A Survey on Machine Learning and Deep Learning based Quality of Service aware Protocols for Software Defined Networks

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October 30, 2023

Abstract

Quality of Service (QoS) is one of the most important parameters to be considered in computer networking and communication. The traditional network incorporates various quality QoS frameworks to enhance the quality of services. Due to the distributed nature of the traditional networks, providing quality of service, based on service level agreement (SLA) is a complex task for the network designers and administrators. With the advent of software defined networks (SDN), the task of ensuring QoS is expected to become feasible. Since SDN has logically centralized architecture, it may be able to provide QoS, which was otherwise extremely difficult in traditional network architectures. Emergence and popularity of machine learning (ML) and deep learning (DL) have opened up even more possibilities in the line of QoS assurance. In this article, the focus has been mainly on machine learning and deep learning based QoS aware protocols that have been developed so far for SDN. The functional areas of SDN namely traffic classification, QoS aware routing, queuing, and scheduling are considered in this survey. The article presents a systematic and comprehensive study on different ML and DL based approaches designed to improve overall QoS in SDN. Different research issues & challenges, and future research directions in the area of QoS in SDN are outlined.

A Survey on Machine Learning and Deep Learning based Quality of Service aware Protocols for Software Defined Networks

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Abstract: Quality of Service (QoS) is one of the most important parameters to be considered in computer networking and communication. The traditional network incorporates various quality QoS frameworks to enhance the quality of services. Due to the distributed nature of the traditional networks, providing quality of service, based on service level agreement (SLA) is a complex task for the network designers and administrators. With the advent of software defined networks (SDN), the task of ensuring QoS is expected to become feasible. Since SDN has logically centralized architecture, it may be able to provide QoS, which was otherwise extremely difficult in traditional network architectures. Emergence and popularity of machine learning (ML) and deep learning (DL) have opened up even more possibilities in the line of QoS assurance. In this article, the focus has been mainly on machine learning and deep learning based QoS aware protocols that have been developed so far for SDN. The functional areas of SDN namely traffic classification, QoS aware routing, queuing, and scheduling are considered in this survey. The article presents a systematic and comprehensive study on different ML and DL based approaches designed to improve overall QoS in SDN. Different research issues & challenges, and future research directions in the area of QoS in SDN are outlined.

Keywords: Quality of Service, Software Defined Network, Machine Learning, Deep Learning, Traffic Classification, Routing, Queuing and Scheduling.

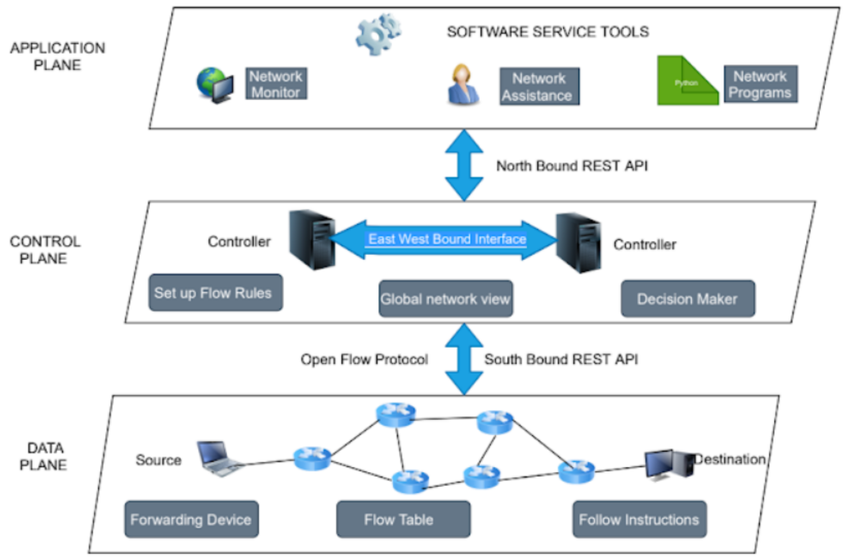
INTRODUCTION

Communication of data in the network is a complex process. The complexity increases when the size of data also increases. The existing network system and the emerging data centers and Internet of Things (IoT) add more to the complexity in data communication. The complexity includes network configurability, network management, scalability, reliability issues, and many more. The size of a network with the increase in its data size becomes rather difficult until the rise of Software Defined Network (SDN). SDN is evolving every day. It aims at making network management and configuration easier with its programming capability. SDN has been an evolutionary change in the field of networking. The vertical integration in SDN [56] is one crucial factor that makes it unique and powerful. SDN architecture has three distinct layers. The topmost layer is called the Application plane, the second or middle layer is known as the Control Plane, and the bottom-most layer is called the Data plane or forwarding plane. The application plane and control plane communicates using an interface known as the Northbound interface (NBI), while the control plane and data plane communicates using Southbound Interface (SBI). Figure 1 shows the architecture of SDN Layered SDN features simplicity in its architecture with simplified networking capability. It has a centralized controller that controls the entire network in terms of decision-making concerning the flow of data. The application plane provides user functionality, while the data plane is considered a forwarding plane with switches that perform the function. Unlike the legacy network where the switches decide, here in SDN, the controller makes the sole decision for data communication. This centralization achieves a great network view to have a bird's eye view of the network [15]. The NBI and SBI are the REST API that allows the planes to communicate with each other. So to say that SDN has many features that make it unique and essential. They are as follows:

1. *Programmability*
2. *Central Intelligent controller*
3. *REST API for communication*
4. *Vendor-neutral architecture*

The features of SDN make it applicable in many areas of networking. The list of applications of SDN is as mentioned below.

1. *Produces a solid and cost-effective connection between different network types such as broadband media, MPLS, and many more.*
2. *Used in Micro-Segmentation.*
3. *They are used in developing software that substitutes specific hardware functions like firewalls and load-balancers. This software will run on the hardware.*
4. *Enables the data centres to connect to the public cloud providers and creates a hybrid cloud network.*
5. *They are used to manage traffic from IoT segments and also help in organizing the data.*
6. *It is applicable in several network areas: data centers, cloud infrastructure, and emerging IoT, fog computing [128].*



In today's world, due to the maximum utilization of the Internet, there has been a tremendous increase in the types of applications and services such as surfing of the web, audio streaming, video streaming, audio/video conferencing, online gaming, and many more. The Internet has been a boon for users. It provides varied services and applications to them. However, it is a tremendous challenge for network administrators to handle and manage the varied application and services with unique characteristics that need to be dealt with differently to provide network quality. QoS, in general, improves network quality and satisfies the users with optimizing network resources. The traditional network focused more on data communication rather than QoS. It is due to its infrastructure and management complexity. However, with the growing demand for data and QoS, the network focus must be diverted towards the quality network. There arises a need for an excellent mechanism to support it, and Internets best effort cannot meet this requirement. In the best-effort method, no traffic is different. Voice, video, and e-mails are handled equally. Traditional IP network has put lot effort to enhance QoS by introducing IntServ or Diffserv. However, flexibility and adaptability were difficult to achieve in IP networks with the increase in data. Network QoS policies are configured statically and managing this static network is difficult. Due to these reasons, in a traditional network, providing quality of service was a big challenge that still exists to be solved today.

The ability of a network to deliver service to the user is called Quality of Service (QoS). Network performance measures the amount of service provided [38]. Network QoS represents the measurement of overall network service performance. QoS depends upon the incoming traffic classification, marking, bandwidth allocation, and congestion control mechanism [86]. It is a service that enhances network performance by prioritizing the traffic and adequately allocating the available resources. The metrics used to measure QoS are mainly bandwidth, delay, loss rate, blocking probability, and delay jitter. QoS is a mechanism of restricting based on specific policies. Today, with the increased Internet usage, the data consumer has increased double-fold while the growth in the existing network is at a languid pace until the rise of a software-defined network. Many studies have been performing to improve and enhance the quality of service in the network. However, there are still many areas where many other kinds of research are yet to done. There are some common problems and issues in the network, making the quality of service a hot topic today for the researchers. The network fills the varied data traffic flows with limited available resources. Some data packets consume larger bandwidth, while some are delay-sensitive. Video flow may have to compete with busty data flow, and real-time traffic needs to prioritize other data types. VoIP, video on demand and video conferencing are sensitive to latency and delay jitter, and differentiate flow based on valuable and invaluable application. For all the data delivery, downtime should be avoided or reduced. For dealing with such issues, QoS plays a significant part. Various approaches can enhance QoS in the network, such as traffic classification, packet marking, traffic shaping, traffic policing, queuing, scheduling, and resource reservation. Based on the types of traffic there are three different types of QoS services. They are:

1. **Hard QoS** : Guarantee QoS requirement but with limiting resources. Such as aircraft information, sensor data, and many more, the system entirely fails if required quality timeliness is not met [51].
2. **Firm QoS** : Traffic that is time-constrained and delivered with missed timing may not suffer system failure, but the delivery is out of bound and does not guarantee QoS.
3. **Soft QoS** : Do not guarantee QoS, and the failure to timely delivery of data will not affect the system to fail but reaches the end with some distortion. It still can provide some information, e.g. Video streaming [51].

In order to achieve QoS in the SDN network, the service provider relies on service level agreement (SLA) between the network service provider and customer. In the traditional network, the vendors provided their own programmed and customized routers and switches. No administrator could reprogram the forwarding intelligence, and hence the flexibility and scalability were a significant issue. Moreover, this stringency made the researcher fail to perform practical measures to work on QoS provisioning. Though there was a method called integrated service (Intsev) and Differentiated service (Diffserv). The mechanism aims to improve the Quality of Service over best-effort Internet service.

Integrated service (Intserv) guarantees hard QoS and reserves resources at each router according to the packet flow path. It uses a resource reservation protocol (RSVP). It is used to reserve resources such as bandwidth between hosts and routers. In this mechanism, the router needs to monitor the incoming traffic and control them. Traffic control has three components, namely, packet scheduler, packet classifier, and admission control. Packet scheduler uses queuing mechanism to schedule packet forwarding. Packet classifier divides the incoming traffic into classes, while admission control will perform a mechanism to check flow for further forwarding or reject it if the policy is not met. Intserv requires routers to monitor the traffic continuously and collect state information for every packet flow, which is a cumbersome task. The router also needs to keep track of admission control, schedule packets, and classify packets. This need creates a considerable overhead on the router. Therefore, another mechanism is available to cope with this, known as Differentiated service (Diffserv) [103].

Differentiated service (Diffserv) Classifies traffic flows into classes. There are two types of traffic flows. They are coarse-grained traffic flow and fine-grained traffic flow. In IP based network, the classification is done using "differentiated services code point (DSCP)." It replaces the TOS field. Packet marking is performed so that they can be distinguished from one class to another. Flow belonging to a single class will be treated equally by the router. It also performs traffic shaping and prioritizing. However, this mechanism does not guarantee hard QoS like Intserv [54][53].

QoS Metrics:

QoS has become one of the important criteria in data communication. Due to the improvement in technology and the growing demands of the users on the Internet today, users need quality service. The traditional network was more to do with data communication, but slowly the trend is changing, and the requirement is tilted more towards the quality of service. However, what determines the quality of an application and services? The major attributes are latency, bandwidth, packet loss, throughput, jitter, and the network's performance is measured based on this. QoS is determined based on the SLA that is signed between the user and the network service provider. QoS metrics or attributes are discussed below [112] [33].

1. **Latency:** Latency is the total time taken for the packet to move from source to destination. Buffering occurs due to high latency. There are three types of delay. They are propagation delay, transmission delay, and queuing delay. *Propagation delay* is the time taken for the packet to travel from one hub to another. The more the distance, the greater will be the propagation delay. *Transmission delay* is the time taken to transmit a data packet to an outgoing link. In this case, bandwidth plays an important part. For queuing delay, the packets are queued and need to be processed accordingly. The time taken

to wait in the queue is the queuing delay. Overall latency for a packet flow should be reduced.

2. **Bandwidth:** The rate at which the data transfers is called bandwidth. The larger the bandwidth higher will be the packet flow. So, there should be high bandwidth for the network to perform better.
3. **Jitter** : It is the maximum variation in packet delay. For improvement of the network, performance jitter should be minimized. The lesser the jitter better will be the network performance.
4. **Packet loss** : The amount of data loss while the packets are transmitted from source to destination is called packet loss. It can be due to network congestion and need to be retransmitted. Loss of packets in the data communication degrades the quality of service, and hence to improve this, we need to minimize packet loss.
5. **Throughput:** It has end-to-end importance. Throughput is the rate at which the packets deliver. It is measured in bits per second. Loss of packet, latency, and jitter affects throughput [113].

With the introduction of SDN today, there seems to be quite a relief to the network administrators in providing quality of service. Using SDN, network management has become flexible and more manageable. It can provision QoS to packet flows efficiently. Instead of using a destination-based routing algorithm, it uses flow-based forwarding. The dynamic flow allows SDN to enhance QoS [51]. SDN uses an OpenFlow protocol to communicate between the data plane and control plane. It supports queue and meter tables. Queuing and metering is done in egress and ingress port, respectively. The Meter table records the rate of flow while monitoring them. It aims to control the rate of flow.

Network monitoring is the crucial element in understanding the network status in order towards the fulfillment of SLA. SDN provides a convenient network monitoring protocol using its global view of the network and can access the network details at a low level [86]. SDN has improved network monitoring. In SDN, we can install rules in switches such that the packets forward to the path with the highest bandwidth rather than the shortest path. There should be continuous monitoring of network status to perform this task. In this protocol, the traffic flow considers per flow. It is one essential criterion for reliable end-to-end data delivery with QoS provisioning. However, in traditional IP, the distributed nature of the network makes it difficult to monitor the network at the lowest level. Moreover, it gets worst when the amount of data in the network is enormous. Another significant area where SDN has impacted is QoS routing. Flow routing has been simpler and faster. SDN allows network administrators to create a good QoS framework for resource reservation, queue management, and packet scheduling. Machine learning-based QoS in SDN can automate the network with the shift of network intelligence from individual hardware elements to the centralized controller [95] SDN finds its application in many areas, and guaranteeing QoS is always a challenge. It can also manage a high-density Wi-Fi network with ease. In [67], the author has proposed a "QoS aware load balancing strategy in SDN Wi-Fi." It shows that unlike in traditional networks where the rigid system restricts its application, SDN finds an extensive application keeping in lieu the QoS provisioning to the end-users. One of the other papers [70] proposes QoS aware SDN in IoT and aims to balance the load of the IoT server. The proposed approach uses a Linear programming model to improve IoT QOS parameters such as throughput and delay. However, IoT devices create vast and heterogeneous data, and the proposed method does not consider the QoS in terms of varied application and size of the data.

Moreover, smart home devices are also becoming very popular. However, due to this popularity, it has become difficult for Internet Service Providers (ISP) to manage bandwidth efficiently. The solution to the problem has been discussed in [50] the use of SDN for managing bandwidth has proved efficient. It has proven beneficial even more to improve on QoS. The framework allows ISP to optimize bandwidth allocation by collecting all the services of smart homes. Priority-based allocation is done based on the type of application, such as delay-sensitive application. The approach can provide QoS and also Quality of experience (QoE) for the user. Even after years of improvements over the traditional network, SDN has yet to resolve the challenges. Table 1 enlists the differences between QoS in traditional networks and QoS in SDN networks [9].

Table 1 Difference between QoS in traditional and SDN networks

QoS in Traditional network	QoS in SDN
Incorporating intelligence using machine learning in network device is difficult due to its distributed nature	Each network
Network devices are managed using command line interface (CLI) and scripts. Automation is difficult	The network r
Every network device needs to learn traffic pattern.	Traffic pattern
Network cost increases with increase in throughput due to decentralization.	Central contro
Cannot adjust with the real time changes in the types of application and user needs. [95]	Can easily cop

Another dimension to add to SDN and QoS provisioning in SDN is Machine Learning (ML). ML is getting exploited in all the significant areas of network research. It provides promises to handle complex problems. Arthur Samuel stated that Machine learning is "the field of computer science that can learn without being explicitly modeled" **[21].** ML algorithms automate a solution to complex problems by learning a model from a given training set and making certain decisions using the patterns extracted from the large datasets. [82] ML research accelerated only from the mid of 2000. The reason behind its acceleration was the Internet. Growth in Internet usage increased the number of datasets, especially multimedia data. An increase in data increased the amount of power used for computation and storage. An ML algorithm handles large and complex data for resolving problems such as classification, clustering, regression, and prediction. The classification process classifies data into different classes or categories. Clustering process groups a large dataset into clusters while predicting builds models using historical data to predict future events.

With the advancement of the Internet, research in networking is getting exploited in both academia and Industry. Due to complex and diverse network features, applying the specific algorithm in the different network environments is complex and cumbersome. ML brings quite a relief when considering networking. It adds a cognitive property to the network. An ML technique heavily depends upon data. The Internet of Things (IoT) connected with many devices also adds to the increasing data in networking. This growth in the amount of data encourages the use of ML in the field of networks. Moreover, recent advances in cloud computing, Graphics processing unit (GPU), Tensor processing unit (TPU) provides more training for large datasets. Regardless of having all the advances and network management, network faults are still quite prevalent [21].

The key contributions made in this survey are enlisted below:

1. The survey presented here highlights the significant research done after 2019 onwards, which is relatively new and not seen in other survey works.
2. This is the first survey that combines both ML and DL-based QoS-aware protocols in SDN. A taxonomy of the ML – DL based protocols for ensuring QoS in SDN has been developed and presented in this paper. This review will surely help academicians, researchers, and students to get a clear understanding of the field.
3. The paper highlights the Machine Learning techniques in ensuring the quality of services in SDN. It also revolves around many Deep Learning techniques that have helped improve the quality of service in traffic classification, routing mechanism, and queuing and scheduling. To the best of our knowledge, this survey is one of the first kinds of a survey that includes both Machine Learning and Deep Learning methods used in SDN for traffic classification, QoS routing and queuing and scheduling. Deep Learning in SDN is the new area of research, and it has been our best effort to survey the most recent advancements in this area concerning the Quality of Services in SDN.
4. The paper highlights the merits and demerits of the ML-based and DL-based QoS aware protocols in SDN. It also highlights their prospects, issues, and challenges.
5. The survey also includes a separate section regarding Deep Learning based research done in SDN.

Rest of the paper is structured as mentioned below. Section II provides a background on machine learning and deep learning, in general. Section III provides a summary of relevant literature and similar survey works. Section IV provides a highlight on Quality of Service based Software Defined Network architecture, followed by section V, in which ML and DL based QoS aware approaches are surveyed. Section VI presents a survey on ML and DL based QoS aware traffic classification techniques. A survey on ML and DL based QoS aware routing techniques for SDN is presented in section VII. The issues of queuing and scheduling in SDN are highlighted in section VIII. Section IX presents various issues and challenges faced by SDN followed by section X in which future research directions in the area of SDN are highlighted. The paper is concluded in section X.

A BACKGROUND ON MACHINE LEARNING AND DEEP LEARNING

ML techniques apply in many application areas such as network security, speech recognition, pattern recognition, outlier detection, network operation automation, network management. However, due to the network complexity, it has become a hot topic of research today. The research extends in the area of Software-defined networks (SDN). SDN being the trending network technology that can handle massive data with minimum network management. ML implementation has become an upcoming research area. ML in networks is very suitable because it can classify and predict certain network problems such as Intrusion detection, network performance, decision making, network scheduling, load balancing, traffic pattern identification, traffic classification, traffic prediction, network states [99]. It provides researchers with new possibilities for solving complex network problems.

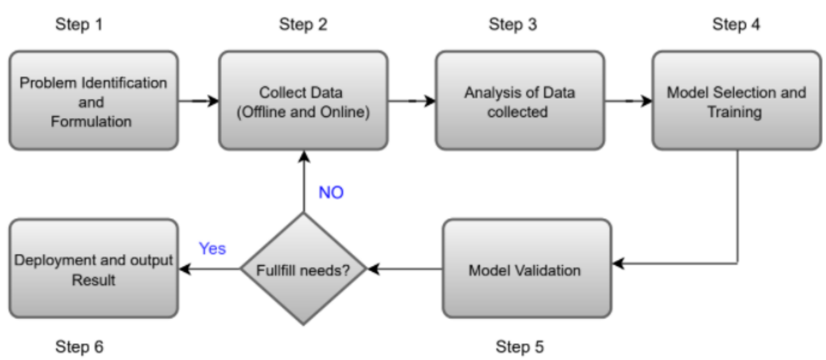


Figure 2.Workflow of ML in networking

Figure 2 shows the workflow of ML in networking having the following six steps:

1. **Problem formulation** : The first step in an ML network is to identify the type of problem and formulate it depending upon whether it is a classification-based, clustering, or prediction-based problem. It helps in determining the type of data to be collected and learning model selection.
2. **Data Collection** : Collecting large and relevant network data is the next stage after problem formulation. Data are generally collected in offline and online modes. Offline mode data are the historical data, while online data are the real-time data. Good data collection depends upon the proper identification of problems.
3. **Data analysis** : During this stage, it performs feature extraction. Proper feature extraction determines the performance of the network. However, before extracting the feature, it performs data preprocessing and cleaning.
4. **Model Construction** : This step involves model selection and training. An ML learning algorithm is carefully chosen based on the problem and the size of the datasets.
5. **Model Validation** : This step validates whether the learning algorithm works well or not. It tests the accuracy of the model and shows whether the model is over-fitting or under-fitting.
6. **Deployment and Inferences** : In this step, the learning system takes the real-time input and gets the output for determining the performance.

The history of the evolution of ML started in 1943. It began with a mathematical model of neural network (NN) for computers given by McCulloch. In 1950, Alan Turing introduced the idea of the learning machine.

In the same year, the approach called Ordinary least square using the least square method was derived. Following this, Maximum entropy and logistic regression were introduced for classification. On the other hand, pattern recognition provides two models. They are K-nearest neighbor and kernel density estimation. During 1950 Naïve Bayes classifier was used for pattern recognition. Then came the usage of the Hidden Markov Model in 1960. In 1963, the first regression algorithm was added to the timeline known as decision tree but found its usage very late in the timeline. In 1965, Deep Neural Network was introduced. This algorithm later gave new dawn for the addition of a new method known as Deep Learning. By the end of 1970, the second part of the decision tree known as ID3 or Iterative Dichotomiser3 was introduced. In 1980 an ML technique known as the Bayesian network came into an application. By 1990, ML research focused mainly on "Neural networks, decision trees, and support vector machine (SVM)." It was followed by the introduction of the ensemble learning method. The method combines one or more of the predictors or classifiers. The various ensemble learning method is Random Forest, Bagging, Adaptive boosting (AdaBoost), stochastic gradient boosting (SGBoost). By the end of 1990, the ML was implemented for many applications such as pattern recognition and data mining. It made a huge shift for ML, making it data-driven ML. The era of 2000 increased the popularity of Deep learning and ensemble learning. Today, its popularity has increased its usage in all the major areas of the network, such as traffic prediction to traffic classification [21].

According to the survey done in [102], the ML learning model applies in many networking areas. It has pointed out the research area on ML in networking. Some of the leading research areas of ML in networking is as below:

1. IP traffic classification
2. Used in solving common issues in wireless sensor networks,
3. Cyber security Intrusion detection.
4. Used for solving common issues in self-organizing cellular networks.
5. ML and Deep learning-based Intrusion detection.
6. Neural networks for solving communication, virtual reality in a wireless network.
7. Internet of Things (IoT) security.

ML has had a significant influence on the networking field. It is this area where researchers have lots of interest. Another important field of research today we can see is software-defined networking (SDN). Studies have continuously been done in this area these days. Today in the 21st century, network advancement is happening at a high-speed rate. The introduction of intelligent devices, the Internet of Things (IoT), has augmented data traffic tremendously. The network is becoming heterogeneous and very complex. The features and characteristics of SDN have attracted many researchers' interest. ML with SDN seems to be one of the most recently researched areas in traffic prediction, traffic classification, QoS provisioning. The vertical integration of SDN and its network programmability with vendor neutrality aims to reduce network complexity. The global view of the network adds to a convenient collection of network status information. As already discussed, ML plays around with data. More the size of the dataset, the ML model accuracy is more. Therefore ML in SDN has been one of the prime research focuses today. As stated in [102], applying the ML technique in SDN is feasible because of the following reason:

1. Recent advances in cloud computing, Graphics processing unit(GPU), Tensor processing unit(TPU) provides an excellent chance for using Machine learning techniques in SDN.
2. ML is based on data, and SDN with its centralized controller can collect huge network data. Therefore this property of SDN makes it very feasible to apply ML algorithms in SDN.
3. SDN programmability allows ML algorithm to provide network management such as network configuration, allocation of resources on the network in real-time.
4. SDN controller can collect huge network data. The ML algorithm uses historical data and real-time data to improve the network intelligence in many applications such as predicting network traffic condition, traffic classification, network optimization, congestion control, intrusion detection, and providing Quality of service

Machine learning algorithm learns from the huge datasets. The larger the dataset, the more accurate is the learning process. SDN network has improved intelligence with a logically centralized controller. It also has a centralized data collection repository that enhances the quality of service.

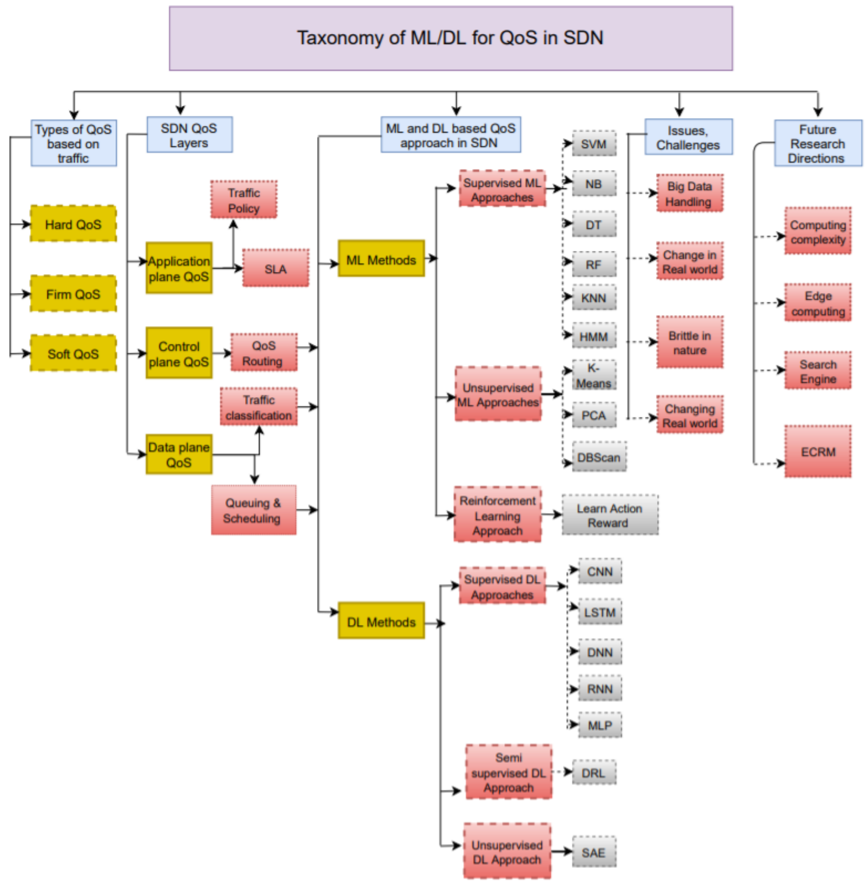
Moreover, machine learning models can be beneficial in learning from the datasets and identify patterns, nature of the network. It enables the network to provide QoS to the user efficiently. ML can be used to predict the congestion in the network. It classifies different types of traffic and provides user service according to the traffic priority. ML has become a trending area in SDN in terms of providing quality of service such that the network functions efficiently. Another vital area that provides network intelligence with QoS is Deep Learning (DL). DL is a type of ML and a sub-class of artificial neural network. ML techniques can make the network intelligent with less computing power, while DL allows the network to learn even from the unstructured such as video, images, and encrypted data. ML, along with DL, brings more enhancements in the research area. ML/DL is the steps towards making the correct decision, predicting a particular outcome by analyzing the pattern created by the huge dataset. DL has multilayered nodes called neurons, and they are intensely connected to extract knowledge while increasing the abstraction. There are different types of DL discussed in the section below. The significant difference between ML and DL is that ML is less automated than DL, but DL has a very complex structure due to the multilayered architecture. ML takes less time to set up but produces result taking time while DL provides the prompt result with more set up time. Bur in SDN, both the approaches are in their initial stage. The researchers are doing research using both techniques in the field of SDN. Furthermore, to bring light to ML and DL approaches in SDN, we have presented a survey here. ML/DL-based QoS aware protocols have been studied by many researchers, which are discussed in section II, section IV, and section V of this paper.

RELATED WORKS

The importance of Machine Learning in providing quality of service is widely understood today. This part of the paper presents the related work that many authors have done on surveying Machine learning and QoS protocols to improve SDN network performance. Zhao *et al.* [111] is very close to our study here. It bases its study on the application of ML approaches in SDN. The paper highlights the performance analysis of different ML algorithms with accuracy towards prediction. It is an exhaustive study on various supervised and unsupervised machine learning algorithms and their future development. However, it leaves out the necessity of improved QoS using varied machine learning techniques. The survey done in [102] presents all the ML techniques implemented in SDN. It highlights a detailed study on SDN's supervised, unsupervised, semi-supervised, and reinforcement learning methods. It brings light to the methods with their advantages and shortcoming. It also provides a general discussion about "Neural networks, deep neural networks, convolution neural networks, and recurrent neural networks." This survey is quite similar to our survey. However, our survey has an additional study on deep learning mechanisms and all machine learning techniques used to provide QoS in SDN concerning traffic classification, routing, queuing, and scheduling. Thupae et al. [94] have highlighted various traffic classification-based SDN in Wireless Sensor Network (WSN). It shows the usage of supervised and unsupervised ML techniques. The paper discusses the challenges faced while using these approaches. Survey in [62], highlights machine learning in classifying traffic for various applications using a supervised, unsupervised and semi-supervised learning algorithm. It draws the limitations of all the learning techniques. A supervised learning algorithm uses labeled datasets and can classify traffic efficiently when the traffic in the network is simple. However, as the traffic increases, supervised learning techniques may not be able to make distinct classes of traffic. This way, it is seen that the unsupervised learning technique is the future of network traffic classification. It does not need to label the datasets, and the traffic class automatically forms. It uses the clustering technique and finds out matching patterns to classify traffic. On the other hand, semi-supervised takes the good of both supervised and unsupervised machine learning techniques. It uses both labeled datasets and unlabelled datasets aiming at reducing workload and improving classification accuracy. Data mining from unlabeled data provides information that is of more use rather than considering labeled datasets. The survey is an extensive study on ML and does not focus on service quality and network performance. The study in [51] is on the QoS characterized by several network metrics such as bandwidth, jitter, delay, packet loss in the SDN using OpenFlow protocol. The survey undertaken by the author highlights QoS according to the benefits of the improvement of QoS using the concept of SDN, based on routing, queuing, scheduling, network monitoring. It also states that this process is ongoing. However, to our knowledge, this paper does not highlight the many opportunities in determining network QoS using machine learning techniques.

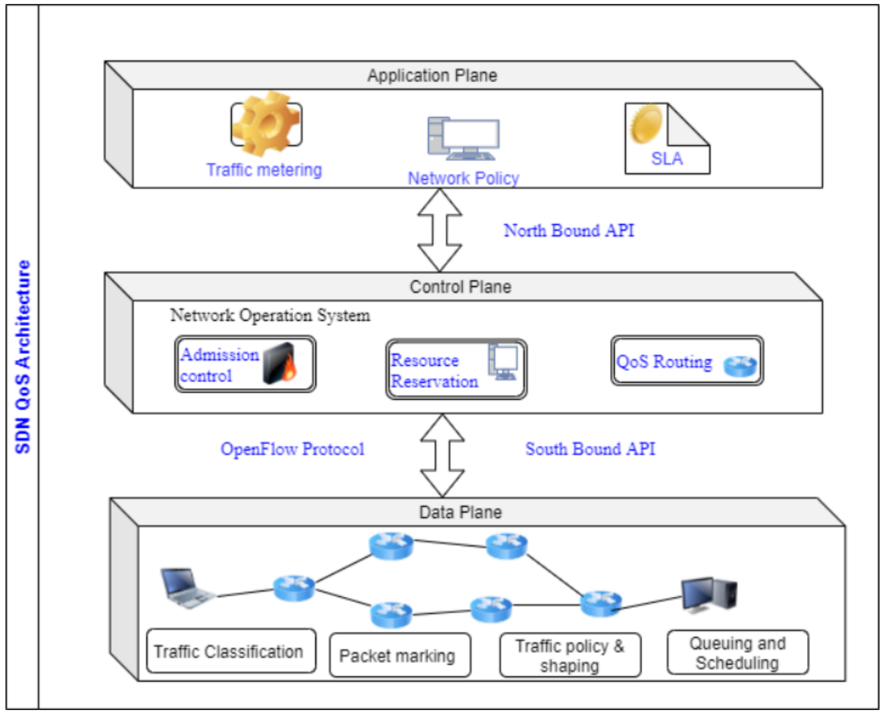
The paper [19] presents a QoS aware state in SDN using the concept of autonomic computing. The main focus is on QoS provisioning the architectural model of autonomic computing. The survey does not focus on ML techniques in detail but has kept it for future study.In [102], the paper highlights SDN that uses ML techniques to enhance network performance and efficiency. It compares different ML approaches based on the learning model, the complexity of an algorithm, and accuracy. The survey accumulates the details about traffic classification, optimum routing, QoS prediction, management, and usage of resources and security. This study is a broader view of ML algorithms in SDN with the issues and challenges in this area. This paper [34] presents the application areas of ML in SDN and NFV. It aims at identifying the role of ML in SDN for improving the network intelligence towards making SDN a self-controlled and self-configured network. It also states the issues and challenges faced in SDN and Network function virtualization (NFV). The survey illustrates different AI and ML applications that apply in SDN and NFV in terms of their network organization and network management. It points out relevant future research needed in the area of ML in SDN. [60] Guaranteeing QoS in the network has always been challenging in the world where the data is increasing rapidly, such as with the future 5G network. The comprehensive study done in this is regarding handling such a huge data using ML techniques in SDN, NFV, and big data. It collects and analyses a huge amount of real-time data and performs quality control using per-flow traffic priorities to guarantee bandwidth utilization. Resource sharing and utilization are one of the major concerns in guaranteeing QoS. Network resources may be network devices, network management such as human resources, scheduling, and many others. Managing these resources is a difficult task, and Machine Learning can manage to a greater extent. The paper [87] discusses the various ML approaches applied in resource management to improve upon QoS. However, the research surveys the resource management and network management in SDN and NFV, leaving out other QoS parameters such as delay, bandwidth that affect the network performance. It identifies many challenges with resource utilization and suggests certain measures to manage resources effectively. The survey presented in [3] compares the QoS protocols in conventional and software-defined networks (SDN). The paper provides an analysis of different QoS protocols and approaches that best suits traditional networks and SDN. This survey paper mainly elaborates the protocols such as RTP, RCP, SIP, RTSP, and RSVP. It also elaborates the QoS-based SDN approach with the use of queuing and scheduling. ML and DL-based QoS is not studied and researched. The survey in [69], highlights different approaches to traffic prediction and classification using Deep Learning. Unlike other survey papers, the major input of this paper is towards traffic prediction that can enhance the quality of service by improving resource utilization or other matrices. Network traffic prediction helps to avoid future congestion. Network analysis is the most important criterion of the prediction; it enables the network to be intelligent enough to decide upon future traffic. Although the paper has highlighted many measures to tackle traffic, the paper is restricted to only the Deep learning approach in SDN and does not focus on provisioning QoS. The survey [43] presents the importance of traffic engineering in SDN. It has mentioned the importance of machine learning for traffic engineering in SDN for handling large amounts of data. It brings about different approaches used by many pieces of literature but only in the area of traffic classification and prediction. The survey does not focus on other avenues that use ML and DL for provisioning QoS in SDN. Whereas the survey performed in this paper is unique. It features the different ML techniques implemented in SDN in different layers of SDN architecture based on QoS aware protocols. It also brings about various comparisons between the many ML approaches, which can help researchers in their studies. When SDN coupled with machine learning, network decision becomes more intelligent. The survey in [36] presents network resource management, security, traffic classification, QoS prediction with future issues and challenges using ML. The study is not specific to only QoS. It generally surveys IoT in SDN and machine learning algorithms, unlike the survey done here, which specifically revolves around machine learning based on QoS aware protocols in SDN.

Figure 3 shows a taxonomy of different protocols that have been built based on ML and DL, for ensuring QoS in SDN. This taxonomy is also a contribution of this paper.



QoS BASED SDN ARCHITECTURE

SDN architecture plays a crucial role in improving the quality of service to increase network performance. SDN architecture comprises three discrete planes: data or forwarding plane, control plane, and application plane. The Control plane is the central point of the architecture. It is said to be the brain of the SDN network. The network intellect is centralized in the control plane. It uses a centralized controller to govern the entire network. It enables a globally centralized collection of flow information. QoS of SDN with regard to controller play a major role in network reliability and scalability [126]. The characteristic of SDN has the most critical effect on enhancing the QoS. SDN networks are programmable, agile, and therefore QoS provisioning is much better than in traditional networks. Many different frameworks exist today, and for our study here, Figure 4 highlights the general QoS framework in SDN.



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In the QoS framework of SDN, the data plane deals with packets, frames, and queues. The Control plane deals with control management, network management, and routing agents. Application plane deals with metering, queue management, and policing. Figure 4 depicts various QoS functions associated with each layer. Each QoS function is discussed in brief below:

Application Plane QoS:

Application plane plays a crucial role in ensuring the quality of service. This layer collects the real-time requests for different applications and the needed QoS, such as the degree of latency, reliability requirement, bandwidth requirement, and many more [41]. They provide service to the control plane through a northbound interface. They also take up a view of the network for making certain decisions. The application plane needs to handle a huge amount of requests for the different applications. This request for different applications handles using traffic metering, traffic policy, and queue management to ensure a quality of service. Each of these services discusses as below:

1. **Traffic metering** : Traffic metering measures and control rate of packet flow entry. It is a measurement of delay, jitter, and packet flow rate. One common traffic metering technique is the token bucket [23]. Token bucket measures the traffic. Token bucket uses a marking policy. Marking enables the packet to be either accepted or dropped [RFC 2697]. The traffic meter decides which packets transmit over the link and which drops to reduce the link load and bandwidth usage [58]. Traffic control is necessary to ensure all the available resources are utilized at their best and do not create any congestion in the network, leading to delay, packet loss[80]. In [88], it has shown the use of a traffic meter for marking the incoming traffic flow and managing token buckets, which helps the controller manage the packet flows such that QoS is guaranteed.
2. **Traffic Policy** : Traffic metering and traffic policy are the essential components of QoS [17]. Traffic classification basis on traffic policy. It is the guidelines for the traffic class to follow for QoS management. Policing performs using a particular policing algorithm such as the leaky bucket algorithm. The packets are dropped or discarded if a particular required policy is not met. Traffic policy in SDN is

not a static policy like the one in the traditional IP network. It is dynamic and plays a significant role in determining user satisfaction with the quality provided [96].

3. **Service level agreement** : Network is proliferating, and there are many networks the data needs to travel to reach its destination. In order to provide end-to-end QoS, all networks need to work with coordination. However, handing a packet from one network to another cannot be based on faith. Therefore Network service provider prepares an agreement known as service level agreement (SLA) [16] [52]. The mutual agreement of service that the service provider will provide and to which the customer agrees also indicates which service to provide. The agreements can be updated from time to time [97]. SLA shows the relationship between the client and network service provider. SDN needs to perform its task of routing and scheduling. This SLA attains SLA defines business rules, responsibilities, description of services, parameters that will measure QoS, violations, and penalties. It is a document that manages QoS [83].

Control Plane QoS:

The Control plane has a centrally located controller and is said to be the brain of SDN. It provides intelligence to the network by making all necessary decisions such as admission control, quality of service-based routing, resource reservation. It is easy to maintain and manage. The controller resides in this plane and is responsible for all decision-making. It can communicate with the application plane and data plane using northbound API and southbound API. It uses OpenFlow protocol and manages the network to ensure that the data traffic is forwarded to have efficient end-to-end data delivery with control on delay, resource utilization, and link failure avoidance[6] [7]. It guarantees the quality of service. SDN uses OpenFlow protocol. This protocol is a standard that allows the data plane to communicate with the control plane. Generally, QoS implements using meters and queues, but in [20], it uses OpenFlow to create a class of service queues. The bandwidth prioritizes according to the class and unused bandwidth with other classes. In this scheme, the controller has the total capacity to monitor flow statistics and meters. The main aim of the proposed scheme is to guarantee QoS for each flow and improve throughput. Such as this mechanism, many focus on improving QoS parameters to have a better quality of experience. Further, as per the QoS architecture specified in figure 1, control plan, QoS is characterized by the following:

1. **Admission control** : It affects QoS, and the controller controls the admission criteria for the traffic. The admission policy decides the incoming traffic access point by the controller in SDN. It uses the admission control method to determine whether it is possible to assign the needed services such as bandwidth based on availability and congestion avoidance. This mechanism is a crucial point for provisioning network QoS. [28]. One such admission control policy discusses in [28]. Since SDN finds lots of importance in IoT, the author designs a control policy known as time-sensitive network standards. This policy aims at guaranteeing allocation of time slot for transmission so that it can schedule the traffic accordingly [117]. In such a way, admission control can be managed so at to provide QoS.
2. **QoS Routing** : QoS routing selects routing paths while meeting strict end-to-end service requirements involving resource constraints while achieving optimum throughput in the network. A network should be able to treat different packets differently for a network to support QoS. It is seen that some data, such as multimedia data, are time-sensitive. QoS aware routing becomes very important wherein [72] discusses reducing end-to-end delay and packet loss during the routing of data using optimal path and energy. Many such approaches aim to improve QoS, and the use of machine learning can enhance more. It is discussed later in this paper.
3. **Resource reservation** : It is a mechanism to reserve resources for different applications. Resource reservation protocol (RSVP) provides QoS. With the growth and popularity of audio and video data or real-time data, QoS is a primary concern. For such applications, resource reservation is suitable enough to fulfill the required QoS [114].

Data Plane QoS:

The Data plane is the bottom-most layer in SDN architecture. It is also called the forwarding plane. The network intelligence is given to the control plane from the data plane. As per the decision made by the controller of the control plane, the switches in the data plane forward the packet accordingly. Even though the data plane does not have any intelligence, it plays a role in determining quality service to the end-user. For determining QoS in the data plane following characteristics are discussed below:

1. **Traffic classification** : It is the process of classifying traffic into traffic classes. Accuracy in classifying traffic is essential for QoS. Traffic classification performs using the port-based method, deep packet inspection method, payload-based method, or machine learning technique. Today the most common method has been using machine learning. This method is based on traffic characteristics such as packet length, inter-arrival time of the packet, and many more. They include many steps. Initially, features are extracted based on flow features; secondly, these features are selected and trained to generate rules for classifying traffic [105]. The QoS aware ML for traffic classification has been studied in this paper in detail.
2. **Packet marking and policy** : it is marking the traffic classes based on the classification that was done previously. The marking relies on traffic policy framed by the network administrators with policing or checking the packets' rate. The packets are marked based on the class, and these marks help the network consider the packet as it is to be treated [116]. It can simplify classification at a later stage.
3. **Traffic shaping** : It is a technique that regulates incoming traffic flow to ensure the quality of service in the network. It is a major criterion for determining QoS. It aims at avoiding packet drops and packet delay. It also shares the available network resources according to the requirement of the application. There are different traffic shaping techniques based on class and weights [14].
4. **Queuing and scheduling** : When a packet arrives in the incoming node, it may not be processed immediately, or queuing is needed. Depending on the types of applications, they can be prioritized and divided into multiple queues scheduled to be processed. There exist many scheduling and queuing algorithms in data communication. Queuing and scheduling is further discussed in the coming section.

The layered architecture of SDN with QoS improves the traditional way of provisioning QoS. Every layer has a role to play. It determines the required demand-based resources are fulfilled from bandwidth requirement and reduce packet delay and jitter with end-to-end timeliness for real-time applications such as audio/video streaming, VoIP, audio/video conferencing. It highlights various studies undertaken for provisioning QoS in SDN to date, which is also discussed in this section. One such study has been done in [95], where SDN OpenFlow protocol fails to provide QoS. It proposes a model of SDN framework that includes resource reservation, route calculation, admission control, and route monitoring. It uses graphical representation with the shortest path algorithm. Managing QoS is another challenging area. The author discuss about the platform in [127] to guarantee the QoS that is promised based on Service oriented architecture (SOA) based SDN. It defines the open gaps required for QoS provisioning with no algorithm for addressing the gaps.

However, the study does not support dynamic changes in the network environment, and the network's intelligence is kept for further prediction. It considers pretty challenging in providing end-to-end QoS in a traditional network due to its distributed nature. With SDN having logically centralized control with the global view and flow-based forwarding scheme, provisioning QoS has improved. The study [40] introduces a "deterministic network model" using network calculus. It calculates the optimal paths for each flow using priority to provide end-to-end QoS in SDN. The study focuses on provisioning QoS on a real-time application using the benefits of SDN. It uses centralized QoS resource allocation planning with network calculus with a deterministic network model based on delay and multipath hops. The main aim of the model is to have a simple calculation for admission control, use multiple queues, and calculate the effect of high priority queues on low priority queues. The end-to-end real-time QoS path planning uses a greedy algorithm and a Mixed Integer Program (MIP). It achieved greater link utilization of over 60%. However, MIP consumes higher resources but can be used as a benchmark for real-time QoS routing problems. Along with QoS routing, further research still needs to be done regarding finding the best pattern set for QoS provisioning.

In [39] it provides a mechanism to improve QoS in Industries using SDN. Industries deals with real-time applications which need end-to-end guaranteed quality of service. To enhance QoS in an industrial environment using SDN, it proposes a model based on network calculus that provides deterministic service (Detserv), namely multi-hop model and threshold-based model. The model aims at reducing packet loss and delay bounds for the queue. It also considers buffer consumptions and flow rate. The threshold-based model is more flexible than multi-hop based on flow characteristics, but it has an increased request processing time according to the priority level. The QoS framework discussed needs further consideration with routing, which is not included here.

Concerning provisioning QoS, SDN seems to provide a strong base for the network to enhance end-to-end delivery quality. The study provided in [44] focuses on QoS metrics such as time to respond and bandwidth for different QoS architecture such as "Real-time Online Interactive Applications (ROIA)," multiple packet scheduler, and NOX. The main of this study is to improve QoS by designing efficient architecture. However, it further aims to enhance QoS considering switch capacity, queues impact, and bandwidth isolation in the future. The paper [1] considers the allocation of bandwidth for cloud users' requests enabling guaranteed QoS provisioning for the end-to-end data delivery. The approach dynamically allocates bandwidth based on priority scheduling using OpenFlow switches. It also introduces queuing approach to set the priorities based on the type of services for allocating bandwidth and have maximum resource utilization. For further study, the paper aims to improve QoS considering the switches and network scale. As the cloud and big data influence the amount of growing data, it has become very challenging to manage networks and optimize the network resources to boost the QoS for various applications and services. The study in [4] aims at designing a policy-based QoS framework for SDN. The flows forwards through the switches based on the policies enforced upon them. It uses Neural Network for congestion avoidance by finding the flows that create congestion, performs rerouting, and limits the flow rate. The approach improves QoS provides to the flows based on throughput, packet loss, and latency. In the future, the study extends to incorporate intelligent decision-making using a proactive approach. SDN has a varied range of applications, and there seems to be a great opportunity for SDN in mobile network operators as SDN can provide lots of benefits. The paper [5] compares a comparative analysis with SDN in LTE-evolved packet core (EPC) and a simple EPC. SDN-based EPC offers better and improved QoS, especially for real-time multimedia applications in the mobile network. This study takes up QoS parameters and evaluates and analyzes real-time services for both EPC with SDN and without SDN considering multiple loads, injecting probe packets. It takes latency, jitter, and packet loss as comparative metrics and outperforms in EPC with SDN. The study does not focus on throughput and resource availability. It also needs to consider other TCP traffic to assess both designs. The scalability factor should also be included in the future.

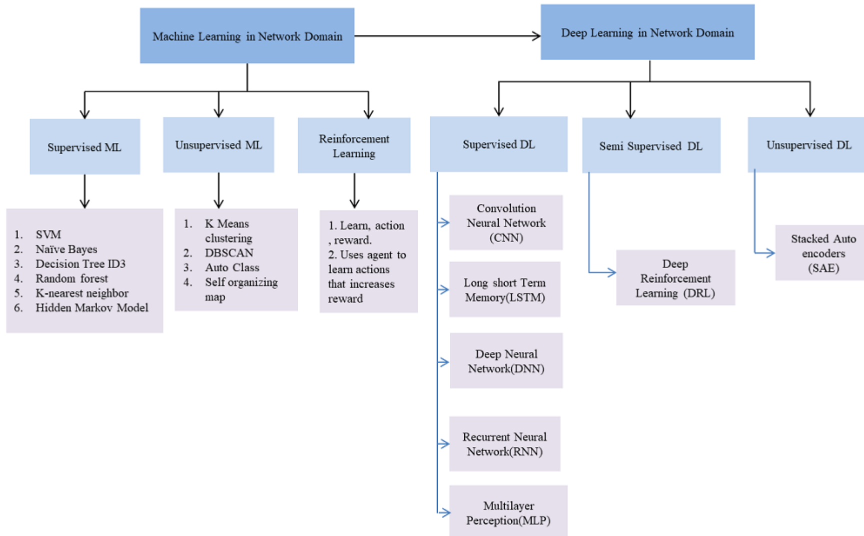
The study in [12] focuses on academic campus networks where there are multiple services requirements such as on-demand video, mobile client and real-time applications, etc. The approach aims at improving latency, jitter, and bandwidth as QoS parameters using SDN. Using a real-time environment, it implements a QoS policy based on the traffic categories with TCP and UDP protocols in SDN. It uses statistical analysis to compare QoS in SDN and traditional networks. The study includes only TCP and UDP traffic, but it does not discuss the scheduling of this traffic and prioritizing criteria. The study presented in [13] proposes a QoS policy framework that is flexible and compatible. It provides an interface for providing QoS based on Service level agreement using SDN OpenFlow. Continuous network monitoring is done to adjust the traffic for certain QoS parameters to meet Service level agreements. The study mainly aims to guarantee three QoS parameters. They are latency, throughput, and reliability. The policy discussed monitors the traffic, check policy and if violates then-manager takes specific action to adapt to the policy and reallocate the available resources. In the future, the study can be further taken up to collect control applications to improve the layers' abstraction. The traditional network may not be feasible for better quality mobility for an autonomous vehicle using the network. Hence, SDN comes to play, but this technique can be more enhanced when combined with edge computing that uses DMM. The paper [32] provides a mechanism "MobQOS" to handle challenges concerning mobility, latency, and connectivity along with intelligence. The technique minimizes latency during real-time communication. In the future, the work can be further optimizing energy utilization that can reduce overall cost. For large-scale data, quality of service plays a major role in network performance. Even for the home users, the network performance for the data, video, and audio is expected to be very good. The author in [85] proposes an application-based architecture for QoS flow for home users using a broadband network. It uses a traffic classifier and rate controller. Users can select the policies from the management plane based on the applications to set priorities for audio streaming, VoIP. The "FlowQoS" classifier classifies HTTP, HTTPS, and other applications based on the QoS selected. It then performs application-layer protocol identification for each flow. After that, the flow rules are installed in the switches and routers. The flows prioritize accordingly using traffic shaper. The proposed mechanism supports improved network performance for adaptive video streaming and VoIP. While in the whole scenario, the delay criterion is not considered, which actually can affect the end-to-end data delivery of such data. Author in [35] proposes a QoS framework that incorporates network monitoring, route determination, designing rules, and network configuration. Network monitoring monitors ports and link delay. Route determination determines the shortest path route with and without QoS guarantee based on the Dijkstra algorithm. The two main QoS parameters considered in this study are port monitoring and link delay. It also uses a port agent in the host to calculate the end-to-end communication delay. The study was undertaken for three different traffics. They are UDP, TCP, and VoIP. However, due to some external queries on the controller, there included some overhead. The designed framework aims to improve overall average delay and packet loss and needs to include other QoS metrics, such as port utilization and jitter. Moreover, path selection also needs to be done based on the applications. SDN on a large scale can induce a larger end-to-end packet delay. Moreover, for real-time data communication, timely data delivery is of utmost need. In the study undertaken [110], the analytical model is discussed to determine end-to-end delay with multiple nodes in SDN. This model considers the time consumed by the switches for installing rules. Not only link delay, but it also considers rules installation delay in each switch. Delay in each switch will have an overall impact on the total delay. Moreover, the study also focuses on the delay caused by Ternary content addressable memory (TCAM).

MACHINE LEARNING AND DEEP LEARNING BASED QoS AWARE APPROACHES IN SDN

SDN is a newly added approach that overcomes many challenges of traditional networks. Provisioning quality of service in SDN is one among all. As already stated, the traditional network is distributed in nature, and manual labor is more than expected. The increase in types of devices and the rise of communication make traditional networks difficult to handle. More network intelligence is a need of an hour because of the increasing communication between smart devices, cloud computing etc. Centralization, programmable and global view characteristics of SDN can be used with machine learning to further improve network intelligence in provisioning QoS. This enables the network to cope up with growing complexity in heterogeneous network communication and management. As stated in [102], the advantages of using machine learning in SDN are:

1. The SDN controller can gather total information and data from the network due to its global view. It allows machine learning algorithm to provide knowledge base intelligence.
2. Machine learning allows data analysis on real-time data and past data. It enables data prediction.
3. It can improve intelligence by optimizing the network and perform automation.
4. Machine learning can benefit from SDN programmability in network management and can run in real-time.
5. Machine learning algorithms in SDN can improve network performance by improving resource utilization and optimization. It can reduce latency, delay, and jitter intelligently.
6. Machine learning can predict congestion and avoid by predicting the network status and working out intelligently. It enables QoS provisioning by efficiently and effectively utilizing network resources such as bandwidth and minimizing packet loss and delay in end-to-end packet delivery.

Machine learning learns a specific pattern from the training set. Machine learning algorithms classify based on the features. The datasets with certain attributes are the input to the machine learning algorithm. Machine learning algorithm has two distinct stages. They are training and decision-making stage. In the training stage, the machine learns a pattern, and in the decision stage, it draws a particular outcome [68]. Figure 5 depicts the different types of machine learning techniques used in many survey papers [106].



One more type can also exist between supervised and unsupervised, known as semi-supervised. Supervised machine learning algorithms are statistical classifiers based on labeled data such as "support vector machine (SVM), decision tree, Naïve Bayes, random forest, K nearest neighbor, neural network, hidden Markov model (HMM), etc." [68] Decision tree is a classification algorithm that uses divide and conquer method. It is an iterative process that forms a tree based on information gain to reach the leaf node to decide. Another ML algorithm is Naïve Bayes classification technique. It uses the Bayesian theorem [51]. A set of attributes are compared and analyzed for classifying them into classes. It uses probability distribution to classify the traffics. K nearest neighbor is based on pattern recognition. This classification algorithm is simple and powerful to implement. However, it is quite a slow classification technique [49]. The unsupervised machine learning algorithm is a clustering technique based on unlabeled data. They include K-means: It is a clustering technique that forms a cluster from the partition made, "DBSCAN", "Self-organizing map (SOM)", "Auto class,". Reinforcement learning includes deep reinforcement learning, RL-based game theory. The study done in [47] highlights the use of big data analytics in ensuring QoS in SDN. The work shows the relationship between key performance indicators and a machine learning algorithm that learns the traffic condition and predicts future traffic that might or might not cause congestion. For adequate QoS in SDN, measuring the QoS parameters is essential. Quantifying QoS parameters such as delay, packet loss, and bandwidth usage are other important factors, and this is possible using a machine learning algorithm. It cleanses the data to handle missing data. The experiment finds out a correlation between delay and jitter. It also makes a future prediction. ML-based SDN finds its application in many fields as in [30] it depicts the use of unsupervised ML in SDN for the future wireless network. The main aim is to improve QoS in every area of networking. And as seen today, the future of SDN with ML for QoS provision will be applied widely.

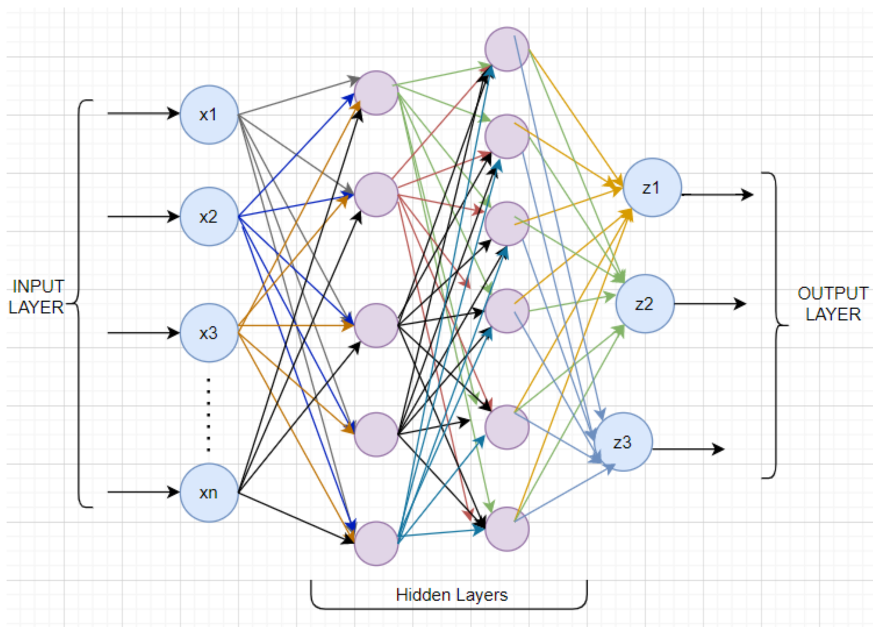
Deep Learning is a subset of the Machine Learning technique. The working of the human brain has inspired DL. It has multiple hidden layers. It has limited human intervention, unlike ML. The features are extracted automatically from a large set of data passing through the different layers. Each layer determines a different level of information extraction. DL has been used in varied applications. It is being used for computer vision, robotics, bioinformatics, natural language processing, cancer diagnosis, new drugs invention. [8]The usage of DL and ML has even been widely explored in SDN for many applications such as traffic classification, prediction, routing.

Application of Deep Learning : DL is mostly used under the following situations:

1. When the size of data is huge and extracting information from it isn't easy.
2. The area where human intervention is not possible.

3. Dynamic environments such as stock market, weather forecasting, and prediction, vehicular tracking.
4. Problems where there are unexplained abilities.
5. Load Balancing in Data centers using SDN [121].
6. Provide QoS in edge computing and solve problems of scheduling. [125]

Deep learning is considered to be universal in nature as this approach can be applicable in almost every domain. Unlike ML, there is no need for specific feature selection, so human intervention is less and improves intelligence. Moreover, DL is also scalable in nature. This all property of DL makes it one such research area that will soon be the most researched are with broader application. It is the present and future of the Network. Artificial neural networks inspire DL. The idea of the human brain inspires neural networks. It is a complex system where there is numerous processing unit interconnected to each other. It is made up of numerous neurons that are interconnected using connection links [64]. The links have weights, and they are adjusted depending upon the required output. The DL framework has three basic layers. They are the input layer, hidden layer, and output layer, as shown in figure 6. The hidden layers are multi-layered, and at every stage, it extracts lower-level features to higher-level features from the given input towards the output layer without manual effort.

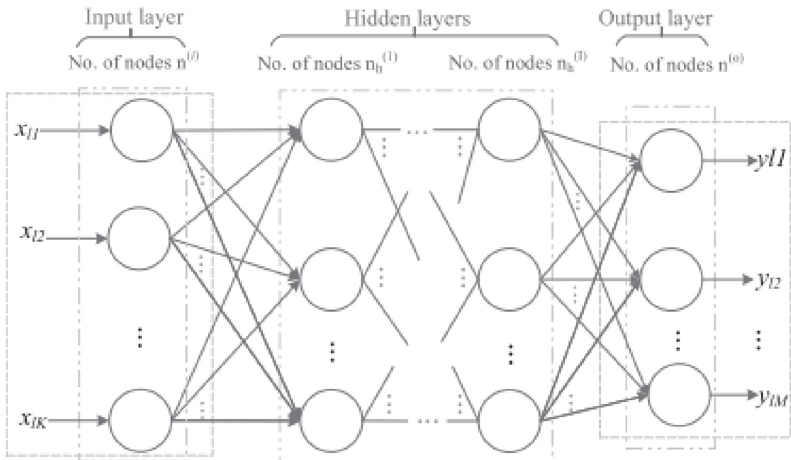


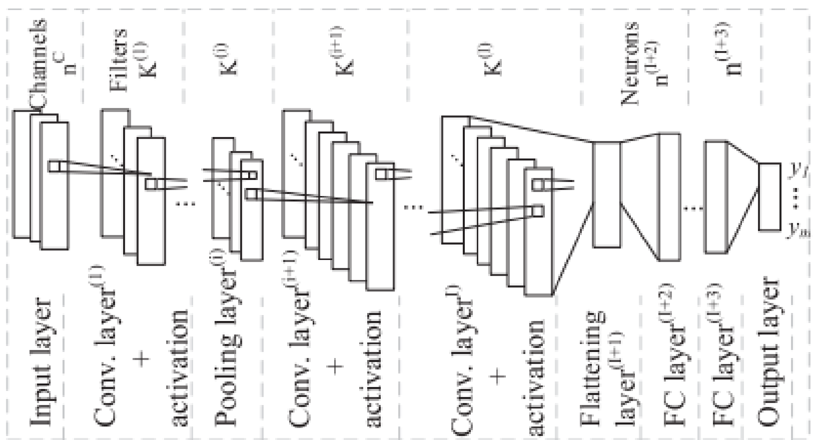
There are three categories of DL. They are supervised, semi-supervised, and unsupervised learning models. It also includes a deep reinforcement learning model. It can be used for various applications such as traffic classification, regression, clustering like ML. Unlike ML, Deep learning has a deeper view of the data. DL includes convolution neural network (CNN), deep neural network (DNN), recurrent neural network (RNN), multilayer perceptron (MLP), long short term memory (LSTM), and stacked auto encoder (SAE) [25] shown in figure 5.

MLP, CNN, LSTM, SAE in General:

[65]In **MLP** there are multiple hidden layers with input and output layers. Figure 7 shows the general architecture of MLP. MLP has two passes. They are forward pass and backward pass. The data sets are given to the input layer in the forward pass, while the backward pass uses loss to decrease error. **CNN** has five layers. They are input, output, multiple convolutions, pooling, flattening, and multiple fully connected (FC) layers. Figure 8 below shows the general architecture of CNN. It has two main phases. They are feature extraction and classification. The convolution layer performs feature extraction while FC performs

classification. The features enter into the input layer. These features pass through the convolution layer, where an activation function transforms the features into a non-linear format. The pooling layer selects the largest element; the flattening layer converts all features into 1 D vector and is given to FC for classification. This is how CNN works. The process of MLP and CNN of the forward pass and backward pass is repeated for all the training sets until a stable weight with good accuracy and precision is met.





LSTM: Long short term memory (LSTM) is another deep learning method. In [57] LSTM has been used to measure and predict traffic flow in the short term when there are no resources for flow counters. The deep flow proposed in this paper can measure such a large number of flows. The main idea behind the use of LSTM for future flow rate prediction is to free the TCAM memory and to have an in-depth view of the network for efficient traffic engineering. Deep Flow promises to expand for the complex interaction of flow in the future. LSTM is a form of recurrent neural network. It uses self-loop with forget-gate. This helps LSTM to collect information and cannot be forgotten. In this paper, LSTM is used for fine-grained flow that can be scaled in a short time. LSTM architecture has three layers. They are input, LSTM unit, and output layer. LSTM unit has a forgotten gate that retains the knowledge acquired and has been an effective deep learning technique that can predict the future flow in SDN.

SAE: A stacked autoencoder or SAE has a stack of layers of the autoencoder. The output of each autoencoder acts as an input to another autoencoder. An autoencoder is an unsupervised neural network. It recreates the input from the output with minimum error. Its objective is to define equal input with equal output. The model uses greedy layer method training. Every layer is trained initially by keeping the weights fixed for all layers; after that, the whole neural network is fine-tuning is done so that the result is accurate. The final layer also uses layers for classification purposes.

Deep Learning has been researched and applied in varied areas. They are natural language processing, computer vision, and many more. DL can learn a complex feature represented in traffic directly. DL-based traffic classification is used mostly to extract service-based information. It can also be used on encrypted traffic and is found to be quite efficient [65]. The approaches discussed in this section are the generalized ML and DL algorithms used in SDN. These algorithms have a significant influence on providing QoS in the network when SDN is used. ML and DL in SDN mainly focus on classifying traffic, queuing, scheduling, QoS provisioning, resource management, and optimizing route selection for end-to-end delivery to ensure QoS. Table 2 depicts the different types of machine learning and deep learning with their limitations and power when used with SDN.

Table 2 Comparison between different Machine Learning and Deep Learning based approaches developed for SDN

Machine Learning Technique	**Machine Learning Algorithm**	**Rate of Data Processing**	**Approach**	**Advantages**	**Application Area in SDN**	**Limitations**
Supervised machine learning algorithm	SVM, Naïve Bayes, Decision tree, random forest, K nearest neighbor	Fast with labeled data	Classification , regression and prediction	Cost effective and simple.	Used for traffic classification and QoS routing and policing.	Cannot handle applications that are not in training dataset.
Unsupervised ML algorithm	K means, DBSCAN	Fast/ unlabeled data	Clustering	Can handle huge datasets and handle application in dynamic environment.	Used for traffic classification, QoS routing and policing with large datasets	Accuracy level may not always be high and is not efficient in handling large set of data accurately.
Semi Supervised ML	Laplacian SVM[26]	Fast/ Both labeled data	Classification and clustering	Good accuracy is managed with improved network performance. Can train and re-train datasets [26]	Can be effective in both control plane and data plane and also in networking management.	Cannot classify encrypted data.

Machine Learning Technique	**Machine Learning Algorithm**	**Rate of Data Processing**	**Approach**	**Advantages**	**Application Area in SDN**	**Limitations**
Deep packet inspection or Payload inspection.	Based on pattern those are defined already. Eg regular expression	Slow	Pattern based identification and obtain pattern to identify protocols.	Good accuracy rate [30]	Packet marking	Cannot identify encrypted data [37], overload system. Pattern updating is needed when protocol changes and lacks user privacy. [64]
Port based traffic classification approach	UDP/TCP port address	Easy and fast extraction process[64]	Port address using TCP and UDP	Cost effective, simple, easy, fast	Used in firewalls and access control list(ACL)	Fails when dynamic ports are used [37]. Not applicable when random ports are assigned.
Reinforcement learning (RL)	RL based Game Theory	Learn action and reward so may sometime take longer to learn.	Based on series of action and reward	Simplifies and improves routing performance in SDN. Dynamic route optimization	QoS Routing , Traffic classification	It is based on trial and error method so may not always provide optimum solution
Deep Learning (DL)	LSTM [57], CNN,SAE, DNN	Medium	Based on multilayered neurons	Effective use in prediction as it can retain the knowledge acquired.	Traffic management, predicting future flow	It requires historical data for acquiring and predicting knowledge. It is used with unlabeled data. it also can identify encrypted efficiently.

For an end-to-end delivery of data with improved quality of service, the survey done in this paper focuses on machine learning-based QoS aware protocols. As depicted in the QoS framework, SDN architecture provides flexibility and can be programmed to improve network performance. Providing quality service has become an integral part of the network. SDN has come to the rescue for a traditional network where quality service provisioning was a great challenge due to its rigidity. Data delivery in SDN can be programmed and controlled centrally using a controller, while the switches and routers act only as forwarding devices. The centralized structure of SDN allows a global view of the network, and provisioning QoS has enhanced compared to the traditional network. The network needs multiple functions to perform to provide quality of service as stated in the service level agreement (SLA). The primary task each plane needs to perform is as depicted in Figure 4, which is QoS framework architecture in SDN. They are traffic classification, traffic shaping, congestion avoidance, packet marking, queuing and scheduling, admission control, QoS routing, and resource reservation. The survey undertaken here is based on QoS-aware protocols that use machine learning approaches in SDN. Our study mainly elaborates three main areas that help SDN to provide QoS. They are traffic classification, QoS routing, and Queuing and Scheduling.

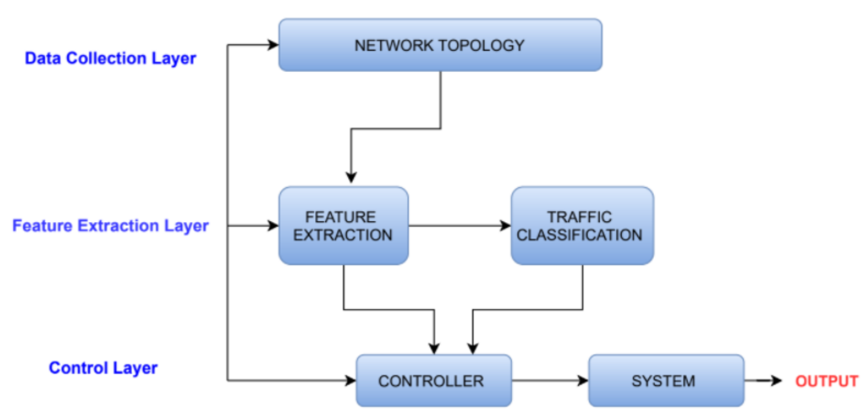
ML/DL BASED QoS AWARE TRAFFIC CLASSIFICATION IN SDN

There exist many different types of traffic in the network. This traffic uses available network resources. However, the network resources are inadequate, and optimum utilization of the resources is of prime importance. Moreover, the incoming traffics are of different types with a varied requirement for resources [79]. Therefore, if it is possible to handle different traffic differently, it would resolve optimum use of network resources for providing quality of service. Classifying traffic is helpful for preferred QoS improvement [117]. It has become essential to identify a varied application that uses the network's resources for good network resource management [64]. Traffic classification with improved accuracy is crucial in managing traffic, fault handling, and providing variations in QoS parameters. With network classification of traffic, the network administration can obtain helpful information about the traffic status and enable an efficient way of allocating resources [76]. In a traditional network, many different mechanisms were used to classify traffic, but most failed to provide reliability and accuracy when the number of flows increases tremendously [62]. In a traditional network, traffic classification was based on port and deep packet inspection (DPI). Port-based traffic classification cannot identify types of an application when the number of applications is huge. DPI classification technique consumes more resources, and it also cannot identify encrypted data.

Therefore, today, to meet the increasing demand with quality of service-based traffic classification, machine learning technology has been integrated with the software-defined network under three main sections, as shown in Figure 4 [106]. There are many applications in the network, and identifying these applications alone is a great challenge. The application can classify into different classes based on their delay, jitter, and bandwidth. This traffic class is QoS class, and this is called QoS aware traffic classification. In an SDN environment, we can acquire it by applying machine learning techniques [37]. One of the traffic classification techniques discussed in [106] is the deep packet inspection (DPI) and machine learning (ML) technique. Using DPI, the controller can identify traffic flow for QoS classification by detecting data packet load. However, DPI has loads of restrictions regarding encryption protocols, and it is impossible to recognize different data flows. In SDN, traffic classification must be done in real-time and at a low cost which DPI cannot. Therefore, the machine learning technique came into play. ML needs to extract the flow characteristics rather than the payload. We can perform a supervised, unsupervised learning framework to classify traffic. However, it is challenging to achieve low complexity traffic classification using the machine learning technique. Classification of traffic has to be real-time with low latency. Therefore in [39], the study considers both the features of DPI and semi-supervised learning classifier for meeting QoS requirements. It provides a framework for QoS aware adaptive flow classification using SDN based on DPI and semi-supervised multiple classifiers and validates it in the real network. Traffic classifier is done in the control layer. This architecture has two distinct functions. Firstly, maintenance of database with ML classifier training and secondly feature extraction and classifier classification. The mechanism has efficient classification and high accuracy. Similar to the work, in [122] a hybrid model for classifying traffic is proposed. It also efficiently and accurately classifies encrypted traffic also.

Traffic classification is a process of identifying data packet flows and assigning it to traffic types. Traffic classification serves as a building block for provisioning QoS in SDN. The study [73] focuses on ensuring QoS by classifying traffic in an enterprise network. An Enterprise network is a network within an organization where data communication is carried out privately. Traffic classification is based on port number, packet load, and flow characteristics. However, with the advent of SDN, port-based classification has been replaced by policy-based and rule-based classification. Another approach of traffic classification, as discussed in [100] classifies traffic into QoS classes for the flows and needs to be updated in real-time. It provides a framework that identifies QoS class for traffic flows. The algorithm functions on two modules, one at the switch and the other at the controller. At the network edge of the switch, it identifies local traffic such as elephant flows. At the controller, it classifies global traffic through a mapping function to enable QoS aware traffic classification. The controller classifies traffic considering traffic characteristics such as packet inter-arrival time, delay. It learns about the traffic using historical datasets and patterns. It also uses machine learning with DPI. The switches identify elephant flows for incoming flow while the controller performs QoS aware traffic for classifying them into classes. DPI detects an application and machine learning classifies the flow based on application. The numbers of devices and user's requirements have increased to a large extent. It is due to the rise of the Internet, IoT, cloud computing, and widespread use. Network has varied type of traffic flows, and segregation of this traffic is necessary as some traffic may be very urgent and some maybe not. Delivering tremendous requested services with minimum network resources is a great challenge for the network providers. Certain data require immediate delivery, while some data can wait. Services can be distinguished based on the type of traffic, so that network resources are not lost and utilized efficiently. Therefore, traffic classification is of utmost importance if we want to provide quality of service delivery to the user. For real-time data such as video and audio conferencing, priorities need to be set high compared to other simple data. The real challenge here is to classify the data traffic such that higher priorities data can be served timely and with utmost care.

The study undertaken by [9] uses a supervised learning method for classifying traffic in SDN. It compares three machine learning algorithms in classifying traffic, Support vector machine (SVM), nearest centroid, and Naïve Bayes (NB). It shows that NB outperforms the other two. The method improved the accuracy by 90% compared to the traditional approach. In the future deep learning, the mechanism needs to be incorporated along with a supervised learning approach. Figure 9 represents the integration of machine learning with SDN with three distinct sections. They are real-time networks, virtual networks, and machine intelligence. The real-time network creates a hybrid network, and the virtual network creates a wired and wireless network while traffic classification is done in the machine intelligence section. The framework discussed in this study collects the data, preprocesses the data, determines flow type and application name. It uses machine learning techniques on the training dataset. The whole mechanism is based on data acquisition, feature extraction, and decision-making to classify data. The proposed model elaborates on data classification and not on network resource optimization. In the future, this module can be added to the framework.



The author studies supervised learning-based traffic classification [59]. It uses a Naïve Bayes machine learning algorithm and big data for future prediction of traffic. Forecasting traffic is essential for ensuring QoS. It uses key performance indicators for traffic prediction. The study is done mainly for the cellular network that accumulates a considerable amount of KPI. So instead of using the history of traffic for prediction, it makes use of KPI for prediction. The significant characteristics of traffic are traffic patterns and changes periodically. The data capture in real-time for future prediction and analyzing traffic patterns with crucial performance indicators to determine the future traffic that handles efficiently. This method enhances the network performance compared to the traditional network.

Using neural networks and machine learning techniques, the study [77] relies on application-aware traffic classification in SDN. It studies neural network estimators such as Multilayer perception (MLP), feed-forward, NARX using Naïve Bayes. The classifier is applied to OpenFlow SDN protocol for traffic recognition and classification and also to allocate the bandwidth dynamically with the demands coming up to provision quality of service to the user. The technique used in the stud aims at reducing controller processing overhead and network overhead. The study compares the classifiers and concludes that the accuracy level of NARX (Naïve Bayes) is highest with 97.6%.

The main challenge in traffic classification is to handle traffic from unknown applications. Many supervised learning techniques cannot provide a solution to handle these unknown applications. Even certain unsupervised learning techniques are not able to correctly represent real-time applications. In [109], the study combines the IP payload with the statistical flow features clustering process to deal with unknown applications. The main aim is to build clusters of good combinations such that valid traffic clusters create traffic classes dynamically based on their payload content. In order to describe payload content, an approach called bag-of-words is used. The clusters are analyzed using latent semantic analysis.

The approach used in this paper [76] is to classify traffic based on specific QoS requirements such as bandwidth and latency using a time-based small set of features. The SDN controller extracts some features that are inter-arrival time, idle time, active time, flow bytes, and flow duration. These features are used to classify the IoT traffics. It uses three supervised machine learning approaches for classification. They are Random forest, Decision tree, and K –Nearest neighbor classifiers. Among the tree classifier, it is seen that the random forest classifier performs well for most of the features. This approach can also classify encrypted traffic from IoT devices.

Apart from traffic classification, the other important area is traffic prediction. In [69] author has used studies on deep Learning-based ML mechanisms for traffic classification and prediction. It brings about a comparative study on different machine learning algorithms for traffic classification and traffic prediction with their techniques and features used. Traffic generation in the network can increase the load in the network tremendously. For provisioning QoS, it becomes essential to handle the load. The best mechanism would be to predict the future load and avoid network congestion due to the traffic. One such algorithm has been discussed in [93]. It proposes a deep learning mechanism to predict traffic load using SDN for traffic generated for IoT devices. It proposes a "Deep learning-based partially channel assignment algorithm (DLPOCA)". Using the "adaptive channel assignment algorithm," a channel is assigned to each link to avoid congestion in the link by reducing the load. The author of this paper [66] proposes a Deep-SDN framework. The main contributor is the application plane where it uses a Deep learning mechanism for traffic classification, having two main parts, the learning phase, and the action phase. Learning is done through a deep learning mechanism. It can identify traffic application types accurately and at a good speed. It exhibits to have 96% accuracy. In this paper [37], random forest-based cross-validation is used for indoor localization using SDN. The application of SDN in the field of IoT has always been of great interest, and using random forest with SDN can locate the accurate position of the user in the indoor environment.

The SDN application is found widely in Fog computing, edge computing, IoT, cloud computing, and many others. One such application of SDN is shown in [31] based on Fog computing, where there are many Fog server or nodes. This paper proposes the allocation of user's requests while preserving the QoS to different Fog servers. For this purpose, it uses reinforcement learning and a random neural network (RNN) approach to optimize users' requested QoS. It proposes an algorithm that is implemented and Service Manager(SM). This algorithm takes up the user's request, allocates the location based on their requests, and aims to reduce overall response time. SDN is an intelligent network, and it can handle traffic, but it can be used with supervised or unsupervised machine technic to handle huge data. In [29] author uses both supervised (C4.5 decision tree) and unsupervised (K-means) to classify traffic in the control plane. Supervised learning works with trained data, and the remaining unclassified flows are treated using unsupervised K-mean clustering technics. The framework proposed has an excellent classification accuracy rate, but the resource utilization seems to be uncontrolled. Therefore this scheme does not ensure QoS. It proposes a self-learning system that uses RL to optimize the allocation of network resources in service chain function (SFC) [96].

It is seen that port inspection, deep packet inspection (DPI), machine learning (ML) has been widely used for application-aware traffic identification and classification in SDN. Deep learning (DL) is another upcoming method in terms of traffic classification in SDN. In [46], the author has proposed a system framework using a convolution neural network (CNN) based deep learning mechanism. It consists of three phases, traffic collection, pre-processing, and traffic application awareness. It uses the OpenFlow protocol with the min-max method. For application identification, CNN is used. CNN has many hidden layers. It has four main parts. They are activation function, pooling function, classification function, and loss function. The OpenFlow switch collects the traffic information. It then uses the min-max method to normalize the features selected. The use of this technique reduces the structure of network complexity and improves the accuracy and precision ratio of classifying different applications.

IoT devices have created a significant challenge in the field of networking. Network resource management for IoT is an issue today. Many ML techniques have come up in solving the challenges of the large dataset. [123] ML model based traffic classification in SDN with Fi-Wi IoT" can intelligently learn and classify traffic based on needed QoS. DL can solve issues regarding imbalanced problem of class in classifying traffic. CNN and SAE is widely used DL approach for this purpose [130]. In [90], Tensor-based deep learning proposes to handle the challenges created by multi-dimensional data using IoT devices. It is known as the IoT train deep learning method for SDN. The main focus of the proposed method is to reduce the flow table size so that the space is not over-utilized and consumes much memory. This might increase the complexity of the network. Therefore in this proposed methodology, it uses deep learning-based intelligent SDN for the IoT environment. It classifies all the incoming traffic into tensor classes using the deep Boltzmann machine learning method. Deep learning abstracts the nature of traffic. This method segregates the different attributes of traffic and transmits only those attributes if traffic attributes require transmission. The intelligence is added to the network flow. It evaluates varied metrics such as throughput, delay, flow entries and is seen to perform efficiently.

The author in [25] proposes classifying traffic in online and offline mode in SDN using Deep Learning. It uses the Tensor Flow neural network model for online mode. The flow statistics are collected from the OVS switch by OpenFlow protocol and given to the SDN controller. The collected datasets preprocess using Hash handles and MinMax Scaler in Sciket learn. It experiments using different traffic collected from Facebook, Gmail chat, hangout chat, skype audio, video, and Youtube. There are seven layers of deep learning and compares three DL models. They are CNN, MLP, and SAE. It is applied in both online and offline classification. The proposed method achieved 93% accuracy in classifying traffic in offline training data while 87% accuracy in online training data. In the future, the author wants to further research in the network slicing in SDN with provisioning QoS.

Another deep learning method discussed in [65] is for provisioning QoS for the encrypted traffic in the Software-Defined cellular network environment. The traffic type is over the top (OTT) service-based traffic, and the traffic from the cellular network is needed to ensure privacy. For this reason, the data is encrypted. It uses multilayer perception (MLP) and convolution neural network (CNN) based on deep learning. The proposed methodology uses a lightweight wrapper function to extract traffic features and QoS characteristics without decryption. It also does not require the traffic to be converted to any other format or checking for packet header. The method does not need any data preprocessing or inspecting packet header. There exists a quality control manager that manages QoS. It allocates QoS class to the encrypted flow and the controller updates the flow rule. DL classifiers used in this paper are MLP and CNN for local traffic classifiers. MLP and CNN predict the service type. The traffic classifier module also needs to retrain the captured traffic, and this is done offline. The local traffic classier adapts to the dynamic traffic environment. The proposed method achieves good accuracy of 86% for MLP and 82% for CNN. The loss value is also minimized by 0.61 in MLP and 0.57 in CNN.

In the network, uncertain traffic burst load can increase the cost of energy consumption, which decreases network performance. The resources may be underutilized at the cost of high energy costs. It is also seen that traffic load plays a significant role in determining the cost of energy consumption and network performance. SDN has a global view, and it can acquire much traffic, and predicting the traffic burst is one primary criterion for reducing the cost of energy consumption. In [27] Recurrent neural network of DL is used to capture and predict the real-time traffic. The traffic captured may be structured or unstructured and non-linear data. The use of DL is that it can handle both types of data. The proposed methodology uses a variant of RNN known as a gated recurrent unit (GRU). It is seen to be more efficient than LSTM. GRU learns from historical data while aiming at reducing the mean square error value. It uses the time sliding window method with GRU for traffic prediction. It also uses the heuristic algorithm for devising a mechanism for reducing energy consumption by the sleep/awake method for the links and devices depending upon traffic load. Hence the use of deep learning achieves a good balance of network load. However, the energy-saving mechanism focuses on traffic loads that are prone to link failure. Therefore in the future, the mechanism must consider network reliability also.

Another intelligent method of classifying traffic in SDN is discussed in [66]. It uses a deep learning method known as Deep SDN with high accuracy and precision in classifying traffic within a shorter period. It has two parts learning and action. Learning phases consists of collecting data, extracting features, and then classification. The learning phase also makes use of historical data for traffic classification. It has a classifier module as a deep learning classifier. This module is responsible for training the random data samples while using the rest data for classification. This model has 14 layers along with input and output. It normalizes the data through sequential layers. The action phase learns the information and uses it for various applications such as load balancing, routing, allocating network resources. The proposed model classifies online traffic with 96% accuracy, high precision. It uses real-time traffic for classification and provides good accuracy. It intends to explore the action phase to many other aspects of the network and use Deep SDN for traffic prediction.

From all the above studies, classifying the traffic in the network to their respective classes is one of the essential features of provisioning QoS. To realize such network services, researchers have provided various traffic classification mechanisms such as port inspection, deep packet inspection, machine learning, and deep learning. Unlike all other methods of traffic classification, deep learning is gaining a lot of researchers' interest. The main reason behind this is due to its ability to mine features that are deep and are efficient with non-linear data. DL can also act over encrypted data, unlike the machine learning approach. Deep Learning has many hidden layers and can work on a large dataset. Due to the ever-growing size of the data in the real world, Deep Learning seems to be the only way to handle and mine the data for accurate traffic classification. This service can directly improve the quality of service that is to be provided according to the user's requirement. Unlike the traditional neural network, deep learning trains the various deep neural network models such as CNN, deep belief network (DBN) for various network services such as network traffic classification, Computer vision, and speech recognition. In [107], an author proposes a hybrid deep neural network methodology for SDN. It uses SAE and the softmax regression model for classifying the network traffic. SAE has three layers. They are visible, hidden, and output layers. SAE takes less time for training compared with CNN or DBN. It is an unsupervised learning model. It uses unlabeled datasets, and the output of the autoencoder is input to the other. SAE in this paper is used so that it can extracts features for deep flow. For classifying traffic to multiple classes, the paper uses a softmax regression model. These two modules are combined in this paper for traffic classification. The framework first monitors the network. It then accumulates the network statistics for data flow and topology information and processes the features to build training sets. It trains and classifies the traffic flow into specific classes based on the features of the flow. The proposed model believes to have higher accuracy than SVM. In the future, the paper wants to explore more using the unsupervised deep learning model. It is also found that the time needed to train huge data is very large, and learning speed is high, so in days to come, this needs to be reduced.

Similar to this work, another DL approach for accurately classifying traffic is discussed in [64]. It proposes an approach called a deep packet that can classify encrypted traffic. Internet users demand privacy, security, and data encryption. This leads to a huge collection of encrypted data in the network. Encrypted data mostly do not create a pattern, and this brings about a challenge in traffic classification. Deep packet using DL identifies traffic at a low level. The manual feature extraction has been removed, and there is no need to find the features and extract them manually. One of the problematic traffic types to classify accurately is P2P, and this method can classify P2P traffic also. The framework uses CNN, and SAE DL approaches to capture traffic, preprocess the traffic, train the model and hence characterize them to classify them into classes. SAE has five layers connected that are stacked. There are different numbers of neurons in each stack, and during the training process, some neurons give zero randomly while others are active. At the end layer, it uses softmax to identify and characterize traffic. On the other hand, the CNN model selects the best result through multiple layers. In both the model the activation function used is rectified linear unit (RLU). The Deep packet model evaluates in terms of three metrics: Recall, precision, and F1 score. These metrics determine using the formula as shown in equation 1 (as per [64]) below:

$$\mathrm{Rc} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}, \quad \mathrm{Pr} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}, \quad F_1 = \frac{2\cdot\mathrm{Rc}\cdot\mathrm{Pr}}{\mathrm{Rc}+\mathrm{Pr}},$$

(1)

TP=True positive, FP=False positive and FN= False Negative

From the experiment conducted and based on the value of three metrics, the Deep Packet performs better than other similar ML approaches. Moreover, Deep packets can be enhanced further to handle composite and complex classification work in the future, where automatic feature extraction can reduce the cost and enhance accuracy. Ensemble algorithms are considered to be a good traffic classifier which is nicely highlighted in [131]. Considering ML approaches, ensemble algorithm outperforms single ML classifier.

Table 3 highlight summary of all ML/DL approaches used in QoS aware traffic classification with their respective focused area, merits and challenges faced, application area, traffic classification accuracy and future scope.

Table 3 Machine Learning and Deep Learning Approaches used in QoS aware Traffic Classification

Study	Approach used	Algorithm used	Focus area	Merits	Challenges faced	Prediction	Accuracy	Application type	Ensure QoS
[106]	Multi classifier Semi-Supervised ML+ DPI	Heteroid Tri training classifier using SVM Naïve Bayes and K nearest neighbor classifier.	Campus network.	Improves system robustness. Adapt to dynamic network environment. Improve ability of perception.	Too many feature extractions may lead to complexity.	Not mentioned but possibility exists.	Higher	Varying types of traffic such as video, voice, bulk data and other interactive data.	Yes
[73]	Rule based approach Policy based classification	Nmet (network meta-data) algorithm,	Traffic classification for enterprise network.	Helps in identifying practical problems in classifying traffic.	Network Intelligence is limited and not compatible with legacy IP network protocols.	No	medium	Not mentioned	yes
[100]	Semi supervised with DPI in SDN	Laplacian SVM	Identifies QoS class for real time traffic flows. DPI detects application accurately and ML classifies traffic.	Traffic can be classified into different QoS class. Cost effective Efficient resource utilization.	Cannot handle unknown and dynamic application.	No	Exceeds 90% when compared with K mean algorithm.	Varying	yes

Study	Approach used	Algorithm used	Focus area	Merits	Challenges faced	Prediction	Accuracy	Application type	Ensure QoS
[9]	Supervised ML technique in SDN	SVM, nearest centroid and Naïve Bayes	Enterprise network and campus network.	Feedback mechanism is used to find updates in network topology.	Do not consider dynamic data.	Yes	NB accuracy is 96.79%, SVM is 92.3% and nearest centroid. 91.02%	Streaming data, HTTP, mail.	Yes
[59]	Supervised with KPI	Naïve Bayes	Cellular traffic	Efficient traffic forecasting. Provide stable performance	Need to study relationship between KPI and future traffic	yes	yes	3G,5G data	Yes
[77]	Supervised ML. Neural network estimator	Multilayer perception (MLP) neural network, feed forward, NARX.	Can be implemented in campus network.	Optimize resource allocation Low processing overhead. low network overhead Improved QoS	Not applicable in distributed platform. It uses supervised learning therefore flows from new application handling is not discussed.	Yes	97.6%	FTP, HTTP, streaming data, P2P.	Yes

Study	Approach used	Algorithm used	Focus area	Merits	Challenges faced	Prediction	Accuracy	Application type	Ensure QoS
[109]	Unsupervised ML	Statistical characteristic of flow with bag-of-words model (BOW). Use latent semantic analysis.	Use real world traffic datasets.	Detect application-based classes. Handles unknown application	BOW features have many noises.	Not mentioned	90%	Unknown applications.	Yes
[76]	Supervised ML approach	Random forest. Decision tree K NN	Applicable for encrypted dataset from IoT devices. Use small set of features.	Effective traffic classification based on QoS	The overhead caused to select minimum features.	Yes	Random forest=91.2% Decision tree=87.2 KNN=79.7%	Encrypted traffic from IoT, VOIP, mail, audio, video, FTP	Yes
[93]	Deep learning mechanism	DLPOCA	IoT devices Could computing	Predict future load Avoid network congestion. Improve transmission quality.	Complexity in the proposed mechanism.	Yes	Accuracy of central traffic load prediction is 90 %.	IoT traffic	Yes
[66]	Deep Learning based ML technique	Deep-SDN	SDN IoT devices.	Identify network traffic application type easily.	Deep learning is still in its infancy time so traffic classification mechanism is complex and time consuming.	Used for identifying traffic type but not used in prediction.	96% overall accuracy.	HTTP,Mail, FTP, attacks, voice and video.	Yes

Study	Approach used	Algorithm used	Focus area	Merits	Challenges faced	Prediction	Accuracy	Application type	Ensure QoS
[37]	Ensemble learning based mechanism	Random forest.	Indoor Localization for IoT devices.	Accurately locate user position in indoor environment.	Over fitting of data.	No	98.3% accuracy using k fold cross validation.	Cross validation data	Yes
[46]	Unsupervised Deep Learning (DL)	Convolution Neural network with DL	Can be applicable in Data centers.	Reduces network structure complexity High precision in classifying traffic	High computation complexity. Speed of application aware classification is low.	Not provided	High precision in classifying traffic	FTP Email FTP WWW Multimedia data	Yes
[90]	Deep Learning	Tensor based Deep Botzmann machine learning	IoT environment	Segregation of unwanted traffic Optimum use of space by flow tables	The focus is only in reducing memory but it does not use DL for traffic prediction.	Not done	High accuracy in determining traffic attributes	Multimedia data VoIP, video audio	No
[25]	Deep Learning	CNN MLP and SAE	Campus network, IoT environment	Very good accuracy and precision value for traffic classification.	Offline training result is better than online training.	Yes done	CNN=94.95% MLP=94.95% SAE=94.86%(offline)	Facebook, Gmail,Skype audio and video, Netflix	Yes

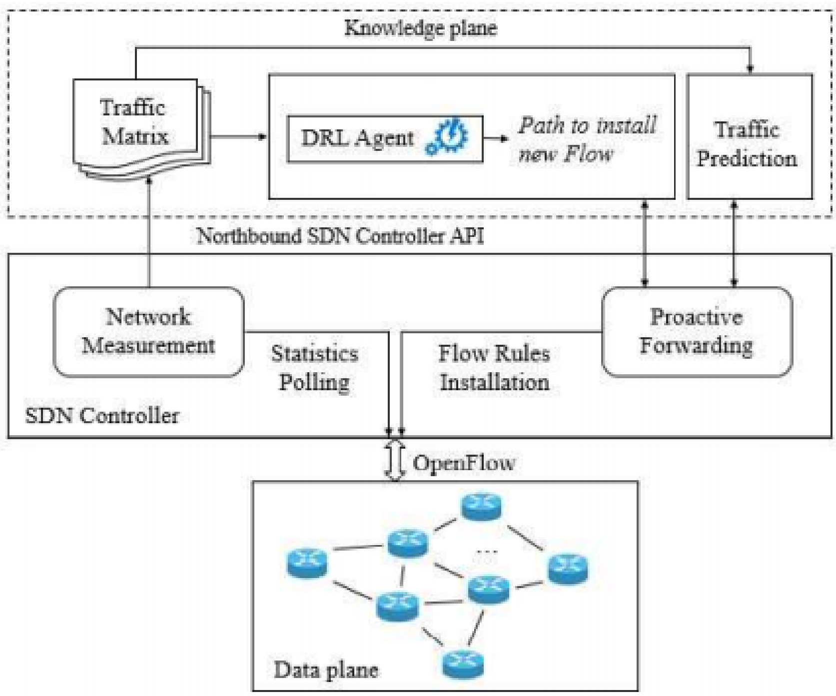
Study	Approach used	Algorithm used	Focus area	Merits	Challenges faced	Prediction	Accuracy	Application type	Ensure QoS
[65]	Deep Learning	Convolution Neural network and MLP	Software defined cellular network	Increased network performance. Low packet loss Minimum delay Less queue size	It might take longer computation time to get the stable weights for the network.	Predict service type traffic	CNN=82%, MLP=86%	Encrypted traffic of video streaming and web browser	Yes
[27]	Deep learning	RNN based grated recurrent unti(GRU)	Any dynamic environment	Simplified gate and neuron state Improved training efficiency	Focus is on network traffic and they are prone to link failure	Traffic prediction	High	Non –linear data	Yes
[107]	Hybrid Deep Learning	SAE and Softmax	Network application classifier	Used for classifying large scale data. No manual labour for feature selection and extraction	Labeled data has been used in DL model	Traffic classificatio	High accuracy	www Mail FTP Multimedia	Yes
[119]	Cost matrix based CNN	CNN	Any dynamic environment	Deals with minority sample of class in encrypted traffic.	No distinction between the types of traffic.	Traffic management	Yes	All minority traffic	Yes

MACHINE LEARNING AND DEEP LEARNING BASED QoS ROUTING IN SDN

Provisioning Quality of service is done in different levels of SDN architecture. QoS Routing is another important area of ensuring QoS in the network. Route optimization is one significant factor that enables Quality of service. Many routing algorithms exist in the traditional network and work well in distributed networks, unlike SDN, a centralized network. Therefore SDN requires a routing algorithm that is intelligent enough to understand the network status and perform routing. The author in [18] proposes an intelligent approach for forwarding traffic with guaranteed QOS. Unlike the traditional network, SDN has proved to be efficient enough to provide QoS. It uses SDN and OSPF hybrid networks with an intelligent traffic forwarding mechanism. The main idea is to improve QoS in industrial applications using a single path minimum cost and K-path algorithm. However, the paper does not discuss machine learning for traffic forwarding. Machine learning enhances and explores more of the data in the network. It adds intelligence to the network and provides fast and accurate decision-making. One such approach is shown in [45]. The author proposes an intelligent routing algorithm using a reinforcement-based machine learning approach. The algorithm also has a module that continuously monitors the Quality of service along with routing. It interacts with the network environment using three signals. They are state, action, and reward. The approach aims to prevent or detect congestion or link overutilization and intelligently route the packet. The controller uses historical traffic information and ongoing traffic class to learn, build and refine the mapping function. SDN is an intelligent network, unlike a traditional network. Internet of Things is at its peak today.

However, the increase in data is quite alarming. SDN with machine learning has come it's way to handle these data quite intelligently. One of IoT sub-applications where SDN usage with machine learning has been studied is the Internet of Vehicle (IoV) [98]. Provisioning QoS with IoT devices data is quite challenging. The author presents a Software-defined cognitive network for IoV(SDCIV). It uses SDN with reinforcement machine learning approach with "Q learning-based cognitive routing." Meeting the need for QoS for heterogeneous data is quite challenging. There are varieties of applications with various needs. A network topology can consist of multiple paths that connect end to end. Each path may consider a different amount of resource requirement such as bandwidth, delay. Due to the availability of multipath, it becomes essential to choose this path intelligently depending upon the type of flow and other related criteria. Depending upon the type of application, the flow can be used to select an appropriate path. In [78], the study achieves the awareness of all the applications in SDN. It is in coordination with machine learning. The ML technique used is in terms of machine learning trainer and machine learning classifier. It also incorporates traffic classification to guarantee QoS in multipath routing. The decision tree or C4.5 algorithm is used as ML approach. The approach used is application-aware multipath routing. The approach makes sure that every flow is selected with an appropriate path such that there is less latency and the throughput is improved. SDN has many features that are not in a traditional network. Despite its promises of intelligence, flexibility, programmability, achieving a reliable end-to-end data delivery is difficult due to the need for Quality of service and fast routing. In [63] author proposes QoS aware routing with multiple master-slave controllers with clustered switches. It uses Reinforcement learning in which the subnet of switches has a domain controller. Domain controller calculates the path of each flow while slave controller collects network status information. The reinforcement learning framework has a reinforcement agent. The agent receives the present state and reward from the system and performs an action based on experience. Based on RL, the RL agent finds the route with the maximum QoS reward based on traffic application type. The approach is said to perform better than Q-learning in terms of guaranteeing QoS and quick convergence. SDN finds its application in many areas. In a smart city environment, the use of SDN is quite prevalent today. In an area where a huge amount of vehicular traffic exists, their management is the key to avoiding congestion, minimizing delays, accidents, and time management. Such use of SDN has been shown in [11], where the SDN uses 3stage fuzzy decision tree model to optimize vehicular traffic in an urban city. It uses SDN in Vehicular Adhoc Network (VNET) environment. SDN-based VANET has proved to improve packet delivery rate and minimize delay. It uses reactive and proactive routing protocols, namely Adhoc on-demand distance vector (AODV) and destination sequenced distance vector (DSDV). A fuzzy decision tree model generates an SDN flow to select routing protocol. It also signals the type of traffic in the intersection. Switches manage flow tables in SDN. As the flow entry increases, the table also increases and occupies a huge amount of storage space. TCAM in switches is limited in size; therefore, in [71], a decision tree model is used to reduce the flow entry into the table. So that QoS provision can be guaranteed by improving bandwidth utilization and congestion, and queuing. It aims at efficiently using TCAM. The model has three modules. The preprocessor module organizes the input, preeminent entry selector (PES) uses ID3 ML to predict flow and classify them. Flow entry bloom (FEB) acts as a temporary storehouse that stores extra flow entries. The decision tree algorithm classifies the traffic using a bloom filter; filters out certain traffic using caching.

QoS aware routing is one of the challenges faced in traditional networks and SDN. However, with the advent of Machine learning, SDN can now address such challenges even when multiple flows are in the network. Network performance needs to be optimized to enable network QoS, which means minimum end-to-end delay and maximum throughput. One such QoS-aware routing-based mechanism has been stated in [22]. It proposes an efficient rule placement algorithm using deep Reinforcement learning (DRL) and prediction of traffic. It finds out the optimal path using the DRL agent and predicts the future traffic using the "long short term memory (LSTM)" prediction method. It aims at route optimization and traffic prediction. Figure 10 shows an SDN framework with three layers. The knowledge plane learns about the nature of the network and processes the network status that is collected network measurement, and finds the optimum route using the DRL agent. The traffic matrix stores the network status that was collected while the traffic prediction module predicts network congestion. DRL agent also uses historical data for determining an optimum route.



In order to meet QoS requests, it is vital that the flows must be routed using the best path. For doing this, the DRL agent uses three signals, state, action, and reward. The state is the network load (NXN), where N is the number of nodes in the network. Action is the path chosen, and Reward r is the parameters related to QoS. They are latency (L), rate (r), and packet loss (P). The following equation determines Reward r (as per [22]).

$$r = \alpha.W - \beta.L - \gamma.PL$$

(2)

α, β, γ [?] [0, 1] in equation 1are the adjustable weights to find an optimal route. A DRL algorithm knows as Deep Q Network (DQN) is used in this process. It is observed that this paper uses both the knowledge plane and control plane module for QoS routing. LSTM predicts the traffic while DRL determines the route optimization policy. This combination shows that QoS parameters such as packet loss are minimum, throughput is increased, and minimize delay, unlike in the traditional network. Deep learning approach is a powerful aid for routing purpose. Generally DL is based on unconstrained features; while for routing constrained features are required. In [120], and intelligent routing method using DL is discussed. It learns the features that are complex and provide intelligent routing.

Deep Q-Routing (DQR) is another proposed mechanism by Jalil et al. in [48]. It finds the optimal path from source to destination. It uses deep learning and Q-learning mechanism along with the greedy online routing method to optimize QoS parameters. The new flow is added in the greedy online method while maintaining the QoS needed for the ongoing flow. Deep reinforcement learning is used for solving complex problems, while Q learning cannot solve a complex problem. However, the combination of the two is very effective in terms of QoS routing. To guarantee QoS the two-module work together to find the optimal path from source to a destination. DQR learns from the network topology rather than using the shortest path. The reward function is also flexible; therefore, it allows DQR to optimize metrics such as delay and reduced cost and bandwidth usage.

Reinforcement learning with SDN overcomes the traditional routing protocols by introducing dynamic adaptability to the growing network. However, in [24], it has been stated that RL with SDN cannot deal with the large data concerning learning. Therefore the author in this paper introduces Deep Reinforcement learning (DRL) and SDN intelligent routing known as DRSIR. It uses a deep Q learning technique. It aims at adjusting to the dynamic changes in the network traffic. The DRL agent in DRSIR uses an appropriate routing policy to select routes for every pair of sources and destination. The major policy used for path selection is based on the path with high bandwidth, distance, low delay, and minimum packet loss. The proposed methodology of using DRL with SDN was made to choose the less congested path and has minimum distance. This leads to improving the quality of service in SDN using deep reinforcement learning. The main property of the proposed system is that it does not need historical labeled data and reduces complexity. In the future, the proposed method can extend to deal with SDN scalability on a larger network with larger data. And since the DRL agent is not self-configurable, it is kept for future work.

Another recent paper [101] proposes an intelligent routing method, especially for SDN-based satellite networks (SDSN). It uses a machine learning model. The existing SDSN fails in coordinating controllers and managing them centrally. The method also has increased network overhead. So to overcome this problem, the paper proposes ML-based intelligent QoS routing in SDSN. It uses an ensemble learning method known as support vector regression (SVR). SVR is build based on a support vector machine. It builds a better link with a low-cost or optimum route. It considers traffic prediction, classification, and routing to ensure the quality of service in the satellite network. The method shares bandwidth with the present, and future traffic flows that may have different QoS requirement and hence unlike many existing routing algorithms it keeps in view the traffic type and predict the requirement based on the traffic flow and hence choose the path.

Table 4 Machine Learning and Deep Learning Approaches used in QoS Routing in SDN

Study	**Approach used**	**Algorithm used**	**Merits**	**Demerits**	**Focused area**	**Guaranteed QoS**	**Future scope**
[18]	SDN and OSPF	K path algorithm.	Provides single path with minimum cost.	Do not include any Ml techniques	Industrial application.	Yes	To implement using ML techniques.

Study	Approach used	Algorithm used	Merits	Demerits	Focused area	Guaranteed QoS	Future scope
[45]	Reinforcement learning based ML approach	Actor critic reinforcement learning (A2C).	Route the packet intelligently. Prevents link overutilization. Optimized routing.	Bandwidth is not considered.	Any dynamic network environment	Yes	To implement in large scale test beds.
[98]	Reinforcement learning	Q learning based cognitive routing	Learn optimal path for routing Handle dynamic environment.	Trial and error mechanism sometimes do not provide proper optimization.	Internet of Vehicle	Yes	More routing protocols can be incorporated and use in traffic prediction and classification also.
[11]	Supervised ML	3 stage Fuzzy decision tree	Optimize vehicular traffic Improved packet delivery rate. Minimum delay	It has more end to end latencies.	Vehicular traffic in urban area	Yes	The protocols can be used for network security and traffic prediction.
[71]	Supervised ML	Decision tree (ID3) based entry reduction (DTER)	Improved bandwidth utilization, congestion and queuing. Predict and classify flow. Prevent flow overflow using caching.	Preprocessing, selecting and filtering processes are time consuming.	Any network environment	yes	To be implemented in real time test beds.
[22]	Deep Reinforcement learning (DRL)	Long short term memory prediction algorithm (LSTM)	Finds an optimal path for routing. Route optimization and also traffic prediction.	DRL is not well suited for predicting the dynamic nature of traffic.	Any network environment	Yes	It uses proactive forwarding and can be further used for actively forwarding the data.

Study	Approach used	Algorithm used	Merits	Demerits	Focused area	Guaranteed QoS	Future scope
[48]	Deep Reinforcement learning	Deep Q Routing in SDN (DQR)	Improves end to end throughput. Optimize QoS metrics	Online for greedy routing.	Applicable for online greedy QoS routing in SDN	Yes	Can be used for other SDN based application also.
[24]	Deep Reinforcement learning	DRSIR uses Deep Q Learning	Select route that is less congested and is shorter. Optimum route selection.	The DRL agent is not self-configurable and not scalable.	Applicable for IoT devices, vehicle routing.	Yes	To make DRL agent self-configurable and also deal with SDN scalability.
[101]	Ensemble learning	Ensemble Support vector regression (SVR).	Provide Intelligent QoS routing in SDSN.	Not tried for larger satellite networks.	Applicable in Satellite network.	Yes	Improve SVR to enhance better stability and accuracy and also to apply in larger and complex satellite.
[129]	Multi agent RL	"Multiagent Deep Deterministic Policy Gradient (MADDPG)" approach.	Optimized multipath routing. Block DDoS attack.	Optimum routing only for DDoS type of attack	IoT based environment	Yes	To increase other types of threats and attacks.

QUEUING AND SCHEDULING

Queuing and scheduling divide traffic into multiple queues so that the scheduler can decide the type of treatment that needs to be given to the traffic in the queue. Based on the types of the traffic class, the scheduler can handle them differently. When considering queuing and scheduling the most crucial attribute that comes into play is bandwidth and buffer. Buffer is the amount of available memory space in the queue or the length of the queue, while bandwidth is the rate at which the data transfers. Buffering value is either determined by time or in terms of the physical size of the queue. Scheduling determines how much is allocated to the queue. The requirement for queuing and scheduling determines traffic congestion. If there is no congestion and enough available network resources, there is no need for queuing and scheduling. Congestion occurs when there are more data in the ingress port than the egress port. Congestion causes the queue to be full and drops incoming packets at the tail of it. These are known as tail drops and create packet loss. However, the queue can also drop packets from the head. Packets travel from tail to head of the queue, and some packets may take an extra-long time to reach the head and never receive a scheduling slot, so that they may face resource starvation. This is called packet aging. [115].Queuing delay can be the other major impact of large buffering. The delay impacts the network performance [118]. The management of queuing delay is another major area that needs attention.

In SDN, the lowermost plane is the data plane. The Data plane includes forwarding devices such as routers. Routers are devices with finite memory space and can run out of space if the incoming packet rate is higher than the outgoing rate. Queuing model needs to be implemented by routers to manage packet in and packet out rates with buffering properly. One major problem that arises due to queuing is queuing congestion. It is caused when the speed of incoming traffic is more than the packets that are taken out from the output interface. To manage these issues, there are different ways of queuing models. They are:

1. **First in First out queuing (FIFO):** This is the default queuing scheme used by routers. The incoming packets are arranged in sequence of their entry and are processed accordingly. When the queue is full, the new incoming packets are not accepted by the router and are dropped, called tail drop. This queuing scheme is acceptable for simple data but not for real-time applications such as VoIP, audio/video conferencing.
2. **Priority queue** : In this queuing scheme, the router divides memory into multiple queues based on application priority such as medium, high and low priority. It then performs FIFO. Higher priority applications are processed first, followed by medium, and then by lowest priority application. The major drawback of this scheme is that the lowest priority application will be processed only if higher priority applications are processed, but, in some cases, the lowest priority application may never process and enter into starvation.
3. **Weighted fair queuing** : Based on traffic flow, the queues are dynamically created and assign bandwidth to the highest priority flow then after to other queues. Traffic flows are identified based on source and destination IP, source and destination TCP or UDP port, IP protocol number, and type of service.
4. **Weighted round-robin** : This method allows all the queues to be serviced during each cycle. The number of packets to be serviced in each scheduling is determined by the weight of the queue.
5. **Deficit weighted round-robin** : It is a modified version of the weighted round-robin. They can handle variable packet sizes.
6. **Priority-based deficit weighted round-robin** : this is the most powerful scheduling.

Queuing delay can be avoided if it is predicted. In [89], there are two means of predicting queuing delay. They are" random early detection (RED) algorithm" and "Xtream gradient boosting (XGBoost)" using ML. XGBoost was first given by Chen et al. to solve the problem of predicting regression. It uses the root mean square error loss function [26] XGBoost to predict the switch queuing delay and outperforms the traditional RED method. However, the focus of this study is not on routing problems.

Queuing in SDN shifts the distributed intelligence to centralized control. Unlike a traditional network, SDN allows central decisions for undertaking queuing mechanisms. In [95], the author uses a priority queue scheme to provide guaranteed bandwidth for flows with higher priority. It performs better than the best-effort shortest path and Intserv. It would be better if an admission control module with a user interface existed soon. As we have already stated to provision QoS, the major attributes that are accountable are latency, throughput, delay, bandwidth, and jitter. The network performance is measured using these attributes. There are different types of traffic in the network that need processing, but providing QoS for real-time applications is of utmost importance as they focus on timeliness. Delay in processing this data needs are to be carefully managed. The Internet provides best-effort service and does not guarantee service quality even though there is many QoS architecture such as Intserv, Diffserv, MPLS, TE, etc. The evolvement of SDN has led to improvement in providing QoS for real-time data in the end-to-end data delivery. However, network delay in data processing is highly affected by the random traffic flows congestion in the queue. The memory for storing data in the queue is limited, and the variation in traffic flow and delay increases the chances of queue congestion. The study in [61] aims to estimate queuing delay with real-time data traffic and end-to-end control over the delay using the queuing model that includes network parameters such as buffer size, queue bandwidth, number of flows, and propagation delay SDN. It also provides a mechanism and model for managing and estimating delay. [62] Measuring one-way delay and round-trip delay can be simply done using ping, but the syncing clock is a real challenge and is not suitable for a network such as the Internet. Moreover, the delay is dynamic, unlike other metrics, and measuring this actively creates traffic overhead. Another important aspect of delay is estimating delay. There are many models of delay estimations provided by various researchers, such as queuing models, rate-based queue scheduling, Poisson distribution. Queues have finite queue sizes with limited bandwidth, which can accept a limited number of flows. Therefore, many of the approaches discussed [108] are not feasible in the traditional network such as the Internet. Therefore, with the advent of SDN, there arises a new way of solving the QoS problem. However, there are very few studies involving queuing and scheduling in SDN. Rate controlled static priority queuing (RCSP) model [55] was applied in SDN to estimate the rate and delay of the queue, but this approach has no practical numerical result. The study [42] builds a delay estimation model that uses a TCP congestion algorithm and measures propagation delay, number of flows, and queue size. It estimates queuing delay in single TCP flow and multiple TCP flows. For both cases, it uses TCP congestion window size. Queuing delay is affected by TCP sending rate or window size. In this work, the total propagation delay of the path, Tp, is given in equation (3) where RTT is the round trip time between controllers and switches (as per [42]).

$$T_p = T_{arrival} - T_{sent} - 0.5 \times (RTT_{C-S_1} + RTT_{C-S_M})$$

(3)

Queuing delay is a constraint that creates congestion in the network. Estimating this constraint and managing it is essential in utilizing network resources and providing end-to-end data delivery to provide quality of service. Delay constraint is vital for real-time applications such as VoIP, video conferencing, audio conferencing, streaming data, online gaming. In SDN, the controller collects flow statistics, and OpenFlow protocol monitors the traffic. The study [42] provides an estimation delay that is scalable to many flows, but it is pretty worst when the number of flows is smaller when considering multiple TCP flows. In the future, the estimation model can be used with other delay constraint scenarios such as QoS routing for real-time applications, multimedia, cloud computing, and IoT. Another vital aspect of QoS is priority queuing for delay-sensitive real-time applications such as VoIP. Network delay can adversely affect the quality of data, especially real-time data such as VoIP. Therefore, if network delay is cautiously handled, the quality of real-time data delivery will improve. The study [74] proposes a queuing scheme based on packet delay to prioritize VoIP calls using SDN. The central focus of the study revolves around prioritizing VoIP. VoIP is sensitive to delay, jitter, and packet loss. The VoIP packets are prioritized based on the time spent in the network. It defines multiple queues with different priority classes. It uses five different VoIP queues to allow packets with different delays. A higher priority VoIP queue serves more delayed packets, while fewer packets will be placed in the lower priority queue. The incoming VoIP flow entries are forwarded to the controller, which then decides which queue the incoming packet places. It uses the RTP header to identify VoIP packets and thereby placing them in the respective queue. However, it is very cumbersome to track every incoming packet making it unrealistic. Therefore, in the future more practical approach can be proposed further and also use selective packet drop.

The Queuing aids in balancing the network load and hence optimize routing for guaranteed QoS. Predicting queue utilization is mentioned by author Yao et al. in [104]. It uses principal component analysis (PCA) to get network statistics while the neural network predicts the usage of the queue. It aims at reliability and achieving real-time QoS. It uses two routing schemes, “machine learning-based load balancing queue utilization (MLQU)” and “deep learning-based load balancing queue utilization (DLQU).” It uses hop count, current usage of the queue, and its predicted usage. PCA can change the multi-related variable to a non-related one. Such at it can get the topology statistics from each router and extract only the non-related variables. This way, it can reduce redundancy a lot. It shows that MLQU and DLQU improve throughput with better load balancing but compared to the shortest routing scheme, it has a 20% higher delay.

Data centers have become very important with new technology such as cloud computing, edge computing, the Internet of Things. These data centers rely on the availability of network resources, bandwidth, load scheduling, resource scheduling, and their proper allocation. In [91], it uses the SDN-based traffic flow management technique for efficient resource scheduling. However, do not use any machine learning techniques. Even though studies performed in queuing and scheduling in SDN, very little study was found regarding the use of machine learning-based QoS in scheduling and queuing in SDN. In traffic scheduling, flow scheduling may induce reduced quality of service. There are many real-time data's that require strict performance, such as multimedia data that are delay-sensitive applications. These applications need their flow to be in sync with the timelines they need to meet to guarantee the QoS. This is called flow completion time (FCT) constraints as stated in [92]. Considering this for provisioning QoS during scheduling will efficiently utilize resources and minimize network congestion. Using a machine learning model in SDN improves network decision-making. This paper [92] proposes "SmartFCT." It is a dynamic flow scheduling that guarantees the traffic to flow within the completion time and improves power efficiency in the data center network. This approach extracts the temporal and spatial traffic classification and uses deep reinforcement learning (DRL). The approach leaves a margin of inactive links and devices such that FCT deadlines are met. This improves network performance. The DRL algorithm dynamically analyses the input features and generates traffic scheduling policy automatically. This paper [81] proposes a QoS-enabled load scheduling approach using the Reinforcement learning (RL) technique. It aims at load scheduling amongst multiple controllers in SDN. Doing this can guarantee QoS by improving resource utilization and performance. RL is a branch of machine learning. It learns from the environment. The main highlight of this paper is the use of RL with multiple SDN controllers. It provides a controller mind (CM) framework to bring about coordination among the controllers dynamically. It aims at optimizing the load scheduling problem. Deep reinforcement learning approach with SDN control has been applied in traffic light scheduling to see the flow of traffic to prevent congestion [124].

The summary of the protocols, features, QoS parameters used by different ML and DL in SDN discussed by the various authors are depicted in Table 5 and Table 6. It is seen that ML and DL in SDN have been effectively used for provisioning QoS. According to the study done, it is found that Deep Learning (DL) is used in many different ways and seems very effective for traffic classification, QoS routing, and also for queuing and scheduling. Machine learning algorithms such as C4.5 Decision tree, Random forest, Support Vector Machine, Reinforcement Learning are also used for provisioning QoS in SDN. Table 7 provides a quick summary and comparison of the ML and DL approach based on QoS aware protocols in SDN. In contrast, Table 8 depicts the summary of the approaches that guarantee the achievement of QoS services in SDN. Despite much research and advancement in this area, there still seem to be quite a few studies regarding QoS in SDN using ML and DL, but this will surely flourish in time to come.

Authors	**ML Approach used**	**QOS Parameters**
Hossain et. Al[45]	RL driven QoS Routing	Delay and packet loss rate
Owusu et al. [76]	Random Forest, Decision tree ,K nearest neighbor	Bandwidth and latency
A. Raikar [9]	SVM, NB, Nearest centroid	Classification accuracy and network resourc
Wang et al [98]	Cognitive network with Reinforcement Learning (RL)	Packet delivery ratio and average end to en
Wang, Pu et al[100]	Laplacian SVM	Delay, jitter and loss rate.
Comaneci et al [29]	C4.5 Decision tree classifier, k-means	Classification accuracy F-score, resource usa
Troia et al [96]	Reinforcement Learning (RL)	Traffic prediction, resource allocation.
Qiu et al. [81]	Reinforcement Learning (RL)	Accuracy, load scheduling, load balancing ,t
Pasca et al.[78]	Decision tree C4.5	Latency, link cost, throughput, jitter
Lin et al. [63]	Reinforcement Learning	Delay, packet loss, throughput, time efficien
Balta et al.[11]	fuzzy decision tree model	Packet delivery rate, delay and jitter
Nallusamy et al. [71]	Decision tree ,ID3	End-to-end packet delay,

Authors	DL Approach used	QOS Parameters
Tang et al. [93]	Deep Learning	Link load
Malik et al. [66]	Deep learning with logistic regression	Latency, accuracy ,speed
Sun, Penghao [92]	Deep RL	Throughput
[22] Bouzidi	Deep Reinforcement Learning and	Latency, delay, throughput
Yao et al. [104]	PCA, Deep Learning	Packet loss rate, throughput,
Jalil et al. [48]	Deep Reinforcement learning with Q Learning	End to end throughput, delay
Chang et. al. [25]	Tensor based Deep learning neural network	Online and offline traffic class
Fröhlich et al. [31]	RNN and Reinforcement learning	Queuing delay, service delay,
Mahboob et. al. [65]	MLP and CNN based Deep learning	Resource utilization, autonon
Lazaris et. al. [57]	Long short term memory(LSTM) based DeepFlow	TCAM utilization
Chen et. at. [27]	RNN based gated recurrent unit (GRU)	Network resource utilization
Zhang et. al. [107]	Hybrid deep neural network with SAE and softmax regression layer.	Accuracy, precision and F me
Lotfollahi et. al. [64]	CNN and SAE	Precision, F1 score, Recall

Study	Machine Learning								Deep Learning								QoS aware service provided
	SVM	KNN	DT	RF	K-means	PCA	NB	RL	CNN	DNN	MLP	LSTM	RNN	SAE	DEEP-SDN	DRL	
[106]	√	√					√										Traffic Classification
[100]	√																Traffic Classification
[9]	√						√										Traffic Classification
[59]							√										Traffic Classification
[77]											√						Traffic Classification
[76]		√	√	√													Traffic Classification
[37]				√													Traffic Classification
[64]									√								Traffic Classification
[25]									√		√			√			Traffic Classification
[65]									√		√						Traffic Classification
[27]													√				Traffic Classification and prediction
[66]										√					√		Traffic Classification
[45]								√									Route packet intelligently
[98]								√									Optimal path routing
[11]			√														Route optimization
[71]			√														Predict traffic flow and flow queuing
[22]												√				√	Route optimization
[48]																√	Improved QoS routing
[24]																√	Traffic routing
[101]	√																QoS routing
[57]												√					Traffic measurement
[25]									√	√	√			√			Traffic classification
[104]						√											Queuing and Routing
[31]								√					√				Queuing
[29]			√		√												Traffic classification
[96]								√									Traffic prediction and classification
[81]								√									Queuing and scheduling
[78]			√														QoS Routing
[92]																√	Flow scheduling and classification

Research Paper	Approaches Used		QoS Parameters Achieved									Applicable SDN Layer			Model Used	
		Throughput	Delay	Packet Loss	Resource /Bandwidth utilization	Latency	Packet delivery ratio	Jitter	Link Load	Queuing Delay	Response time	Application Plane	Control Plane	Data Plane	ML Approach	DL Approach
[45]	RL driven QoS Routing using advanced actor critic(A2C) protocol		√	√									√		√	
[76]	Random Forest, Decision tree, K nearest neighbour				√	√								√	√	
[9]	SVM, Naïve Bayes, Nearest centroid		√		√						√			√	√	
[98]	Q Learning based cognitive routing using RL		√				√						√		√	
[100]	DPI with ML using Laplacian SVM		√	√				√						√	√	
[96]	Self-learning system using RL				√	√								√	√	
[81]	QoS based load scheduling using RL				√				√	√				√	√	
[78]	Application aware multipath routing (AMPS)using decision tree	√				√		√				√			√	
[63]	QoS aware adaptive routing using RL	√	√	√									√		√	
[11]	AODV and DSDV using fuzzy decision tree		√				√	√								
[93]	Adaptive channel assignment using DL								√				√			√
[66]	Deep SDN using DL with logistic regression					√					√		√			√
[31]	RNN with RL									√	√			√		√
[92]	Deep RL for flow scheduling and classification	√							√					√		√
[22]	LSTM and DQN algorithm based on Deep RL	√	√			√			√				√			√
[104]	MLQU and DLQU algorithm based on DL and PCA	√	√	√						√			√			√
[48]	Greedy online QoS routing using Deep RL and Q learning	√	√	√									√			√
[25]	Tensor based Deep neural network													√		√
[65]	MLP and CNN based DL				√					√			√			√
[57]	LSTM based Deep Flow				√									√		√
[27]	RNN based GRU		√		√							√	√			√
[107]	Hybrid DL using SAE and Soft max						√					√				√

ISSUES AND CHALLENGES

In this section, various issues and challenges related to SDN are highlighted.*Big data handling*:

With the advent of cloud computing and the Internet of things, the number of devices users use has increased tremendously. Before 2020, if the number of devices was 3 per user now, this has tripled more. After the ongoing pandemic and lockdown, the users' increase is double more than what was estimated. Due to digital teaching and learning, the work from home scenario dramatically changed from what was expected to increase. The change is many folds. In such a scenario, having a distributed network is a curse. Thanks to SDN. SDN can solve many issues that prevail in a traditional network. The first being network management. It is automatized and agile now.

Moreover, the network can now be programmed as per requirement rather than buying an inbuilt controller. Provisioning quality of service in SDN has also been improved using SDN. QoS support network provides and meets user requirements according to service level agreement (SLA). Today QoS has been one very important aspect in improving the quality network. To meet user demand dynamically is the need of an hour. It also needs to utilize network resources carefully and optimally. The available network resources need to be distributed optimally to meet the demands. Due to the amount of traffic based on application, it is essential that the traffics is carefully classified into classes. Some applications may require good bandwidth; some may be needed to deliver in time. So as per their need traffic class is to be done. However, performing this task with such big data is another great challenge. Machine learning techniques have been incorporated in SDN to cope with this. However, as the traffic increases, even machine learning techniques may take a longer timer to classify traffic, train the datasets; delay in result production, which may affect QoS, While DL will take a lot of computation time to learn from the giving datasets. ML model requires much work, and handling such huge and massive data from big data is a challenging task. ML needs labeled data, and this is not easy to achieve and incurs high costs as well. RL method also needs huge resources for computation for training the massive data, and it is high in complexity.

Constant change in Real-world with Unknown application **:**

Nothing is constant in the environment we live in. The ML, DL models are trained to the datasets given as an input. Since the environment that prevails in our real world is continuously changing, it is expected that these models can adapt and handle uncertain changes in the datasets. However, it may be tough to represent the unknown data and application by these models. It is found that supervised machine learning may learn based on certain training datasets among the huge application. However, if any unknown application comes into the network, this approach will have no means to handle such an unknown application. Unsupervised machine learning may come into the scene in such cases. However, even with this technique, the handling may be difficult if the number increases. The efficiency of the algorithm may decrease to a great extent. Moreover, the quality of training sets should be high for improved accuracy, failing which the classification, prediction accuracy falls far below.

Brittle in nature:

It is known that both ML and DL models can be used for classification and prediction. The dataset determines the output. It can use both labeled and unlabelled data. The feature extraction process and training model determines the output of the model. They perform very well with the specific task but are brittle. This means that it performs well within the domain it has been trained in, but if any small changes are made in the input data or a sudden change of rules, the DL and ML system will not perform accurately. Many studies highlighted in this paper ensure a 90 to 98% accuracy rate in classifying traffic for different applications and make traffic classes for respective application types and the dynamic changing demands. Practical experiments prove that the accuracy rates are high, but it is still not so sure about the accuracy in actual implementation as it is known that SDN is yet to be matured and applying ML and DL approaches are practically being implemented in real-world networking. Therefore, accuracy in the study may reduce when implemented in the real networking world.

QoS provisioning **:**

Even though there have been many pieces of research going on in this particular area, the challenge of ensuring the multi-constrained quality of service is great. There are approaches and mechanisms to improve upon QoS in a new environment of a software-defined network. Classifying encrypted traffic and unbalanced data is still an area where there is dire need for exploring the solutions. However, until date, there seems to have no mature approach to be implemented in a real-time environment.

Computation Time and Energy Consumption:

ML approach may take less time to compute, but they take longer to train the datasets and perform classification and prediction. Moreover, the feature extraction process is done manually, and the dataset's quality will affect the result. On the other hand, DL approaches automatically extract features passing through multiple layers. It extracts low-level features to high-level features. However, if the layers are more, it will take a longer time to compute. The DL approaches also consume more power due to more computation time. There exist many approaches that aim to reduce this, but there remains a practical implementation for it.

FUTURE RESEARCH DIRECTIONS

Future research directions in the area of SDN are enlisted in this section.

Incorporating ML and DL in edge computing using SDN based Internet of Things for provisioning QoS:

In the field of IoT, edge computing has played a significant role. This provides services from the cloud to the edge of the network. Incorporating ML and DL in the edge will efficiently reduce the load of the network, prioritize network traffic types and classify them based on their quality of service requirement. It will reduce network delay and can have efficient traffic classification and prediction. Since till today, edge computing is at the beginning of its technological development with many challenges, but in the future, edge computing can provide IoT services using SDN efficiently to handle the huge data that is produced by the IoT devices such that it can provision QoS. [2]

Efficient Search engine

ML and DL is the effective tool for creating search engines. As the number of data increases, the current search engines can face challenges. Moreover, the traditional network may not be effective for search engines. The use of ML and DL with SDN networks can be an efficient search engine. Even though the researchers are working on it, the work is still in its infancy. However, in the days to come, the use of SDN in the network with DL and ML can change the common perception of network efficiency to larger objectives. Today, the SDN framework has been used in Data centers such as Google and Amazon, but still, they are at the initial level of development and in future days are not so far when ML, DL will be used in many applications.

ML/DL for ECRM network

Understanding and providing service to the customer is of utmost importance. In the days to come, ML/DL approach will be used widely to predict customer behavior from analyzing patterns from the available datasets. SDN is another critical approach that is sure to replace the current network used for the e-commerce network. The huge data accumulation can be used to identify the customer's pattern and use this information to classify the type of customer and predict their future needs. SDN with ML/DL approach is sure to be the future of e-commerce.

Reducing the cost and complexity of Computation

SDN is programmable network architecture. SDN has played a vital role in IoT. SDN network is efficient in handling the data acquired from IoT devices. Moreover, in this study, we have seen the use of ML and DL-based QoS-aware protocols in SDN. The performance and QoS provisioning are enhanced by implementing the network traffic classification and prediction using ML, and DL approaches. This combination of IoT with SDN using ML and DL is undergoing the research trend today. The main challenge is still the cost and complexity of computation for generating, extracting features, and classifying the traffic. Even though DL approaches aim to reduce the manual feature extraction and immediate output categories, they need a long way until they have their real-time practical implementation [2].

CONCLUSION

Quality of service is the most critical requirement for network users. Today, traditional networks do not ensure the needs of the users and available resources. Moreover, the rise in real-time applications such as audio/video conferencing, audio/video streaming, VoIP, has increased the need for QoS. The available resources such as bandwidth are allotted based on service level agreement, packet delay, jitter is also reduced. The real-time applications are served based on their priority using queuing and scheduling to ensure timely end-to-end data delivery. SDN QoS framework architecture focuses on handling QoS. The paper has studied various machine learning and deep learning techniques based on QoS aware protocols in SDN. The primary focus of the study has been to bring out the comprehensive study on the research trends on ML and DL based approaches used to classify the traffic into classes such that the entry point to the network will avoid any congestion, delay, and packet loss and hence the network QoS is ensured. The study shows that DL-based approaches are sure to be the basic need for tomorrow. DL, along with SDN, can bring about wonders in the field of network tomorrow. Today, the study of DL in SDN may be in the infancy level, but this is what will be the need of hour tomorrow. DL and ML can be extensively used for traffic identification, traffic classification, QoS-based routing, and queuing and scheduling. The research can also be further explored in other areas of the QoS framework, such as traffic metering, traffic policy. In the future, the study can be further extended to other QoS criteria.

List of Acronyms:

Acronym	Description
ANN	**Artificial neural network**
SDN	**Software Defined Network**
CNN	**Convolution neural network**
SAE	**Stacked auto encoder**
MLP	**Multilayer Perception**
DNN	**Deep Neural Network**
ML	**Machine Learning**
DL	**Deep Learning**
QoS	**Quality of service**
IoT	**Inter of Things**
ECRM	**Electronic customer relationship management**
SLA	**Service Level Agreement**
RNN	**Recurrent Neural network**
GRU	**Gated Recurrent Unit**
LSTM	**Long short term memory**
SM	**Service Manager**
DRL	**Deep Reinforcement Learning**
DT	**Decision Tree**
RF	**Random Forest**
SVM	**Support Vector Machine**
PCA	**Principal component analysis**
KNN	**K nearest neighbor**
SVR	**Support vector regression**
EPC	**Evolved packet core**

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