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A PROPOSAL TO SUPPORT 5G MOBILE USE CASE BY APPLYING MACHINE LEARNING TECHNIQUES IN THE TCP/IP LAYERS

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Abstract: **The launch of the 5G mobile technology has various benefits as it defines three use case scenarios: enhanced mobile broadband (eMBB), massive machine type communication (MMTC) and ultra-reliable low latency communication (URLLC). This extends mobile communication services into new application domains, namely the so-called vertical domains including the smart factory, smart vehicles, smart home, smart city, remote robotic surgery, etc. Supporting these vertical domains comes with very demanding, challenging and mission critical requirements in terms of ultra-reliability and low latency attributes. In order to address these new issues, the 5G mobile network researchers uses different machine learning algorithms, however they do not provide any justification for their choice. In our article, we suggest appropriate machine learning (ML) techniques applicable to each TCP/IP layers thus increasing efficiency and meeting mission-critical demands in 5G mobile networks. With detailed recommendations for how to apply cutting-edge ML approaches in 5G and 6G mobile networks, we hope that this study will pique the curiosity of researchers.**

Key Word: **5G network, Machine Learning, TCP/IP, Supervised learning, unsupervised learning**

I. INTRODUCTION:

In today's digitally connected world, mobile communication systems have become an integral part of our daily lives, enabling us to stay connected, communicate, and access information anytime and anywhere. These systems have transformed the way we interact and have revolutionized the concept of communication. Mobile communication systems refer to the technologies and infrastructure that allow wireless communication between mobile devices, such as smartphones, tablets, and laptops. Mobile communication systems are a complex network of components and technologies that work together to ensure seamless communication. At the heart of these systems are mobile devices, which connect to base stations to form a cellular network. The telecommunication infrastructure – antennas, gateways, routers, switches, etc enable the transmission of voice and data signals between base stations and the core network. Mobile communication standards such as GSM, CDMA, LTE and NR have evolved over time, providing faster data speeds, improved capacity, and enhanced user experiences. Service providers invest in expanding network coverage and capacity to meet the growing demand for mobile communication services.

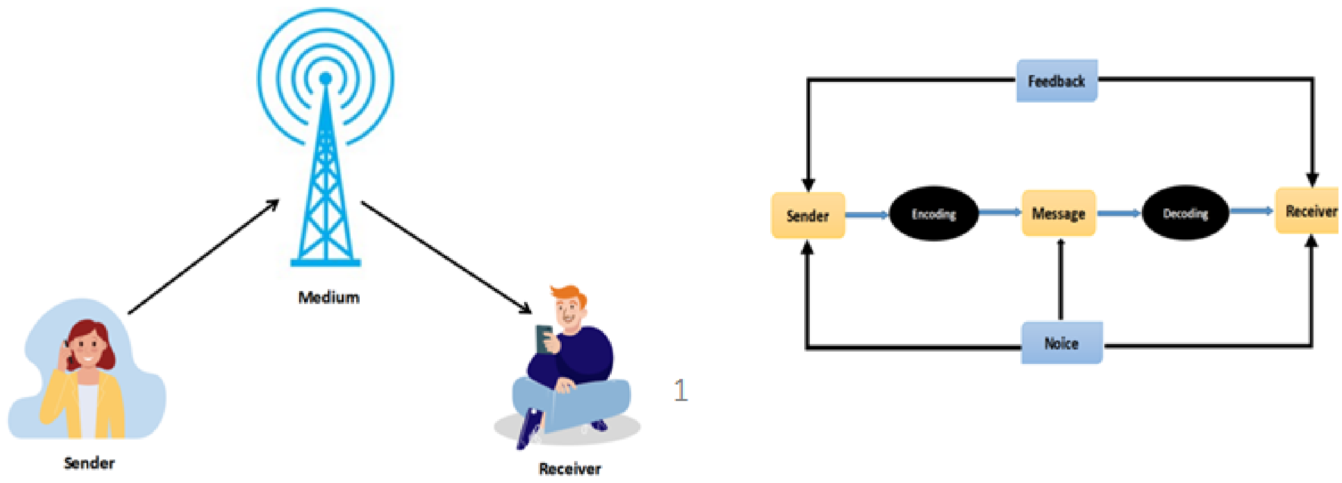


Figure 1: Communication process

We have improved wireless communication greatly and expanded the capabilities of our wireless communication system. Any recent changes to the way mobile phones communicate are referred to as generations. The phrase "mobile communication generations" describes how mobile telephony has developed as well as the techniques, features, and connections required to create an electronic network that enables a telecom network operator to provide services. Mobile telephony in a mobile communications system includes data transmission and reception, data routing, and data management.

1.1. **Generations of Mobile Communication:**

Let's examine each generation mobile communication technology in brief:

A. 1stGeneration(1G): Introduced in the year 1980, typical technology was AMPS,TACS,NMT-900 and NTT. First-time calling was first introduced via mobile systems. Analogue signals with FM modulation were employed. It utilized an FDD Access method and typically had a 30 KHz channel band width. Drawback was poor audio quality and no capability for roaming between different service providers. It only had a small coverage area i.e., within a cell.

B. 2ndGeneration(2G): Introduced in the year 1990, typical technology was GSM,IS-136,IS-95. The 2G shifted from analogue to digital signal communication with digitally encrypted phone conversations. Audio quality improved tremendously. GMSK and QPSK digital modulation were employed. It utilized TDMA access method in the case of GSM and IS-136 technology with 200 KHz and 30 KHz channel band width respectively. In the case of IS-95 the access method was CDMA with a channel bandwidth of 1250 KHz. Both voice and SMS were supported in this generation. The 2G GSM offered a data rate per user of 22.8 kbps with extensive coverage by cell migration.

C. 2.5/2.75 Generation (2.5/2.75 G): During 1995 came wide area mobile data networks with TETRA, cellular digital packet data (CDPD) and General Packet Radio Service (GPRS) technology. This is also known as 2.5G mobile technology. These networks operated in packet switched mode. These are exclusive data networks intended for SMS, video telephony, digital T.V. reception on mobile phone, web browsing and Internet data transmission. GPRS technology is overlay on GSM infrastructure. Typical data rate is 14.4 to 115 Kbps. To support high speed data communication an enhanced version of packet switching technology evolved known as Enhanced Data Rate for GSM Evolution (EDGE). This is also referred as 2.75G mobile technology which supports maximum data rate of 384 Kbps.

D. 3rd Generation (3G): Introduced in the year 2000, typical technology was WCDMA, cdma 2000,TD-CDMA,TDD & DECT+. The 3G mobile was evolved to provide multimedia email and real-time multimedia in addition to voice services. The voice quality to be comparable as wireline. Data rate 144Kbps to users in high-speed motor vehicles.384 Kbps for slow moving pedestrians and 2.048 Mbps for indoor office use. Seamless international roaming and support for several simultaneous multimedia connections.

E. 4th Generation (4G): Introduced in the year 2009, typical technology is Long Term Evolution (LTE) and LTE-Advance. Entirely packet switched IP based network. Evolved to meet needs of high-performance applications like multi-media, full-motion video, wireless teleconferencing and capable to provide data to the tune of 100 Mbps at high mobility and 1 Gbps for low mobility situations.

Up until 4G, the communication was between human to human and human to machine, but 5G, will allow communication between machine to machine.

F. 5[th] Generation (5G): Introduced in the year 2019.Typical technology is 5G NR(new radio) and 5G TF (technology forum).Intended to cover three use cases as follows:

1. EMBB (Enhanced Mobile Broadband): To support 20Gbps data rate for down link and 10 Gbps for uplink for e.g., 3-D & UHD video, cloud gaming, augmented & virtual reality systems, scenario.
2. MMTC (Massive Machine Type Communication): To support one million devices per Sq.km for e.g., smart city, shopping malls, airports, scenario.
3. URLLC (Ultra-Reliable Low-Latency Communication): To support reliability to the tune of 99.999% and latency below 1ms for e.g., Industrial automation, remote robotic surgery, telemedicine, driverless car, scenario.

Now conventional communication technology will fail to achieve the stringent requirements of 5G use cases and hence has to rely on artificial intelligence (AI) and ML techniques.

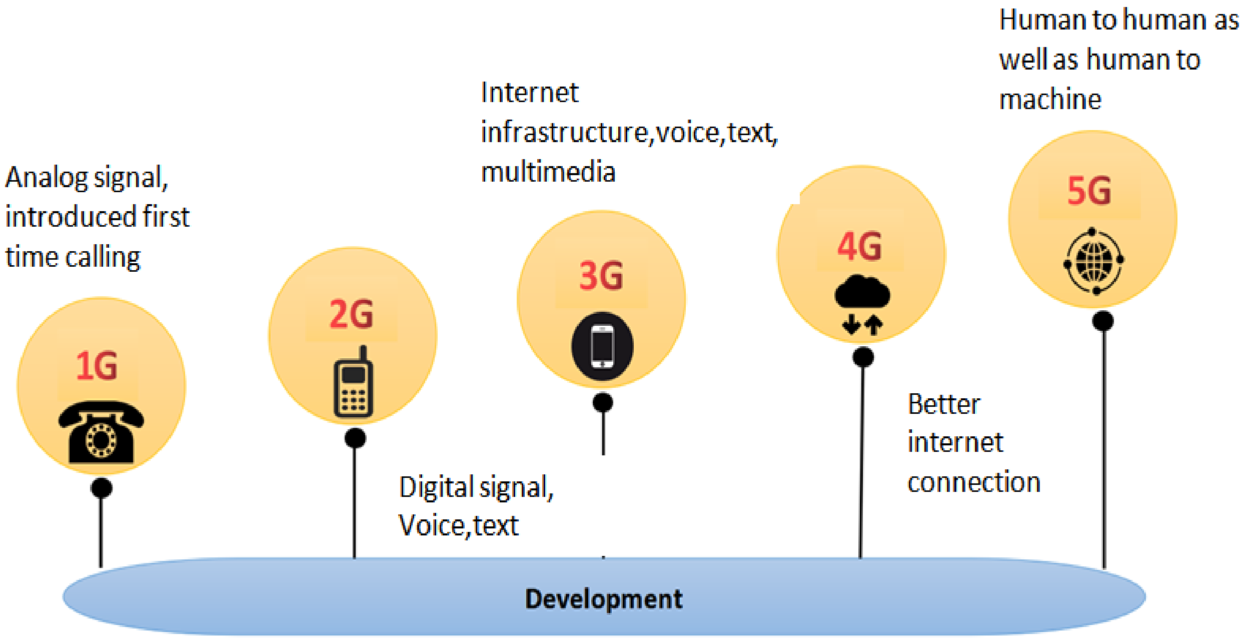


Figure 2:1G to 5G evolution

1.2. **AI and ML in Communication:**

AI and ML technologies have become increasingly important in the field of mobile communication systems and networks.AI-powered chatbots and virtual assistants can understand and respond to user queries, providing instant assistance and improving customer service experiences. Speech recognition systems leverage machine learning techniques to convert spoken language into written text, while text-to-speech synthesis systems utilize ML algorithms to convert written text into natural-sounding speech. AI and ML also facilitate sentiment analysis, optimizing network performance and reliability, enabling personalized and context-aware communication experiences. AI and ML are critical to meet the requirements of 5G technology. With the large influx of connected devices and the necessity for high-speed data transfer, AI and machine learning algorithms can optimize network performance by analyzing real-time data and making intelligent judgement. By monitoring network traffic patterns and dynamically assigning resources to meet demand, these solutions offer effective resource management while providing an ideal user experience. Furthermore, AI and ML aid intelligent traffic management by recognizing bottlenecks, rerouting traffic, and prioritizing key applications in real time. They also improve network security by detecting irregularities in network traffic and forecasting security breaches, allowing for quick response and preemptive steps. Furthermore, AI and ML techniques enable intelligent edge computing, allowing for low-latency processing and speedier decision-making at the network edge.

However, there are no clear guidelines for where, how and which machine learning algorithms can be used to build a most efficient communication system which will comply the stringent standards of 5G NR by 3GPP. This drives us to associate different ML methods with the TCP/IP network model, as the TCP/IP model forms the backbone of all the electronic communication systems.

1.3. **Literature Survey:**

We reviewed a number of articles, numerous researchers have put out various theories regarding the implementation of machine learning (ML) in 5th Generation mobile networks. For example, J. Kaur et al.'s article[1] offers a current evaluation of the benefits of ML techniques in a number of upcoming wireless systems, including 6G. They gave a thorough explanation of the conceptual model for 6G and demonstrated how ML methods are integrated into each layer of the model. In the context of wireless communication networks, they examine some traditional and cutting-edge machine learning (ML) techniques, including supervised and unsupervised learning, reinforcement learning, deep learning, and federated learning. In their paper[2], J. SUOMALAINEN et al. examined the challenges ML poses for 5G networks as well as potential solutions. This effort's main objective was to spark interest in future research on the safe integration of ML techniques in 5G and other upcoming wireless networks. The topic of the article by M. EUGENIO MOROCHO-CAYAMCELA et al. [3] is hypothetical 5G solutions based on ML. In order to use machine learning (ML) in the context of mobile and wireless communication, they establish the fundamental concepts of supervised, unsupervised, and reinforcement learning. They also investigate the promising approaches for ML's support of each target 5G network requirement, highlighting their unique use cases and weighing their advantages and disadvantages for network operation. Additionally, the article makes recommendations for future research on how ML might influence the development of Beyond 5G (B5G), which is an analysis of potential B5G characteristics. In their research [4]D. Bega et al. provide a network slice admission control method that (i) automatically learns the proper acceptance policy and (ii) ensures that the service guarantees provided to the tenants are always met in order to solve the problem. The following are the contributions made by their study: (i) an analytical model for the admissibility region of a network slicing-capable 5G network; (ii) analysis of the system (modelled as a Semi-Markov Decision Process) and optimisation of the revenue of the infrastructure providers; and (iii) creation of a machine learning algorithm that can be applied in real-world scenarios and performs almost as well as optimally. In their study [5], Y. E. Sagduyu et al. analyse the expanding attack surface of adversarial machine learning and related approaches targeted at wireless communications. The focus is on attacks against (i) 5G user equipment (UE) and (ii) physical layer authentication of 5G user equipment (UE) in order to enable network slicing. The first assault modifies the signal-level inputs to the deep learning classifier that is placed at the Environmental Sensing Capability (ESC) to assist the 5G system by broadcasting during data transmission or spectrum sensing times. In the second attack, the attacker sets up a physical layer authentication system based on deep learning classifiers at the target location and uses a generative adversarial network (GAN) to simulate wireless signals in order to breach itIn their study, G. Leoni Santos et al. [6] give a systematic evaluation of the ways deep learning models are being used to 5G-related issues. It looks at research that addresses various 5G-specific issues as well as data from the last ten years. Additionally, it examines the primary difficulties in conducting research and points out a number of problems that require more attention. Many significant advancements have already been made as a result of the usage of deep learning in 5G, and more are predicted. This article examines the advancement of deep learning solutions for 5G communication. H. Huang, et al. [7] discussed how deep learning techniques have the potential to optimise wireless communications. It offers effective solutions for 5G scenarios based on deep learning, such as NOMA, large MIMO, and mmWave hybrid precoding. To fully address wireless physical layer concerns using deep learning ideas, however, remains a long way off.In their study [8], T. Wang et al. highlighted the use of machine learning to take advantage of the enormous amounts of data provided by the network, such as proactive load balancing. The data-driven paradigm has the potential to advance mobile wireless communication technology. According to N. Haider1 et. al. [9], AI and ML can be extremely useful in building, simulating, and automating effective security policies against a variety of threats. This article highlights applications for 5G network security powered by AI and ML, along with its ramifications and potential future research areas. Although further study is required to fully automate it, AI-assisted solutions can dramatically increase security for distributed ad-hoc creation of network infrastructure. In their study, He. Fang et al.[10] state that machine learning-based intelligent authentication systems leverage characteristics in the multi-dimensional domain to deliver more reliable, continuous, model-free, and situation-aware device validation at lower costs. They can be applied to research human-device interaction, database security, Internet and cyber-security, incident handling, hacking, biometric techniques, smart cards, infrastructure protection, risk management, and better decision making. They can also be used to enhance the quality of services in 5G and beyond networks.

The articles as discussed above proposes variety of machine learning algorithms in different phases and for diverse purposes without ever stating their intended application or justification. As a result, it is not sure which particular ML algorithm will be used in an application or in a stage of communication system. If we take a look at the most recent European Open project, HEXA-X[23], they too acknowledged the significance of ML in the next 6G technology and described the utilization in various TCP/IP

layers, but they did not explained which AI or ML algorithm to be used in a particular layer.
In this paper we clearly mention which ML algorithm to be used in a particular TCP/IP layer facilitating overall performance improvement in 5G communication system.

II. MACHINE LEARNING METHODOLOGY:

Machine learning is a branch of Artificial Intelligence that helps computer systems learn and improve from experience by developing computer programs that can automatically access data and perform tasks via predictions and detections. When asked Alexa to play your favorite music station on Amazon Echo, she will go to the station you played most often, and you can further improve and refine your listening experience by telling Alexa to skip songs, adjust the volume, and many more possible commands. Here comes the advantages of machine learning over traditional system. In a traditional computer-based system, we give the computer a program to follow, which it uses to process input and generate output, but in a machine-learning system, we give the computer certain inputs& outputs, and the computer-based system learns the trend of inputs & outputs and program on its own, allowing it to produce appropriate output based on input in the future.

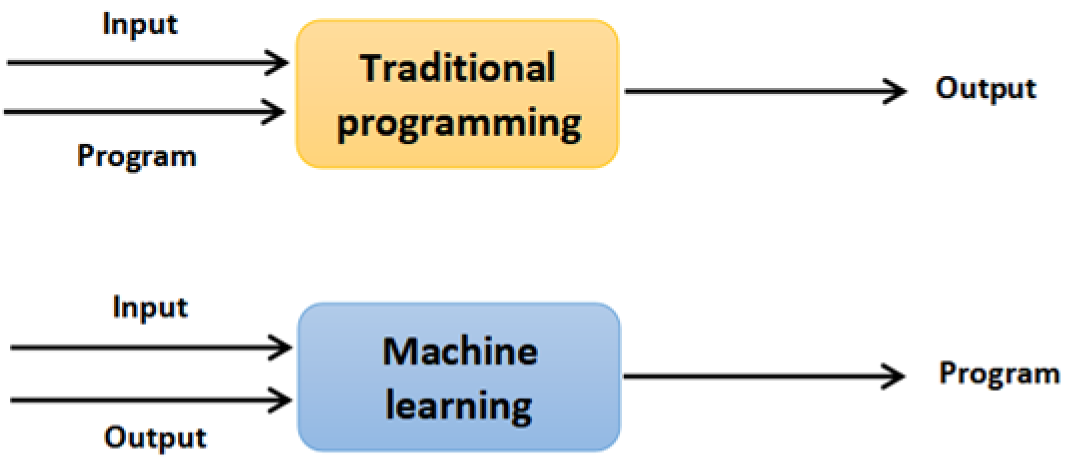


Figure 3:Traditional programming vs machine learning

Machines are distinguished by two types - one is adaptive which can change itself with the respect of its environment and other is non-adaptive which can't change itself with the respect of its environment.
To make all machines adaptive ML involves two stages: the first is **training**, during which the system is taught by giving it a set of inputs and the appropriate outputs, and the second is **testing**, during which the machine is put on test by giving it a set of inputs, obtain the output, and then calculate the error of how close the output actually is.

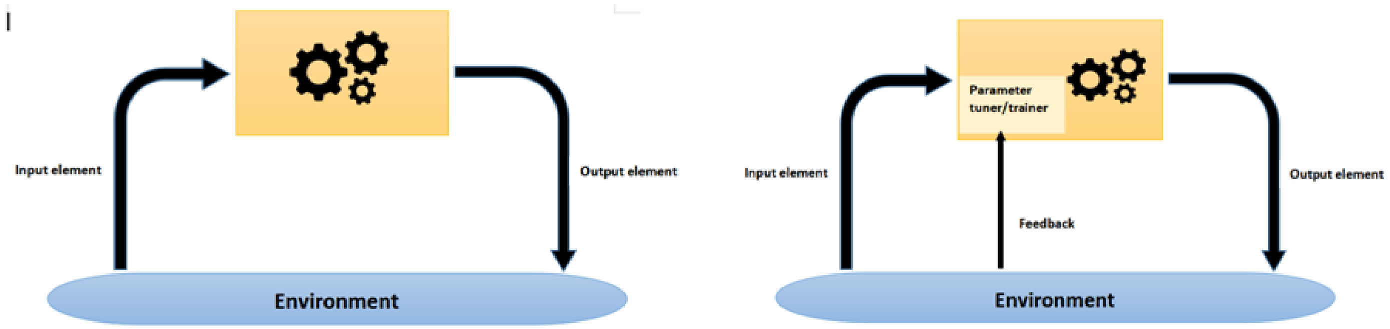


Figure 4: Adaptive and non-adaptive machine

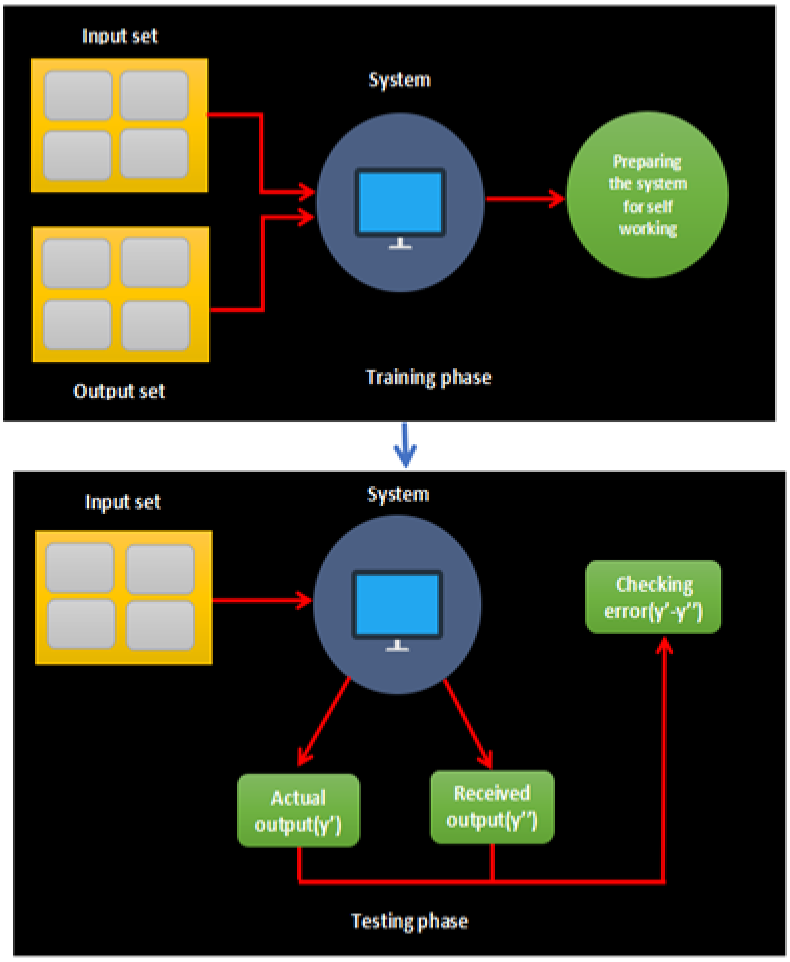
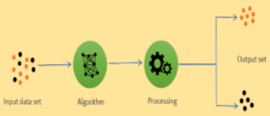
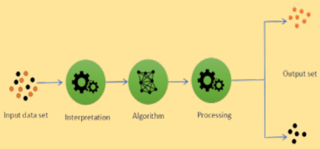


Figure 5:Training and Testing phase of ML

Types of ML and their distinctions: There are three types of ML– Supervised, Unsupervised and Reinforcement which are distinguished as in Table 1

Table 1: Supervised vs Unsupervised Reinforcement

Supervised learning	Unsupervised learning	Reinforcement learning
1. Training data is most important part. 2. Both input and output is given during the training session. 3. Output is based on either Classification or Regression Machine Learning. 	1. Only input is given during training time. 2. Output is based on Clustering Machine Learning. 	1. Reward and loss based system 

Algorithm: 1. Linear recognition 2. Logistic regression 3. Support vector machine 4. K-Nearest neighbour 5. Decision tree etc. Note: Need external supervision to train model(Classification and regression)	Algorithm: 1. K-Mean algorithm 2.Hierarchical clustering 3.DBSCAN 4. Principal Component Analysis etc. Note: Don't need any supervision to train model(Clustering and association)	Algorithm: 1. Q-learning 2. SARSA 3. Monte Carlo 4. Deep Q Network Note: Don't need any supervision to train model(Reward basis)
Application: 1. Weather prediction 2. Sales forecast 3. Stock price etc.	Application: 1. Customer Segmentation 2. Chum analysis etc	Application: 1. Building gamer 2. Training robots

1.4. Mobile Communication Network Architecture:
A simple diagram is shown in figure 6.A mobile communication network consists of broadly two parts: Radio Access network (RAN) and Core network (CN). The RAN with the help of radio link gives access to the mobile unit (handset/phone) to the CN. The RAN coordinates the management of resources across the radio sites. The handset in turn is wirelessly connected to the core network. The core network is the backbone of a network. It provides connectivity between different entities of the network. It offers numerous services to the handsets (subscribers) who are interconnected by the access network. It also connects other networks.

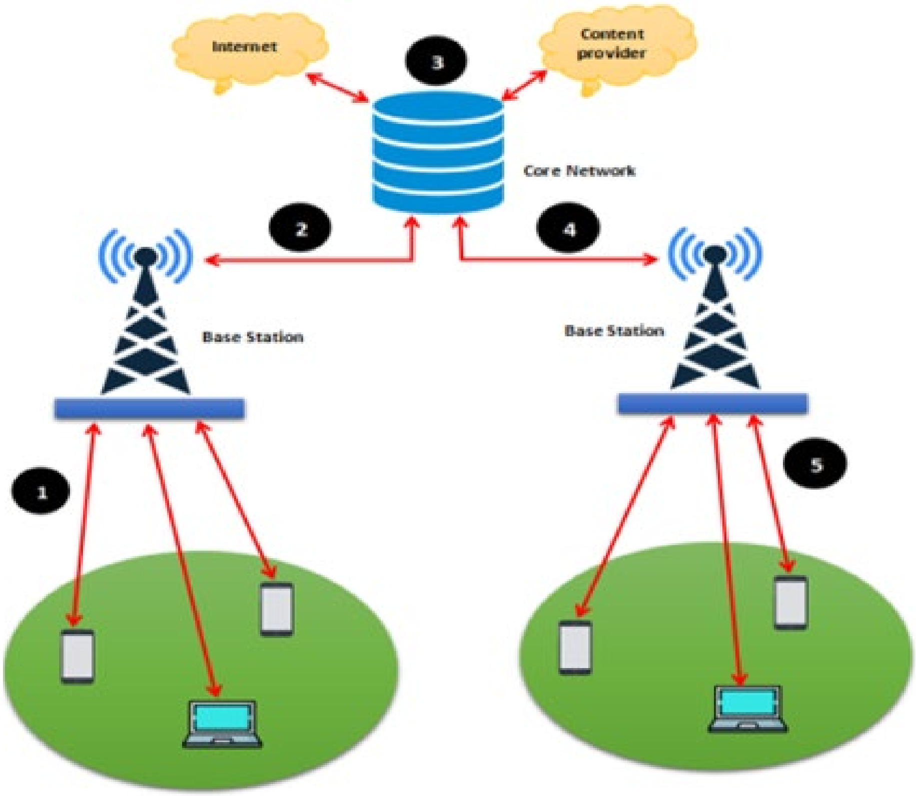


Figure 6: A typical mobile communication network system

There are numerous entities present in the network both hardware and software. The entire network must adhere to certain protocols in order to conduct successful and secure communication across the network. The network can be modeled as TCP/IP five layer model, viz. application, transport , network , data link and physical layer.

1. Application layer: The application layer is the TCP/IP model's highest level, allowing end-users to interact with software applications. It implements communicating components, but data interpretation is outside the model's scope. Examples include file transfer, email, and remote login.

2. Transport layer: The transport layer is responsible for data transport between systems, ensuring error-free and sequenced data delivery. It hosts on single or multiple networks and maintains service quality. It controls link reliability through flow control, error control, and segmentation. The transport layer acknowledges successful data transmission and sends the next if no errors occur. TCP is a well-known example of this layer.

3. Network layer: The internet layer, also known as the network layer, is the second TCP/IP layer and handles packet transmission from any network to the destination. It offers functional and procedural methods for transferring data sequences, but does not provide a guaranteed reliable protocol.

4. Data link layer: The frames that travel over the network are made by the Data Link layer. MAC addresses are used in these frames to specify the source and destination of the packets while encapsulating them.

5. Physical layer**:** The transceiver, which transmits and receives signals via the network, is part of the Physical layer, which also encrypts and decrypts the bits contained in a frame.

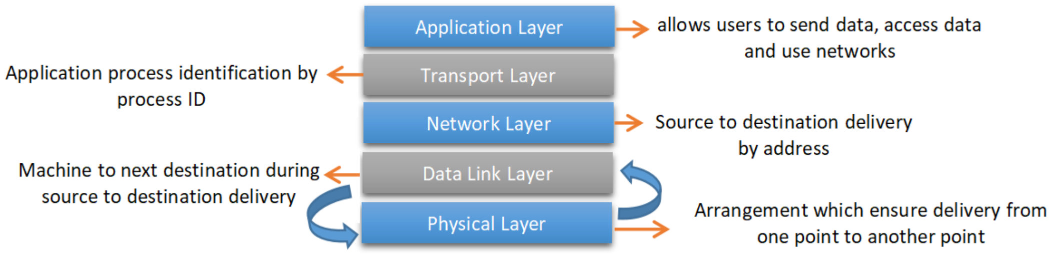


Figure 7: TCP/IP model with function of each layer

The term "5G TCP/IP model" refers to the way in which 5G technology has been integrated with the existing TCP/IP architecture.

The following table describes the redesigned TCP/IP [24] in light of the 5G communication model. -

Table 2: TCP/IP vs 5G TCP/IP

TCP/IP Conventional	TCP/IP Conventional in 5G
Application layer	Application(Service)
Transport layer	Open transport protocol(OTP)
Network layer	Upper network layer Lower network layer
Data link layer	Open wireless architecture(OWA)
Physical layer	

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We now link various 5G elements to the 5G TCP/IP tiers. This will facilitate the association of various algorithms with the various components of the network.

Table 3: Different Devices in different layer of TCP/IP

Layer in 5G communication	Device
Application(service)	Computer with associated devices, mobile, Iot device , Intalligent device etc.
Open transport protocol (OTP)	Base station, Centralized unit, Edge server, Core network elements, Data centers, Network gateways.
Upper network layer	Router, Switches, Gateways, Session border controllers, Packet core network elements, firewalls, load balancer, traffic management system.
Lower network layer	Transceivers, antennas, radio frequency components, digital signal processors, analog to digital and digital to analog converters, fiver optic cables, power amplifiers, cooling system, base band processors.
Open wireless architecture (OWA)	Open radio access network equipment, software define networking controllers, white box hardware, commercial-of-the-self-server, general purpose processor accelerators, fibre optic cables, power amplifiers and RF components, cooling system.

Note: Upper tier devices can used as lower tier devices.

1.5. ML Algorithms and Network Devices:
The above mention conventional devices used many algorithm to perform communication process. Here we have proposed the corresponding Machine Learning Algorithm which can be used to further smoothen the communication process which is depicted by the following table.

Table 4: Current algorithm with a comparable machine learning approach for various network devices

Devices	Algorithm	Machine Learning Algorithm
1.Hub	Flooding Algorithm[18],[20]	1.Support Vector Machine[20] 2.Decision Tree[20] 3.Random Forest[20] 4. Deep Neural Network[18] 5.Loght Gradient Booting Machine[18] 6.Extreame Gradient Booting Machine[18] 7.Cascade Forest Model[18]
2.Router	Distance Vector board Routing Algorithm[17]	1.Decision Tree Machine learning based routing protocol[17] 2.Support Vector Machine[17] 3.Artificial Neural Network for Ad-hoc on demand Distance Vector routing protocol[17]
3.Modem	Medium Access Control(MAC) Algorithm[16]	1 Any Supervised Machine learning Algorithm[16] 2.Reinforcement learning[16]

		3.Deep Reinforcement learning[16]
4.Switch	Backword Learning Algorithm[21] and Spanning Tree Algorithm[22]	1.Artificial Neural Network[21] 2.Deep Learning[21] 3.long-short term memory network (LSTM)[22]
5. Firewall	DES and 3DES[14]	1.K-Nearest Neighbour[14] 2.Random Forest[14] 3.Deep Neural Network[14]
6. Antenna	Beam Alignment and Beam turning etc[12],[13]	1.Support Vector Machine Algorithm In Machine Learning[12],[13] 2.Deep Convolution Neural Network[12],[13]
7. Gateway		1.K-Means Clustering Algorithm[11] 2.K-Medoids Clustering Algorithm[11]

The TCP/IP architecture consists of five layers, and depending on the application, different machine learning techniques may be applied at each layer. We can infer from the aforementioned survey that the following algorithm may be utilized by many layers, and the following lists these layers which is represented by the flowing table:

Table 5: The deployment of several machine learning category in various layers of TC P/IP

Layers	Layers in 5G	Machine Learning Algorithm
1. Application Layer	Application(Service)	1. Deep Learning Algorithm 2. Any Supervised Machine Learning Algorithm(as per requirement of the user level)
2.Transport Layer	Open transport protocol(OTP)	1.K-Nearest Neighbour 2.Random Forest 3.Deep Neural Network 4.K- Means Clustering Algorithm 5.K- Medoids Clustering Algorithm
3.Network Layer	Upper network layer	1.Decision Tree Machine learning based routing protocol 2.Support Vector Machine 3.Artificial Neural Network for Ad-hoc on demand Distance Vector routing protocol
	Lower network layer	
4..Data Link Layer		1.Artificial Neural Network 2.Deep Learning

5.Physical Layer	Open wireless architecture(OWA)	1.Support Vector Machine 2.Decision Tree 3.Random Forest 4. Deep Neural Network 5.Light Gradient Booting Machine 6.Extreame Gradient Booting Machine 7.Cascade Forest Model 8. Any Supervised Machine learning Algorithm 9. Reinforcement learning

However, depending on the user's needs and application service, this may change.
The equipment used for 5G communication have a different structure and operation from the devices previously in use. In order to implement the 5G use cases, including EMBB (Enhanced Mobile Broadband), MMTC (Massive Machine Type Communication), and URLLC (Ultra-Reliable Low-Latency Communication), machine learning algorithms are crucial. Different types of software, including software defined radio, encryption software for security and dependability, and software for flexibility to enable MMTC and URLLC, are already utilized to run 5G networks. Therefore, there is a lot of potential for using ML algorithms to improve performance.

III. CONCLUSION AND FUTURE SCOPE:

Since we have several machine learning algorithms for various devices, a machine learning algorithm can be selected based on the demands of the particular instance.
The above-mentioned machine learning algorithms, which are applied to various network model levels, have varying time complexities that is time required to execute the algorithm and the following table represent the complexity of the few well known and most useful algorithm-

Table 6: Time complexity of each machine learning algorithm

Machine Learning Algorithm	Time Complexity
1.Support Vector Algorithm	0(N^3)/ 0(N^2)
2.Decision Tree Algorithm	0(depth)
3.Random Forest Algorithm	0(NlogN)
4.Light Gradient Boosting	0(0.5*#feature*#bin)
5.Extreme Gradient Boosting	0(tdxlogN)
6.Reinforcement Learning	0(N^3)
7.K-Nearest Neighbour	0(N*D)
8.k-Means Clustering	0(N*T*K)
9.K-Medoids Clustering	0(N^2*K*T)

Here
N= Number of Data sets
D= Number of features
K= total number of partitions
T= number of iterations in the clustering process

Our proposal suggests that machine learning is an important tool for applications in the future, but implementation is key to achieving the intended outcomes because we must select the appropriate machine learning algorithm depending on the application. Since time and space complexity are inversely proportional, there is a trade-off when selecting the best algorithm to solve a problem. Our work can assist other researchers in choosing the best machine learning strategy to address problems in a variety of domains and also help beyond 5G where we can implement Machine learning algorithm. Most 5G machine learning implementations take place in the cloud the process could lead to the widespread use of AI and Machine learning as contemporary in communication. Hence it may be inferred or concluded that AI or ML may be implemented in every phase of modern communication.

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