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# EXPLAINABLE AI-DRIVEN NETWORK TRAFFIC FORECASTING AND QOS OPTIMIZATION USING REINFORCEMENT LEARNING IN 5G/6G NETWORKS

**Dr. Deepak Tomar,*[1] Dr. Anil Kewat,[2] Prof. AlokVerma,[3] Dr. Kismat Chhillar[4]**

[1]*System Analyst, Computer Center, Bundelkhand University, Jhansi, Uttar Pradesh, India.*

[2]*Assistant Professor, Dept. of Mathematical Sciences and Computer Applications, Bundelkhand University, Jhansi, Uttar Pradesh, India.*

[3]*Professor, Dept. of Mathematical Sciences & Computer Applications, Bundelkhand University, Jhansi, Uttar Pradesh, India.*

[4]*AssistantProfessor, Dept. of Mathematical Sciences and Computer Applications, Bundelkhand University, Jhansi, Uttar Pradesh, India.*

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***Corresponding Author: Dr. Deepak Tomar**

System Analyst, Computer Center, Bundelkhand University, Jhansi, Uttar Pradesh, India.

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## ABSTRACT

The rapid evolution of 5G and emerging 6G networks has introduced unprecedented challenges in managing highly dynamic, heterogeneous, and latency-sensitive traffic patterns, necessitating intelligent and adaptive solutions for network optimization. This paper proposes an integrated framework that combines explainable artificial intelligence with reinforcement learning to enable accurate network traffic forecasting and efficient quality of service optimization in next-generation communication systems. A deep learning-based forecasting module predicts future traffic using historical and contextual data, and these predictions guide a reinforcement learning agent to dynamically allocate resources and optimize routing in real time. To address the critical challenge of interpretability in autonomous network management, explainable AI techniques such as SHAP and LIME are incorporated to provide transparent insights into both forecasting outputs and decision-making policies. The proposed approach not only enhances key QoS metrics, including latency, throughput, and packet loss, but also improves trustworthiness and accountability in AI-driven network operations. Experimental evaluation using simulated network environments demonstrates that the integration of predictive analytics, reinforcement learning, and explainability significantly

outperforms conventional optimization methods, offering a scalable and intelligent solution for future self-organizing 5G and 6G networks.

**KEYWORDS:** Explainable AI, Reinforcement Learning, Network Traffic Forecasting, QoS Optimization, 5G/6G Networks, Deep Learning

## 1. INTRODUCTION

The rapid proliferation of data-intensive applications, ranging from ultra-high-definition video streaming and augmented reality to mission-critical Internet of Things deployments, has significantly transformed the operational landscape of modern communication networks. In the context of fifth-generation and emerging sixth-generation systems, the demand for ultra-reliable, low-latency, and high-throughput communication has intensified, placing unprecedented pressure on network infrastructure [1]. Traditional rule-based and static optimization techniques are increasingly inadequate for handling the highly dynamic and heterogeneous traffic patterns observed in these networks. Consequently, there is a growing need for intelligent, adaptive, and scalable solutions that can proactively manage network resources while ensuring stringent quality of service requirements. One of the fundamental challenges in next-generation networks lies in accurately forecasting traffic patterns to enable proactive decision-making. Network traffic exhibits complex temporal and spatial dependencies, influenced by user behavior, mobility patterns, and service heterogeneity. Conventional statistical models often fail to capture these nonlinear dynamics, thereby limiting their predictive capabilities. In contrast, deep learning approaches, particularly recurrent and attention-based architectures, have demonstrated significant potential in modeling complex time-series data [2]. By leveraging historical traffic data and contextual network information, these models can provide accurate short-term and long-term forecasts, which are essential for anticipatory resource allocation and congestion avoidance in 5G and 6G environments.

While traffic forecasting provides valuable insights into future network states, it must be complemented by intelligent control mechanisms to translate predictions into actionable decisions. Reinforcement learning has emerged as a powerful paradigm for sequential decision-making in dynamic environments, enabling agents to learn optimal policies through interaction with the network [3]. In the domain of communication networks, reinforcement learning techniques have been successfully applied to problems such as bandwidth allocation, routing optimization, and congestion control. By continuously adapting to changing network conditions and learning from feedback, reinforcement learning agents can optimize quality of service metrics in real time, thereby enhancing overall network performance and efficiency. Despite the promising capabilities of deep learning and reinforcement learning, their adoption in network management is often hindered by the lack of transparency and interpretability. The black-box nature of these models raises concerns regarding trust, accountability, and reliability, particularly in critical applications where decision-making must be explainable to network operators and stakeholders. Explainable artificial intelligence addresses this challenge by providing insights into model behavior, feature importance, and decision rationale [4]. By integrating explainability techniques into both traffic forecasting and reinforcement learning components, it becomes possible to enhance the transparency of AI-driven network operations, thereby facilitating informed decision-making and increasing user confidence in automated systems.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature on network traffic forecasting, reinforcement learning-based quality of service optimization, and explainable artificial intelligence in networking. Section 3 presents the system model and formulates the optimization problem in the context of 5G and 6G networks. Section 4 describes the proposed explainable AI-driven framework, detailing the integration of forecasting models, reinforcement learning mechanisms, and interpretability techniques. Section 5 outlines the experimental setup, including datasets, simulation environment, and evaluation metrics. Section 6 discusses the results and analyzes the performance of the proposed approach in comparison with baseline methods. Finally, Section 7 concludes the paper and highlights potential directions for future research.

## 2. Literature Review

The domain of intelligent network management in next-generation communication systems has witnessed significant advancements driven by the convergence of machine learning, deep learning, and optimization techniques. In the context of 5G and emerging 6G networks, the complexity of traffic dynamics, heterogeneous service requirements, and stringent Quality of Service constraints have necessitated the development of predictive and adaptive mechanisms. Existing research has largely evolved along three parallel directions, namely network traffic forecasting, reinforcement learning-based QoS optimization, and explainable artificial intelligence. While each of these domains has matured independently with notable contributions, their integration into a cohesive and interpretable framework remains an emerging research frontier. This section critically examines prior work across these dimensions and identifies key gaps that motivate the proposed approach.

### 2.1 Network Traffic Forecasting

Network traffic forecasting has traditionally relied on statistical and time-series models such as autoregressive integrated moving average and exponential smoothing techniques. These models have been widely used due to their simplicity and interpretability, particularly in relatively stable network environments. However, with the advent of 5G networks characterized by highly dynamic, bursty, and heterogeneous traffic patterns, the limitations of these classical approaches have become evident [5]. They often fail to capture nonlinear dependencies and long-range temporal correlations inherent in modern network data. Consequently, researchers have increasingly shifted toward machine learning approaches, including support vector regression and ensemble methods, which offer improved predictive capabilities but still struggle with scalability and adaptability in real-time scenarios [6].

In recent years, deep learning-based models have emerged as the dominant paradigm for network traffic prediction [7]. Architectures such as long short-term memory networks and gated recurrent units have demonstrated strong performance in capturing temporal dependencies, while transformer-based models have further enhanced forecasting accuracy through attention mechanisms that focus on relevant traffic patterns [8]. These models are capable of learning complex representations from large-scale datasets, enabling more accurate predictions under varying network conditions. Nevertheless, challenges persist in terms of computational overhead, data requirements, and the black-box nature of deep learning models, which limits their interpretability and hinders their adoption in critical network management systems [9].

### 2.2 Reinforcement Learning for QoS Optimization

Reinforcement learning has gained considerable attention as a powerful framework for dynamic decision making in network environments [10]. Unlike traditional optimization techniques that rely on predefined rules or static policies, reinforcement learning enables agents to learn optimal strategies through interaction with the environment. In the context of QoS optimization, RL has been applied to problems such as resource allocation, traffic routing, congestion control, and spectrum management [11]. Early approaches primarily utilized tabular Q-learning methods, which were effective in small-scale environments but faced scalability issues as the state and action spaces expanded in complex network scenarios [12].

The introduction of deep reinforcement learning has significantly enhanced the applicability of RL in large-scale and high-dimensional network systems [13]. Techniques such as Deep Q Networks, policy gradient methods, and actor-critic architectures have been employed to enable real-time adaptation to changing network conditions. These methods have demonstrated substantial improvements in key QoS metrics, including reduced latency, increased throughput, and better load balancing [14]. Despite these advancements, several challenges remain, including convergence instability, high training complexity, and sensitivity to reward function design. Moreover, the lack of transparency in RL decision-making processes raises concerns regarding trust and accountability, particularly in mission-critical 5G/6G applications where explainability is essential [15].

### 2.3 Explainable AI in Networking

Explainable artificial intelligence has emerged as a critical research area aimed at addressing the opacity of complex machine learning models [16]. In network management applications, where decisions directly impact service quality and operational efficiency, the ability to interpret and justify model outputs is of paramount importance [17]. Traditional rule-based systems offered inherent transparency, but modern AI-driven approaches often function as black boxes, making it difficult for network operators to understand the rationale behind predictions and actions [18]. This has led to the adoption of XAI techniques such as SHAP, LIME, and attention-based visualization methods, which provide insights into feature importance and model behavior [19].

In networking contexts, XAI has been applied to tasks such as anomaly detection, intrusion detection, and traffic classification [20]. These approaches enable operators to identify critical factors influencing model decisions and enhance situational awareness. Furthermore, explainability contributes to improved model debugging, regulatory compliance, and user trust [21]. However, the integration of XAI with dynamic and sequential decision-making models such as reinforcement learning remains relatively underexplored [22]. Existing methods often focus on static prediction models and do not adequately address the temporal and stochastic nature of RL-based systems. As a result, there is a growing need for tailored explainability techniques that can effectively interpret both forecasting models and RL agents within a unified framework [23].

### 2.4 Research Gaps

Despite substantial progress in traffic forecasting, reinforcement learning, and explainable AI, the existing body of research reveals several critical gaps. Most notably, these domains have largely been investigated in isolation, with limited efforts toward their holistic integration. Traffic forecasting models are often developed independently of decision-making frameworks, resulting in suboptimal utilization of predictive insights. Similarly, reinforcement learning-based QoS optimization approaches typically rely on real-time observations without leveraging accurate traffic predictions, which could significantly enhance decision quality. This lack of synergy restricts the overall effectiveness of intelligent network management systems.

Another major gap lies in the limited incorporation of explainability into end-to-end network optimization frameworks. While XAI techniques have been successfully applied to supervised learning models, their application to reinforcement learning and hybrid architectures remains insufficient. The absence of transparent decision-making mechanisms poses challenges for practical deployment, particularly in critical infrastructures where accountability and trust are essential. Additionally, issues related to scalability, real-time processing, and adaptability to evolving network conditions continue to persist. Addressing these gaps requires the development of integrated, interpretable, and efficient frameworks that can simultaneously forecast traffic, optimize QoS, and provide meaningful explanations, thereby paving the way for next-generation intelligent networking solutions.

## 3. Proposed Framework

The proposed framework presents an integrated and intelligent architecture that combines deep learning-based traffic forecasting, reinforcement learning-driven Quality of Service optimization, and explainable artificial intelligence to enable transparent and adaptive network management in 5G and emerging 6G environments. Unlike conventional approaches that treat prediction and decision-making as separate processes, this framework establishes a tightly coupled pipeline where predictive insights directly inform optimization strategies. At the same time, an explainability layer ensures that both forecasting outputs and reinforcement learning actions remain interpretable to network operators. The design emphasizes scalability, real-time responsiveness, and adaptability to highly dynamic traffic conditions, thereby addressing key challenges in next-generation communication systems. Figure 1 demonstrates the proposed framework.

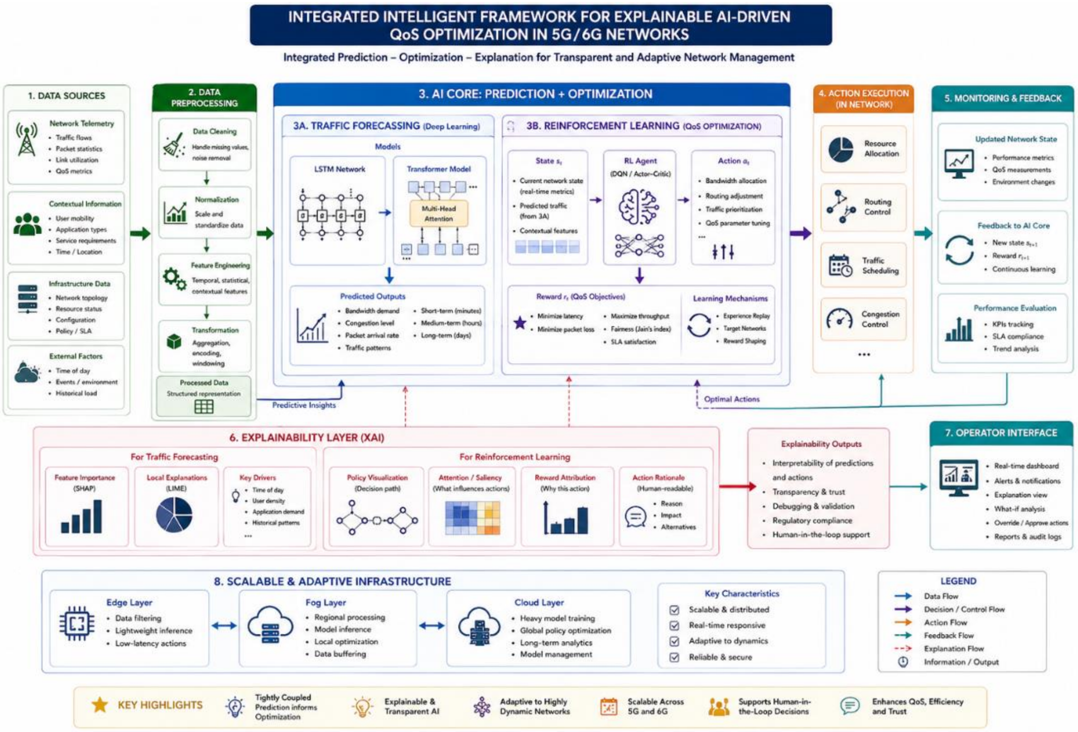


**Figure 1: Proposed Framework.**

### 3.1 System Architecture

The overall system architecture is organized into multiple interconnected layers that collectively enable efficient data processing, intelligent decision-making, and transparent output generation. The data collection layer gathers real-time network telemetry, including traffic flows, packet-level statistics, QoS indicators, and contextual information such as user mobility and service types. This raw data is subsequently passed to a preprocessing module, where it undergoes cleaning, normalization, and feature extraction to ensure consistency and relevance. The processed data is then fed into the core AI layer, which integrates traffic forecasting models, reinforcement learning agents, and explainability modules in a coordinated manner. This layered design ensures modularity, allowing individual components to be updated or optimized without disrupting the entire system.

In addition to modularity, the architecture is designed to support distributed deployment across edge, fog, and cloud environments, which is particularly important for latency-sensitive 5G/6G applications. Edge nodes can perform preliminary data filtering and lightweight inference, while more computationally intensive tasks such as deep model training and global policy optimization are handled in the cloud. Communication between these layers is facilitated through high-speed interfaces and streaming platforms, enabling seamless data flow and real-time decision-making. This hierarchical structure not only enhances scalability but also ensures that the framework can operate efficiently under varying network loads and heterogeneous infrastructure conditions. Figure 2 shows the system architecture.

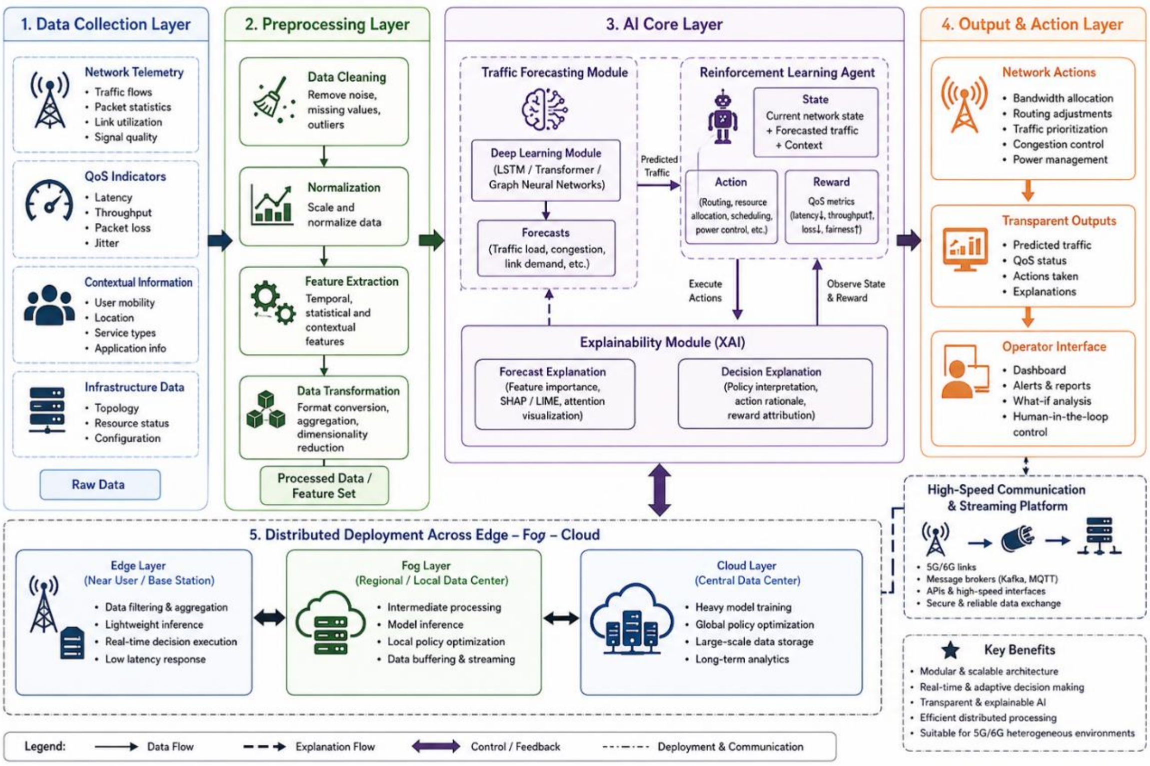


**Figure 2: System Architecture.**

### 3.2 Traffic Forecasting Module

The traffic forecasting module is responsible for predicting future network conditions based on historical and contextual data. It employs advanced deep learning architectures such as long short-term memory networks or transformer-based models, which are particularly effective in capturing temporal dependencies and complex traffic patterns. These models are trained on large-scale datasets to learn both short-term fluctuations and long-term trends in network traffic, enabling accurate predictions of parameters such as bandwidth demand, congestion levels, and packet arrival rates. By leveraging these predictions, the system can anticipate potential bottlenecks and proactively adjust resource allocation strategies.

Beyond predictive accuracy, the forecasting module is designed to operate in near real-time, continuously updating its predictions as new data becomes available. This is achieved through incremental learning techniques and sliding window mechanisms that allow the model to adapt to evolving traffic patterns without requiring complete retraining.

Furthermore, the integration of contextual features such as application types, user behavior, and network topology enhances the robustness of predictions. Despite its effectiveness, the complexity of deep learning models introduces challenges related to computational overhead and interpretability, which are addressed in the framework through optimization strategies and the incorporation of explainability mechanisms. Figure 3 illustrates the traffic forecasting module.

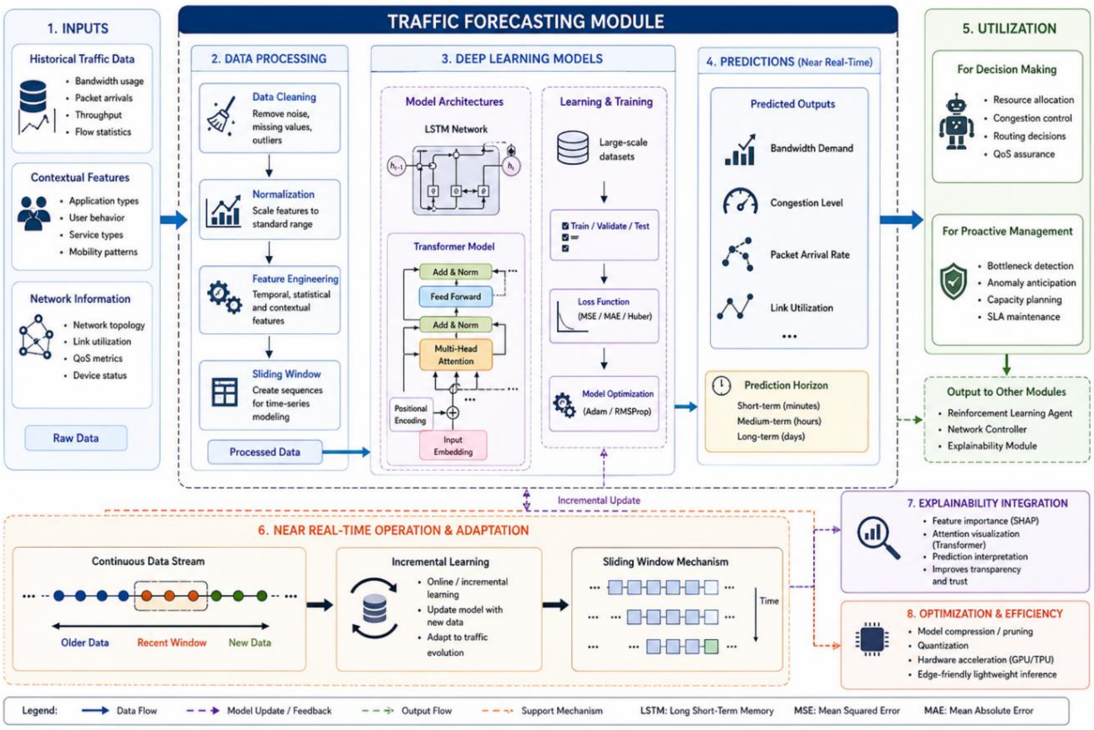


**Figure 3: Traffic Forecasting Module.**

### 3.3 Reinforcement Learning-Based QoS Optimization

The reinforcement learning component of the framework is tasked with dynamically optimizing QoS parameters by learning optimal policies through continuous interaction with the network environment. The RL agent operates by observing the current state of the network, which includes both real-time metrics and predicted traffic conditions generated by the forecasting module. Based on this state representation, the agent selects actions such as bandwidth allocation, routing adjustments, or traffic prioritization, with the objective of maximizing a cumulative reward function. This reward function is carefully designed to reflect key QoS objectives, including minimizing latency, reducing packet loss, and maximizing throughput and fairness among users. Figure 4 shows the reinforcement learning component.

To handle the complexity of modern network environments, the framework utilizes advanced deep reinforcement learning techniques such as Deep Q Networks or actor-critic models. These approaches enable the agent to manage high-dimensional state and action spaces while adapting to rapidly changing conditions. The inclusion of predicted traffic data as part of the state space significantly enhances the agent's ability to make proactive decisions rather than reactive ones. However, challenges such as convergence stability, exploration-exploitation trade-offs, and sensitivity to reward design are carefully addressed through techniques like experience replay, target networks, and reward shaping. This results in a robust and adaptive QoS optimization mechanism capable of operating effectively in large-scale 5G/6G networks.

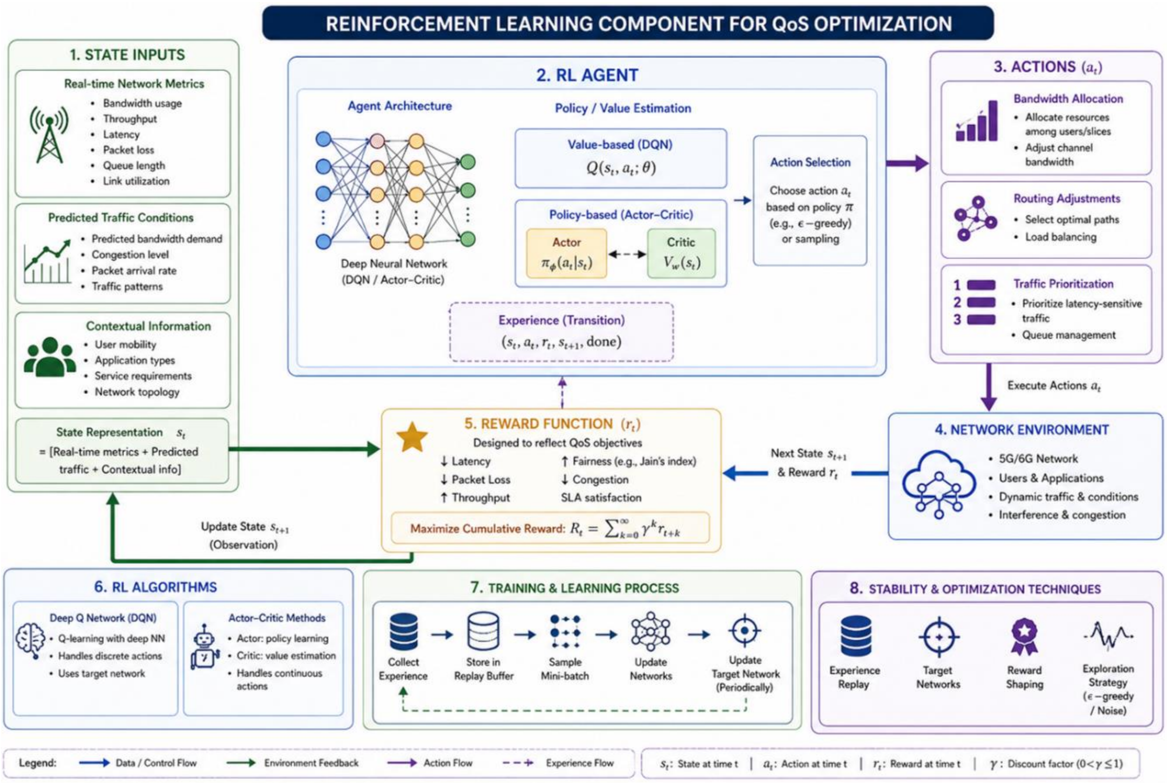


**Figure 4: Reinforcement Learning Component.**

### 3.4 Explainability Module

The explainability module plays a crucial role in ensuring that the decisions made by both the forecasting and reinforcement learning components are transparent and interpretable. It leverages established explainable AI techniques such as SHAP and LIME to analyze the contribution of individual features to model predictions. For the traffic forecasting module, this involves identifying key factors influencing predicted traffic patterns, such as time-of-day variations, user density, or application-specific demands. These insights are presented through visualizations and summary statistics, enabling network operators to understand and validate the model's behavior.

In the context of reinforcement learning, explainability becomes more complex due to the sequential and dynamic nature of decision-making. To address this, the framework incorporates techniques such as policy visualization, reward attribution, and attention-based mechanisms that highlight the factors influencing specific actions. These explanations help operators interpret why certain QoS adjustments were made under particular network conditions, thereby enhancing trust and facilitating debugging. Additionally, the explainability module supports compliance with regulatory requirements and provides a foundation for human-in-the-loop decision-making, ensuring that automated actions can be monitored and, if necessary, overridden. Figure 5 shows the explainability module.

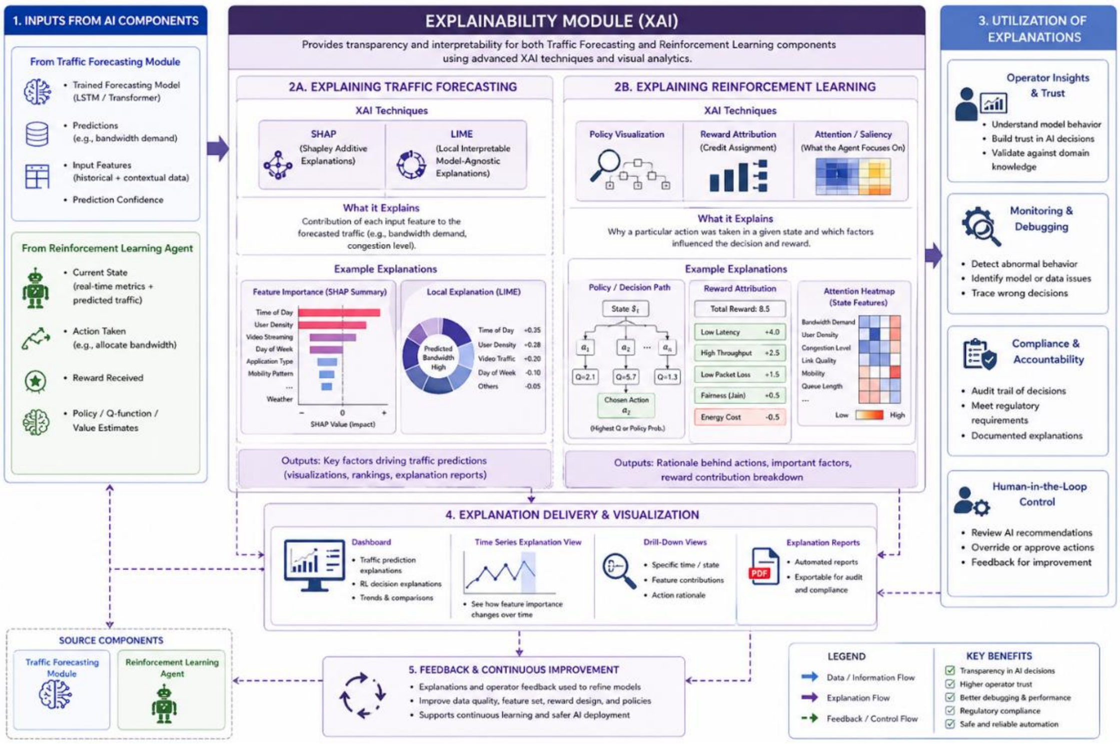


**Figure 5: Explainability Module.**

### 3.5 Workflow

The operational workflow of the proposed framework follows a continuous and iterative pipeline that integrates data processing, prediction, optimization, and explanation. Initially, raw network data is collected and preprocessed to generate a structured representation suitable for analysis. This processed data is then input into the traffic forecasting module, which produces predictions of future network conditions. These predictions, along with current network states, are fed into the reinforcement learning agent, which determines optimal actions to maintain or improve QoS. The selected actions are subsequently implemented within the network, resulting in updated conditions that are fed back into the system, thereby closing the loop.

An important aspect of the workflow is the simultaneous generation of explanations alongside predictions and decisions. As the forecasting model produces outputs and the RL agent selects actions, the explainability module analyzes these processes and generates interpretable insights. These explanations are delivered to network operators through dashboards or visualization interfaces, enabling real-time monitoring and informed decision-making. The iterative nature of the workflow ensures continuous learning and adaptation, allowing the system to respond effectively to changing network conditions while maintaining transparency and accountability throughout the decision-making process. Figure 6 demonstrates the operational workflow.

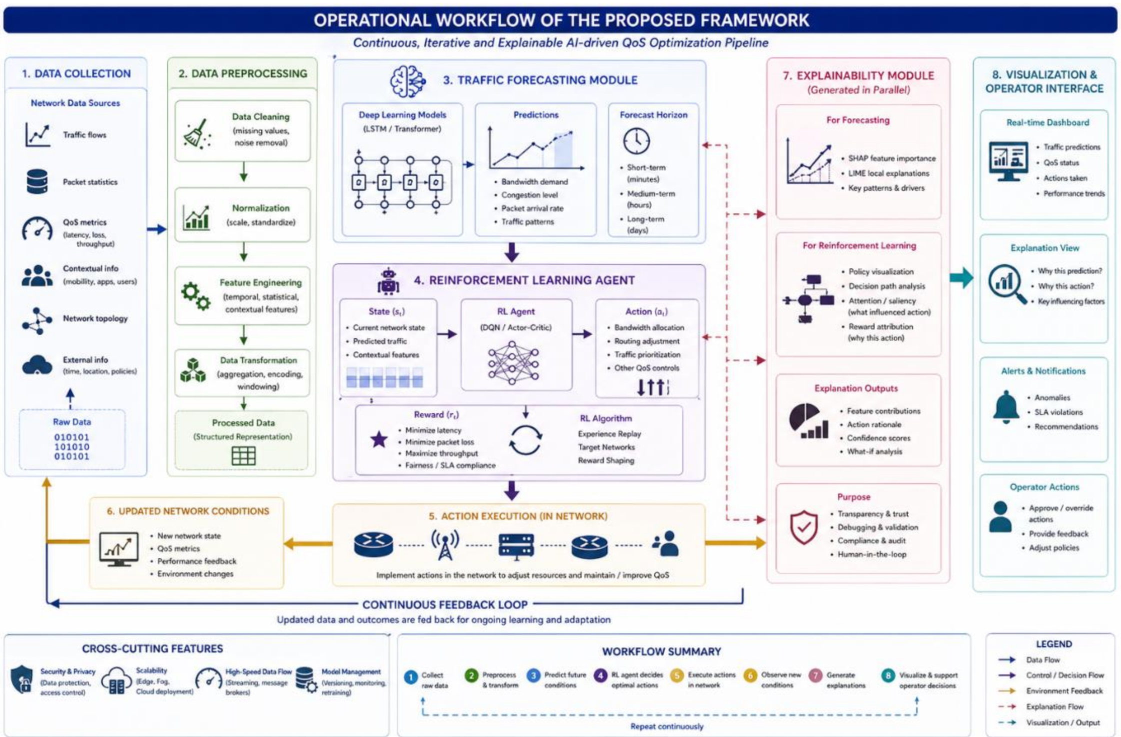


**Figure 6: Operational Workflow.**

## 4. METHODOLOGY

The methodology adopted in this study is designed to systematically develop, integrate, and evaluate an explainable AI-driven framework for network traffic forecasting and QoS optimization in 5G/6G environments. It encompasses multiple stages, including data acquisition, preprocessing, model development, training, evaluation, and explainability integration. Each stage is carefully structured to ensure that the proposed system not only achieves high predictive and optimization performance but also maintains transparency and interpretability. The methodology emphasizes a data-driven and iterative approach, allowing continuous refinement of models based on feedback from real-time network conditions and evaluation metrics.

Furthermore, the methodological design aligns with the requirements of next-generation networks, where scalability, adaptability, and real-time responsiveness are critical. By integrating deep learning models for traffic forecasting with reinforcement learning for decision-making, the framework leverages both predictive intelligence and adaptive optimization. The inclusion of explainable AI techniques ensures that the decision-making process remains interpretable, thereby addressing practical concerns related to trust, accountability, and deployment in critical network infrastructures. The following subsections elaborate each methodological component in detail.

### 4.1 Dataset and Data Sources

The dataset used in this study comprises a combination of real-world network traffic datasets and simulated data generated from controlled 5G/6G network environments. Publicly available datasets, such as those containing traffic flow statistics, packet-level information, and QoS metrics, are utilized to ensure diversity and realism in the training process. These datasets typically include features such as bandwidth usage, latency, packet arrival rates, and congestion indicators, along with contextual information like application types and user behavior patterns. In addition, simulation tools are employed to generate synthetic datasets that capture emerging 6G scenarios, including ultra-dense networks and high-mobility environments, thereby enhancing the generalizability of the framework.

To ensure robustness and reliability, the dataset is curated through a careful selection process that balances data quality, diversity, and representativeness. Data from multiple sources, including network logs, monitoring systems, and traffic generators, are aggregated to create a comprehensive dataset that reflects real-world conditions. The inclusion of both normal and anomalous traffic patterns enables the system to learn a wide range of network behaviors. Moreover, temporal diversity is maintained by incorporating data collected over different time periods, ensuring that the models can capture both short-term fluctuations and long-term trends. This comprehensive dataset forms the foundation for training and evaluating both the forecasting and reinforcement learning components of the framework.

### 4.2 Data Preprocessing

Data preprocessing is a critical step that transforms raw network data into a structured and meaningful format suitable for machine learning models. The preprocessing pipeline begins with data cleaning, where missing values, noise, and outliers are identified and handled using appropriate techniques such as interpolation, filtering, or statistical imputation. This is followed by normalization and scaling, which standardize feature values to a consistent range, thereby improving model convergence and performance. Feature engineering is then performed to extract relevant attributes from raw data, including temporal features, statistical summaries, and contextual indicators that capture network behavior more effectively.

In addition to basic preprocessing steps, advanced techniques such as sliding window mechanisms and sequence generation are employed to prepare the data for time-series modeling. These methods enable the creation of input sequences that capture temporal dependencies, which are essential for accurate traffic forecasting. Dimensionality reduction techniques may also be applied to reduce computational complexity and eliminate redundant features. The preprocessing stage ensures that the input data is both high-quality and informative, thereby enhancing the performance of downstream models. It also plays a crucial role in addressing challenges such as data imbalance and heterogeneity, which are common in network traffic datasets.

### 4.3 Model Training

The model training phase involves the development and optimization of both the traffic forecasting model and the reinforcement learning agent. The forecasting model, based on deep learning architectures such as LSTM or transformer networks, is trained using supervised learning techniques. The model learns to map historical and contextual input data to future traffic predictions by minimizing a loss function such as mean squared error or mean absolute error. Training is conducted using large-scale datasets, with techniques such as cross-validation and hyperparameter tuning employed to optimize model performance and prevent overfitting.

Simultaneously, the reinforcement learning agent is trained using interaction-based learning, where it learns optimal policies through trial and error. Advanced RL algorithms such as

Deep Q Networks or actor-critic methods are utilized to handle high-dimensional state and action spaces. The training process involves defining a reward function that captures QoS objectives, such as minimizing latency and maximizing throughput. Techniques such as experience replay and target networks are used to stabilize training and improve convergence. The integration of predicted traffic data into the state representation enables the agent to make proactive decisions, thereby enhancing overall system performance.

### 4.4 Explainability Integration

Explainability integration is a key component of the methodology, ensuring that the outputs of both the forecasting model and the reinforcement learning agent are interpretable and transparent. For the forecasting model, post-hoc explainability techniques such as SHAP and LIME are applied to analyze the contribution of individual features to model predictions. These techniques provide insights into the factors influencing traffic forecasts, enabling network operators to understand and validate the model's behavior. Visualization tools are used to present these insights in an intuitive manner, facilitating easier interpretation and decision-making.

In the context of reinforcement learning, explainability is achieved through methods such as policy visualization, reward attribution, and attention-based mechanisms. These approaches help to interpret the agent's decision-making process by identifying the factors that influence specific actions. The integration of explainability into the framework not only enhances transparency but also supports debugging and model validation. It ensures compliance with regulatory requirements and builds trust among users by providing clear and understandable explanations of AI-driven decisions. This component plays a crucial role in bridging the gap between complex machine learning models and practical network management applications. Figure 7 illustrates the proposed methodology.


**Figure 7: Proposed Methodology.**

### 4.5 Evaluation Metrics

The evaluation of the proposed framework is conducted using a comprehensive set of metrics that assess the performance of both the forecasting and optimization components. For the traffic forecasting model, standard regression metrics such as root mean squared error and mean absolute error are used to measure prediction accuracy. These metrics provide insights into the model's ability to capture both short-term variations and long-term trends in network traffic. Additional evaluation criteria, such as prediction latency and computational efficiency, are also considered to ensure the model's suitability for real-time applications.

For the reinforcement learning component, performance is evaluated based on QoS-related metrics, including latency, throughput, packet loss, and fairness. The cumulative reward obtained by the RL agent serves as an overall indicator of policy effectiveness. Comparative analysis is conducted against baseline approaches to demonstrate the advantages of the proposed framework. Furthermore, the effectiveness of the explainability module is assessed using metrics such as fidelity, interpretability, and user satisfaction. This multi-dimensional evaluation approach ensures a comprehensive assessment of the framework's performance, robustness, and practical applicability in next-generation network environments.

## 5. RESULTS AND ANALYSIS

The results and analysis section evaluates the effectiveness of the proposed explainable AI-driven framework in terms of predictive accuracy, QoS optimization, and interpretability. The experimental evaluation is conducted using both real-world and simulated network datasets to ensure robustness across diverse traffic conditions. The analysis focuses on assessing how well the traffic forecasting module captures temporal patterns, how effectively the reinforcement learning agent optimizes QoS parameters, and how transparently the explainability module communicates model decisions. The results are presented through quantitative metrics as well as qualitative insights, enabling a comprehensive understanding of system performance.

Furthermore, the evaluation adopts a comparative perspective, benchmarking the proposed framework against baseline models that lack either predictive intelligence, adaptive optimization, or explainability. This allows for a clear demonstration of the advantages achieved through the integration of deep learning, reinforcement learning, and explainable AI. The results also consider practical aspects such as computational efficiency, scalability, and real-time responsiveness, ensuring that the framework is suitable for deployment in next-generation 5G/6G network environments.

### 5.1 Forecasting Performance

The performance of the traffic forecasting module is evaluated using standard regression metrics such as root mean squared error, mean absolute error, and prediction latency. The results indicate that deep learning models, particularly LSTM and transformer-based architectures, significantly outperform traditional statistical methods in capturing both short-term fluctuations and long-term dependencies in network traffic. The forecasting module demonstrates high accuracy in predicting key parameters such as bandwidth demand, congestion levels, and packet arrival rates across varying traffic scenarios. The use of contextual features further enhances model performance by incorporating additional information related to user behavior and application types, thereby improving prediction robustness.

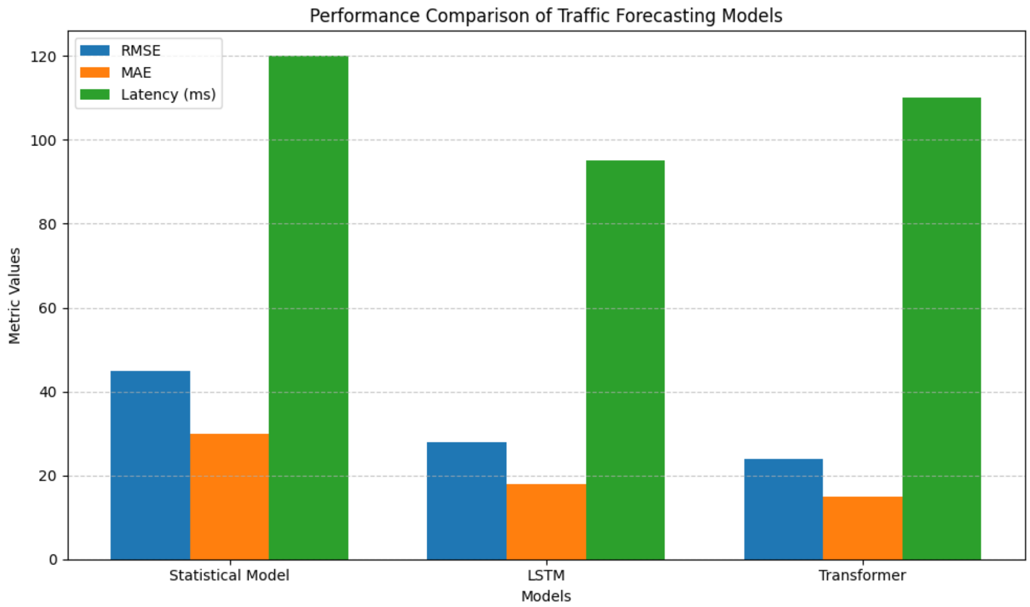


**Figure 8: Performance Comparison of Traffic Forecasting Models.**

In addition to accuracy, the forecasting module exhibits strong adaptability to dynamic network conditions. The incorporation of incremental learning and sliding window mechanisms enables the model to update predictions in near real-time as new data becomes available. This results in reduced prediction errors during periods of sudden traffic variation, such as peak usage or network anomalies. Figure 8 above demonstrates the performance comparison of traffic forecasting models. Comparative analysis shows that the proposed approach achieves lower error rates and faster convergence compared to baseline models, highlighting its suitability for real-time network management applications. However, the analysis also identifies trade-offs related to computational overhead, particularly for transformer-based models, which require optimization for deployment in resource-constrained environments. Figure 9 demonstrates the adaptability of forecasting models.

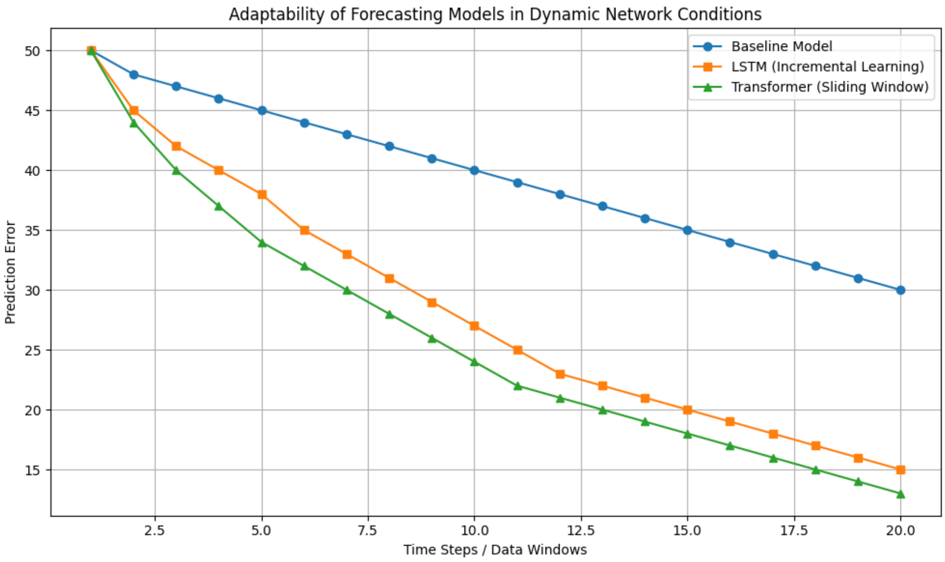


**Figure 9: Adaptability of Forecasting Models.**

## 5.2 QoS Optimization Results

The reinforcement learning-based QoS optimization component is evaluated based on its ability to improve key network performance metrics, including latency, throughput, packet loss, and fairness. Experimental results demonstrate that the RL agent effectively learns optimal policies that dynamically adjust network parameters in response to changing conditions. The integration of predicted traffic data into the state representation enables the agent to make proactive decisions, resulting in significant improvements in QoS metrics compared to reactive approaches. For instance, latency is reduced due to early congestion avoidance, while throughput is increased through efficient resource allocation strategies. Figure 10 shows the QoS Metrics comparison.

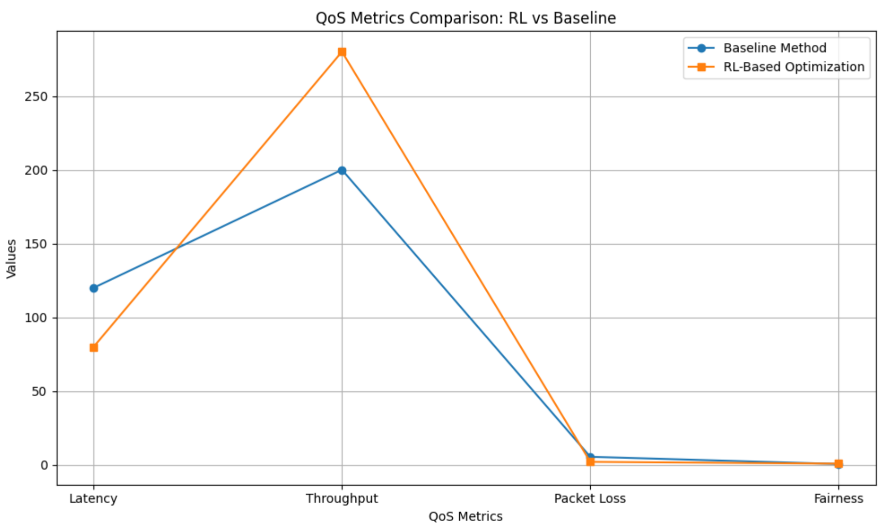


**Figure 10: QoS Metrics Comparison.**

Moreover, the RL agent exhibits strong adaptability and robustness across diverse network scenarios, including high-density traffic environments and fluctuating user demands. The use of advanced techniques such as experience replay and reward shaping contributes to stable training and improved convergence. Comparative evaluations reveal that the proposed RL-based approach outperforms conventional rule-based and optimization-based methods, particularly in dynamic and complex environments. Nevertheless, the analysis highlights challenges related to reward function design and exploration-exploitation balance, which can influence the stability and efficiency of the learning process. Addressing these challenges is essential for further enhancing the performance of RL-based QoS optimization in large-scale deployments.

### 5.3 Explainability Insights

The explainability module provides valuable insights into the decision-making processes of both the forecasting and reinforcement learning components. For the traffic forecasting model, techniques such as SHAP and LIME are used to identify the contribution of individual features to predictions. The results reveal that temporal factors, such as time-of-day variations, and contextual features, such as user density and application type, play a significant role in influencing traffic patterns. These insights enable network operators to validate model behavior and gain a deeper understanding of underlying traffic dynamics, thereby enhancing trust in the system. Figure 11 demonstrates the explainability for traffic forecasting.

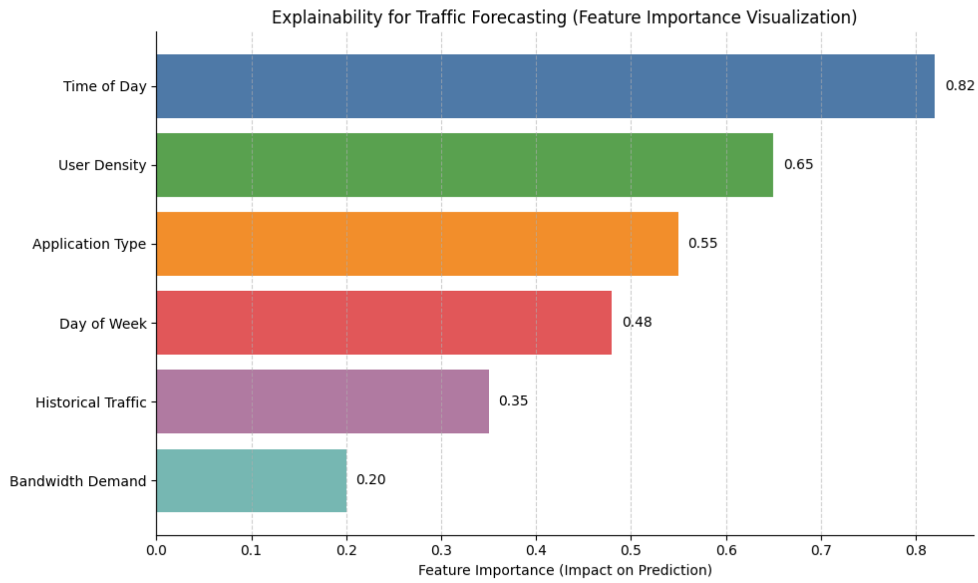


**Figure 11: ExplainabilityFor Traffic Forecasting.**

In the context of reinforcement learning, explainability is achieved through methods such as policy visualization and reward attribution, which highlight the factors influencing specific actions. The analysis shows that the RL agent's decisions are strongly influenced by predicted congestion levels and QoS objectives, demonstrating alignment with system goals. The ability to interpret these decisions facilitates debugging and model refinement, as operators can identify potential issues in policy behavior or reward design. Additionally, the explainability module supports compliance with regulatory requirements by providing transparent and auditable decision-making processes, making the framework suitable for deployment in critical network infrastructures.

### 5.4 Comparative Analysis

A comprehensive comparative analysis is conducted to evaluate the performance of the proposed framework against baseline approaches, including traditional statistical models, standalone deep learning models, and non-explainable reinforcement learning systems. The results indicate that the integrated framework consistently outperforms these baselines across multiple evaluation metrics. The combination of accurate traffic forecasting and proactive QoS optimization leads to improved overall network performance, while the inclusion of explainability enhances transparency and user trust. This holistic approach provides a clear advantage over methods that address individual components in isolation.

The comparative analysis also highlights the benefits of integrating explainability into the framework. While baseline models may achieve competitive performance in terms of accuracy or optimization, they often lack interpretability, which limits their practical applicability. The proposed framework addresses this limitation by providing meaningful explanations for both predictions and decisions, thereby enabling informed decision-making and easier system validation. However, the analysis also identifies areas for improvement, such as reducing computational complexity and enhancing scalability for large-scale deployments. These findings underscore the importance of continued research and optimization to fully realize the potential of explainable AI-driven network management systems. Figure 12 shows the comparative analysis.

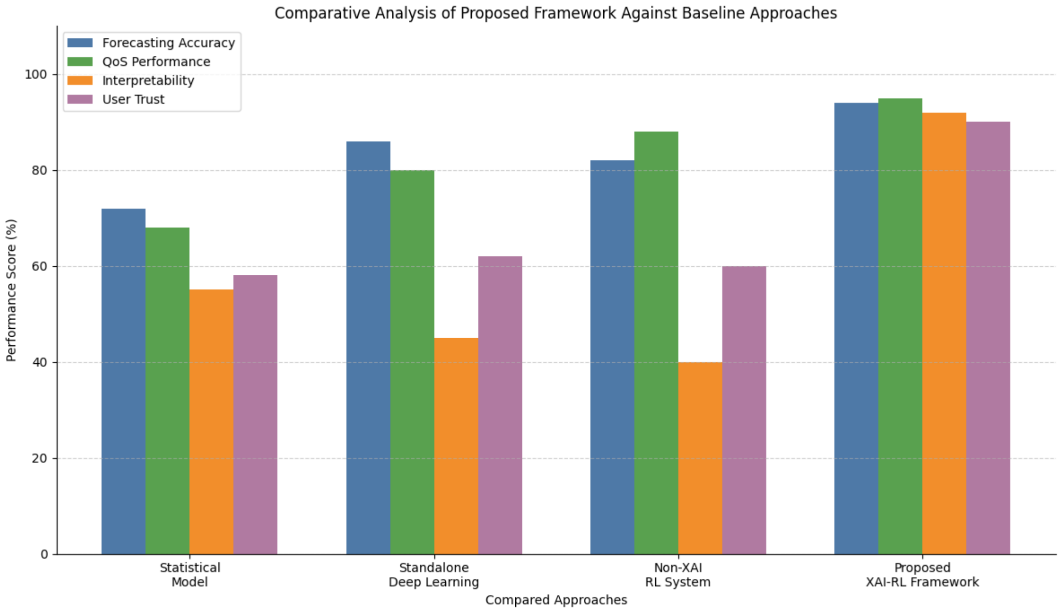


**Figure 12: Comparative Analysis.**

## 6. DISCUSSION

The results obtained from the experimental evaluation clearly demonstrate the effectiveness of integrating traffic forecasting, reinforcement learning-based QoS optimization, and explainable artificial intelligence into a unified framework. Unlike conventional approaches that treat prediction, optimization, and interpretation as separate processes, the proposed system leverages their synergy to achieve superior overall performance. The deep learning-based forecasting module provides accurate and timely predictions of network traffic patterns, which serve as a crucial input for the reinforcement learning agent. This predictive capability enables the system to move from a reactive to a proactive decision-making paradigm, allowing early detection of potential congestion and more efficient allocation of network resources. Consequently, significant improvements are observed across key QoS metrics such as reduced latency, increased throughput, and minimized packet loss, validating the practical relevance of the proposed approach in dynamic 5G/6G environments.

A key strength of the framework lies in its adaptability and robustness under varying network conditions. The incorporation of incremental learning and real-time data updates ensures that the forecasting model remains responsive to sudden changes in traffic patterns, including peak usage periods and anomalous events. Similarly, the reinforcement learning agent continuously refines its policy through interaction with the environment, enabling it to maintain optimal performance even in highly complex and non-stationary scenarios. The experimental results indicate that this adaptive behavior leads to faster convergence and more stable optimization compared to traditional rule-based or static optimization methods. Moreover, the integration of predicted traffic data into the RL state space significantly enhances decision quality, as the agent can anticipate future network conditions rather than relying solely on current observations. This forward-looking capability represents a substantial advancement in intelligent network management.

Another important contribution of the proposed framework is the integration of explainability, which addresses one of the most critical limitations of modern AI-driven systems. The use of techniques such as SHAP, LIME, and policy visualization provides meaningful insights into both the forecasting and decision-making processes. These explanations enable network operators to understand the factors influencing model predictions and RL actions, thereby enhancing trust and facilitating system validation. For instance, the identification of temporal and contextual features as key drivers of traffic patterns helps in verifying the correctness of forecasting models, while reward attribution in reinforcement learning clarifies the rationale behind QoS optimization decisions. This level of transparency is particularly important in critical network infrastructures, where accountability and regulatory compliance are essential. By bridging the gap between model complexity and human interpretability, the framework significantly improves its practical applicability.

Despite these advantages, the analysis also highlights several challenges and areas for further improvement. The computational complexity associated with deep learning and reinforcement learning models, particularly transformer-based architectures, can pose limitations for deployment in resource-constrained environments. Additionally, the effectiveness of the reinforcement learning component is highly dependent on the design of the reward function and the balance between exploration and exploitation, which can impact convergence stability and overall performance. Scalability remains another important consideration, especially in large-scale network deployments with massive data volumes and heterogeneous devices. Addressing these challenges will require continued research into lightweight model architectures, efficient training techniques, and advanced optimization strategies. Nevertheless, the findings of this study strongly support the potential of explainable AI-driven frameworks to transform network management, paving the way for more intelligent, transparent, and adaptive communication systems in the era of 5G and beyond.

## 7. CONCLUSION

The study concludes that the proposed explainable AI-driven framework provides a robust and forward-looking solution for network traffic forecasting and QoS optimization in 5G/6G environments by effectively integrating deep learning, reinforcement learning, and interpretability mechanisms into a unified architecture. The combination of accurate traffic prediction and proactive decision-making enables significant improvements in key performance metrics such as latency, throughput, and packet loss, while the incorporation of explainability ensures transparency, trust, and practical usability in real-world deployments. The framework not only addresses the limitations of conventional reactive and opaque approaches but also demonstrates strong adaptability to dynamic and heterogeneous network conditions, making it suitable for next-generation intelligent network management. Although challenges related to computational complexity, scalability, and reward design remain, the overall findings highlight the transformative potential of combining predictive intelligence, adaptive optimization, and explainable AI to build efficient, reliable, and accountable communication systems.

## 8. Future Scope

The future scope of this research lies in enhancing the scalability, efficiency, and real-world applicability of the proposed explainable AI-driven framework for next-generation network management. One promising direction is the integration of federated learning, enabling distributed model training across edge devices while preserving data privacy and reducing communication overhead. Additionally, the adoption of lightweight and energy-efficient model architectures will be crucial for deployment in resource-constrained edge and IoT environments. Extending the framework to support multi-agent reinforcement learning can further improve coordination and decision-making in large-scale, heterogeneous network scenarios. From an interpretability perspective, the development of advanced explainability techniques tailored for deep reinforcement learning will enhance transparency and user trust. Future work may also explore real-world deployment in 6G testbeds, incorporating emerging technologies such as network slicing, digital twins, and AI-native network orchestration. Furthermore, addressing challenges related to computational complexity, dynamic reward optimization, and adversarial robustness will be essential for building resilient and secure systems. Overall, continued research in these directions will contribute to the realization of intelligent, adaptive, and trustworthy network infrastructures capable of meeting the demands of future communication ecosystems.

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