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EXPERIMENTAL MODELING OF FEED FORWARD NEURAL NETWORKS FOR OUT OF STOCK PREDICTION: A COMPARATIVE HIDDEN LAYER APPROACH

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Abstract
It is always not a pleasant experience when a customer comes to a commercial enterprise to purchase a product and that product is not available. To solve the problem, this paper presents an out-of-stock (OOS) prediction model. Achieving this aim involves methodologies such as data collection from OOS records, then data processing using standardized techniques such as imputation for replacement of missing values, Chi-square for feature selection, and principal component analysis (PCA) or feature transformation, respectively. The processed data were applied to train a neural network architectures varied with five different hidden layers, and the results obtained were evaluated and validated through comparative analysis. Findings showed the modeling of neural networks with increased depth of neurons has a great impact on the performance of OOS prediction models; however, one has to be careful in the modeling to address issues of overfitting.

Keywords: Feed forward neural network, hidden layer, Out of stock, MSE, Regression

1. INTRODUCTION

Out-of-stock (OOS), according to Giacona and Chamas (2023), is the unavailability of a product upon customer request. Over the years, these issues have continued to attract research attention with a view to developing a reliable solution that can predict when a particular stock is running out and hence facilitate immediate restocking. Andaur et al. (2021) revealed that due to the issues of OOS, the annual loss of revenue globally amounts to 984 billion dollars, negatively impacting revenue and profitability, business sustainability, and future customer patronage. Recently, machine learning algorithms have continued to dominate the literature in the scientific community on approaches to help solve this problem of OOS through prediction models, particularly using artificial neural network (ANN) algorithms as the most popular choice of training algorithm. ANN, according to Ebere et al. (2021), is a machine learning algorithm that is biologically inspired by the human brain and has the ability to learn complex patterns and solve both classification and regression problems. In the context of this study, ANN has been applied by many researchers to predict OOS in supermarkets.

For instance, Ahakonye et al. (2024) applied the rectified linear unit activation function in modeling Multi-Layered Perceptron (MLP) and trained with inventory data of stocks to generate

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a prediction model for OOS in the manufacturing industry, while Vidal et al. (2022) improved the ANN with a genetic algorithm to develop a stock-keeping unit model. Similarly, Guan et al. (2022) applied the particle swarm optimization approach and the back propagation algorithm to improve the modeling of neural networks and then trained with inventory data of stocks while generating a model for inventory management. Hajeb and Banafi (2022) also used the ANN technique for the prediction of inventory management efficiency. The goal of this research is to create a model that can forecast inventory management effectiveness, assisting creditors, real and potential investors, and other stakeholders in preventing significant losses in the capital market. Chaudhary et al. (2023) applied several ML algorithms, such as random forest, linear regression, ANN, support vector machines, and reinforcement learning, for the prediction of stock inventories. While existing methods have made a great contribution to predicting OOS, there is still a challenge in determining the best neural network architecture to generate the best version of the prediction model (Uzair & Jamil, 2020; Kaloev & Krastev, 2021). Deep neural network architecture offers the potential to capture complex patterns in data and improve model performance; however, determining the optimal depth of the neurons is challenging and relies heavily on rigorous experimental validation (Czarnecki and Moj, 2023).

Therefore, this study proposes to explore various neural network architectures in developing a prediction model for OOS in a supermarket. This will be achieved by experimenting with different hidden layers and training the network with OOS data, and then data analysis will be applied to interpret the results. The study will benefit stakeholders such as supermarket owners, stock managers, manufacturing companies, and customers, among others. It will improve the profit and revenue generation of businesses and, in turn, boost the gross domestic product of the country. The primary purpose of this research will be to experiment with different hidden layers and determine their impacts on the success of OOS prediction in a supermarket.

2. REVIEW OF RELEVANT LITERATURES

Praveen et al. (2020) researched the use of machine learning technology for inventory management. The XGBoost regression model was trained with data on company product stocks to generate a model to forecast product demand. The result of the system implementation shows that the machine learning model had a root mean squared error (RMSE) score of 0.6778 with week 3 data and an RMSE of 0.7015. Vidal et al. (2022) researched the use of combined fuzzy multicriteria methods such as genetic algorithms and artificial neural networks for decision support frameworks in inventory management. In order to support the Maintenance, Repair, and Operation (MRO) inventory management decision-making process of a railway logistics operator, the study uses a decision support framework for inventory management and combines multicriteria decision-making (MCDM) and ML techniques. In order to rank and choose stock-keeping units (SKUs) based on importance and criticality, the first stage of the framework applies a hybrid MCDM method that combines fuzzy logic with the Analytic Hierarchy Process (AHP) method. Following the identification of the most important SKUs, a second phase of the framework is presented to anticipate the demand for these SKUs using a machine learning model that combines an artificial neural network (ANN) and a genetic algorithm (GA). The result of the system implementation shows that the GA-ANN model has a mean average precision error (MAPE) rate of 14.44%. Ahakonye et al. (2024) present a study on the use of the Multi-Layer Perceptron (MLP) prediction model for the management of inventories in Manufacturing Execution Systems (MES). For the purpose of MES inventory management prediction, this study

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suggests an MLP model using the LightGBM feature selection method. Because MLP can handle non-linear correlations between variables, achieve high forecasting accuracy, adapt to changes, handle expanding datasets, and automate forecasting, it is a preferred choice for inventory management. Multiple perceptrons make up an MLP; the input layer receives data, and the output layer anticipates it. An arbitrary number of hidden layers lies between them, forming the linked core of the MLP. It provides the ability to train models in real-time and the benefit of building non-linear models. Three tightly stacked layers, each having 100, 50, and 25 neurons, make up the MLP module. ReLU activations are employed in every dense layer. There is a single neuron with sigmoid activity in the last dense layer. The system's output indicates that the model produced a regression of 0.5099, an MSE of 0.1225, a root mean square error (RMSE) of 0.3504, and a mean absolute error (MAE) of 0.2331. Ferretti and Marchi (2024) researched the application of Q-learning for inventory management. The evaluation of a machine learning model based on reinforcement learning, which enables machine-level inventory optimization and enhances system ordering and inventory management, is presented in this research. This study's objective is to assess the best replenishment strategy utilizing the reinforcement learning model-based Q-learning algorithm. In addition, the overall cost, which is determined by including the costs for backorders, inventory holding, and order issuance, is used to gauge success. The order and inventory management problem must be formulated as a reinforcement learning (RL) model in order to be addressed by the machine learning process. When the Q-learning model is applied to a real-world industrial scenario, the overall cost is reduced by 22.22%, which is a reasonable decrease in inventory expenses when compared to the standard inventory policy. Guan et al. (2022) researched the use of the Improved Particle Swarm Optimization-based Back Propagation Neural Network (IPSO-BPNN) algorithm for the optimization of inventory management in the green supply chain. The purpose of this study is to improve services for green supply chain management and minimize resource waste in supply chain inventory management. Initially, the ecological environment is used to examine the key technologies of intelligent and green supply chains. Subsequently, the PSO algorithm is refined by the incorporation of the speed mutation operator and the adaptive enhancement of the learning factor. It is then used in the BPNN's training and learning process. Initializing the particle's dimensions, size, velocity, and position is the first step in the system's flow. Next, particle fitness values are calculated and compared to the rest to select a better value. Finally, the system determines whether the error condition is satisfied and produces the maximum number of iterations. If the previous step is not satisfied, the particle's position and velocity are updated. Finally, the optimal solution is obtained. The findings demonstrate that while training a single BPNN model, significant mistakes would be produced. The error of BPNN optimized by IPSO is 0.0163, but the final error of BPNN optimized by the conventional PSO method is 0.0259. Overall, while these studies have made a great contribution to improving OOS or inventory management, there is a need to provide a deeper understanding of how the depth of the neural network affects the model, and this will be addressed in this study by exploring different neural network architectures and comparing and evaluating their performance.

3. METHODOLOGY

The methodology used for the study are data collection of OOS reports for past 7 years, then data processing using key techniques such as visualization, feature selection, feature transformation and then training 10 separate neural network algorithm, to generate a prediction model for OOS.

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To evaluate the model, comparative analysis was performed and insights on how the depth of neural network affects model performance was revealed.

3.1 Data collection

The data used for this study is the OOS report information collected from shop-rite mall, Enugu, State, Nigeria. The sample size of data collected is 221,000 recorded between July 2018 and may 2023, considering 57 different products grouped across 8 classes as shown in the data description Table 1.

Table 3.1: Data description of the Out-of-stock dataset

Variables	Data type	Data description
Sale channel	Categorical	The channel through which the product was sold
Priority order	Integer	The priority level of the order
Quantity in stock	Integer	The quantity of the product available in stock
Unit price	Integer	The price of one unit of the product
Total price	Integer	The total price of the product(s) sold
Total cost	Integer	The total cost incurred for the product(s)
Total profit	Integer	The total profit generated from the product(s) sold
Sale value	Integer	The value of the sales transaction
Available stock	Integer	The quantity of the product currently available for sale
Stock status	Categorical	The current status of the stock (e.g., In Stock, Out-of-stock)

3.2 Data processing

The data processing was performed on the collected OOS records by first visualizing this data using excel software, visualization process, it was physically observed that the data has several missing values, road range of feature vector values and some attributes which are not very necessary such as sale channel, and priority order for instance. To process the issues of missing values, the mean imputation techniques (Alotaibi et al. 2023) was applied. To identify the key attributes of the dataset, the Chi-square technique (Rufai and Longo, 2024) was applied, while for feature transformation and dimensionality reduction, the principle component analysis (PCA) (Rufai and Longo 2024) was applied.

3.3 Mathematical modelling of the FFNN with different hidden layers

The neuron is a unit of computation that reads the inputs given, processes the input and gives the output in processed form. To get the output of the Artificial Neuron from the activation function, we compute the weighted sum of the inputs as; (Wesam et al., 2020)

$$v_k = \sum_{i=1}^{N} w_{ki} x_i \tag{3.1}$$

Where x_i is the neuron's input from the training dataset.
w_{ki} is the corresponding weight to the input x_i

The neuron's output is obtained by sending the weighted sum v_k as the activation function φ input that resolves the output of the specific neuron. $y_k = \varphi(v_k)$. A step function with threshold t can be used to express a simple activation as (Wesam et al., 2020);

$$\varphi(x) = \begin{cases} 1 \; if \; x \; \geq t \\ 0 \; if \; x \; < t \end{cases} \quad (3.2)$$

However, bias is most time used instead of a threshold in the network to learn optimal threshold by itself by adding $x_o = 1$ to every neuron in the network. The step activation function for the bias becomes;

$$\varphi(x) = \begin{cases} 1 \; if \, x \; \geq 0 \\ 0 \; if \; x \; < 0 \end{cases} \quad (3.3)$$

For the learning process to speed up and also adaptive learning capacity, multiple neurons are were used as a multi layered network of neurons formed by feeding the output of one neuron to the input of another neuron as shown in figure 1. The neurons are connected by a link that has a weight which represents the connection strength between each interconnected neurons. w_{ij}^{l} donates the weight for a link between unit j in layer l and unit i in layer $l+1$. Also b_i^lrepresents the bias of the unit i in layer $l+1$.

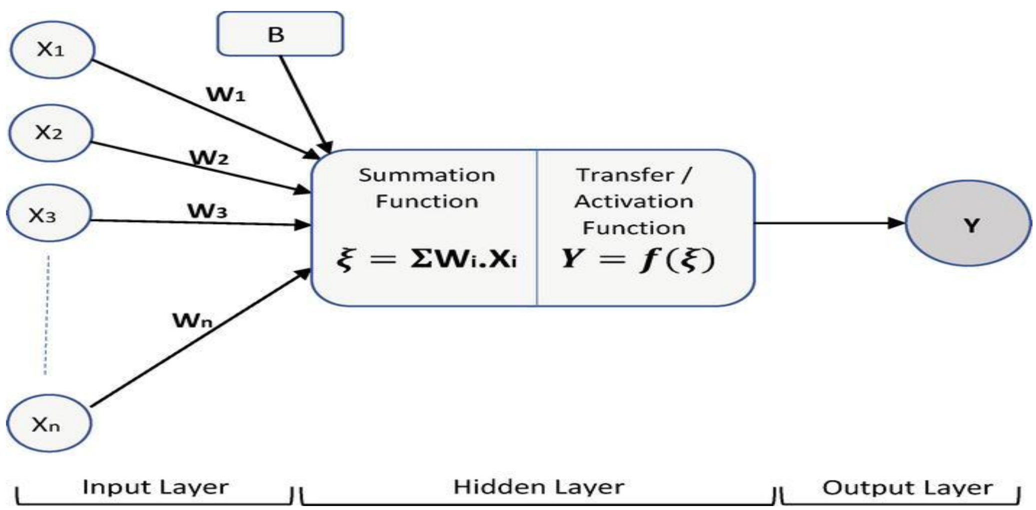

Figure 1: A simple neural network architecture (Wesam et al., 2020)

The figure 1 presents simple neural network architecture which forms the foundation of the multi layered feed forward neural network used for this study. For the FFNN modelling, let the activation of unit i in layer l be represented by a_i^l, then the input for the layer labelled as L_1 we have $a_i^1 = x_i$ for the ith input of the whole network. Other layers are given by $a_i^l = f(z_i^l)$, where z_i^l is the total weighted sum of the inputs to unit i in layer l in addition to the bias term. The activation function of the ANN with bias is presented as;

$$a_{\mathrm{n}}^2 = f(w_{\mathrm{n}1}^1 x_1 + w_{\mathrm{n}2}^1 x_2 + w_{\mathrm{n}3}^1 x_3 \dots \dots \dots \dots \dots \dots \dots . + b_{\mathrm{n}}^1) \quad (3.4)$$

Where n is the number of input classes, and b is the bias term. To determine the neural network architecture with multiple hidden layers, the equation 3.5 was applied from equation 3.4;

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$$a_i^l = f\, j w_{ij}^{l-1}\, a_{ij}^{l-1} + b_{ij}^{l-1} \qquad (3.5)$$

Where a_j^0 represents the input x_j; a_{ij}^{l-1} is the activation of the $i-th$ neuron in the $l-th$ layer. w_{ij}^{l-1} are the weights connecting neurons from layer $l-1$ to layer l; b_{ij}^{l-1} are the bias terms for the neurons in layer l; f is the activation function. For l= 1, 2, 3, 4, 5 respectively, while the number of neurons per hidden layer is 16. The architecture of the neural network with 5 hidden layers was presented in figure 2.

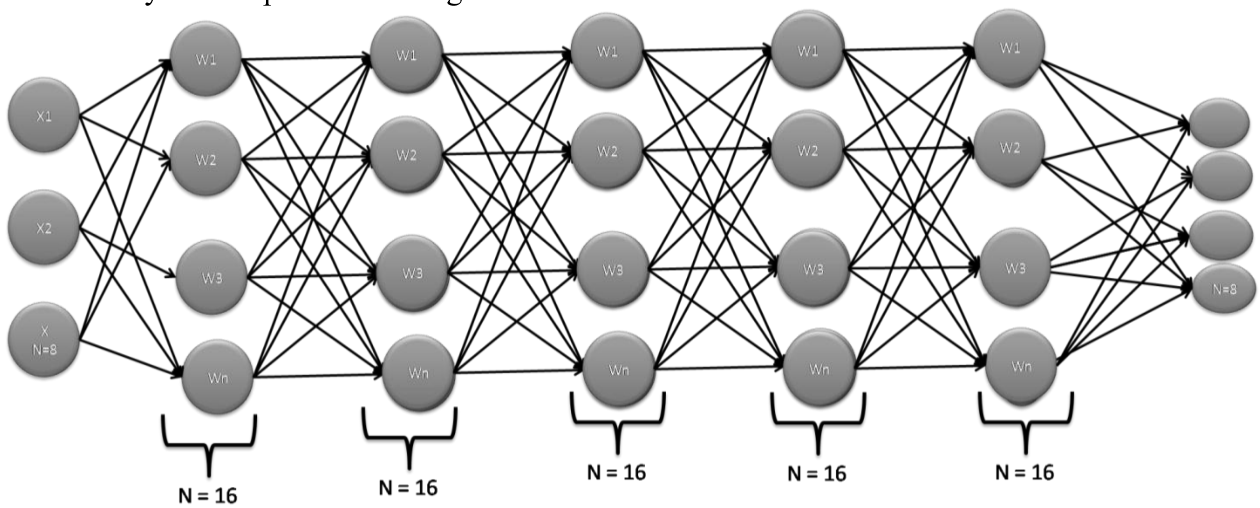

Figure 2: Architecture of the FFNN with 5 different hidden layers

3.3.6 Training of the neural network

To train the FFNN algorithm, the stock data processed was feed to the neural network algorithm inside neural network application software in Matlab, the hidden layers were selected and then back-propagation algorithm (Habor et al., 2021; Obaji et al., 2022) was applied to train the neural network as shown in the figure 3.

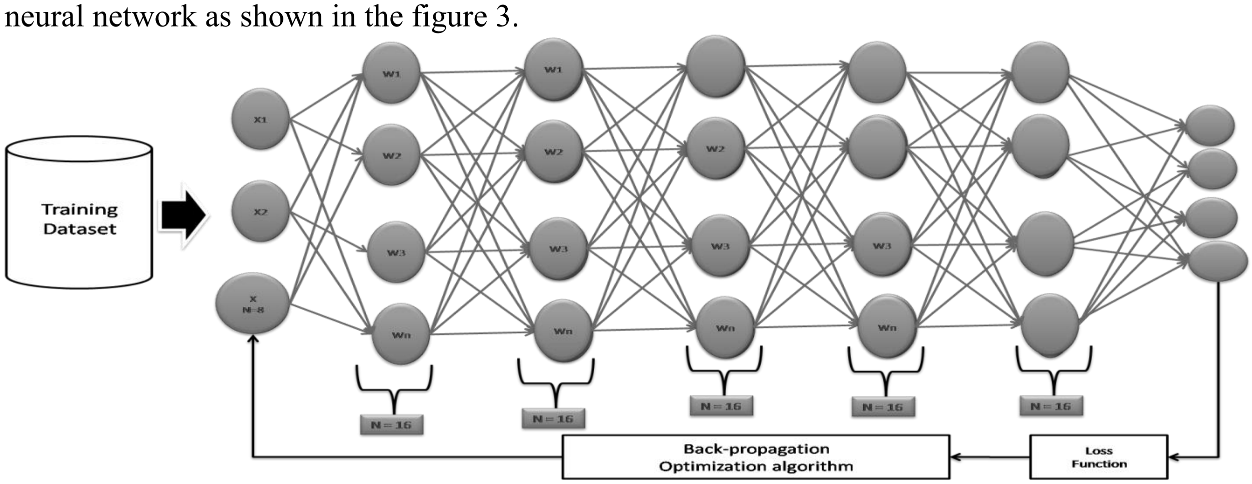

Figure 3: Training of the neural network

During each training process, the defined number of hidden layers was selected as input to configure the neural network. This was done five different times, with each training done with hidden layers varying from 1 to 5, and 16 neurons. The aim was to assess the impact of neuron depth on the network performance. Before the training, the data was splitted into training, test and validation set in the ratio of 70:15:15 in this order. The training dataset was used to train the neurons, while the test and validations et was applied to evaluate the model, and the results measured considering metrics such as coefficient of determination (R^2) in equation 3.6, Root Mean Square (RMS) in equation 3.7 and Mean Absolute Error (MAE) in equation 3.8 to evaluate the training performance of each architecture and the results are all reported in the section 4.

$$R^2 = \frac{\sum_{i=1}^{r} x_i - x_{mean}^2 - \sum_{i=1}^{r} x_i - x_i^2}{\sum_{i=1}^{r} x_i - x_{mean}^2} \tag{3.6}$$

$$RMSE = \frac{\sqrt{\frac{1}{r}\sum_{i=1}^{r} x_i - x_i^2}}{x\_\max - x\_min} \tag{3.7}$$

$$MAE = \sqrt{\frac{1}{r}\sum_{i=1}^{r} x_i - x_i^{;}} \tag{3.8}$$

Where x_i is the $i-th$ actual value obtained in the experimental part, while x_i is the $i-th$ value predicted by the network, x_{mean} is the average of the real values. The training performance was also validated using 10-fold cross validation approach in the equation 3.9.

$$\frac{1}{10}\sum_{i-1}^{i} X_i \tag{3.9}$$

Where X are the metrics defined in equation 3.6 to 3.8, i is the number of folds.

4. RESULTS AND DISCUSSIONS

This section presents the results of the neural network trained to generate the OOS prediction model. It presents all the readings reported from each model training considering the metrics in equation 3.6 to 3.8. The results reported the reading of the model after the one experiments, then 10 fold cross validation model in equation 3.9 was performed and the results after each fold was reported as shown in the table 2 and table 3 respectively.

Table 2: Cross validation of the neurons with 1, 2 and 3 different hidden layers sizes

Fold	Hidden layer 1			Hidden layer 2			Hidden layer 3		
	RMSE	R^2	MAE	RMSE	R^2	MAE	RMSE	R^2	MAE
1	0.1906	0.6042	0.1387	0.1530	0.6593	0.1043	0.1213	0.7044	0.0984
2	0.1834	0.6053	0.1342	0.1605	0.6465	0.1074	0.1227	0.6975	0.0656
3	0.1879	0.7064	0.1254	0.1574	0.6635	0.1042	0.9745	0.7483	0.0744
4	0.1863	0.7012	0.1220	0.1556	0.6667	0.1074	0.1222	0.7447	0.0658
5	0.1905	0.6046	0.1253	0.1583	0.6541	0.1050	0.1234	0.6973	0.0634
6	0.1889	0.6053	0.1294	0.1603	0.6733	0.1034	0.0982	0.7425	0.0653
7	0.1901	0.6086	0.1323	0.1635	0.6456	0.1037	0.1301	0.7144	0.0788
8	0.1916	0.6033	0.1370	0.1534	0.6763	0.1043	0.1233	0.7543	0.0680
9	0.1890	0.6094	0.1347	0.1603	0.6435	0.1062	0.0994	0.6883	0.0673
10	0.1886	0.6042	0.1333	0.1604	0.6765	0.1035	0.1342	0.6948	0.0834
Average	0.18869	0.62525	0.13123	0.15827	0.66053	0.10494	0.20493	0.71865	0.07304

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Table 3: Cross validation of the neurons with 4 and 5 different hidden layers

Fold	Hidden layer 4			Hidden layer 5		
	RMSE	R^2	MAE	RMSE	R^2	MAE
1	0.0676	0.8854	0.0764	0.0270	0.9842	0.0230
2	0.0664	0.9033	0.0805	0.0265	0.9855	0.0256
3	0.0670	0.8078	0.0821	0.0034	0.9645	0.0125
4	0.0709	0.8944	0.0787	0.0237	0.9301	0.0144
5	0.0678	0.8932	0.0797	0.0243	0.9233	0.0243
6	0.0660	0.8974	0.0757	0.0234	0.9882	0.0225
7	0.0706	0.8856	0.0809	0.0237	0.9801	0.0144
8	0.0603	0.8854	0.0811	0.2658	0.9886	0.0277
9	0.0656	0.8897	0.0709	0.0243	0.9872	0.0254
10	0.0706	0.8869	0.0766	0.0256	0.9886	0.0217
Avg.	0.06728	0.88291	0.07826	0.04677	0.97203	0.02115

The table 2 and table 3 presents the results of the neural network with one, two and three hidden layers respectively considering MAE, R-square and RMSE. From the results, it was observed that the average RMSE after 10 fold cross validation for the neural network with one hidden layer is 0.18869, R-square is 0.62525, MAE is 0.13123. For the network with two hidden layers the average RMSE is 0.15827, R-square is 0.66063, MAE is 0.10494; for three hidden layers the average RMSE is 0.20493, R-square is 0.71865, MAE is 0.07304. For the neural network with four hidden layers the average RMSE is 0.06728, R-square is 0.88291, MAE is 0.07826, and finally the neural network with five hidden layers the average RMSE is 0.04677, R-square is 0.97203, MAE is 0.02115. The summary of the results were reported in the figure 4.

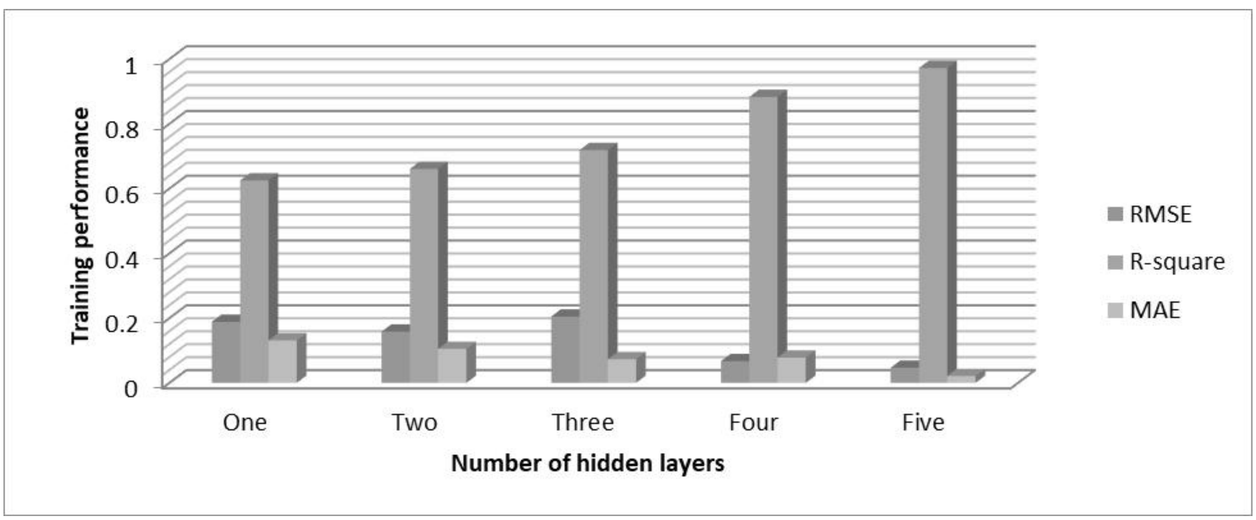

Figure 4: Summary of results

The figure 4 showed that increasing the number of hidden layers and neurons in a neural network can significantly improve its performance on OOS prediction. Going from 1 hidden layer with 16 neurons to 2 hidden layers with 32 neurons reduces the RMSE from 0.18869 to 0.15827 and increases the R^2 from 0.62525 to 0.66053. Further increasing the number of layers to 3 with 48 neurons and 4 with 64 neurons continues to improve the RMSE to 0.06728 and the R^2 to 0.88291, although the MAE fluctuates. The best performance is achieved with 5 hidden layers and 80 neurons, with an RMSE of 0.04677, R^2 of 0.97203, and MAE of 0.02115. These results demonstrate the potential for deep neural networks with multiple hidden layers to learn complex patterns in the stock data and achieve high accuracy on OOS prediction, but also highlight the need for careful experimentation to determine the optimal architecture for a given problem. Comparative analysis of the results with other state of the art algorithms was presented in the table 4 and then analyzed graphically in figure 5.

Table 4: Comparative analysis with other algorithms

Author	Technique	RMSE
Praveen et al. (2020)	XGBoost	0.6778
Hajeb and Banafi (2022)	ANN	0.353
Ahakonye et al., (2024)	MLP	0.3504
Vidal et al., (2022)	GA-ANN	0.1444
New work	Model with one layer	0.18869
	Model with two layer	0.15827
	Model with three layer	0.14943
	Model with four layer	0.06728
	Model with five layer	0.04677

The table 4 presents the comparative analysis of the new prediction models with five different hidden layers and then other state of the art algorithms. The results were graphically analyzed in figure 5.

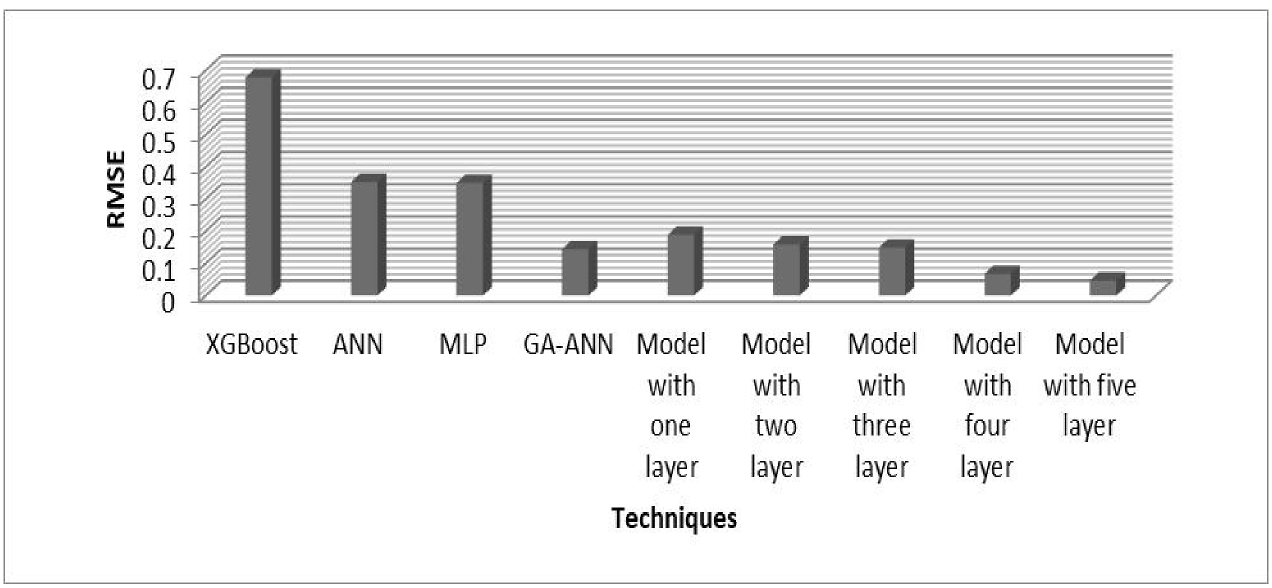

Figure 5: Comparative analysis of the existing algorithm with the new model

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From the results, the MSE performance of the new and existing algorithms was compared and it was observed that the new model with 5 hidden layers achieved the best results with lowest RMSE compared to the other algorithms.

5. CONCLUSION

This paper has demonstrated the application of diverse neural network architectures for the prediction of OOS in a supermarket. From the study, data was collected, processed and then applied to train five different neural network algorithms. The results after comparative analysis showed that increasing the layered of neural network provided great potential for model optimization, because from the results obtained, the neural network with five hidden layers recorded the best RMSE, MAE and R-square performance respectively. Finally it has to be pointed out the excess increase in the number of neural network layers might results to issues of over fitting.

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