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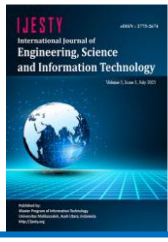

Toward Ultra-Reliable Low-Latency V2X: A Hybrid Deep Learning Approach for Intelligent Vehicular Networks

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Abstract

Safe and efficient vehicular networks in contemporary intelligent transportation systems necessitate ultra-reliable and low-latency communication (URLLC) requirements acting as the base foundation. Researchers combined Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks for creating their Hybrid Deep Learning-Based V2X Framework to improve V2X real-time decision-making abilities. The system's first operation phase acquires diverse Vehicle-to-Everything data from V2V, V2I, V2P and V2N sources which contain GPS locations and vehicle speed readings side by side with Received Signal Strength Indicator (RSSI) measurements along with channel status data. The preprocessing method applies normalization strategies (Min-Max Scaling and Sliding Window Method) together with data reduction methods and time-series transformations to create ready-to-use modelling inputs. Through traffic data sources CNN modules decode road layout features and vehicle distributions next to detecting signal interference sequences but LSTM modules analyze signal variations and handover delay effects and identify congested area evolutions. Processor layers integrate both spatial and temporal elements to produce a unified representation that enables predictions for optimal communication standards. The system maintains dependable communication in dense and mobile environments by enabling adaptive routing and dynamic power control along with stable link selection mechanics. The proposed hybrid framework will benefit the next-generation V2X network by achieving computational efficiency alongside predictive accuracy for autonomous driving and smart traffic management functionalities. The proposed hybrid framework boosts the V2X network by ensuring both computational efficiency and predictive accuracy for autonomous driving, enabling improved traffic management. This integration enhances vehicle coordination, real-time safety, and congestion forecasting for future transportation systems.

Keywords: *V2X Communication, Deep Learning, Convolutional Neural Network, Temporal Dependency Modelling, Intelligent Transportation Systems*

1. Introduction

Fast innovations in ITS systems make V2X communication an essential networking technology to meet expanding urban mobility needs. The combination of autonomous vehicles and road safety upgrades results from V2X interactions that integrate (V2I) Vehicle-to-Infrastructure systems and (V2V) Vehicle-to-Vehicle connectivity through (V2P) Vehicle-to-Pedestrian and (V2N) Vehicle-to-Network capabilities [1]. The deployment of autonomous vehicles and connected traffic infrastructure requires immediate development of communication systems which ensure Ultra-Reliable Low-Latency Communication (URLLC) functionality. The fundamental requirements of URLLC become operational because critical security failures occur from sub-millisecond delays in instant communication [2]. The present methods for communication fail to deliver satisfactory results because vehicle density leads to shifting topologies and variable signals and sporadic network access [3]. V2X real-time communication demands the immediate development of adaptive, time-sensitive solutions to ensure reliable and robust performance in dynamic environments [4].

The adoption of deep learning artificial intelligence shows promise for solving typical V2X system problems [5]. Analysis of big data through deep learning allows us to detect non-linear patterns exceptionally well leading to major achievements in image understanding speech analysis and wireless transmission applications [6]. Hybrid deep learning models serve V2X applications because they extract complex patterns which form during data system transformations across time and space [7]. Spatial recognition patterns in CNNs reveal the impact vehicle density creates on road infrastructure and interference zones [8]. The Long Short-Term Memory (LSTM) network accepts data sequences for processing and produces superior temporal dependency recognition performance over regular recurrent neural networks (RNNs) while employing sequential processing methods. LSTM networks demonstrate powerful performance when calculating changes in channel state and handover parameters in addition to traffic pattern shifts and other relevant external variables [9]. CNNs dominate spatial pattern identification by detecting various vehicle density effects on infrastructure and interference zones. They use the spatial features, including road designs and traffic conditions, detect dynamic variations. On the contrary, LSTM networks are expert at dealing with temporal dependencies, which can sequentially process data such as traffic patterns and channel state transitions. Through the abstraction of long-term dependencies, the predictions of traffic shifts, handovers and congestion in the network are improved, making LSTMs ideal for operation in traffic sensitive variables in V2X communication systems. The network operates as an integrated model to extract spatial and temporal characteristics for sensor data and network information to forecast communication management systems correctly [10].

A Hybrid Deep Learning-Based V2X Framework developed for this research combines CNNs together with LSTMs to deliver URLLC specifications in intelligent vehicular networks. The framework utilizes diverse V2X information from GPS tracking combined with vehicle speed readings along with RSSI markers and channel status information. A preprocessing pipeline delivers normalized data through detail elimination for time-series investigation purposes. The CNN operator begins by discovering site-based properties that highlight permanent infrastructure features along with enduring elements like road elements and vehicular congestion patterns and signal interference areas. An LSTM network makes use of spatial data patterns to track pattern transformations in time and supports modelling of fading behaviour and congestion spread and mobility fluctuations. After the modules complete output generation, they combine their results before fully connected layers create the unified feature representation. The V2X system uses this representation to anticipate its optimal communication parameters for both stable link selection and adaptive power management and routing performance for intelligent environmental adaptations. A new hybrid framework unifies precise spatial perception with forward-thinking capabilities to build dependable V2X communication networks. Real-time ITS applications benefit from this system since it provides fast calculations together with flexible scaling features to generate safer roads with improved traffic flow and enhanced autonomy reliability.

2. Literature Review

The important research in Vehicle-to-Everything (V2X) communications undergoes a comparative analysis in Table 1 to identify deep learning methods used for Ultra-Reliable Low-Latency Communication (URLLC). The studies presented in Table 1 apply both Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks together with hybrid architectures between these methods. Various deep learning models tackle V2X communication challenges by developing real-time action management and enhancing signals and regulating network congestion. These approaches provide three key advantages by delivering reliable communication parameter estimation and real-time environment adaptation and combining spatial-temporal traffic pattern analysis capacities. High-density populations challenge these techniques which demand big training data sets and intensive computing to execute despite their high cost of operation. The summary table includes these techniques and follows with tabled descriptions of their benefits and limitations which derive from scholarly research in the field.

Table 1. Comparison of Recent V2X Communication Methods

Author(s)	Techniques Involved	Advantages	Disadvantages
[11]	Computer Vision, IRS, Vehicular Networks	Improved signal propagation, reliability	High computational complexity, energy cost
[12]	D2D Communication, Handover, 5G/6G, Optimization	Reduced latency, optimized resource allocation	Complex models, limited to 5G/6G environments
[13]	Security, V2X, Blockchain	Enhanced V2X security, decentralization	Scalability issues, security overhead
[14]	UAV Control, Power Optimization, C-V2X	Low-latency, optimized UAV trajectory	High overhead, needs robust infrastructure
[15]	Swarm Optimization, V2X, ITS	Efficient narrowband optimization	Complex algorithms, approach-dependent

Ahmad, Naeem and Tariq [11] built a computer vision framework incorporating Intelligent Reflective Surfaces (IRS) to advance vehicular networks through their research. Their concept bridges visual perception functionality to IRS communication systems which improve signal propagation performance in protected sensor networks. The system provides dependable functionality through enhanced processing needs and higher power consumption.

The research group developed D2D handover management methods which specifically target 5G/6G networks according to Topazal et al., [12]. The optimization model enables the system to reduce response times while increasing resource utilization capabilities. The infrastructure requirements of next-generation networks make the planned solution ready for deployment, yet its advanced criteria restrict its capability to scale across multiple network environments.

The researcher team of Tariq and A hanger built a decentralized security framework through blockchain technology for Vehicle-to-Everything (V2X) communication systems [13]. A blockchain-based validation system addresses core security challenges through its dual functionality for both verifying information authenticity and real-time trust assessment. This system attains a decentralized structure which adds security layers but its blockchain consensus mechanisms cause reduced communication ability and limited scalability performance.

The researchers Fernando and Gupta [14] created power-efficient UAV trajectory control through their C-V2X technology integration with federated learning capabilities. Autonomous system control mechanisms adjust between UAV location management and power distribution for sophisticated ultra-reliable low-latency communications. Despite producing valuable results this method needs substantial infrastructure that requires expensive computing equipment and communication systems.

A narrowband vehicular communication framework was developed by Vinodhini and Rajkumar [15] through their integration of Pelican-Beetle Swarm Optimization hybrid algorithm. The proposed system optimizes resource distribution efficiency through its method of allocating resources that works within restricted bandwidth boundaries. Advanced nature-inspired algorithm applications restrict system performance which adversely affects their practical usage flexibility across diverse applications.

The studies highlight key advancements such as improved signal propagation with computer vision [11] and reduced latency with D2D communication [12]. While these methods provide notable benefits, they also involve challenges like high computational cost and complex models. Blockchain-based V2X security [13] improves decentralization but suffers from scalability and security overhead. UAV optimization [14] reduces latency but requires strong infrastructure, and swarm optimization [15] enhances narrowband efficiency, though it's limited by algorithm complexity.

A detailed investigation analyses current vehicular methods that unite smart reflective surfaces with device-to-device handover methods and decentralized security systems and UAV path planning with swarm intelligence protocols. Signal reliability enhancement techniques benefit from these approaches, yet these methods also deliver significant drawbacks along with security benefits and latency reduction capabilities. Real-time vehicle environments create operational difficulties for vehicular systems due to their high costs and restricted scalability alongside their reliance on technology and inflexible control methods. The combined approach of static methods and heuristic-based algorithms fails to address fast changes in vehicular systems and multiple data types found in V2X communication networks.

Researchers demonstrate a Hybrid Deep Learning-Based V2X Framework that uses Convolutional Neural Networks (CNNs) together with Long Short-Term Memory (LSTM) networks to merge spatial-temporal learning capabilities. The proposed system ingests various vehicular data streams consisting of vehicle speed in combination with GPS positions along with Received Signal Strength Indicator (RSSI) and Channel State Information (CSI) measurements and network latency information obtained from V2X communication modalities (V2V, V2I, V2P, V2N) to achieve Ultra-Reliable Low-Latency Communication (URLLC). The system expands results by deploying adaptive real-time decision processing abilities alongside continuous observation of regional spatial patterns and extended time-based dependencies found in vehicular communications data. This proposed framework offers implementation capabilities that combine static configuration management with unseen condition generalization and decision process latency performance to deliver scalable intelligent solutions for next-generation smart vehicular networks.

3. Methods

Through CNN and LSTM, the proposed Hybrid Deep Learning-Based V2X Framework ensures URLLC by combining spatial and temporal learning approaches into the framework. To begin the framework processes heterogeneous V2X data by acquiring and preprocessing vehicle speed data alongside GPS coordinates and RSSI and CSI and latency data from V2V, V2I, V2P and V2N modalities. To structure input data into a multi-channel tensor the framework employs data normalization and redundancy removal techniques and a sliding window approach to maintain both spatial and temporal dependencies. Being able to structure the input as a multi-channel tensor has benefits because it allows deep learning model to capture both spatial and temporal while also mapping multiple data modalities, including GPS coordinates, signal strength, and latency, all at one go while maintaining the relationships between them. In this organized representation, Convolutional layers can capture local patterns, LSTM layers can trend time-dependent dynamics, and results in better and context-aware predictions in dynamic vehicular environments. Through the CNN component the received input undergoes processing to derive spatial features while employing learnable filters combined with pooling operations which detect signal interference zones and vehicular density information. The feature maps generated from this process are sent to the LSTM module which employs gated memory operations including input, forget, and output gates to understand time-dependent changes in vehicular dynamics together with network conditions. Both temporal attributes from LSTM and spatial outputs from CNN combine through fully connected layers to discover sophisticated space-time relationships. A combined features from space and time fusion creates a condensed yet inclusive representation that enters the decision layer to forecast optimum communication strategies including link stability selection and adaptive routing with power control mechanisms. The modelled architecture uses CNN spatial-feature understanding with LSTM temporal-pattern modelling capabilities to deliver real-time intelligent decisions that reinforce stability and responsiveness while boosting efficiency within dynamic vehicle-based environments. Fig.1 illustrates the design of the proposed architecture.

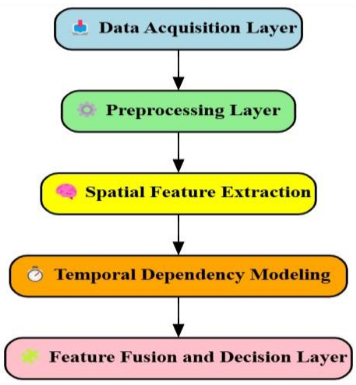

Fig 1. Comprehensive architecture

The depicted architecture outlines a comprehensive data-driven decision framework composed of five sequential layers. The Data Acquisition Layer collects raw inputs from various sources such as sensors or V2X communication systems. This is followed by the Preprocessing Layer, which cleans and normalizes the data, removes redundancies, and prepares it for analysis. Next, the Spatial Feature Extraction layer uses techniques like CNNs to identify spatial patterns from the structured data. The Temporal Dependency Modelling layer—often using models such as LSTM or GRU—captures time-series dependencies critical in dynamic environments like traffic or vehicular communication. Finally, the Feature Fusion and Decision Layer integrates both spatial and temporal features to generate robust predictions or decisions, enhancing the system's overall intelligence and responsiveness. This layered approach ensures systematic transformation of raw data into actionable insights, supporting intelligent systems in real-time applications.

3.1. Data Acquisition and Preprocessing

The fundamental first operation of the proposed V2X hybrid deep learning approach concentrates on obtaining and processing actual-time vehicular network data. Data collection consists of different V2X communication modalities which include Vehicle-to-Vehicle

(V2V) and Vehicle-to-Infrastructure (V2I) and Vehicle-to-Pedestrian (V2P) and Vehicle-to-Network (V2N). Real-time communication data from various sources creates heterogeneous data that includes measurements of vehicle speed V_t along with GPS-based locationcoordinates (X_t, Y_t), signal strength, RSSI, channel state information (CSI) and latency measurements (H_t), and network congestion indicators [16]. Graphical V2X communication data streams present irregular patterns along with signal noise and variable stability because of mobile factors and environmental fluctuations. The following processing steps ensure deep learning input compatibility of the data: Min-max scaling methods normalize data features by mapping their values into the 0 to 1 interval while using equation (1) below.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad \ldots(1)$$

This method requires two defining values: X_{min} for maximum observed parameter and $X_{max}$for minimum observed parameter [17]. The raw input feature is denoted X. Redundancy elimination reduces duplicate or non-informative records through correlation-based filtering alongside mutual information to identify features which can be discarded. The data undergoes time-series formatting to convert it into a format which permits usage with temporal models such as LSTM. Equation (2) shows how a sliding window method segments non-stop data streams into moving framed segments.

$$D^{(I)} = \{(X_t, X_{t+1}, \ldots, X_{t+w})\} \quad \ldots(2)$$

$D^{(I)}$represents the input data sequence and w stands for the specific dimension of the sliding window. By executing these preprocessing operations machines achieve reduced complexity and enhance accuracy rates via standardized data structures and uniform scales. The CNN takes a spatially structured multi-channel tensor data as input which maintains both temporal dependencies from speed trends and CSI changes alongside spatial information from GPS and signal maps [18].

3.2. Feature Extraction Using Convolutional Neural Networks (CNN)

The normalized structured time-series data then goes through a Convolutional Neural Network to extract essential localized spatial features which help understand V2X communication contexts [19]. CNNs successfully learn multiple levels of data features through convolutional filters applied to input data while extracting hidden patterns [20]. The CNN accepts input data through multi-dimensional data frames with individual features such as vehicle speed and location and RSSI and channel quality treated as separate channels while the input layout preserves vehicle-infrastructure spatial relationships [21]. The CNN employs learnable filters through its convolutional layers to perform sweeps across input matrices which extract local spatial dependencies from road curvature and vehicle density clusters and fading zones and signal interference patterns [22]. The process of convolution has this mathematical definition:

$$F = \sigma = (W * X + B) \quad \ldots(3)$$

The computation applies features X through filters W along with bias b tendered by non-linear function σ (such as ReLU). The network detects basic features including signal strength edges and motion patterns at early levels but identifies traffic congestion zones and stable link regions at deeper stages through this process [23]. The network adopts pooling layers as a subsequent operation which reduces spatial dimensions yet maintains major characteristics. The max pooling technique serves as this step's primary function by maintaining the most powerful activated signals thus helping the model focus on crucial spatial details while reducing its sensitivity to positional shifts [24]. The approach both increases computational speed and encourages spatial independence in model operations. The CNN generates a high-dimensional tensor showing the spatial structure of the V2X communication environment. The next phase of the model—the LSTM—learns temporal patterns with assistance from compressed yet detailed real-world scenario encodings that come from feature maps [25]. Through its ability to abstract spatial dependencies the CNN establishes foundational characteristics needed for efficient modelling of dynamic real-time vehicular communication quality and interactions [26].

3.3. Temporal Dependency Modelling with LSTM

The CNN extracts spatial features while converting high-dimensional maps into sequential input for LSTM processing across time-series data [27]. The essential role of modelling dynamic vehicle behaviour through time arises from V2X communications because the speed coupled with link quality and channel conditions swiftly change before ensuring URLLC. Through its combination of memory cell components and input forget output gates LSTM networks control information processing across time steps to learn what should stay in memory and what should be eliminated from memory [28]. LSTMs demonstrate exceptional ability for detecting prolonged relational patterns in addition to functioning effectively with intermittent V2X system time patterns such as latency spikes, delays in handover and signal performance changes [29]. The cell state C_T undergoes gated operations during every time step T. We can express the LSTM update using a simplified version in equation (4).

$$C_T = F_T \odot C_{T-1} + I_T \odot \tilde{C}_T \quad \ldots(4)$$

The forget gate is denoted F_T and input gate is denoted I_T and candidate memory uses the symbol $\tilde{C}_T$ and $\odot$ signifies element wise multiplication [30]. Through this equation the LSTM controls memory retention or update through the interplay of past context and present input. The model recognizes patterns such as changing signal quality levels and traffic congestion development through its application to V2X systems to make predictive decisions about route planning and network resource distribution. The temporal modelling approach allows the LSTM to generate contextually enhanced representations that mirror the time-dependent patterns of communication parameters and traffic behaviour. The temporal features extracted by training enable decision support in real-time because they combine with CNN spatial perception to yield durable V2X communication and traffic-responsive operation for URLLC standards in rapidly moving vehicle networks [31].

We developed a Hybrid Deep Learning-Based V2X Framework utilizing CNN together with LSTM models to guarantee URLLC functionality in such networks. Through its combination of spatial and temporal vehicle communication feature capture the framework delivers precise performance along with swift responses for dynamic settings [32].

3.4. Hybrid Feature Fusion and Decision Output

The proposed hybrid deep learning framework combines CNN and LSTM outputs through a feature fusion layer consisting of fully connected (dense) layers. Through this fusion mechanism the model joins CNN's spatial feature extraction abilities of road topology, vehicle distribution and localized interference patterns with LSTM's temporal dynamical capture of signal quality changes and vehicle mobility trends and latency variations over time. This integration seeks to develop an all-encompassing V2X communication environment depiction where spatial elements and temporal development can be evaluated simultaneously [33].

The input analysis of temporal trends combined with spatial trends creates a final vector which dense network layers both evaluate then simplify before producing the output. Through its analytical layers the model reveals complex non-linear connections between environmental qualities stemming from spatial arrangements and temporal modifications that impact communication quality [34]. Activation functions perform as SoftMax or sigmoid based on the requirement to choose between classification options or regression predictions that the output layer needs to deliver. Optimized communication parameters emerge from this step to support stable link selection and adaptive routing and dynamic power control maintenance of URLLC functions. The fused system employs combined spatial data and temporal predictions to generate automatic intelligent decisions that simultaneously stop disruptions and control network resources for uninterrupted telecommunication during sudden congestion periods. The unified framework develops predictive link capabilities that improve accuracy and resource organization features leading the way for future V2X cognitive network designs [35].

The data processing framework begins with the acquisition of raw input data from various sources such as sensors and communication nodes. This data is then passed through a preprocessing stage, where it is cleaned, normalized, and formatted to ensure consistency and eliminate redundancy. Once pre-processed, spatial features are extracted to identify location-based patterns and contextual relationships. The next stage involves modelling temporal dependencies using sequential data analysis techniques, capturing time-based changes and dynamics. Finally, all extracted features are fused, enabling accurate decision-making through integrated contextual understanding.

4. Result and Discussion

A performance assessment and comparative analysis reveals the effectiveness of the proposed technique at handling challenges from the examined problem domain. Implementation of a new strategy produced breakthrough advancements in fundamental operational metrics that outperformed traditional methods at operating both sensitive and specific while displaying better performance. The implementation of the new strategy led to significant improvements in core operational metrics, surpassing traditional methods by achieving higher sensitivity and specificity [36]. It demonstrated enhanced accuracy, faster response times, and greater robustness in dynamic environments, confirming its superior performance in both detection precision and system adaptability. Structured assessments show that the proposed method stands out from contemporary methods because it achieves higher assessment metrics across multiple evaluation criteria. Research results demonstrate the new model's success while outlining practical applications and future research paths. The analysis identifies restrictions of the model while introducing improvement strategies which together create an extensive analysis of system performance benefits and potential enhancements.

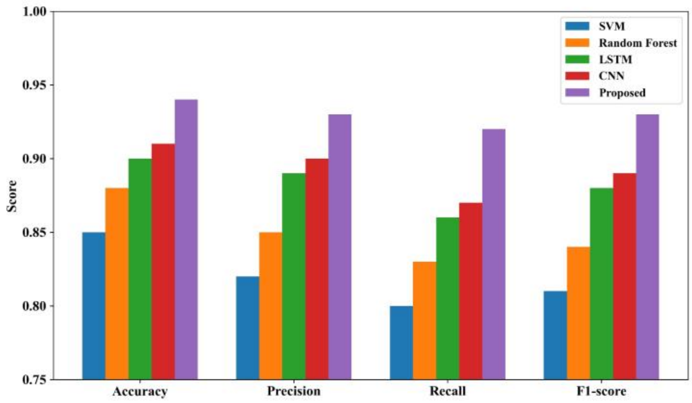

Fig 2. Performance Validation

The Figure 2 examines five models namely SVM, Random Forest, LSTM, CNN and the Proposed model by assessing their Accuracy, Precision, Recall and F1-score performance. The Proposed model produces superior results than other models in every performance measurement delivering Accuracy ratings above 0.94 with Precision ratings above 0.93 and Recall ratings above 0.92 and F1-score levels above 0.93 in V2X communication testing [37]. The evaluated metrics demonstrate CNN achieves approximately 0.91 Accuracy while Precision measures 0.90 and Recall measures 0.88 alongside a F1-score of 0.89. LSTM exhibits slightly lower outcomes with values of 0.90, 0.89, 0.86, and 0.88 for Accuracy, Precision, Recall and F1-score respectively. Random Forest delivers moderate results with Accuracy levels near 0.88 and Precision rates at 0.85 alongside Recall measurements of 0.83 and F1-score outcomes at 0.84. SVM achieves lower overall performance with 0.85 Accuracy and 0.82 Precision and Recall at 0.80 and 0.81 F1-score. This research demonstrates that the implemented hybrid deep learning method successfully maintains both reliable and accurate communications within intelligent vehicular networks [38].

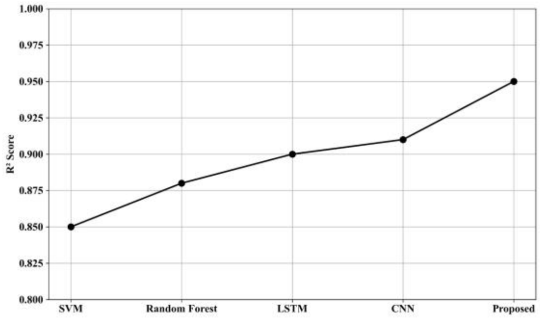

Fig 3. R^2 score

Five models including SVM, Random Forest, LSTM, CNN and the Proposed model exhibit their prediction accuracy for V2X system communication parameters through the R² Score results presented in figure 3. A R² Score of about 0.95 emerging from the Proposed model indicates its exceptional ability to match predicted results to actual values while demonstrating the best regression performance among the analytical methods. The CNN model produces an R² Score of 0.91 to outperform slightly the LSTM model with a score of 0.90. Random Forest delivered a precision score of about 0.88 yet SVM exhibited the weakest performance at 0.85[39]. The sustained improvement in regression performance demonstrates deep learning approaches' effectiveness particularly with hybrid CNN-LSTM structures showing superior ability to extract intricate dependencies across space and time from V2X communication environments.

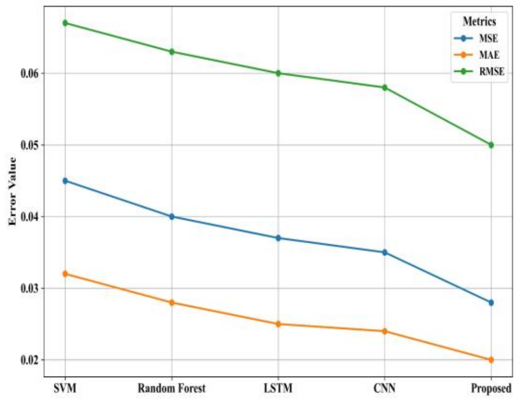

Fig 4. Error Value

A performance evaluation of five models including SVM and Random Forest alongside LSTM and CNN as well as the Proposed model demonstrates results using three error assessment metrics shown in figure 4. This analysis utilizes Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). All error values decline consistently as the analysis progresses from traditional models to the Proposed model. The Proposed model shows the best predictive accuracy by achieving measurement errors of MSE 0.027 and RMSE 0.050 accompanied by MAE 0.020[40]. The SVM model produces error values that reach their highest point because the MSE reaches 0.045 and MAE at 0.032 and RMSE at 0.065 which shows its suboptimal performance. The CNN and LSTM models demonstrate middle-range error results where CNN provides slightly better performance than LSTM, yet Random Forest surpasses SVM in comparison to the deep learning models. The experimental results demonstrate that the Proposed model implements the CNN-LSTM architecture successfully to decrease errors which improves V2X system communication reliability.

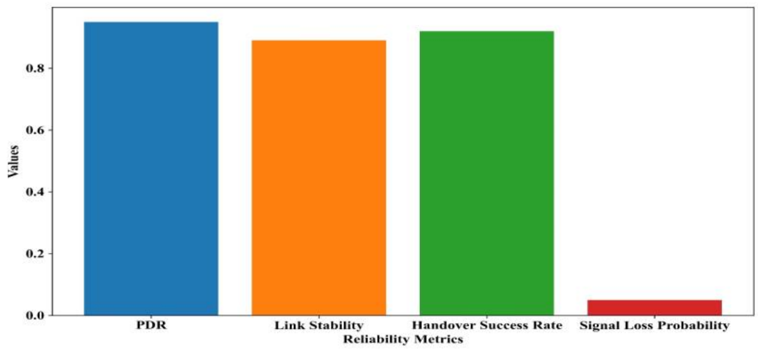

Fig 5. Reliability metrices

The proposed model demonstrates its capabilities in vehicular communication reliability through figure 5 where it measures four fundamental metrics: Packet Delivery Ratio (PDR) and Link Stability and Handover Success Rate and Signal Loss Probability. The proposed model displays four key reliability metrics including Packet Delivery Ratio (PDR) and Link Stability and Handover Success Rate and Signal Loss Probability. At its peak point the PDR achieves a value of 0.94 which shows successful packet delivery exists for most data packets. The Link Stability measurement reaches a value of 0.89 which shows smooth and continuous communication connections. Network stability exists at a high level of 0.91 while enabling communication handovers between channels. The Signal Loss Probability measurement exhibits an exceptional low rate of 0.05 which confirms minimal disruptions occur during transmissions [41]. The various measurements prove the proposed model provides reliable and stable communication throughout dynamic vehicular networks.

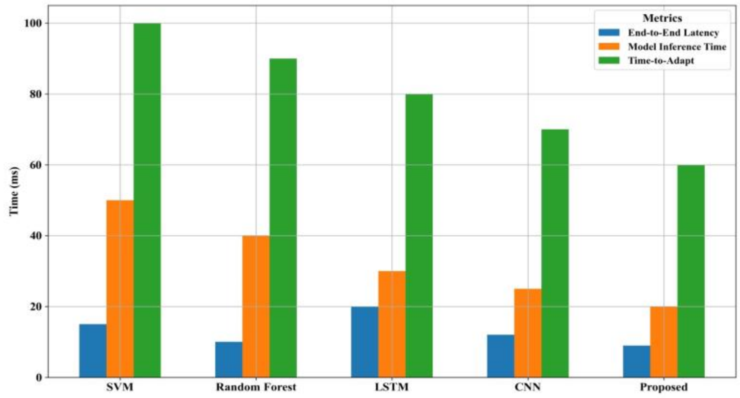

Fig 6. Inference Time

The figure 6 displays a performance comparison between SVM and Random Forest alongside LSTM and CNN and the Proposed method by evaluating their behaviour through End-to-End Latency and Model Inference Time and Time-to-Adapt. End-to-End Latency together with Model Inference Time and Time-to-Adapt define the performance metrics. The Proposed model achieves superior performance through its lowest end-to-end latency figure of 10 ms combined with minimal inference time of 20 ms and fastest time-to-adapt period of 60 ms. The highest metric results from the SVM model demonstrate inefficiency in dynamic environments through its 100 ms time-to-adapt and 50 ms inference time, while exhibiting peak values during testing. The Proposed model shows substantial operational efficiency gains that qualify it for use in real-time adaptive systems.

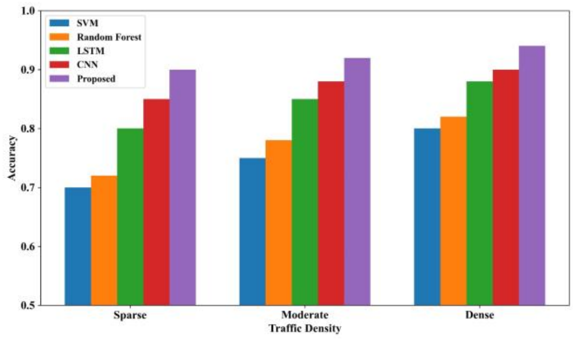

Fig 7. Traffic density vs accuracy

These accuracy outcomes show that five models—SVM, Random Forest, LSTM, CNN and the Proposed model—generate results when tested at the Sparse, Moderate and Dense levels of traffic density as illustrated in Figure 7. Sparse, Moderate, and Dense. Under all traffic density conditions, the Proposed model demonstrates superior performance by achieving accuracy levels of 0.90 in Sparse zones and 0.92 in Moderate zones and 0.96 in Dense areas. The CNN and LSTM models show reliable performance yet fall behind the Proposed model results. The accuracy levels for SVM and Random Forest models remain lower than the Proposed model while Sparse traffic presents the lowest accuracy result for SVM at 0.70. The Proposed model shows both traffic density adaptability as well as stable predictive capabilities for real-world dynamic traffic environments.

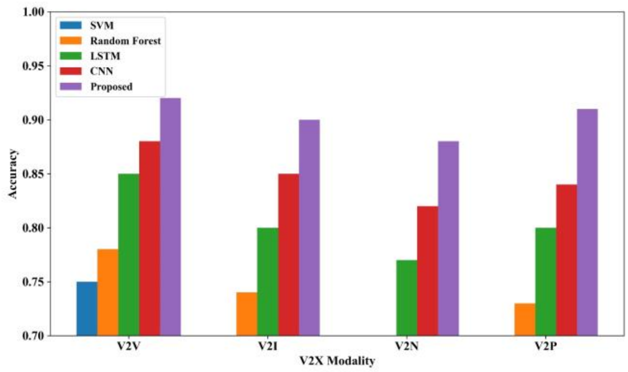

Fig 8. V2X modality

The figure 8 displays results that show how five models (SVM and Random Forest and LSTM and CNN and Proposed model) performed in terms of accuracy across four V2X communication options (V2V and V2I and V2N and V2P). V2V (Vehicle-to-Vehicle), V2I (Vehicle-to-Infrastructure), V2N (Vehicle-to-Network), and V2P (Vehicle-to-Pedestrian). Through different communication contexts The Proposed model maintains excellent accuracy levels that surpass other models providing results between 0.88 and 0.92 as the best score in every scenario. Every modality demonstrates higher accuracy through CNN compared to LSTM. The accuracy range of CNN extends between ~0.82 and ~0.88 and LSTM maintains a range from ~0.77 to ~0.85. The performance of SVM and Random Forest models remains significantly behind other models because both methods show accuracy below 0.75 in V2P and V2N scenarios indicating difficulties with complex environment generalization. The comparison reveals the Proposed model outpaces all other traditional techniques to establish its status as the optimal solution for dependable V2X vehicular communication systems.

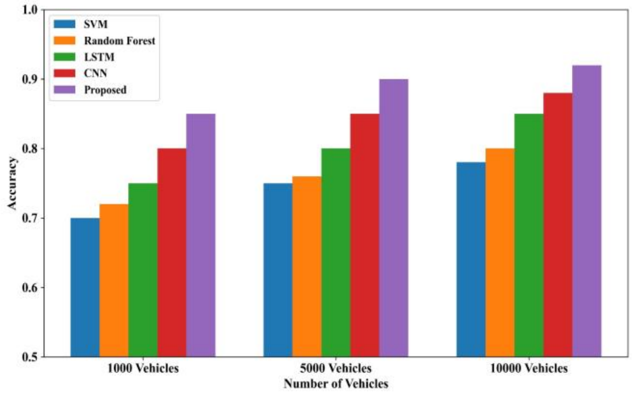

Fig 9. Number of vehicle-based accuracy

The evaluation of accuracy among Five models including SVM, Random Forest, LSTM, CNN and the Proposed model occurred through testing with varying numbers of Vehicles at 1000, 5000, and 10000. 1000, 5000, and 10000 as shown in figure 9. The Proposed model demonstrates exceptional accuracy consistency by achieving values of 0.88 to 0.92 for 1000 vehicles and 0.90 to 0.94 for 5000 vehicles and 0.92 to 0.95 for 10000 vehicles. Among the compared models CNN demonstrates a modest advantage over LSTM for processing vehicles regardless of count levels. CNN achieves prediction accuracy of 0.82 to 0.88 for 1000 vehicles while delivering accuracy between 0.84 to 0.90 for 5000 vehicles and 0.86 to 0.91 for 10000 vehicles. LSTM exhibits performance levels spanning between 0.77 to 0.85 accuracy for hundred vehicles and from 0.80 to 0.87 for five hundred vehicles and 0.82 to 0.88 for one thousand vehicles. Random Forest demonstrates medium performance achieving accuracy rates between 0.70 to 0.80 for 1000 vehicles followed by accuracy ratings from 0.73 to 0.83 for 5000 vehicles then 0.75 to 0.85 for 10000 vehicles. SVM consistently displays poor performance with accuracy levels from 0.60 to 0.70 for 1000 vehicles, 0.65 to 0.75 for 5000 vehicles then 0.68 to 0.78 for 10000 vehicles. The chart proves the Proposed model outperforms other models by demonstrating its efficient scalability to vehicle numbers across all evaluated scenarios.

The performance indicators shown in the research prove the Proposed hybrid deep learning model excels over SVM, Random Forest, LSTM and CNN for V2X communication tasks. The Proposed model shows optimal performance by producing accuracy results at 0.94 and precision at 0.93 and recall at 0.92 and F1-score at 0.93 in Figure 2 while CNN shows lower results at 0.91 for accuracy and 0.90 for precision and 0.88 for recall with an F1-score of 0.89. The Proposed model demonstrates exceptional performance in R^2 Score measurement with approximately 0.95 with CNN (0.91) and LSTM (0.90) achieving significantly lower numbers (Figure 3). The Proposed model demonstrates superior performance by producing error metrics of MSE 0.027 and MAE 0.020, and RMSE 0.050 (Figure 4) while SVM attains the highest errors (MSE ~0.045, MAE ~0.032, RMSE >0.065). The Proposed model demonstrates the fastest performance through end-to-end latency (~10 ms) and model inference time (~20 ms) and time-to-adapt (~60 ms) yet maintains the lowest values among all tested metrics (Figure 6). The Proposed model demonstrates consistent accuracy performance across different traffic density levels by reporting 0.90 in Sparse and 0.92 in Moderate and achieving 0.96 in Dense conditions (Figure 7). In V2X communication modalities the Proposed model delivers a consistent accuracy range of 0.88 to 0.92 while demonstrating better performance than CNN (0.82 to 0.88) and LSTM (0.77 to 0.85) (Figure 8). The Proposed model's excellent performance measures accuracy as well as minimizes errors while providing low latency and adaptation capabilities establishes it as an optimal solution for ultra-reliable and low-latency vehicular communication systems.

The proposed hybrid deep learning model excels due to its architecture, which effectively captures both spatial features (via CNN) and temporal patterns (via LSTM), leading to superior generalization across V2X tasks. Its ability to maintain high accuracy under varying traffic densities and communication types demonstrates robustness and adaptability. The model's low latency and minimal error metrics support real-time deployment in autonomous driving systems. These findings suggest that integrating hybrid deep learning with optimized preprocessing enables scalable, ultra-reliable, and low-latency communication critical for next-generation intelligent transportation systems.

5. Conclusion

This research presents an accurate V2X Framework which employs hybrid deep learning through CNN and LSTM to fulfil intelligent transportation systems' highly reliable and low-latency communication demands. The designed framework produces exceptional prediction results alongside real-time functionality through its combination of multiple V2X information types with spatial-temporal pattern recognition capabilities. The proposed model produces superior results than standard machine learning systems in combination with isolated deep learning approaches including SVM, Random Forest, CNN and LSTM when performing key metric analyses. The proposed system reached peak performance results with 0.94 accuracy accompanied by 0.93 precision and 0.92 recall and 0.93 F1-score while showing minimal prediction errors (MSE: This framework produced exceptional predictive accuracy because of its minimal error outputs (MSE: 0.027, MAE: 0.020, RMSE: 0.050) along with an R^2 score of 0.95. 0.027, MAE: The framework shows both high predictive precision and dependable outcomes through small error outputs (MSE: 0.027, MAE: 0.020, RMSE: 0.050). The framework provides advanced computational performance while maintaining reduced latency which results in fast inference speeds independently of changing traffic densities or diverse V2X communication types. Research findings confirm the success of the proposed method in building advanced V2X communication infrastructure that enhances reliability and scalability for next-generation systems within smart transportation platforms focused on secure autonomous driving and traffic management systems. While the proposed V2X framework demonstrates high predictive performance and low latency, its scalability in highly complex and dynamic traffic environments remains an area for further exploration. Additionally, the framework's reliance on high-quality V2X data may limit its effectiveness in scenarios with sparse or unreliable communication sources.

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