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Wireless Network Interferences Prediction and MAC-Layer Optimization Using QNN

Patikala Girija[1] and Dr.M.Karthikeyan[2]

[1] PG Scholar, Dept. of CSE Siddharth Institute of Engineering & Technology, Puttur, Andhra Pradesh, India

[2] Associate Professor, Dept. of CSE Siddharth Institute of Engineering & Technology, Puttur, Andhra Pradesh, India

Email: girijapadmanabh1@gmail.com drkarthi.sietk@gmail.com

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ABSTRACT

Millions of devices are using wireless communication, which is expanding quickly. These devices can interact with one another in a dynamic environment, and providing uninterrupted services is more crucial. Conventional machine learning techniques were utilized to deliver good services, but they have significant drawbacks, such as their inability to handle correlated signals, their reliance on probability theory, and their inability to handle nonlinear signals. In order to improve MAC layer decision prediction accuracy and give users uninterrupted services, we implemented QNN (Quantum Neural Network) based wireless communication in this study. QNN is able to handle multiple network interactions at a time with limited features. In this model we used three qubits with two hundred layers variable circuit, dataset opted with more real-time wireless interactions with high SNR values, abnormal behavior, a greater number of retry requests, and with heave inferences. Experiments are carried out to evaluate performance of QNN approach, the results are also compared with TNN, LSTM, RF, XGBoost, and SVM are evaluated are evaluated in terms of MSE, MAE, RMSE, R2, PDR, Connection probability, Collision Reduction, variance, Cosine Similarity, and Euclidian error. QNN exhibits low MSE value, low MAE value, low RMSE value, high PDR value, high R^2 value, high connection probability, high collision reduction value, low variance, high cosine similarity, and low Euclidian error when compared with other similar approaches that are used for prediction purpose.

1. INTRODUCTION

From past decades to current, the drastically change in wireless technology in terms of millions of devices connected, occurred traffic due to over usage of bandwidth, many organizations show interest towards this technology, and millions of peoples adopted IoT devices and wireless communications are part of their life [1]. These usage in many applications and already experienced with 5G network are the basis to use advanced 6G network to provide communication under different types of conditions like mobility of nodes changes dynamically and these devices are used in many decision-making applications [2]. Conventional machine learning techniques are reached functional limits due to produce heavy latency time, high computational overhead, and cannot handle certain problems with large number of states [3]. In order to solve these issues quantum computing is developed with several advantages like parallelism of quantum, tangle, superposition, these processors are capable to handle problems with large number of states with help of qubits, and this method can be suitable for many decision-making applications [4]. In the same context, we developed hybrid approach by combining quantum computing with neural networks called QNN (Quantum Neural Network) to achieve high performance to handle large values of data with large number of state spaces [5]. QNN is one of the trending researches filed to provide number of solutions for wireless communications and that are management of mobilities, sharing of spectrums, routing with less energy utilization, managing congestions, modelling of inferences, prediction of various channel states, and resources allocated dynamically [6].

Apart from all these benefits QNN is also facing certain issues when it is adapted into real time deployment, still many service providers are not preferred to use quantum hardware, need to provide special training to adopt and use these technologies to resolve classification issues [7]. A symmetric model is required to provide communication with help of QNN (end to end) and also encourage new researches towards these areas to solve research issues with help of QNN based approaches [8].QNN with advanced features provide new learning approach that can be compactable to multiple applications, provide best solutions with high correlation approaches, and also enhanced the model robustness even the data samples consist of noise data samples [9].

In this research developed QNN approach for wireless communication to predict its behavior at the time of service providing by minimizing number of decisions in MAC layer under various types of conditions. The objective of QNN is to provide quality services by overcoming existing problems, to implement quantum encryption to optimize SNR values, variation learning opted to enhance overall efficiency of the model, to optimize faults in inference while communication data, and to facilitate noise free communication outcome over wireless network.

2. LITERATURE REVIEW

Authors in [10] developed a hypothetical framework by combing ML with quantum computing, their method discuss how quantum technique incorporate with machine learning by working with help of Hilbert spaces, and developed quantum variation techniques for encoding by using limiter parameters. Authors in [11] introduced quantum learning technique by mapping various NN layers with a greater number of parameters, discussed about quantum spaces and how it is useful to resolve classification problems, and also described how their more is suitable to handle certain problems that are facing by similar kind of approaches in wireless communication.

Authors in [12] worked on variation quantum techniques with learning capability by minimizing feedback loops, this concept is taken as a basic in our QNN prediction model, these variation learning can be able to measure probability of collisions, problems of inferences, and also useful to study behavior of certain network features. Authors in [13] proposed NISQ (Noisy Intermediate Scale Quantum) technique to study the problems faced by the earlier quantum circuits, facing few scalability issues when it is deployed into applications, their model facing certain issues like usages of only few qubits, decoherence of network signals, and cannot be able to handle noises.

Authors in [14] worked on quantum spaces to prove how these circuits mapping data samples into quantum states with help of linear separability, exhibits good results when handling kernels in some ML applications, and the model is suitable for wireless communication to handle fading issues, to identify up and downs in inferences. Authors in [15] studied the problems that are encounter in quantum encryption, proposed certain method to observe communication channel phases, faults due to noises, network biases, and signal amplitude. Performance of their model is depending on channel gain value, number of times retry occurred, level of network inference occurred, and SNR value. Their work is also taken as a basic to design our proposed QNN approach for wireless communication.

Authors in [16] worked on quantum techniques and tried to simulate with wireless communication with limited operations and proved only algebra functions is enough to classify data samples, discussed about predictions benefits on MAC layer, and optimized network beamforming. Authors in [17] tried to apply quantum computing directly to wireless communication, developed model acting like an assistive to predict inferences, classify modulations, and identify various kinds of network signals. Their model is appropriate for low noisy environments and exhibits high accuracy under these environments, and authors also tried to combine wireless simulation with quantum computing.

Authors in [18] worked on quantum security, sensing, and computing for 6G networks, the work combines wireless communication with quantum computing to provide high connectivity under heavy mobility environment and objective is to lower the latency time. Authors in [19] conducted research towards quantum computing, tried to prove that it is one of the essential technologies used in edge computing and their main contribution is to support autonomous wireless communication.

Authors in [20] conducted a detailed survey on quantum computing and from survey he proved that QNN offering best wireless communication than traditional NN models, designed quantum circuits for wireless communication operations but the method is facing certain issues under noisy environment. Authors in [21] described quantum learning approach for wireless networks to handle inference issues, optimize processing time in MAC layer, model is out performing then other similar models but struggling when it is applied under different types of whether conditions under different noisy values.

After conducting detailed survey we identified list of research gaps that are some models are lacking with limited qubits, encryption of high dimensional data is a one of the challenging task, most of the quantum circuits developed so far are facing certainissues when handling noisy data, many of the organizations not interested in quantum computing due to its standards, produces high overhead during training phase to handle frequent parameter shifting rule, need to develop hybrid models for wireless communication to improve scalability, and still lot of developments are required to provide sophisticated communication.

3. QNN PREDICTION MODEL

In this research we introduced QNN (Quantum Neural Network) based wireless communication to enhance MAC layer decision prediction accuracy to provide uninterrupted services to users. QNN is able to handle multiple network interactions at a time with limited features. In this model we used three qubits with two hundred layers variable circuit, dataset opted with more real-time wireless interactions with high SNR values, abnormal behavior, a greater number of retry requests, and with heave inferences. The proposed QNN architecture is visualized in Figure 1.

Step 1: Dataset: The dataset consist of data about wireless devices interactions like back off data, features of collisions, number of times retry requests, levels of interference, and SNR (signal to noise ratio) vales. The dataset is applied to train QNN model about the wireless communication features that can be useful to mapping MAC decision predictions.

Step 2: Preprocessing: Identify various types of noise present in the dataset and eliminate it by using pre-processing methods, apply min-max approach for scaling continuous values, dimensions are reduced with help of principle component analysis, list of features $\{x_1, x_2, \ldots, x_n\}$ are identified for quantum encoding, and data samples are applied to splitting approach to partition the data samples for training, validation, and testing.

Step 3: Quantum encoding layer: each discovered feature (x_k) is mapping to qubits with help of encryption techniques ($R_y(\pi * x)$), all categorical features are mapping to states with help of bias encryption approach, the encryption approach prepare quantum states ($|\Psi.\text{in} = \text{U.encode}(x)|$), and therefore the variation circuit working with dependent quantum vector spaces.

Step 4: QNN Block (variation quantum circuit): it consists of stack of two hundred layers, each layer consists of qubits rotations ($R_x(\theta), R_y(\theta), R_z(\theta)$) that is followed with entangling features (CNOT), these features spread data between qubits and the circuit can be represents all possible dependent features (inferences, SNR, collisions), and the features ($\theta_1, \theta_2, \theta_3, ..$) is easily trainable and can learn feature from data samples.

Step 5: Qubits Measurement: qubits are calculated from network environment observations, expected values are represented with Z_i. Map all measured values into cosine vectors ($z = \{z_1, z_2, z_3\}$), and finally calculate average values to optimize noise values in the inference signals.

Step 6: Post Processing: the calculated z value is applied to quantum layers ($y^1 = W_k * z + b$) to calculate predicted outcome, the layer first apply inverse scaling operations, and the apply decision threshold value to determine exact predicted outcome.

Step 7: Loss Calculations: performance of proposed QNN compared with TNN, LSTM, RF, XGBoost, and SVM are evaluated are evaluated in terms of MSE, MAE, RMSE, R^2, PDR, Connection probability, Collision Reduction, variance, Cosine Similarity, and Euclidian error.

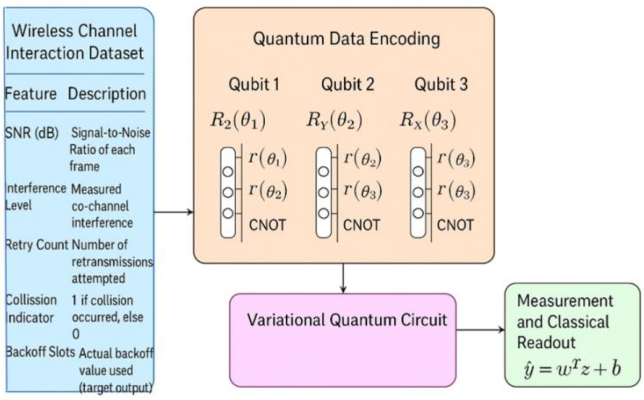

FIGURE 1. Architecture of QNN Prediction Model

4. PERFORMANCE EVALUATION

Performance of QNN, TNN, LSTM, RF, XGBoost, and SVM are evaluated are evaluated in terms of MSE (Mean Square Error), MAE (Mean Absolute Error), RMSE (Root Mean Square Error), R^2(Coefficient of Determination), PDR (Packet Delivery Ratio), Connection probability (P_C), Collision Reduction (C_R), variance (V), Cosine Similarity (C_S), and Euclidian error (E_E). MSE value of models QNN, TNN, LSTM, RF, XGBoost, and SVM are evaluated. The results are visualized in Figure 2. Proposed QNN approach achieved low MSE value than other similar kind of approaches, exactly fit for wireless communication under noisy environment.

MAE value is calculated over the difference values between actual and predicted to decide performance of prediction approach. MAE values of different MAC layer decision prediction approaches like QNN, TNN, LSTM, RF, XGBoost, PSO, and SVM are evaluated.PSO approach exhibits high MAE values, second highest MAE value shown by SVM, next highest value shown by RF approach, and proposed QNN approach achieved low MAE value than other similar kind of approaches. The results are visualized in Figure 3.

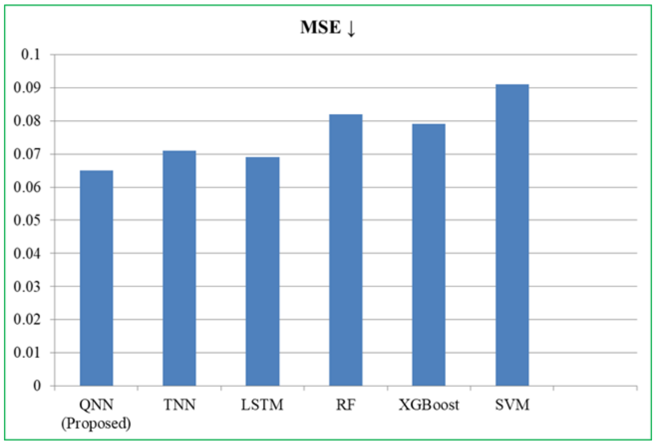

FIGURE 2. MSE values various MAC layer Decision Prediction Model

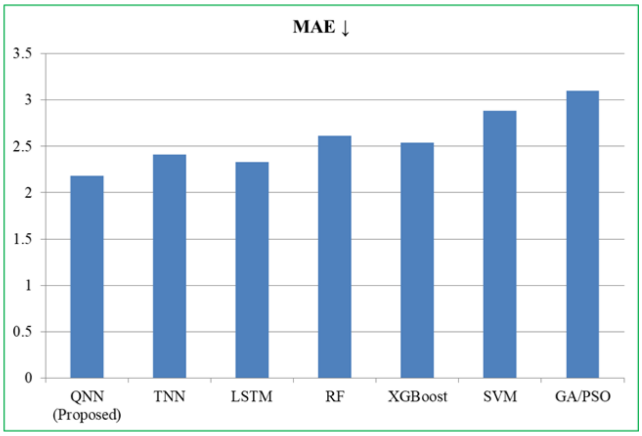

FIGURE 3. MAE values various MAC layer Decision Prediction Model

RMSE values are calculated to identify errors in prediction approach in terms of root mean square differences over actual and predicted values, less RMSE value means prediction approach shows high accuracy in the prediction process, and useful to decide performance of a prediction technique under noisy data samples. RMSE values of different MAC layer decision prediction approaches like QNN, TNN, LSTM, RF, XGBoost, and SVM are evaluated. SVM approach exhibits high RMSE values, second highest RMSE value shown by RF, next highest value shown by XGBoost approach, and proposed QNN approach achieved low RMSE value than other similar kind of approaches. The results are visualized in Figure 4.

$R^2$is calculates the variations in original data by comparing errors in prediction, if the value is equal to one then the model is treated as perfect fit, if the value is in between zero and one then the model is treated as partial fit, if the value is equal to zero then the model is not fit to predict, and if the value less than zero then the model is not at all useful to prediction purpose. R^2Values of different MAC layer decision prediction approaches like QNN, TNN, LSTM, RF, XGBoost, PSO, and SVM are evaluated. QNN approach exhibits high R^2 value, second highest R^2 value shown by TNN, next highest value shown by LSTM approach, SVM approach achieved low R^2 value, andthe results are visualized in Figure 5.

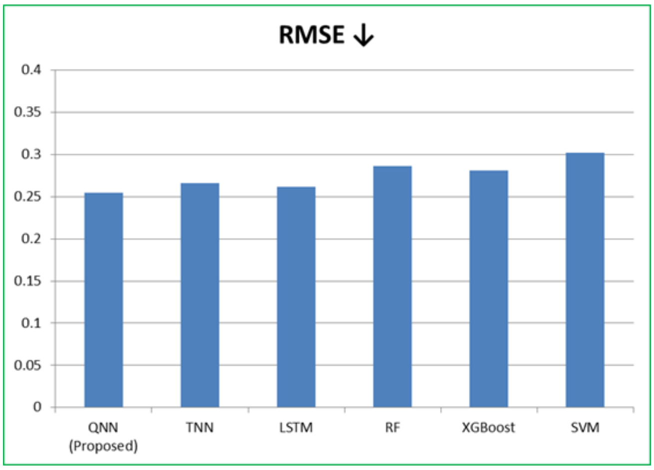

FIGURE 4. RMSE values various MAC layer Decision Prediction Model

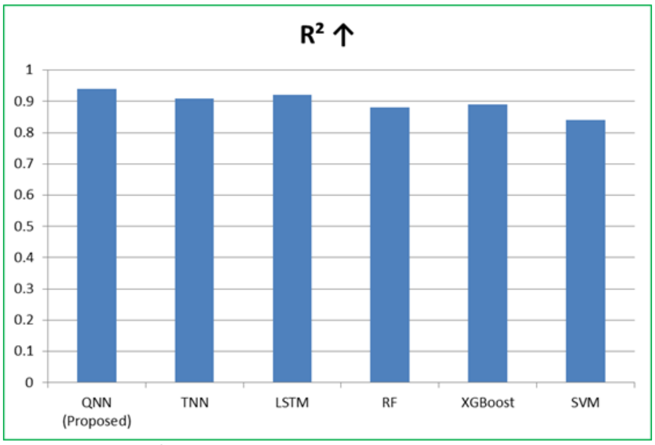

FIGURE 5. R^2values various MAC layer Decision Prediction Model

PDR value is calculated over the number of data packets received and total number of data packet sent, high PDR (81% to 100%) represents the approach shows high reliability and scalability, medium PDR (50% to 80%)represents the approach shows average reliability and scalability, and low PDR (0% to 49%)represents the approach shows low reliability and scalability. PDR values of different MAC layer decision prediction approaches like QNN, TNN, LSTM, RF, XGBoost, and SVM are evaluated. QNN approach exhibits high PDR values, second highest PDR value shown by TNN and LSTM, next highest value shown by RF and XGBoost approach, SVM approach achieved low PDR value, and the results are visualized in Figure 6.

P_C value calculate over the number of connections were established and number of time attempted to establish connections, the value quantifies reliability of a network connection under different types of constraints, the values between 0.8 to 1.0 indicates high P_C value, the values from 0.5 to 0.8 indicates medium P_C value, and the values less than 0.5 indicate very poor P_C. P_C values of different MAC layer decision prediction approaches like QNN, TNN, LSTM, RF, XGBoost, PSO and SVM are evaluated. QNN approach exhibits high P_C value, second highest P_C value shown by LSTM, next highest value shown by TNN approach, PSO approach achieved low P_C value, and the results are visualized in Figure 7.

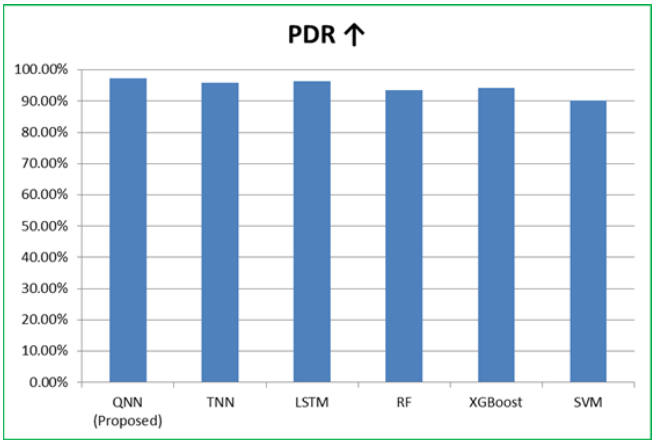

FIGURE 6. PDR values various MAC layer Decision Prediction Model

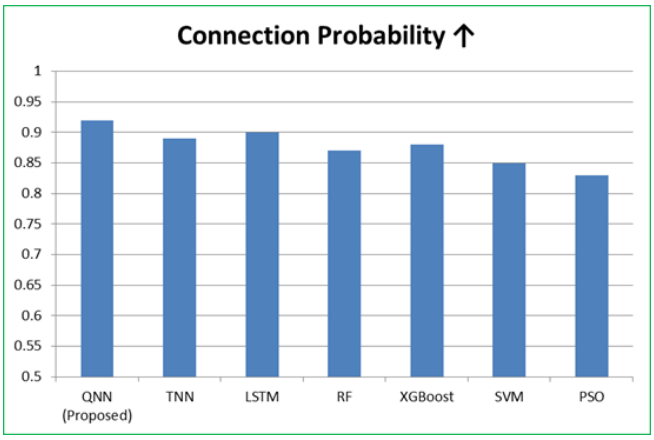

FIGURE 7. P_C values various MAC layer Decision Prediction Model

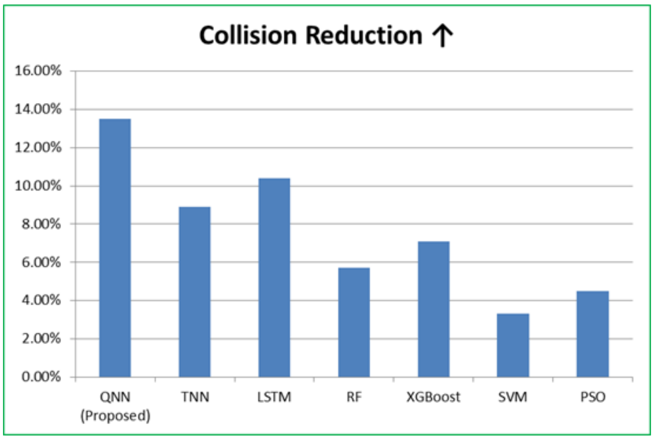

FIGURE 8. $C_R$values various MAC layer Decision Prediction Model

$C_R$value calculate over the number of collision occurred before establishment of connections and the number of collision occurred after establishment of connections, the value quantifies collision of a network connection under different types of constraints, the value more than seventy percent indicates high C_R value, the values from 40 percent to 70 percent indicates medium C_R value, and the values less than 40 percent indicate very poor C_R. C_R Values of different MAC layer decision prediction approaches like QNN, TNN, LSTM, RF, XGBoost, PSO and SVM are evaluated. QNN approach exhibits high C_R value, second highest C_R value shown by LSTM, next highest value shown by TNN approach, SVM approach achieved low C_R value, and the results are visualized in Figure 8.

Variance value calculate as a quantify that the rate of dispersion or spread of data samples average value, the values shows how much deviation is there in the mean value, the value quantifies dispersion of a network connection under different types of constraints, high value indicates more fluctuations occurred, low value indicates the samples are very close to mean, and zero value indicates both are identical. Variance Values of different MAC layer decision prediction approaches like QNN, TNN, LSTM, RF, XGBoost, PSO and SVM are evaluated. SVM approach exhibits high value, second highest value shown by RF, next highest value shown by XGBoost approach, QNN approach achieved low value and shows high performance, and the results are visualized in Figure 9.

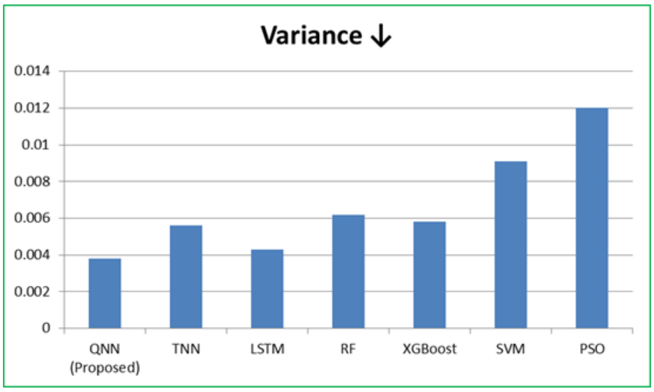

FIGURE 9. Variance values various MAC layer Decision Prediction Model

C_S value calculates the behaviour of two identical vectors without considering its magnitude, it is calculated in terms cosine angle over two vector space, if the value is equal to one then both vectors are in the same direction, if the value is equal to zero then both vectors are in the orthogonal direction, and if the value is equal to minus one then both vectors are in opposite direction. C_S values of different MAC layer decision prediction approaches like QNN, TNN, LSTM, RF, XGBoost, PSO and SVM are evaluated. QNN approach exhibits high C_S value, second highest C_S value shown by TNN, next highest value shown by LSTM approach, SVM approach achieved low C_S value, and the results are visualized in Figure 10.

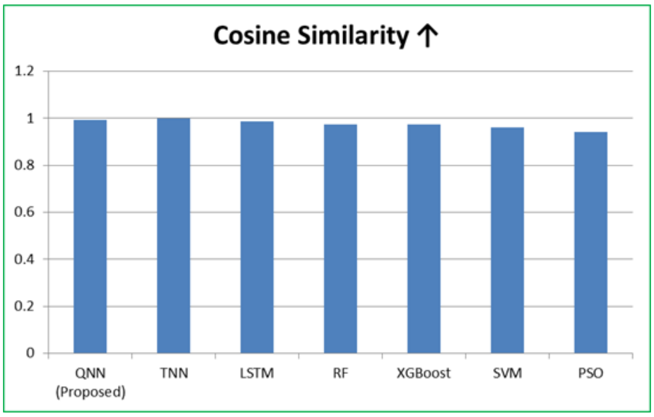

FIGURE 10. C_S values various MAC layer Decision Prediction Model

E_E value calculates the distance over original sample and predicted sample in terms of Euclidean, the value quantifies how of deviation is performed by the prediction approach, if the value is low then predictions are very close to actual samples, and if the value is high then predictions are deviated from actual samples. E_E values of different MAC layer decision prediction approaches like QNN, TNN, LSTM, RF, XGBoost, PSO and SVM are evaluated. PSO approach exhibits high E_E value, second highest E_E value shown by SVM, next highest value shown by RF approach, QNN approach achieved low E_E value, and the results are visualized in Figure 11.

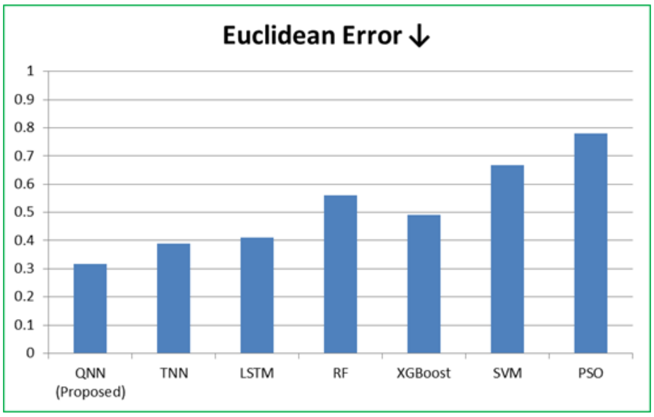

FIGURE 11. E_E values various MAC layer Decision Prediction Model

5. CONCLUSION

These usage of wireless devices in many applications are increased day by day and already peoples are experienced with 5G network are the basis to use advanced 6G network to provide communication under different types of conditions like mobility of nodes changes dynamically and these devices are used in many decision-making applications. Conventional machine learning techniques are reached functional limits due to produce heavy latency time, high computational overhead, and cannot handle certain problems with large number of states.

In this research we introduced QNN (Quantum Neural Network) based wireless communication to enhance MAC layer decision prediction accuracy to provide uninterrupted services to users. QNN is able to handle multiple network interactions at a time with limited features. In this model we used three qubits with two hundred layers variable circuit, dataset opted with more real-time wireless interactions with high SNR values, abnormal behavior, a greater number of retry requests, and with heave inferences.

Experiments are carried out to evaluate performance of QNN approach, the results are also compared with TNN, LSTM, RF, XGBoost, and SVM are evaluated are evaluated in terms of MSE, MAE, RMSE, R2, PDR, Connection probability, Collision Reduction, variance, Cosine Similarity, and Euclidian error. QNN exhibits low MSE value, low MAE value, low RMSE value, high PDR value, high R2 value, high connection probability, high collision reduction value, low variance, high cosine similarity, and low Euclidian error when compared with other similar approaches that are used for prediction purpose.

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