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DESIGN AND PERFORMANCE OPTIMIZATION OF CAMPUS WI-FI NETWORK (CASE STUDY OF UNIZIK)

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Abstract
A Wi-Fi network is a wireless local area network designed to provide internet connectivity to people within a particular area. In the context of this study, the University of Nnamdi Azikiwe (UNIZIK) Wi-Fi Campus was considered the network of choice for optimization. To solve this problem, three years of data, which model the network at congestion and normal conditions, were collected and then used to train a Multi-Layered Neural Network (MLNN) algorithm and generate a model for real-time tracking and detection of congestion. The methodology used for this project began with a technical investigation of the quality-of-service performance at the case study campus network through collection of data. The collected data were presents and analyzed to determine the impact of user and application diversity on quality of service. Secondly, a machine learning algorithm was trained with data of dynamic congestion collected from UNIZIK campus network to develop a model for the detection of dynamic congestion. The model generated was integrated with a congestion management system and used to improve quality of service optimization at UNIZIK, using Simulink and classification learner software. The new model was integrated into the campus network and evaluated for 2 hours, with data collected at a 5-minute interval. The result, when evaluated considering throughput, reported 83.4% In conclusion, the integration of MLNN with Early Warning Systems (EWS) has demonstrated success in optimizing the campus network. Recommendations to extend the new congestion solution to other network types apart from campus networks were suggested.

Keywords: Wi-Fi; UNIZIK; Congestion Control; Multi-Layered Neural Network; Machine Learning.

1. INTRODUCTION

Over the years, the integration of wireless network technologies into the educational sector has transformed the processes of teaching, learning, administrative operation, and overall academic activities within the education sector (Ibrahim and Abubakar, 2021). With the proliferation of digital resources, the initiation of online collaboration platforms, electronic learning systems, and the interconnectivity of things (IoT), the need for a robust and reliable Wi-Fi campus network has become indispensable for modern tertiary institutions (Khan et al., 2024).

In many universities today, campus Wi-Fi networks are used to power administrative educational activities and have undergone massive expansion to meet the growing demand for quality service by student, academic, and non-academic staff, like in the case of Nnamdi Azikwe University, Awka, Anambara State, Nigeria. While this expansion was able to provide more access points and allow massive input and output connectivity within the campus, it has also suffered several challenges, which include congestion, limited coverage, security vulnerability, interference, and performance degradation. This challenge not only impacts the productivity and efficiency of administrative and academic functions but also hinders the capability of the institution to provide seamless interconnectivity among various institution-based stakeholders (Khanji and Özceylan, 2023;Besjedica et al., 2023).

According to Umar et al. (2023), congestion has remained one of the most challenging issues that impacts the quality of service (QoS) sustainability of Wi-Fi networks. Due to this, it has remained one of the most active research topics in the scientific community. Sun et al. (2018) define congestion as the overload of data-produced network physical layer devices, resulting in the overload of the network channel bandwidth and hence impacting the network quality of service. In the context of the campus Wi-Fi network, while a large number of campus staff and students are connected to the network, which is bandwidth constrained and has ineffective network traffic control and management mechanisms, this impacts negatively on the overall network quality of service and results in issues such as packet loss, security concerns, reduced throughput, latency increase, and poor routing, among other consequences (Starchenko, 2021). Therefore, recognizing the impact of a well-designed campus Wi-Fi network is vital to supporting the academic and administrative functions within an institution (Obelovska et al., 2021).

Many studies have been presented that offer promising solutions for Wi-Fi network quality of service. For instance, Gava et al. (2023) proposed the application of Long Range (LoRa) for the optimization of wireless networks using a spanning tree algorithm. The application of LoRa was used to facilitate low-cost communication processes across various frequency bands without licenses and with low power consumption. In another study, Akhter et al. (2023) applied a channel bonding strategy to boast quality of service and address congestion problems, while Zhang et al. (2019) applied a mobile crowd sensing approach for continued monitoring of network performance and management of service quality. While these studies have provided a significant solution capable of sustaining QoS in campus networks, no solution has been obtained that considers the complexity and dynamics of campus Wi-Fi networks for congestion management (Simma et al., 2021).

In UNIZK, for instance, the campus network is designed to support diverse applications, devices, operating systems, user behavior diversity, and mobility. The heterogeneous user activities can result in a dynamic congestion problem, which is a complex problem that has yet to be addressed by existing researchers. Therefore, this thesis proposes a dynamic congestion detection algorithm that utilizes the power of artificial intelligence to learn features of dynamic congestion and develop a model for network behavioral analysis and congestion detection in real time.

2. RESEARCH METHODOLOGY

The methodology used for this project began with a technical investigation of the quality-of-service performance at the case study campus network through data collection. The collected data were presents and analyzed to determine the impact of user and application diversity on quality of service. Secondly, a machine learning algorithm was trained with data of dynamic congestion collected from UNIZIK campus network to develop a model for the detection of dynamic congestion. The model generated was integrated with a congestion management system and used to improve quality of service optimization at UNIZIK, using Simulink and classification learner software.

2.1 TO DEVELOP A DYNAMIC CONGESTION DETECTION ALGORITHM USING MACHINE LEARNING TECHNIQUE

To develop the dynamic congestion detection algorithm, the methods used are data collection, data processing, artificial neural network, training, and model for the detection of congestion.

2.2 Data collection and processing

The data used for this study was collected from the UNIZIK campus network as the primary source of data collection, considering parameter which model dynamic heterogeneous congestion such as throughput, data size, and time. The data was collected considering the network behaviour for three years starting from May 2020 till May 2023. The sample sizes of data collected are in two classes of congestion features with 2182 samples and non-congestion condition with 1372 samples. The data description table was presented in table 1;

Table 1: Data description

Variable	Data type	Data description
Throughput	Integer	Size of data successfully uploaded
Data size	Integer	Size of data upload
Result	String	Output o congestion or no congestion

The table 1 presents the data description. The collected data was presented in excel and visualized in to remove missing and duplicate values. The data were feed to train a neural network algorithm for training and generation of the model for the detection of dynamic congestion in campus Wi-Fi network. Before using the data for training a machine learning algorithm, Lee and Lin, 2021) suggested the application of data transformation using Principal Component Analysis (PCA). The PCA algorithm for feature transformation is presented as;

PCA Algorithm (Lee and Lin, 2021)

1. Start
2. Apply data standardize
3. Apply Covariance Matrix computation
4. Calculate Eigen-values and Eigenvectors
5. Sort Eigen-values
6. Select Principal Components
7. Transform Data
8. End

2.3 Machine learning algorithms

The machine learning algorithm used for the work is a Multi-Layered Neural Network (MLNN). MLNN is formulated from single neurons, interconnected with multiple hidden layers as shown in the figure 1.

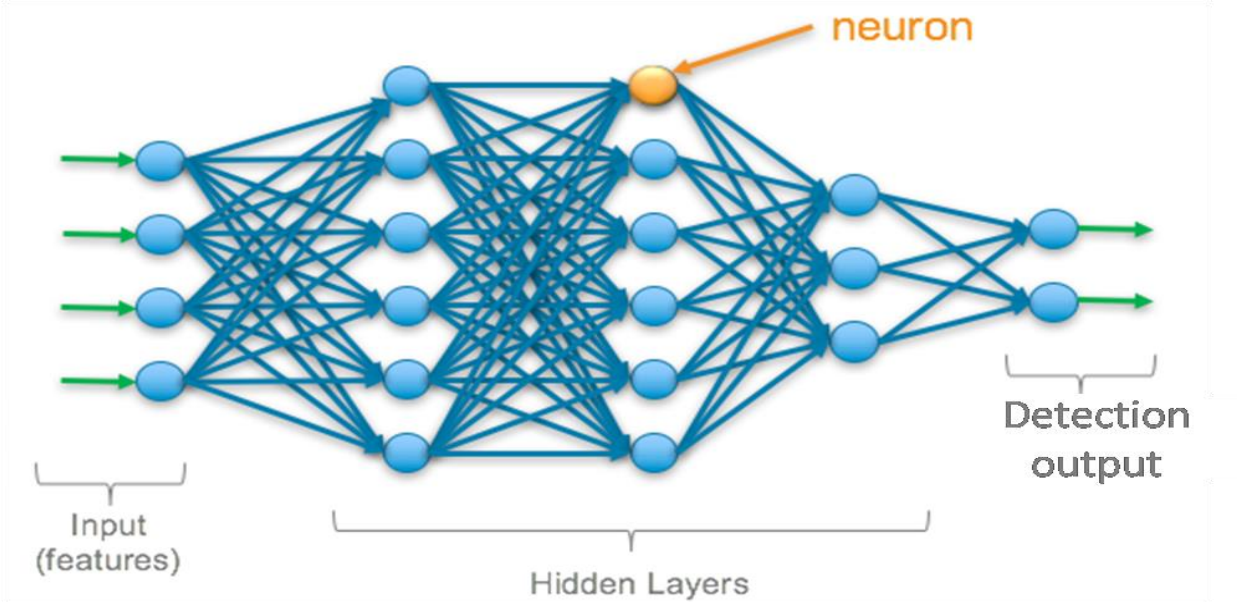

Figure 1: Architecture of the multi-layered neural network (Sildir et al., 2020)

The figure 1 presents the neural network architecture which is made of input X_n, hidden layer P_n and output layer Y. The relationship between the input and output is given as equation 1 (Stienecker and Hagemeier, 2023);

$$Y = f(X_1 \dots \dots \dots \dots .. X_n) \quad (1)$$

To formulate the MLNN with two hidden layers, let define the following parameters;

X is the input vector with n dimension; W^n as the weight of the neurons connected to the n hidden layer; m is the number of neurons inP_n layer; A^n is the activation function in the n layer b^n is the bias in the n layer. To formulate the neural network architecture in the first layer, the equation 2 was applied;

$$Y^1 = A^1.\ X.W^1 +\ b^1 \quad (2)$$

$$Y^2 = A^2.\ X.W^2 +\ b^2 \quad (3)$$

$$Y^3 = A^3.\ X.W^3 +\ b^3 \quad (4)$$

Where equation 3 presents the second layer and equation 4 presents the output layer. The activation function A is given as;

$g^3(Y) = \frac{1}{1+e^{-z}}$ and gives a probability values of 1 for congestion and 0 for non congestion, the type activation function used is sigmoid.

The training process began with the input of the processed data to the neural network algorithm. This data was used by the neural network to configure itself and then split into training, test and validation sets respectively, before applying back propagation algorithm (Stienecker and Hagemeier, 2023) to adjust the neurons to learn the training set. During the training process, the actual data was used to test the predicted values and the difference is measured as error and used to adjust the neurons through back-propagation. This process continues iteratively until the least error is achieved, then the model is tested and validated, while evaluated considering metrics such as accuracy, precision, recall, positive predictive value and then the model for the detection of congestion is generated. The step wise of the MLNN training and generation of the model is presented as;

1. Initialization: Initialize the network parameters, including weights and biases, randomly or using a specific initialization method.

2. Forward Propagation:

- ❖ Input Layer:
- ❖ Receive input data.
- ❖ Compute the weighted sum of inputs and biases.
- ❖ Apply an activation function

3. Loss Calculation: Compute the loss between the predicted output and the actual labels using binary cross-entropy.

4. Back-propagation: Calculate the gradients of the loss function with respect to the network parameters

5. Update: Update the network parameters using stochastic gradient descent to minimize the loss.

5. Training: Iterate through the training dataset multiple times (epochs), adjusting the weights and biases to improve performance.

6. Validation: Evaluate the trained model on a validation dataset to assess its generalization performance.

7. Testing: Evaluate the final trained model on a separate testing dataset to obtain unbiased performance estimates.

8. Deployment: Deploy the trained model as congestion detection solution in the Wi-Fi network.

The step wise algorithm for the congestion detection model is presented as;

The congestion detection algorithm

1. Start
2. Initialize network protocols
3. Incoming packet from access layer
4. Identify real-time network information
5. Analyze network information through classification of throughput and data size.
6. For
   - Congestion detection =true
     - Output “1”
7. Else
   - Output “0”
     - Return to step 3
8. Output classification results
9. End

2.4 Congestion control model

The Exponentially Weighted Moving Average (EWMA) method is used in network quality of service management to control the acceptance rate of incoming packets over time intervals. In this work, EWMA gives different weights to previous observations, favoring current data while smoothing out volatility (Yasar et al. 2023). The maximum number of packets allowed (Ni) in each time interval is obtained by averaging the packet count over time using equation 4. The process iteratively updates an exponentially weighted sum (Si) of prior intervals using a recursive formula in equation 5 (Marlenne et al., 2006; Manjeet 2019).

$$N_i = \frac{N - \gamma S_{i-1}}{1-\gamma} \quad 0 \leq \gamma < 1 \tag{4}$$

While $S_{i-1} = (1-\gamma)X_{i-1} + \gamma S_{1-2}$ (5)

Where γ controls the weighting of previous data on the network. A smaller γ number prioritizes recent observations, improving response to unexpected traffic changes, whereas bigger γ values result in smoother adjustments. When γ = 0 and Ni remains constant. This adaptive nature enables the algorithm to effectively manage network congestion by dynamically adjusting packet acceptance rates based on real-time and historical traffic data. The congestion control algorithm is presented as;

Congestion control algorithm

1. Initialization
2. Set the initial value of the exponentially weighted sum (S_0) to an appropriate value.
3. Receive Incoming Packets from campus
4. Update Exponentially Weighted Sum of packet with equation 5
5. Determine Maximum Packet Acceptance rate with equation 4
6. Compare incoming packets to the maximum allowed packet count (Ni) for the current interval.
7. Accept incoming packets up to the maximum allowed count (Ni)
8. Repeat Process
9. Monitor the network performance and congestion levels over time.
10. End

3 SYSTEM INTEGRATION

The system integration presented the congestion detection and control system merged to improve quality of service in the campus Wi-Fi network. From the model, the incoming packet to the network was used for network analysis through the congestion detection model with neural network algorithms, considering metric such as throughput on the network. The output of the network which suggest congestion is detected, results to the initialization of the control model which used the exponential sum of weight to measure the network packet size and then compare with the maximum sum of weights for the network, to confirm the detection no congestion, before adjust the control parameter for packet acceptance control until quality of service is sustained in the network.

3.1 Implementation of the improved Wi-Fi network

The implementation of the new Wi-Fi network, featuring congestion detection using a neural network and a control model employing exponential weight averaging, was executed through the Classification Learner software in MATLAB. The congestion detection model was then exported into the MATLAB editor workspace for congestion control programming. Subsequently, it was integrated into the Wi-Fi network and assessed across various user densities and streaming applications using simulation parameters outlined in Table 2. The evaluation encompassed diverse data types, with throughput measured under each scenario.

Table 2: Simulation parameters (Source, UNIZIK campus network)

Parameters	Values
Time of simulation (min)	100
Number of users	100
Data rate per user	10Mbps
Channel capacity	1024Mb
Maximum packet weight	950Mbps
Network Topology	Mesh network with multiple access points
Frequency Band	2.4 GHz and 5 GHz
Channel Width	20 MHz, 40 MHz, 80 MHz
Modulation	802.11ac (Wi-Fi 5)
MIMO (Multiple Input, Multiple Output)	2x2, 4x4, 8x8
Antenna Type	Omni-directional or directional
Transmission Power	Adjustable based on regulatory requirements
Security Protocol	Wi-Fi Protected Access-3
Encryption Method	Advanced Encryption Standard
Authentication Method	802.1X (EAP)
Quality of Service (QoS)	WMM (Wi-Fi Multimedia)
Band Steering	Automatic selection of 2.4 GHz or 5 GHz band
Load Balancing	Exponential weight computation

4 RESULTS AND DISCUSSION

The congestion detection model was evaluated using confusion matrix presented in the figure 2 and showing the data observation in the class for congestion and non-congestion.

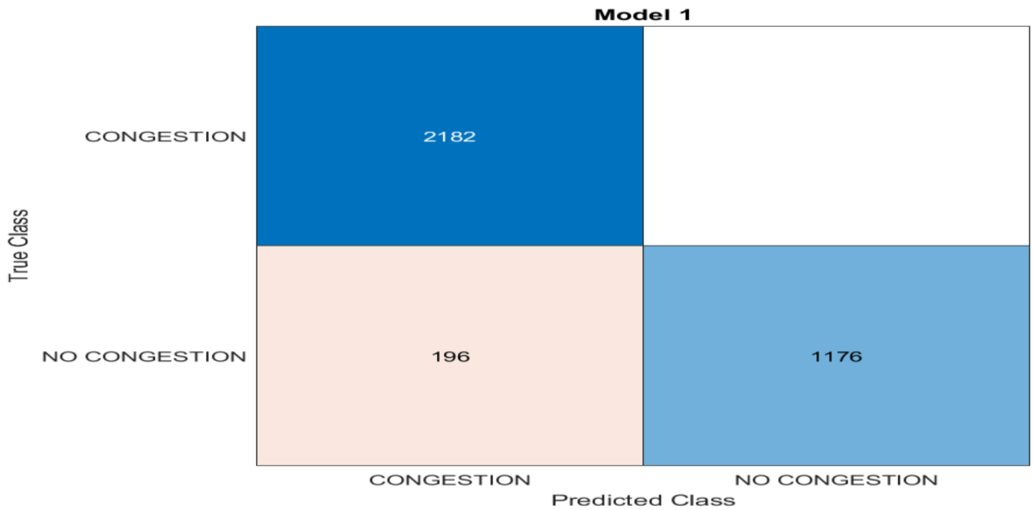

Figure 2: Result of the data distribution across classes

The figure 2 presents the data distribution across classes for congestion which is 2182 features and non-congestion which are 1372 features. The results showed that the overall features of congestion used to test the model was correctly predicted, while in the case of non-congestion, out of the 1372 features of non-congestion, 1176 was correctly predicted as non-congestion, while 196 was correctly predicted as congestion. To measure the TPR and FNR, the figure 3 was reported.

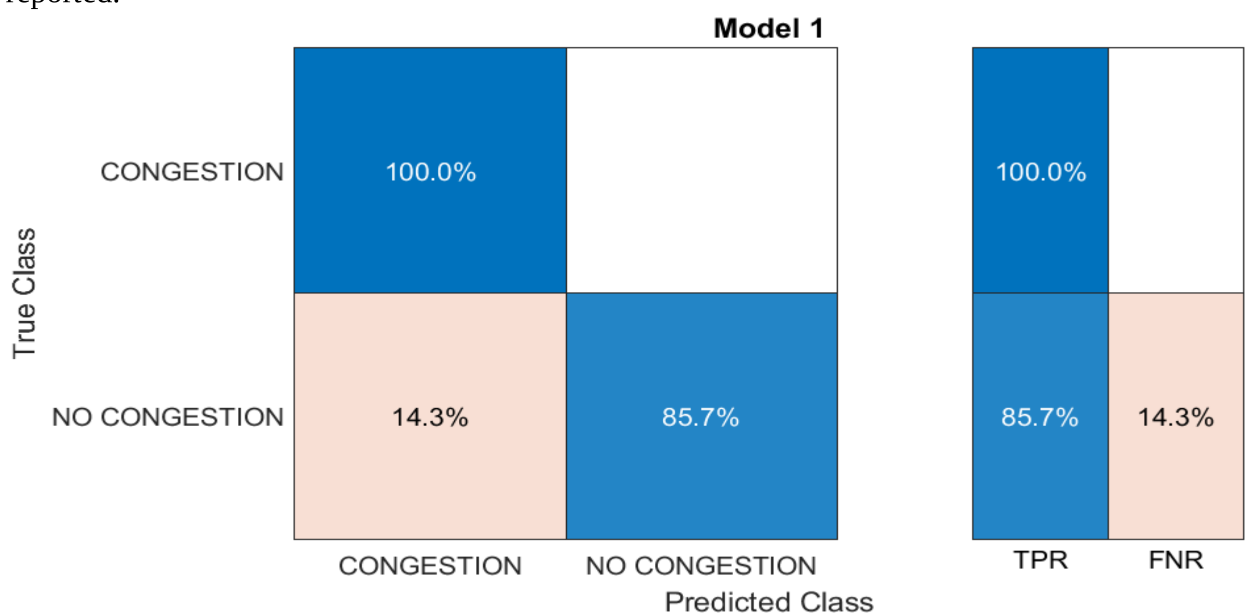

Figure 3: TPR and FNR of the congestion detection model

The figure 3 showed that the model was able to correctly predict congestion with 100% TPR, while in the case of no congestion, the TPR reported 85.7% which implied that 14.3% of the data was misclassified. This result showed that while the model was able to correctly classify congestion and non-congestion with high success rate, the model was best in predicting congestion on the network and this is very good. To evaluate the Positive Predictive Value (PPV) and False Discovery Rate (FDR), the figure 4 was presented.

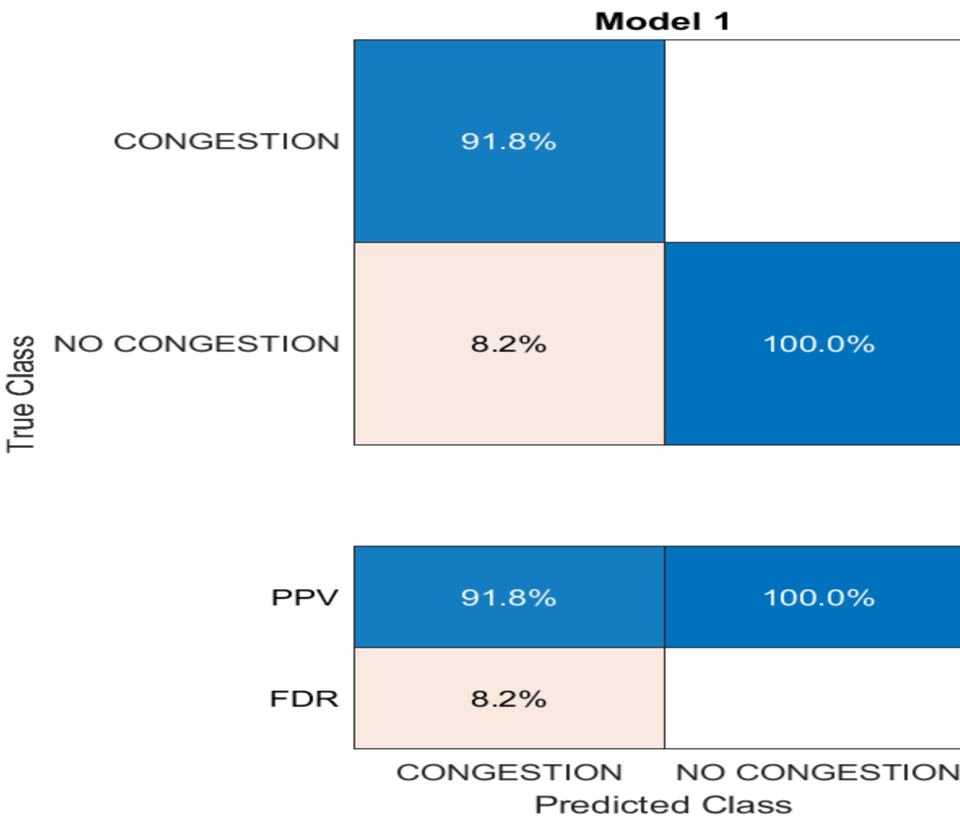

Figure 4: PPV and FDR results

The figure 4 presents the PPV and FDR results of the congestion detection model using MLNN. From the results, it was observed that the PPV recorded 91.8% for congestion detection and 100% for non-congestion detection. This implied that the model was able to positively predict the network behavior and detect when there is congestion and when there is no congestion. In the same vein, the FDR of the model was evaluated to determine the rate of false alarm. The results showed that when there is congestion, the model reported 8.2% false alarm, and when there is no congestion, the model reported 100% collect prediction. In addition, the accuracy of the model generated reported 98%, which is very good and implied that the model was trained excellently and recorded good classification performance for congestion. In the next result, the relationship between the TPR and FPR was valuated using the area under the curve as shown in the figure 5;

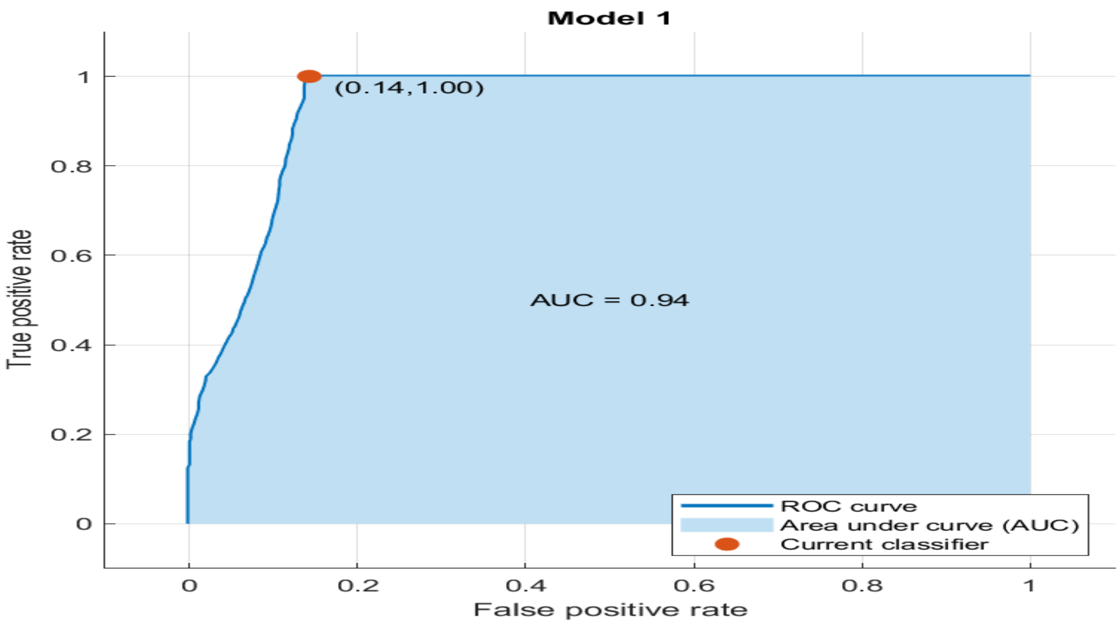

Figure 5: AUC results of MLNN model

The figure 5 presents the AUC of the MLNN. From the results, it was observed that the MLNN recorded an AUC value of 0.94. These results implied that the model was able to correctly identify and analyze the network behavior in diverse condition and identify when there is congestion correctly and when there is no congestion.

5.1 Result of the Congestion Control Performance

This section presented the results of simulation performance on the Wi-Fi network using the congestion detection and control model developed for quality-of-service optimization. To evaluate the model, 100 users, with each transmitting 10mb of packet per seconds was used to simulate congestion on the network and at the same time, the effectiveness of the congestion detection and control system was monitored. From the results, in figure it was observed that when congestion was induced on the network, and tested, the neural network algorithm trained for congestion detection was able to correctly detect the congestion problem on the network and then initialize the control model which computed the exponential weight sum of the Wi-Fi network load at every time using equation 4 and then compared with the set threshold for congestion confirmation as shown in the figure 6, to detect congestion.

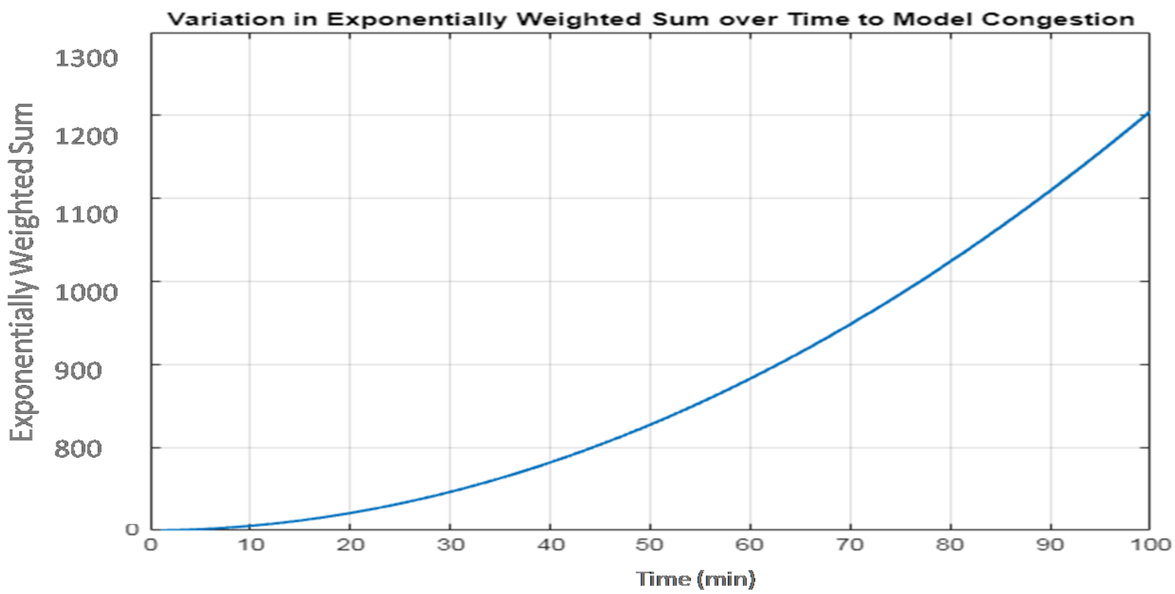

Figure 6: Congestion management result through EWS computation

The figure 6 presents the congestion management process with the EWS computation, which measured the weights of the network condition at a particular time. From the result it was observed that over time, the weight of the network load size has increased which indicated a confirmation of congestion, it is has exceeds the maximum packet size set for the network to maintain quality of service. At this point, the control parameter as in equation 5 as applied to adjust the acceptance rate of incoming packet, while monitoring the network until quality of service is restored. The impact on throughput was evaluated and reported in the figure 7.

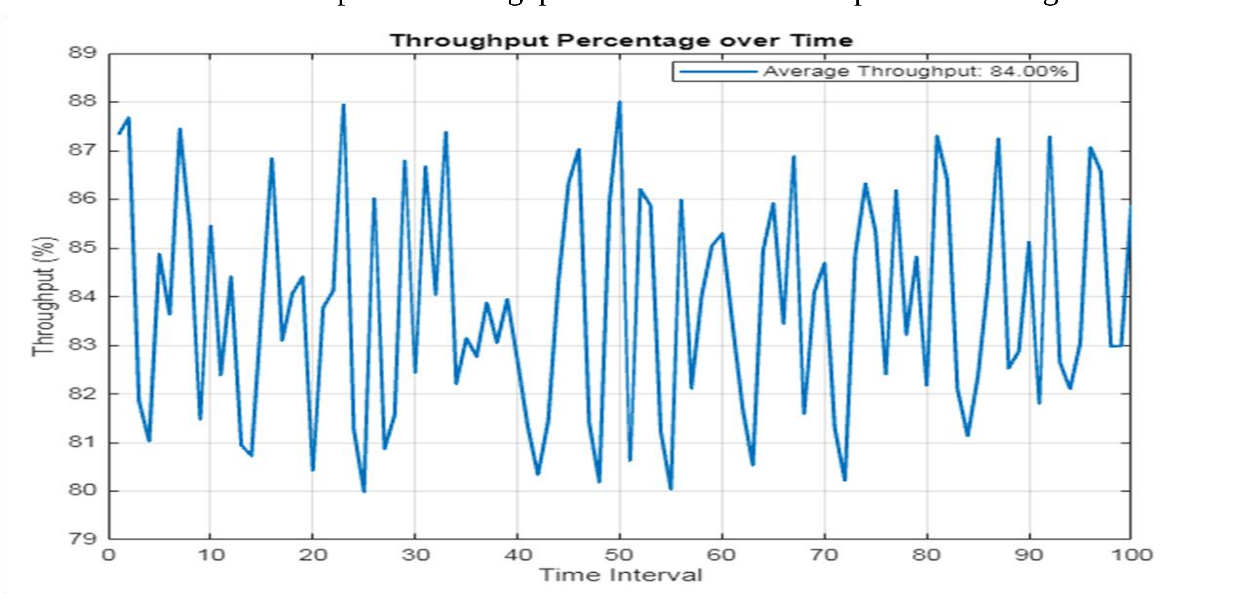

Figure 7: Throughput result on the network

The figure 7 presents the throughput performance on the network. From the results, it was observed that while the user activities on the network impacted on the throughput, which is normal by the way, the quality of throughput was maintained between 80 % and 88%, with an average throughput recording 84%. The reason was because, while the user activities keep increasing on the network, the neural network-based congestion detection model through network analysis, detect congestion and notify the control model which computes the EWS of the network to confirm the congestion problem and the control the acceptance rate of incoming packets until quality of service is achieved.

5 CONCLUSION AND RECOMMENDATION

This study has demonstrated the efficacy of integrating artificial neural networks into the exponential weight sum congestion control model for enhancing quality of service within the UNIZIK campus network. By enhancing the traditional congestion control mechanism with neural network capabilities, this research contributes to the field by offering a more adaptive and responsive approach to network traffic management. The application of neural networks enables the system to learn and adapt to changing network conditions in real-time, ultimately leading to improved QoS for network users. The findings highlight the potential of this approach to effectively manage network congestion and optimize resource utilization, ultimately improving the overall user experience. Moving forward, the insights gained from this research can inform the development of more robust and adaptive network management systems, with implications for both academic research and practical network deployment.

5.1 Recommendation

Based on the findings of this study, it is recommended that further research be conducted to explore the scalability and generalizability of the proposed approach beyond the UNIZIK campus network. Additionally, efforts should be made to evaluate the performance of the integrated model under different network conditions and traffic scenarios to assess its robustness and effectiveness in diverse environments.

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