

An AI-Driven Intelligent Network Optimization Framework Using Machine Learning and Deep Learning Techniques for Efficient Traffic Routing, Dynamic Resource Allocation, and Quality of Service Enhancement in Modern Computer Networks

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ABSTRACT

The rapid growth of modern computer networks, driven by data-intensive applications, Internet of Things ecosystems, and emerging next-generation communication technologies, has introduced significant challenges in efficient traffic management, dynamic resource allocation, and Quality of Service assurance. Traditional network optimization techniques often rely on static configurations and rule-based mechanisms, which are inadequate for handling the complexity and dynamic nature of contemporary network environments. To address these limitations, this paper proposes an AI-driven intelligent network optimization framework that leverages machine learning and deep learning techniques to enable adaptive, data-driven decision-making. The proposed framework integrates multiple AI paradigms, including supervised learning for traffic prediction, deep neural networks for pattern recognition, and reinforcement learning for real-time routing and resource allocation decisions. By combining these approaches, the system is capable of dynamically adapting to varying network conditions, such as traffic congestion, fluctuating bandwidth demands, and node failures. A multi-objective optimization strategy is employed to simultaneously enhance key performance indicators, including throughput, latency, packet delivery ratio, and overall QoS. Furthermore, the framework incorporates a feedback-driven learning mechanism that continuously refines its decision policies based on real-time network performance metrics. This enables the system to achieve higher levels of scalability, robustness, and efficiency compared to conventional methods. The proposed architecture can be seamlessly

integrated with Software-Defined Networking environments, allowing centralized control and improved network programmability. Extensive simulations are conducted using standard network simulation tools to evaluate the performance of the proposed model against traditional routing protocols and baseline machine learning approaches. The results demonstrate significant improvements in network performance, including reduced end-to-end delay, increased throughput, and enhanced QoS stability under dynamic traffic conditions.

Keywords— Artificial Intelligence, Network Optimization, Traffic Routing, Dynamic Resource Allocation, Quality of Service, Deep Learning, Reinforcement Learning, Software-Defined Networking.

1- Introduction:

Due to the fast development of digital communication technologies, the scale, complexity, and heterogeneity of contemporary computer networks have grown unprecedentedly. As data-intensive applications like cloud computing, big data analytics, Internet of Things (IoT), autonomous vehicles, industrial automation, smart healthcare systems, and next-generation wireless communications have emerged, network infrastructures have been under a constantly growing strain to support larger bandwidth, lower latency, enhanced reliability, and smooth Quality of Service (QoS). Such changing demands have altered the old static communication networks into extremely dynamic and responsive ecosystems, where traffic conditions rapidly and unpredictably vary [1]. Consequently, this has made efficient traffic routing, intelligent congestion control, dynamic resource allocation and QoS maintenance a key issue in current network management. Conventional network optimization techniques were developed to work with the comparatively predictable and stable network settings. These techniques are usually based on a static routing algorithm, traffic engineering based on rules, congestion control by fixed threshold, and the preset bandwidth allocation policies. Although these methods work well in small or less dynamic systems, they cannot effectively deal with the complex and dynamic traffic conditions of intelligent networks that are now a reality. The decision in statistic routing usually does not consider the changes in real-time traffic and this leads to poor bandwidth usage, an increase in the rate of packet loss, network congestion, and end to end delay [2]. In addition, traditional optimization algorithms do not have the ability to learn and they are therefore inappropriate in a setting where the network conditions constantly change. Over the past few years, the adoption of Artificial Intelligence (AI) into communication networks has been an innovative paradigm of overcoming these shortcomings. AI allows networks to transcend reactive control to predictive, adaptive, and autonomous decision-making. Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL) have demonstrated strong shows of making smart traffic forecasts, adaptive routing, anomaly detection, and dynamic bandwidth optimization. With such technologies, the network systems are able to process high amounts of historical and real-time traffic data, detect underlying patterns, and make decisions with a bit of human intervention. Machine learning methods can be especially useful to predict network traffic loads, as well as to forecast congestion patterns. Random Forest, Support Vector Machines and Gradient Boosting algorithms are supervised learning models, which can study the past trends of traffic to determine the bandwidth requirements in the future [3]. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and

Long Short-Term Memory (LSTM) networks are deep learning models that provide more developed functionality in learning nonlinear and temporal relationships in a complex traffic dataset. Reinforcement learning also improves network intelligence by allowing autonomous agents to acquire the best routing and resource allocation policies by interacting with dynamic network environments. Although there has been a considerable advancement in the field of AI-based networking research, much of the literature concentrates on separate optimization issues like traffic forecasting, routing optimization, or congestion management on their own. These disjointed solutions do not reflect the interrelationship between routing, resource allocation, and the assurance of quality of services. These functions need to work together to be globally optimized in real-life large-scale communication systems. Thus an integrated intelligent framework is increasingly in demand that can comprehensively tackle a variety of network optimization targets in a single architecture. A combination of these complementary AI paradigms allows the system to dynamically adjust to network congestion, changing traffic loads, bandwidth changes, and node failures and constantly enhances the accuracy of decision-making due to feedback-driven learning [4]. The major benefit of the suggested framework is that it is compatible with Software-Defined Networking (SDN) which allows centralized intelligent control and network programmability. SDN offers a scalable design, whereby AI models can be effectively deployed by gathering global network state data and applying adaptive optimization policies to distributed network nodes. This integration greatly enhances scalability, responsiveness, and efficiency in heterogeneous communication settings. Table 1 summarizes the comparative development of traditional methods of network optimization to AI-guided intelligent structures.

Table 1: Comparison between Traditional and AI-Driven Network Optimization Approaches

Feature	Traditional Methods	AI-Driven Intelligent Framework
Routing Mechanism	Static / Rule-Based	Adaptive / Learning-Based
Traffic Prediction	Limited or None	Real-Time Predictive Analytics
Resource Allocation	Fixed Allocation	Dynamic Adaptive Allocation
Congestion Handling	Reactive	Proactive and Predictive
Scalability	Limited	Highly Scalable
QoS Adaptability	Low	High
Failure Recovery	Manual or Delayed	Automated Intelligent Recovery
Decision Making	Predefined Rules	Autonomous Data-Driven Decisions

The proposed framework aims to address the shortcomings of static network control through the provision of an intelligent, adaptable and autonomous optimization through various dimensions of the network. The system achieves through multi-objective optimization an optimal throughput, latency reduction, packet loss reduction, and stability of QoS. These features are fundamental to the supporting of future communication paradigms of 5G, 6G, IoT ecosystems, smart grids, edge-cloud integrated networks. The key contributions of this work are a single AI-driven network optimization architecture, integrating various AI learning paradigms in a collaborative framework, developing adaptive routing and resource allocation policies, creating QoS aware multi-objective optimization policies and an SDN compatible scalable intelligent networking model that can be deployed in next-generation communication networks.

2- Traditional Network Optimization Techniques:

Traditional network optimization methods have traditionally been the basis of communicational network management and routing control. Most of these techniques rely on deterministic mathematical algorithms, non-adaptive routing schemes and heuristic traffic engineering schemes which were initially developed in the context of fairly stable and predictable network systems. With a moderate amount of traffic and few topology changes, they offered a reliable and computationally efficient solution to routing and resource allocation in early-generation computer networks. Nevertheless, as the sizes of large-scale heterogeneous networks started to grow, the Internet of Things (IoT) ecosystems, cloud infrastructures, and highly adaptive patterns of data traffic, the weaknesses of the conventional optimization schemes have become more noticeable. The shortest path algorithm developed by Dijkstra is one of the most common classical routing algorithms, that calculates the shortest path between the source and the destination node using known link weights [5]. Likewise, Open shortest path first (OSPF) is a link state protocol that calculates the shortest paths and dynamically updates the routing tables. These other conventional methods are heuristic load balancing algorithms, Equal Cost Multi-Path (ECMP) routing and the static bandwidth reservation schemes. The strategies prove to be useful where network traffic is reasonably stable and predictable but fail to scale well where there are sudden traffic variations, variable bandwidth demand and unpredictable node failures. One of the greatest shortcomings of the classical network optimization techniques is based on the fact that they rely on the use of fixed or semi-fixed routing path choices. After routing paths have been determined, they do not usually change, unless a manual update or routing table recalculation is performed. This slowed adaptability is disastrous in network environments with high dynamism. To illustrate this, at times when the network lies in an overload condition, the routing protocols might not reject the use of overloaded paths under the sway of its stature routing rules, instead of dynamically choosing alternative less-congested paths. Consequently, network congestions arise, and consequently result in higher end-to-end latency, lost packets and decreased throughput [6]. The other crucial limitation is the use of predefined rules and control systems based on thresholds. Conventional systems are based on policy settings that are manually established like set congestion limits, hard-coded bandwidth assignments and routing priorities set by the administrator. Although such rules are easy to enforce, they do not have the smarts necessary to learn based on changing traffic parameters or even predict future congestion situations. As a result, traditional approaches are not able to actively optimize network behavior prior to network performance deterioration. In contemporary smart communication systems like 5G and 6G as well as edge-cloud networks and SDN-based networks, traffic behavior is multidimensional and extremely dynamic. The devices produce streams of variable data in both directions at the same time, resulting in nonlinear traffic patterns, which cannot be optimally managed with fixed optimization logic [7]. The conventional routing models are unable to reflect latent traffic correlations, temporal traffic dependencies as well as adaptive resource demand variability. This renders them inappropriate to next generation autonomous networking systems which need real-time intelligent decision making. A comparison of leading traditional methods of network optimization and their drawbacks is laid in Table 2.

Table 2: Comparative Analysis of Traditional Network Optimization Techniques

Technique	Description	Strengths	Limitations
Dijkstra's Algorithm	Shortest path routing based on minimum path cost	Simple and efficient	Cannot adapt dynamically to real-time congestion
OSPF	Link-state dynamic routing protocol	Widely deployed and reliable	Slow adaptation under rapid traffic changes
ECMP Routing	Load balancing over equal-cost paths	Improves traffic distribution	Limited path intelligence
Static Load Balancing	Fixed traffic allocation across links	Easy implementation	Poor responsiveness to fluctuating loads
Rule-Based Threshold Control	Predefined congestion thresholds	Simple management	No predictive intelligence

Figure 1 depicts the working design of the conventional network optimization frameworks, which portrays that the decisions about routing are held in static settings using predefined setups with no learning adjustments.

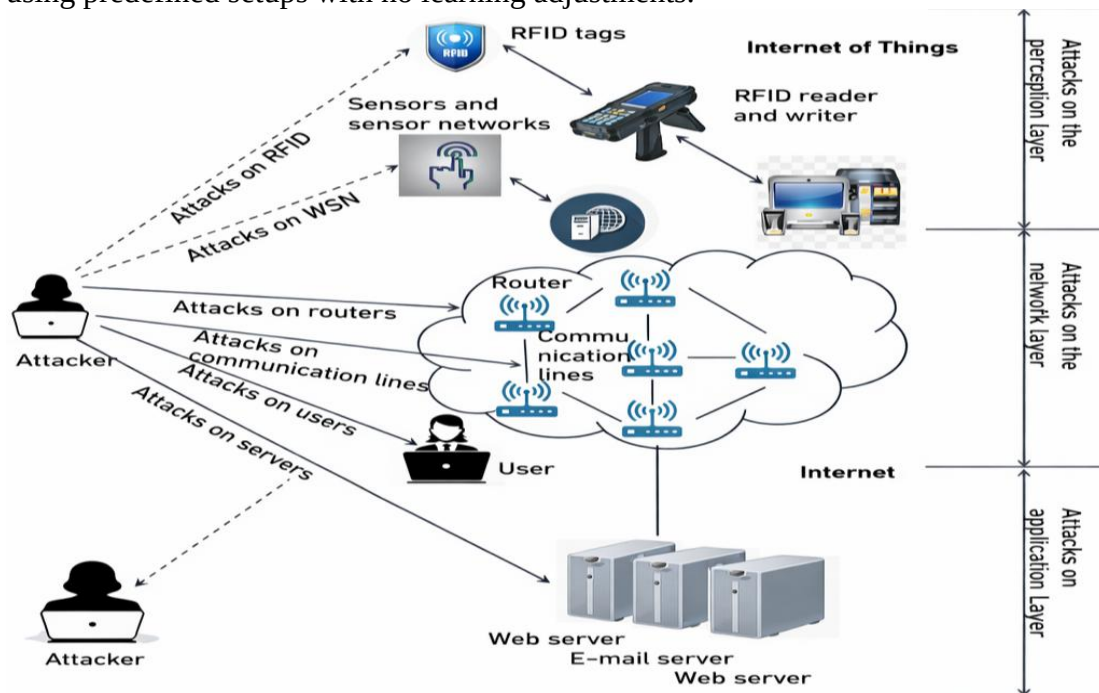


Figure 1: Traditional Network Optimization Workflow

Another advantage of traditional systems is that security and resiliency is lesser than in the predictive system because the mechanisms of failure recovery are reactive instead of predictive [8]. In the event of link failures or node outages, recalculation routing can cause delays during routing without success, until alternative paths are found. In this period, there exists the possibility of service failure and thus lacks consistency in mission-critical systems like healthcare systems, industrial automation systems, and autonomous transportation systems.

3- Software-Defined Networking and AI Integration:

Traditional distributed network infrastructure routing devices independently make forwarding decisions based on local information that constrains global visibility and adaptability. SDN resolves this weakness by introducing a logically centralized

controller, which ensures a global view of the overall network topology, traffic patterns, bandwidth consumption, level of congestion and the condition of the link-state [9]. Machine learning systems handle traffic data to forecast future patterns of congestion, deep learning systems detect latent patterns of traffic behavior, and reinforcement learning agents dynamically decide on ideal routes to take, given real-time environmental information [10]. Combined, these technologies make SDN into a self-adaptable and self-organizing intelligent control system, not just a programmable networking platform. Centralized traffic intelligence is one of the biggest benefits of the SDN-AI integration. Because the SDN controller collects data across all network devices, AI can be used to analyze the traffic trends of the whole world, not just local incidents. Such a holistic visibility allows predicting traffic more accurately, finding anomalies, and optimizing the routing. As an illustration, once a congestion starts developing in one of the network segments, the SDN controller can reroute traffic proactively, before performance is impacted by the congestion. Another significant advantage of SDN-AI systems is programmable adaptive routing. In traditional routing architectures routing policies are defined and updated very rarely. Conversely, AI-based controllers of SDN are able to adjust dynamically the routing decisions by reacting to the changing traffic conditions. Autonomous path optimization can be achieved by reinforcement learning agents integrated into the SDN controller that continually assess routing rewards, which include lower latency, increased throughput and reduced packet loss. SDN-AI collaboration contributes significantly to the real-time congestion mitigation. Deep learning models implemented by the SDN controller are able to observe congestion patterns prior to the bottlenecks becoming critical. As soon as it is detected, the controller may induce an immediate traffic redistribution, bandwidth reallocation or path reconfiguration [11]. The bandwidth, buffer memory, and channel capacity of the resources in cloud data centers, IoT ecosystems, and 5G/6G mobile networks have to be dynamically allocated. The models of AI process traffic demand patterns and modify resource distribution policies automatically, to keep the utilization as efficient as possible without over-provisioning and under-utilizing. Table 3 shows a comparative description of the traditional networks and AI-enabled SDN architectures.

Table 3: Comparison between Traditional Networking and AI-Integrated SDN

Feature	Traditional Networks	AI-Integrated SDN
Control Structure	Distributed	Centralized
Decision-Making	Static / Rule-Based	Intelligent / Adaptive
Traffic Visibility	Localized	Global Network View
Routing Adaptability	Limited	Dynamic Real-Time
Congestion Management	Reactive	Predictive and Proactive
Resource Allocation	Fixed or Manual	Autonomous Dynamic Allocation
Scalability	Moderate	High
Learning Capability	None	Continuous Self-Learning

As shown by Figure 2, the AI-enriched SDN controller is the smart brain of the network that is fed in real-time with the distributed infrastructure devices and produces adaptive optimization policies. The feedback provides a continuous refinement of AI model decisions with network outcomes, allowing intelligent control

to improve itself.

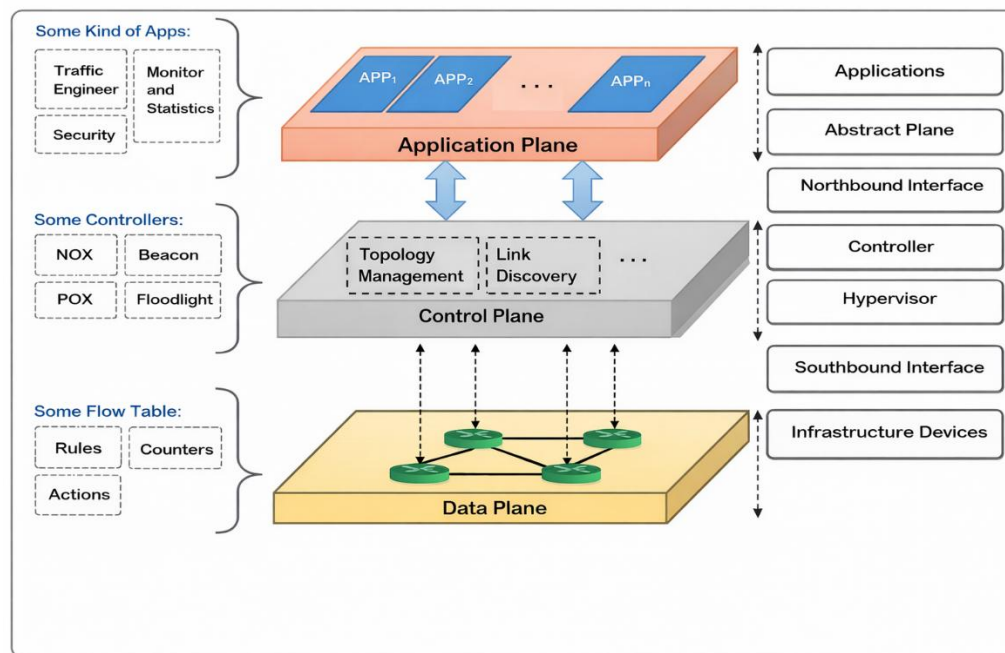


Figure 2: AI-Integrated SDN Intelligent Network Architecture

Recent sources consider SDN-AI integration as a technology base to autonomous future networks, especially in next-generation communication models like 6G, network slicing, edge intelligence and ultra-reliable low-latency communications (URLLC). Scholars are more focused on the fact that AI-based SDN systems will be at the heart of zero-touch network management, with networks being managed with minimal human use. Even with these benefits, there are also a number of challenges of SDN-AI integration. One significant problem is scalability of controllers centralized controllers might prove to be bottlenecks in very large-scale networks. The security weaknesses are also enhanced as hacked controllers may influence numerous infrastructures [12]. SDN implementations prefer different protocols and APIs, and therefore, the standardized AI implementation is complicated. The computationally heavy models can also impact the time-sensitive routing decisions in case of the latency in the AI inference processes. Still, the merging of SDN and AI can be considered one of the most promising changes in the intelligent communication systems.

4- Methodology:

The presented AI-based intelligent network optimization framework will strive to increase the efficiency of traffic routing, dynamic resource allocation, and Quality of Service (QoS) in contemporary computer networks where the conventional methods of network optimization, which rely on a lasting, static approach, are not always going to work with ever-shifting traffic patterns. Network environments have become increasingly complex and highly dynamic with the growing number of Internet of Things (IoT) devices, cloud computing services, real-time applications, and next-generation communication systems like 5G and 6G. These dynamism demand smart systems capable of studying network behavior on the fly and adaptive decisions to allow stable and efficient performance.

4.1- Research Framework Overview:

The conditions of computer networks in the modern world are highly dynamic as traffic loads are constantly changing depending on the user demands, the activity of IoT devices, cloud applications, multimedia streaming, and mobile communication services [14]. After the preprocessing stage, the data is fed to the machine learning traffic prediction layer which is tasked with predicting the demand and potential congestion of the future traffic using supervised learning algorithms [15]. This predictive intelligence allows this framework to predict overload in the network even before it is congested. The deep learning traffic pattern analysis layer then involves analyzing both the temporal and nonlinear traffic pattern, to identify concealed traffic trends and abnormal congestion patterns that would not be detected by the conventional models. The adaptive routing layer is the reinforcement learning that is the intelligent decision-maker. During this step, the RL agents perform continuous interaction with the network environment and learn the best routing approaches by maximizing performance rewards in terms of minimized latency, increased throughput and minimized packet loss. Table 4 summarizes the key methodological steps of the proposed framework.

Table 4: Main Stages of the Proposed Research Framework

Stage No.	Methodological Stage	Description
1	Network Data Collection	Acquisition of real-time traffic and network state data
2	Data Preprocessing	Cleaning, normalization, filtering, and feature extraction
3	Traffic Prediction	Forecasting future traffic load using supervised ML models
4	Traffic Pattern Analysis	Identifying nonlinear traffic trends using deep learning
5	Adaptive Routing	Intelligent route selection using reinforcement learning
6	Dynamic Resource Allocation	Real-time bandwidth and resource optimization
7	QoS Performance Evaluation	Measuring throughput, delay, packet loss, and reliability

The interconnectedness and layering of the framework are evidenced by figure 3, as each optimization stage is part of one giant intelligent control cycle. The adaptive capability of the system is based on the feedback loop, which is necessary to make sure that it learns continuously and becomes improved in real time.

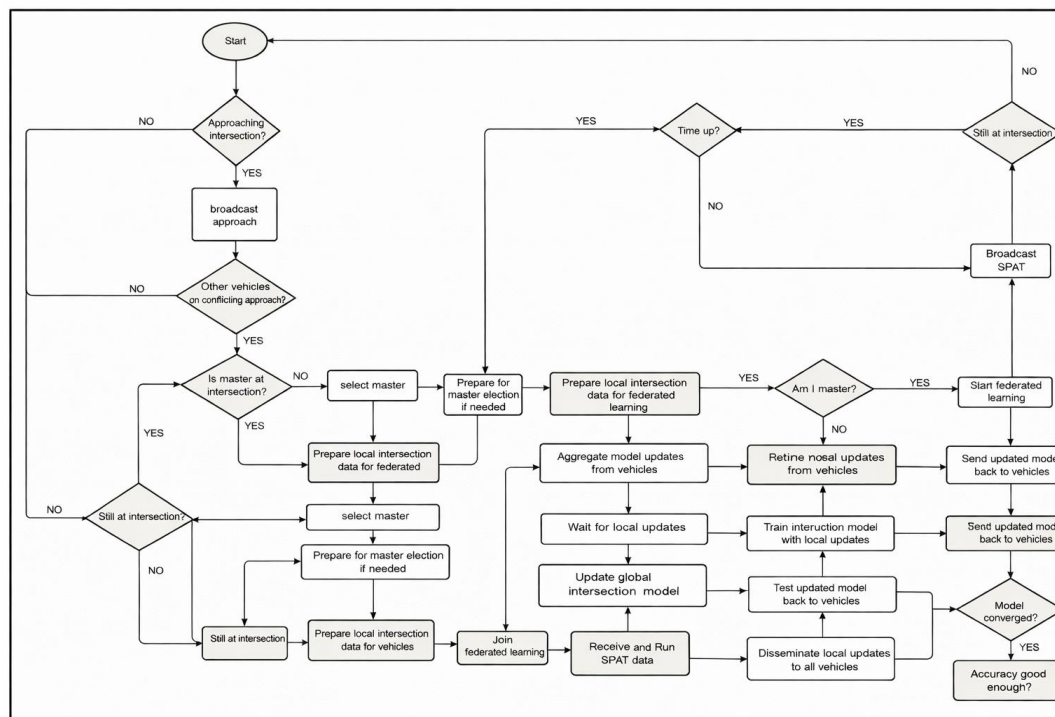


Figure 3: Proposed Research Framework for AI-Driven Intelligent Network Optimization

The research architecture unites predictive analytics, deep traffic intelligence, adaptive routing control, and dynamic resource management in a single architecture, making it scalable and future-ready to provide intelligent next-generation network optimization [17]. It is the basic model of operation that all the further stages of implementation, simulations and performance evaluation of this study are based.

4.2- Network Data Collection and Dataset Preparation:

Network data gathering and data set preparation are the baseline phase of the proposed AI-originated intelligent network optimization system since the success of machine learning, deep learning, and reinforcement learning algorithms largely rely on the quality and completeness of the traffic data involved in the training and testing phases. Traffic conditions in current communication networks vary dynamically as a result of user demand changes, varying bandwidth needs and the movement and distribution of congestion. Thus, it is crucial to gather a wide range and representative traffic data that can represent the actual network behavior [18]. In this study, the network traffic data is collected using various heterogeneous sources such as routers, switches, Software-Defined Networking (SDN) controllers and simulated network nodes. These sources offer a clear picture of various levels of the communication infrastructure and enable the framework to receive the local traffic variations and global network conditions as well. The other fifteen percent is allocated to testing and this is an independent set of data to evaluate the final model performance under unseen traffic conditions. Table 5 contains the datasets and traffic sources that are employed in the proposed framework.

Table 5: Network Dataset Sources and Their Roles [19].

Data Source	Category	Role in Framework
Routers and	Real-time network	Provide packet statistics and queue

Switches	devices	measurements
SDN Controllers	Centralized network controller	Supply global traffic state information
CAIDA Dataset	Benchmark traffic dataset	Real-world Internet traffic analysis
CICIDS Dataset	Labeled benchmark dataset	Traffic pattern classification
NS-3 Simulation Logs	Simulated dataset	Controlled congestion and routing experiments

A schematic representation of the process of converting raw traffic data to an optimized prepared dataset that can be used to train AI models is shown in figure 4. The heterogeneity of data sources offers better diversity in the dataset as a number of heterogeneous data sources are integrated, and preprocessing guarantees consistency and reliability.

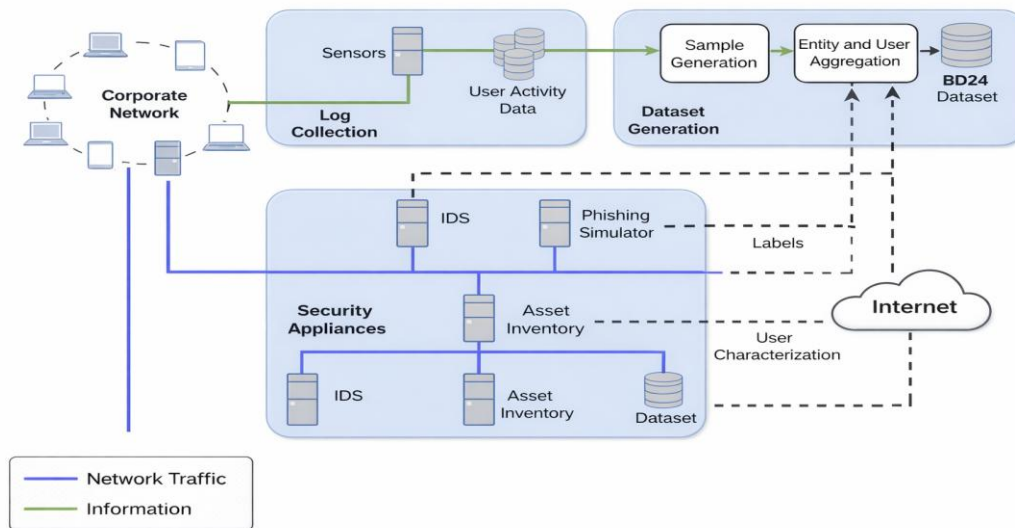


Figure 4: Network Data Collection and Dataset Preparation Process [20].

Data collection through networks and preparing datasets forms the basis of data intelligence of the whole research structure. This step makes it possible to predict traffic accurately, provide routing intelligence and efficiently allocate resources as well as reliably improve QoS in current computer networks by providing complete, clean, labeled, and balanced traffic data.

4.3- Traffic Prediction Using Supervised Machine Learning:

Traffic prediction is a critical part of the intelligent network optimization framework proposed as it enables the system to anticipate the future network traffic loads, so that the system is not congested. The conditions of the traffic in the contemporary computer networks vary quickly as the means of connected equipment, cloud-computation, IoT systems, and real-time communication services accumulate. It is due to these dynamic conditions that traffic behavior needs to be predicted beforehand in order to change the routing paths and the allocation of the resources in advance. Within this framework, the future traffic loads and the propensities of congestion on the network are predicted by supervised machine learning using historical network data. Supervised learning models are trained on labeled traffic data sets, with previous traffic conditions associated with the known output patterns [21]. The support vector

machine is effective in classified traffic problems particularly where the patterns of traffic are extremely nonlinear. XGBoost Regression is chosen due to high predictive accuracy and processing speed, in large-scale traffic data [22]. These models are trained on past records of network traffic and are applied to predict future traffic. Anticipated traffic performance is relayed to the adaptive routing and dynamic resource allocation modules, whereby the routing paths and bandwidth decisions are pre-adjusted. This proactive prediction of traffic can greatly minimize the risk of congestion and enhance the Quality of Service (QoS). Table 6 provides a summary of the supervised machine learning algorithms to predict traffic.

Table 6: Supervised Machine Learning Algorithms for Traffic Prediction

Algorithm	Main Advantage	Limitation
Random Forest	High accuracy and stable performance	Higher memory consumption
Support Vector Machine	Strong classification capability	Slower on very large datasets
XGBoost Regression	Fast and highly efficient prediction	Requires parameter tuning

Figure 5 explains the use of supervised learning models to process historical traffic information to produce future traffic forecasts. This prediction mechanism allows the framework to make preventative action prior to the occurrence of congestion leading to increased routing effectiveness, minimized latency as well as network stability.

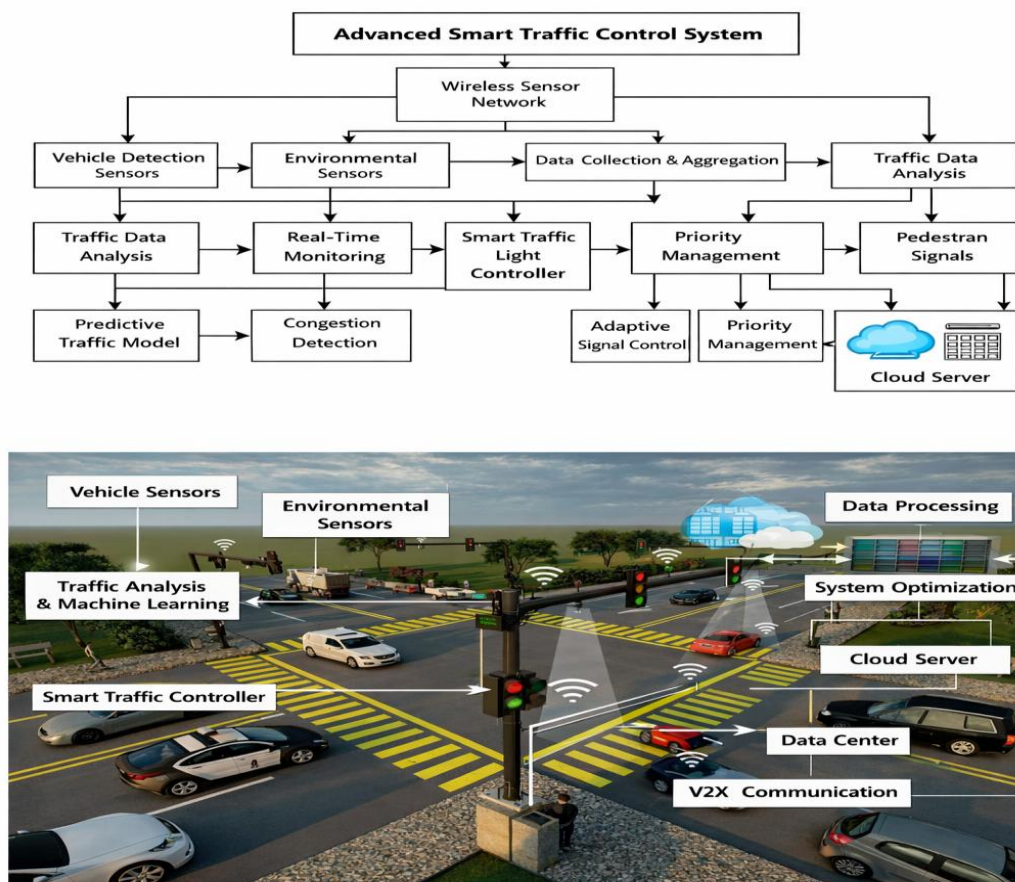


Figure 5: Traffic Prediction Workflow Using Supervised Machine Learning

Monitored machine learning delivers the predictive intelligence to enable proactive optimization of networks. The proposed framework will enhance the efficiency of traffic management and will facilitate more efficient and dynamic decision-making in current dynamic computer networks as the traffic condition is predicted beforehand.

4.4- Adaptive Routing Using Reinforcement Learning:

The routing agent monitors the prevailing condition of the network which may include the status of the traffic, length of the queue, delay and degree of congestion where the most appropriate routing path is chosen. Once a routing decision has been made, the agent will be fed back with rewards that are based on the network performance results including less delay, better throughput, and packet loss [23]. The agent constantly recalculates its routing strategy as time passes, to achieve maximum efficiency in the network in the long run. The RL routing model in the proposed framework has three components: the network state, routing action, and the reward signal. The state is the present state of the network such as the degree of congestion and the use of links. The action can be defined as the routing path that the agent chooses to forward packets. The reward represents the performance improvement since the routing decision, and used to influence the system to select routes maximizing Quality of Service (QoS). By experiencing the environment repeatedly, routing agent learns the most appropriate policy of path selection [24]. Reinforcement learning in routing offers a number of benefits compared to the conventional routing techniques. It enables the system to dynamically change according to changes in the traffic, automatically find an improved route, and react smartly to any unforeseen events on the network. As an illustration, when congestion arises on a route, the RL agent may rapidly acquire knowledge to divert traffic on other paths with lower delay than the first one (without requiring a human operator). This renders routing process more flexible, autonomous and efficient. The proposed framework includes adaptive routing based on reinforcement learning shown in Figure 6.

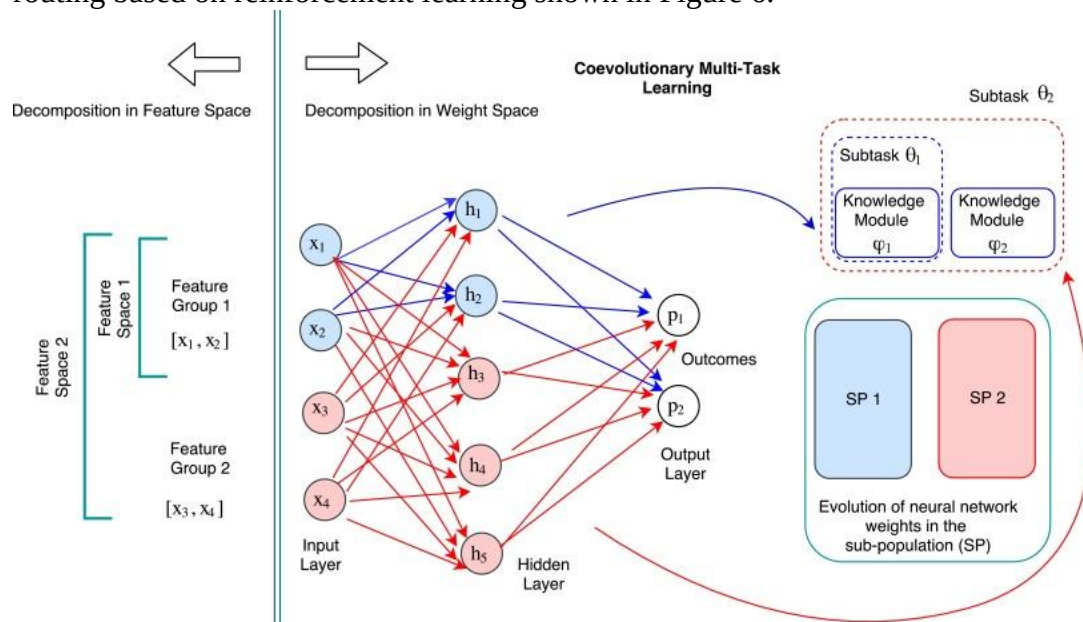


Figure 6: Adaptive Routing Process.

Reinforcement learning is an efficient approach in solving routing adaptively in smart networks. The proposed framework reduces delay, maximizes throughput, limits congestion and improves overall performance of the network QoS in dynamically

changing network communication environments by feedback-driven refinement of routing decisions.

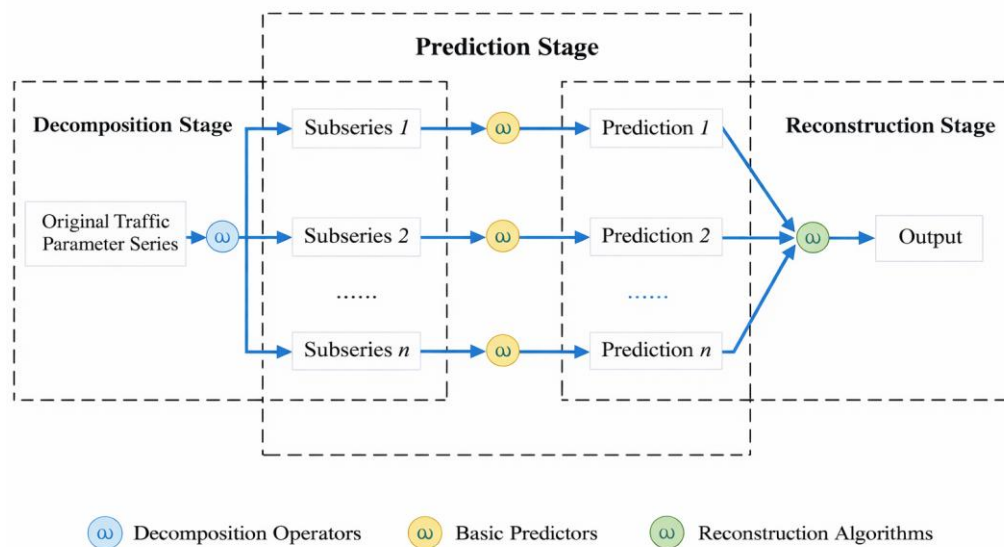
4.5- Dynamic Resource Allocation Mechanism:

The proposed AI-driven intelligent network optimization framework includes dynamic resource allocation as a key component due to the highly dynamic nature of the contemporary computer network environment where the bandwidth demand varies throughout the time. The methods of allocating resources in a static manner are usually unable to respond to sudden changes in traffic that creates congestion, underutilization of resources, loss of packets as well as low Quality of Service (QoS). To address these shortcomings, the proposed framework uses a dynamic resource allocation model that constantly reallocates network resources based on the predicted traffic demand and adaptive routing decisions. Resource allocation decision is arrived at, in this model, following a traffic prediction and routing optimization step. After estimating the future traffic loads and the optimal routing paths, the system dynamically allocates the available resources in the network to ensure that performance is stabilized. The allocation mechanism is aimed at adjusting network capacity to the demand of real-time traffic considering that paths with high load should be given enough resources whereas those experiencing minimal load should not be allocated too much resources [25]. The key resources governed in this mechanism consist of bandwidth capacity, buffer memory, link channel priority, and queue scheduling slots. Bandwidth capacity is modified in response to varying traffic levels in various routes. Buffer memory is assigned to avoid loss of packets due to temporary bursts in the traffic. Link channel priority is adjusted to prioritize important or delay-sensitive traffic streams, whereas the queue scheduling slots are optimized to enhance the efficiency in transmitting packets and to reduce waiting delays. Dynamic resource allocation is aimed at the main objectives of maximizing network throughput and reducing latency and packet loss. In contrast to fixed allocation algorithms, dynamic allocation constantly recalculates resource allocation according to the current traffic conditions, anticipated congestion patterns, and the alterations in routing [26]. This enhances the network to be more flexible, scalable and effective in managing unpredictable traffic pattern. Table 7 show the key resources in the process of dynamic allocation.

Table 7: Resources Managed in Dynamic Resource Allocation

Resource Type	Function in Network Optimization
Bandwidth Capacity	Adjusts transmission capacity based on traffic demand
Buffer Memory	Stores temporary packets during congestion periods
Link Channel Priority	Assigns priority levels to important traffic flows
Queue Scheduling Slots	Controls packet transmission order and timing

To support intelligent resource allocation (figure 7), it is demonstrated that forecasted traffic data and routing choices are jointed to help steer the process. Continuous analysis of network conditions and the reallocation of resources by the allocation controller enhance performance and sustain the QoS.

**Figure 7:** Dynamic Resource Allocation Workflow

Its dynamic resource allocation mechanism is more efficient as it also makes sure that the resources are allocated where they are most required. This is an adaptive mechanism that enhances the throughput, latency, minimizes packet loss and the operation of intelligent communication networks today is reliable.

5- Results and Discussion:

The effectiveness of the proposed AI-based intelligent-network optimization system has been assessed using large-scale simulation experiments to determine its ability to enhance the efficiency of traffic routing, dynamically allocate resources, and improve the Quality of Service (QoS) given dynamic network performance conditions. To determine superiority of the proposed model over the traditional OSPF routing and a baseline machine learning routing model, the proposed model was compared to them to identify the model that was best in dealing with the changing loads of traffic, congestion control and adaptive routing. Experimental simulations were performed on NS-3 with Python-based machine-learning and reinforcement-learning modules. The topology was a 100-node network topology with mixed patterns of traffic that consisted of low traffic, moderate traffic, heavy traffic, and peak congestion. Traffic traces on benchmark datasets and network loads that were produced by simulations were used in real-time to test the behavior of the system in realistic conditions [27]. The quantitative comparative results of simulation experiments are displayed in Table 8.

Table 8: Comparative Performance Results of Network Optimization Models

Performance Metric	Traditional OSPF	Baseline ML Model	Proposed AI Framework
Throughput (Mbps)	72.5	84.3	96.8
End-to-End Delay (ms)	48.6	35.2	21.4
Packet Delivery Ratio (%)	89.7	93.5	98.2
Packet Loss Rate (%)	10.3	6.5	1.8
QoS Stability Index (%)	78.4	86.1	95.6
Congestion Recovery Time (sec)	8.9	5.4	2.1

Bandwidth Utilization	68.2	81.7	94.3
Efficiency (%)			

The throughput rate rose to 96.8 Mbps; a considerable improvement compared to OSPF and the original machine learning model. This means that traffic traversal and bandwidth usage is done in a more efficient manner in changing network conditions. The end-to-end delay dropped to 21.4 ms, indicating that the proposed framework helps to minimize transmission latency with adaptive routing and predictive congestion control. Reduced delay will be important in applications that are sensitive to latency like telemedicine, video conferencing and autonomous systems. In a similar manner, the ratio of packet delivery increased to 98.2 and the rate of packet loss decreased to 1.8 indicating that the framework can ensure the consistency and reliability of packet delivery even when there is a high level of congestion. The high consistency of the service quality provided by the proposed system can also be estimated by the QoS stability index of 95.6%. Figure 8 shows a comparison of throughput under varying conditions of traffic load.

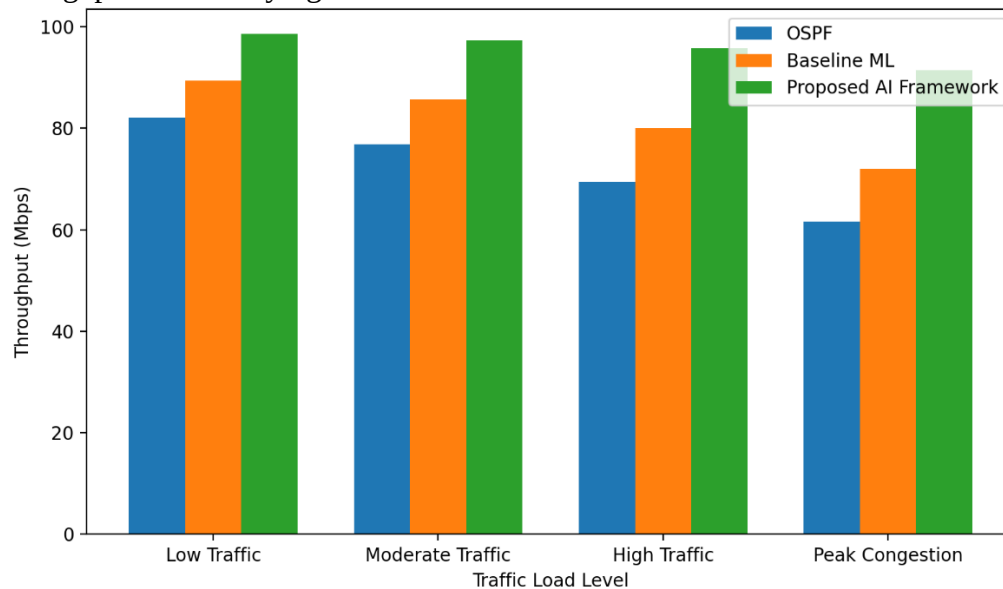


Figure 8: Throughput Performance Comparison under Traffic Load Conditions

Figure 8 indicates that the suggested AI structure is able to retain the throughput rate under any traffic conditions, even during peak congestion. The intelligent framework uses a dynamic response to support the stability of performance in contrast to the traditional OSPF routing that suffers extreme throughput deterioration when there is heavy traffic. Figure 9 shows the comparison of end-to-end delay of the three assessed models.

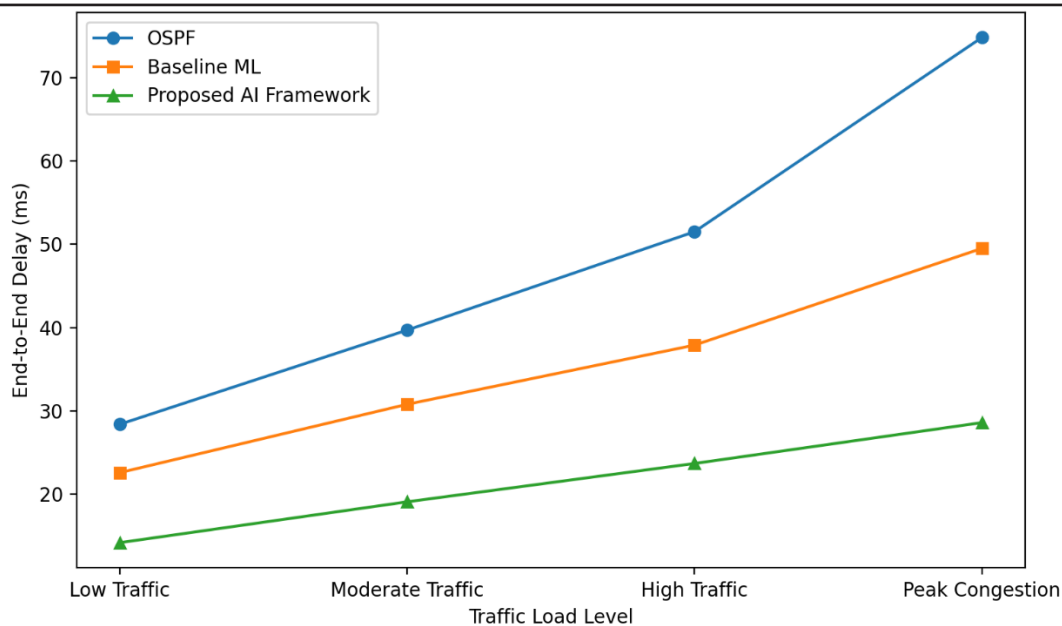


Figure 9: End-to-End Delay Comparison under Dynamic Traffic Conditions

It is shown in Figure 9 that even with an increase in the intensity of traffic, the proposed framework has much lower delay. Adaptive routing based on reinforcement learning is used to provide this reduction in latency by choosing less congested paths dynamically, in real time. Another important result is congestion recovery performance. The given framework decreased the time spent on the congestion recovery to just 2.1 seconds in comparison to 8.9 seconds in OSPF routing. This fast recovery can be achieved through the capability of the reinforcement learning agent to reroute traffic fast as well as the properties of dynamically redistributing bandwidth through the fast bandwidth redistribution module. The efficiency of bandwidth utilization also increased by 100 points to 94.3, which can be interpreted as the framework using resources more reasonably and will not over-provision. This makes the system very appropriate to be scaled to large networks like SDN infrastructures, cloud data centers, IoT ecosystems and next generation wireless networks.

6- Future Work:

Even though the suggested AI-based intelligent network optimization framework has shown that it already has a strong competitive edge in terms of traffic routing rate, dynamic resources distribution, and Quality of Service (QoS) improvement, there are still a variety of potential ways in which the framework can be advanced in the future and extended to the real world in terms of capabilities [28]. The use of explainable artificial intelligence (XAI) techniques is another useful extension. Although machine learning and deep learning models have good predictive accuracy, their decision-making models are not always easy to understand. Future studies can be directed towards the creation of transparent AI models which will explain routing decisions, congestion prediction, and resource allocation strategies, which will render the framework more trustworthy in critical applications like healthcare network, autonomous vehicles, and industrial automation systems [29]. The existing structure also has the ability to be upscaled to accommodate 5G and 6G next-generation communication networks, in which ultra-low latency, connecting very many devices,

and slicing networks pose new optimization issues. The future research can implement changes in the proposed architecture to support network slicing operations, ultra-reliable low-latency communication (URLLC), and smart radio resource allocation in wireless mobile systems [30]. Moreover, the next generation of work can explore the multi-agent learning methods of reinforcement of works wherein two or more intelligent routing agents collaborate in a distributed network segment.

Conclusion:

The framework of the paper suggested an intelligent network optimization system that monitors traffic, assigning resources dynamically to minimize network congestion, Quality of Service (QoS), and traffic routing using AI. The conventional network optimization techniques can fail to manage the dynamically shifting traffic patterns effectively, particularly in the setting that includes IoT facility, cloud facilities, and next-generation communication framework. The framework proposed tackles these issues by integrating supervised machine learning, deep learning, and reinforcement learning in a single architecture to optimize networks adaptively and in real-time. The framework applies supervised machine learning in predicting traffic, deep learning in analyzing patterns of traffic, and reinforcement learning in making adaptive routing decisions. Moreover, a dynamic resource allocation system is used to adjust bandwidth and network resources based on the requirement of the traffic.

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