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# ARTIFICIAL NEURAL NETWORK MODEL FOR TRACKING AND DETECTION OF DYNAMIC HETEROGENEOUS CONGESTION IN BANKING NETWORKS

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**Abstract -**The recent adoption of a cashless policy in Nigerian banks and customers increased the data transfer rate in the banking wireless network infrastructure, resulting in Dynamic Heterogeneous Congestion (DHC) issues. This paper addresses DHC in banking network infrastructure by utilizing machine learning techniques to develop a model for tracking and detecting congestion. The methodology involved collecting data on DHC from the Nigerian banking area network. This data was used to train a neural network considering several hidden layer sizes, specifically 15, 20, 30, and 145 layers. The results showed that the neural network with 30 hidden layers performed the best, demonstrating superior performance compared to the others. In addition, it was revealed that whereas increasing the number of hidden layers can enhance performance, it must be carefully managed to avoid overfitting, which can occur with excessive hidden layers.

**Keywords: 5G Network; Artificial Neural Network; Machine Learning; Congestion Detection; Dynamic Heterogeneous Congestion (DHC).**

## 1. Introduction

In 2022, the Governor of the Central Bank of Nigeria reported that approximately 85% of the Nigerian Naira (₦) in circulation was held outside of banks' vaults (Ayodeji, 2022). This uneven distribution of currency contributed to several economic issues, including inflation, ineffective monetary policies, and a distorted financial market (Oluemi et al., 2022).

To address this issue, a new monetary policy was implemented on November 26th, 2022. The goal of this policy was to recover the excess cash held outside the banking system by introducing a redesigned Naira and encouraging a shift towards online banking. The policy officially took effect on February 10th, 2023 (Inwalomhe, 2023). As part of this policy, a substantial number of banking transactions migrated to online platforms, placing a heavy burden on the wireless network infrastructure responsible for managing these transactions (Metlo et al., 2021). This shift caused a significant increase in digital transactions through wireless networks. Customers increasingly accessed banking websites, used mobile banking apps, and conducted online transactions, which led to fluctuations in network traffic and resource demands, making congestion management more complex (Sudhamani et al., 2023). The variety of devices used for these transactions, along with different operating systems and connectivity modes, added to the congestion management challenges, resulting in a problem known as dynamic heterogeneous congestion (Hui et al., 2022).

Over time, traditional congestion control mechanisms, such as the Buffer-Based Congestion Avoidance Scheme, Dynamic Alternative Path Selection, Wireless Rate Control Protocol, Tuneable Reliability with Congestion Control for Information Transport, Machine Learning, and Decentralized Predictive Congestion Control (Razmara et al., 2022; Ren et al., 2017; Juang et al., 2016; Zhao et al., 2015) have struggled to manage congestion effectively. This is due to the constantly evolving patterns of online transactions and the diverse characteristics of the devices involved. As a result, online banking transactions continue to face significant challenges, highlighting the need for urgent and innovative solutions. This study proposes the development of a proactive technique for real-time congestion detection, addressing the changing nature of congestion and the diverse network components. By tackling these issues, the study aims to enhance performance, reliability, and quality of service in wireless networks, improving the overall user experience and ensuring the seamless operation of various applications and services in the banking industry. The contributions of this paper include:

i. Tracking and detection of dynamic heterogeneous congestion in 5G banking network infrastructure.
ii. Experimentation with different neural network architectures, focusing on hidden layer optimization.
iii. Identification of the most suitable model for managing dynamic heterogeneous congestion (DHC) in 5G networks.

## 2. Literature Review

Razmara et al. (2017) developed a Buffer-Based Congestion Avoidance Scheme for banking networks. They employed buffer management techniques to dynamically adjust buffer sizes based on network load. The results showed reduced packet loss and improved network stability during congestion. However, the approach had limited effectiveness under extremely high traffic conditions and struggled with rapid traffic spikes. This method provided stability but was less effective in highly dynamic and varied network conditions due to its static buffer size adjustments. Zhao et al. (2018) proposed Dynamic Alternative Path Selection for congestion management in banking networks. Their method involved a dynamic path selection algorithm that rerouted traffic through less congested paths. This approach significantly reduced latency and improved throughput during peak times. The primary limitation was the increased complexity of path calculations with network size, leading to higher computational overhead. While this approach improved the management of dynamic congestion through real-time path adjustments, the complexity limited its efficiency in larger, heterogeneous networks.

Juang et al. (2019) introduced the Wireless Rate Control Protocol for congestion control in banking networks. They utilized rate control mechanisms to adjust the sending rate of data packets based on real-time network conditions. This method enhanced data transmission efficiency and reduced congestion instances. However, it struggled with real-time adjustments in highly dynamic network environments. Ren et al. (2020) developed the Tuneable Reliability with Congestion Control for Information Transport (TRCCIT) model. This model combined reliability and congestion control techniques to ensure efficient data transport while managing congestion. The results indicated improved data reliability and reduced congestion-related delays. The model's performance was heavily dependent on accurate network state information, which was sometimes difficult to obtain. Hui et al. (2021) investigated dynamic heterogeneous congestion in banking networks. They used a combination of machine learning techniques to predict and manage congestion based on network traffic patterns. This approach achieved better congestion prediction accuracy and improved network performance. However, the model required extensive training data and significant computational resources for real-time implementation. Sudhamani et al. (2022) proposed a Decentralized Predictive Congestion Control model for banking networks. The methodology involved employing decentralized machine learning algorithms to predict and control congestion at the network edge. This approach enhanced network scalability and reduced congestion. The primary challenge was coordinating predictions across different network nodes, which faced some difficulties. Metlo et al. (2023) developed a neural network-based model for congestion tracking and detection in 5G banking networks. They trained an artificial neural network using parameters such as throughput, latency, packet loss, and load factor, with various hidden layer sizes.

The results revealed that the model with 30 hidden layers performed the best, improving detection and tracking of congestion. However, there was a risk of overfitting with too many hidden layers and a dependency on diverse training data. This model demonstrated effective management of dynamic congestion with real-time network metrics but required careful tuning to avoid overfitting and handle heterogeneous conditions effectively.

## 3. Methodology

The methodology applied for the development of the congestion detection model begins with the collection of network behavior data during periods of congestion in the bank. This data is then imported into an artificial neural network (ANN) model, which is trained using the back-propagation optimization algorithm. The trained model aims to accurately detect congestion in a 5G network. To evaluate the performance of the model, various performance metrics will be used to assess its effectiveness in predicting congestion. These metrics will determine the success of the congestion prediction model. The model will undergo validation through experiments involving different hidden layer sizes, and the results will be thoroughly analyzed to ensure robustness and accuracy.

### 3.1 Data Collection

The data for this study was collected from the 5G network infrastructure at a commercial bank in Enugu State, Nigeria. The data collection was focused on the quality assessment of the operational 5G network considering the routing device which is the core element of the network structure responsible for coverage capacity, resource allocation and performance of the data network used within the bank. The routing system was modelled using the traffic-based congestion management scheme.

The network traffic data for the system was requested from MainOne Limited, the company responsible for maintaining the banking network and possessing records of network behaviour over time. The data collected spans the dates of August 18th, 20th, and 22nd, 2023, covering banking operation hours from 7 AM to 4 PM. The parameters considered for data collection included load utilization factor, data uplink, packet loss, throughput, and latency. During data analysis, operation time, peak congestion periods, and off-peak periods were also considered. Packet type data was collected and sampled every 30 minutes during banking operation hours, with the load factor determined based on the maximum site capacity of 1024 Mbps per second.

### 3.2 Artificial neural network

Feed-forward Neural Network (FNN) is made of neurons, weights, bias, activation function, and interconnection of layers which formulated the network architecture as depicted in the figure 1.

Where $X_n$ presents the n number of neuron, $P_p$ is the number of hidden layers, Y is the output of the neural network. To activate the neuron, hyperbolic tangent activation function (Sandeep, 2020; Idam et al., 2022) was applied and the output is presented in equation 1.

$$Y = f(b + \sum_{p=1}^{n} X_n w_i) \qquad 1$$

Where w is the weight, b is the bias function, n is the number of neurons, while p is the hidden layers, X neurons, and f is the activation function. The equation 1 presents a model of a simple neural network structure, which was trained in this research for the detection of congestion.

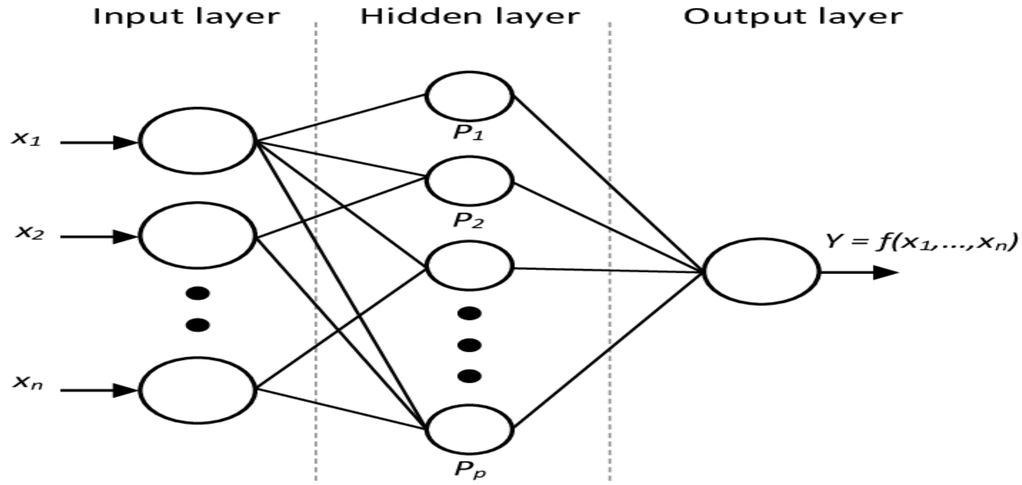


**Figure 1: Architectural Model of the neural network**

The training of the neural network was conducted by importing the data into the neural network toolbox and applying the Back-Propagation Optimization (BPO) algorithm was applied to facilitate the training process. The process begins by splitting the data into training, test, and validation sets, followed by the initialization of hyper-parameters such as learning rate, momentum, weight, and bias. The BPO algorithm adjusts the weights of the neurons during forward propagation while monitoring the gradient loss for error (Obaji et al., 2022). When the error is not tolerable (i.e., approximately zero), it feeds back to the hyper-parameters and fine-tunes the values to reflect on the loss function and minimize the error until convergence. Once convergence is achieved, training stops and an intelligent congestion tracking and detection model for the 5G network is generated. To validate the model, the neural network's hidden layers were adjusted to 20, 30, and 145 neurons, respectively, and the impact on the model was evaluated. The neural network training algorithm is presented as Algorithm 1;

**Algorithm 1: Neural Network Training**

1. Start
2. Load network traffic parameters
3. Split data into training, test and validation sets (70:15:15)
4. Initialize hyper-parameters parameters
5. Set gradient loss (E) ≈1e-6
6. Begin neuron adjustment
7. Monitor gradient loss
8. For E ≈1e-6
9. Test and validate results
10. Else
11. Back-propagation
12. Apply step 6
13. For E ≈1e-6
14. Stop training
15. Generate intelligent congestion tracking and detection model
16. Stop

### 3.3 Intelligent Congestion Tracking and Detection (ICTD) Model

The ICTD model was used for the monitoring of network parameters such as throughput, latency, loses, and load utilization factor. During the banking hours, these network performances keep changing based on user behaviour, within and outside the bank that are carrying out financial transactions. These network parameters which model these behavioural changes in the 5G are identified by trained neural network model and then classified through pattern matching process to detect congestion on the network; however, when congestion is not detected, the process returns and continued in the same cycle until congestion is detected. The algorithm 2 presents the ICTD pseudocode while figure 2 presents the flow chart of the ICTD

**Algorithm 2: The Intelligent Congestion Tracking and Detection Algorithm**

1. Start
2. Parameters initialization
3. Monitor network traffic information
4. Apply the trained ICTD model
5. Initialize classification

6. For
7. Congestion classified
8. Initialize the control algorithm
9. Else
10. Return to step 3
11. End

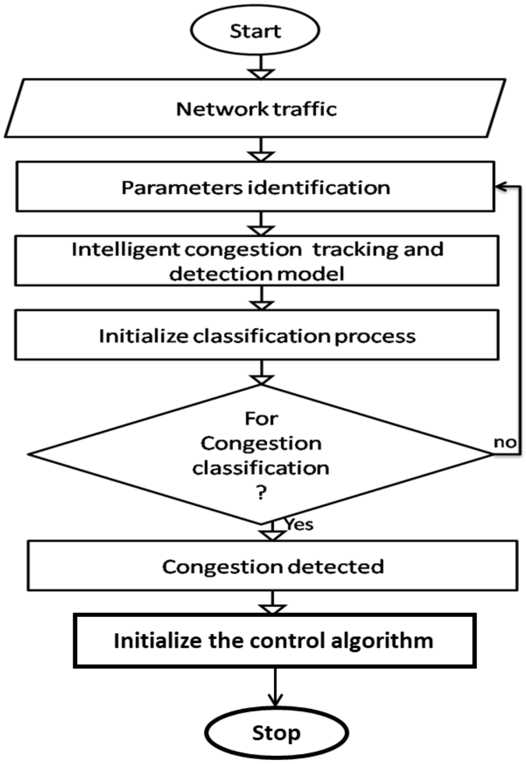


**Figure 2: The flow chart of the intelligent congestion tracking and detection model**

While the network traffic builds up due to the heterogeneity of user devices and varieties of user activities, the network traffic patterns changes continuously and the attributes which model these behaviours such as throughput, latency, loss and load utilization factor of the cell are identified by the trained ICDT and then classify through pattern matching process to detect congestion on the network and initialize the control model, but if congestion is not detected, the monitoring process returns and the cycle continues until congestion is detected. The figure 3 presents the architectural model of the intelligent congestion tracking and detection model that will be developed with the neural network.

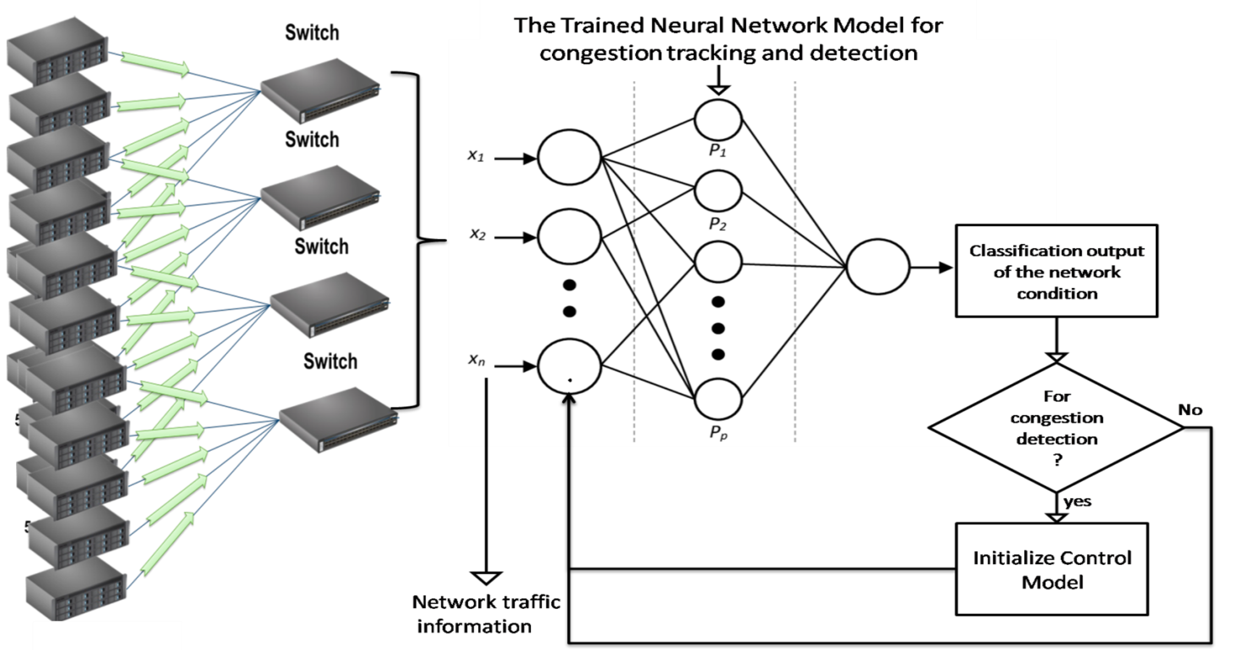


**Figure 3: Architecture of the ICTD model**

The figure 3 presents the architectural model of the ICTD used for the detection of congestion in the network. During the banking operation, the user equipment in the access layer are connected to the switches that feed the network traffic information such as throughput, loss, latency and load utilization factor to the trained neural network model for the monitoring and detection of congestion. For successful classification of congestion, the control model is initialized to balance the load, else the process continued in the same cycle until congestion is detected and control.

## 4. System Implementation

The system was implemented in a 5G network distributed layer component using MATLAB. To achieve this, the neural network toolbox was used to train the neural network model and generate the congestion tracking and detection algorithm. The model was evaluated using key performance metrics such as, RMSE, MAE, MSE and $R^2$. The modelling implementation for the three proposed neural network architectures are in the figure 4 to figure 6 using MATLAB environment.

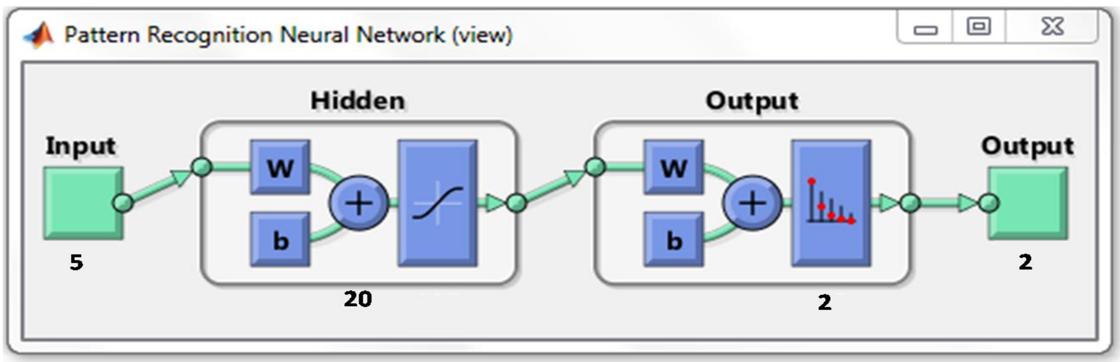


**Figure 4: Neural network model in MATLAB with 20 hidden layers**

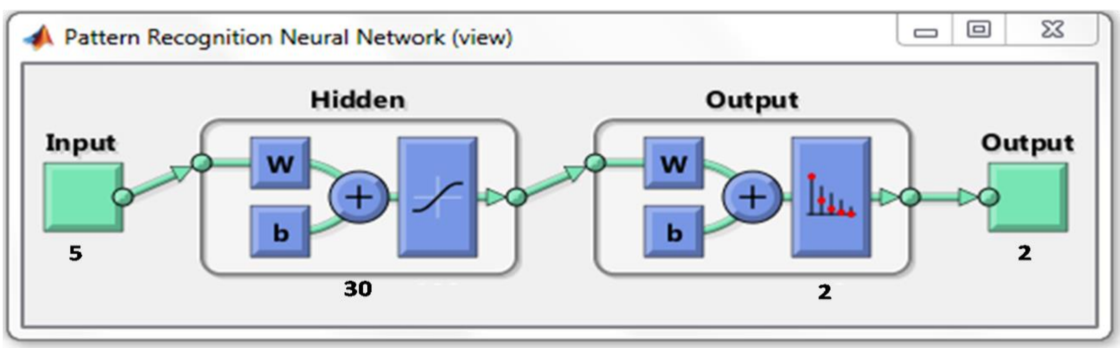


**Figure 5: Neural network model in MATLAB with 30 hidden layers**

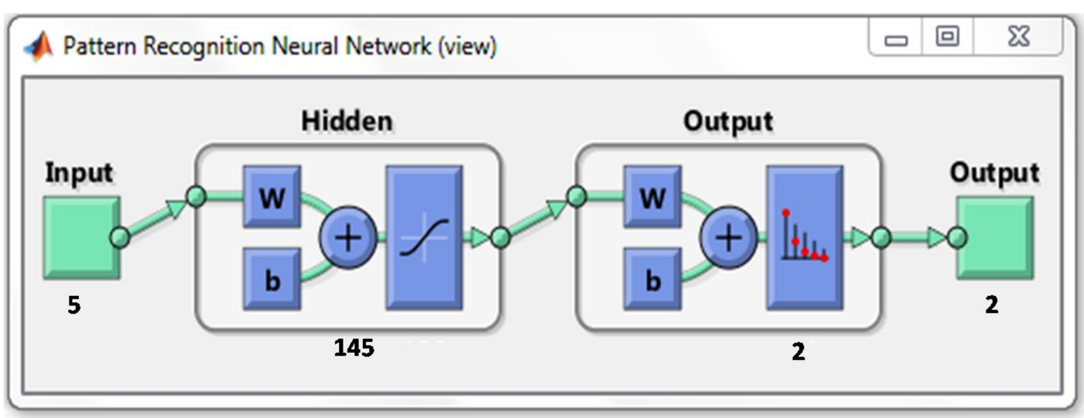


**Figure 6: Neural network model in MATLAB with 145 hidden layers**

The figure 4 to figure 6 showcased the results of the neural network implementation with three different hidden layers, using Matlab environment.

### 4.1 Performance Evaluation Metrics

These metrics RMSE, MAE, MSE and $R^2$are central to understanding the neural network model performance in regression analysis, providing insights into efficiency of the congestion tracking and detection process.

**a. Root Mean Squared Error (RMSE)**

RMSE is the square root of the mean of the squared differences between the predicted and actual values. It measures the standard deviation of the prediction errors, indicating how far, on average, the predictions are from the actual outcomes. The model is presented as equation 2.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad 2$$

Where $y_i - \hat{y}_i$ is the error difference between actual value and predicted value in $i^{th}$observation, n is the number of data samples.

**b. Mean Squared Error (MSE)**

MSE is the mean of the squared differences between the predicted and actual values. Like RMSE, it measures the quality of a model. The equation 3 presented the model of the MSE.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad 3$$

**c. R-Squared ($R^2$)**

$R^2$ is the coefficient of determination, a statistical measure that represents the proportion of the variance for the dependent variable that's explained by the independent variable (s) in a regression model. The equation 4 presented the $R^2$.

$$R^2 = 1 - \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad 4$$

**d. Mean Absolute Error (MAE)**

MAE is the mean of the absolute differences between the predicted and actual values. It provides a linear score indicating how close predictions are to the actual outcomes without indicating the direction (under or over-prediction). The equation 5 presented the MAE model.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad 5$$

## 5. Results

This section discusses the results of the neural network algorithm trained as a congestion tracking and detection model. To evaluate the model, RMSE, MSE, R-square, and MAE were utilized to assess its performance. This was done to ensure the model's performance is reliable and capable of detecting and tracking congestion before being deployed in the case study system. The Table 1 showcased the performance of the neural network training.

**Table 1: Result of neural network training with 15 hidden layers**

| Parameters | Results |
|---|---|
| RMSE | 0.000963 |
| MSE | 9.28E-07 |
| R-Squared | 0.999986 |
| MAE | 0.00079 |

The table 1 indicates a high performance of the neural network model in its training and validation phase. The RMSE and MAE values are notably low (0.000963 and 0.00079, respectively), suggesting minimal deviation between the model's predictions and the actual values. This is further reinforced by the MSE (9.28E-07), which, being the square of RMSE, confirms the small magnitude of errors. The R-Squared value of 0.999986 is near perfect, implying that the model explains virtually all the variance in the dependent variable, making it highly effective at predicting outcomes of congestion in the 5G network. Overall, these metrics collectively suggest that the model is highly accurate, with very tight error margins. To validate the results, the neural network was trained again considering different hidden layers of 20; 30 and 145 respectively and measured using the metrics in table 1 and the results presented in table 2.

The results in the table 2 present the training performance of the neural network for congestion tracking and detection using different hidden layer sizes. The results showed that while the hidden layers increased from 20 till 30 layers, the neurons performance also increases, however when the hidden layers were increased to 145, the neurons recorded overfitting problem with is evident in the MAE as despite the neurons recoding good RMSE and MSE, the R and MAE results was poor. The result showed that while increasing the hidden layer of neural network can improve the performance, it is also necessary to control the layer size as to address issues of over-fitting. The validation of the model was presented using comparative analysis in the figure 7 considering MSE, MAE in figure 8, RMSE in figure 9 and R-square in figure 10 respectively.

**Table 2: Result of neural network training with 20; 30; 145 hidden layers**

| Parameters | Results with 20 layers | Results with 30 layers | Results with 145 layers |
|---|---|---|---|
| RMSE | 0.000463 | 0.000017 | 0.00019 |
| MSE | 5.12E-07 | 1.04E-08 | 9.28E-07 |
| R-Squared | 0.999988 | 0.999998 | 1.000000 |
| MAE | 0.00065 | 0.00042 | 1.1200149 |

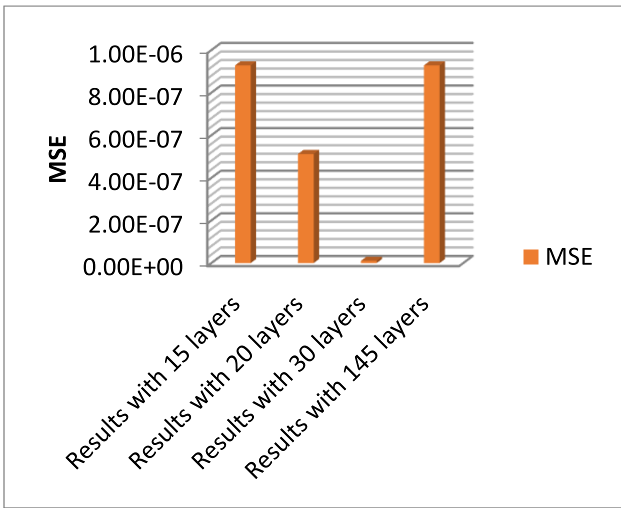


**Figure 7: Comparative MSE results**

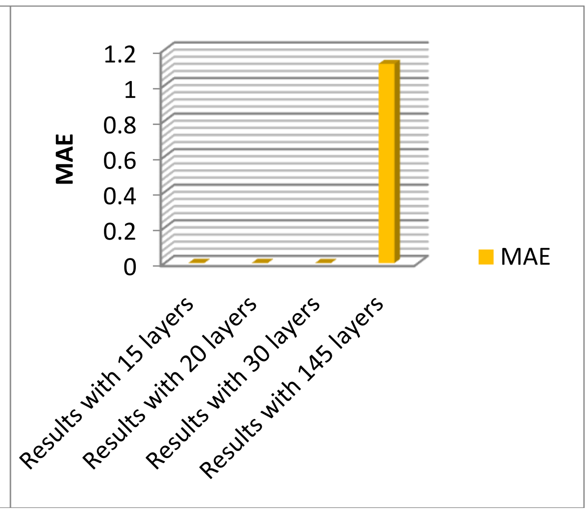


**Figure 8: Comparative MAE results**

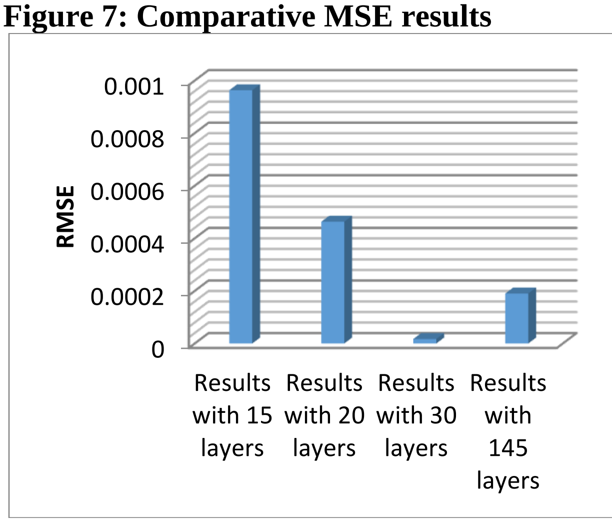


**Figure 9: Comparative RMSE**

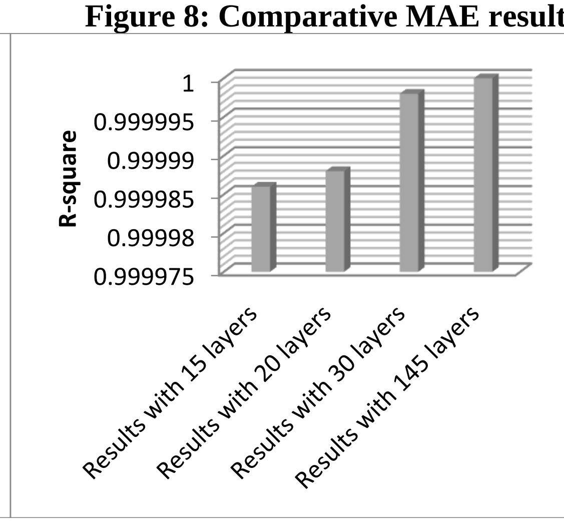


**Figure 10: R-square analysis**

The figure 7 to figure 10 compared the results of the neural network algorithm used for the detection of congestion in 5G network. From the results it was observed that the trained network with 30 layers was the best as it recorded the best results when compared with the others.

## 6. Conclusion

This study developed a dynamic and heterogeneous congestion detection model for banking network infrastructure using a machine learning approach. The model utilizes a trained artificial neural network (ANN) to track and detect congestion in 5G networks. Comprehensive testing with various neural network architectures revealed that a configuration with 30 hidden layers achieved the best performance. This configuration provided the best balance between accuracy and computational efficiency, while mitigating the risk of overfitting.

**7. Contribution to Knowledge**

This study makes significant strides in network management and congestion detection by employing artificial neural networks (ANNs) to address congestion in complex and dynamic environments. It identifies the optimal neural network architecture for real-time congestion detection, highlighting the crucial role of hidden layers in improving model accuracy. The model demonstrates robustness by adapting to various network conditions and holds promise for applications beyond the banking sector.

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