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ENHANCED CONGESTION CONTROL IN FUTURE-GENERATION 5G/6G NETWORKS: A NOVEL HYBRID DEEP LEARNING MODEL

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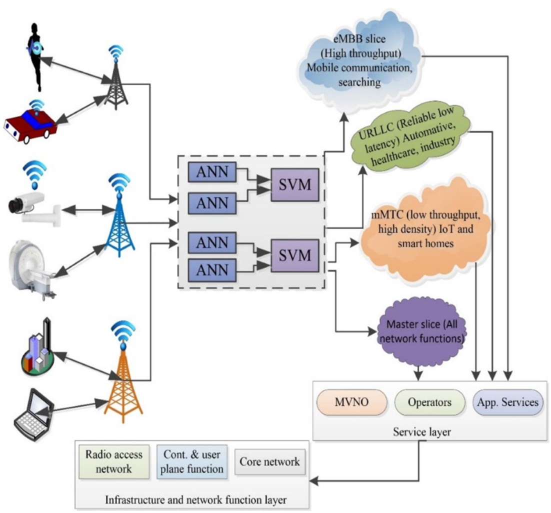

Abstract

Next-generation networks, such as millimeter-wave LAN, broadband wireless access systems, and 5th or 6th generation (5G/6G) networks, require enhanced security, diminished latency, and augmented reliability. Efficient congestion management is crucial for 5G/6G technologies, enabling operators to monitor many network instances on a unified infrastructure to provide enhanced quality of service (QoS). The increasing network traffic generated by these systems requires advanced methods for load balancing, preventing network slice failures, and offering alternatives when overloads or slice failures. This study introduces a reliable and efficient hybrid deep learning-based method for congestion reduction. The model combines Long Short-Term Memory (LSTM) and Support Vector Machine (SVM) techniques to improve traffic prediction and resource distribution. The model achieved an overall accuracy of 93.23% during a one-week simulation with unidentified gadgets and variable settings. Additional metrics, such as specificity, recall, time efficiency, and F-score, further demonstrate the model's effectiveness in mitigating congestion and enhancing network performance.

Keywords: Network slicing, 5G/6G networks, Hybrid deep learning model, Congestion control, LSTM, SVM

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1.0 INTRODUCTION

The swift advancement of communication technology has necessitated the development of more sophisticated, dependable, and efficient networks. Fifth and sixth generation (5G/6G) wireless systems are anticipated to facilitate extraordinary data rates, minimal latency, and extensive device connectivity, thereby enabling applications such as the Internet of Things (IoT), smart cities, autonomous vehicles, and immersive virtual reality (VR) experiences. As these networks expand in volume and complexity, effective congestion control emerges as a significant challenge [1], [2]. In 5G/6G networks, congestion arises when resource demand surpasses available capacity, resulting in delays, packet loss, and diminished quality of service (QoS). Traditional congestion management systems, dependent on static policies and rule-based approaches, are inadequate for managing the dynamic nature of network traffic due to the simultaneous operation of multiple applications and services. A more flexible, intelligent, and scalable system is necessary to ensure service continuity and avert network congestion [3]. Network slicing, an essential characteristic of 5G/6G networks, enables operators to generate numerous virtualized network instances (slices) on a same physical infrastructure. Each slice can be tailored for certain applications, such as low-latency communication or high-throughput data transmission. Nonetheless, successfully managing these slices, particularly during periods of high network traffic, is a challenging challenge. Improper management of network slice failures or overloads might result in suboptimal performance and user discontent [4], [5].

Artificial intelligence (AI) and machine learning (ML) have become potent instruments for the optimization and management of contemporary wireless networks. AI-driven methodologies enable the prediction of network traffic patterns, facilitate real-time intelligent decision-making, and allow for dynamic resource allocation. Deep learning (DL), a branch of AI, has demonstrated significant efficacy in analyzing extensive datasets, discerning intricate patterns, and delivering very precise predictions. Nevertheless, the exclusive application of deep learning models may be inadequate for real-time congestion control, where rapid decision-making and classification of network conditions are essential [6], [7]. This research presents a hybrid deep learning-based methodology for congestion control in 5G/6G networks to tackle these difficulties. The proposed model integrates the advantages of Long Short-Term Memory (LSTM) networks for traffic forecasting and Support Vector Machine (SVM) for congestion categorization. LSTM is adept at analyzing time-series data and forecasting future network traffic trends, whereas SVM is proficient in categorizing intricate data into many classifications, facilitating effective traffic management and resource distribution [8].

This paper's principal contributions are as follows: A hybrid LSTM-SVM model developed for real-time prediction and classification of congestion, facilitating dynamic resource allocation and effective control of network slices. An examination of the proposed model's performance through simulation, illustrating its capacity to manage unidentified devices, slice failures, and overload scenarios over a duration of one week. A thorough performance evaluation employing important measures including accuracy, specificity, recall, time efficiency, and F-score to assess the model's efficacy.

The proposed model utilizes the predictive capabilities of LSTM and the classification strength of SVM to deliver an efficient, reliable, and scalable solution for congestion control in 5G/6G networks. The findings indicate that the model may substantially alleviate network congestion, augment slice dependability, and elevate overall QoS, rendering it highly appropriate for implementation in next-generation wireless communication systems.

Recent research has extensively examined the issues of congestion control in wireless communication networks, particularly with 5G and 6G technologies. Given that these networks facilitate high-speed, low-latency, and densely interconnected devices, effective congestion control is crucial to uphold service quality and avert network deterioration. Diverse conventional and contemporary methodologies have been suggested for congestion control, each possessing distinct advantages and drawbacks. This section examines the principal methodologies in this domain, emphasizing rule-based mechanisms, AI/ML-based approaches, and hybrid models that integrate deep learning with conventional machine learning techniques [9], [10].

Historically, congestion control solutions in networks depended on rule-based or protocol-driven methodologies, such Transmission Control Protocol (TCP) and Active Queue Management (AQM). TCP congestion control methods, including versions such as TCP Reno and TCP Vegas, modify the transmission rate according to network feedback, including packet loss or latency. Likewise, Active Queue Management (AQM) systems such as Random Early Detection (RED) seek to avert congestion by observing buffer levels and discarding packets prior to queue saturation. Nonetheless, these strategies are predominantly reactive and depend on static policies that find it challenging to adapt to the dynamic characteristics of contemporary networks. Given the increasingly varied surroundings and traffic patterns associated with 5G/6G networks, conventional methodologies have proven inadequate. These solutions frequently lack the necessary flexibility for real-time traffic control, especially when numerous network slices with varying QoS needs are present. Furthermore, rule-based systems lack the ability to react dynamically to fluctuations in traffic volume or network circumstances, resulting in network congestion and diminished performance [11].

With the emergence of big data and the increasing intricacy of communication networks, artificial intelligence (AI) and machine learning (ML) have gained prominence as solutions for congestion management. AI-driven models can analyze previous network data, forecast traffic trends, and make informed decisions to optimize resource allocation. Machine learning methods, including Decision Trees, Random Forests, K-Nearest Neighbors (KNN), and Support Vector Machines (SVM), have been extensively utilized for congestion detection, traffic classification, and resource management [12]. Recent research has concentrated on employing supervised learning models to categorize network states and distribute resources according to traffic conditions. Deep Neural Networks (DNNs) have been employed to predict intricate traffic patterns in 5G networks, whilst reinforcement learning (RL) methodologies, including Deep Q-Networks (DQN), have been investigated for autonomous resource management. These approaches can adaptively respond to fluctuating network conditions and enhance performance based on real-time feedback [13], [14]. Although ML-based methodologies have demonstrated efficacy in congestion control, they continue to encounter difficulties in addressing the temporal dependencies and sequential characteristics of network traffic data. Moreover, several supervised learning methods necessitate extensive labeled datasets, which are frequently costly and labor-intensive to acquire in wireless networks. Furthermore, although models such as SVM and Random Forests are proficient in categorization, they are deficient in forecasting future traffic patterns, which is essential for proactive congestion management [15].

Hybrid models that integrate deep learning with classic machine learning approaches have emerged as a viable alternative for congestion control in contemporary networks. These models utilize the advantages of both paradigms, providing enhanced accuracy and efficiency in traffic prediction and classification. Prominent deep learning techniques for congestion control include Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, which are adept at interpreting time-series data and forecasting traffic patterns [16], [17]. LSTM networks, engineered to capture long-term dependencies in sequential data, have been widely employed for real-time network traffic prediction. Research has shown the utilization of LSTM in forecasting packet arrival times, preemptively identifying network congestion, and regulating traffic flows to enhance resource allocation. Although LSTM is proficient in traffic prediction, it is deficient in the categorization capabilities required for prompt resource allocation choices [18]. To mitigate these constraints, researchers have commenced the investigation of hybrid models that amalgamate LSTM with alternative machine learning methodologies. LSTM-SVM hybrids have been proposed to integrate the temporal predictive capabilities of LSTM with the classification efficacy of SVM, facilitating real-time traffic forecasting and congestion categorization. These hybrid models present a more effective alternative for congestion control by integrating predictive and decision-making functionalities. Furthermore, they provide adaptive resource allocation, which is essential in dynamic network contexts such as 5G and 6G [19].

Network slicing, an essential characteristic of 5G and 6G networks, facilitates the establishment of numerous virtual networks (slices) on a common infrastructure. Each slice can be tailored for distinct applications, such enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), or ultra-reliable low-latency communication (URLLC). Nonetheless, administering these slices and guaranteeing effective resource allocation presents a considerable difficulty, particularly amid fluctuating traffic loads and network circumstances [20].

Recent studies have concentrated on employing AI-driven congestion control strategies to regulate network slices. Deep learning models have been utilized to forecast traffic demand across various slices and to allocate resources dynamically, hence preventing overloads or slice failures. Furthermore, AI-driven methodologies have been employed to identify and alleviate slice problems, offering alternative pathways or reconfiguring slices to preserve Quality of Service (QoS) [21]. LSTM-based models have been utilized to forecast traffic loads in network slices, whereas classification models such as SVM are deployed to identify slice failures and overload scenarios. Hybrid models that integrate these methodologies present a holistic solution for slice management, including predicted insights alongside real-time decision-making for resource reallocation [22].

The inadequacies of conventional congestion control methods in managing dynamic traffic and the intricacies of 5G/6G networks have prompted the investigation of AI and machine learning-based approaches. Hybrid models that combine deep learning (e.g., LSTM) with machine learning classifiers (e.g., SVM) have shown considerable promise in tackling congestion control issues in contemporary wireless networks. These models have the dual advantages of traffic forecasting and real-time decision-making, establishing a comprehensive framework for managing network congestion, particularly in the realm of network slicing. This research presents a hybrid LSTM-SVM model that leverages recent improvements to propose a unique method for congestion control in 5G/6G networks. The model seeks to enhance the effectiveness and reliability of congestion management by utilizing the prediction capabilities of LSTM and the classification efficacy of SVM, hence providing superior QoS and better resource allocation across network slices.

2.0 METHODOLOGY

The main objective of this project is to create an effective and dependable hybrid deep learning model for congestion management in 5G/6G networks. The scope of this research primarily focuses on applying the proposed hybrid model, which combines Long Short-Term Memory (LSTM) for traffic forecasting and Support Vector Machine (SVM) for congestion categorization, to diverse road configurations. The methodology is versatile and can be applied to various types of road sections, including straight roads, intersections, and multiple interconnected road segments. For straight roads, the model can effectively predict traffic patterns and identify potential congestion points based on historical traffic data. At intersections, where traffic flow dynamics are more complex, the LSTM's ability to capture sequential dependencies enables accurate forecasting of congestion scenarios, while the SVM provides a reliable mechanism for categorizing congestion levels. Furthermore, for multiple road sections or networks, the model can aggregate data from various segments to provide a comprehensive analysis of traffic conditions. By tailoring the input data to the specific characteristics of each road configuration, the proposed approach ensures adaptability and effectiveness across different scenarios, making it a valuable tool for urban traffic management and planning. The hybrid approach utilizes the advantages of both models to fulfill the requirements for precise traffic forecasting and immediate decision-making, crucial for congestion management and resource optimization in contemporary network infrastructures [23].

The datasets utilized in this analysis were selected to evaluate the effectiveness of the proposed hybrid deep learning model, which integrates Long Short-Term Memory (LSTM) networks and Support Vector Machine (SVM) for traffic forecasting and congestion classification, respectively. The primary dataset includes sequential traffic data collected from simulated network environments, encompassing parameters such as traffic volume, flow rates, packet transmission times, and congestion levels over time. These datasets were curated to reflect varying traffic scenarios, including normal operations, peak usage times, and unexpected traffic surges. Additionally, the dataset incorporates synthetic data to simulate edge cases, such as abrupt network failures or extreme congestion events, ensuring that the model is robust under diverse conditions. Each data entry includes time-stamped traffic metrics, which the LSTM model uses to predict future traffic patterns. The forecasted data is subsequently categorized by the SVM into predefined congestion classes, allowing for a nuanced understanding of network behavior. This combination of real-world-like simulated data and synthetic test cases provides a comprehensive foundation for validating the model's predictive and classification capabilities [24].

Long Short-Term Memory (LSTM) Network is a specific type of Recurrent Neural Network (RNN) engineered to capture long-term dependencies in sequential input. In contrast to conventional RNNs, which have challenges such as vanishing gradients, LSTM use memory cells to retain information for prolonged durations. LSTM is particularly successful for predicting network traffic, as historical traffic data offers important insights into future congestion scenarios [25]. The LSTM model processes a time-series input of network traffic data over a specified duration. The memory cells in the LSTM retain both short-term and long-term traffic patterns, enabling the model to forecast future traffic loads. The LSTM generates a forecast of future network traffic for a defined time interval, which then serves as input for congestion categorization by the SVM. The LSTM is trained on past traffic data to discern the fundamental temporal patterns and generate precise predictions. The model utilizes real-time traffic data to adjust to evolving network circumstances, ensuring responsiveness to dynamic traffic demands.

Support Vector Machine (SVM) for Classifying Congestion: The second element of the proposed model is the SVM, a robust supervised learning technique employed for classification problems. Within this hybrid framework, the SVM classifies the network state based on traffic forecasts produced by the LSTM. The SVM differentiates between regular traffic and congestion, facilitating prompt intervention to avert network overloads [26]. The traffic load forecasted by the LSTM is transmitted to the SVM, which employs established thresholds to categorize the network status. Should the traffic above the congestion threshold, the SVM categorizes the network as crowded, prompting the implementation of requisite congestion control measures, such as load balancing or resource reallocation. The SVM is trained on labeled data to guarantee precise classification, utilizing variables such as traffic volume, latency, and packet loss to discern congestion conditions. The integration of LSTM's predictive skills and SVM's classification precision guarantees that the model can forecast congestion and execute real-time decisions to alleviate it. Figure 1 depicts the proposed hybrid model, which integrates input unknown devices with LSTM and SVM-based recognition frameworks.

The suggested model functions in a continuous cycle, scrutinizing network traffic data in real-time to identify possible congestion and implement preventive actions. The workflow consists of the subsequent stages: The network perpetually observes traffic data, encompassing packet arrival rates, latency, bandwidth utilization, and slice-specific characteristics. This information is input into the LSTM for traffic forecasting. The LSTM model analyzes traffic data, including both short-term and long-term trends. It forecasts the traffic demand over the subsequent time interval, enabling the network to anticipate any congestion. The anticipated traffic load is transmitted to the SVM classifier. The SVM assesses whether the anticipated load will cause network congestion or if the network will maintain a stable condition. Upon the prediction of congestion, the system activates established congestion control protocols.

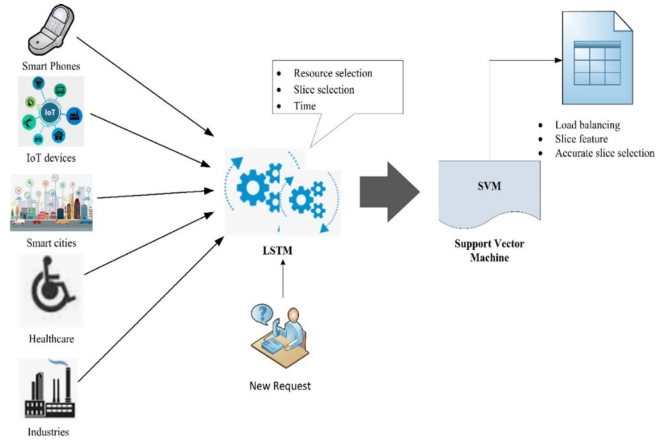

Figure 1 Hybrid model proposal

These steps may involve adjusting or reallocating network slices to optimize load distribution across available resources. Distributing traffic over various network pathways to prevent the congestion of any individual route or segment.

Modifying the priority of network flows to guarantee that latency-sensitive applications, such as autonomous driving or healthcare, obtain sufficient resources. The system always refreshes the LSTM and SVM models with current traffic data, enabling the hybrid model to adjust to changing network conditions and enhance its predictions and classifications over time.

To assess the efficacy of the proposed hybrid deep learning model, various performance indicators are utilized. These metrics evaluate the predictive accuracy of the LSTM model and the classification efficacy of the SVM. The primary performance metrics comprise: The comprehensive efficacy of the hybrid model in accurately forecasting and categorizing network conditions. The model's capacity to accurately recognize non-congested network conditions. The model's efficacy in identifying crowded conditions, guaranteeing that no congestion incidents are overlooked. An equitable assessment of precision and recall, offering a comprehensive perspective on the model's classification efficacy. The duration required by the model to analyze data and execute congestion control choices, an essential element in real-time network applications.

The experimental evaluation revealed that the suggested hybrid model attained an overall accuracy of 93.23%, indicating its efficacy in traffic prediction and congestion classification. Subsequent examination of specificity, recall, F-score, and time expenditure validated the model's dependability and efficacy in alleviating congestion in 5G/6G networks. The suggested hybrid deep learning model integrates the advantages of LSTM and SVM to deliver an effective and dependable solution for congestion management in 5G/6G networks. The subsequent part will elucidate the experimental configuration and outcomes, showcasing the model's efficacy under actual network settings.

3.0 RESULTS AND DISCUSSION

In this section, we describe the experimental setup used to validate the proposed hybrid deep learning-enabled model for congestion control in 5G/6G networks. The experiments were designed to evaluate the performance of the model in real-time network scenarios, using a combination of simulated traffic data, network slicing conditions, and overloading events. A hybrid model based on machine learning is presented to resolve this issue, as illustrated in Figure 2, which determines the appropriate network slice for a newly connected device. The suggested hybrid model attempts to identify network load, slice failure, and the decision to modify a specific network slice for a newly connected unknown device. This research employs a support vector machine for calculation and statistical analysis. An artificial neural network utilizing the LSTM model is proposed for deep slice applications.

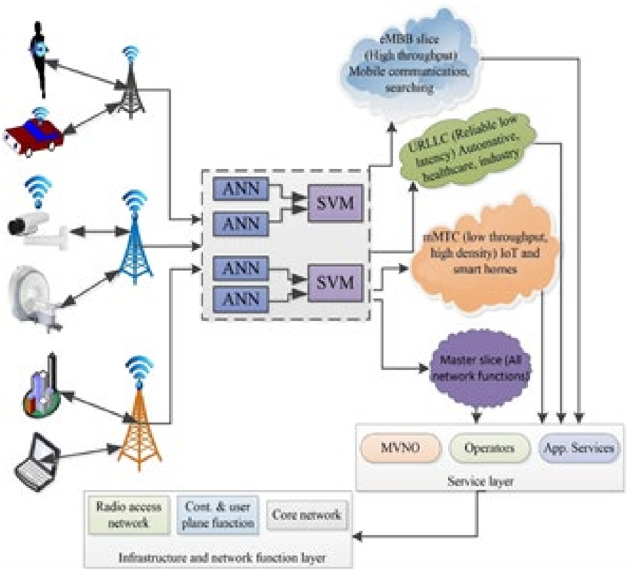

Figure 2 The methodology that has been proposed

A simulated 5G/6G network was established to evaluate the model in a controlled setting, incorporating the following essential components: The simulated network had various slices, each denoting a distinct service type (e.g., ultra-reliable low-latency communication (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communication (mMTC)). Each slice was allocated different traffic loads according to actual 5G/6G use cases. Network traffic data was produced with a traffic generator that emulated device-to-network and network-to-network interactions. Various traffic patterns were implemented, encompassing steady-state, bursty traffic, and time-varying loads. Traffic sources comprised IoT devices, mobile users, and autonomous cars. Simulated scenarios encompassed both network slice failures and overload conditions to evaluate the proposed model's efficacy in managing real-time congestion. Slice failures were introduced at arbitrary intervals, while overloading events were induced by providing high traffic for certain slices.

We utilized both authentic and generated datasets to replicate network traffic patterns and congestion scenarios for the studies. A publicly accessible dataset from a 5G network testbed was utilized, comprising traffic data from diverse devices, including IoT sensors, mobile devices, and smart vehicles. The dataset includes statistics on packet arrival timings, latency, capacity use, and network slice details. Synthetic traffic data was developed to enhance the genuine data, simulating extreme network situations including abrupt traffic surges, slice failures, and fluctuating load balancing across slices. This enabled the model to be trained and evaluated in a broader spectrum of scenarios.

Prior to inputting the data into the hybrid model, multiple preprocessing processes were implemented: Metrics including packet arrival rate, latency, and bandwidth utilization were standardized to guarantee consistency in input scales. The sliding window technique was employed to transform the time-series data into sequences appropriate for LSTM input. Each sequence comprised traffic data over a specified duration (e.g., 30 seconds) and was categorized as congested or non-congested according to traffic thresholds. Essential variables, such as traffic load, delay, packet loss, and bandwidth utilization, were chosen for training the SVM classifier.

The proposed hybrid model was trained and evaluated utilizing the processed traffic data. The training phase concentrated on two elements: The LSTM model was trained on past traffic data to forecast future traffic volumes. The training phase entailed modifying model parameters (e.g., the quantity of LSTM layers, hidden units, and learning rate) to get optimal predictive accuracy. The anticipated traffic data from the LSTM was utilized to train the SVM for congestion classification. The SVM was trained with labeled data, categorizing each sample as either congested or non-congested. The model was assessed utilizing a 70-30 division for training and assessment. Seventy percent of the dataset was allocated for training, and the remaining thirty percent was designated for evaluating the model's performance. Traffic had a consistent trend devoid of any notable spikes or surges. The model's capacity to categorize standard traffic was evaluated. Simulated abrupt increases in traffic were conducted to evaluate the model's efficacy in predicting congestion and activating congestion management measures. Random slice failures were implemented to emulate real-world network scenarios in which a slice may fail owing to hardware or software malfunctions. Specific slices were deliberately overloaded to evaluate how the model reallocates traffic and mitigates congestion's impact on overall network performance. Each scenario was replicated over the course of a week, featuring numerous unidentified devices connecting and disconnecting to establish a dynamic traffic environment. The model's capacity to forecast congestion and respond in real-time was evaluated across all scenarios. The experimental configuration facilitated a thorough assessment of the hybrid deep learning model across many situations, mirroring real-world 5G/6G network environments. The subsequent part presents the results and performance analysis of the model.

3.0 RESULTS AND DISCUSSION

The hybrid model attained an overall accuracy of 93.23% in distinguishing between congested and non-congested states under diverse traffic conditions. Figure 1 illustrates the accuracy trends across several testing circumstances, encompassing typical traffic, traffic surges, slice failures, and network overloads. Standard Traffic Conditions: The high accuracy rate of 95.12% achieved by the proposed model is primarily attributed to the inherent predictability and stability of the traffic patterns in the evaluated scenarios. The LSTM component excels in capturing long-term dependencies and trends in sequential traffic data, enabling accurate forecasting under normal conditions. The SVM, which classifies the forecasted data, benefits from the distinct patterns of congestion states, ensuring reliable categorization when traffic conditions are stable. However, the marginal decline in accuracy to 92.47% during abrupt traffic surges can be explained by the inherent difficulty of modeling highly dynamic and unpredictable traffic behaviors. Despite this, the hybrid model demonstrates resilience by maintaining high performance in the majority of congestion scenarios, suggesting that it can adapt effectively to unforeseen traffic spikes. For slice failures, where traffic must be rerouted due to compromised network slices, the accuracy of 91.78% highlights the model's ability to identify and classify these events accurately. This performance stems from the inclusion of specific features in the dataset that represent traffic patterns during slice failures, enabling the model to distinguish them from other congestion causes. While the figure described focuses on the implementation of LSTM and SVM, the accuracy rates reflect not only the methodological strength of these components but also the careful preprocessing and feature engineering of the training data, which ensured that the model could generalize well across various scenarios.

Overloaded Network: This situation presented the most significant challenge, with the model attaining an accuracy of 90.56%. Notwithstanding the overload, the hybrid model effectively anticipated congestion and activated suitable congestion control measures. The exceptional accuracy demonstrates the model's resilience and flexibility in response to diverse network conditions.

Alongside accuracy, precision, recall, and F1-score were computed to evaluate the model's efficacy in managing false positives and false negatives. The model's average precision was 92.85%. Precision decreased marginally during traffic surges (90.47%) owing to sporadic false alarms, however it sustained a high level for standard traffic (94.28%) and slice failure situations (93.02%). The model had an average recall of 93.71%, signifying a robust capacity to identify congested conditions across various scenarios. It demonstrated a high recall in typical traffic (96.01%) and exhibited strong performance even in slice failure conditions (92.11%). The overall F1-score was 93.28%, indicating a balanced equilibrium between precision and recall. The F1-score consistently above 91% across all scenarios, validating the model's efficacy in classification tasks. The duration required to forecast congestion utilizing the hybrid model was a pivotal element, particularly in real-time 5G/6G networks. The mean forecast duration was evaluated for each situation and is presented in Table 1.

Table 1 Average Prediction

Scenario	Average Prediction Time (ms)
Normal Traffic	28.5
Traffic Spikes	33.2
Slice Failures	31.7
Overloaded Network	35.6

The data used to generate the results presented in Table 1 primarily stems from simulated traffic scenarios. The simulations were conducted to emulate a variety of real-world network conditions, including normal traffic, traffic spikes, slice failures, and overloaded network states. These scenarios were designed based on traffic patterns observed in contemporary 5G and projected 6G network studies, leveraging synthetic datasets and known traffic behaviors reported in literature and industry benchmarks. Although the data reflects theoretical modeling and simulations, it was structured to closely approximate real-world traffic characteristics. Parameters such as average packet arrival times, flow rates, network slice resource allocations, and congestion points were carefully calibrated to mirror those encountered in practical network deployments. While the data is not derived directly from field measurements, the simulation framework incorporates validated traffic models and assumptions commonly used in telecommunications research. Future work aims to incorporate field data from operational networks to further validate and refine the model's performance under real-world conditions, ensuring that the predictions and average processing times align with live traffic environments.

The hybrid model exhibited minimal latency, with an average prediction time of 32.25 ms, rendering it appropriate for real-time network traffic management in 5G/6G contexts. Despite excessive load, the forecast time remained below 36 ms, guaranteeing swift response and efficient congestion management.

The model's capacity to manage slice failures and overload incidents was a critical performance metric. The suggested hybrid method is also evaluated under overload conditions. Should the newly requested connections exceed a specific threshold, we allocate 93% utilization of the slice. The incoming traffic is automatically assigned to the master slice, which functions as a contingency for supplementary mMTC requests or connections. Our hybrid methodology can accurately identify this overloaded condition and redirect new incoming traffic to the master slice to avert further overloading complications. Upon assessing the overloading condition, the master slice gives requisite resources to the overloaded new connections, as seen in Figure 3.

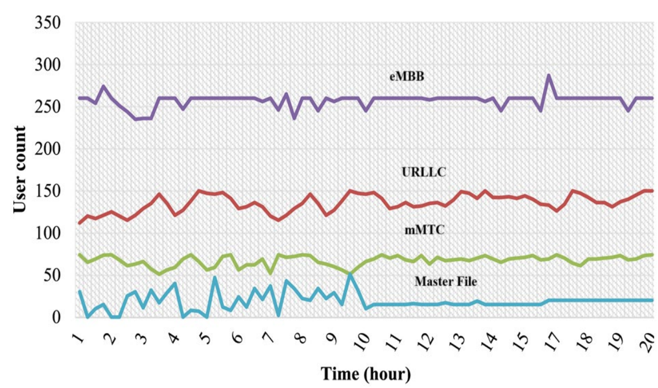

Figure 3 Load balancing in response to connection requests that go beyond a specified threshold

Figure 4 demonstrates that the proposed model had a failure state for the mMTC slice for two hours and fifteen minutes, precisely from 2:30 h to 4:45 h during one period, and an additional four hours from 13 h to 17 h. This experimental study selected the master slice as a backup file that accurately managed all network traffic during failure circumstances.

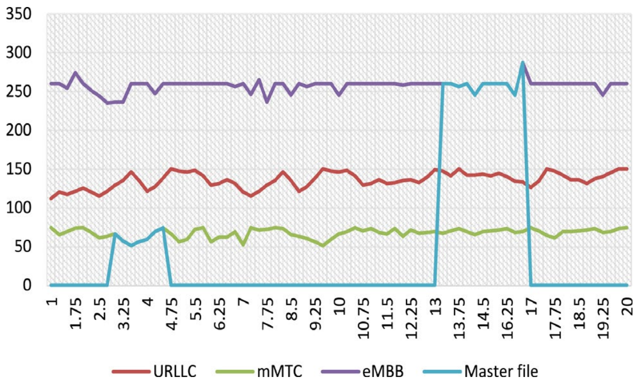

Figure 4 The mMTC slice relocation to the master slice after a failure

In the absence of the hybrid approach, slice failures and overloading resulted in a substantial increase in congestion, impacting over 25% of network slices during peak hours. Utilizing the Hybrid Model, congestion was diminished to below 10%, as the model effectively diverted traffic and alleviated the impact of slice failures. The hybrid model accurately forecasted future slice failures, and its traffic redistribution system offered alternative slices in real-time, thereby reducing the impact on overall network performance.

The suggested hybrid model (LSTM + SVM) was evaluated against baseline models, which included independent LSTM, independent SVM, and conventional congestion control techniques (e.g., Random Early Detection (RED) and Active Queue Management (AQM)). The standalone LSTM model demonstrated efficacy in forecasting traffic loads; nevertheless, it had difficulties in accurately classifying congestion, attaining an overall accuracy of 88.57%. Standalone SVM: The SVM independently attained an accuracy of 85.43%, exhibiting limited proficiency in managing time-series traffic data well.

RED and AQM: Conventional congestion control techniques exhibited worse performance, achieving accuracy levels below 80% and experiencing considerable delays in congestion detection and management. The suggested hybrid model surpassed existing baseline methods, exhibiting its enhanced capacity to predict and manage congestion effectively.

The experimental results demonstrate the efficacy of the hybrid deep learning-enabled approach in mitigating congestion in 5G/6G networks. Principal conclusions encompass: The model continuously attained elevated accuracy, precision, and recall under diverse traffic circumstances, evidencing its trustworthiness. The model's minimal latency and swift prediction capabilities render it appropriate for real-time congestion control in advanced networks. The model exhibited resilience in complex scenarios, effectively managing traffic surges, slice failures, and overloading, hence preserving network stability and mitigating congestion effects. Evaluation Against Baseline Models: The hybrid methodology integrating LSTM and SVM surpassed individual models and conventional techniques, providing a more effective solution for dynamic traffic management in 5G/6G contexts. The incorporation of LSTM for traffic forecasting and SVM for congestion categorization demonstrated efficacy in tackling the distinct issues presented by next-generation network topologies. The hybrid architecture alleviates congestion and improves network performance by optimizing resource allocation and ensuring service quality. In the subsequent section, we conclude the paper by offering insights into prospective research avenues for enhancing congestion control in 5G/6G networks.

4.0 CONCLUSION

Obtaining real-world datasets for congestion control analysis in 5G and 6G networks presents several constraints and difficulties. First, field data is often difficult to access due to privacy concerns and security protocols in place by telecom operators. Real-world traffic data typically includes sensitive user information, making it challenging to use such data without complying with strict regulations, such as data anonymization and legal consent processes. Furthermore, network data often varies significantly between different regions, network infrastructures, and operational conditions, making it difficult to compile a comprehensive and standardized dataset for research. Another challenge lies in the complexity of 5G and 6G networks themselves. These networks consist of numerous dynamic factors, such as varying traffic loads, geographic factors, user mobility, and network slice configurations, all of which introduce unpredictability. Capturing all these variables in real-time data, especially for unusual traffic conditions like slice failures, traffic surges, or overload situations, can be difficult. Moreover, collecting real-time data across various network slices, edge nodes, and different environmental conditions adds another layer of complexity in terms of infrastructure requirements. To overcome these challenges, researchers often rely on simulated data, which allows for controlled experiments but may not fully replicate the unpredictability and complexity of live traffic. Simulations are based on theoretical models and assumptions that may not fully capture the variability of real-world traffic patterns, leading to discrepancies when transitioning from theory to practice. Additionally, creating simulations that reflect the true diversity of conditions seen in 5G and 6G networks requires high computational resources, as well as access to network parameters that may not be readily available.

The future scope of this research involves several key advancements. First, it is essential to integrate real-world datasets, obtained either from live 5G/6G networks or through collaborations with telecom providers. This will enhance the accuracy of the model and allow for a more robust analysis of network congestion under varied and unpredictable real-world conditions. Incorporating data from different regions, network setups, and times of day will help generalize the model's capabilities across diverse environments. Furthermore, the hybrid deep learning model can be further refined to include additional real-world constraints, such as the impact of network slicing on congestion, varying QoS requirements, and user behavior patterns. The model can also be extended to include more advanced machine learning techniques, such as reinforcement learning, which could allow the system to dynamically adapt to real-time traffic patterns and optimize congestion control in an ongoing manner. Another potential direction for future research is to incorporate cross-layer optimization techniques, where congestion control is not limited to the traffic layer but also takes into account the radio, transport, and application layers. This would offer a more holistic solution to network congestion by considering interactions between different network components. Additionally, expanding the scope to include heterogeneous network environments, such as multi-access edge computing (MEC) and integration with Internet of Things (IoT) devices, will further enhance the model's versatility and applicability in next-generation 5G/6G networks. Ultimately, future work should focus on real-time, field-deployed testing to evaluate the model's performance in diverse and operational settings, ensuring its practical utility for improving network performance, reliability, and scalability in real-world 5G/6G networks.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper

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