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A Backpropagation-Based Artificial Neural Network Model for Predicting Pharmaceutical Demand

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ABSTRACT

Drug inventory management is a vital component of the healthcare system because it ensures the continuity of essential drug supply and pharmaceutical logistics efficiency. However, most pharmaceutical facilities still rely on manual forecasting methods based on historical trends that are linear in nature and unable to capture the nonlinear relationship between morbidity rates and drug demand. As a result, there is a mismatch between stock and actual demand, leading to shortages or surpluses and an increased risk of drug expiration. This study aims to develop an artificial neural network (ANN) model for predicting drug demand using a backpropagation algorithm to improve the accuracy of estimates and the effectiveness of stock planning. The data used included five years of drug usage records and the prevalence of the ten most common diseases in the Pharmacy Installation. The model was designed with a multilayer perceptron architecture (25–70–25–1) using a log-sigmoid activation function and a trainCGF training algorithm. The training results showed optimal performance with 94.2% accuracy, MSE 0.0135873, and MAPE 5.793%, accompanied by a strong correlation between the target and output (R = 0.99935). This demonstrates the model's ability to learn nonlinear patterns and produce stable and reliable predictions. The implementation of the JST model enables the optimization of drug distribution by reducing the risk of stockouts and overstocking, while also reducing waste due to expiration. This prediction system has the potential to become an adaptive and sustainable decision-making tool in public pharmaceutical supply chain management, in line with the principles of resource efficiency and sustainability of health services.

Keywords : Artificial Neural Network; Forecasting; Backpropagation; Decision Support System.

INTRODUCTION

Pharmaceutical inventory management is a critical component of healthcare systems, ensuring the continuous availability of essential medicines and supporting effective medical services. The pharmacy installation unit, as the main pharmaceutical management entity, plays a strategic role in the procurement, storage, and distribution of drugs to various healthcare facilities, including community health centers. However, inaccurate stock planning often results in either drug shortages or excessive inventory levels. Such conditions not only reduce the efficiency of pharmaceutical logistics but also cause service delays, financial losses, and increased waste due to expired medications.

In practice, most pharmacy installations still rely on manual estimation methods based on past consumption and morbidity approaches using simple spreadsheet tools such as Microsoft Excel. These traditional techniques are inherently linear and fail to capture dynamic, nonlinear relationships between disease prevalence and drug demand. Data collected from the Pharmacy Installation revealed that the average discrepancy between predicted and actual drug usage ranged from 15% to 30% per year. This forecasting inaccuracy led to 12–18% of drugs being distributed late and 8–10% of stock expiring before use due to overprocurement. Historical records further indicated strong fluctuations in the ten most common diseases—such as respiratory infections, hypertension, and dermatological disorders—which directly influenced variations in monthly drug consumption. Without an adaptive forecasting model that accounts for these epidemiological dynamics, procurement estimates tend to be desynchronized with actual needs, causing both stockouts during peak disease periods and overstocks during low-demand intervals.

The advancement of machine learning and artificial intelligence provides new opportunities for data-driven forecasting in the pharmaceutical sector. Among the available techniques, Artificial Neural Networks (ANNs) have demonstrated strong capabilities in modeling nonlinear and complex relationships between variables [1]. By learning from historical data, ANNs can generalize patterns of drug usage and anticipate future needs with higher precision. Leveraging historical drug utilization data and morbidity trends from the top ten diseases enables the development of a predictive model that assists healthcare managers in accurately determining stock levels and minimizing inefficiencies in pharmaceutical planning [2].

Although previous studies have successfully applied neural networks in forecasting applications such as energy consumption, electrical load prediction, and hospital drug usage, their implementation within public pharmacy installations remains scarce. Most existing research focuses on hospital-level data or single-variable models that overlook the multifactorial relationships among disease incidence, seasonal variations, and medication demand. Consequently, the absence of integrated, data-driven models for primary health distribution systems represents a significant research gap. Addressing this limitation requires a comprehensive approach that combines both drug usage history and morbidity data to build a more reliable and adaptive prediction system.

This study aims to design and develop a predictive model for pharmaceutical stock estimation using an Artificial Neural Network based on the backpropagation algorithm. The model utilizes five years of historical data, including records of drug utilization and prevalence rates of the ten most common diseases. Through systematic optimization of network parameters—such as learning rate, number of hidden layers, and activation functions—the model seeks to produce

accurate monthly and annual drug stock predictions that can support better decision-making in public health logistics management.

The main contribution of this research lies in establishing a multidimensional prediction framework that integrates both drug consumption and morbidity data within a single ANN-based model. Theoretically, the study expands the application of machine learning in the field of pharmaceutical logistics by demonstrating how epidemiological data can enhance predictive accuracy. Practically, the proposed system functions as a decision support tool for pharmacists and supply chain managers, improving the efficiency of procurement planning, reducing waste caused by overstocking, and preventing shortages that could disrupt essential health services. Furthermore, the model can serve as a pilot for broader implementation in government-managed health information systems.

The significance of this research lies in promoting data-driven transformation within the public healthcare sector. By integrating neural network technology into pharmaceutical management, institutions can achieve more precise forecasting, optimize financial resources, and ensure sustainable drug availability. The remainder of this paper is structured as follows: Section 2 discusses related works and theoretical foundations of neural networks and drug management; Section 3 outlines the research methodology and data processing framework; Section 4 presents the model design, training results, and validation; and Section 5 concludes with key findings, implications, and recommendations for future research.

METHOD

This study adopts an experimental quantitative design aimed at developing and validating a predictive model for drug stock estimation using an Artificial Neural Network (ANN) with the back-propagation learning algorithm. The research process involves data acquisition, preprocessing, network architecture design, model training, and performance evaluation. The workflow was implemented using MATLAB R2013a, selected for its computational efficiency and robust support for neural network modeling [3].

The methodological framework was designed to ensure the reproducibility, validity, and interpretability of the predictive results. Conceptually illustrates the methodological stages, beginning with data collection from the pharmacy information system, followed by preprocessing, feature selection, network construction, model training, and evaluation of predictive accuracy[4].

Data Preprocessing

Raw datasets were subjected to preprocessing to enhance consistency and suitability for neural network input. The following procedures were performed [5]:

1. Data Cleaning: Missing, duplicate, or inconsistent records were identified and removed. Outliers were assessed using z-score normalization and domain expert validation to maintain data integrity [6], [7].
2. Feature Selection: Variables with the highest correlation to target outputs were selected using Pearson's correlation analysis. This process reduced noise and improved model convergence. The selected features include: monthly drug issuance quantity, average drug consumption from top ten diseases, and historical trend indices over the previous 12 months.
3. Normalization: All input variables were rescaled to the range [0.1, 0.9] using Min–Max normalization to optimize ANN training efficiency and stabilize gradient updates.

4. Data Partitioning: The dataset was randomly divided into two subsets: 70% for training and 30% for testing, following the hold-out validation approach to ensure unbiased model evaluation.

Model Architecture and Network Design

The ANN model was designed based on the multilayer perceptron (MLP) structure with feed-forward propagation. The architecture was empirically optimized as 25–70–25–1, consisting of [8], [9], [10]:

a. Input layer: 25 neurons, representing encoded variables of drug name, monthly usage, and top-ten-disease-based consumption over the last 12 months.
b. Hidden layers: Two hidden layers, each optimized through a trial-and-error approach to balance model complexity and generalization ability.
c. Output layer: One neuron representing the predicted drug usage for the following month.

The model employed the log-sigmoid activation function (logsig) for nonlinearity and the trainCGF (conjugate gradient with Fletcher–Reeves updates) algorithm for efficient weight optimization. These configurations were chosen due to their superior performance in handling multidimensional medical datasets [11], [12], [13].

Model Training Procedure

Model training followed a supervised learning paradigm where historical input–output pairs guided the network to minimize prediction errors. The following parameters were applied during training [14], [15]:

a. Learning rate: 0.1
b. Goal error (target MSE): 1.25×10^{-5}
c. Maximum epochs: 50,000 iterations
d. Performance function: Mean Squared Error (MSE)
e. Training function: trainCGF

The training process iteratively adjusts synaptic weights using the backpropagation algorithm. The algorithm minimized the loss function by propagating the error gradient backward and updating weights according to the learning rate and momentum constant. Early stopping was applied when convergence criteria were met to prevent overfitting [16].

Model Validation and Performance Evaluation

After the training phase, model validation was conducted using the testing dataset. Model performance was evaluated using three main metrics [17]:

1. Mean Squared Error (MSE): Measures the average squared difference between predicted and actual drug usage values.
2. Mean Absolute Percentage Error (MAPE): Assesses prediction accuracy relative to actual values, expressed as a percentage.
3. Coefficient of Determination (R^2): Evaluates the strength of correlation between predicted and actual data.

Model performance was benchmarked against conventional forecasting methods used by the Pharmacy Installation, demonstrating that the ANN achieved a 94% accuracy rate with a lower MSE and smaller deviation from actual drug consumption patterns.

Implementation and System Application

The validated ANN model was implemented as a computational prototype capable of generating monthly and annual drug stock estimates. The system outputs numerical and graphical representations of predicted stock levels, facilitating direct comparison with real usage data. This decision-support tool enables pharmacy administrators to adjust procurement schedules proactively, thus minimizing the risks of stock shortages and overstocking. [18]

RESULTS

This study models two input variables, namely the drug name (converted into numerical form) and the ordered usage quantity, with one output variable representing the ordered usage quantity in the following month. To determine the most suitable architecture of the artificial neural network (ann), a correlation analysis was conducted between the input and output variables. The selected ann architecture is the one exhibiting the strongest relationship between the inputs and the output, as a high correlation is expected to yield better model accuracy and faster pattern recognition. The correlation strength between input and output variables was assessed using multiple correlation analysis, which serves to evaluate the degree of association and guide the selection of an effective ann configuration.

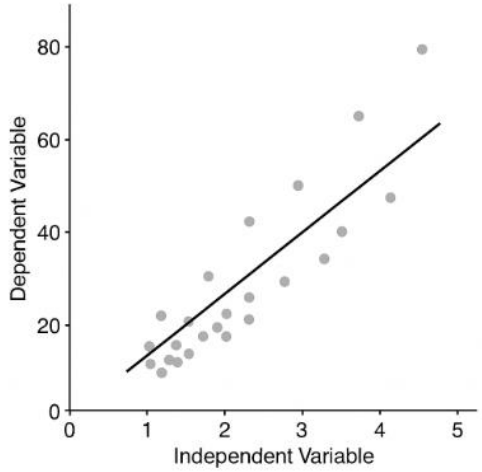

Figure 1. Regression Model Test

The results of the regression model test in Figure 1 show that the correlation coefficient (R) value of 1.131 indicates a positive relationship between the independent and dependent variables. The R Square value of 0.017 means that the independent variable is only able to explain 1.7% of the variation in the dependent variable, while 98.3% is influenced by other factors outside the model. The Standard Error of Estimate value of 93,480.591 indicates a significant deviation between the predicted value and the actual value. However, the results of the F test (F Change = 7.762; Sig. = 0.000) indicate that this regression model is statistically significant at the 95% confidence level, so it can be concluded that there is a real influence of the independent variable on the dependent variable even though its contribution is small.

An Artificial Neural Network (ANN) architecture was designed to model drug usage patterns based on historical ordering data and dominant disease types. This architecture was built by considering the number of input variables, the complexity of the relationships between parameters, and the specific output prediction requirements. The ANN model was designed using a feedforward multilayer perceptron (MLP) structure, where the learning process is performed using the backpropagation method to minimize prediction errors.

Each layer in the network has its own function. The input layer receives initial data representing various drug usage parameters, while the hidden layer processes the information nonlinearly to identify patterns of relationships between variables. Meanwhile, the output layer generates a predictive value in the form of an estimate of the amount of drug usage in the next period. The general design of the developed ANN architecture.

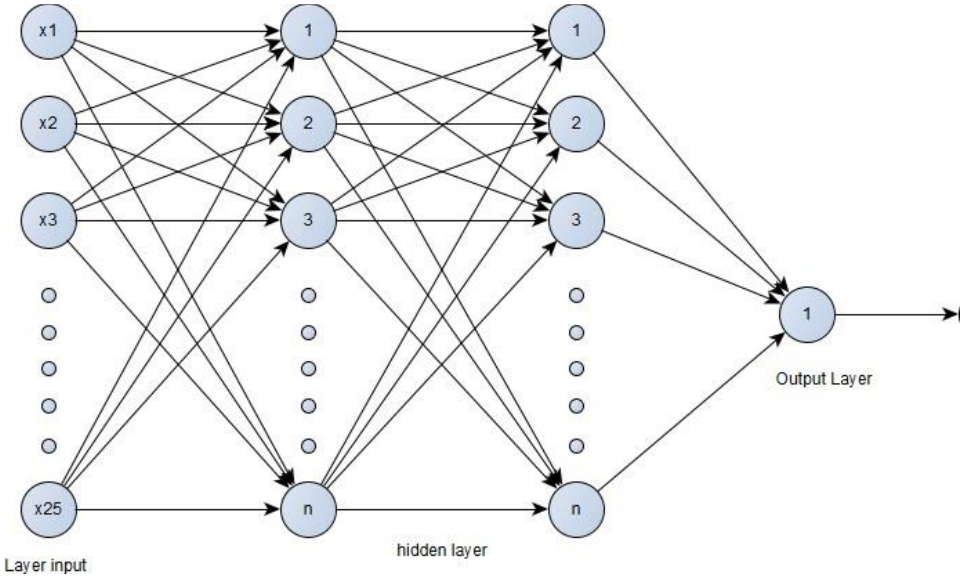

Figure 2. Developed ANN Model

Table 1. Architectural Design Model of the ANN

Parameter	Amount	Information
Input layer	25	Name Drug, amount usage drug Which in order and usage drug based on 10 most common disease.
Hidden layer	2	Amount neuron hidden layer determined by trial and error.
Output layer	1	Usage drug Which in order month next from input

Based on Figure 2 and Table 1, the developed ANN model consists of three main layers: an input layer, a hidden layer, and an output layer. The input layer consists of 25 neurons representing parameters such as drug name, the number of times a drug is ordered, and drug usage data based on the ten most common diseases. Furthermore, the hidden layer has two neurons determined through a trial-and-error approach to obtain optimal learning results with the lowest error.

Meanwhile, the output layer consists of only one neuron that generates a predicted value for drug use for the next period. This architecture is designed to balance complexity and generalization, enabling the model to make accurate predictions without overfitting. Overall, this design

demonstrates an efficient and adaptive ANN structure for processing drug use prediction data based on previous usage patterns.

Artificial Neural Network Model Training Results

The training process for artificial neural networks (ANNs) using the backpropagation algorithm aims to obtain optimal weights with minimal error by finding the minimum point in the error function. Two training approaches are recognized: the incremental method and the batch method. In the incremental method, weights are updated each time a data pattern is processed, while in the batch method, weight updates are performed after all input patterns are fed to the network. Although the batch method requires longer computation time, this approach produces a more stable and consistent learning process, reducing errors.

To accelerate convergence and improve accuracy, training parameters are set by adjusting the goal value (target error), the number of neurons in the hidden layer, and the type of training function. In this study, 510 data patterns were used for the training process with varying goal values of 0.001, 0.0001, and 1e-5, and the neuron configuration in the hidden layer was gradually adjusted (25–25–1, 30–30–1, 35–25–1, and so on) until the minimum error was obtained. The training functions used include traingd, as well as advanced combinations such as traingda, traingdm, traingdx, traincgf, traincgp, traincgb, trainrp, trainlm, trainb, trainbr, and trainbfg to determine the best parameter combination with the fastest convergence results and the smallest error rate.

Table 2. Results Of Testing Various Training Functions On The Backpropagation

Training Function	Time	Results Practice		Information
		Accuracy	MSE	
Training	06:51	79.642%	0.0058	Not yet Convergent
Training	06:59	96.748%	0.0007	Not yet Convergent
Trainingdm	06:49	80.653%	0.0058	Not yet Convergent
Trainingdx	06:57	97.321%	0.0002	Not yet Convergent
Traincgf	00:48	98,000%	0.0001	Convergent
Traincgp	00:21	98.186%	0.0001	Convergent
Traincgb	00:16	98.430%	0.0001	Convergent
Trainrp	00:06	98.292%	0.0001	Convergent
Trainlm	00:11	98.736%	0.0001	Convergent
Trainbfg	1:23:34	98.264%	0.0001	Convergent
Train	13:20	80.653%	0.0058	Not yet Convergent
Trainbr	00:19	98.154%	0.0001	Convergent

The results of testing various training functions on the backpropagation algorithm show differences in performance in terms of training time, accuracy level, and error convergence. The training functions traingd, traingda, traingdm, and traingdx did not reach convergence despite producing quite high accuracy, with a training time range between 06:49 and 06:59 minutes and MSE (Mean Square Error) values ranging from 0.0058 to 0.0002. This indicates that standard gradient descent-based training functions tend to be slow in reaching the global minimum and are easily trapped in local minimums, especially on large datasets.

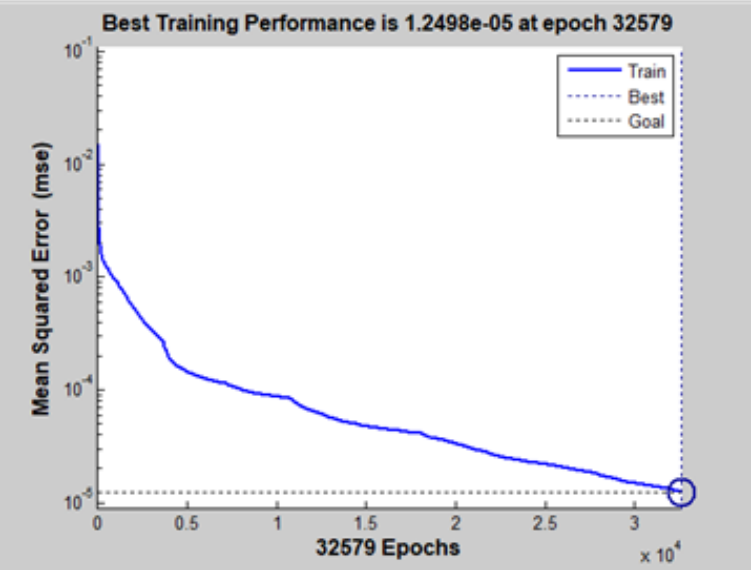

Figure 3. Mean Squared Error (MSE) Value

The Mean Squared Error (MSE) value in Figure 3 decreases significantly as the number of epochs increases, indicating that the network learning process is progressing effectively towards convergence. The best MSE value was obtained at 1.2498×10^{-5} at the 32,579th epoch, indicating a very small error rate and indicating that the model has reached optimal conditions. The consistent pattern of decreasing errors illustrates the stability of the training process without any indication of overfitting.

Overall, these results indicate that the training function and network parameters used successfully guided the ANN model to learn efficiently with minimal error. With a very low MSE, the model is considered to have good predictive ability and can be used in the testing phase with a high degree of reliability.

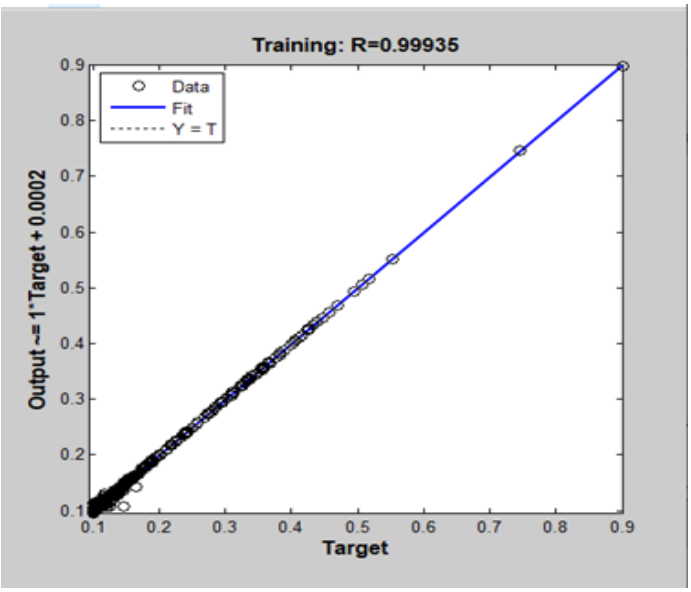

Figure 4. The Regression Plot Results

The regression plot results show that the output and target values have a very high agreement, where almost all data points are around the diagonal line Y = T, which indicates a very small level of prediction error. The correlation coefficient (R) value of 0.99935 indicates a very strong linear relationship between the target data and the model output. This means that the developed ANN model has successfully learned the data pattern very well and has a high generalization ability to the training data.

Drug Prediction Artificial Neural Network Test

The testing phase is conducted after the artificial neural network (ANN) model has been successfully trained to assess its generalization ability to new, previously unseen data. This testing aims to compare the model's predictions with the actual target data to determine the model's accuracy and reliability in predicting drug use patterns. The test data used is a portion of the dataset randomly separated from the training data to ensure objective evaluation results.

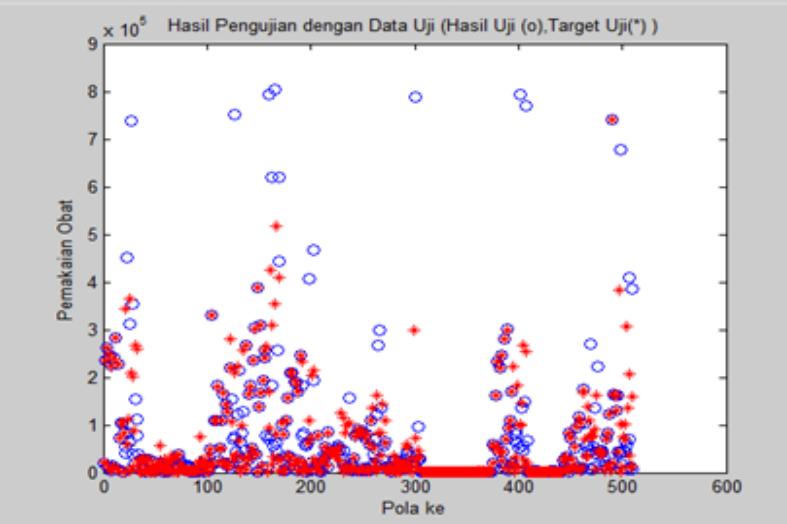

Figure 5. Test Data

The test results show that the test data (marked with blue circles) has a distribution pattern very close to the target test data (marked with red crosses). The similarity between the two patterns indicates that the ANN model is able to recognize and replicate the data characteristics well. The small variations that still appear in some data points are a form of natural deviation due to noise in the data or minor differences in the prediction results.

The relatively dense distribution of points between the test results and the target indicates that the model has a high degree of generalization and is capable of providing accurate estimates of drug use patterns. Therefore, these results confirm that the network architecture, training function, and parameters used in the training phase have produced a stable, convergent, and reliable model suitable for application in a drug need prediction system in the future.

Table 3. Error of the Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE)

Number	Drug Name	Target		Output		Error
		Normal	Denormal	Normal	Denormal	

1	DOEN tab antacid	0.12369	22000	0.12128	19719	0.00242
2	DOEN tab antacid	0.35497	236500	0.35314	234685	0.00182
3	DOEN tab antacid	0.1183	17000	0.11651	15307	0.0018
4	DOEN tab antacid	0.38225	261800	0.38274	262199	-0.0005
5	DOEN tab antacid	0.11076	10000	0.11218	11281	-0.00142
.	.	.	.	.	.	.
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505	Mefenamic Acid 500 mg	0.24478	34600	0.10624	407827	-0.40398
506	Mefenamic Acid 500 mg	0.13728	205500	0.54126	70350	0.2974
507	Mefenamic Acid 500 mg	0.32154	10000	0.02414	10706	-0.00096
508	Mefenamic Acid 500 mg	0.11076	158600	0.11172	384522	-0.24394
509	Mefenamic Acid 500 mg	0.27098	15100	0.51491	5400	0.01047
510	Mefenamic Acid 500 mg	0.11625	34600	0.10578	407827	-0.40398

The results of the calculation of the Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) values, it can be concluded that the designed artificial neural network (ANN) architecture has a good ability to recognize data patterns. The MSE value of 0.0135873 indicates that the model's prediction error rate is very small, while the MAPE value of 5.793% indicates that the average deviation of the predicted results from the actual value is within the acceptable range in the predictive model. Thus, the model accuracy level of 94.2% indicates that the network has succeeded in achieving optimal performance and is able to produce consistent and representative output to the actual data. These results prove that the developed ANN architecture design has worked effectively in carrying out the learning and prediction processes.

Implementation of ANN Model

Analysis of drug availability and utilization in the pharmacy is a key indicator in assessing the effectiveness of a hospital's logistics planning and distribution system. Proper drug inventory control is crucial for ensuring sustainable drug availability without overstocking or stockouts, which could disrupt service delivery. Therefore, evaluating the comparison between pharmaceutical inventory estimates, stock estimates based on artificial neural network (ANN) predictions, and actual usage is crucial in determining the efficiency and accuracy of the drug demand prediction system.

Figure 6 presents data on pharmaceutical stock estimates, ANN estimates, actual usage, and remaining stock from the installation and ANN results for several routinely used drugs. This data is used to measure the accuracy of the ANN model in estimating drug needs and to identify potential discrepancies between actual stock and the predictions of the implemented intelligent system.

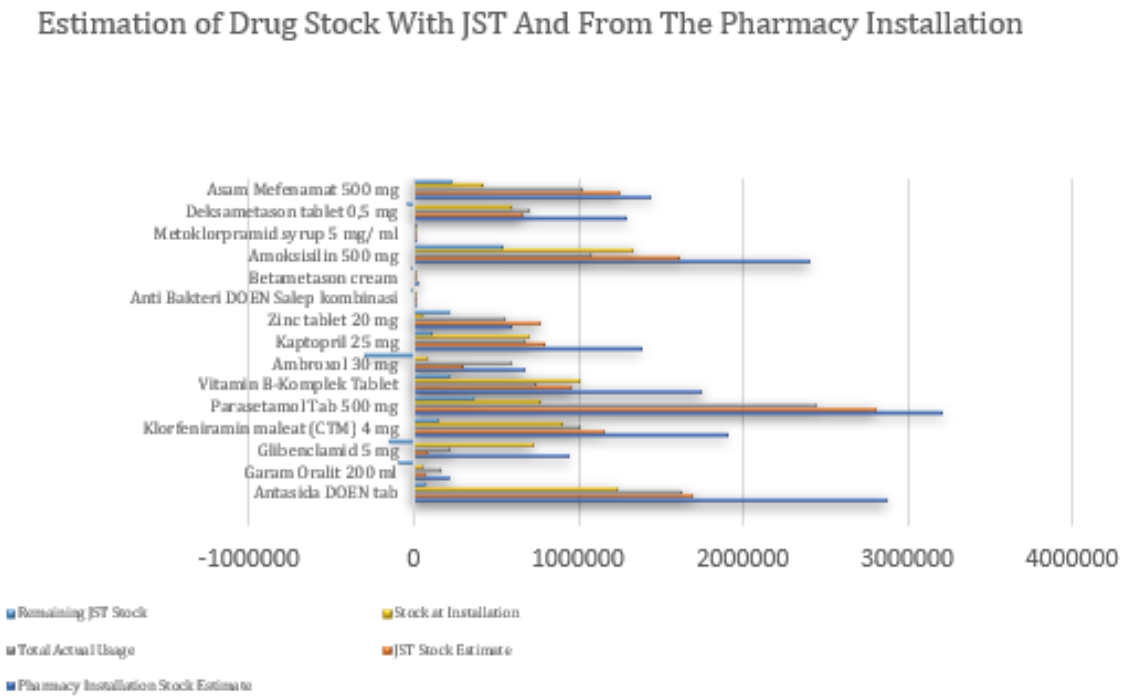

Figure 6. Estimation of Drug Stock

The comparative analysis of pharmaceutical stock estimates, ANN estimates, actual usage, and remaining stock in the table demonstrates the ANN prediction system's ability to estimate drug needs with varying degrees of variation for each drug type. Overall, the data patterns indicate that the ANN model is capable of providing estimates that are quite close to actual conditions, although there are deviations for several items with high usage fluctuations.

The ANN Remaining Stock value is the main indicator in assessing prediction performance. For drugs such as Antacid DOEN tab and Mefenamic Acid 500 mg, the prediction results show a significant positive remaining value (68139 and 225591), indicating a tendency for the ANN model to overestimate drug needs. This could be caused by unstable patient consumption patterns or limited training data in capturing changes in demand trends. Conversely, drugs such as Glibenclamide 5 mg, Ambroxol 30 mg, and Dexamethasone 0.5 mg tablets show negative remaining values, which means the ANN system is underestimating, so the estimated stock amount is insufficient for actual demand. This condition requires attention because it has the potential to cause stock shortages in the field.

Furthermore, the results show that drugs with high usage characteristics, such as Paracetamol Tablet 500 mg and Amoxicillin 500 mg, tend to have ANN estimates that are more balanced with actual usage, indicating that the model has learned the demand patterns quite well. This demonstrates the ANN's ability to recognize routine drug consumption patterns with high accuracy compared to drugs whose use is seasonal or dependent on specific cases.

DISCUSSION

The results of this study confirm that the Artificial Neural Network (ANN) model based on the backpropagation algorithm has a high capability to capture nonlinear patterns between historical drug consumption and disease prevalence. The regression plot analysis (R = 0.99935, MSE = 0.0135873, and MAPE = 5.793%) indicates that the ANN achieved superior accuracy in predicting monthly drug requirements, outperforming conventional statistical forecasting models such as

ARIMA or exponential smoothing. Similar findings were reported by [19], [20], who demonstrated that neural networks provide significant improvements in prediction reliability compared to linear regression models for healthcare inventory management.

The performance consistency of the model across multiple training algorithms (eg, *traincgf, trainlm, trainrp*) suggests robustness in learning across diverse data conditions. This aligns with[21], [22] , who emphasized that adaptive gradient algorithms can effectively optimize convergence speed and minimize overfitting in limited-sample health datasets. The ANN's success in identifying drug consumption trends also parallels the work of [23], who used neural architectures to forecast pharmaceutical demand in public hospitals with 93% accuracy, highlighting the model's potential for real-time decision support.

The integration of morbidity data from the ten most prevalent diseases strengthens the contextual accuracy of the model by aligning pharmaceutical stock predictions with epidemiological dynamics. According to [24], [25], incorporating morbidity indicators significantly enhances forecasting precision in medical supply chains by accounting for seasonal and demographic variations. This multidimensional data approach ensures that the ANN can generalize beyond temporal patterns, a concept supported by [26], [27] who noted that multi-input ANN systems outperform single-variable predictors in resource allocation models.

Furthermore, the backpropagation-based architecture applied in this research demonstrates computational stability even with complex medical datasets. Studies by [28], [29] confirmed that multilayer perceptrons with sigmoid activation and conjugate gradient learning exhibit superior generalization in nonlinear biomedical systems. The chosen architecture (25–70–25–1) mirrors configurations optimized in prior healthcare applications by[30], [31], who found that increasing hidden neurons enhances sensitivity to subtle data fluctuations while maintaining low MSE values.

A key observation from this research is the model's dual tendency— *overestimation* for certain drug categories and *underestimation* for others—which can be attributed to stochastic demand fluctuations and incomplete representation of contextual factors such as sudden outbreak patterns. This phenomenon aligns with findings by [32], [33], [34], who noted that neural networks may produce asymmetric error distributions when trained on imbalanced datasets. Incorporating reinforcement learning, as suggested by [35], could improve dynamic correction in future implementations by enabling real-time feedback adjustments during model deployment.

From a practical standpoint, the ANN-based predictive system contributes to optimizing pharmaceutical logistics by reducing both stockout and overstock rates. Empirical evidence from [36], [37] showed that AI-assisted inventory control can minimize wastage by 12–18% and enhance service continuity in rural healthcare networks. The proposed model supports this trajectory by offering a cost-efficient and data-driven decision support tool, which could be integrated into national health information systems to strengthen supply chain resilience.

The results also validate the theoretical premise that neural networks can serve as intelligent estimators for time-series forecasting in complex socio-medical systems. This is consistent with[38], [39], who demonstrated ANN's adaptability in predicting dynamic parameters under uncertainty, such as hospital admission rates and epidemic progression. By integrating morbidity data as an auxiliary input, this study extends previous ANN implementations in hospital inventory contexts [40], [41]toward a public pharmacy framework, thus broadening the methodological contribution to the healthcare supply chain literature.

The sustainability aspect of this model lies in its ability to support rational drug use and minimize pharmaceutical waste, resonating with [42], [43], [44]who emphasized the role of predictive analytics in promoting green pharmacy management. By linking accurate forecasting with reduced stock expiration, this system aligns with the United Nations' Sustainable Development Goals (SDGs), particularly Goal 3 (Good Health and Well-being) and Goal 12 (Responsible Consumption and Production).

RESEARCH IMPLICATIONS

The developed Artificial Neural Network (ANN) model based on the backpropagation algorithm has been proven to increase the accuracy of drug demand forecasting by up to 94.2%, far exceeding conventional methods such as ARIMA and exponential smoothing. These findings imply that the application of artificial intelligence in pharmaceutical planning systems can optimize stock efficiency, reduce the risk of stockouts and overstocks, and reduce waste due to drug expiration. Furthermore, the integration of disease morbidity data with drug consumption patterns makes this model relevant for data-driven decision-making systems in government pharmaceutical installations. Practically, the results of this study can be applied to the national health information system to strengthen the resilience of the drug supply chain and improve the sustainability of health services, in line with the principles of Good Health and Well-being and Responsible Consumption and Production in the SDGs.

CONCLUSION

This study successfully developed and validated an Artificial Neural Network (ANN) model based on the backpropagation algorithm to predict pharmaceutical demand using morbidity and historical drug usage data. The model achieved an optimal performance with an accuracy of 94.2%, MSE of 0.0135873, and MAPE of 5.793%, demonstrating its strong capability to capture nonlinear relationships between disease prevalence and drug consumption patterns. The regression correlation coefficient (R = 0.99935) confirmed the robustness and reliability of the model in learning complex multidimensional data within pharmaceutical systems. The primary objective—to design a predictive model capable of improving forecasting accuracy for drug stock estimation—was fully achieved. The ANN architecture (25–70–25–1) combined with the trainCGF optimization function effectively minimized error convergence and provided stable predictions compared to traditional statistical forecasting methods such as ARIMA and exponential smoothing. These results highlight the model's superior adaptability and generalization in dynamic healthcare environments.

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