Machine Learning Based 5G Network Channel Quality Prediction

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Abstract –

Channel quality feedback is very important for operation of 4G or 5G wireless complex because it allocate user equipment (UE) connections, transmission scheduling, or control over modulation or rate of data spread over wireless connection. Though, if comments like this occur frequently and the number of UEs within a cell is large, channel may be overloaded by signaling messages, reducing throughput or loss of data. Therefore, optimizing this signaling process is an important challenge. This thesis focuses on channel quality indicator (CQI) report irregularly transmitted from the UE to base station, and provides a mechanism to optimize reporting procedure with aim of reducing signaling overhead or avoiding overload of connected channel and detect channel quality and reconstruct node, For this purpose, machine learning techniques are applied to predict the stability of the channel. Implemented CNN and SVM Algorithm for channel quality estimation. And proposed the utilization of Particle Swarm Optimization (PSO) in Convolutional Neural Networks (CNNs), which is one of the basic methods in deep learning. The use of PSO on the training process aims to optimize the results of the solution vectors on CNN in order to improve the recognition accuracy. This Simulation Has Performed on the MATLAB Simulation. The simulation results show that all provide high prediction accuracy when compared to traditional methodologies.

Keywords - Channel Quality Prediction, 5G Network, Machine Learning, CNN,SVM

I. INTRODUCTION

Machine learning is made up of algorithms that can learn from data and make predictions based on what they have learned. These kinds of algorithms make predictions or decisions by building models based on the information they are given, rather than by following a set of rules. This set of algorithms has been used well in many different fields, such as computer security, bioinformatics, computer vision, medical diagnostics, and search engines, to name a few. All of these systems have one thing in common: they can automatically look at database data to find actionable insights and make decisions based on that data. Mobile networks are known for being hard to understand, and it seems likely that the new 5G communication systems will be even harder to understand. They need to be able to handle a growing number of situations that can't be fully communicated with mobile systems of today. Some examples of these scenarios are multiple deployments of powerful power lines, intelligent transportation systems, low-latency connections, and networks' company[1]. To deal with this level of complexity, we need to come up with sophisticated ways to look at 5G data. In order to make decisions, these methods need to be able to gather information, reduce the number of people needed to run these communication networks, cut down on the amount of work that comes with managing networks, and predict how users and networks will act in the future.

Channel Quality Indicator-

The Channel Quality Index, which is also written as CQI, is a measure of how well information can be sent over a wireless channel. A CQI can be a value or many values, and it stands for a metric that measures how good a certain channel is. Most of the time, a CQI with a high charge means that the channel also has a high charge, and vice versa. Use performance indicators like the signal-to-noise ratio (SNR), the signal-to-interference plus noise ratio (SINR), the signal-to-noise plus distortion ratio (SNDR), etc. to figure out the Channel Quality Index (CQI). By figuring out these or other values for a channel, you can then use those values to figure out the CQI for that channel[2]. The CQI of the channel can be affected by the type of transmission (modulation) used by the communication system. For example, a communication company that uses multi-input distribution code (CDMA) can use a wider range of CQIs than one that uses orthogonal division multiplexing (OFDM). In more complicated communication systems, like those that use multi-channel input (MIMO) or space coding, the CQI may also depend on the type of receiver being used. Things that can be taken into account in CQI include the failure to carry out the demonstration, Doppler shift, the evaluation of the information channel, interference, and so on.

II. RELATED WORK

Sihem Bakri et.al. 2020 [1] Channel quality feedback is crucial for the operation of 4G and 5G radio networks, as it allows controlling User Equipment (UE) connectivity, transmission scheduling, and the modulation and rate of the data transmitted over the wireless link. However, when such feedback is frequent and the number of UEs in a cell is large, the channel may be overloaded by signaling messages, resulting in lower throughput and data loss. Optimizing this signaling process thus represents a key challenge. In this paper, we focus on Channel Quality Indicator (CQI) reports that are periodically sent from a UE to the base station, and propose mechanisms to optimize the reporting process with the aim of reducing signaling overhead and avoiding the associated channel overloads, particularly when channel conditions are stable. To this end, we apply machine learning mechanisms to predict channel stability, which can be used to decide if the CQI of a UE is necessary to be reported, and in turn to control the reporting frequency. We study two machine learning models for this purpose, namely Support Vector Machines (SVM) and Neural Networks (NN). Simulation results show that both provide a high prediction accuracy, with NN consistently outperforming SVM in our settings, especially as CQI reporting frequency reduces obtained the best ASE using this method.

Lubov Berkman et.al (2019)[2] the change in channel capability appears as a change in a number of objectives, which are proposed to determine the value of state-of-the-art control technology. It is recommended to use the gradient prediction method to predict the state of the channel. Analyze the parameters that characterize the separate channel state. The control element needs to consider the characteristics of the control channel and put in place to improve the efficiency of the control. Consider how to evaluate the quality of a communication channel. We define the algorithm that is proposed to be used on a network with packet packets during the processing of access to limit the network bandwidth. According to the general and partial details of the improvement, consider the possibility of choosing the best method. Analyze the measurement of quality and service standards. It is very convenient to use a continuous measurement method and a clear output method to measure the load. A network exchanges packages when measuring service quality indicators (number of reports, expected time to start service and τ). π) It is very convenient to use the method of directly counting the number of reports.

V. A. Babkin et.al (2019)[3] In order to ensure the quality of traffic flow in a communication network, it is necessary to ensure the value of the quality index within an acceptable time frame. One of these indicators is the traffic transmission rate reported in the traffic data processing. By checking whether the user's traffic management file matches the configuration file specified in the configuration file, the quality control value can be kept within a single value. of the traffic, thus maintaining the quality of the user's traffic.

Hesham M. Elmaghraby et al. (2018)[4] this paper solves the problem of channel distribution for femtocells that share the common use of macrocells. The program problem of the femto base camp (FBS) is presented in the form of a Restless Armed Rogue (RMAB) system. Our goal is to select a branch / channel that optimize the amount of expected reduction reward over an indefinite period of time, while minimizing the interference caused by cell division channel distribution. Instead of directly monitoring the actual channel quality, we use a cellular user feedback called the Channel Quality Index (CQI). In general, the RMAB problem is a PSPACE problem. In order to estimate the available channels in the FBS, we propose an indexing strategy with low inference difficulty, called the Wit Le average index. Finding a closed channel reservation solution often means that there are closed channel reservations that have an active program but are based on partial channel information in the CQI. We also highlight the benefits of a referral policy over a short -sighted policy.

III .PROPOSED SYSTEM

5G networks can give users a better experience because they have more capacity or better management, but they also need more accurate channel predictions than older mobile networks did. In this thesis, a machine learning method, including the CNN and SVM algorithms, was suggested as a way to predict the Channel Quality Index (CQI). Reflection, diffraction, and signal scattering are the three things that, in a typical cellular communication scenario, When compared to LTE, the physical layer resources available in a 5G network are more plentiful but also more difficult. As a result, algorithms for scheduling that are more flexible and dependable, in addition to CQI values that are more accurate, are of utmost significance for the advancement of NR. networks. CQI creation and reporting have traditionally been carried out by favor the idea of delaying the timetable, which will inevitably lead to a decrease in the system's overall performance. Utilizing tools of prediction such as The CQI's accuracy can be improved with the help of deep learning techniques. which is finally something that helps out the NR system.

0+/8A. The Prediction of CQI Through the Use of Deep Learning Algorithms At the moment, we are concentrating on the wideband CQI, which is a positive integer. between 1 and 15. Considering that the CQI is merely a discrete value while UEs are continuous, the It is not possible to merely train because conditions are constantly shifting. a component that can predict the actions of any user based solely on their history importance of the CQI. In the event that a user is going in the direction of the base station at whereas at other times it is moving away from the BS, it is moving away from the BS this time. Because of this, the module won't know how to respond to the user's actions. Afterward, all it does to learn is how to mimic the conduct it has already seen. This being said, in this manner, the training module will only require a few steps to complete, and the result indicates that there was an apparent delay in the CQI result when compared to the actual value that has been reported. In addition to this, the actions taken by users ar vary, hence the BS ought to have different models for each single variation. users who connected themselves to it.

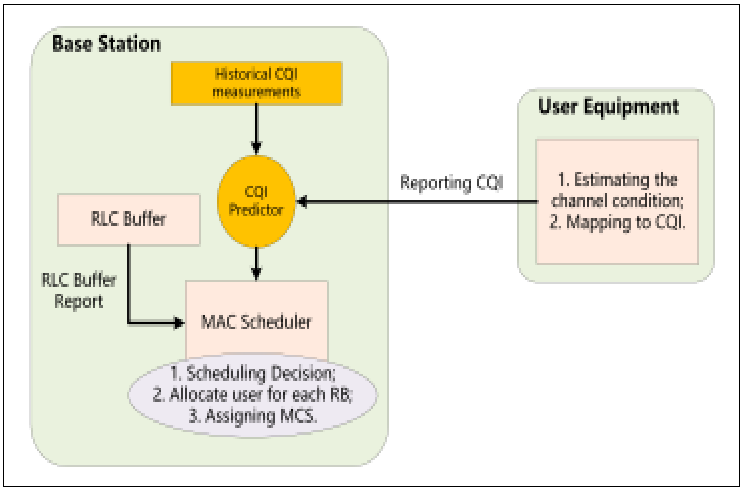

Figure1 . Illustration of CQI prediction module.

At the physical layer of a 5G network, there are not only more and better resources than in an LTE network, but there are also more of them. Because of this, it is very important to improve NR networks by making their scheduling algorithms more flexible and reliable and by giving them more accurate CQI values. Over the course of CQI's history, its production and reporting have been known to cause schedule delays, which in turn have led to a drop in system performance. We can improve the accuracy of the CQI by using prediction methods like deep learning algorithms, which is good for the NR system in the long run.

A downlink scheduler, which is also called a MAC Scheduler, is part of the NR system's medium access (MAC) layer. This scheduler's job is to get the user's personal schedule information when the user connects to the base station. This information includes the CQI as well as Quality of Service messages and buffer status reports (BSRs) sent by the Radio Link Control (RLC) layer (QoS). The scheduler will then pick a user to represent each RB based on the information that has already been given. The value of the CQI is used to figure out the MCS, which then gives information about the Transport Block Size. When RBs are given out to users, this is what happens (TBS). There are limits on how much data can be sent during this time, which are set by both the MCS and the TBS. Users have to give the CQI at every time interval that has already been set. The base station had to send the CQI before it could get the feedback, so there will be a delay between when it asks for the CQI feedback and when it gets it[5-7].

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When RBs are given to users, this is what happens (TBS)[8]. The MCS and the TBS both put limits on how much data can be sent at this time. Users are required to give the CQI at every predetermined time interval. The base station had to send the CQI before it could get the feedback, so there will be a delay between when it asks for the CQI feedback and when it finally gets it.

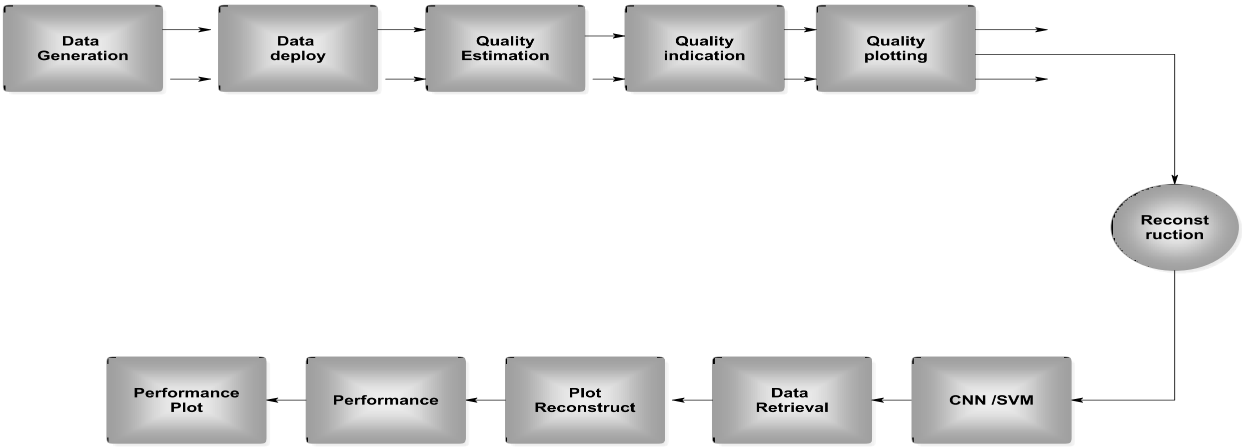


Figure. 2 Flow Diagram

IV SYSTEM DESCRIPTION

Using machine learning to make a system that can predict the future To make a prediction system, a machine learning algorithm goes through the next two steps.

a) Training phase: Seventy percent of the feature vectors and their labels are used to train the classifier (which reflect the actual classes). During the training step of machine learning, a function that maps inputs (called "feature vectors") to outputs is made (labels). Then, this function is used to put new vectors into groups. At this point, the NN algorithm can handle both linear and nonlinear functions, while the SVM method only learns linear functions.

b) Test and validation phase: In this step, we use the remaining feature vectors (30 percent). It involves comparing the predicted classes for these vectors with the labels that have already been given to them.

Particle Swarm Optimization (PSO)- After that, this method can be used to improve the way CQI data messages are sent, which will lead to less signalling overhead in the long run. And showed how Particle Swarm Optimization (PSO), which is one of the most important deep learning techniques, can be used in Convolutional Neural Networks (CNNs). During the training phase, PSO is used to improve the accuracy of the recognition process by making the results of the CNN-generated solution vectors as good as possible.

Imagine a network with N nodes of user equipment and one base station. All of the nodes can talk to each other (BS). As part of these conversations, the Channel Quality Index (CQI) of the communication frequency bands is given so that the conditions of those frequency bands can be looked at. This makes it easier for people to talk to each other in a way that works better. Because of this, the signal-to-noise ratio (SNR) for each subcarrier is a good choice of CQI, and it will be used as such for the rest of this investigation. In reality, the CQI is either a 4-bit value (for 5G) or a 5-bit number, and it encodes the channel gains as well as the modulation and coding scheme being used (MCS). Sub bands are smaller, more specific parts of each frequency bandwidth that are made as it is divided further. After that, each sub-band is divided into physical resource blocks (PRB), which are made up of sub-carriers in the end (SC)

Table 1- Network Parameters

Parameters		Value
Number of nodes		150
Area length(m)		400
Area width (M)		400
Expected sensors readings		30
Size of data buckets (bytes)		400

5G Dataset with Channel and Context Metrics-An example of a 5G trace file from a large mobile network provider in Ireland, which is part of the United Kingdom. Ireland is home to the headquarters of the company that runs this service. The data set was made by putting together two different application patterns and two different mobility patterns—the static pattern and the vehicle pattern (video streaming and file download). During the data collection process, the following are the most important performance indicators of the client-side cellular network: (KPIs). Some of the key performance indicators (KPIs) that are included here are throughput, indicators about cells, metrics about context, and metrics about channels. A well-known Android programme called G-NetTrack Pro was used to take these measurements. It was made for network monitoring and doesn't require the device to be rooted in order to work. As far as we know, this is the first time that information about the throughput, channel, and context of 5G networks has been made public[9].

	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
1	NetworkMod	RSRP	RSRQ	SNR	CQI	RSSI	DL_bitrate	UL_bitrate	State	PINGAVG	PINGMIN	PINGMAX	PINGSTDEV	PINGLOSS	CELLHEX	NODEHEX	LACHEX
2	5G	-99	-15	6	12	-90	7	1	D	-	-	-	-	-	C	A81B	9CBA
3	5G	-99	-15	6	12	-90	7	1	D	-	-	-	-	-	C	A81B	9CBA
4	5G	-99	-15	6	12	-90	0	0	D	-	-	-	-	-	C	A81B	9CBA
5	5G	-102	-14	6	12	-90	0	0	D	-	-	-	-	-	C	A81B	9CBA
6	5G	-102	-14	6	12	-90	9	12	D	-	-	-	-	-	C	A81B	9CBA
7	5G	-102	-14	4	12	-90	0	0	D	-	-	-	-	-	C	A81B	9CBA
8	5G	-102	-14	4	12	-90	0	0	I	-	-	-	-	-	C	A81B	9CBA
9	5G	-102	-13	4	12	-90	0	0	I	-	-	-	-	-	C	A81B	9CBA
10	5G	-102	-13	4	12	-90	0	0	D	-	-	-	-	-	C	A81B	9CBA
11	5G	-102	-13	4	15	-92	0	0	D	82	79	86	3	0	C	A81B	9CBA
12	5G	-103	-15	-6	10	-90	149	15	D	-	-	-	-	-	C	A81B	9CBA
13	5G	-103	-15	-6	9	-	14316	227	D	-	-	-	-	-	C	A81B	9CBA
14	5G	-102	-12	6	9	-	10620	99	D	-	-	-	-	-	C	A81B	9CBA
15	5G	-102	-12	6	9	-	16739	119	D	-	-	-	-	-	C	A81B	9CBA
16	5G	-101	-11	7	14	-	18803	167	D	-	-	-	-	-	C	A81B	9CBA
17	5G	-101	-11	7	14	-	8023	107	D	-	-	-	-	-	C	A81B	9CBA
18	5G	-100	-10	5	14	-	7399	92	D	-	-	-	-	-	C	A81B	9CBA
19	5G	-100	-10	5	13	-86	10045	80	D	-	-	-	-	-	C	A81B	9CBA
20	5G	-101	-11	2	12	-89	12042	94	D	-	-	-	-	-	C	A81B	9CBA
21	5G	-101	-11	2	12	-91	12772	100	D	-	-	-	-	-	C	A81B	9CBA
22	5G	-99	-14	7	12	-91	16067	135	D	-	-	-	-	-	C	A81B	9CBA
23	5G	-99	-14	7	12	-91	5862	57	D	-	-	-	-	-	C	A81B	9CBA

Figure 3. dataset

Both a real-time 5G production network dataset and a MATLAB modelling framework for large-scale multi-cell 5G networks. Now that the 5G/mm wave module for the ns-3 mm wave network simulator is available, we will be able to learn more about how adaptive clients in 5G multi-cell wireless situations come to their conclusions.

The main goal of our framework is to give end users more information, such as a variety of metrics that are only relevant to users who are connected to the same cell10-12]. This will give end users access to information they couldn't get any other way about the environment of the base station (eNodeB or eNB) and the scheduling principle. We make it possible for other academics to look into this interaction by letting them use our technology to make their own fake datasets.

V SIMULATION RESULTS

When judging the quality of the communication model as a whole, it is important to take into account the signal-to-noise ratio. The Modulation Schemes and the Common Quality Index. It is very important to understand how each of these parts fits into the whole. The correlation quality index (CQI) and the signal-to-noise ratio (SNR) are related, according to the results of this research project (CQI). It was decided that this deal would give a better data rate than other partnerships that were already in place. When judging the overall quality of a communication model, it is important to look at the Signal-to-Noise Ratio (SNR), the Channel Quality Index (CQI), and the Modulation Schemes. It is very important to understand how each of these parts fits into the whole. The correlation quality index (CQI) and the signal-to-noise ratio (SNR) are related, according to the results of this research project (CQI). It was decided that this deal would give a better data rate than other partnerships that were already in place.

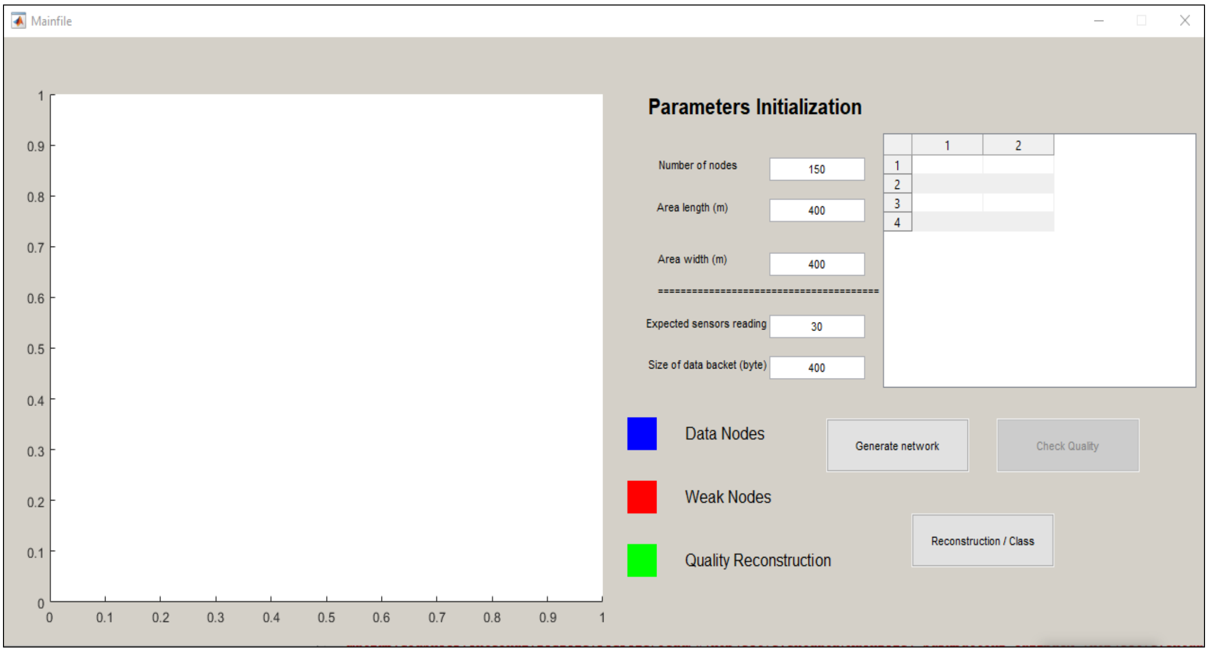


Figure.4 parameters initialization

Fig 5 window showing the parameters initialization, the initial parameters given number of nodes, area, widths, packets rates and expected sensor reading.

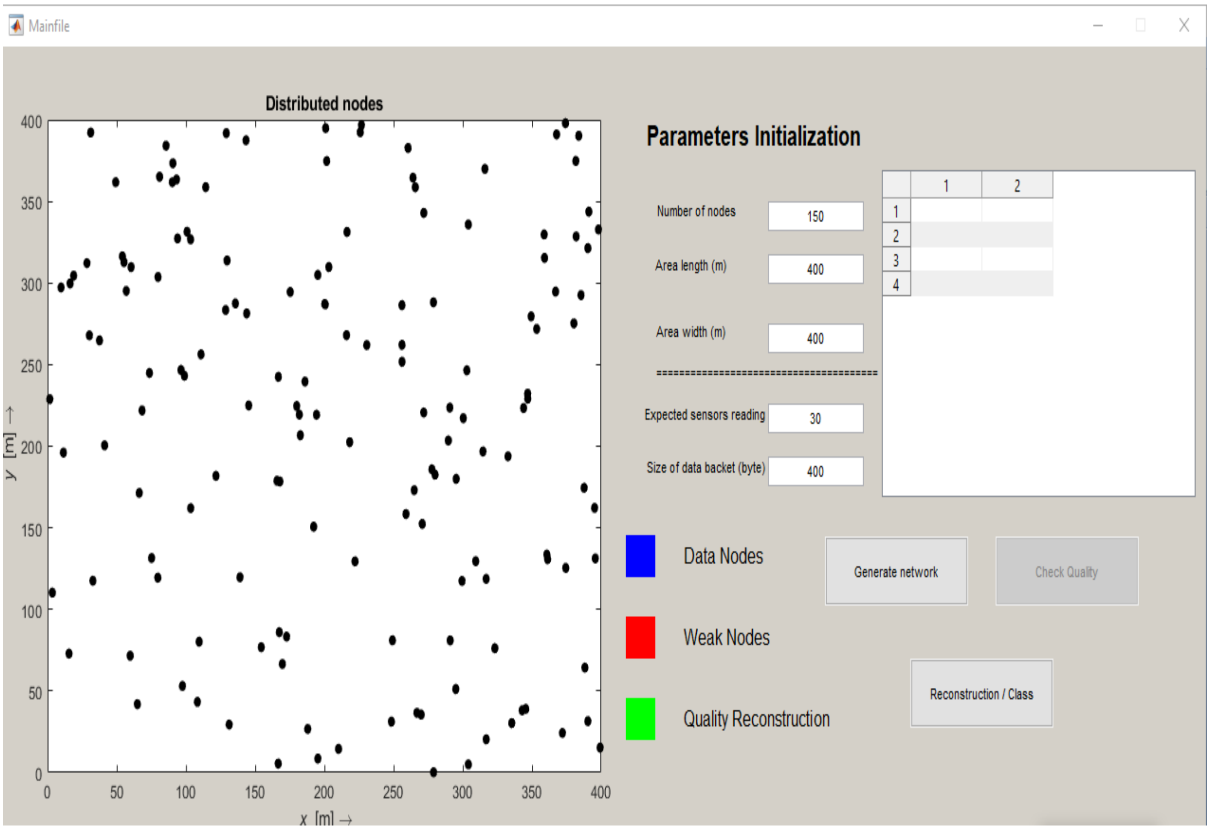


Figure 5 node deployed in the network

Fig 6 showing the node deployed in the network, in this simulation 150 nodes deployed in the network

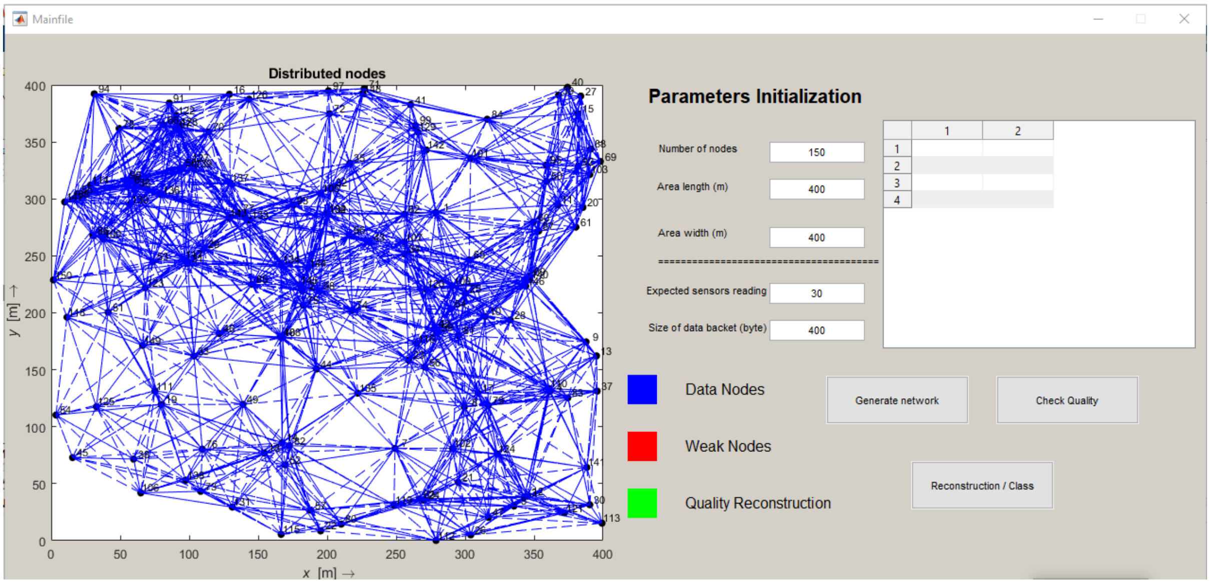


Figure.6 network creation and node deployment of nodes

The figure 7 depicts the initialization of parameters in this network, which has 150 nodes and a length and width of 400m.and size of the data bucket 400.

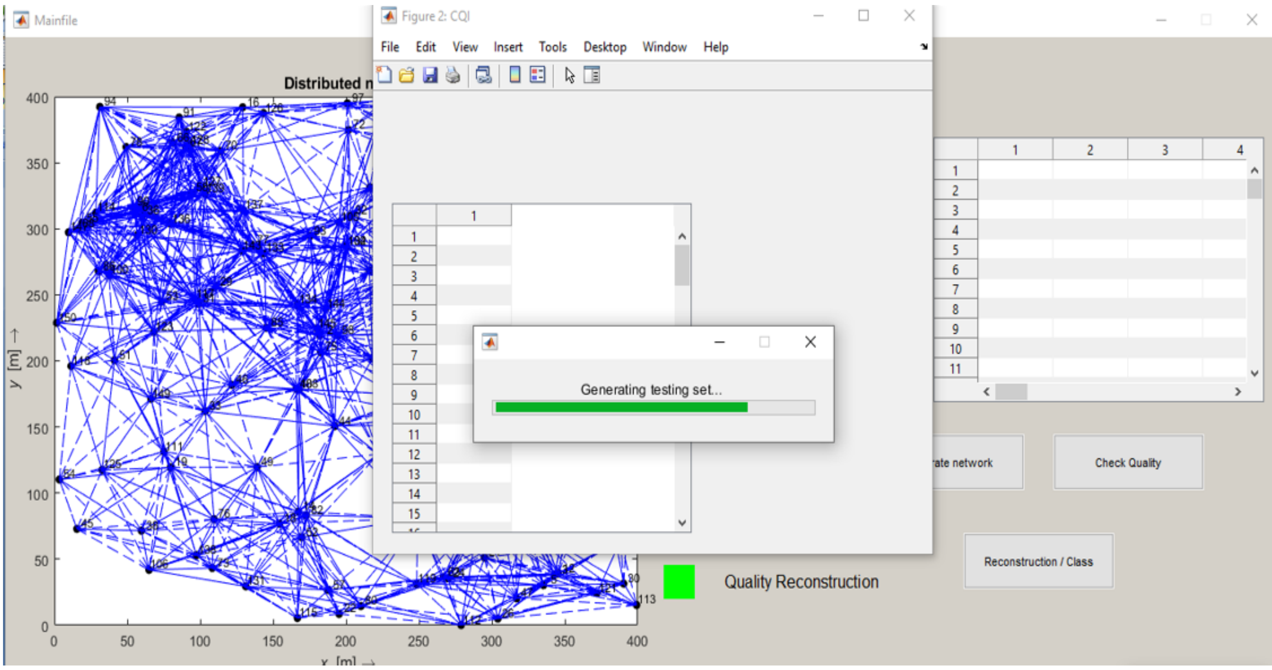


Figure.7 check quality of node in the network

After the network has been set up, all of the nodes are spread out randomly across the network. From there, packets are sent from one node to the next. All over the blue node, you can see where the data nodes are. This node's job is to make it possible for information to move from one node to another. Figure 8 shows us this.

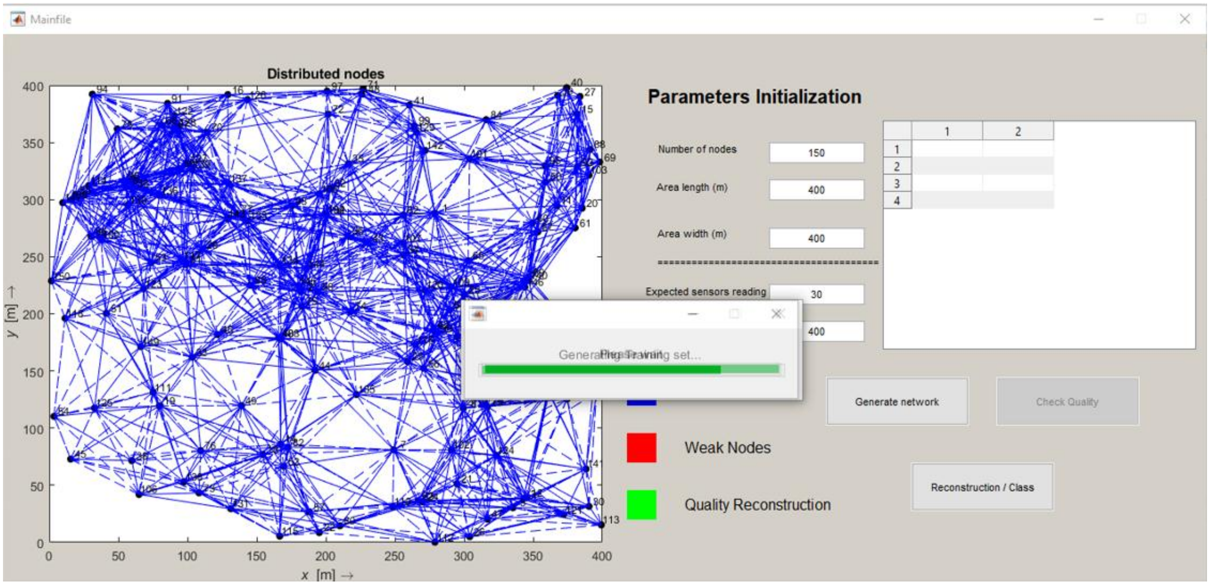


Figure. 8 check quality of node in the network

Some nodes may be weak and unable to send packets from one node to another while others are sending packets from one node to another. Machine learning was used to check the quality of the node, and the weak node in the network is shown by the red node. Figure 9 shows the channel quality indicator for this network, which was based on the channel quality dataset.

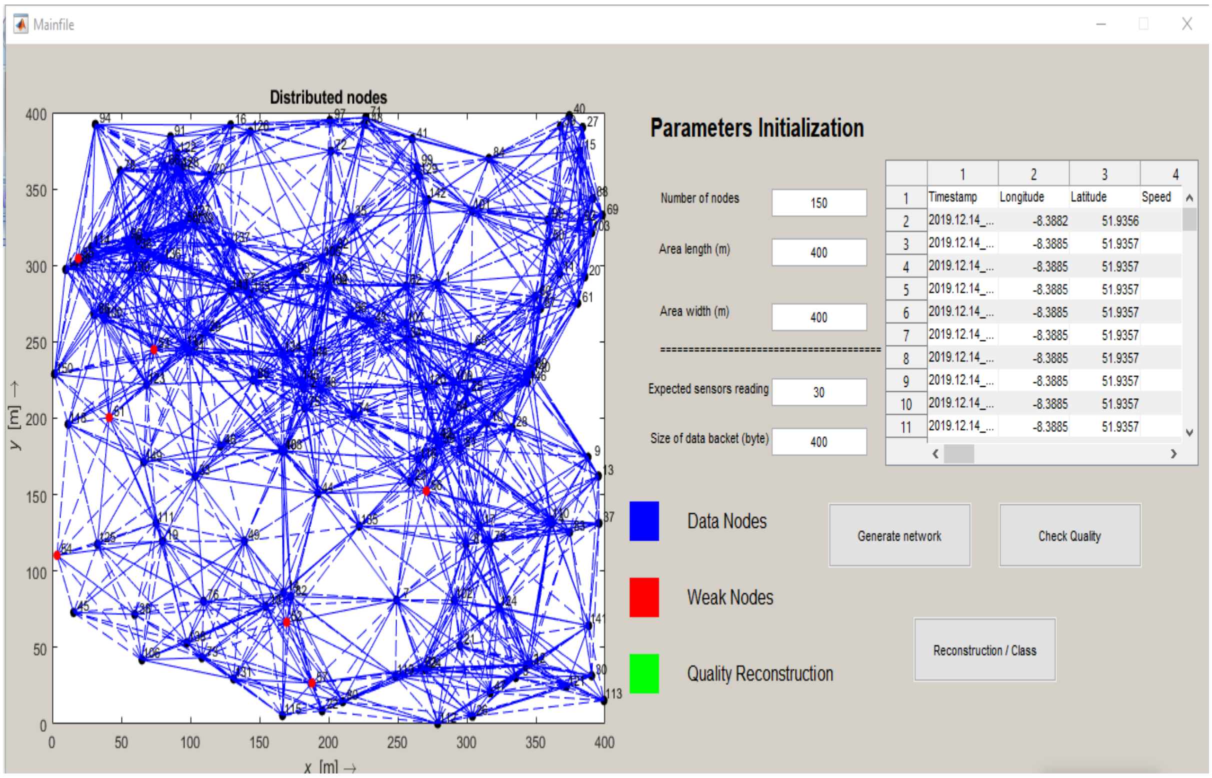


Figure.9 weak nodes

Fig 10 showing the weak nodes in the network those node not full fill the requirement of the channel quality consider as a weak node in the network.

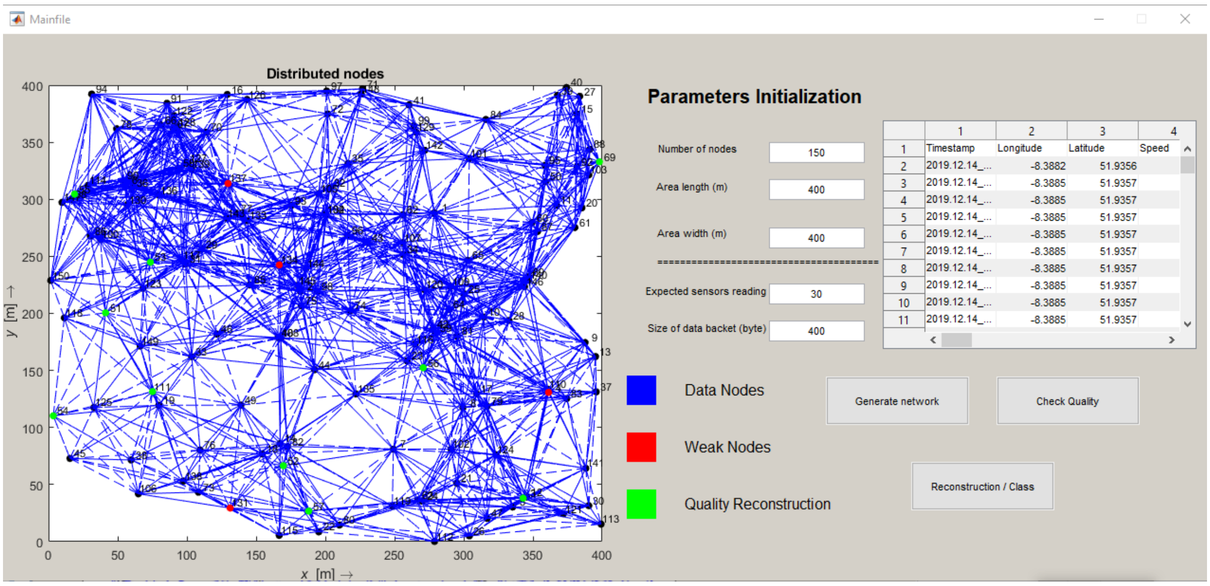


Figure.10 reconstruct node in the network

After applying a machine learning algorithm, the green node represents the reconstructed node in the network, showing in fig 11

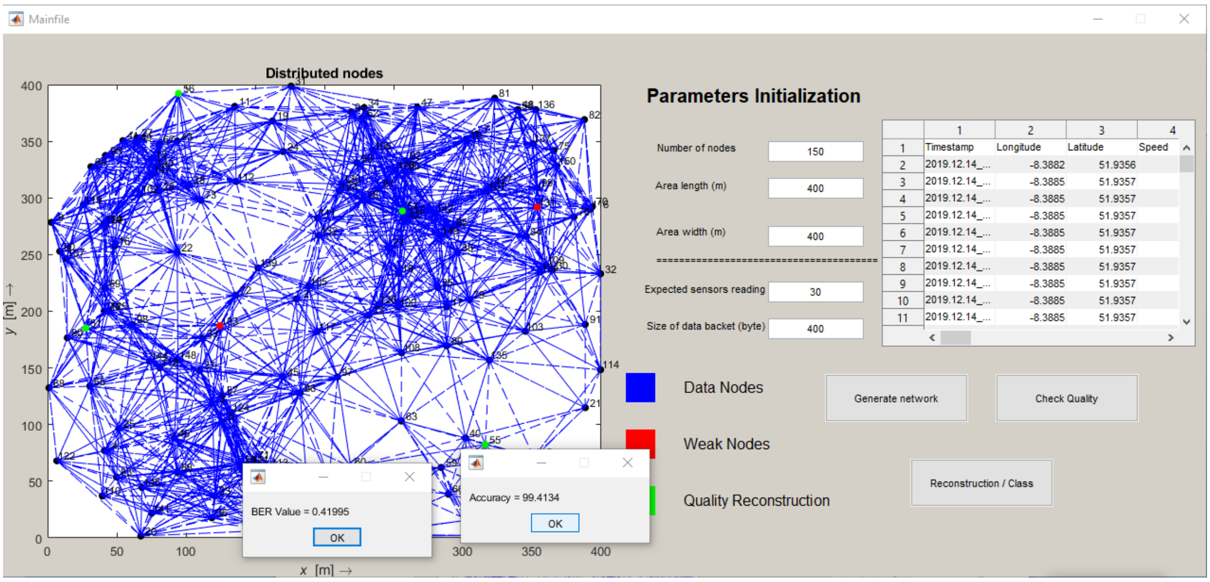


Fig.11-performance of network

Fig. 12 showing the performance of the network in terms of PSNR, BER, MSE, accuracy .

CQI Value Ranges=On a scale from 0 to 30, where 30 means the channel is the best and 0 means it is the worst, 30 is the best rating that can be given to the channel. The size of the transport blocks that the network uses to send data varies and is based on what is reported to the EU. When user equipment (UE) transmits a high CQI to the network, the network responds by sending larger block sizes. When the opposite is true, smaller block sizes are used to send information.

Even though the user says that the CQI is low, it is still possible that the network is sending a lot of data. If the UE has a CRC error, it is likely that it won't be able to figure out what the information is. Because of this, the network will have to send it again, which is a waste of the radio resources that are available.

What should a user do if the actual channel quality is low even though the UE claims to have a high CQI? In this case, if the network sends a big transport block size, it's more likely that the UE won't be able to decode it, which would cause a CRC error on the UE side of the communication. This would mean that the network would have to send it again, which would waste radio resources. In this case, the CQI value will tell the network that each transport block needs to carry a lot of data.

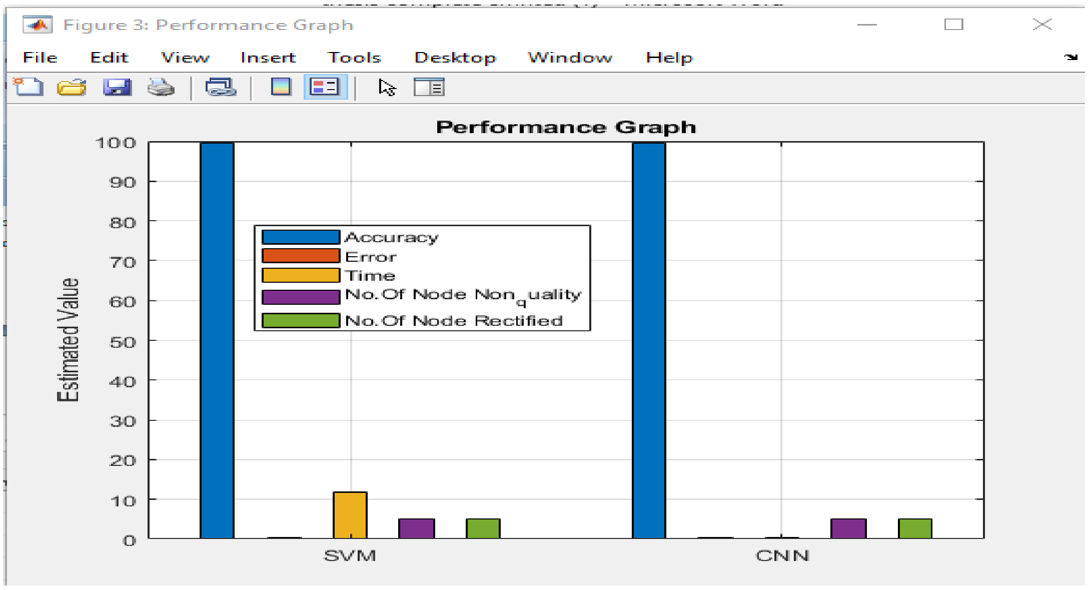


Fig. 12- Performance Graph

Training Results

- numbatches = 0.0200
- epoch 1/1
- Elapsed time is 0.157340 seconds.
- Training error = 100%
- TIME2 = 0.426
- Testing error = 150 Nodes
- TIME1 = 5.4759

Performance Evaluation Model-Bit Error Rate (BER): The Bit Error Rate (BER) is a way to figure out how many bit errors happen in a certain amount of time. Divide the total number of bit errors that happened during this time period by the total number of bits that were sent. This is called a bit error rate (BER) (BER). BER is almost always given as a percentage lower than units when measuring performance. To figure out how likely it is that a bit will go wrong, you must first figure out the predicted bit error rate. The bit error rate is a measurement that can stand in for the chance that a bit error will happen. This estimate is correct for times that are longer than one second and for errors that involve more than one bit. The formula can be used to show that the BER is a function of Eb/N0 for both QPSK and AWGN modulation.

$$\text{BER} = \frac{1}{2}\,\text{erfc}\,(\sqrt{E_b}/N_0)$$

There are several ways to figure out how good a picture compression is. Two of these ways are the mean square error (MSE) and the peak signal-to-noise ratio (PSNR). The MSE statistic shows the total squared error between the compressed image and the original image, while the PSNR statistic shows the error in its worst form. As the total number of errors goes up, the MSE value will start to go down.

Peak signal-to-noise ratio (PSNR) - It is the signal-to-noise ratio that shows how well a signal can be shown at its highest possible value (power) compared to how much noise affects its accuracy (PSNR). This percentage is shown as a number.

$$\text{PSNR} = 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

$$10.\log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$$

$$20.\log_{10}(\text{MAXI})-10.\log_{10}(\text{MSE})$$

The MAX_I command shows the maximum value that can be used for a given pixel in an image. Using 8 bits per sample to show the pixels, this value is the same as the number 255. When samples are encoded with linear PCM and B bits per sample, MAX_I is often the same as 2B1.

Mean squared error (MSE) - MSE or MSD is a way to measure the average square of an estimator's mistakes or the average square of the difference between what was estimated and what was measured. This number is also called the "mean squared error," the "mean squared deviation," and other names.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$$

MSE} = mean squared error

{n} = number of data points

Y{i} = observed values

{Y}{i} = predicted values

Table 2- Comparison result with exiting work

	Technique	Optimization Technique	Accuracy (%)
Proposed System	Convolution Neural Network	Particle Swarm Optimization (PSO)	99.41
	Support Vector Machine		95.21
Existing System	Support Vector Machine		92.86

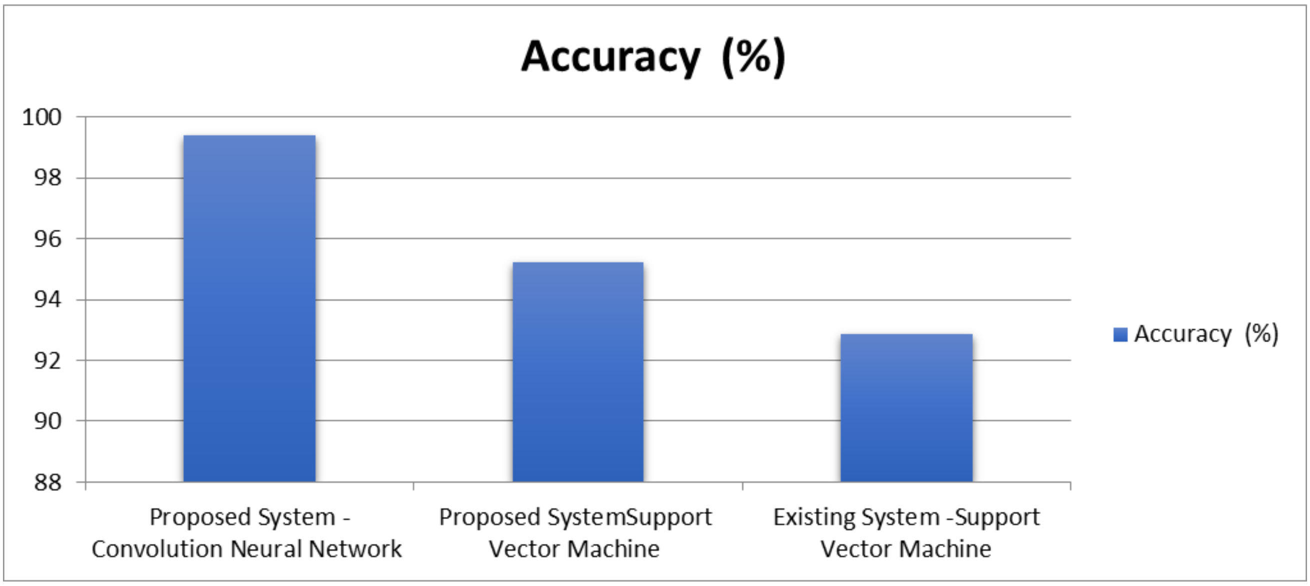
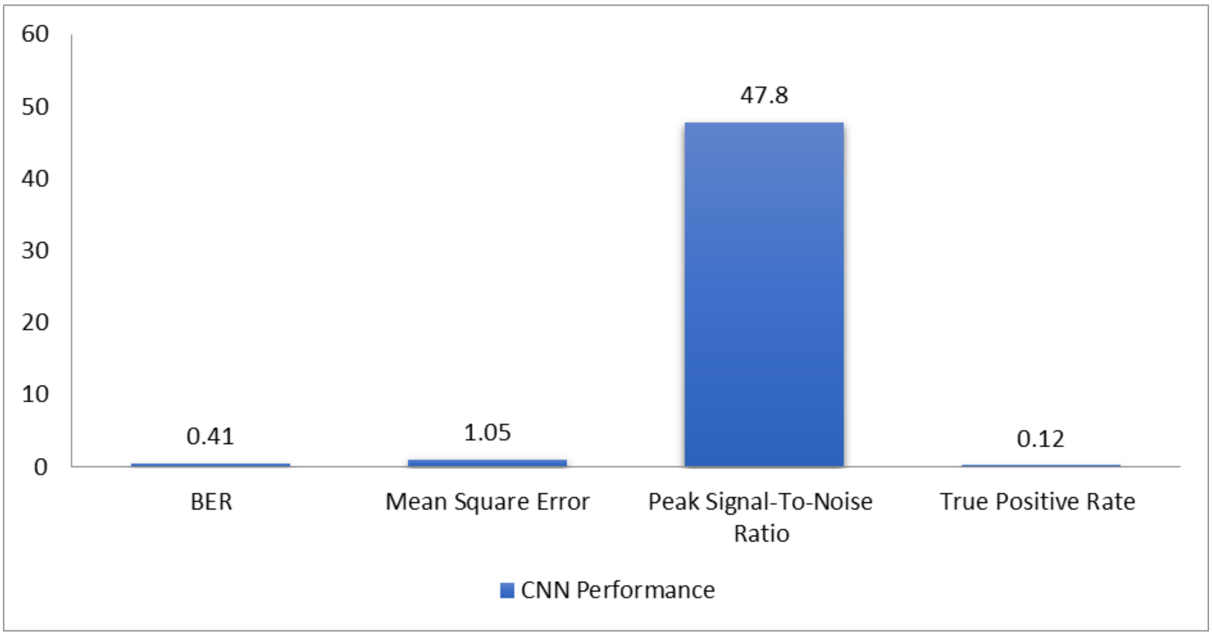


Table 3- Performance of proposed algorithm

	Technique	BER	Mean Square Error	Peak Signal-To-Noise Ratio	True Positive Rate
Proposed System	Convolution Neural Network	0.41	1.05	47.8	0.12



V CONCLUSION

The routine sending of CQI reports, which give information about the quality of the channels in 4G and 5G mobile networks, adds to the amount of signalling that needs to be done to keep the networks running. The CQI reports tell us how good the channels in 4G and 5G mobile networks are. We looked into a lot of different ways to lower the total cost. We think that if we think about how stable the channel is, we won't have to send CQI signals when it's not necessary to do so. To put it another way, we will send out fewer CQI reports when the value of the CQI doesn't change much over time. This means that the channel is working as it should. To do this, we put a lot of time and effort into making machine learning-based strategies that only need CQI data as an input. The goal of this exercise was to figure out how to make accurate predictions about how the channel would behave. So, the way our mechanisms work is in line with the standards and doesn't need any cross-layer or other outside information, like where the users are or how they move around the environment.

In this particular situation, we looked at how well Support Vector Machines (SVM) and Convolution Neural Networks (CNN) could predict the results. We also looked into whether there is a link between how accurate our predictions are and how quickly we get new information. The results of our tests showed that neural networks always did better than SVMs in every situation we tested them in. During this investigation, we spent most of our time trying to figure out how well the ML systems we were looking at could predict the future. The next step is to start a more in-depth study of how the proposed method and processes affect the 5G network slice management architecture that we proposed in our earlier study. The next step in the process will be to do this. At the moment, our main goal is to figure out how to improve signaling and what effect our ideas will have on how available resources are used and how well 5G networks

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