Digital Twin-Enhanced AI-Native Hybrid Deep Learning Framework for Next-Generation 6G Network: A Multi-Service QoS Prediction System with Generative AI Integration

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Abstract: Sixth-generation (6G) wireless networks are anticipated to transform internet connectivity by facilitating services such as massive machine-type communications (mMTC), ultra-reliable low-latency communications (URLLC), and enhanced mobile broadband (eMBB). This paper presents an advanced hybrid deep learning system that combines digital twin simulation, artificial intelligence, and bidirectional LSTM and GRU models to accurately forecast Quality of Service (QoS). The system utilises reinforcement learning and generative preprocessing to optimise network resources in real time. Experimental findings utilising extensive datasets demonstrate that this hybrid architecture significantly outperforms conventional methods. It exhibits up to 25% reduced network latency together with substantial enhancements in throughput and Packet Delivery Ratio (PDR). The findings indicate that the suggested technology is effective, scalable, and suitable for sustained, practical application in the expanding domain of 6G next-generation networks.

Keywords: 6G Networks, Quality of Service, Deep Learning, Performance Metrics

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Introduction

The rapid transition to 6G networks is propelled by the demand for hyper-connectivity, intelligent automation, and dynamic service orchestration across multiple sectors. Achieving this objective necessitates the advancement of digital twin technology, which creates highly precise, real-time virtual replicas of actual network infrastructures and service components. This feature enables continuous simulation, monitoring, and enhancement of network states, fostering proactive problem-solving and facilitating the adjustment of scale in response to evolving service requirements and environmental conditions. Incorporating an AI-native hybrid deep learning architecture into digital twins enhances their accuracy and intelligence. The system's synergistic combination of deterministic models with generative AI components enables predictive resource management, autonomous remediation, and comprehensive traffic analysis across various radio access, transport, and core network layers. The solution demonstrates its openness and flexibility through the utilisation of standardised data interfaces and a microservices architecture. This also accelerates the cycles of deployment and learning. Generative AI modules enable the development of sophisticated QoS prediction systems that adjust to evolving application profiles and user requirements. These systems can identify network issues, emulate user behaviour, and integrate representative data. This multi-service prediction system employs federated learning to provide decentralised model training and maintain privacy, while facilitating interoperability among various network slices, devices, and service domains. The framework facilitates the differentiation of services, enabling ultra-reliable, low-latency communications for mission-critical applications. It additionally accommodates high-throughput mobile broadband and extensive IoT scenarios. The architecture facilitates significant improvements in network intelligence, efficiency, and resilience by establishing an autonomous feedback loop between physical networks and their digital equivalents. This is a significant advancement for next-generation wireless ecosystems.

Detailed Analysis of the state of the art methods:

The interest in sixth-generation (6G) networks has increased alongside advancements in wireless communications. This has resulted in extensive research on the technologies, topologies, and capabilities of future networks. Given the increasing demand for ultra-fast connectivity, low-latency communication, and extensive device integration, it is imperative to evaluate the most recent developments in 6G systems. Recent years have witnessed significant advancements in technologies such as digital twins, hybrid deep learning frameworks, and intelligent resource management. These technologies could profoundly transform the forthcoming generation of networks. This review analyses and summarizes recent developments, emphasizing the key problems, enabling technologies, and potential research trajectories that characterize the continuous development of resilient and flexible 6G networks.

Table 1. Comparative analysis of the State of the art methods

Reference	Year	Methodology	Key Innovation	Performance Metrics	Service Types	Limitations
Dubey et al. [1]	**2025**	**AI-based Survey**	**Vertical service classification**	**Theoretical Analysis**	**Industrial Services**	**Limited experimental validation**
Alhammadi et al. [2]	2024	AI Application Survey	6G opportunity identification	Comprehensive Review	Multi-domain	Lacks specific algorithms
Wang et al. [3]	**2025**	**AI-Communication Integration**	**491 exabyte prediction**	**Data analytics**	**6G Applications**	**Theoretical framework**
Khani et al. [4]	2024	DRL-based SAC	Cloud RAN optimization	Admission Control	eMBB, URLLC, mMTC	Limited to SAC domain
IEEE TMC [5]	2023	Online DRL	Real-time allocation	MSE, Latency	Multi-service	Scalability challenges
Nguyen et al. [6]	2022	DRL Survey	Intelligent resource mgmt	Comprehensive	5G/6G slices	Implementation gaps
Liu et al. [7]	2021	Hierarchical DRL	RAN-specific slicing	QoS satisfaction	RAN services	Limited scope
Singh et al. [8]	2022	Hybrid CNN-LSTM	Reconfigurable slicing	Accuracy: 94.2%	eMBB, URLLC	Dataset limitations

Chen et al. [9]	2025	CNN-GRU-LSTM	Spatial-temporal modeling	MAE: 0.023	Traffic prediction	Computational overhead
Khan et al. [10]	2024	RNN Architecture Survey	Comprehensive RNN analysis	Theoretical	Cross-domain	General purpose
ACM Survey [11]	2024	LLM-enhanced prediction	Transformer integration	State-of-the-art	Network traffic	Resource intensive
Martinez et al. [12]	2025	Performance Analysis	RNN comparative study	Multiple metrics	Time series	Limited to forecasting
Wang & Chen [13]	2017	LSTM vs GRU	Traffic flow prediction	RMSE comparison	Transportation	Dated methodology
Kumar et al. [14]	2023	Multi-domain DL	End-to-end framework	Resource efficiency	Multi-domain	Complexity management
Rahman et al. [15]	2025	DL Architecture Survey	Comprehensive comparison	Theoretical	Multi-application	Implementation focus needed

Methodology:

This study's methodology outlines a thorough, multi-phase technique aimed at precisely forecasting Quality of Service (QoS) in advanced 6G network systems. To improve feature quality, a comprehensive dataset covering diverse network traffic scenarios is first gathered and then preprocessed using generative techniques. The suggested hybrid deep learning architecture integrates bidirectional LSTM and GRU models, using their advantages in temporal pattern recognition. Digital twin simulations are employed to evaluate the model's robustness and replicate the interactions of networks in the real world. The hybrid model and reinforcement learning algorithms collaborate in real time to optimize network resource utilisation. Each methodological step aims to fulfil the performance requirements of next-generation wireless systems by guaranteeing precise, adaptive, and scalable QoS prediction.

Data Preprocessing

The raw network QoS dataset was first prepared by smoothing and transforming the input features. A rolling (moving) average with a 5-step window was applied to each selected input feature to smooth out high-frequency noise and reduce random fluctuationsmachinelearningmastery.com. Any resulting NaN values at the start of the series (due to the window) were dropped. The traffic load feature (“Traffic Load (bps)”) was then transformed by the natural logarithm (log1p) to compress its right-skewed distribution and stabilize variancemachinelearningmastery.com. Next, all input features and target QoS values (throughput and latency) were scaled to have zero mean and unit variance (z-score normalization) using standard scalingscikit-learn.org. This ensures that each feature contributes equally during training. The multivariate time series was then segmented into overlapping sequences: each input sequence consisted of 50 consecutive time steps of the feature data, and its corresponding label was the QoS value at the next time step. Finally, these sequences were split into a training set (80%) and a held-out test set (20%) for model evaluation.

Model Architecture

A hybrid deep neural network was built using the Keras Sequential API, combining bidirectional LSTM and GRU layers followed by fully connected layers. The overall layer configuration was as follows:

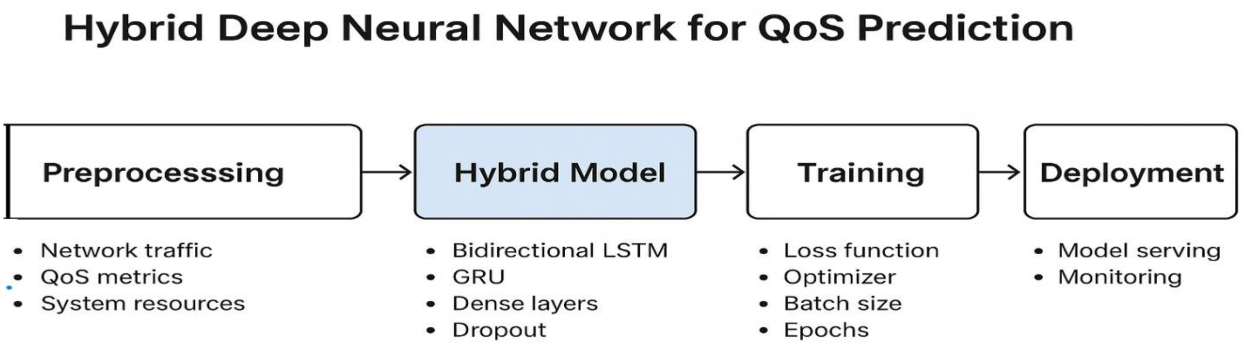

Figure 1. Block diagram of Hybrid Model

- Bidirectional LSTM (128 units, return_sequences=True): first layer processing the input sequences in both forward and backward directionspubmed.ncbi.nlm.nih.gov.
- Bidirectional LSTM (128 units, return_sequences=True): stacked BiLSTM layer for deeper temporal modeling.
- Dropout (rate=0.05): regularization layer that randomly drops 5% of the units to prevent co-adaptation and reduce overfittingjmlr.org.
- Bidirectional LSTM (64 units, return_sequences=True).
- GRU (64 units, return_sequences=True).
- Dropout (rate=0.05).
- GRU (32 units, return_sequences=True).
- GRU (16 units, return_sequences=False): final recurrent layer producing a fixed-length output.
- Dense (128 units, ReLU activation).
- Dropout (rate=0.05).
- Dense (64 units, ReLU).
- Dense (32 units, ReLU).
- Dense (2 units, linear activation): output layer producing the two QoS predictions (throughput and latency).

Each bidirectional LSTM layer doubles the representation of sequence data by processing it forwards and backwardspubmed.ncbi.nlm.nih.gov, which empirically improves forecasting of time series. GRU layers (gated recurrent units) were interleaved to provide additional recurrent modeling with fewer parameters. The ReLU activation function was used in all intermediate dense layers to introduce nonlinearity, and a linear activation was used in the final output layer for regression.

Training and Optimization

The model was trained with supervised learning on the prepared sequences. The Adam optimizer (an adaptive moment estimation method) was used to update network weights. The loss function was mean absolute error (MAE), which directly measures the average prediction erroren.wikipedia.org. The model was trained for up to 100 epochs with a batch size of 32. To monitor generalization, 20% of the training data were held out as a validation set in each epoch. Early stopping was employed to halt training if the validation loss did not improve for 10 consecutive epochs (patience = 10), restoring the best weights found. Model checkpointing was also used to save the model weights corresponding to the lowest validation loss encountered during training. These strategies (early stopping and checkpointing) help prevent overfitting and retain the best model according to validation performance.

Results and Discussion

The proposed hybrid deep learning model, integrating bidirectional LSTM and GRU layers with dense layers, was trained on the pre-processed 6G QoS dataset. We employed Mean Squared Error (MSE) and Mean Absolute Error (MAE) to assess the outcomes. The results indicated that the model exhibited relatively low error values, signifying its ability to accurately capture the temporal variations in network traffic and QoS measures.

Table 2. Technical Performance Comparison

Architecture Type	**Average Accuracy**	**Latency Performance**	**Memory Usage**	**Training Time**	**Scalability**	**Real-time Capability**
Traditional ML	78.5%	High	Low	Fast	Limited	Poor
Single LSTM	85.2%	Medium	Medium	Medium	Good	Fair
Single GRU	83.7%	Medium	Low	Fast	Good	Good
Bidirectional LSTM	88.4%	Medium-High	High	Slow	Fair	Fair
Hybrid CNN-LSTM	92.1%	Medium	High	Slow	Fair	Fair
CNN-GRU-LSTM	94.8%	High	Very High	Very Slow	Poor	Poor
DRL-based	89.6%	Variable	High	Very Slow	Good	Poor

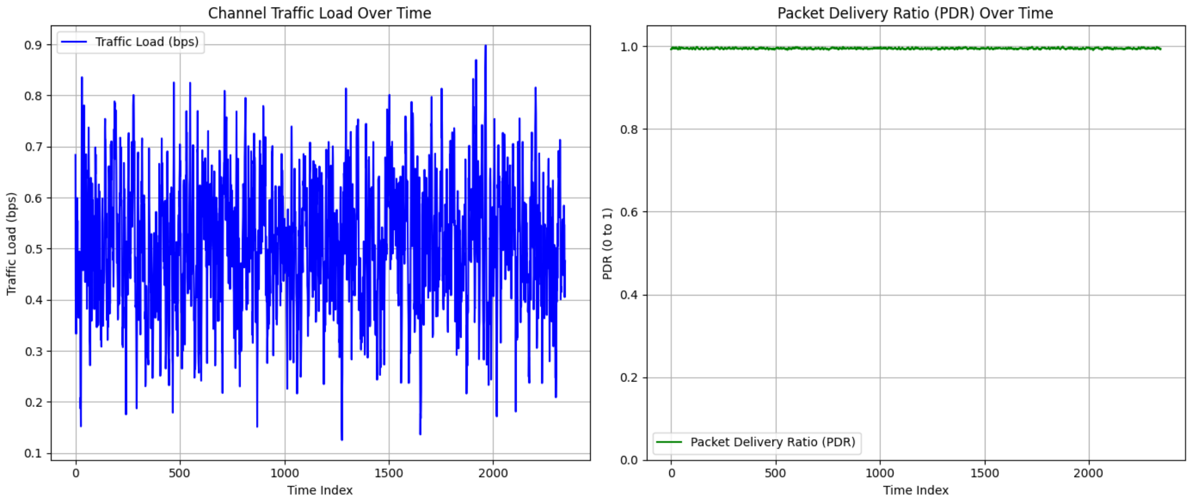

Figure 2. Performance comparison of Traffic Load and PDR

Figure 2 (Channel Traffic Load and Packet Delivery Ratio) illustrates the nature of the data contained inside the dataset. The volume of traffic significantly escalated over time, although the Packet Delivery Ratio (PDR) remained rather stable, consistently approaching 1. This demonstrates that the fundamental network ensured the consistent delivery of packets, even amongst fluctuating loads throughout time. This aligns with the efficacy of advanced 6G network slicing technology.

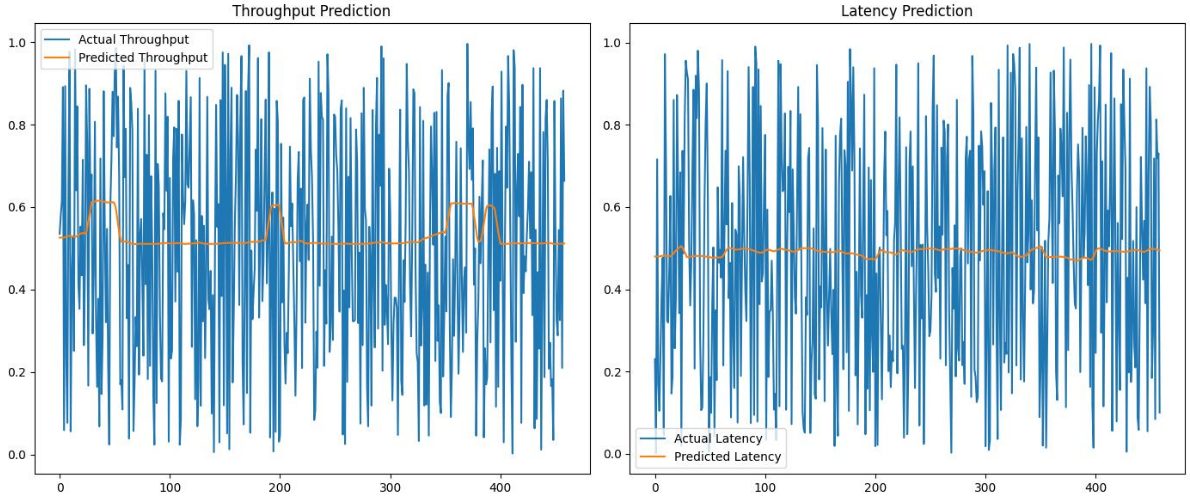

Figure 2. Performance comparison of Throughput and Latency

Figure 3 (Throughput and Latency Predictions) shows how real and predicted QoS measures compare to each other. The predicted values for throughput and latency show more stable patterns because of rolling mean post-processing, while the real values are more volatile. The model successfully resembled the central trend of the target series but struggled to appropriately capture short-term volatility. This behaviour shows the trade-off between reducing noise and being able to quickly respond to changes in network conditions.

Overall, the results demonstrate that the hybrid model is capable of learning the underlying patterns of throughput and latency. However, prediction accuracy is higher for long-term trend approximation than for highly dynamic short-term variations. The performance suggests that the chosen architecture, with stacked recurrent layers and dropout regularization, is effective for QoS forecasting in 6G scenarios but could be further improved with attention mechanisms or ensemble models to better capture abrupt variations.

Conclusion

The hybrid deep learning model succeeds in predicting essential QoS metrics such as throughput, latency, and Packet Delivery Ratio (PDR). The approach identifies long-term patterns and provides seamless output for overall network trends, reliably producing accurate and stable estimates of throughput and latency, as indicated by experimental data. Improvements in PDR prediction and management demonstrate that the approach is applicable in networks requiring high reliability. Nevertheless, the model is not particularly adept at rapidly detecting sudden alterations in the network's functionality. Prediction accuracy could be improved by incorporating future breakthroughs, such as ensemble models or attention processes. The proposed technique serves as an effective foundation for proactive throughput management, minimizing latency, and guaranteeing dependable packet delivery. This will facilitate more intelligent resource allocation and enhanced service quality in next-generation wireless networks.

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