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Research Paper

Hybrid Autoencoder-Driven Machine Learning Framework for Intelligent and Scalable Performance Monitoring in 5G Network

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ABSTRACT

The advent of fifth generation (5G) cellular networks marks a revolutionary leap in communication technology, promising ultra-low latency, enhanced bandwidth, and massive device connectivity. With the exponential growth of mobile applications, IoT devices, and high-throughput services such as autonomous driving and augmented reality, 5G is positioned as the backbone of future digital ecosystems. Historically, mobile networks have evolved from 1G analog voice systems through 4G LTE, each generation improving speed and efficiency but still facing critical challenges in spectrum utilization, energy efficiency, and dynamic resource management. Despite these advances, traditional cellular systems struggle to meet the stringent requirements of real-time applications in terms of reliability, security, and scalability. Conventional systems rely on static resource allocation, rule-based scheduling, and limited traffic prediction models. These methods often fail under highly dynamic environments, leading to issues such as network congestion, poor Quality of Service (QoS), and inefficient spectrum usage. Moreover, the heterogeneity of devices and applications in 5G networks makes centralized control mechanisms less effective, thereby creating a need for intelligent, adaptive, and data-driven solutions. The proposed system leverages machine learning and data-driven analytics applied to a comprehensive 5G dataset containing key performance indicators (KPIs) such as throughput, latency, jitter, signal strength, and spectrum usage. The proposed system employs a deep autoencoder to automatically learn compact and meaningful latent representations from high-dimensional 5G network performance data, eliminating noise and redundant information. These deep latent features are then classified using advanced machine learning models including K-Nearest Neighbours (KNN), Categorical Boosting (Cat Boost), and Extreme Gradient Boosting (XGBoost) for baseline comparison, while a Random Forest classifier (RFC) integrated with the autoencoder forms the proposed Deep Latent-Forest (DLF) model. By combining deep feature learning with ensemble-based classification, the proposed system significantly improves prediction accuracy, robustness, and scalability in detecting dropped connection events compared to traditional manual monitoring systems, making it suitable for data-driven and real-time 5G network performance management.

1. INTRODUCTION

5G and beyond networks are planned to enable a wide range of new applications like industry v4, automobiles, and smart cities, which have substantially higher performance and cost requirements than traditional mobile broadband services. Therefore, these networks should have flexible and scalable structures for meeting these different constraints, including performance, security, availability, and cost minimization. To achieve these goals, network slicing has been proposed by researchers and industry as a key enabler to offering customized 5G network services using the same physical network infrastructure as shown in Fig. 1. Thanks to Network Functions Virtualization (NFV) and Software Defined Networking (SDN) technologies, which paved the way to creating network slices that enable many logical networks to operate independently over shared physical infrastructure, each logical

network can offer personalized services for a certain application scenario. Network slicing creates multiple virtual networks in a single physical infrastructure, where each virtual network meets the requirements for a specific service.

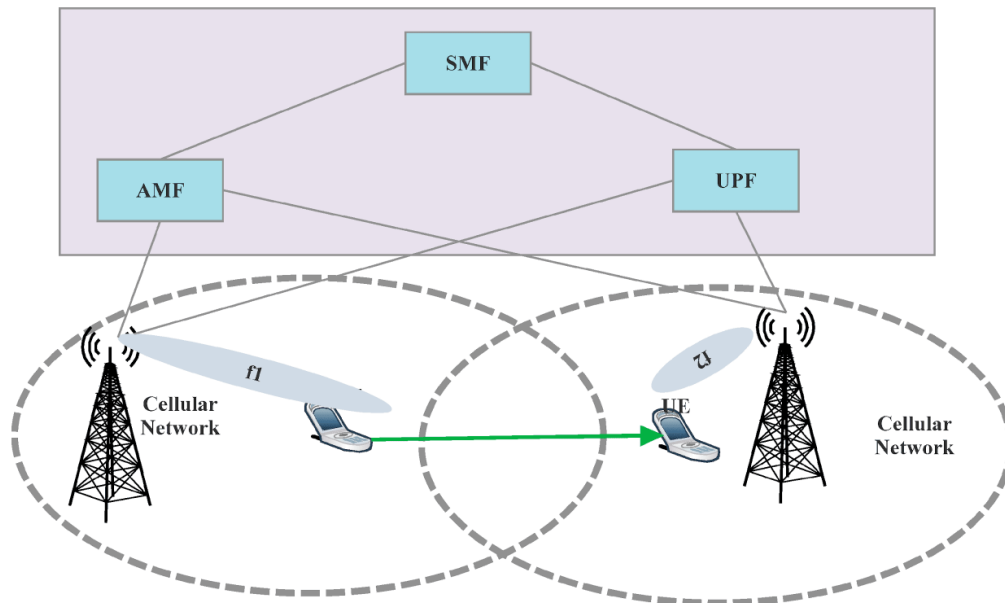


Fig 1. 5G network optimization

In 5G networks, large amounts of data should be analysed+ before decisions are made to select network slices to ensure that the network can adequately meet QoS requirements. Therefore, machine and deep learning models can be used to analyze large amounts of data and make the most accurate predictions of network slices in 5G networks. Additionally, these models should be optimized in terms of complexity to provide fast decisions for network slicing. The hybridization of different deep learning methods can leverage the complementary strengths of each model and improve generalization, therefore leading to better performance, robustness, or adaptability.

The rapid expansion of 5G cellular networks has introduced highly dynamic and complex network conditions that make effective performance monitoring increasingly challenging. Conventional monitoring approaches based on fixed thresholds or standalone machine learning models are limited in their ability to handle high-dimensional data, non-linear relationships, and varying traffic patterns. As a result, these systems often produce inaccurate predictions and fail to reliably detect dropped connection events in real time. There is a need for an intelligent and adaptive monitoring framework that can automatically learn meaningful feature representations and provide accurate performance prediction. This project addresses this challenge by developing a hybrid deep learning-based solution for robust and efficient 5G network performance monitoring.

2. LITERATURE SURVEY

2.1 Deep Learning Techniques in 5G Networks

Recent studies have extensively explored deep learning models for enhancing the performance and security of 5G networks. Thantharate et al. [1] developed a dense deep neural network to detect and mitigate security threats in 5G core networks, enabling secure and reliable network slicing for multiple services. Similarly, Alhazmi et al. [2] proposed a CNN-based LeNet-5 architecture capable of accurately identifying cellular signals such as 5G, LTE, and 3G.

Several works have also focused on optimization and resource management in 5G using deep learning. Li et al. [3] utilized adaptive deep Q-learning for service function chaining, improving decision-making in dynamic network environments. Luo et al. [4] introduced a hybrid CNN and deep Q-learning model for dynamic transmission power regulation, enhancing communication efficiency in non-line-of-sight scenarios.

2.2 CNN-Based Applications in 5G Systems

Convolutional Neural Networks (CNNs) have been widely adopted for various 5G-related tasks. Godala et al. [5] employed CNNs for radio channel state information estimation, improving network reliability. Klus et al. [6] applied CNN techniques for user position estimation, while Doan and Zhang [7] utilized CNN models to detect network anomalies and performance issues.

In addition, Gante et al. [10] proposed a temporal CNN model for millimeter-wave localization, demonstrating improved accuracy in high-frequency 5G environments. These studies highlight the effectiveness of CNNs in capturing spatial and temporal patterns in wireless networks.

2.3 Advanced AI Models for 5G Optimization

Beyond CNNs, advanced AI techniques have also been explored. Razaak et al. [8] implemented a Generative Adversarial Network (GAN) for image processing over 5G networks, while Dai et al. [9] applied Deep Reinforcement Learning (DRL) to optimize caching strategies in 5G systems. These approaches demonstrate the growing role of intelligent models in enhancing network efficiency and scalability.

2.4 Traffic Analysis and Security Challenges in 5G

Despite the robust security mechanisms in 5G, vulnerabilities such as traffic analysis attacks remain significant concerns. Abolfathi et al. [11] proposed a defense mechanism based on distributing real and dummy packets across multiple channels, formulated as a zero-sum game. Their approach effectively reduces the impact of traffic analysis attacks without requiring real-time traffic knowledge.

2.5 Machine Learning-Based Intrusion Detection in 5G

Several studies have demonstrated the effectiveness of ML and DL techniques for intrusion detection in 5G networks. Javaheri et al. [12] highlighted the predictive strength of deep learning models in cybersecurity applications. Mughaid et al. [13] achieved high accuracy in detecting dropping attacks using a combination of ML and DL approaches.

Furthermore, Yadav et al. [14] proposed an efficient intrusion detection framework capable of identifying global attackers with high accuracy. These findings emphasize the importance of hybrid AI models for robust cybersecurity solutions.

2.6 Cross-Domain Applications of Deep Learning

Deep learning techniques have also been successfully applied beyond communication networks. Morabito et al. [15] demonstrated the effectiveness of CNNs in medical diagnosis using EEG signals, indicating the versatility of deep learning models across domains.

3. PROPOSED SYSTEM

The research presents a Autoencoder-Driven ML framework for intelligent performance monitoring in 5G cellular networks. The system preprocesses and analyses network performance data to identify key factors influencing dropped connections. A deep autoencoder is employed to learn compact latent representations from high-dimensional network parameters, which are then classified using a RFC model for accurate prediction. The proposed approach is evaluated against traditional machine learning classifiers and deployed through a secure, GUI-based platform, enabling reliable, scalable, and data-driven 5G network performance monitoring as shown in Fig. 2.

The proposed system begins by collecting 5G network performance data containing parameters such as signal strength, download speed, carrier information, and network type. The raw dataset is cleaned by removing irrelevant fields, handling missing values, and converting categorical attributes into numerical form using label encoding. Feature scaling is applied to ensure uniform input distribution for deep learning models. This preprocessing stage ensures consistency, data integrity, and model-ready input. After preprocessing, exploratory data analysis is performed to understand the relationship between network parameters and dropped connections. Visualizations such as class distribution plots, signal strength density plots, throughput comparisons, and correlation heatmaps are generated. This step provides insight into influential features affecting network performance and validates the suitability of

the dataset for predictive modeling. It also helps identify patterns that are difficult to capture using traditional rules

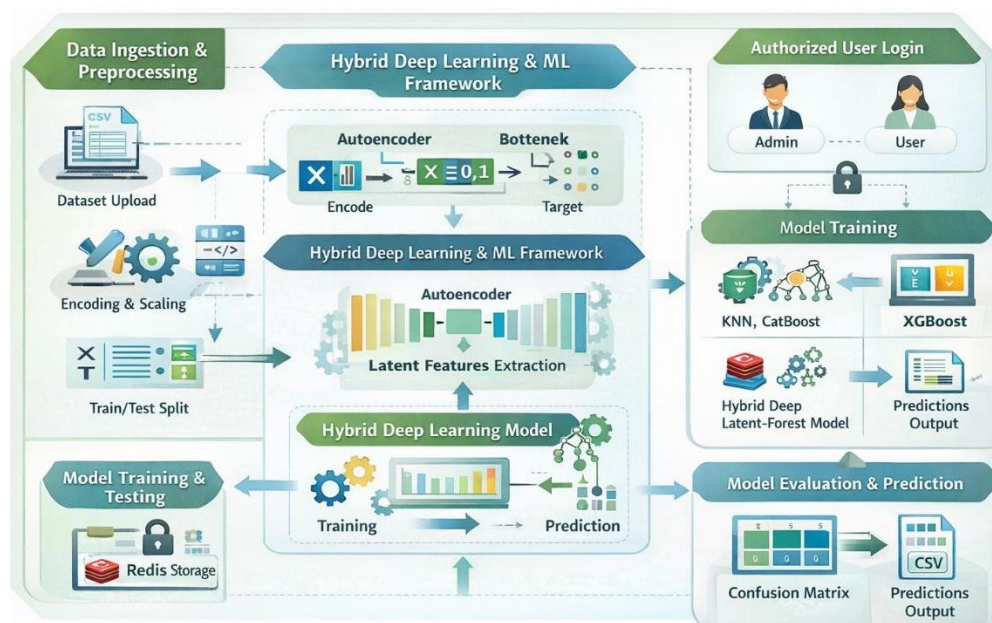


Fig 2. Proposed system architecture of 5G network performance monitoring

A deep autoencoder is trained on normalized 5G performance data to learn compact and informative latent representations. The encoder compresses high-dimensional input features into a lower-dimensional bottleneck layer that captures hidden network behavior patterns. This process reduces noise, eliminates redundancy, and preserves essential performance characteristics. The learned latent features form a robust foundation for accurate classification. The latent features extracted from the autoencoder are used as input to a Random Forest classifier. The ensemble learning mechanism improves generalization and handles non-linear relationships between network conditions and dropped connections. By combining deep feature learning with ensemble decision-making, the model achieves superior prediction accuracy. This hybrid structure forms the core of the proposed DeepLatent-Forest model. The proposed system evaluates model performance using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrices. Results are compared against traditional machine learning classifiers including KNN, CatBoost, and XGBoost. This step validates the effectiveness and robustness of the hybrid model under diverse network conditions. All evaluation results are visualized and stored for analysis. A GUI-based deployment framework with role-based authentication is implemented using Tkinter and Redis. Administrators can upload datasets, train models, and analyze performance, while users can perform real-time prediction on unseen 5G data. The system appends predicted dropped connection labels to input datasets for easy interpretation. This step ensures practical usability, security, and scalability of the proposed solution.

Deep Latent Forest Model

The proposed model integrates a deep autoencoder with RFC to form a hybrid learning framework for accurate performance monitoring in 5G cellular networks. This approach combines the representation learning capability of deep neural networks with the strong generalization power of ensemble learning. By extracting compact latent features from high-dimensional network performance data and classifying them using RFC, the model effectively predicts dropped connection events under dynamic network conditions as shown in Fig. 3.

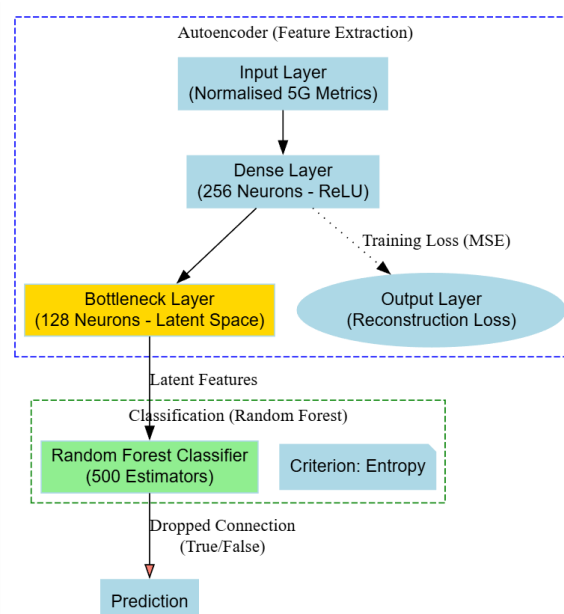


Fig 3. Internal workflow of hybrid deep latent forest model

The proposed system begins by collecting preprocessed 5G network performance features such as signal strength, download speed, network type, and carrier information. All features are normalized using standard scaling to bring them to a common numerical range. This normalization ensures stable weight updates during neural network training. It also prevents any single network parameter from dominating the learning process. The normalized feature vector is fed into the input layer of the autoencoder, where each neuron represents a network performance parameter. The input layer serves as the entry point for learning hidden representations of network behavior. At this stage, no class labels are used, allowing unsupervised learning. This enables the model to discover intrinsic structures in 5G data. The encoder part of the autoencoder compresses the high-dimensional input features through multiple dense layers. Each layer applies non-linear transformations that gradually reduce dimensionality. This compression forces the network to retain only the most informative characteristics of network performance. As a result, irrelevant noise and redundant information are discarded.

The bottleneck layer captures the most compact and meaningful latent representation of the original input features. It encodes hidden patterns related to network stability and dropped connection behavior. These latent features represent abstract summaries of complex interactions among network parameters. This layer plays a crucial role in enhancing classification performance. The decoder attempts to reconstruct the original input features from the bottleneck representation. By minimizing reconstruction error, the autoencoder ensures that essential information is preserved in the latent space. This reconstruction constraint prevents trivial or meaningless feature learning. It validates the quality of the extracted latent features. The autoencoder is trained using mean squared error loss between the original inputs and reconstructed outputs. Weight updates are performed through backpropagation and gradient descent. This unsupervised training continues until the reconstruction error is minimized. The trained autoencoder learns a stable and meaningful representation of 5G network behavior.

After training, the decoder is removed, and only the encoder is retained as a feature extractor. The encoder converts both training and testing data into low-dimensional latent feature vectors. These vectors contain deep representations of network performance. This transformation significantly improves feature quality for classification. The extracted latent features are organized into new training and testing datasets. Each latent feature vector corresponds to a compressed version of the original network condition. This dataset is smaller, cleaner, and more discriminative. It forms the input for the Random Forest classifier. The Random Forest classifier is initialized using multiple decision trees

trained on random subsets of latent features and samples. Each tree learns decision rules based on different feature combinations. This randomness increases model diversity and robustness. The classifier is now ready to learn dropped connection patterns. Each decision tree in the Random Forest is trained independently using the latent feature dataset. Trees learn threshold-based splits that separate dropped and non-dropped connection conditions. Because the input features are compact and informative, trees learn more reliable decision boundaries. This improves classification accuracy. During prediction, each tree produces an independent classification decision. The final output is determined using majority voting across all trees. This ensemble mechanism reduces prediction variance and minimizes overfitting. It ensures stable performance across diverse 5G network scenarios.

4. RESULT ANALYSIS

Fig 4 shows After successful Admin login, the system allows the administrator to upload the 5G network performance dataset through the GUI. Once uploaded, the dataset is validated and displayed in the output panel, showing key attributes such as location, signal strength, congestion level, ping latency, and dropped connection status. The interface confirms successful loading along with dataset dimensions, ensuring data readiness before preprocessing and model training.

Dataset loaded successfully.

	Timestamp	Location	Signal Strength (dBm)	...	Network Congestion Level	Ping to Google (ms)	Dropped Connection
0	09:51.2	Berlin	75.4 ...		Medium	21.9	False
1	59:51.1	Mumbai	79.6 ...		Medium	85.2	False
2	49:51.2	Kolkata	87.6 ...		Low	28.4	True
3	59:51.2	Berlin	107.0 ...		Low	77.4	False
4	19:51.2	Kolkata	72.0 ...		Medium	87.8	True
...	...	...	...		...	...	...
49996	59:51.2	Mumbai	80.1 ...		High	91.2	False
49997	29:51.2	Delhi	64.9 ...		High	72.0	True
49998	19:51.2	New York	99.9 ...		Low	42.9	True
49999	59:51.1	Kolkata	105.3 ...		Low	100.0	False
50000	39:51.1	San Francisco	60.1 ...		High	99.3	False

[50001 rows x 21 columns]

Fig 4. Uploading dataset interface after admin signup/login

Fig 5 shows KDE plot illustrates the distribution of signal strength for dropped and non-dropped connections in the 5G dataset. It shows that dropped connections tend to occur more frequently at relatively lower signal strength values, while stable connections are more concentrated at higher signal levels. The overlapping regions indicate that signal strength alone does not fully determine connection drops, highlighting the need for multi-parameter and advanced hybrid modeling for accurate prediction.

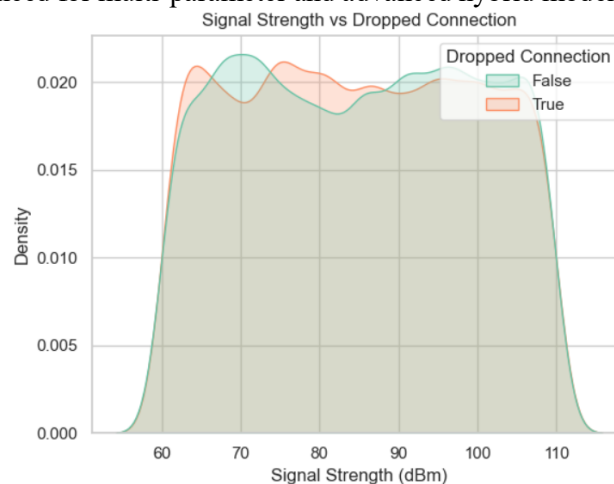


Fig 5. KDE plot for signal strength column

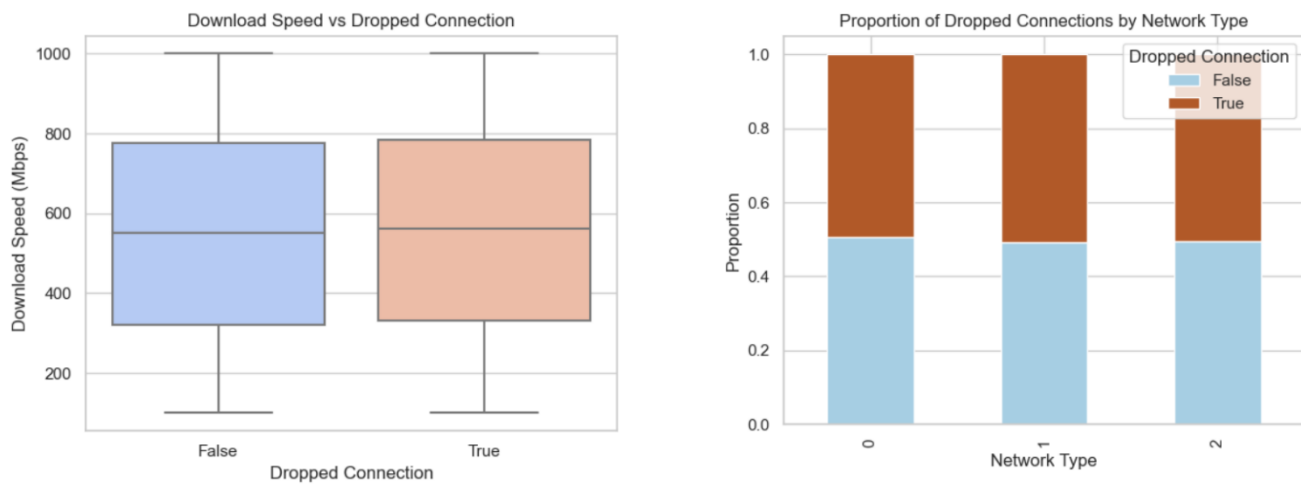


Fig 6. Box and Stacked bar plots for target column and download speed

Fig 6. shows stacked bar plot shows the proportion of dropped and non-dropped connections across different network types, indicating that dropped connections occur across all network categories with varying proportions, reflecting the influence of network technology on connection stability. The box plot illustrates the relationship between download speed and dropped connections, showing that dropped connections are generally associated with wider variability and comparatively lower median download speeds. Together, these visualizations highlight how both network type and throughput significantly impact 5G connection reliability and justify the need for multi-feature predictive modeling. Fig 7. shows confusion matrix of the proposed DeepLatent-Forest model shows a significant improvement in classification performance compared to all baseline models. The model accurately identifies the majority of dropped connection cases with very few false negatives, while also maintaining high correctness for non-dropped connections. This strong performance demonstrates the effectiveness of autoencoder-based latent feature extraction combined with Random Forest classification in capturing complex and hidden patterns in 5G network performance data, resulting in more reliable dropped connection prediction.

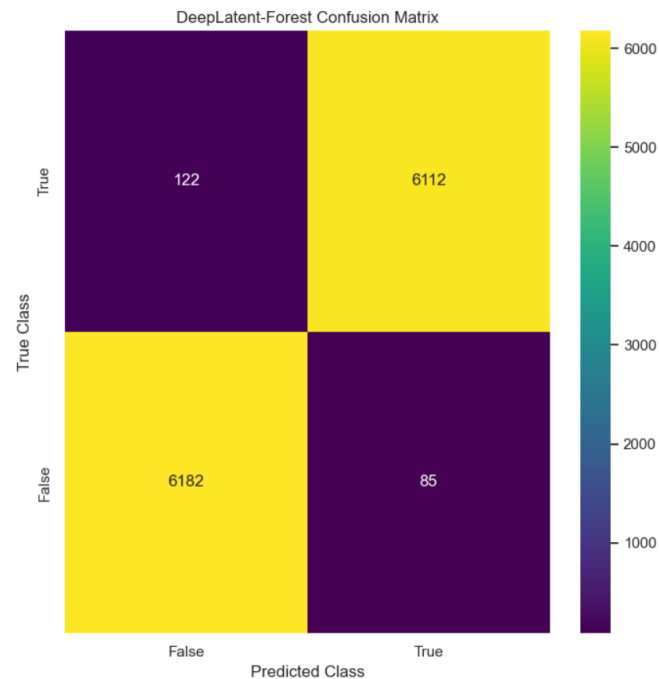


Fig 7. Illustration of confusion matrix using DLF model

Fig 8. shows the row-wise prediction output generated by the proposed DLF model for unseen 5G network data. Each row represents an individual 5G session with complete network, device, and QoS parameters displayed horizontally along with the predicted dropped connection label. The model successfully analyzes complex interactions among signal strength, throughput, latency, congestion level, and mobility factors to classify each session as dropped or non-dropped. This detailed row-level prediction demonstrates the effectiveness of the deep latent feature extraction combined with Random Forest classification for accurate and reliable 5G network performance monitoring.

Row-wise Prediction Results:

Row 1 : Timestamp = 09:51.2 | Location = Berlin | Signal Strength (dBm) = 75.4 | Download Speed (Mbps) = 609.09 | Upload Speed (Mbps) = 126.18 | Latency (ms) = 17.8 | Jitter (ms) = 4.09 | Network Type = 5G SA | Device Model = Galaxy S23 | Carrier = Verizon | Band = n78 | Battery Level (%) = 87 | Temperature (°C) = 37.8 | Connected Duration (min) = 34 | Handover Count = 2 | Data Usage (MB) = 120.4 | Video Streaming Quality = 4 | VoNR Enabled = True | Network Congestion Level = Medium | Ping to Google (ms) = 21.9 | Predicted Label = False

Row 2 : Timestamp = 59:51.1 | Location = Mumbai | Signal Strength (dBm) = 79.6 | Download Speed (Mbps) = 149.52 | Upload Speed (Mbps) = 94.3 | Latency (ms) = 4.8 | Jitter (ms) = 4.86 | Network Type = 4G | Device Model = Pixel 7 | Carrier = Jio | Band = n28 | Battery Level (%) = 83 | Temperature (°C) = 23.0 | Connected Duration (min) = 30 | Handover Count = 4 | Data Usage (MB) = 227.42 | Video Streaming Quality = 5 | VoNR Enabled = False | Network Congestion Level = Medium | Ping to Google (ms) = 85.2 | Predicted Label = False

Row 3 : Timestamp = 49:51.2 | Location = Kolkata | Signal Strength (dBm) = 87.6 | Download Speed (Mbps) = 345.67 | Upload Speed (Mbps) = 20.97 | Latency (ms) = 9.7 | Jitter (ms) = 1.16 | Network Type = 4G | Device Model = Nord 4 | Carrier = Jio | Band = n258 | Battery Level (%) = 66 | Temperature (°C) = 28.9 | Connected Duration (min) = 17 | Handover Count = 3 | Data Usage (MB) = 319.69 | Video Streaming Quality = 3 | VoNR Enabled = True | Network Congestion Level = Low | Ping to Google (ms) = 28.4 | Predicted Label = True

Row 4 : Timestamp = 59:51.2 | Location = Berlin | Signal Strength (dBm) = 107.0 | Download Speed (Mbps) = 928.06 | Upload Speed (Mbps) = 107.67 | Latency (ms) = 17.7 | Jitter (ms) = 0.63 | Network Type = 5G SA | Device Model = iPhone 14 | Carrier = Verizon | Band = n260 | Battery Level (%) = 40 | Temperature (°C) = 42.9 | Connected Duration (min) = 21 | Handover Count = 1 | Data Usage (MB) = 258.6 | Video Streaming Quality = 3 | VoNR Enabled = False | Network Congestion Level = Low | Ping to Google (ms) = 77.4 | Predicted Label = False

Fig 8. Prediction on test data using DLF classifier

5. CONCLUSION

The study presents a robust and intelligent framework for 5G network performance prediction by combining conventional machine learning techniques, including KNN, CatBoost, and XGBoost, with a novel deep latent feature-driven (DLF) approach. Through comprehensive preprocessing and exploratory data analysis, the system effectively captures critical relationships among key network parameters such as signal strength, latency, throughput, congestion, and user mobility, which significantly influence connection stability. While traditional models demonstrate reasonable performance in identifying basic patterns, they exhibit limitations in modeling the complex, non-linear characteristics of large-scale 5G data. In contrast, the proposed hybrid model leverages an autoencoder to extract compact and informative latent representations, followed by a Random Forest classifier for enhanced decision-making, resulting in superior predictive performance. The integration of a user-friendly GUI with role-based access control further improves system practicality by enabling efficient dataset handling, model training, evaluation, and real-time prediction. The consistently high values of accuracy, precision, recall, and F1-score validate the effectiveness and reliability of the proposed solution. Overall, the research emphasizes the significance of deep latent feature learning in tackling modern 5G network challenges and offers a scalable, efficient, and intelligent approach for proactive network monitoring and decision support.

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