International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(12s) 2026 pp. 43-20
https://doi.org/10.70917/ijcisim-2026-3876
Article

Machine Learning–Based Prediction of Channel Stability for Efficient CQI 5G Networks

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Abstract: Whether the 4G and the 5G mobile networks are effective or not is highly interconnected with the management of signaling overhead, especially Channel Quality Indicator (CQI) reporting. Regular updates in CQI, though necessary to ensure reliability, may lead to traffic congestion in the signaling which may impact on the overall network performance. This paper introduces a machine learning-driven scheme that minimizes cases of unneeded CQI transmissions by directly predicting channel stability based on CQI data. The analysis of prediction accuracy under different conditions is achieved by using modeling, e.g. Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs). The findings reveal that CNNs are always more effective in predicting channel stability than SVMs, which proves that they are the most appropriate in terms of optimizing adaptive CQI reporting. The proposed solution is not only able to guarantee the efficient signaling, but also the basis of the next-generation networks on low-latency and high-throughput communication.
Keywords: Channel Quality Indicator (CQI), Support Vector Machines (SVMs), Convolutional Neural Network(CNN)

1. Introduction

The demand for high-speed, low-latency communication in 4G and 5G systems has placed increasing pressure on network resources.[1][2] One of the key contributors to this challenge is the management of Channel Quality Indicator (CQI) reports, which are vital for ensuring reliable data transmission but also generate significant signaling overhead when transmitted too frequently. [3-6] While CQI values provide critical information on channel conditions, sending them at short intervals can burden the system and reduce overall efficiency. This has created a need for more intelligent methods that adaptively regulate CQI reporting without compromising performance.[16-19]

Machine learning techniques have shown great promise in addressing this issue by predicting channel behavior and reducing redundant signaling. Unlike traditional methods, which rely on limited parameters or cross-layer information, machine learning models can learn directly from CQI data to estimate future channel stability. [7-10] This study focuses on comparing the effectiveness of CNNs and SVMs in predicting channel quality trends. [20][21]By integrating these predictive models into CQI management, the research aims to optimize signaling efficiency, minimize unnecessary updates, and contribute to the advancement of 5G network performance in terms of both throughput and latency.[11-15][22-26] In our

previous two papers we have covered the Literature review with objectives and problem statement in 1 paper and in paper 2 we have completely discussed the proposed methodology. Now in this paper we are going with their result analysis and performance analysis.

2. Result Analysis:

The channel quality index (CQI) measures how well a given channel sends or receives data. The UE uses the CSI-RS to figure out and report its own CQI index as part of the channel state information (CSI) it sends to the gNB.

The CQI uses numbers between 0 and 15 for its values. This paper describes the best target block error rate (BLER). The maximum allowable BLER is based on two rules, with the second rule being derived from the first by using the higher layer parameter. In this case, a 0.1 BLER condition and cqi are used. We compare the CQI value we get with a realistic estimate of the channel to the CQI value we get with an ideal estimate of the channel. The SINR measures how well a signal can overcome background noise. The SINR metric is missing from the 3GPP definition. UE (user equipment) does not relay the results back to the network. In UE, SINR is the only metric that is measured and utilised. It's a way to more clearly describe the connection between signal strength and throughput in radio transmissions. For instance, it can be used to determine the CQI score. It's up to the manufacturer to decide how to implement this measurement, and there may be variations. This is making tough to compare findings of different devices. Even in UMTS and 5G NR, SINR is a metric that is measured.

CQI (Channel Quality Indication) - CQI was stated in the form of the data rate that the terminal (UE) is able to support in the current radio environment. SINR has to be used to calculate CQI. In LTE, CQI has just 15 codes. The value of MCS parameter is selected according to the value of CQI. The CQI is shown in fig 1.

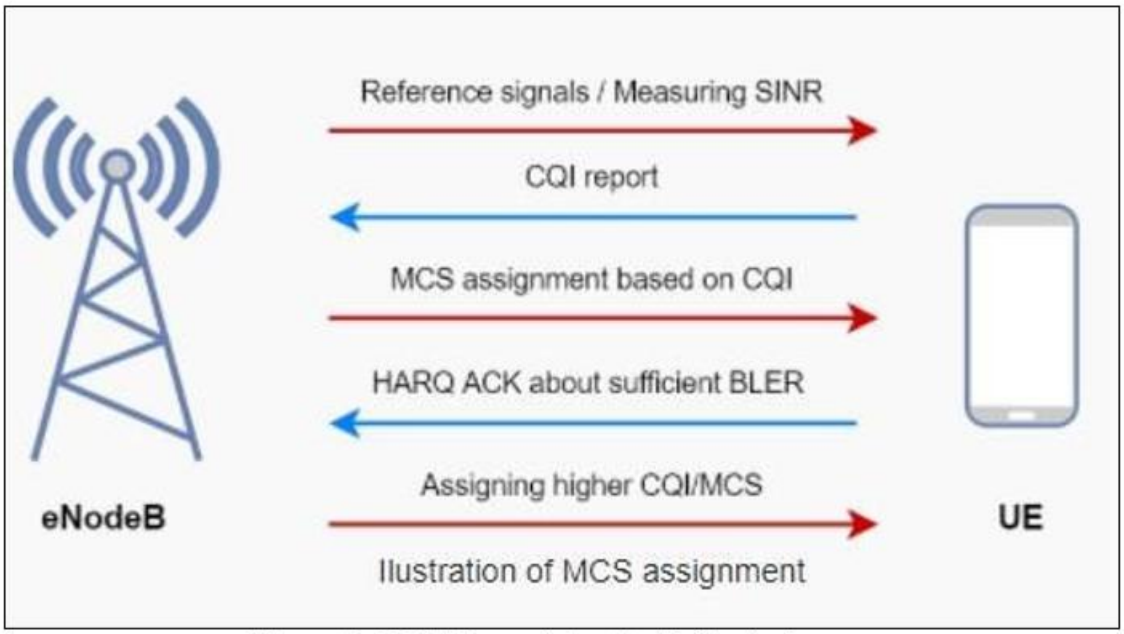

Figure 1: CQI (Channel Quality Indication)

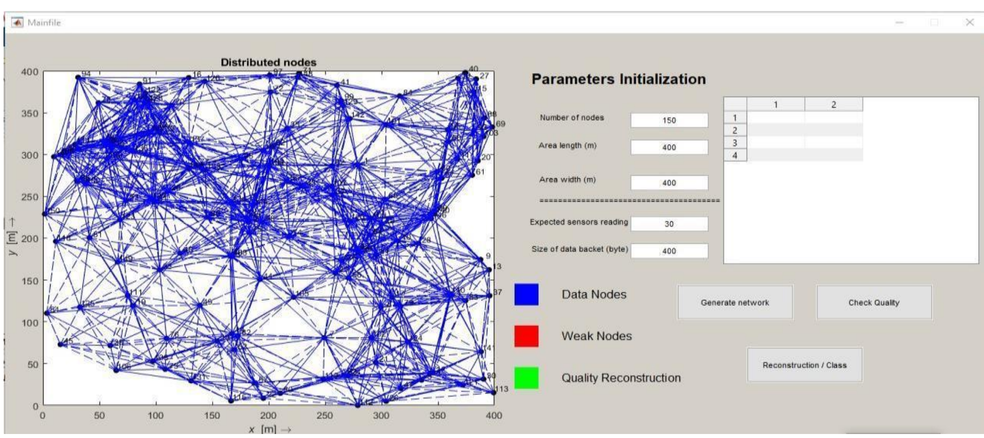

Figure.1 Creating a network and a node setting up of nodes

Figure 2 shows creation of a network and a node setting up of nodes. This network has 100 nodes, a length and width of 500m, and a data bucket size of 500m.

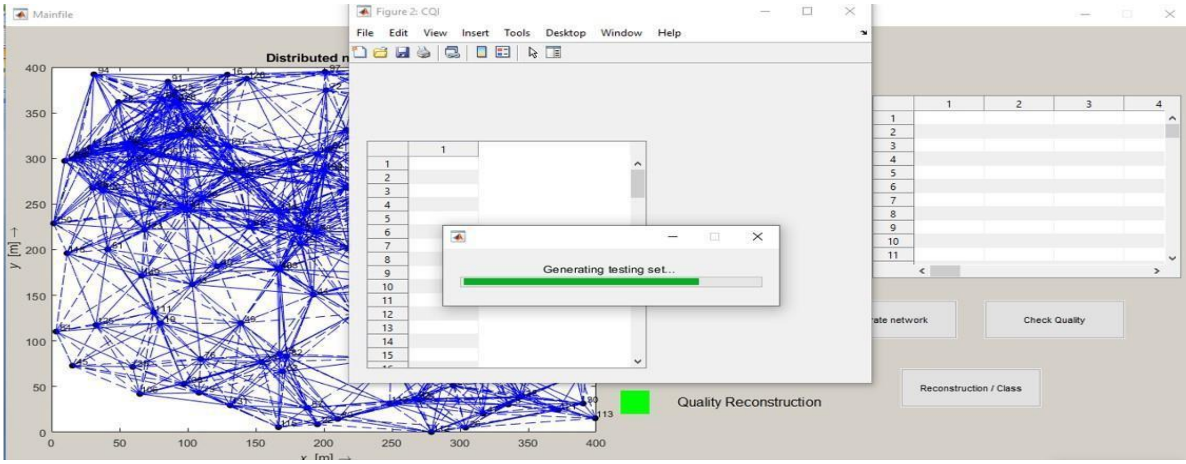

Figure. 2 check the quality of each network node

After the network has been set up, the nodes are put in random places and packets start moving between them. The full blue node shows where the data nodes are. This node's main job in a network is to send messages between other nodes. Figure 2 shows the quality check of each network node.

When data is sent from one node to another, some nodes may not be strong enough to do the job. Here, we use machine learning to figure out which nodes are the best, and we see that the red ones are the weakest in the network.

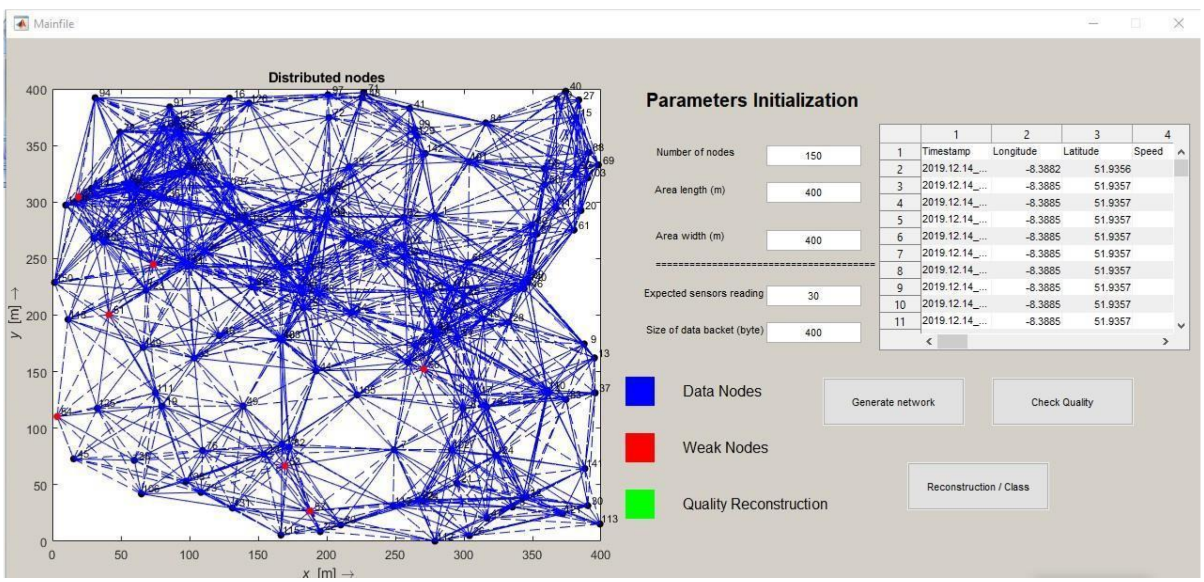

Figure 3: Network Nodes that are considered to be weak

Figure 3 illustrates the network's nodes that are considered to be weak. A node that does not fulfill the requirements for the quality of the channel is referred to as a weak node.

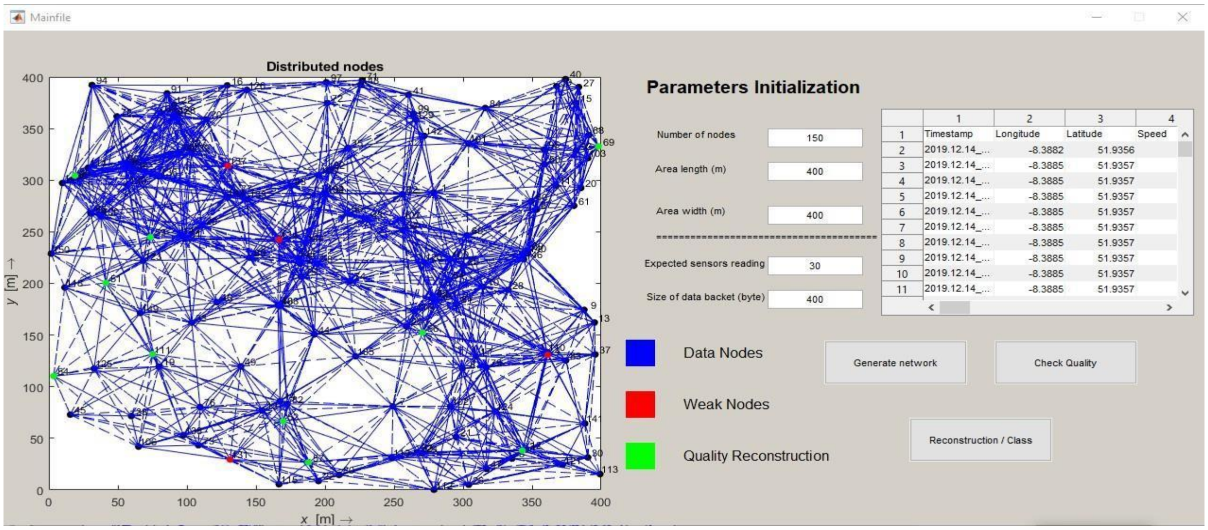

Figure 4: Rebuild the network node that was destroyed.

Following the implementation of a method for machine learning, the reconstructed node in the network can be identified as the green node, as shown in figure 4.

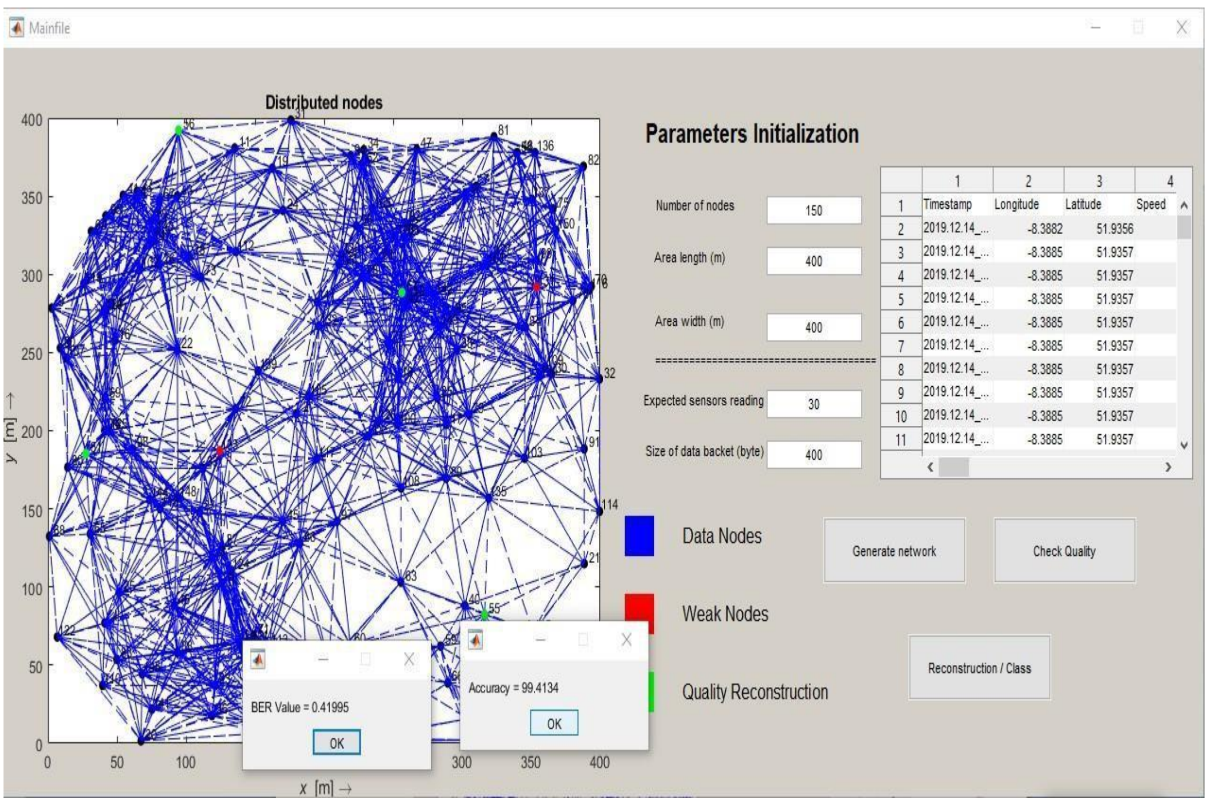

Figure 5: functionality of the network

Illustrating the functionality of the network, data nodes, weak nodes, quality reconstruction in Figure 5.

3. Performance Analysis:

Bit Error Rate (BER) is a measurement that shows how often bits get messed up during a transmission. Divide the total number of bits sent by the number of errors to get the percentage of wrong bits. This is called "bit error rate" (BER). In performance reviews, BER is often given as a percentage of nominal. The expected bit error rate tells us how likely it is that a bit error will happen. There is a link between the bit error rate and how likely it is that a bit error will happen. This estimate is good for mistakes with more than one bit and delays longer than a second. Mean square error (MSE) and peak signal-to-noise ratio (PSNR) are both ways to measure the quality of an image compression. The MSE shows the total squared error, while the PSNR shows the biggest difference between the compressed and original images. As the number of mistakes goes up, the MSE becomes less important.

Peak signal-to-noise ratio (PSNR) - The peak signal-to-noise ratio (SNR) is the maximum signal power divided by the amount of noise that makes the signal's representation less accurate (PSNR). There is a number that shows what this ratio is.

$$
\begin{aligned}
PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\
&= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \\
&= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE)
\end{aligned}
$$

The maximum value that a pixel can possess is displayed by MAXI. This figure is equivalent to 255 when the pixels are represented using 8 bits per sample. In the case of data coded by linear PCM and B bits/sample, MAXI tends to be 2B1.

The mean squared error (MSE), which is also known as the mean squared deviation (MSD), is the mean squared error between the predicted and observed values. This value is also referred to as mean squared error or mean squared deviation. Table 1 shows the comparative result with the existing work in terms of optimization technique and accuracy. Fig 6 shows the accuracy performance with the existing works.

Table 1 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

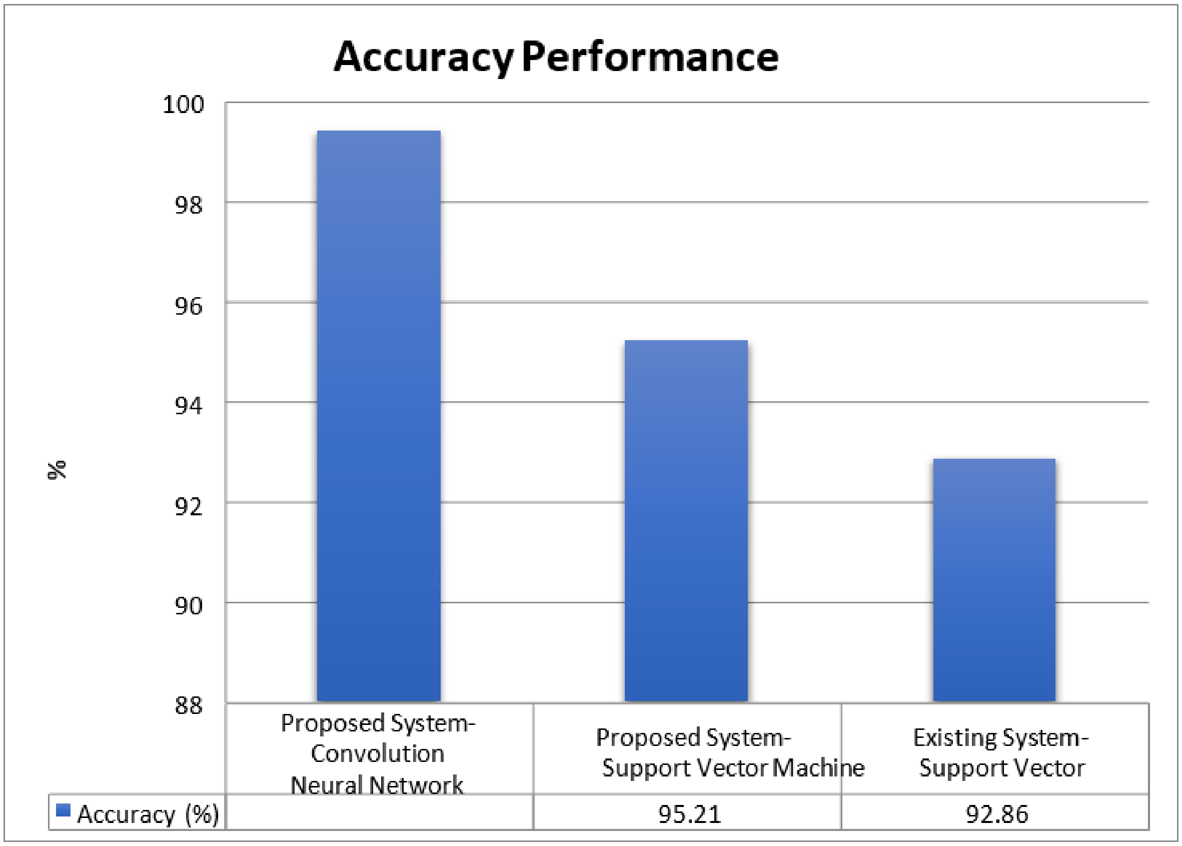

Figure. 6 Comparison result with exiting work

Table 2 shows the performance of proposed algorithm in terms of BER, Mean square error, peak signal to noise ratio, true positive rates and the respective graph is shown in figure 7.

Table 2 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

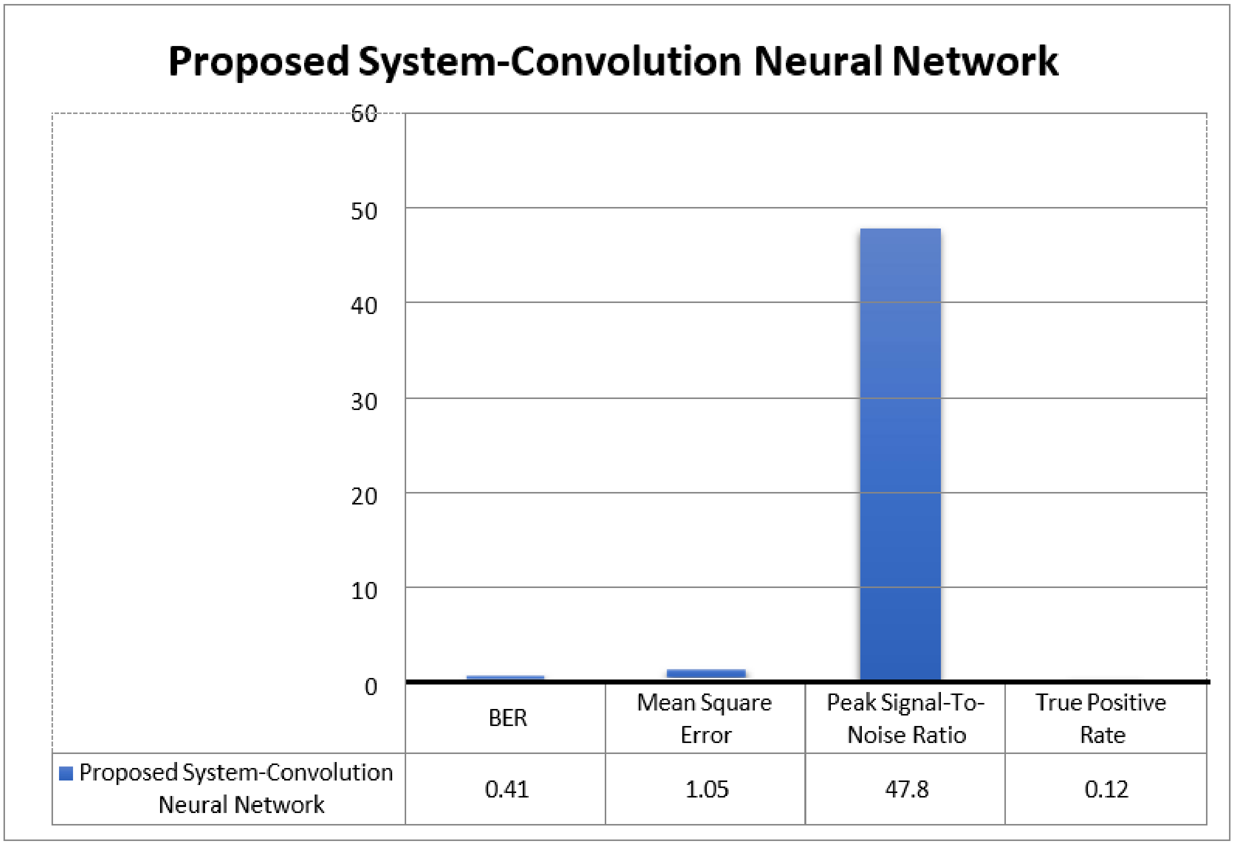

Figure. 7 Performance Graph of propsoed algorithm

4. Conclusion

In this study, we explored ways to reduce the signalling overhead in 4G and 5G networks by optimizing how Channel Quality Indicator (CQI) reports are generated. Since frequent CQI updates increase signalling traffic, we proposed ML-based methods that learn from CQI data alone to predict channel stability and decide when updates are truly necessary. This is because this selective reporting method is reliable and minimizes unwarranted signaling. We used Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), and the former outperformed the latter in accuracy of prediction. These findings suggest machine learning as a viable option in adaptive signaling, which is the direction towards more reliable and efficient next-generation networks. Moving forward, future studies ought to aim at creating more in-depth and live metrics which can reflect the entire spectrum of variables influencing the quality of channels. The existing assessment tools are usually based on few parameters thus they are less versatile in different situations. More dynamic models of uncertainty and complex relationship between variables could be offered by techniques like Bayesian networks. Along with this, there should be improvements in strong spectrum sensing and real-time SINR estimation, which would help in increasing reliability and reducing false alarms. With these enhancements incorporated into the network slice management, the future systems will be able to be more efficient in signaling besides being better in 5G and beyond in terms of latency and throughput.

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