Journal of Smart Internet of Things (JSIoT)
VOL 2023, No.01 | 23-35 | 2023
DOI: 10.2478/jsiot-2023-0003

Article

Applications of Machine Learning in Mobile Networking

Muhammad Habib Hadi Hassan [1,*]

[1] Factuality of engineering, Computer and Communication Engineering, Khaldeh, Lebanon

*Corresponding author: Muhammad Habib Hadi Hassan (email: Mh77968@net.iul.edu.lb)

Received xx March 2023; Accepted x July 2023; Published xx July 2023

Abstract: Communication networks are constantly increasing in size and complexity. Hence, the traditional rule-based algorithms of these networks will probably not operate at their most effective efficiency. Machine learning (ML) is being used these days to solve tough problems in a variety of industries, including banking, healthcare, and enterprise. Communication network performance can be improved using computational models that can deliver ML algorithms. This paper investigates the use of ML models in communication networks for prediction, intruder detection, route and path allocation, quality of service enhancement, and resource management. A review of the current literature suggests that there is a wealth of potential for researchers to leverage ML to solve challenging network performance problems, especially in the development of software-based networks and 5G.

Keywords: Machine Learning Applications, Mobile Networking, 5G Network, Machine Learning.

1. Introduction

With expanding bandwidth and latency-sensitive applications like Voice over Internet Protocol, long-term 5G research, and on-demand video, network traffic has increased tremendously in recent years. Therefore, to effectively control traffic and adhere to service level agreements, current communication network technologies must be enhanced (SLAs). However, the increasing number of applications with different quality of service (QoS) needs, the steadily rising subscriber base, and the complexity of resource allocation and administration are pushing network designers to maximise network performance.

Artificial intelligence (AI) technologies that enable computers to learn automatically and offer predictions or solutions based on experience are collectively referred to as machine learning (ML). In a broad range of fields, including control systems [5], communication networks [6], image and speech recognition [1]– [4], ML adds intelligence. In certain circumstances, ML may outperform humans in terms of output quality because to its higher categorization and optimization performance, which has been utilised to intelligently approach complicated challenges [8].

This study examines current developments in the use of ML algorithms in communication literature from 2017 to 2020. This article provides an overview of how ML algorithms may be integrated into many networks, including multi-domain, multilayer, optical, Internet of Things, and 5G networks, rather than just concentrating on a single network like software-defined networking (SDN). Given that networks are becoming exponentially more complex and that traditional algorithms are gradually becoming obsolete, machine learning (ML) can be seen as a revolutionary solution to the problems that networks face. This paper will survey the most recent developments in the use of ML in addressing these problems and will highlight its advantages over traditional approaches. Here is a list of this paper's contributions:

The supervised and unsupervised learning models, deep learning (DL), and reinforcement learning are all covered in this white paper's review of machine learning algorithms (RL).

In this white paper, key ML applications from 2017 to 2020 are examined. Congestion control, predictive modelling, intrusion detection systems (IDS), routing, QoS enhancement, and resource management are some of these uses.

This white paper highlights the drawbacks of old algorithms as well as the benefits of the most recent ML algorithm implementations.

This paper discusses upcoming issues and developments in the use of ML algorithms in networks.

2. RELATED WORKS

The use of ML in networks has been the subject of extensive research. Deep neural networks (DNNs) have been widely investigated as a means of protecting networks against assaults by Miller et al. In their evaluation of the literature on the use of RL for routing, Mariette et al. A few more recent reviews of the use of DL in networks can be found in [10]. IDS's ML and DL solutions have been extensively examined by [10] for use in sensor networks. To increase accuracy and shorten training times, [11] analysed the existing optimization methods employing various deep architecture types. Based on DL, [12] examined DL-based mobile and wireless research. An overview of unsupervised learning applications in the network realm was provided by [13]. [12] reviewed recent problems in applying deep RL to communications and networks. These researches concentrate on certain ML techniques or uses.

This paper offers an overview of current developments in the application of ML to networks and an introduction to the topic, keeping in mind that research in this area is still in its early stages and has a wide range of potential applications. Provides an overview of the latest advancements. This white paper also identifies gaps that future research on embedding ML in networks can fill. According to our latest research, the most prominent.

3. OVERVIEW OF THE ML MODEL

ML is being applied to many aspects of our lives these days, including finance, healthcare, robotics, and customer service, and pattern recognition. By using past data without any significant re-programming, ML algorithms can provide low-complexity solutions to performance problems [1]. The usage of the ML algorithm has grown commonplace because to the rising volume of complicated data being created and the necessity for intelligent data analytics. ML has gained respect in academia and business for its capacity to efficiently extract information from a huge dataset as a result of developments in computer power [2]. ML is utilised every day by hundreds of firms to anticipate the next great business due to the excellent predictive accuracy of ML techniques and the speed at which an ML model can be produced. The kind of training data is frequently a factor in ML jobs. The ML framework is trained to do a specific task throughout the training phase, such as making a choice, forecasting a value, or completing a classification. Without requiring any human involvement, training enables the ML framework to identify possible correlations between the input and output data. The online ML method is a different type of ML that updates the model for each new input feature after each prediction [3].

The ML algorithm may be used to create a model using historical data or a database. From that point onward, the model is surveyed to see whether the planned exactness has been accomplished and to check whether more streamlining is important to help execution. The model is then used to make expectations utilizing new information. The new expected results are refreshed in the model for online ML models. Here is a list of the key distinctions between rule-based and ML algorithms. [4]:

Without following any set rules, machine learning builds its models based on the complex and dynamic input properties of the data.

In comparison to a manually created rule-based system, machine learning is frequently more accurate, automated, quick, flexible, and scalable.

To provide future forecasts for a specific issue, ML may be trained to recognise trends and patterns from a massive amount of multidimensional data.

Classification, regression, and control have all benefited from the use of machine learning (ML), a kind of artificial intelligence that learns patterns from empirical data. In Figure. 2, the fundamental process flow of ML algorithms is shown. The dataset is used to train the algorithms on the ML platform. The model is then created by the ML platform, and its correctness is assessed afterwards. It is necessary to continue optimising if the accuracy is not encouraging. This procedure is carried out repeatedly until the algorithm's accuracy converges. The trained ML system is then further tested on fresh data to make sure it continues to deliver high accuracy. Another significant Run regression or categorization is this one. The system is aware of both the input and the expected output when using tagged data. When there is a substantial amount of historical data available, supervised learning techniques are frequently applied. Unlabeled datasets are also supplied to some ML algorithms. The model searches for grouped or linked patterns for which the dataset lacks an appropriate response. Unsupervised learning's fundamental objective is to look at data and immediately infer some structure from unlabeled data. Unsupervised learning methods include K-means, self-organizing maps (SOM), expectation-maximization (EM), and generative adversarial networks. If you don't have labelled data for your application, unsupervised learning is crucial. RL is a different kind of ML model. Agents can behave and engage with the environment in RL to increase their total benefit. In this document, the fundamental RL procedure is described in depth. The split of ML algorithms, comprising RL, supervised ML, and unsupervised ML, is shown in Figureure 3.

3.1. Decision Tree (DT):

It is possible to employ the DT method to solve classification and regression issues. In the first stage, the algorithm divides all input traits and features into groups of partitions by taking them into account at the root. The split with the lowest cost is chosen after calculating the accuracy of each split using a cost function. Because each partition that is created may be further split using the same method, DT is recursive. The trimming of trees comes next. It recognises and eliminates branches that are noise- or outlier-reflecting [5]. The DT algorithm is referred to be a greedy algorithm as a result of this phase. DT wants to decrease costs excessively. The cost function looks for the set of branches with the most homogenous and comparable results. The length of the longest route from the root to the leaf is referred to as the maximum depth of DT.

Depth is set to a number that accounts for model accuracy while preventing the training data from being overfit. The pros of DT are:

Easy to implement and visualize. Perform feature selection implicitly. When Insensitive to non-linear relationships between parameters. DT, however, might overfit the training data because it is too complicated. This algorithm is also susceptible to instability. Data variations of a small magnitude in two entirely distinct trees [6]. It's possible that this model can't manage complicated systems with irregular properties.

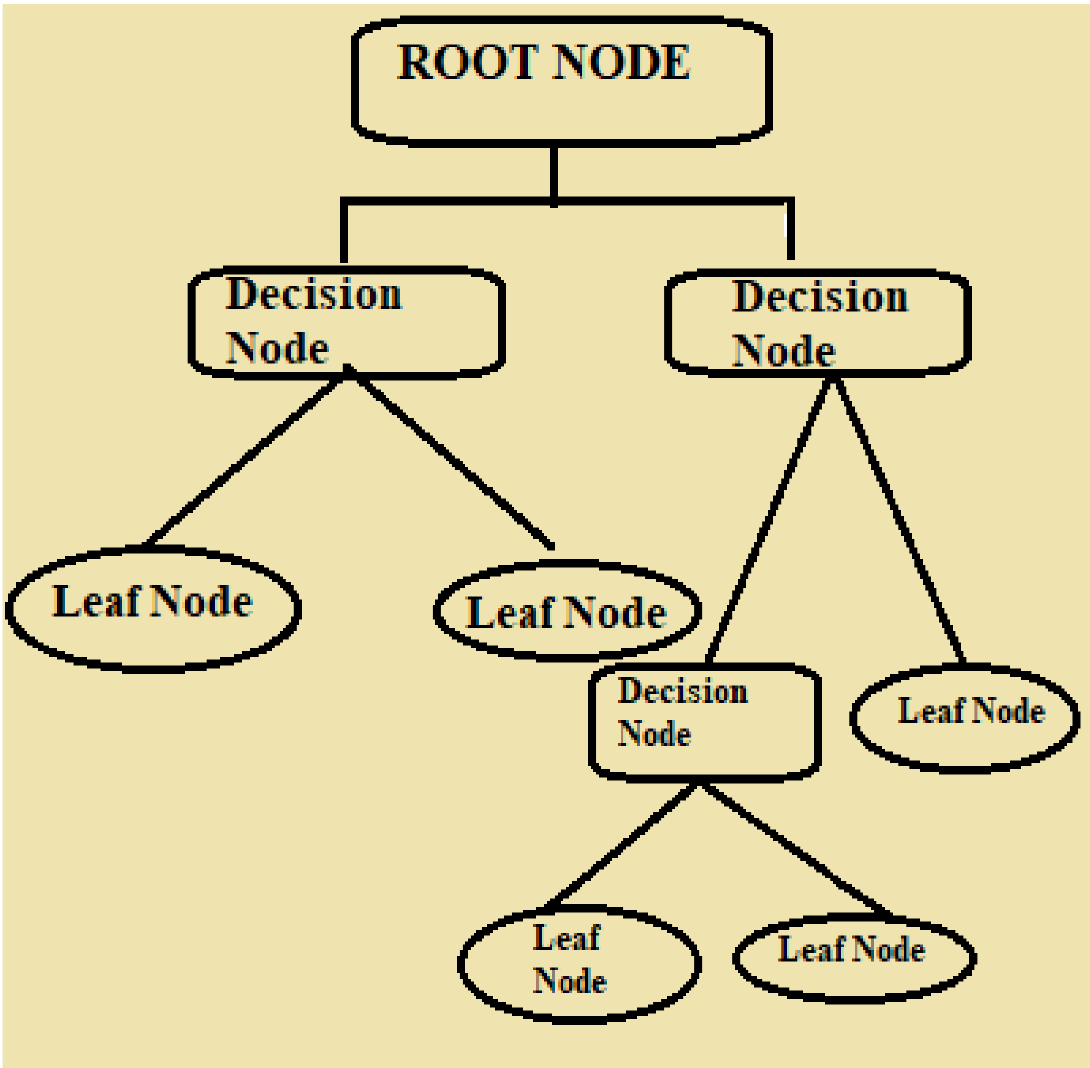

Figure 1: Decision Tree of application of ML.

Above mentioned diagram i.e., Figure 1. Shows the decision tree algorithm. This decision tree algorithm plays important role in various industries such as banking and e-commerce to predict behavior and outcomes.

This algorithm consists of Decision Node & Leaf Node.

A tree-like structure is formed with the help of this decision tree. Its overview helps us understand the working criteria of the algorithm. Decision nodes, Leaf nodes, and root nodes are the three main components of decision tree algorithm.

The features of the phone are represented by the Decision Tree's Root Node and Decision Nodes. Whether we have to purchase it or not, the leaf node indicates the ultimate product.

3.2. Resource Requirement (CPU/Memory):

The fact that the top level of the tree has a significant influence on the output is one of the shortcomings of DT. If the distribution of the new data differs from that of the training data set, DT may not be accurate. Such issues are lessened by the HF model [7]. The DT model serves as the foundation of the RF model. The HF model, as its name implies, is made up of several individual DTs working together as an ensemble [8]. The class with the greatest votes is chosen from the model predictions by each DT in the RF, as seen in FIGURE. Any of the individual constitutive models outperforms a large number of uncorrelated trees working together as a committee. Each tree in RF has the potential to forecast incorrectly while also producing accurate results. To obtain an absolute and steady value, RF constructs many DTs and then combines them. It is mostly used for class prediction and training [9]. As a result, groups of this tree improve predictions. RF likewise powers extra variety in the model, at last decreasing the relationship between branches because of broadening. The upsides of the HF calculation incorporate a few relationship capacities, strength to loud datasets, and fundamentally further developed precision. Besides, not at all like DT, RF is powerful against overfitting. As well as being a strong characterization model, RF can process the significance and precision of every variable utilized in grouping.

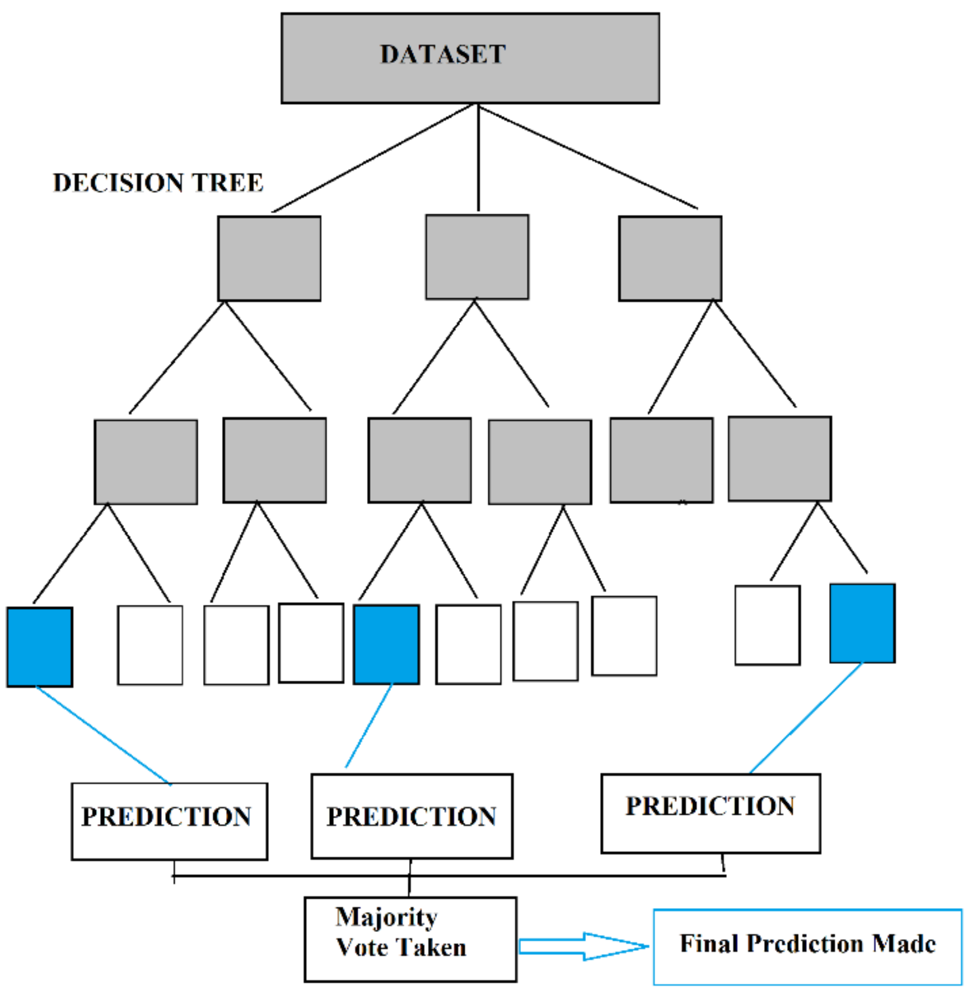

Figure 2: Random Forest (RF) Classifiers.

Above mentioned diagram i.e., Figure 2 shows the algorithm of Random Forest. Every RF consists of many decision trees. The Random Forest algorithm generates “FOREST” and this forest is trained through Bootstrap aggregating/ Bagging. Bagging here is an ensemble meta-algorithm and helps improve the accuracy of machine learning algorithms. The outcome of this algorithm is based on the predictions of the decision trees. Their predictions are actually based on the average and the mean output of various trees. The precision of the outcome increases as there is an increment in the number of trees [10].

3.3. Access to Resources – Datasets:

SVM is preferred by many due to its high accuracy and low computational power. Like DT, SVM may be used to resolve issues with classification and regression. SVM targets finding hyperplanes in the N-Dimentional space that remarkably group data of interest, as displayed in Figure. 5. To isolate pieces of information for numerous classes, numerous hyperplanes can be developed. Finding the plane with the best distance between classes is the essential goal of SVM. Here the hyperplane shares the blue and red pieces of information, but there is a classification error. Maximizing the best edge distance allows for more accurate classification of future data points. The higher the number of features, the more complex the construction of the hyperplane. Along with fitting both linear and nonlinear data, SVM also employs kernel approaches. It's a mathematical concept that can "wrap" the space in which your data resides. SVM can find better bounds in this closed space and make the bounds nonlinear in the original space [11]. SVMs have good generalization performance, so this model is suitable for small, feature-rich datasets.

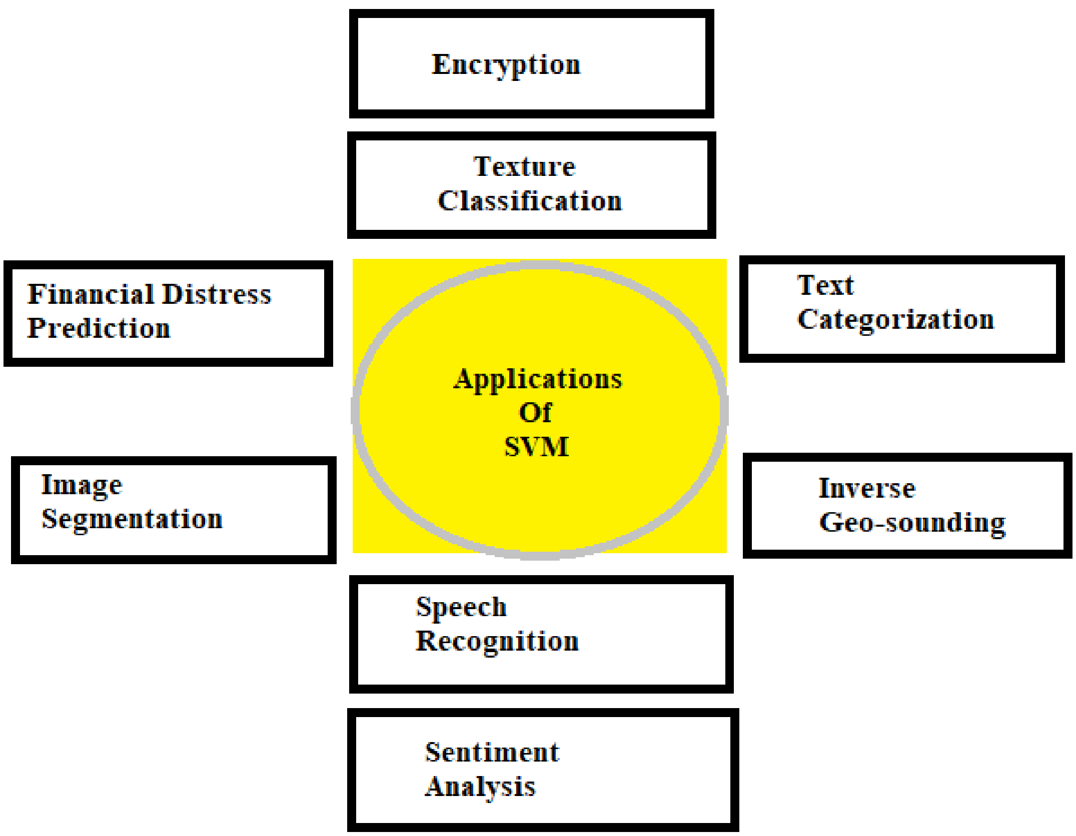

Figure 3: Applications of SVM (Support Vector Machine)

As we know Support Vector Machine (SVM) depends on supervised learning algorithms. The objective of using SVM is to classify unseen data correctly. It has a number of applications in several fields. A few applications of SVM are mentioned above in the diagram i.e., Figure 3. Such as Encryption, Text categorization, Sentiment analysis, Face detection, texture Classification, and so on.

3.4. Deep Learning (DL):

Big data analytics, natural language processing, and computer vision are just a few fields where DL has been used. DL is particularly effective in extracting features from inputs and discovering associations between various metrics through training on vast volumes of data, leading to precise and prompt responses. It can also be used to do both supervised and unsupervised learning. DL contains Artificial Neural Networks (ANNs), which focus the central processing unit on uncovering underlying patterns and connections in data sets, much like the human brain decide. The structure of the DL resembles the arrangement of neurons in the human brain.

3.5. Reinforcement Learning (RL):

RL is a different kind of ML model. In Figureure 12, the RL procedure is displayed. On information gathered by the model itself, RL is iteratively trained. Finding the optimum approach for a particular agent is the aim of RL, which seeks to learn from the environment. RL models do not learn from a specific dataset, in contrast to supervised ML models. Instead, RL agents study activity semantics and make decisions based on both prior knowledge and fresh options.

4. CONGESTION CONTROL IN THE NETWORK BASED ON MACHINE LEARNING

Numerous congestion management techniques are used in various network contexts. Traditional routing techniques don't take into account previous instances of network abnormalities like congestion. The network is put under a lot of stress by the rising network traffic, which makes resource management and allocation difficult. His QoS of network traffic is impacted since the majority of networks use routing frameworks that were created decades ago. The shortest route was first determined using distance vectors or connection costs while designing the traditional routing techniques for fixed networks. Ultimately, an overabundance of traffic might cause the network's performance to entirely decline. Traditional routing systems would likely commit the same error if a similar circumstance ever occurred again

This routing method eliminates bottlenecks and traffic congestion, in contrast to conventional routing, where the shortest path is the preferred route. The congestion window for the following transmission is then modified using the anticipated size of the subsequent congestion window. CHLA-QSCACAR may increase throughput by 10.49%, end-to-end latency by 11.51%, interference-to-noise ratio by 19.33%, and routing overhead by 12.48%, according to Yuvalai et al. This outcome demonstrates that network congestion may be further reduced by utilising ML to enhance existing link processing algorithms. Baseline routing protocols are the only DL implementations available for congestion control. The set of initialization weights for each neuron in the input layer of the ANN is used by DL, as described in Section III. DL often uses Open Shortest Path (OSPF) as a baseline to address network congestion issues, but it lacks the intelligence to handle novel circumstances. To remedy this shortcoming, [12] A novel Deep Convolutional NN (Deep CNN)-based real-time intelligent network traffic control technique is used to represent the backbone of the under consideration wireless mesh network. I offered a strategy. All routers in the network first determine and record potential routes for each destination node instead of utilising

OSPF as a foundation. Based on metrics like hop count and distance, all pathways are sorted into least-priority queues. A periodic real-time update phase follows training once there is sufficient training data. The suggested deep CNN model then uses intelligence to choose and execute valid route combinations. The simulation results show that the DL-based routing scheme is superior than existing routing protocols in avoiding 97.9% of congestion scenarios when the proposed scheme is compared to OSPF, Intermediate System to Intermediate System, and Routing Information Protocol.

5. ML IN COMMUNICATION SYSTEM AS A PREDICTIVE MODEL

Predictable network metrics, including pathways and links, quality, latency, throughput, optical signal-to-noise ratio, and incoming traffic, are all crucial to the operation and administration of a network. To increase the effectiveness of the entire network system, machine learning (ML) seeks to learn from past data or the environment and generate predictions about network characteristics.

5.1. Volume of Traffic Prediction:

A significant number of transponders should be put in the virtual network architecture because the network must be able to manage the highest daily traffic projected during the planning period. However, they frequently provide over-provisioning capabilities, retaining the majority of the network's capacity. To forecast traffic demand, [13] developed ML-based virtual network topology reconFigureuration (VENTURE). The VENTURE framework is shown in Figureure 1. First, the data for each origin-destination (OD) pair is collected and stored in the modeled data store. A projected OD traffic matrix for the following time is then produced by a forecasting engine using ML techniques. Third, the decision module decides whether to use the VENTURE optimizer to reorganise the present virtual network architecture. The network controller makes the necessary adjustments to the network once the algorithm has found a solution. By redesigning the virtual topology to adhere to anticipated changes in traffic direction and dynamically manage capacity, VENTURE can make the most of the transponders that are currently available. In addition, VENTURE can save users up to 40% more on transponders than threshold-based approaches.

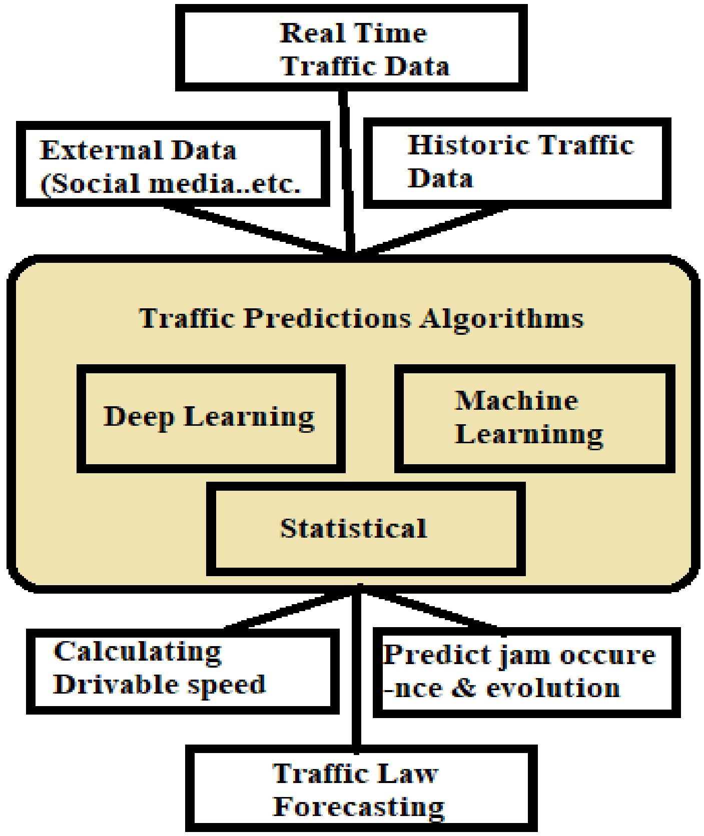

Figure 4: Traffic Predictions algorithm.

Forecasting the Density and Volume of traffic flow is the meaning of traffic flow, usually for the purpose of reducing congestion, managing vehicle movement, and generating the optimal route. There are several factors that influence traffic, and we cannot ignore any of them. We have to consider all of them to make accurate predictions that involve Forecasting drivable speed on certain road segments, as well as jam occurrence and so on.

5.2. 5-G Structure Revenue Prediction:

With the promise of 5G networks' high data speeds, wide coverage, and sub-millisecond latency, this new technology is anticipated to gain pace as it is implemented. One of the commodities in the 5G infrastructure, which includes network resources like airwaves and transformers, may be network slicing.

To maximize revenue for infrastructure providers, we developed an analytical model of permissible domains using the NN-deep RL algorithm. This model entails interactions between agents and their environment, decision-making in relation to certain situations, and estimations of rewards. Sales are the prize in this situation. Two NN algorithms anticipate the income for each state when the specified action is granted or rejected after receiving a request, and they then base their choice on the expected value. The proposed method outperforms native techniques like B. Intelligent heuristics with quick convergence, and its performance is near to the optimum in a variety of settings. It supports large-scale scenarios and has proven useful in real-world environments.

6. ML FOR ENHANCING ROUTING DECISIONS IN COMMUNICATION NETWORKS

Network traffic routing is one of the basics of networking.The function of selecting a route to transmit a packet. Proper routing management enables route decisions while minimizing costs and meeting QoS requirements. It is challenging to route traffic using an ML technique because various types of traffic have varied QoS requirements and complicated, dynamic topologies. Traffic and route matrices can be used to characterise the inputs and outputs of ML algorithms for routing optimization issues. To forecast or identify the direction of incoming traffic, machine learning algorithms must understand correlations between traffic inputs and network states. Recent research that aims to enhance routing decisions in networks, such [10] and others, like, mostly rely on NNs. studies using RL are found. This section goes into depth about this recent research that used different ML algorithms.

6.1. Dl-Based Routing Algorithm:

In Mobile Heterogeneous Wireless Sensor Networks (MHWSNs), sensors are frequently utilised to increase the precision of data monitoring. But if nodes are deployed heavily, it's possible for numerous nodes to encounter the same anomaly, leading to substantial data redundancy. A data fusion technique based on ELM optimised by MHWSN's Bat algorithm is suggested as a practical solution to these redundancy problems. Another variety of feedforward NN with a single hidden layer is ELM. The output weights and thresholds are calculated in a single step since the ELM only has one hidden node layer. In comparison to backpropagation (BP), RBF, and SVM NN and SVMs, this increases the learning pace of ELM by a factor of thousands. Bat algorithms, on the other hand, are motivated by the strong global search capabilities of bat echolocation.

It chooses and sends just the best nodes after optimising the ELM algorithm thresholds and input learning weights. The BAT-ELM-based data fusion algorithm's simulation results demonstrate its effectiveness in reducing network traffic, conserving network energy, increasing network efficiency, and significantly extending network life. The proposed BAT-ELM method has a greater node survival rate than existing protocols including stable election protocols, BP NNs, and ELM-based NNs, reaching 87% at the 400th iteration. The node survival rates of BP NN and ELM-based NN, on the other hand, are 55.0% and 51.7%, respectively. The BAT-ELEM method outperforms the other algorithms in terms of load performance and node reduction. The efficiency of the system may be increased even further by combining the ML algorithm with additional optimization methods.

6.2. RL-Based Routing Protocol:

Multi-Agent RL (MARL) is used in this situation to employ several agents in the learning process, with each node exchanging its local knowledge and decisions with other nodes in the network to enhance optimization. Be cautious though, as this method is quite intricate and computationally demanding. Self-learning RL-based algorithms are employed in several articles to determine the ideal route. [11] suggested user-specific shortest-path routing with optimum capacity. A user's resource-based optimal capacity shortest path between source-destination pairs in a 5G network is determined using RL. This assignment takes into account the distance between source and destination pairs and the available capacity of network nodes because the shortest route is not always the optimal route and does not satisfy QoS criteria. In order to fulfil throughput or bitrate demands, RL algorithms employ Q-learning to find the shortest path and minimise congestion in network nodes with high physical resource blocks (PRBs). When the PRB is more than 70%, RL identifies a node as busy. If not, RL labels these nodes as being accessible. The suggested RL method quickly finds the shortest road with the best capacity, according to simulation findings.

7. OTHER SUPERVISED LEARNING ML-BASED ROUTING ALGORITHM

Due to the fixed-route orientation of circuit-switched networks, routing performance is constrained by the rigidity of route selection. The Least Loaded Routing (LL) protocol is the preferred routing method for circuit-switched networks. However, this approach may perform poorly due to excessive capacity consumption in high-load scenarios, reducing overall efficiency.

7.1. Reducing Network Delay:

[9] developed a distributed cooperative multi-agent routing issue in a multi-hop CRN modelled using a distributed partially observable Markov decision process in order to reduce the latency of the Cognitive Radio Network (CRN) (DEC-POMDP). The objective of this strategy is to reduce disturbance to main users (PUs) while minimising end-to-end delay. Cognitive Users (CU) or Secondary Users (SU) are allowed access to the licenced spectrum in CRN. Sending SUs to a PU doesn't go above a certain limit. Due to the PU's stochastic nature, which sets CRN apart from conventional multi-hop wireless networks, routing is exceedingly challenging in this network. Implementing a routing system that can be adjusted to the spectrum windows offered by CRN is the key problem here. In [46], DEC-POMDP was utilised to model the routing issue. To address this issue, a gradient-based learning technique was used. The end-to-end latency suffered by packets is kept to a minimum by the suggested method, according to simulation findings, and it performs better than comparable techniques, such as OPERA and fictitious learning approaches, in terms of interference control.

Since frame-level queuing is disregarded by current QoS-aware routing algorithms, they cannot be used to centralised fronthaul radio access networks (C-RAN). In order to overcome queuing delays, Nakayama et al. devised a routing strategy that employs a Markov chain Monte Carlo algorithm to lower the worst-case end-to-end latency of all fronthaul flows and ensures that all flows satisfy the delay requirement. The path computation element (PCE) in the proposed work employs the IS-IS routing algorithm to gather data before using the k-shortest path method to provide a set of potential pathways for each fronthaul flow.

8. ML FOR NETWORK RESOURCE MANAGEMENT

Ageing and resource distribution throughout the meshing process. When network resources are completely exploited and the required QoS standards can be satisfied, effective resource management is possible. Switches, routers, bandwidth, and spectrum are regarded as network resources in a telecommunications network. The majority of traditional resource management strategies rely on static data. B. The desired bandwidth is exceeded. Network inefficiencies and inevitable delays are the results of such ineffective resource allocation. Two main areas that contribute to network resource management are admission control and resource allocation [11]. By keeping an eye on and controlling the resources on your network and approving or rejecting incoming traffic based on network availability, admission control tries to maximise resource utilisation. The network provider earns more money by accepting new requests all the time, but this compromises the quality of her existing services and violates SLAs. Therefore, access control optimises the number of requests that may be allowed while still adhering to the SLA. In order to accomplish long-term objectives, resource allocation is a decision-making challenge that involves managing resources like bandwidth. ML models may learn and forecast resource management deployments by utilising its advantages.

9. CONCLUSIONS

In particular, this study looks at current uses of ML algorithms in networks for things like B. congestion control, predictive network models, intrusion detection systems, route and path allocation, QoS enhancements, and resource management. Additionally, it covers the fundamental processes used by contemporary ML models, such as supervised, unsupervised, and semi-supervised learning. Along with the aforementioned application descriptions, we also go through current ML concerns and associated projects. Flexible and intelligent network management is crucial to fulfil bandwidth-hungry and strict latency requirements as network traffic rises dramatically. Although the standard method may be used to tackle it, certain network issues may not be able to handle future network complexity. These methods have certain drawbacks, such as manual conFigureuration with preset matrices, poor processing power, lengthy execution durations brought on by heavy overhead loads, and sluggish network change reaction. By overcoming the performance and computational complexity gaps, ML has lately come to be recognised as a revolutionary solution to address network issues [13]. Because it may offer a framework for resolving issues involving extensive data processing, categorization, and intelligent decision-making, ML has grown to be quite popular. In order to make judgments dynamically as these networks develop, ML algorithms may learn from the complexity of networks [14].

Funding Statement*:* The authors received no specific funding for this study.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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