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Hybrid deep learning-based congestion prediction for intelligent traffic management in 5G/6G networks

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ABSTRACT

Future-generation communication networks, including millimeter-wave local area networks, broadband wireless access systems, and emerging fifth- and sixth-generation (5G/6G) networks, require intelligent traffic management to satisfy stringent quality of service (QoS) requirements, including ultra-low latency, high reliability, and massive device connectivity. As network traffic becomes increasingly dynamic and heterogeneous, accurate congestion prediction is essential for preventing resource overloading, maintaining network slicing performance, and ensuring efficient resource utilization. This paper proposes a hybrid deep learning (DL)-based congestion prediction model that combines long short-term memory (LSTM) and support vector machine (SVM) techniques to capture temporal traffic characteristics while improving prediction accuracy. The proposed framework was evaluated through a one-week simulation involving heterogeneous devices operating under varying network conditions to assess its robustness and generalization capability. Experimental results demonstrate that the proposed model achieved an overall prediction accuracy of 93.23%, while also exhibiting strong performance in terms of specificity, recall, F-score, and computational efficiency. By accurately predicting network congestion before service degradation occurs, the proposed framework enables proactive traffic management and adaptive resource allocation. These findings demonstrate that the hybrid LSTM–SVM model provides an effective, reliable, and scalable solution for intelligent congestion prediction in next-generation 5G/6G communication networks.

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1. INTRODUCTION

Future-generation communication networks, particularly fifth and sixth generation (5G/6G) systems, are transforming the landscape of wireless communications by providing ultra-high data rates, ultra-low latency, massive machine-type communications (mMTC), and ubiquitous connectivity. These capabilities enable a wide range of emerging applications, including the internet of things (IoT), autonomous vehicles, smart cities, industrial automation, immersive virtual and augmented reality, and intelligent healthcare. As communication infrastructures continue to evolve, they must accommodate an unprecedented number of heterogeneous devices while maintaining stringent quality of service (QoS) requirements. Consequently, intelligent traffic management has become a fundamental requirement for ensuring reliable, scalable, and sustainable operation of next-generation wireless communication networks [1]–[4].

One of the most significant challenges in 5G/6G networks is network congestion, which occurs when communication demand exceeds the available network resources. Congestion leads to packet loss, increased transmission delay, reduced throughput, and degraded user experience, thereby limiting the performance of latency-sensitive and mission-critical applications. The introduction of network slicing further increases management complexity by allowing multiple virtualized network instances to coexist on the same physical infrastructure while supporting diverse service requirements such as enhanced Mobile Broadband (eMBB), ultra-reliable low-latency communications (URLLC), and mMTC. Under dynamic traffic conditions, overloaded network slices may experience severe performance degradation or service interruption, making accurate congestion prediction an essential prerequisite for proactive resource allocation and reliable QoS management [5]–[8].

To address these challenges, numerous congestion management techniques have been proposed over the past decades. Conventional approaches, including transmission control protocol (TCP)-based congestion control algorithms and active queue management (AQM) mechanisms such as random early detection (RED), primarily rely on predefined control rules and reactive feedback obtained from packet loss or queue occupancy. Although these methods have demonstrated satisfactory performance in traditional communication networks, they are insufficient for highly dynamic 5G/6G environments characterized by heterogeneous traffic patterns, network slicing, edge computing, and continuously changing service demands. More recently, artificial intelligence (AI), machine learning (ML), and deep learning (DL) techniques have been introduced to improve congestion detection, traffic prediction, and adaptive resource management. Supervised learning algorithms such as support vector machines (SVM), decision trees, random forests, and k-nearest neighbors have shown promising classification performance, while recurrent DL architectures, particularly long short-term memory (LSTM) networks, have demonstrated remarkable capability in modeling temporal traffic behavior and forecasting future network conditions [3], [9]–[14].

Despite these advances, several research challenges remain unresolved. Traditional congestion control mechanisms exhibit limited adaptability to rapidly changing traffic conditions, whereas many AI-driven approaches focus either on traffic prediction or congestion classification independently. DL models such as LSTM effectively capture long-term temporal dependencies within sequential traffic data but generally provide limited decision capability for rapid congestion categorization and resource allocation. Conversely, conventional ML classifiers such as SVM achieve robust classification performance but cannot effectively model the temporal traffic evolution required for proactive congestion prediction. Furthermore, relatively few existing studies have investigated hybrid learning architectures that simultaneously exploit temporal prediction and robust classification to support intelligent traffic management in network slicing environments. As communication networks continue to become increasingly decentralized, dynamic, and service-oriented, integrating complementary learning mechanisms into a unified congestion prediction framework represents an important research opportunity [4], [15]–[18].

Motivated by these challenges, this paper proposes a hybrid DL-based congestion prediction framework for intelligent traffic management in 5G/6G networks. The proposed framework integrates LSTM networks with SVM to exploit the complementary strengths of both learning paradigms. Specifically, the LSTM network models sequential traffic behavior and predicts future congestion trends from time-series network observations, while the SVM classifier utilizes the learned feature representations to accurately identify congestion states and support adaptive resource allocation decisions. By combining temporal prediction and robust classification within a unified architecture, the proposed model enables proactive traffic management capable of minimizing network congestion, preventing network slice overloading, and improving overall QoS under highly dynamic communication environments [17], [19].

The main contributions of this work are summarized as follows. First, a hybrid LSTM–SVM framework is developed to integrate congestion prediction and congestion state classification within a unified intelligent traffic management architecture for 5G/6G networks. Second, the proposed framework supports proactive resource allocation by accurately predicting congestion before severe service degradation occurs, thereby improving network slice reliability and communication efficiency. Third, comprehensive simulation experiments involving heterogeneous devices operating under varying traffic conditions are conducted to evaluate the robustness and generalization capability of the proposed framework using multiple performance metrics, including accuracy, precision, recall, specificity, F-score, and computational efficiency. Finally, the experimental results demonstrate that the proposed hybrid model provides an effective, reliable, and scalable solution for intelligent congestion prediction, offering practical insights for future AI-enabled traffic management and autonomous network optimization in next-generation wireless communication systems.

The remainder of this paper is organized as follows. Section 2 reviews recent advances in congestion management, AI, and hybrid learning techniques for 5G/6G communication networks. Section 3 presents the proposed hybrid LSTM–SVM framework, including the system architecture, data preprocessing, model development, and experimental methodology. Section 4 discusses the experimental results, comparative performance analysis, and practical deployment considerations. Finally, section 5 concludes the paper and outlines several promising directions for future research.

2. METHOD

This section presents the proposed hybrid DL framework for intelligent congestion prediction in next-generation 5G/6G communication networks. The methodology comprises six major stages, including the overall framework, hybrid LSTM–SVM architecture, data preparation and preprocessing, model training, congestion prediction workflow, and performance evaluation. The proposed framework is designed to predict future congestion conditions proactively, enabling intelligent traffic management and adaptive resource allocation before severe network performance degradation occurs.

2.1. Overall framework

The rapid growth of heterogeneous wireless devices and data-intensive applications has significantly increased the complexity of traffic management in next-generation communication networks [20]. Conventional congestion control mechanisms primarily react after congestion has occurred, resulting in delayed mitigation actions and degraded QoS. To overcome these limitations, this study proposes a hybrid DL framework that integrates temporal traffic prediction with intelligent congestion classification to support proactive traffic management in 5G/6G environments.

As illustrated in Figure 1, the proposed framework consists of five sequential modules: network traffic acquisition, data preprocessing, traffic prediction using a LSTM network, congestion classification using a SVM, and adaptive traffic management [20], [21]. Initially, traffic data generated from heterogeneous devices and multiple network slices are continuously collected from the communication infrastructure. The acquired traffic records include packet arrival rate, bandwidth utilization, transmission latency, packet loss, and slice-specific information that collectively characterize the current network condition. Before model training, the raw traffic data undergo preprocessing to remove inconsistencies, normalize feature scales, and transform sequential observations into an appropriate format for DL.

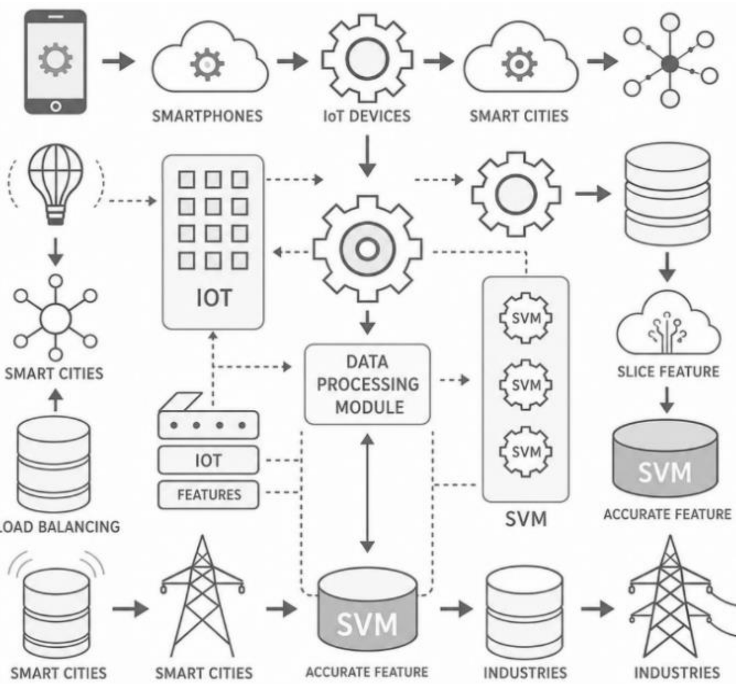

Figure 1. Overall architecture of the proposed hybrid LSTM–SVM framework for intelligent congestion prediction and traffic management in 5G/6G networks

The preprocessed traffic sequences are subsequently processed by the LSTM prediction module, which learns temporal dependencies from historical network observations and estimates future traffic conditions over a predefined prediction horizon. Unlike conventional recurrent neural networks (RNN), LSTM effectively captures both short-term fluctuations and long-term traffic evolution through its memory cells and gating mechanisms, making it particularly suitable for modeling highly dynamic wireless communication environments. The predicted traffic representations are then transferred to the SVM classifier, which determines whether the anticipated network condition corresponds to normal operation or an impending congestion event.

Based on the congestion classification results, the proposed framework initiates adaptive traffic management strategies, including resource reallocation, load balancing among network slices, and priority adjustment for latency-sensitive services such as URLLC. This proactive decision-making process enables congestion mitigation before service degradation occurs, thereby improving network reliability, resource utilization, and overall QoS. Furthermore, the framework continuously updates its prediction model using newly observed traffic data, allowing the proposed system to adapt to changing network conditions and maintain robust performance under dynamic communication environments.

Overall, the proposed hybrid framework combines the temporal learning capability of LSTM with the robust nonlinear classification capability of SVM within a unified intelligent traffic management architecture. This complementary integration enables more accurate congestion prediction than individual learning models while supporting efficient and scalable network management for future 5G/6G communication systems.

2.2. Hybrid LSTM–SVM architecture

The proposed hybrid framework integrates LSTM networks and SVM within a unified learning architecture to perform intelligent congestion prediction and traffic state classification in 5G/6G communication networks. The integration is motivated by the complementary strengths of both techniques. LSTM networks are highly effective for modeling temporal dependencies in sequential traffic observations, whereas SVM classifiers provide robust nonlinear decision boundaries for distinguishing congested and non-congested network states. By combining these two learning paradigms, the proposed framework simultaneously exploits temporal prediction and accurate classification, thereby enabling proactive traffic management under dynamic communication environments.

The overall architecture of the proposed hybrid model is illustrated in Figure 2. The framework consists of two sequential processing stages. In the first stage, network traffic observations are represented as time-series sequences containing multiple traffic attributes, including packet arrival rate, bandwidth utilization, packet delay, packet loss, and network slice utilization. These sequential observations are processed by the LSTM prediction module to capture both short-term fluctuations and long-term traffic evolution. The resulting latent feature representations contain rich temporal information describing future traffic behavior and potential congestion trends.

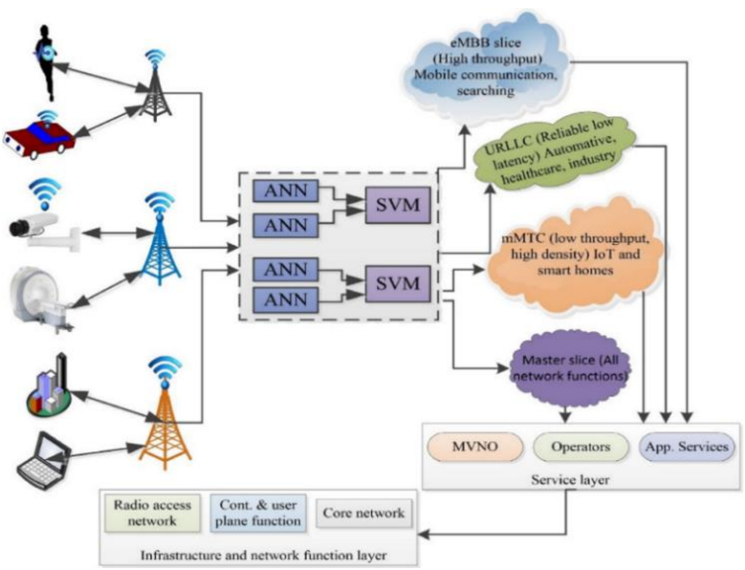

Figure 2. Hybrid LSTM–SVM architecture for intelligent congestion prediction and traffic state classification

Unlike conventional RNNs, which often suffer from vanishing gradient problems when processing long sequences, LSTM introduces memory cells regulated by input, forget, and output gates to selectively retain relevant historical information while discarding unnecessary observations. This gating mechanism enables the network to learn complex temporal relationships over extended periods and significantly improves prediction stability for highly dynamic wireless communication traffic [22]. Given an input traffic sequence X={x1, x2,…, xT}, the LSTM recursively updates its hidden state and memory cell to generate a predicted traffic representation,

$$h_t = \text{LSTM}(x_t, h_{t-1}, c_{t-1})$$

where h_t and c_t denote the hidden state and memory cell at time step ttt, respectively. The final hidden representation summarizes the temporal characteristics of historical network traffic and serves as the input feature vector for congestion classification.

In the second stage, the predicted traffic representation generated by the LSTM network is forwarded to the SVM classifier. Rather than learning temporal patterns, the SVM focuses on identifying the optimal decision boundary that separates congested from non-congested network conditions. By maximizing the margin between the two classes within a transformed feature space, the SVM provides robust classification performance even when traffic characteristics exhibit nonlinear relationships [23]. The classification decision can be expressed as,

$$f(x) = \text{sign}(w^T \phi(x) + b)$$

where ϕ(x) denotes the nonlinear feature transformation, www represents the separating hyperplane, and bbb is the bias term. Traffic samples classified as positive correspond to predicted congestion events, whereas negative outputs indicate normal network operation.

The hybrid integration enables the proposed framework to perform prediction and decision making simultaneously. While the LSTM forecasts future traffic evolution before congestion occurs, the SVM rapidly classifies the predicted network condition and determines whether adaptive traffic management should be initiated. Whenever congestion is anticipated, the framework proactively triggers resource reallocation, network slice adjustment, or traffic load balancing to prevent service degradation. Consequently, the proposed architecture transforms congestion management from a reactive mechanism into a predictive decision-support system capable of maintaining stable network performance under continuously changing traffic conditions.

Compared with standalone LSTM or SVM models, the proposed hybrid architecture offers several advantages. The LSTM effectively captures temporal dependencies that cannot be modeled by conventional ML algorithms, whereas the SVM improves classification robustness by providing reliable nonlinear decision boundaries using the learned traffic representations. This complementary combination enhances congestion prediction accuracy, reduces unnecessary false congestion alarms, and improves the scalability of intelligent traffic management for future 5G/6G communication networks.

2.3. Data preparation and preprocessing

The performance of DL models for network traffic prediction is highly dependent on the quality and consistency of the input data. Network traffic collected from heterogeneous communication environments typically contains missing values, inconsistent feature scales, redundant information, and highly dynamic temporal characteristics that may adversely affect model convergence and prediction accuracy. Therefore, a comprehensive preprocessing pipeline was developed to transform the raw traffic records into a structured dataset suitable for the proposed hybrid LSTM–SVM framework.

The experimental dataset was constructed using both publicly available 5G network traffic data and synthetically generated traffic traces to emulate realistic communication environments. The dataset contains traffic generated from heterogeneous devices, including IoTs sensors, mobile terminals, autonomous vehicles, and machine-to-machine communication nodes operating under multiple network slices. Three representative service categories were considered, namely eMBB, URLLC, and mMTC. To improve model robustness, synthetic traffic scenarios were incorporated to simulate burst traffic, network slice failures, sudden traffic surges, and varying resource utilization conditions that frequently occur in practical 5G/6G deployments.

Each traffic record consists of multiple network performance indicators describing the operational state of the communication system. Representative input features include packet arrival rate, bandwidth utilization, transmission latency, packet loss ratio, queue occupancy, traffic volume, and network slice utilization. These traffic attributes collectively characterize network behavior and provide sufficient information for predicting future congestion conditions.

Prior to model training, several preprocessing operations were performed to improve data quality and ensure consistent feature representation. Missing observations and duplicate records were removed to eliminate inconsistencies within the dataset, while abnormal or invalid traffic values were filtered to reduce noise that could negatively influence model learning. Since network traffic attributes possess different numerical ranges, all input variables were normalized using Min–Max normalization, which scales each feature into the interval [0,1][0,1][0,1]. The normalized feature value is computed as

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

where x denotes the original feature value, while x_{min} and x_{max} represent the minimum and maximum values of the corresponding feature, respectively. Feature normalization prevents variables with larger numerical magnitudes from dominating the optimization process and improves convergence stability during neural network training.

Because LSTM networks require sequential input, the normalized traffic data were subsequently transformed into time-series sequences using a sliding-window mechanism. Rather than treating each traffic observation independently, consecutive traffic samples were grouped into fixed-length sequences that preserve the temporal evolution of network conditions. Let WWW denote the window length; each training sample is represented as,

$$X_t = \{x_{t-W+1}, x_{t-W+2}, \dots, x_t\}$$

where X_t contains the most recent W observations used to predict the network condition at the subsequent time step. This sequence construction enables the LSTM network to learn temporal dependencies that cannot be captured using conventional static learning algorithms.

Following preprocessing, the complete dataset was randomly divided into training and testing subsets using a 70:30 ratio, where 70% of the samples were used to train the hybrid model and the remaining 30% were reserved for independent performance evaluation. The separation between training and testing data ensures that the proposed framework is evaluated using previously unseen traffic observations, thereby providing an unbiased assessment of its generalization capability. The overall preprocessing workflow adopted in this study improves data consistency, enhances model stability, and establishes a reliable foundation for intelligent congestion prediction in dynamic 5G/6G communication networks.

2.4. Model training

The proposed hybrid LSTM–SVM framework was trained using supervised learning to accurately predict future network congestion and classify network traffic conditions. During the training phase, the LSTM network first learned temporal traffic characteristics from historical network observations, while the SVM classifier was subsequently trained using the learned feature representations generated by the LSTM model. This two-stage learning strategy enables the proposed framework to exploit both sequential traffic dependencies and robust nonlinear classification, thereby improving congestion prediction performance under dynamic network conditions.

Prior to training, all input traffic features were normalized and transformed into fixed-length sequential samples using the preprocessing procedure described in the previous subsection. Each input sequence represents consecutive network observations collected over a predefined time window and contains traffic attributes such as packet arrival rate, bandwidth utilization, transmission delay, packet loss, and network slice utilization. The corresponding target label indicates whether the subsequent network state is congested or non-congested. The prepared sequences were then used to train the LSTM prediction model, while the predicted feature vectors produced by the LSTM served as inputs to the SVM classifier.

The LSTM network was implemented using the TensorFlow/Keras DL framework. Model optimization was performed using the Adam optimizer, which provides adaptive learning rates and fast convergence for nonlinear optimization problems. Binary cross-entropy (BCE) was adopted as the objective function because congestion prediction is formulated as a binary classification problem. The network parameters were updated iteratively through backpropagation over multiple training epochs until the validation loss converged. Table 1 summarizes the principal hyperparameters adopted in this study.

To minimize overfitting and improve model generalization, the training process monitored both training and validation losses throughout successive epochs. Model convergence was assessed using the validation performance, ensuring that the learned representations remained stable across unseen traffic samples. After completion of the LSTM training stage, the extracted temporal feature representations were forwarded to the SVM classifier for congestion state identification. The SVM was trained using a radial basis function (RBF) kernel to effectively separate congested and non-congested traffic patterns within the transformed feature space. This hybrid learning strategy enables the LSTM to concentrate on temporal feature extraction while allowing the SVM to construct an optimal nonlinear decision boundary for congestion classification.

The complete training procedure is summarized in Algorithm 1. Initially, historical network traffic sequences are preprocessed and normalized before being supplied to the LSTM prediction model. The trained LSTM generates high-level temporal representations that capture both short-term fluctuations and long-term traffic evolution. These representations are subsequently utilized by the SVM classifier to identify impending congestion events. During deployment, newly observed traffic sequences are processed using the same pipeline, enabling continuous congestion prediction and adaptive traffic management in real time. This training strategy significantly improves the robustness and scalability of the proposed framework for intelligent congestion prediction in future 5G/6G communication networks.

Table 1. Hyperparameter configuration of the proposed hybrid LSTM–SVM model

Parameter	Value
Optimizer	Adam
Learning rate	0.001
Batch size	64
Number of epochs	50
Loss function	Binary Cross-Entropy
Activation (Hidden)	ReLU
Activation (Output)	Sigmoid
LSTM units	128
Validation split	20%

Algorithm 1. Hybrid LSTM–SVM congestion prediction framework

```
Input:
 Network traffic dataset D
 Sliding window size W
 Training ratio r
 LSTM model parameters
 SVM classifier

Output:
 Congestion prediction (Congested / Normal)
1: Load network traffic dataset D
2: Remove invalid and duplicate records
3: Normalize all traffic features using Min–Max normalization
4: Generate sequential traffic samples using sliding window W
5: Split dataset into training and testing sets
6: Train the LSTM network using training sequences
7: Extract learned temporal feature representations
8: Train the SVM classifier using LSTM features
9: Input testing traffic sequences into trained LSTM
10: Generate predicted traffic representations
11: Classify congestion state using trained SVM
12: if Congestion detected then
13: Trigger traffic management
14: Reallocate network resources
15: Adjust network slice allocation
16: else
17: Maintain current network configuration
18: end if
19: Evaluate model using Accuracy, Precision, Recall, Specificity, F-score, and Execution
Time
20: Return congestion prediction
```

2.5. Congestion prediction workflow

After the hybrid LSTM–SVM model has been successfully trained, it is deployed as an intelligent congestion prediction engine for real-time traffic management in 5G/6G communication networks. During deployment, the framework continuously monitors network traffic generated by heterogeneous devices and virtual network slices, allowing congestion conditions to be predicted before significant performance degradation occurs. Unlike conventional congestion control mechanisms that react only after congestion has been detected, the proposed framework performs proactive traffic prediction and classification, enabling adaptive resource management based on anticipated network conditions.

The operational workflow of the proposed framework is illustrated in Figure 3. Initially, real-time traffic measurements are collected from the communication infrastructure. Representative traffic indicators include packet arrival rate, bandwidth utilization, transmission delay, packet loss ratio, queue occupancy, and network slice utilization. These traffic observations are subsequently subjected to the same preprocessing procedures applied during model training, including feature normalization and sequential data construction using the predefined sliding-window mechanism. Maintaining an identical preprocessing pipeline ensures consistency between the training and deployment phases and improves prediction reliability.

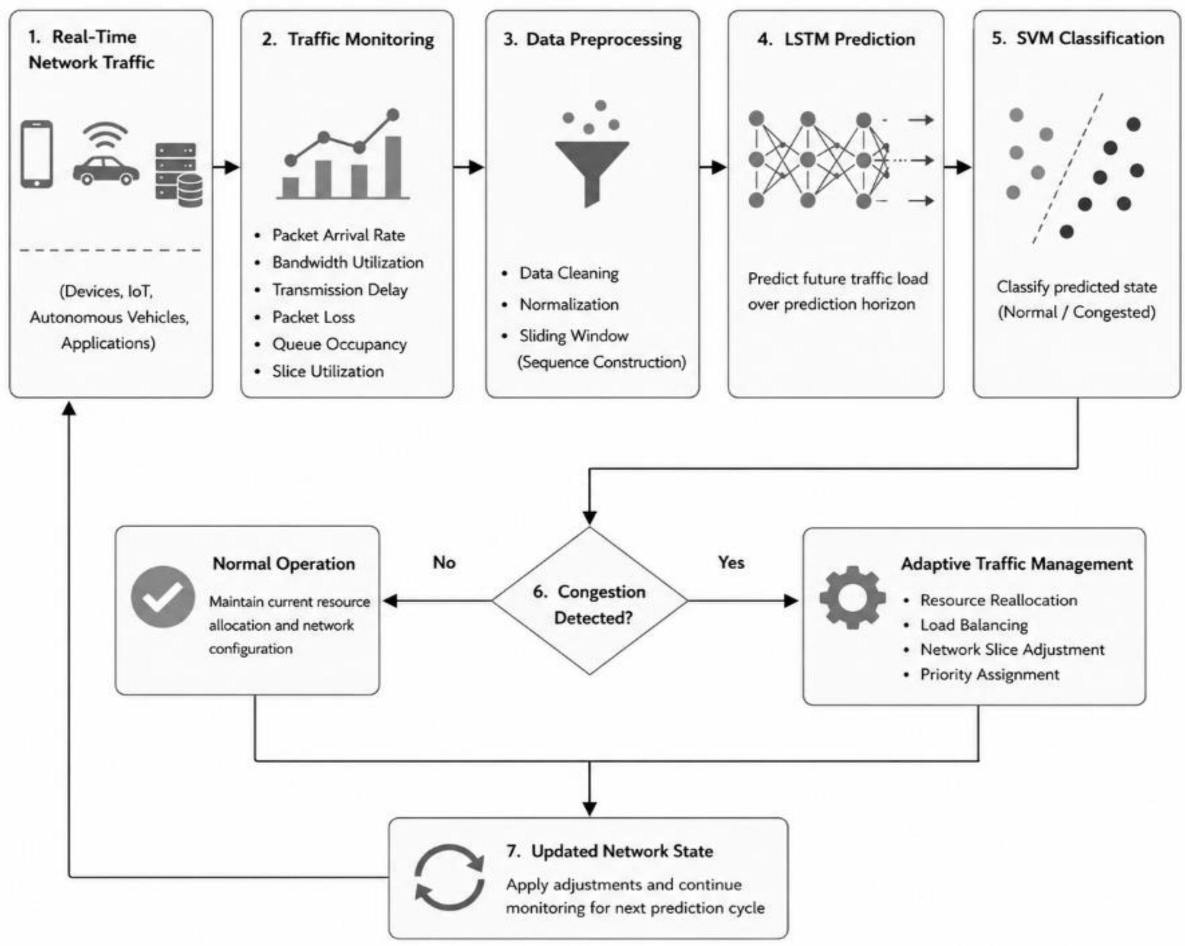

Figure 3. Operational workflow of the proposed hybrid LSTM–SVM framework for real-time congestion prediction and adaptive traffic management in 5G/6G networks

The normalized traffic sequences are then forwarded to the trained LSTM prediction model, which analyzes historical traffic evolution and estimates future network conditions over the predefined prediction horizon. Rather than simply identifying current congestion, the LSTM forecasts the future traffic load by exploiting temporal dependencies embedded within sequential network observations. This predictive capability enables the framework to anticipate congestion events before network resources become saturated, thereby providing sufficient time for preventive traffic management actions.

The predicted traffic representations generated by the LSTM network are subsequently processed by the trained SVM classifier. Based on the learned decision boundary, the classifier categorizes each predicted network state into either normal operation or congested operation. If the predicted traffic remains within the acceptable operating range, the communication system continues normal resource allocation without additional intervention. Conversely, when impending congestion is identified, the framework immediately activates adaptive traffic management mechanisms to minimize service degradation.

The congestion mitigation strategy includes several resource optimization operations. These include dynamic network slice reallocation, traffic load balancing across available communication resources, bandwidth redistribution, and priority assignment for latency-sensitive services such as URLLC. By performing these corrective actions before congestion fully develops, the proposed framework improves resource utilization while maintaining stable QoS across heterogeneous communication services. The overall operational workflow therefore transforms congestion management from a reactive process into a predictive decision-support mechanism capable of supporting intelligent autonomous network operation.

The deployment process is continuously repeated as newly observed traffic data become available. The framework periodically updates its congestion predictions using the most recent network observations, allowing it to adapt to continuously changing traffic characteristics and communication environments. This online prediction capability enhances the robustness and scalability of the proposed hybrid framework and makes it suitable for practical deployment in future intelligent 5G/6G communication infrastructures.

3. RESULTS AND DISCUSSION

The hybrid model achieved an overall accuracy of 93.23% in classifying congested and non-congested states across various traffic conditions. Normal Traffic Conditions: In this scenario, the model achieved a high accuracy rate of 95.12%, as the traffic patterns were predictable and relatively stable. Traffic Spikes: The model showed slightly reduced accuracy (92.47%) due to the sudden surges in traffic. However, it was still able to handle most congestion instances efficiently. Slice Failures: The model maintained an accuracy of 91.78% in this scenario, detecting congestion caused by the failure of network slices and managing traffic rerouting effectively.

Overloaded network: This scenario posed the greatest challenge, with the model achieving an accuracy of 90.56%. Despite the overload, the hybrid model successfully predicted congestion and triggered appropriate congestion control mechanisms. The overall high accuracy reflects the model's robustness and adaptability to varying network conditions. In addition to accuracy, precision, recall, and F1-score were calculated to assess the model's performance in handling false positives and false negatives. Precision: The average precision for the model was 92.85%. Precision was slightly lower during traffic spikes (90.47%) due to occasional false alarms, but it remained high for normal traffic (94.28%) and slice failure scenarios (93.02%). Recall: The model demonstrated an average recall of 93.71%, indicating a strong ability to detect congested states across scenarios. It showed high recall in normal traffic (96.01%) and performed well even in slice failure conditions (92.11%). F1-Score: The overall F1-score was 93.28%, demonstrating a balanced trade-off between precision and recall. The F1-score remained above 91% for all scenarios, confirming the model's effectiveness in classification tasks. The time taken to predict congestion using the hybrid model was a critical factor, especially in real-time 5G/6G networks.

The proposed hybrid LSTM–SVM model demonstrated low computational latency, achieving an average prediction time of 32.25 ms, making it suitable for real-time network traffic management in 5G/6G environments. Even under network overloading conditions, the average prediction time remained below 36 ms, ensuring rapid congestion detection and timely traffic management decisions. This low inference latency is particularly important for latency-sensitive applications in next-generation wireless networks, where rapid adaptation to changing traffic conditions is essential for maintaining QoS.

The ability to manage network slice overloading and failure scenarios represents one of the primary performance indicators of the proposed framework. To evaluate its robustness, overload conditions were intentionally introduced during the experiments. Whenever the utilization of a network slice exceeded a predefined threshold of 93%, the hybrid model identified the slice as overloaded and automatically redirected newly arriving traffic to a designated master slice, which served as a backup resource for additional mMTC requests. By proactively detecting impending congestion and reallocating incoming traffic, the proposed framework effectively prevented further overloading while maintaining uninterrupted service availability. Following congestion detection, the master slice dynamically allocated additional resources to the overloaded connections, as illustrated in Figure 4.

The robustness of the proposed framework was further validated through network slice failure experiments. As shown in Figure 5, the mMTC slice experienced two simulated failure periods: the first lasting 2 hours and 15 minutes (from 02:30 h to 04:45 h) and the second lasting 4 hours (from 13:00 h to 17:00 h). During both failure intervals, the master slice functioned as a backup network slice, successfully rerouting network traffic while maintaining service continuity. This adaptive recovery mechanism minimized service interruption and demonstrated the capability of the proposed framework to sustain network operation even under prolonged failure conditions.

To quantify the effectiveness of the proposed congestion management strategy, network performance was evaluated with and without the hybrid framework. Without intelligent congestion prediction, network slice failures and traffic overloading resulted in severe congestion, affecting more than 25% of network slices during peak traffic periods. In contrast, when the proposed hybrid model was deployed, the congestion ratio decreased to less than 10%, owing to its ability to predict congestion in advance and dynamically redistribute traffic across available network slices. These results demonstrate that predictive traffic management substantially improves network resilience while reducing the likelihood of service degradation.

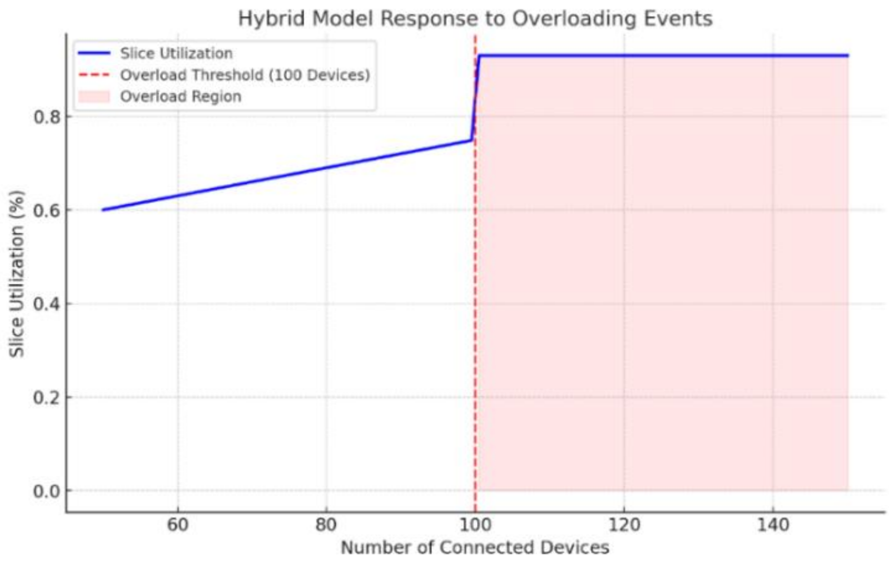

Figure 4. Load balancing in response to connection requests that go beyond a specified threshold

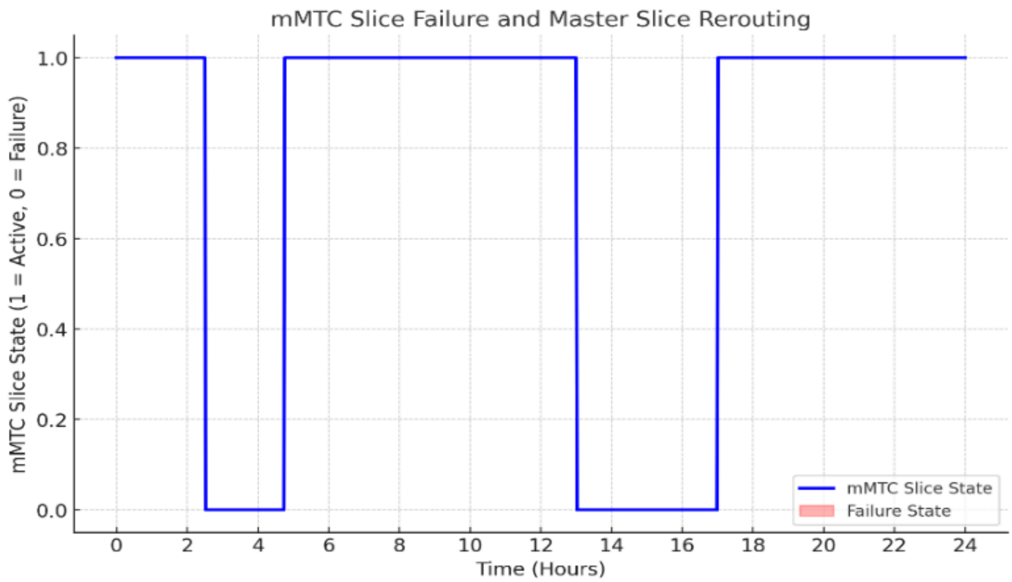

Figure 5. The mMTC slice relocation to the master slice after a failure

The proposed hybrid model was also compared with several baseline approaches, including standalone LSTM, standalone SVM, and conventional congestion control mechanisms such as RED and AQM. The standalone LSTM model achieved an overall classification accuracy of 88.57%, demonstrating strong traffic prediction capability but limited performance in congestion classification. Conversely, the standalone SVM achieved an accuracy of 85.43%, providing effective classification but lacking the temporal learning capability required to model sequential traffic dynamics. Traditional RED and AQM algorithms performed considerably worse, achieving accuracies below 80% while exhibiting slower responses to rapidly changing network conditions because of their reactive congestion control strategies.

Overall, the proposed hybrid LSTM–SVM framework consistently outperformed all baseline methods across both prediction accuracy and congestion management effectiveness. By integrating the temporal forecasting capability of LSTM with the robust classification performance of SVM, the proposed framework provides accurate congestion prediction, reliable congestion detection, and intelligent adaptive traffic management. These experimental results demonstrate that the proposed approach is a practical and scalable solution for real-time congestion prediction and resource management in future 5G/6G wireless communication networks.

The results of the experiments highlight the effectiveness of the hybrid DL-enabled model in managing congestion in 5G/6G networks. Key findings include: High Accuracy: The model achieved consistently high accuracy, precision, and recall across various traffic conditions, demonstrating its reliability. Real-Time Responsiveness: The model's low latency and rapid prediction times make it suitable for real-time congestion management in next-generation networks. Robustness in Complex Scenarios: The model performed well under challenging conditions such as traffic spikes, slice failures, and overloading, maintaining network stability and minimizing the impact of congestion. Comparison with Baseline Models: The hybrid approach combining LSTM and SVM outperformed standalone models and traditional methods, offering a more efficient solution for dynamic traffic management in 5G/6G environments. The integration of LSTM for traffic prediction and SVM for congestion classification proved to be an effective strategy for addressing the unique challenges posed by next-generation network architectures. The hybrid model not only mitigates congestion but also enhances the overall performance of the network by optimizing resource allocation and ensuring QoS. In the next section, we conclude the paper with insights into potential future research directions for further improving congestion control in 5G/6G networks.

4. CONCLUSION

This paper presented a hybrid DL-based congestion prediction framework for intelligent traffic management in 5G/6G networks by integrating LSTM and SVM. The proposed framework exploits the temporal learning capability of LSTM to predict future traffic conditions, while SVM performs congestion state classification to support adaptive resource allocation and network slice management. This hybrid architecture enables proactive congestion mitigation rather than conventional reactive congestion control. Experimental results demonstrate that the proposed framework achieves an overall classification accuracy of 93.23%, while maintaining high precision, recall, and F1-score across diverse traffic scenarios. Furthermore, the framework exhibits low inference latency, with an average prediction time of 32.25 ms and less than 36 ms under overloaded network conditions, indicating its suitability for real-time deployment in latency-sensitive 5G/6G environments. The proposed approach also effectively handled network slice failures and traffic overloading by dynamically redirecting traffic to backup (master) slices, reducing congestion during peak traffic periods from over 25% to below 10%. Comparative experiments further showed that the hybrid LSTM–SVM framework consistently outperformed standalone LSTM, standalone SVM, and conventional congestion control approaches, including RED and AQM, in both prediction accuracy and congestion mitigation capability. Overall, the proposed framework demonstrates that combining sequential traffic prediction with ML-based congestion classification provides an effective solution for intelligent traffic management in future wireless networks. The framework contributes to improving QoS, network reliability, and adaptive resource utilization in virtualized 5G/6G infrastructures. Future work will focus on validating the proposed framework using real-world operational datasets, investigating more advanced hybrid architectures incorporating Transformer-based temporal models and graph neural networks (GNNs), and deploying the framework within software-defined networking (SDN) and network function virtualization (NFV) environments to support autonomous network orchestration in beyond-5G and 6G systems.

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