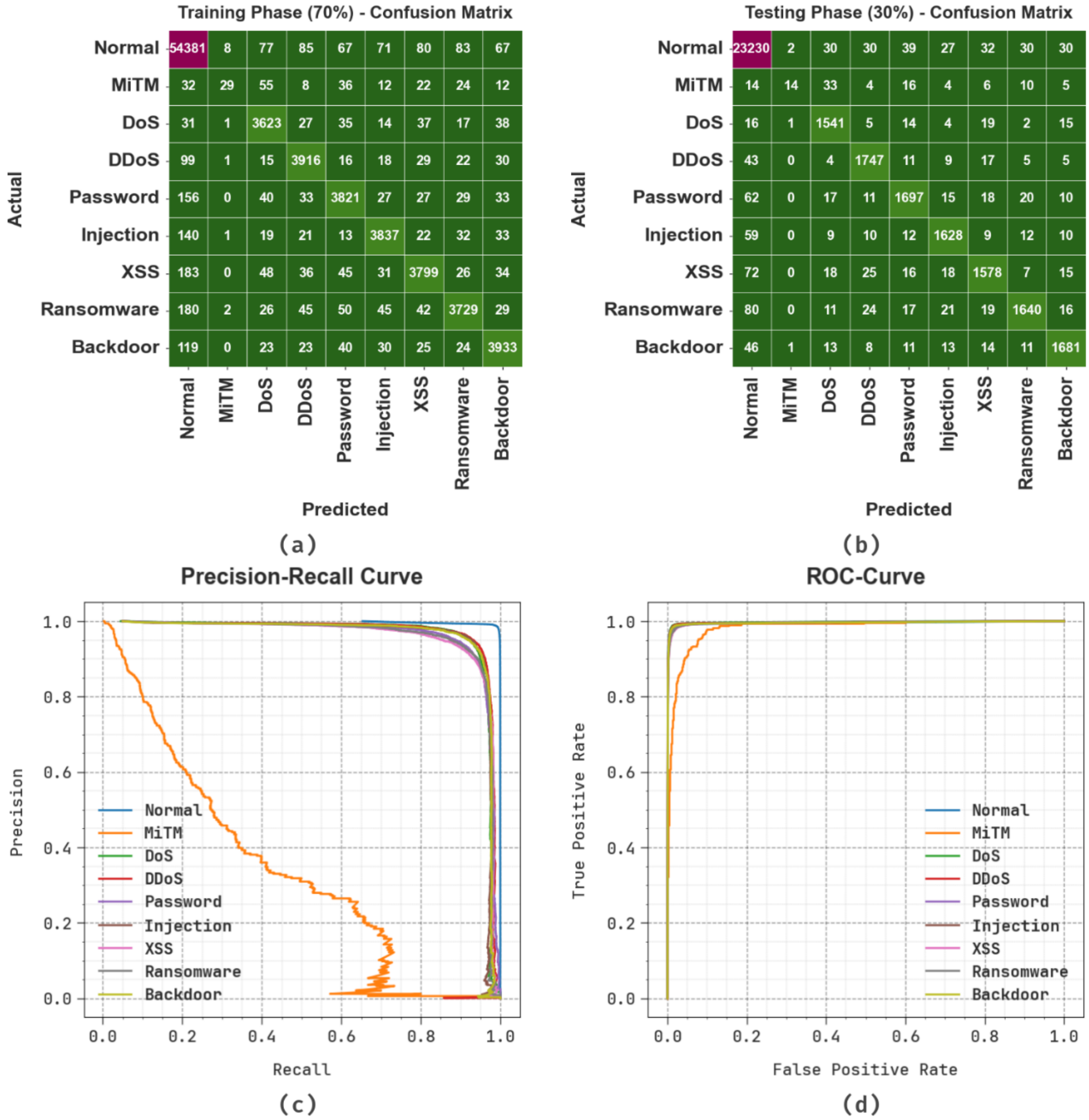

Fig. 3: (a-b) Confusion matrix and (c-d) Curves of PR and ROC

Table 2: Overall Classifier outcome of PPV2XT-HDLOA algorithm under 70%TRASE and 30%TESSE

Class Labels	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{Score}$	$G_{Measure}$
		TRASE (70%)			
Normal	98.24	98.30	99.02	98.66	98.66
MiTM	99.75	69.05	12.61	21.32	29.51
DoS	99.40	92.28	94.77	93.51	93.52
DDoS	99.40	93.37	94.45	93.91	93.91
Password	99.23	92.68	91.72	92.19	92.20
Injection	99.37	93.93	93.18	93.55	93.55
XSS	99.18	93.04	90.41	91.71	91.72
Ransomware	99.19	93.55	89.90	91.69	91.71
Backdoor	99.33	93.44	93.27	93.35	93.35
Average	**99.23**	**91.07**	**84.37**	**85.54**	**86.46**
		TESSE (30%)			
Normal	98.30	98.34	99.06	98.70	98.70
MiTM	99.73	77.78	13.21	22.58	32.05
DoS	99.41	91.95	95.30	93.59	93.61
DDoS	99.41	93.72	94.89	94.30	94.31
Password	99.20	92.58	91.73	92.15	92.15
Injection	99.36	93.62	93.08	93.35	93.35
XSS	99.15	92.17	90.22	91.19	91.19
Ransomware	99.21	94.42	89.72	92.01	92.04
Backdoor	99.38	94.07	93.49	93.78	93.78
Average	**99.24**	**92.07**	**84.52**	**85.74**	**86.80**

4.1 Limitations and Mitigation Strategies

Although the PPV2XT-HDLOA model has a higher detection accuracy and reliability, there are still some challenges:
Computational Complexity: The hybrid BiTCN-BiGRU network with MGO optimization adds to the level of training overhead, and this can limit real-time processing of embedded vehicular units.

Mitigation: Future applications can use model compression, quantization, and edge-based inference to decrease the computational load without accuracy loss.
There exist various strategies that can be employed to achieve scalability in large-scale V2X networks. Scalability of Large-Scale V2X Networks: It is possible to have communication bottlenecks in real-time because thousands of vehicles communicate.
Reducing the effect of this scaling and latency: Parallel scalability and latency reduction can be enabled by adding distributed learning structures and federated edge aggregation.
Overheads in Data Privacy and Security: Even though the framework is privacy-preserving, encryption and anonymization introduce minor processing delays.
Mitigation: Lightweight cryptographic primitives and secure multiparty computation can be deployed to ensure keeping the latency is kept low.
Hardware Constraints: The implementation of the model on processors in vehicles (e.g., NVIDIA Jetson systems) might require memory consumption and inference time optimization.
Solving these limitations will help the easy real-world implementation of PPV2XT-HDLOA in the next generation of vehicular communication systems.

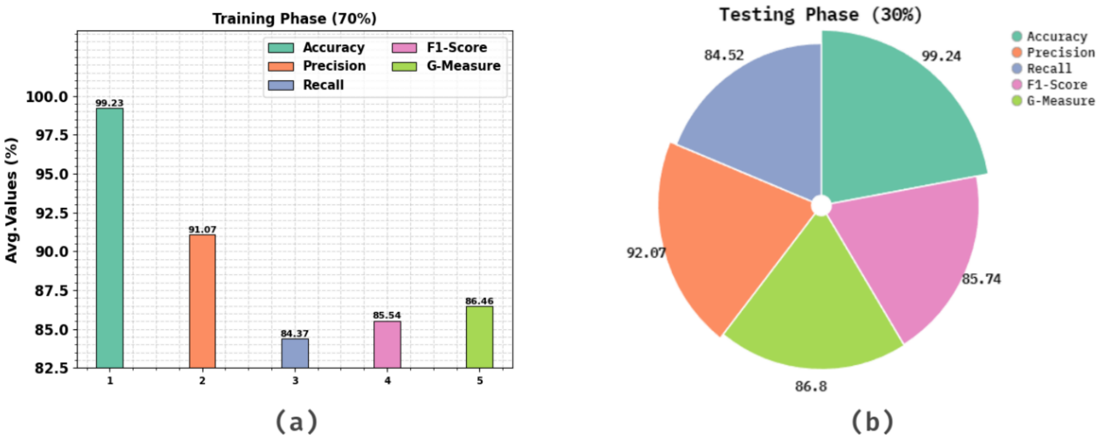

Fig. 4: Average outcome of PPV2XT-HDLOA algorithm (a) 70%TRASE and (b) 30%TESSE

4.2 Practical Implementation in the Dubai Smart Transportation Environment.

In addition to the present validation based on the CIC-ToN-IoT data, future research will cover further testing in the urban mobility ecosystem of Dubai and use 5G/6G pilot corridors and the autonomous vehicle projects of the Roads and Transport Authority (RTA).
Possible pilot applications are the coordination of autonomous taxis, the detection of intrusion at smart intersections, and the monitoring of traffic using VAVs.

- Challenges that are expected in the real-world validation include:
- High-density vehicular and environmental interference 5G reliability.
- Hardware interconnection to ECUs and units of vehicles.
- Regulatory adherence to Dubai Smart Mobility Vision 2050.

These validation procedures will confirm the performance of the models in heterogeneous and high traffic conditions and enable the deployment preparation of the future smart-city infrastructure of Dubai.

Fig. 5: $Accu_y$ curve of the PPV2XT-HDLOA algorithm

In Fig. 5, the TRA $accu_y$ (TRAAY) and validation $accu_y$ (VLAAY) performances of the PPV2XT-HDLOA method are depicted. The values of $accu_y$ are computed across a time of 0-25 epochs. The figure underscored that the values of TRAAY and VLAAY present an increasing trend, indicating the competency of the PPV2XT-HDLOA algorithm with maximum performance through multiple repetitions. In addition, the TRAAY and VLAAY values remain close across the epochs, indicating decreased overfitting and expressing superior performance of the PPV2XT-HDLOA approach, which guarantees reliable calculation on unseen samples.

In Fig. 6, the TRA loss (TRALO) and VLA loss (VLALO) graph of the PPV2XT-HDLOA technique is showcased. The values of loss are computed across a time of 0-25 epochs. It is exemplified that the values of TRALO and VLALO demonstrate a diminishing tendency, which indicates the capacity of the PPV2XT-HDLOA system to equalize a tradeoff between data fitting and generalization. The succeeding dilution in values of loss also assures the superior performance of the PPV2XT-HDLOA and tunes the calculation results after a while.

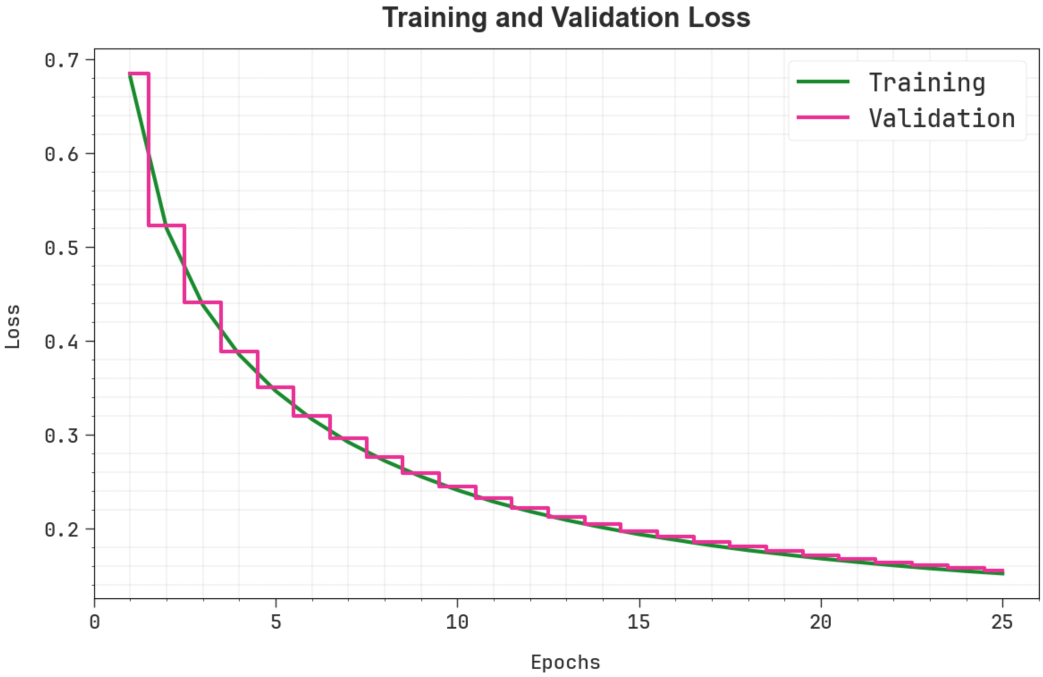

Fig. 6: Loss curve of the PPV2XT-HDLOA algorithm

In Table 3 and Fig. 7, the experimental analysis of the PPV2XT-HDLOA approach with recent techniques is specified [23, 24]. The performances display that the kNN method has presented poorer performance with $accu_y$, $prec_n$, $reca_l$, and $F1_{score}$ of 93.25%, 90.78%, 79.32%, and 84.69%, correspondingly. Simultaneously, the CNN-GRU technique has attained moderately enhanced solutions with $accu_y$, $prec_n$, $reca_l$, and $F1_{score}$ of 95.45%, 91.23%, 82.19%, and 79.64%, correspondingly. Also, the LDA, CART, CCNN-LSTM, and CCNN-BiLSTM algorithms have gained judiciously closer performance. In the meantime, the VNID-CDLAMVM technique has succeeded in significant solutions with $accu_y$, $prec_n$, $reca_l$, and $F1_{score}$ of 98.20%, 88.88%, 83.02%, and 80.58%, correspondingly. However, the PPV2XT-HDLOA system outperforms the other techniques with improved $accu_y$, $prec_n$, $reca_l$, and $F1_{score}$ of 99.24%, 92.07%, 84.52%, and 85.74%, respectively.

Table 3: Comparative outcome of the PPV2XT-HDLOA algorithm with other existing systems

Methods	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{Score}$
PPV2XT-HDLOA	99.24	92.07	84.52	85.74
VNID-CDLAMVM	98.20	88.88	83.02	80.58
CCNN-BiLSTM	97.48	90.24	83.13	83.96
CCNN-LSTM	97.27	87.48	81.00	80.07
CNN-GRU	95.45	91.23	82.19	79.64
LDA Model	96.31	90.63	82.37	82.82
CART Method	96.34	87.75	82.66	81.31
kNN Algorithm	93.25	90.78	79.32	84.69

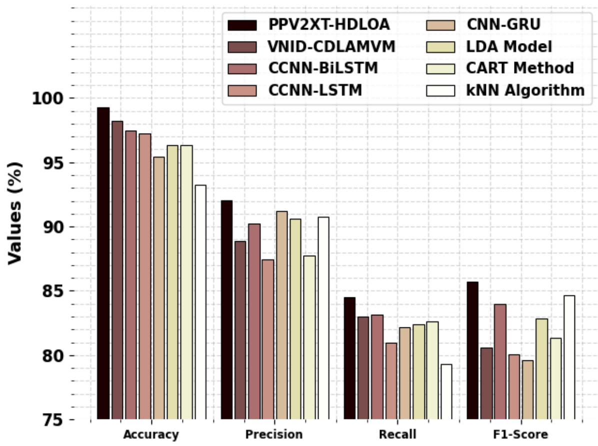

Fig. 7: Comparative outcome of the PPV2XT-HDLOA system with other existing models

5. Conclusion

In this paper, we focus on the design and implementation of the PPV2XT-HDLOA model for Smart Transportation in Dubai. The presented PPV2XT-HDLOA model enhances V2X transportation by leveraging advanced data-driven techniques to optimize vehicle communication. The PPV2XT-HDLOA model gives Dubai a chance to improve its smart transportation system using AI, deep learning, and optimization. Based on its progressive vision, this model would improve vehicle coordination, security, and efficiency to help the city lead smart mobility. Dubai can lead the world in autonomous and connected transport by mimicking established economies and embracing V2X-driven AI technology, making the future safer and more efficient. To accomplish that, the PPV2XT-HDLOA model applies the z-score normalization approach for data normalization to ensure data uniformity and enhance model convergence. To reduce dimensionality, the RSA can be employed to recognize the most relevant features. For the classification process, the hybrid DL model combining the BiTCN-BiGRU technique is exploited. Finally, the parameter tuning of the BiTCN-BiGRU has been carried out using the MGO algorithm to achieve optimal fine-tuning of parameters, ensuring superior classification performance. To demonstrate the better solution of the PPV2XT-HDLOA technique, a huge range of simulations has been tested, and the outcomes are inspected under several measures. The comparison investigation reported the improvement of the PPV2XT-HDLOA technique under various metrics.
The research in the future will be targeted at extrapolating the PPV2XT-HDLOA framework into the field of real-world deployment and integration with the next-generation communication technologies. Specifically, the model can be implemented in 6G-enabling V2X settings where ultra-low-latency and high-bandwidth features will be used to improve the responsiveness and reliability of autonomous networks. The future research will address edge and federated learning systems to enhance scalability and preserve data privacy among distributed vehicular systems. Moreover, by incorporating blockchain-based trustworthiness, the data integrity and authentication between the vehicles and infrastructure nodes can be enhanced. Regulatory and ethical aspects will also be highlighted, making sure that sensitive vehicular and user data will be handled responsibly. Lastly, testing the framework in different smart city ecosystems, such as comparing Dubai with other urban centers in the world, should be used in future research to confirm the flexibility and role of the framework in achieving the smart, safe, and sustainable transportation goal of Dubai in the vision 2050.

Declarations:

Data Availability Statement

The dataset analyzed in this study, CIC-ToN-IoT, is publicly available at https://www.kaggle.com/datasets/dhoogla/cictoniot.

Competing Interests and Funding

The authors did not receive support from any organization for the submitted work.

Human Participants and/or Animals

Not applicable

Conflict of Interest

The authors have expressed no conflict of interest.

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