Volume 4 Issue VIII, August 2025, No. 72, pp. 940-952
Submitted 2/8/2025; Final peer review 9/9/2025
Online Publication 12/9/2025
Available Online at http://www.ijortacs.com

MACHINE LEARNING-BASED INTERFERENCE DETECTION AND MANAGEMENT SYSTEM FOR5G HETEROGENEOUS NETWORK

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Abstract

Interference remains a critical challenge in next-generation wireless networks, affecting both quality of service (QoS) and spectral efficiency. This study proposes a machine learning–based interference detection and management framework to address these challenges. A dataset consisting of key interference indicators including transmit power, path loss, antenna gain, user density, frequency reuse factor, and signal-to-interference-plus-noise ratio (SINR) was used to train and evaluate several machine learning algorithms. Artificial Neural Networks (ANN), Support Vector Machines (SVM), Logistic Regression, Decision Trees, and K-Nearest Neighbours (K-NN) were benchmarked using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and classification accuracy. Among these, the ANN achieved superior performance with a prediction accuracy of 99.78%, alongside the lowest error rates (MAE = 0.0022, RMSE = 0.0469), demonstrating strong generalization and robustness. To extend this predictive capability to real-time interference management, the study introduces a Dynamic Channel Sensing and Queuing Transmission Model (DCSQTM), which leverages Markov and Poisson processes for probabilistic estimation of channel availability and queuing delays. Machine learning predictions were integrated into DCSQTM to enable dynamic channel selection and adaptive transmission strategies. The combined framework significantly enhances interference detection and management, providing a scalable and intelligent solution to improve spectral efficiency and ensure reliable QoS in next-generation wireless networks.

Keywords: 5G Network; Interference ; Machine Learning; Optimization Algorithm

1. INTRODUCTION

Interference in 5G networks has continued to present several challenges, including reduced quality of service, poor coverage, decreased throughput, handover failures, and reduced network efficiency, all of which have significantly impacted the user experience.A Self-Optimising Network (SON) is an intelligent network system designed to optimise its performance with minimal human intervention, operating automatically. SONs leverage advanced algorithms and machine learning techniques to manage and enhance the performance of wireless networks. The primary goal of a SON is to improve network efficiency, reduce operational costs, and enhance the overall user experience by adapting to changing network conditions in real-time. By continuously monitoring and analysing network data, SONs can autonomously adjust parameters such as power levels, frequencies, and resource allocation to maintain optimal performance (Srivastava et al., 2024).

This estimated increase in data size has necessitated the need for a robust network architecture that will be able to manage the traffic while providing a quality user experience. To achieve this, researchers in the scientific community have continued to explore different areas of wireless communication, identifying problems that can affect the quality of service due to increased data traffic and making recommendations for solutions. Some of the fruits of their research resulted in the present-day 5G network, with a potential data rate per second increased to 10 GB/s, reduced latency of less than 1 ms, increased mobility speed greater than 1000 km/h, and 99.9% targeted reliability of the network (Qamar et al., 2020; Alzubaidi et al., 2022).

The Dynamic Heterogeneous Interference (DHI) in the 5G network originates from the diverse and varying interference patterns in HetNet as a result of the interplay between different cells such as macro, pico, femto, device-to-device and wifi access points. This DHI nature stems from several factors, such as changing user mobility, traffic patterns, adaptive transmission techniques such as millimetre-wave frequencies, co-channel deployment, which allows multiple cells to operate on the same frequency, and variability in cell types.

Machine learning has become a powerful tool for interference detection in wireless communication networks, offering a more dynamic and accurate approach to identifying and mitigating interference compared to traditional methods. Interference in wireless networks occurs when multiple devices or signals overlap within the same frequency spectrum, leading to degraded signal quality, reduced data rates, and higher latency (Siddiqui et al., 2020). Traditional interference detection techniques often rely on predefined rules and static configurations, which may not adapt well to the constantly changing network environment. Machine learning, on the other hand, leverages data-driven approaches to detect interference patterns in real time, providing a more flexible and responsive solution(Alzubaidi et al., 2022).

One of the key advantages of using machine learning for interference detection is its ability to analyse large volumes of network data and identify complex patterns that may not be apparent through manual analysis. For example, supervised learning algorithms can be trained on labelled datasets containing examples of interference events, allowing the model to learn and recognise similar patterns in live network data(Meyer et al., 2020; Okello et al., 2024). Moreover, machine learning enables proactive interference detection, allowing networks to anticipate potential interference before it impacts performance. Predictive models, such as those based on time-series analysis or recurrent neural networks (RNNs), can forecast interference events by analysing historical data and current network conditions (Hedge, 2021; Kumar et al., 2023).

While many studies have applied different algorithms for the detection of interference, one of the notable studies is Okello et al., (2024) who applied a reinforced deep learning algorithm for the management of interference, but despite the success, there is need for improvement in detecting dynamic interference due to changing network behaviour, and this will be addressed in this research using machine learning based resource coordination technique.

2. METHODOLOGY

The methodology for this work is a mixed method which involves practical measurements and simulation experiments. In realising this methodology, drive test measurement on a 5G network was carried out in three different regions, which are urban, suburban and rural locations for data collection. The data collected from each region were separately analysed to read the impact of interference on user experience. To solve the interference problem, a machine learning algorithm was applied to develop a prediction model capable of detecting in time series channels with potential interference.

The prediction outcome formed the foundation of a proposed interference resource coordination model. Results obtained were discussed before system integration on the real 5G network under study. Comparative analysis was used to validate the results and weaknesses of the work, and suggestions for further studies were identified and submitted.

2.1 Data Acquisition

The data for the implementation of this study was collected through characterization, which involves performing a drive test in different locations. The sites were selected from rural, urban, and suburban areas within Enugu State, Nigeria. The results were obtained during the measurement process of the drive test while considering metrics such as RSRP, carrier-to-interference ratio, and reference signal receive quality, respectively, from 500 meters to 1500 meters away from the test site. The data were collected in the morning from 8 am to 10 am, then in the afternoon from 2 pm to 4 pm. The results obtained from sire T6320 were reported in Table 1.

Table 1: Results of site T6320 (Urban)

Distance (M)	Morning			Afternoon		
	RSRP (dBm)	RSRQ (dB)	CIR (dB)	RSRP (dBm)	RSRQ (dB)	CIR (dB)
500	-79	-8	28	-91	-12	20
600	-81	-10	26	-93	-14	18
700	-83	-10	25	-95	-15	17
800	-85	-11	24	-97	-17	15
900	-87	-12	22	-101	-18	13
1000	-92	-14	18	-107	-21	10
1100	-95	-15	17	-109	-22	8
1200	-97	-17	15	-115	-24	7
1300	-101	-20	11	-117	-26	5
1400	-109	-24	9	-121	-29	4
1500	-112	-27	7	-125	-31	3
Average	-92.8182	-15.2727	18.36364	-106.455	-20.8182	10.90909

Table 1 presents the result of the site T6320 characterised in the urban area. The results obtained from the site vary with distance, which is normal. However, the average RSRP reported is -92.82 dBm, the average RSRQ reported is -15.27 dB, and the carrier-to-interference ratio reported is 18.36 dB. These results indicated that in the morning, the quality of service on the cell was fair, the quality of the signal was also fair, and the CIR reported 18 dB, which is considered fair. Overall, the performance of the network is fair, which suggests the need for improvement through the management of interference. From the data collected in the afternoon, the average signal quality is -20 dB, which is poor. The average signal strength is -106 dBm, which is also poor. The CIR reported 10 dB, which is poor. These results collectively implied that the network performance significantly deteriorates in the afternoon due to increased interference levels. The drop in RSRQ to -20 dB suggests a higher level of noise and signal degradation, likely caused by increased user activity, environmental changes, or multipath fading. Table 2 presents the measurement results in the rural area.

Table 2: Results of site EN0457 (Rural)

Distance (M)	Morning			Afternoon		
	RSRP (dBm)	RSRQ (dB)	CIR (dB)	RSRP (dBm)	RSRQ (dB)	CIR (dB)
500	-65	-5	35	-67	-6	33

600	-67	-6	34	-68	-7	33
700	-69	-7	34	-69	-8	31
800	-71	-7	31	-71	-9	29
900	-73	-8	28	-73	-10	27
1000	-75	-9	27	-77	-11	25
1100	-79	-10	25	-78	-11	25
1200	-85	-10	25	-84	-14	21
1300	-87	-11	23	-87	-16	20
1400	-90	-12	20	-93	-16	17
1500	-92	-13	17	-96	-19	15
Average	-77.5455	-8.90909	27.18182	-78.4545	-11.5455	25.09091

The results from Table 2 indicate that site EN0001, located in a rural area, experienced relatively stable network performance throughout the day but with slight degradation in the afternoon due to interference. In the morning, the average RSRP of -77.55 dBm and RSRQ of -8.91 dB suggest strong signal strength and quality, with a CIR of 27.18 dB indicating minimal interference and efficient data transmission. However, in the afternoon, the RSRP slightly drops to -78.45 dBm, while the RSRQ deteriorates to -11.55 dB, and the CIR reduces to 25.09 dB, reflecting an increase in interference. Table 3 presents the results of measurements carried out in the suburban area.

Table 3: Results of site EN0001 (Sub-Urban)

Distance (M)	Morning			Afternoon		
	RSRP (dBm)	RSRQ (dB)	CIR (dB)	RSRP (dBm)	RSRQ (dB)	CIR (dB)
500	-73	-7	31	-85	-10	25
600	-75	-7	30	-87	-11	23
700	-79	-8	28	-90	-12	21
800	-85	-10	25	-92	-13	19
900	-87	-11	23	-95	-14	17
1000	-90	-12	20	-97	-15	15
1100	-92	-13	17	-99	-16	14
1200	-95	-14	15	-102	-18	12
1300	-97	-15	14	-105	-19	10
1400	-99	-16	12	-108	-20	8
1500	-102	-18	10	-110	-21	7
Average	-88.5455	-11.9091	20.45455	-97.2727	-15.3636	15.54545

Table 3 presents the site performance at varying distances. Averagely, the morning results reported -88.55dBm for the RSRP, the RSRQ reported -11.9dB, and the CIR reported an average of 20.45dB over the 1500-meter distance measurement. For the afternoon measurement, the average RSRP reported -97.27 dBm, the average RSRQ reported -15.36dB, and the average CIR reported 15.44dB. The meaning of these results, considering interference impact on the cell, is that the network experiences a noticeable degradation in performance from morning to afternoon due to increased interference. In the morning, the relatively stronger RSRP of -88.55dBm and an RSRQ of -11.9dB suggest a fair signal strength and quality, with a CIR of 20.45dB indicating moderate interference levels.

2.2 To Train Machine Learning Model

This section considered several machine learning models trained for the prediction of channels with potential interference problems. From the literature reviewed, it is clear that several machine learning algorithms have been applied by researchers for the prediction of interference; however, the recommendation made by researchers (Li et al., 2021; Ali et al., 2023)contradicts each other because different algorithms were recommended by different researchers. Based on this evidence, we argue that selecting the best machine learning for a particular problem should not be based on assumptions or performance from another model; rather, it should be based on experimentation with different selected popular algorithms from literature. Based on this, this research proposed to train five machine learning algorithms, which are the neural network, support vector machine, decision tree, linear regression and K-nearest neighbour.

2.2.1 Neural Network

The neural network is a machine learning algorithm which is developed with several neurons, activation functions and layers. The type of neural network used is multiple-layered neural networks (Li et al., 2024). The activation function used is sigmoid, the training algorithm used is backpropagation, and the regularisation model used is dropout(Sarikaya and Hinton, 2019). The number of inputs to the neural network is 13, the number of hidden layer neurons is 30, and the output layer is 2. The neural network was trained in a Python programming environment, using the data of network information for the 5G network collected from MTN.

2.2.2 Support Vector Machine (SVM)

SVM is an algorithm that operates by finding the best hyperplane that separates the instances of different classes in feature space. In this context, the SVM will be trained to classify the instances of interference based on real-time network information. SVM has a simple structure but a strong generalisation ability to solve problems with high dimensionality, and small sample numbers (Guo et al., 20221).For the SVM in this study, the Gaussian radial basis function is selected as the kernel function. By using the grid search method in combination with 10-fold cross-validation, the optimal parameters are determined as $C = 3$ and $\gamma = 0.003$.

2.2.3 Decision Tree (DT)

DT determines the categories of the samples in the dataset by assigning the sample data to a certain leaf node. The DT, when trained with the network information, was able to correctly predict channels with potential interference and prevent its impact on user experience(Ali et al., 2023). In the DT, each leaf represents the final prediction output when trained, and those leaves with wrong high loss values are pruned using the Gini index. This process continued recursively until the model for the detection of interference was detected.

2.2.4 Linear regression

Linear regression is a popular machine learning algorithm which models the relationships between feature spaces using a straight line. It determines the line of best fit, which perfectly relates the dependent and independent variables. Then it uses the value to predict changes in any of the variables based on new data input. The line of best fit is calculated with a regression line model$y = mx + b$, where m is the slope.x is the data and y is the output. To measure the error, the least squares method is applied, which computes the best line with a minimised sum of square difference between the actual and predicted data points(Montgomery et al., 2021).

2.2.5 K-Nearest Neighbour (K-NN)

K-NN is an effective machine learning algorithm which operates by assigning a class label to an instance based on the majority class of its K-NN in the feature space (Bathija et al., 2023). For our problem of interference detection in a 5G network channel, the K-NN determines whether a new instance corresponds to interference based on the similarity of its value to those of previously observed instances. K-NN can handle non-linear relationships and is robust to noise (Biscaglia et al., 2023), making it a viable option for the prediction of interference channels in networks.

2.3 Training of the Algorithms

This section discusses training the various machine learning models to predict interference-prone channels in a 5G heterogeneous network. The training utilised the dataset comprising essential interference-related parameters, such as transmit power, path loss, antenna gain, frequency reuse factor, user density, and SINR. The dataset underwent pre-processing, which included normalising feature values and addressing missing data as needed using the imputation technique. The training phase was designed to enhance each algorithm's performance according to its specific learning methodology. The Neural Network model employed a back-propagation algorithm for iterative weight updates aimed at minimising prediction error. The SVM was trained by projecting data into a high-dimensional space via a kernel function to create a hyperplane that optimised class separation. Similarly, the DT model was trained by recursively partitioning the dataset based on Gini impurity, facilitating optimal decision-making for interference classification. The Linear Regression model employed a least-squares optimisation technique to minimise the discrepancy between predicted and actual interference levels. Conversely, the K-NN model was trained by retaining the dataset and classifying new instances according to the predominant class of the nearest neighbours. Hyperparameters for each model were fine-tuned through cross-validation to improve generalisation. The dataset was divided into training (70%) and testing (30%) subsets, ensuring performance evaluation occurred on unseen data. The training process utilised Python-based machine learning libraries, including TensorFlow, Scikit-learn, and Keras, contingent upon the algorithm. The models' performance was evaluated using metrics like accuracy, precision, recall, F1-score, and Mean Squared Error (MSE) for regression models. The results obtained from the training phase provided insights into the best-performing model for predicting co-channel interference in 5G networks

2.4 Resource Coordination Model

To develop the resource coordination model for the management of interference, a Dynamic Channel Sensing and Queuing Transmission Model (DCSQTM) was proposed. The model consists of four major components, which are channel sensing, dynamic channel switching, queuing re-transmission and adaptive transmission resumption as depicted in Figure 1. The channel sensing monitors channel availability through their frequency band; the dynamic channel switching allows for alternative reallocation of free channel frequency when interference is detected on available channels. The queue transmission is activated when no free channel is found; this initialises a temporal queue of 2ms (Alozie et al., 2022), instead of assigning a channel with potential interference to the user.

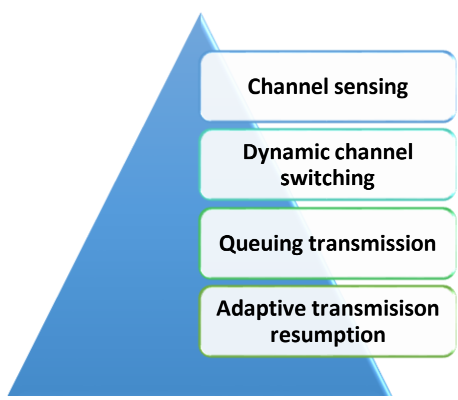

Figure 1: The component of the proposed DCSQTM

Let the set of channels in the 5G network be defined as C= $\{c_1, c_2,, \ldots\ldots\ldots\ldots.. c_n\}$. The probability that the channel c_i is available at the time t is modelled using the Markov process in Equation 1.

$$P_a(c_i, t) = P_b(c_i, t-1). P_{release}(c_i) + P_a(c_i, t-1). (1 - P_{occupy}(c_i)) \quad (1)$$

Where $P_a(c_i, t)$ is the probability that c_i is available at time t, $P_b(c_i, t)$ is the probability that c_i is busy, $P_{release}(c_i)$ is the probability that an occupied channel is released, $P_{occupy}(c_i)$ is the probability that an available channel gets occupied. While the probability that a channel is occupied at t time is given as a Poisson process in Equation 2;

$$P_{occupy}\ (c_i) = 1 - e^{-\lambda_i T} \quad (2)$$

Where λ_i is the mean arrival rate of new transmission on c_i channel, T is the sensing interval. The available channel is determined when Equation 2 (which is the SINR) model is less than the set threshold of 5dB. However, when the channel has interference, the signal is queued for the available channel. The probability that the signal is queued is given in Equation 3, while the expected queue time is defined in Equation 4.

$$P_{queue}(t) = P_{occupy}(c_i) . \left(1 - P_a(c_i, t)\right) \quad (3)$$

$$T_q = \frac{1}{\mu - \lambda} \quad (4)$$

The expected queue waiting time T_q, arrival time is λ, and the rate of channel availability is μ. Once the channel becomes available $(P_a(c_i, t) > P_{th})$ the signal is transmitted immediately. The models describe the dynamic channel selection and allocation mechanism to minimize interference. The model began with a set of channels in which the transmitter chooses an interference-free option. The availability of the channel at time t is modelled using the Markov process $P_a(c_i, t)$depending on the channel state. If the channel is free, the probability that it is released is given as $P_{release}(c_i)$, while the probability that the channel is occupied is $=$ $P_{occupy}(c_i)$, while the mean arrival rate λ_i is an exponential function. The channel is usable when the SINR is below the set threshold of 5db. The expected queuing time is 2ms. Once a channel is available, the queuing transmission is processed.

While the Markov model in Equation 1 estimates the availability of the channel based on transition probabilities, it failed to capture nonlinear interference patterns in a dynamic 5G environment. In addition, the Poisson distribution in Equation 2 relies on a fixed arrival rate, which may not model the actual real-world variation. In contrast, machine learning, which has been trained for the prediction of interference, has been applied to optimise DCSQTM and provide a proactive interference management model for improved quality of service. Figure 2 presents the flow chart of the machine learning-based interference management model.

Figure 2 presents the flow chart of the machine learning-based interference management model. The flow chart began with the initialization of the network parameters, setting of values for queuing time, and SINR. The machine learning-based prediction model was loaded and used to improve channel monitoring and selection of available channels upon detection as free from interference. The free channel is assigned for the management of user resources When a channel is predicted with interference potential, the user is queued and re-accessed until an interference-free channel is detected and then used to manage user equipment

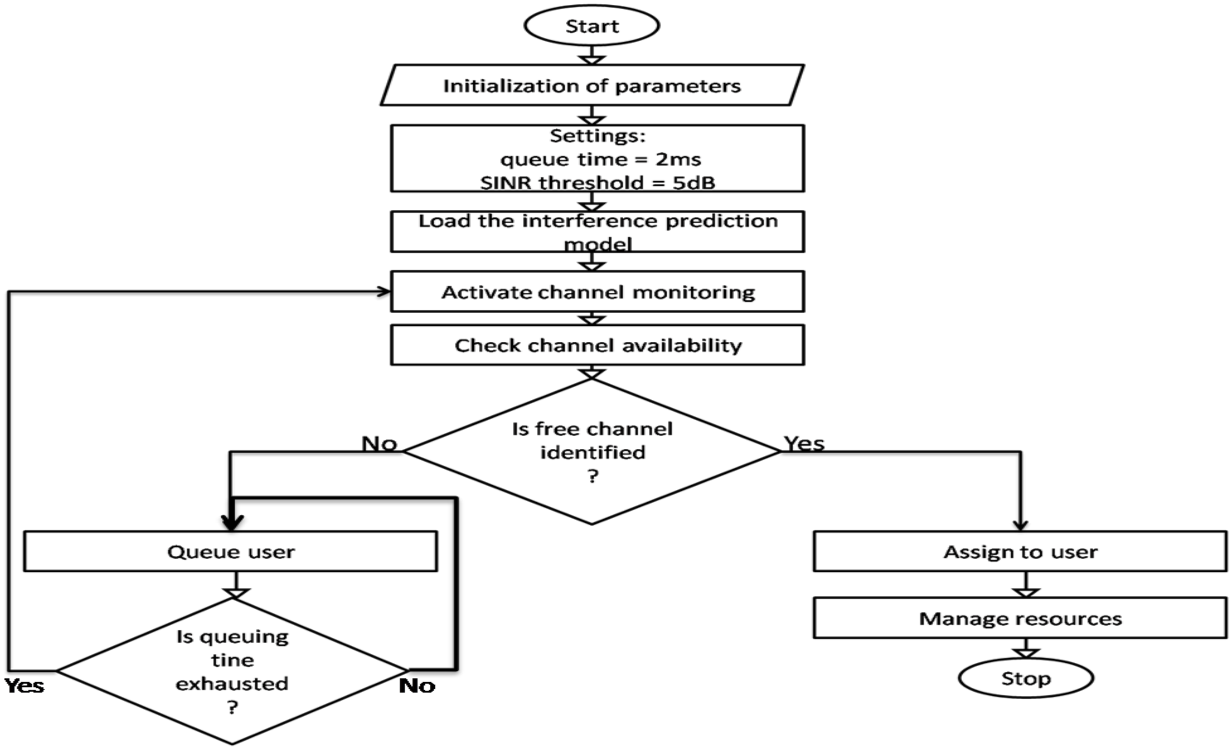

Figure 2: Flow chart of the machine learning-based interference management model.

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3. RESULT OF THE ML

This section presents the results of the machine learning algorithm training. The training process first imported the dataset, which contains information on interference and non-interference records from the testbed, collected at varying periods of the day. The distribution of targets in the data was reported in Figure 3.

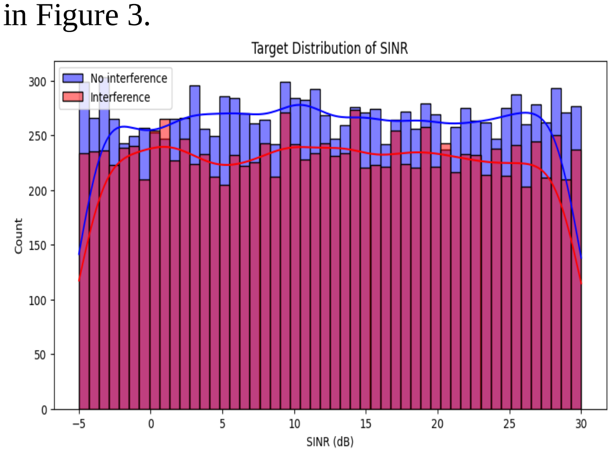

Figure 3: Result of SINR target distribution

Figure 3 presents the class distribution of targets for the data collection. The result showed that while the two classes are not the same, there is limited difference among them, thus suggesting that there is a balanced class in the dataset and the issues of classification bias will not occur when it is applied to train models for the detection of interference. In training machine learning, several algorithms such as DT, ANN, logistic regression, SVM and K-NN were trained. The training process was evaluated using metrics such as MAE, MSE and RMSE. The results obtained are reported in Figure 4.

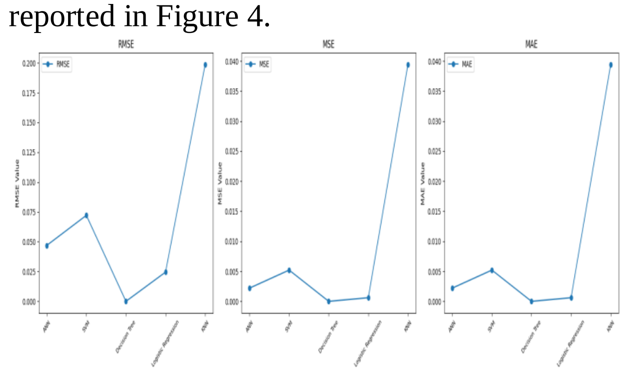

Figure 4: Training performance of ML

The performance of different machine learning algorithms in detecting interference was evaluated using key error metrics such as MAE, MSE, and RMSE are reported in Figure 4. These metrics provide insights into the accuracy, stability, and overall reliability of each model. From the results, the ANN model reported an MAE of 0.0022, MSE of 0.0022, and RMSE of 0.0469. These results indicate that the ANN had minimal errors in predicting interference levels. The low RMSE value suggests that ANN generalises well across different interference conditions, making it a reliable choice for real-time interference detection.

The SVM model showed moderate results with an MAE of 0.0052, MSE of 0.0052, and RMSE of 0.0721. While SVM performed reasonably well, it exhibited slightly higher error values compared to ANN, suggesting that it might struggle with certain interference conditions. This could be attributed to the difficulty in finding optimal decision boundaries in highly dynamic network environments like the urban environment. Interestingly, the Decision Tree model produced an MAE, MSE, and RMSE of 0.0, indicating perfect prediction accuracy on the dataset. However, such a result raises concerns about potential overfitting. Decision Trees are known for their tendency to memorise training data rather than generalising patterns. While this result appears ideal, we cannot adopt it as the best model because of the potential overfitting problem.

Logistic Regression performed well, with an MAE of 0.0006, MSE of 0.0006, and RMSE of 0.0245. This suggests that the model effectively captured interference patterns while maintaining low errors. Despite its simplicity, Logistic Regression showed remarkable accuracy, making it a suitable choice for this work. The KNN model exhibited the highest error values among all models, with an MAE of 0.0394, MSE of 0.0394, and RMSE of 0.1985. These results indicate that KNN struggled with interference prediction, likely due to its sensitivity to noisy data and distance-based dependency. The high RMSE value suggests that KNN may not be well-suited for real-time interference classification in dynamic 5G networks. Figure 5 presents comparative accuracy in the correct prediction of interference.

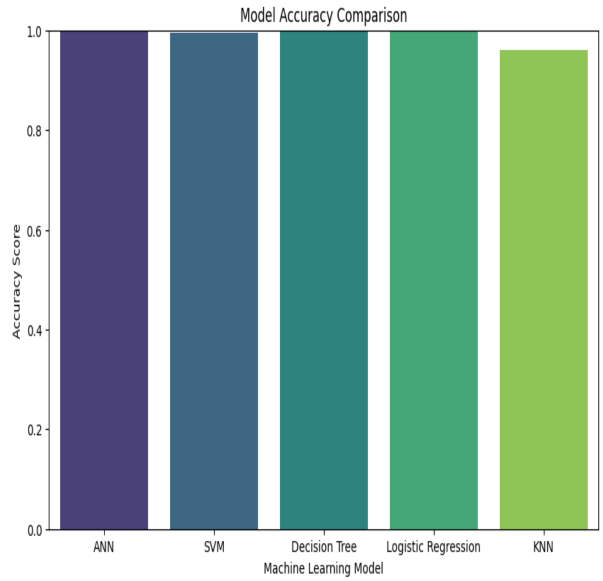

Figure 5: Comparative accuracy in prediction of interference

Figure 5 compares the prediction accuracy of the five machine learning models trained for the detection of interference. From the results obtained, ANN reported 0.9978 accuracy, SVM reported 0.9948, DT reported 1.000, logistic regression reported 0.9994, and K-NN recorded 0.9606. From the results obtained, it was observed that while the models all recorded very good accuracy in predicting interference, DT will have a potential overfitting due to the ideal results reported. K-NN recorded the least accuracy, while logistic regression recorded the most acceptable result for the correct prediction of interference on the 5G network. Figure 6 presents the confusion matrix for ANN performance.

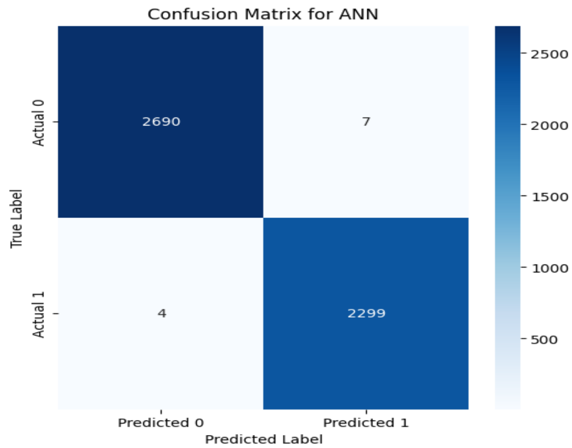

Figure 6: Confusion matrix of the ANN

Figure 6 presents the performance of the ANN model while trying to predict the behaviour of cells during interference and without interference. From the results, it was observed that the predicted model was able to correctly predict 2690 features of no-interference data on the network and then predicted 4 as interference. These results implied that the positive prediction value of the model in detecting interference is 99%, while the false detection rate is less than 1%. For the prediction of the network performance during interference, it was observed that out of the 2303 features of interference data, only 7 features were wrongly classified, while 2299 features were correctly classified as interference on the network. Figure 7 presents the confusion matrix of the SVM model.

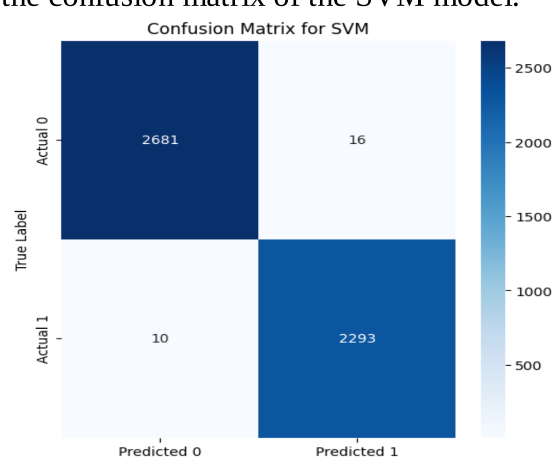

Figure 7: Confusion matrix of the SVM model

Figure 7 shows the confusion matrix of the SVM model. From the results, it was observed that out of the 2697 features of network data without interference, the results obtained showed that 2681 of the features were correctly predicted as normal network behaviour without interference, while 10 of the features were wrongly reported as interference. The interference class contained 2303 features of interference data; however, the results reported 2293 features of interference, which were correctly detected, while 16 features were wrongly classified. Figure 8reports the confusion matrix of the DT model.

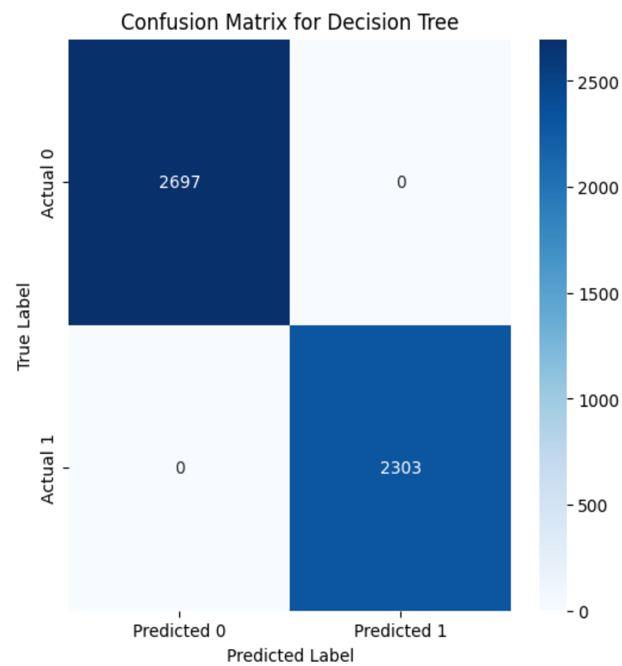

Figure 8: Confusion matrix of DT

Figure 8 shows the confusion matrix of the DT model predicting interference and non-interference on the network. In the results, it was observed that the total 2697 features of the steady network were correctly classified, while 2303 features used to test for interference were correctly predicted. Figure 9 presents the logistic regression confusion matrix.

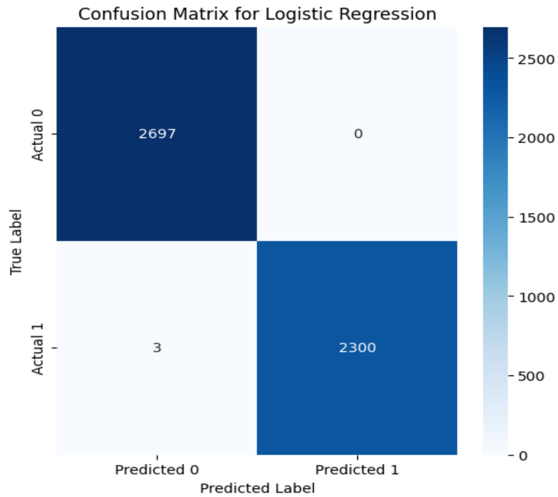

Figure 9: Confusion matrix of logistic regression

From the results in Figure 9, it was observed that 2700 features of the network without interference were applied to test the logistic-based model. In the results, only 3 features were wrongly classified, while 2679 were correctly classified. Out of the 2300 features of interference used to test the model, all were correctly predicted as interference. Figure 10 also reports the result of the K-NN model applied for the detection of interference and normal network conditions.

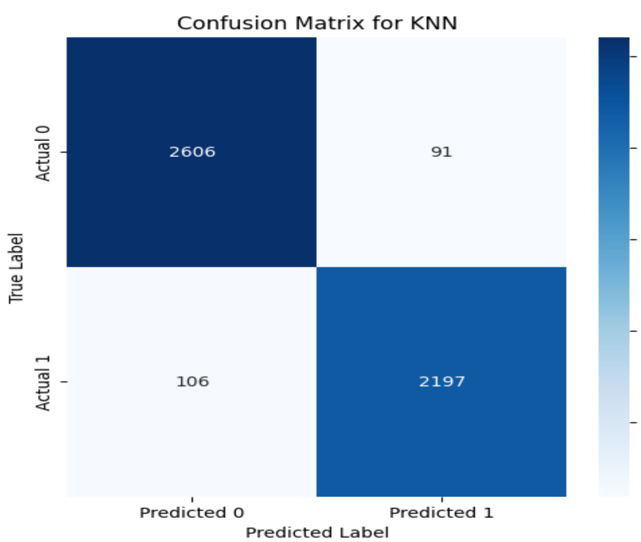

Figure 10: Confusion matrix of the K-NN model

Figure 10 presents the confusion matrix of the K-NN model applied for the prediction of interference. In the result, it was observed that 2606 features of normal packets were correctly classified, while 106 features were wrongly classified. For the prediction of interference, it was observed that 2288 features used to test the model recorded 2197 features as interference and then 91 features as wrong classification. From the results obtained generally, the logistic regression model was selected as the most reliable and then applied for system integration and tested through simulation.

4. CONCLUSION

This study worked on developing a machine learning-based interference detection and management system for 5G heterogeneous networks. In the study, a variety of machine learning algorithms such as Artificial Neural Networks (ANN), Support Vector Machine (SVM), Decision Tree (DT), Logistic Regression, and K-Nearest Neighbours (K-NN)were trained using a dataset containing key interference-related features such as transmit power, path loss, antenna gain, user density, frequency reuse factor and Signal-to-Interference-plus-Noise Ratio (SINR). Each algorithm was trained and evaluated, and the ANN algorithm emerged as the most effective, reporting low error rates (MAE = 0.0022, RMSE = 0.0469) and high prediction accuracy (99.78%) while maintaining generalisation across interference conditions. Furthermore, Logistic Regression also performed remarkably well with minimal error and high accuracy. Although the Decision Tree model achieved a training accuracy (100%).

In addition to model training, the study proposed a Dynamic Channel Sensing and Queuing Transmission Model (DCSQTM) to manage interference proactively. The model includes key components channel sensing, dynamic channel switching, queue retransmission, and adaptive resumption underpinned by probabilistic models (Markov and Poisson) to estimate channel availability and queuing delay. To address the limitations of traditional stochastic models in capturing dynamic and nonlinear interference, machine learning models were integrated into the DCSQTM framework to optimise channel selection and improve quality of service.

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