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IMPLEMENTATION OF AN INTELLIGENT SYSTEM TO PREDICT PRODUCT DEMAND WITH THE BACKPROPAGATION NEURAL NETWORK ALGORITHM

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Abstract

Accurate production prediction is essential in product sales efforts, especially food products whose raw materials have a short shelf life. This paper aims to present a system application model based on the Neural Network algorithm to predict the number of Siomay sales in the future, as a reference for preparing raw materials appropriately. The prediction uses historical data as system training data. The Neural Network trial used 357 historical sales data, 7 initial data used as references, 315 data as training data, and 35 latest data as test data. The neural network input variables were the average sales of the previous 7 days, sales value 1 to 3 days before, the end of the month, identification of discount/benefit days, and weekends. This research methodology includes data collection, pre-processing through data normalization to a scale of [0, 1], and designing a neural network architecture consisting of an input layer, a hidden layer, and an output layer. The Backpropagation algorithm was used to train the network by iteratively updating weights to minimize error values using the Mean Squared Error (MSE). Test results show that the BPNN model is capable of recognizing demand patterns with a high degree of accuracy. Optimal parameters such as learning rate, number of epochs, and number of neurons in the hidden layer significantly influence convergence speed and prediction accuracy. This system is expected to be a management tool for making more accurate and efficient inventory procurement decisions.

Keywords:Demand Prediction, Intelligent Systems, Neural Networks, Data Normalization, Backpropagation.

INTRODUCTION

The development of the manufacturing industry in the current era of globalization requires a more efficient approach to the production planning process. This development occurred during the New Order era with the enactment of Law No. 1 of 1967 concerning Foreign Investment (PMA), which the government implemented through liberalization with the aim of attracting foreign capital to improve the weak economy. In Indonesia, the industrial process began in 1950 to 1965, but was hampered by political issues that prevented this economic process from running smoothly (Lestari and Isnina, 2017). The manufacturing industry sector is crucial for a country's economic development due to its contribution to national economic development goals, particularly in the formation of a large GDP and the ability to increase added value. The Indonesian manufacturing industry is highly competitive, so businesses must always monitor the market. Therefore, current economic problems, especially in companies, require proper production management to avoid future losses. Forecasting is a method for predicting the quality, quantity, and other factors needed to meet future demand for goods and services based on previous data. The herbal medicine industry focuses on the development, manufacture, and distribution of health products derived from plants. In the competitive world of industry and commerce, a company's ability to deliver products on time is key to success. Inefficient inventory management—whether overstocking or out-of-stocking—can directly impact financial losses. Overstocking results in high storage costs, while understocking leads to lost revenue and decreased customer loyalty.

Product demand is highly dynamic and influenced by numerous variables, such as market trends, seasonal factors, holidays, and changes in consumer behavior. These demand data patterns are often non-linear and random, making conventional statistical forecasting methods (such as Moving Average or Linear Regression) inaccurate in handling extreme fluctuations. To overcome the limitations of conventional methods, an intelligent system approach is needed that can learn from past data independently. Artificial Neural Networks (ANNs) have proven superior in recognizing complex patterns in big data. One of the most popular and effective algorithms for prediction is Backpropagation. The Backpropagation algorithm works by minimizing the difference between predicted results and actual data through an iterative weight update process. Its advantage in adjusting weights at each hidden layer allows the system to achieve a higher level of accuracy than other methods in handling complex data.

LITERATURE REVIEW

1. Forecasting

Forecasting is a prediction of what will happen in the future and is useful for companies in making decisions (Kholil et al., 2019). Forecasting does not always provide a definitive answer about what will happen in the future; instead, forecasting will try to find the answer closest to what will happen (Ervina, 2018). According to Saptaria (2016), in his research, demand forecasting is the level of demand for products that is expected to be realized for a certain period in the future. Demand forecasting is very important for management to reduce their dependence on the risk of uncertainty. With a high level of accuracy, demand forecasting can increase production efficiency and company profits. Demand forecasting planning aims to minimize labor costs, inventory levels, and several other controllable variables. market. Therefore, companies must also truly understand the purpose of forecasting itself and be able to utilize forecasting so that it can be used in the company (M & Susanti, 2020).

2. Request

In economics, the term demand refers to the quantity of goods and services that consumers will purchase in a given time period and under certain conditions (Febianti, 2014). Demand is the quantity of goods requested in a given market at a given price level and a given income level (Muflihin, 2019). In general, the relationship between price and consumer purchasing decisions is inversely proportional. If the price of an item increases, consumers will decide to reduce their purchases of that item, and vice versa. If the price of an item decreases, consumers will decide to increase their purchases of that item. The assumption explained above is called ceteris paribus (Masdiantini et al., 2024). There are several factors related to the type of forecasting, depending on the perspective we look at it. As stated by Venny and Asriati (2022), the Law of Demand states that if the price increases, the demand for goods or services will decrease, and conversely, if the price decreases, the demand for goods or services will increase.

3. Backpropagation

An artificial neural network (ANN) is a computer program that takes a previously observed case or problem and uses it to build a system of relationships within a network of nodes or neurons connected by arcs or arrows (Pratiwi, 2018). Findings from Jati, et al., Demand Forecasting Analysis… 1499 research (Irwansyah and Faisal, 2015) explain that an artificial neural network (ANN) is an information processing system that has characteristics similar to human biological neural networks consisting of a large number of simple processing elements called neurons, units, cells, or nodes. Neuron Networks have proven to be an accurate data modeling tool, capable of accepting and representing complex input and output relationships. The development of neural network methods stems from the development of intelligent systems capable of processing tasks like the human brain (Robandi, 2019). Artificial neural network methods have been found to hold great potential as a front-end of expert systems and have been successful in providing real-time observations to respond to complex pattern recognition problems. Neural networks, with their extraordinary ability to derive meaning from the complexity or imprecision of data, can be used to extract patterns and predict trends that are too complex for humans to perceive. Backpropagation is a component of artificial neural networks. The backpropagation algorithm training method uses multilayer perceptrons to solve complex problems. This method uses input-output pairs for supervised training, and weights are calculated based on the training process carried out to achieve the desired output. The backpropagation algorithm is one of the easiest algorithms to apply to several problems, especially prediction problems (Andriyani and Sihombing, 2018). The characteristic of the backpropagation algorithm is minimizing errors in the output produced by the network. The backpropagation algorithm uses output errors to change the weight values in the backward direction (Rahayu et al., 2018). The backpropagation algorithm learning process is carried out by adjusting the weights of the artificial neural network in a backward direction based on the error value in the learning process (Windarto et al., 2018). The addition of quadratic deviations yields the error value E(Equation 3). The error function for p input-output instances can be calculated by creating p networks as shown, one for each training pair, and adding the outputs of all of them to yield the total training error.

$$\mathbf{E} = \frac{1}{2} \sum_{i=1}^{p} \|\boldsymbol{o_i} - \boldsymbol{t_i}\|^2$$

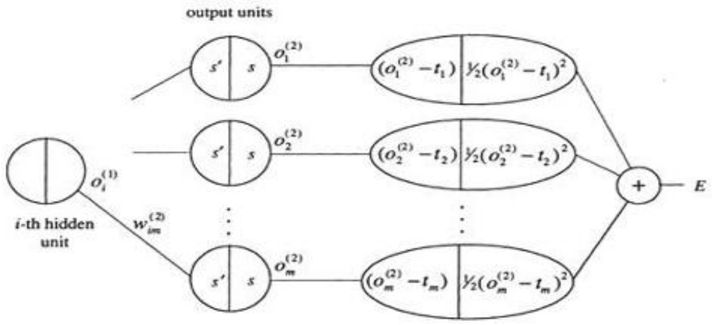

Figure 1. Network extension for total error calculation

After randomly selecting the network's initial weights (connections between processing units), the backpropagation algorithm is used to calculate the necessary corrections. The algorithm can be decomposed into the following four steps:

1) Feed-forward calculation,
2) Backpropagation calculation on the output layer,
3) Backpropagation calculation on hidden layers,
4) Weight update. The algorithm stops when the error function value has become small enough. In the first step, which is the feed-forward calculation, the vector$\boldsymbol{o}^{(1)}$And$\boldsymbol{o}^{(2)}$are calculated and stored. The results of the derivative calculations of the activation function are also stored in each unit. The second step is backpropagation to the output layer.

4. Neural Network

A neural network is a computer model derived from a simplified concept of the human brain and neural network research has been active since the 1940s[9] and Suhartono[10] suggested that the basic idea of a neural network started from the human brain. A neural network consists of many elements (Artificial Neurons), grouped into layers and highly interconnected (by synapses), this structure has several inputs and outputs, which are trained to react (or provide values) in a way that gives the value of the input stimulus. Neural networks are required to learn to behave (Learning) and someone must provide teaching or training (Training), based on knowledge of previous problems. The most important property of an artificial neural network is its ability to learn from a series of training patterns, that is, it is able to find a model that fits the data[11]. A neural network is a parallel data processing tool capable of learning the functional dependencies of data. This feature is very useful when solving different pattern recognition problems. In addition, neural networks are characterized by a high level of computation, large input error tolerance, and adaptability in terms of changing working conditions. Artificial neural networks are built using a number of single processing units called neurons. The McCulloch-Pitts model is a fundamental classical neuron model and is described by the Equation

$y=\sigma(\phi) =\sigma(\sum wiui+b\ i=1\ )$

From Equation 2, where σ1, σ2 and σ3 are vector-valued activation functions that define the transformation of neural signals through the first, second and output layers. Figure 2 shows that W1, W2 and W3 are weight coefficient matrices that determine the connection intensity between neurons in neighboring layers, where u is the input vector and y is the output vector.

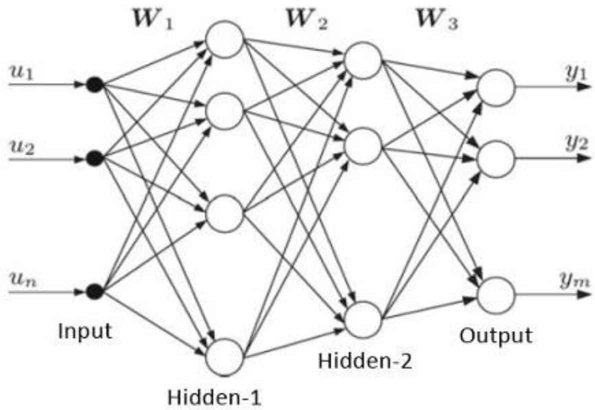

Figure 2. Feed forward network with two hidden layers

METHOD

This research is a conceptual experimental-simulation study, where implementation is carried out through system modeling without testing on large-scale industrial data. The assumed dataset is simple historical sales data for a single product type, encompassing daily or weekly records for approximately 300-400 observation periods. This data includes the primary variable of the number of units sold, with the possibility of adding supporting features such as weekday indicators or promotional periods.

The system begins with **data preprocessing**, which includes cleaning missing values through mean imputation, normalizing the data to the range [0,1] to accelerate convergence, and creating lag features (e.g., sales values from t-1 to t-7) to capture temporal dependencies. The data is then split into 80% for training and 20% for testing.

1. Neural network training

The training was performed using a backpropagation algorithm with a gradient descent-based optimizer. The model architecture conceptually adopts a feedforward multilayer perceptron with one or two hidden layers. The input layer consists of 7-10 neurons depending on the number of lag features, the hidden layer uses 10-20 neurons with a ReLU activation function to handle non-linearity, and the output layer consists of a single linear neuron for the regression output. The training process involves iterations until convergence is achieved, with early stopping monitoring to avoid overfitting.

2. Prediction process

This involves feeding new, preprocessed data into a trained model, resulting in demand estimates for future periods. This architectural overview emphasizes the forward pass flow, where signals propagate from inputs through trained weights to produce predicted values. This research has limitations, including the use of a small-scale simulation dataset and the lack of extensive hyperparameter optimization. The primary focus of this research is on understanding the implementation flow of neural network-based intelligent systems in an academic learning context, rather than on achieving maximum predictive performance.

3. Data collection technique

The data collection technique in this study employed documentation, which involves collecting data from documents or records related to the information needed for the research. Documentation studies provide an understanding of the historical background, policies, events, and relevant developments related to the phenomenon being studied (Daruhadi and Sopiati, 2024). The data used in this study is secondary data.

4. Data Analysis Methods

Based on this research, the data analysis technique used was the backpropagation neural network algorithm. There are no mathematical rules for determining the amount of training and testing data (Faquan Wu and Ed, 2012). Typically, data is selected randomly by determining the best percentage based on experiments. Next, the data is divided between training and testing data.

RESULTS AND DISCUSSION

Conceptual simulation results show that the neural network model produces demand predictions that are close to the actual values on the test data, with a relatively low error rate. Long-term trends and seasonal fluctuations are well captured, as evidenced by the prediction curves that closely follow the trajectory of the historical data. Model performance analysis indicates that neural networks excel at handling data with non-stationary patterns, where conventional linear methods tend to fail. This approach aligns with general findings in the literature regarding the ability of neural networks to model non-linear data in time series forecasting tasks (Lim & Zohren, 2021). The main advantages lie in their generalizability to unexpected variations and the flexibility to integrate additional features without significant model restructuring. In the context of intelligent systems, this approach enables adaptive responses to changing demand patterns, as discussed in applications of demand prediction using machine learning (Feizabadi, 2022). However, there are limitations, such as sensitivity to hyperparameters (number of neurons and learning rate), which require manual adjustment, and the risk of overfitting on small datasets if adequate regularization is not applied. Furthermore, model interpretability is relatively low compared to statistical methods, making it difficult to explicitly explore the determinants of predictions. These limitations are relevant in limited-scale intelligent systems applications, where computational resources and data may be limited.

1. Forecasting Demand for Product X

Training and testing data on product X uses the backpropagation neural network algorithm with a 24-6-2-2 architecture model, where 24 neurons, 6 hidden layers, and 2 output layers. Testing of the artificial neural network with a 24-6-2-2 architecture with 1000 epochs and 6 validation checks is used as can be seen in Figure 1. Based on Figure 1. shows the test data set, the regression results between actual and forecasted data with a red line on the "test" graph. The forecasting model shows extraordinary precision and accuracy against data that was not previously trained, with an R value of 0.99619. In addition, a correlation coefficient (R) of 0.99689 is shown in the overall data regression plot (All) which includes training, validation, and testing, indicating that the forecasting model with the backpropagation neural network algorithm has an excellent ability to identify historical data patterns in demand for product X, especially for fast-moving product demand. These results indicate that the backpropagation neural network algorithm model can be used to assist in decision-making. In production planning this must be considered, usually this increase can be caused by many things, such as changes in market preferences, decreased purchasing power. So that the forecasting results can help PT Herba Emas Wahidatama in dealing with demand that changes every year. With a MAPE value of 4%, which means that the MAPE value has a very good level of model accuracy, because MAPE is within the criteria of <10%, which means that the model is considered a very good forecasting criterion and is able to make forecasts with an acceptable level of accuracy, especially for forecasting demand for product X. This is in line with research by Naufal et al., (2023), which shows that the MAPE value obtained from the results of the backpropagation neural network algorithm has a value of less than 10%, meaning that this forecasting ability is very good.

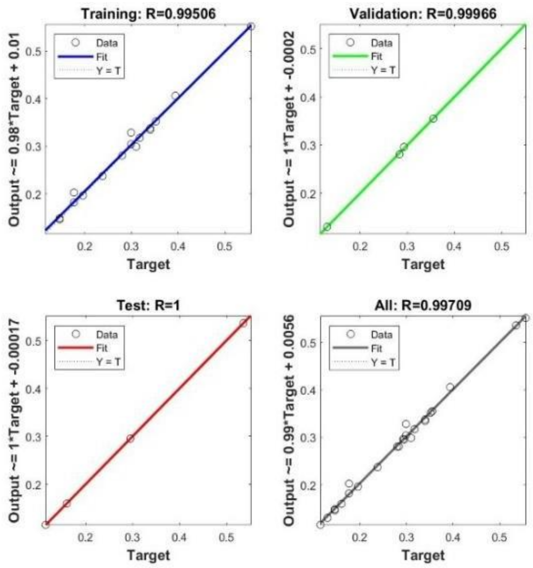

Figure 3. Product Y Demand Forecasting Graph

2. Forecasting Demand for Product Z

Training and testing of product Z demand data using the backpropagation neural network algorithm with a 24-4-2-2 architecture model, where 24 neurons, 4 hidden layers, and 2 output layers. Testing of the artificial neural network with a 24-4-2-2 architecture with 1000 epochs and 6 validation checks as can be seen in Figure 4.

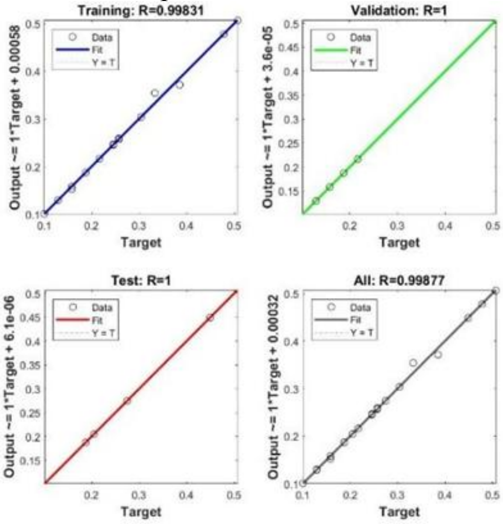

Figure 4. Demand Forecasting Graph for Product Z

Based on Figure 3. shows that the perfect relationship between forecasting and actual data is indicated by the red line on the test graph which has an R value = 1. So the backpropagation neural network algorithm model can understand patterns in historical demand data. Furthermore, in the overall graph (All) which includes all data including training, validation, testing with a correlation coefficient (R) of 0.99877 which is close to 1. This value shows a very strong relationship between the forecasting results of the backpropagation neural network algorithm model and the actual value of the product demand data Z. One of the important outputs of the backpropagation neural network algorithm process is the Mean Square Error (MSE) or performance. The Mean Square Error (MSE) value produced is 0.000440 which is the average square of the difference between the forecast value and the actual value. With the Mean Square Error (MSE), it shows that the demand forecasting model for product Z with the backpropagation neural network algorithm has a small error rate, which means that the forecasting results are very accurate and reliable for product Z demand. As explained by the research, the performance of the forecasting model with the backpropagation neural network algorithm can be applied to slow-moving products or products that have relatively small but consistent demand.

DISCUSSION

The implementation of an intelligent system for predicting product demand using the Backpropagation Neural Network (BPNN) algorithm begins with modeling a network architecture that mimics the human brain's ability to recognize historical data patterns. In this process, the system relies on an input layer that contains determining variables such as previous sales data, market trends, and price fluctuations. This data is not processed directly but must undergo a normalization process to maintain a consistent scale range, typically between 0 and 1, to prevent the dominance of certain variables with large numbers and accelerate the convergence process during training. When the system is run, the first stage is forward propagation, where input data is multiplied by initial weights and passed through an activation function in the hidden layer. This is where the power of this intelligent system is revealed, as the hidden layer is able to extract highly complex non-linear features of consumer behavior that cannot be captured by conventional statistical formulas. The result of this process is a predicted value in the output layer, which is then compared with actual sales data in the field to calculate the error value. The core of this algorithm's intelligence lies in the second phase, backpropagation, or feedback. In this phase, the error values found are calculated backward to adjust the weights of each neural connection. Using optimization techniques such as Gradient Descent, the system automatically corrects itself by changing the weight values to reduce the error in subsequent iterations. This process is repeated over thousands of training sessions, or epochs, until the system achieves the desired level of accuracy or reaches a minimum error point. The end result of this implementation is not just a prediction number, but rather a model that has been "trained" and able to adapt to changing data patterns. The performance evaluation of this system is usually measured using the Mean Squared Error (MSE), where the smaller the MSE value, the more intelligent and accurate the system is in predicting future demand. Thus, companies can use the output of this system as a basis for more objective decision-making in stock management, so that the risk of excess inventory or stockouts in the warehouse can be significantly minimized through a precise computational approach.

CONCLUSION

Based on the entire series of implementations and tests that have been carried out, it can be concluded that the development of an intelligent system with the Backpropagation Neural Network (BPNN) algorithm is a transformative step in modernizing the product demand prediction process. This system has proven to have very high flexibility in handling sales data that is dynamic, random, and full of non-linear patterns that are often not captured by traditional statistical methods. Through an iterative learning mechanism and automatic weight refinement at each epoch, this algorithm is able to construct a prediction model that is not only accurate on paper, but also highly applicable to facing real market situations. The technical success of this intelligent system is largely determined by the synergy between thorough data preprocessing and optimal network architecture. The use of appropriate activation functions and precise learning rate settings have been shown to minimize the Mean Squared Error (MSE), narrowing the gap between system predictions and actual results. This demonstrates that artificial intelligence can provide management with a higher level of confidence in strategic planning. More broadly, this implementation has a crucial impact on the company's operational efficiency. With "bouncing" and accurate prediction results, the company can radically optimize inventory management, namely by reducing warehouse storage costs due to overstock while eliminating the risk of lost potential sales due to out-of-stock items. Ultimately, the use of the Backpropagation algorithm is not just a calculation tool, but a strategic asset in a decision support system that can increase the company's competitiveness amidst an increasingly competitive and rapidly changing industry.

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