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Implementation and Evaluation of Artificial Neural Networks for Product Sales Prediction at Basmalah Stores

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Abstract: This study aims to develop a product sales prediction system for Toko Basmalah in Malang Regency using the Artificial Neural Network (ANN) algorithm. A quantitative approach was employed with time series sales data obtained from the Marketing Division of PT. Sidogiri Pandu Utama covering the period from January 1, 2023, to December 31, 2024. The research process involved data preprocessing, normalization using the min–max scaling technique, data partitioning into training and testing sets, model experimentation, and performance evaluation based on the Mean Squared Error (MSE) metric. The model was evaluated across five data-split scenarios using the Kaggle Editor platform. The ANN-E model with a 7–6–3–1 architecture achieved the lowest MSE value of 0.343, indicating its superiority in predicting product sales. These results demonstrate the model's potential to support data-driven decision-making in inventory management, sales planning, and retail strategy optimization. This study contributes to the limited literature on Sharia-based retail forecasting using real-world data from Indonesia, offering empirical evidence of how ANN can be effectively applied in local retail operations.

Keywords: Sales prediction, artificial neural network, MSE, time series, toko basmalah sidogiri.

INTRODUCTION

The retail industry in Indonesia has experienced rapid growth in recent years, supported by rising consumer purchasing power and technological advancement (Har et al., 2022). Major retail chains such as Indomaret and Alfamart now operate over 20,000 outlets nationwide, while Sharia-based retailers have also emerged to meet the needs of Muslim consumers seeking halal and ethical shopping alternatives (Sihombing, 2025). Despite this rapid expansion, Toko Basmalah, one of the leading Sharia-based retail chains in East Java, faces supply chain and stock optimization challenges due to limited capital turnover and the absence of an integrated demand forecasting system. These issues often result in overstocking or stockouts, which can disrupt operations and reduce profitability.

One successful example of a Sharia-based retail model is Toko Basmalah. Managed by PT Sidogiri Mitra Utama, a business unit of the renowned Sidogiri Islamic Boarding (Wijaya, 2018) School, this retail chain has strategically positioned itself to serve consumers who value halal products and ethical business practices. As of 2024, Toko Basmalah operates more than 294 branches across Indonesia, including 17 locations in Malang Regency and City (Romadhon et al., 2024). By adopting a Sharia-compliant business model, the store not only ensures the halal status of its products but also upholds values like honesty, transparency, and fairness, reflected in practices such as profit-sharing and avoiding interest-based transactions (Awais et al., 2024). These principles not only attract loyal customers but also showcase how Islamic boarding schools can actively contribute to developing a just and inclusive economic system for the community.

However, behind this impressive expansion lies a series of operational challenges, especially in terms of financing. Unlike conventional retail chains that have easy access to bank loans, Toko Basmalah relies solely on internal funding sourced from its members or investors. This capital is raised only once a year, creating limitations in responding to dynamic and ever-changing market demands. Without precise and efficient capital management, the company risks either overstocking, leading to waste, or understocking, which results in lost sales opportunities. Additionally, since the capital comes from member investors, management must ensure that it generates consistent

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and attractive returns to maintain investor confidence and encourage ongoing participation. Poor financial planning can lead to cash flow imbalances, which may disrupt store operations and hinder business growth in the long run (Lijuan et al., 2023).

In addition to capital constraints, logistics and distribution present another major challenge for Toko Basmalah. As its store network continues to grow, efficient supply chain management becomes crucial to ensure the timely and accurate delivery of goods. Issues such as delayed shipments, inventory mismatches, and logistical barriers in remote areas can negatively impact customer satisfaction. According to data from the Ministry of Trade, over 30% of retail businesses in Indonesia face supply chain issues due to inadequate logistics infrastructure, especially in rural or hard-to-reach areas (Huria, 2019). Furthermore, economic fluctuations, inflation, and changes in consumer behavior also affect purchasing patterns. For example, during the COVID-19 pandemic, many customers became more cautious with their spending, shifting to more frugal consumption habits. Retail businesses that fail to anticipate or respond to these shifts risk experiencing a decline in revenue and losing their competitive edge (Roggeveen & Sethuraman, 2020).

Prediction is an attempt to estimate what will happen in the future based on previous data with a basis of scientific and qualitative methods carried out systematically (Filippo et al., 2012). Prediction methods are currently widely used by researchers through a quantitative approach, which is divided into two types, namely the regression method and the time series method, including Boosted Decision, Linear Regression, Bayesian Linear Regression, Numerical Network, Random Forest, Gradient Boosted Trees, and Generalized Linear Model (Sahi et al., 2023). Then, in previous studies, prediction techniques were applied to estimate digital product sales by investigating several algorithms, especially the Artificial Neural Network (ANN) and Linear Regression algorithms, to determine their level of performance. The synthesis of this research shows that ANN is the best algorithm in predicting digital product sales with an accuracy value of around 97.4% (Massaro et al., 2018), compared to the Linear Regression algorithm with an accuracy value of around 96% (Catal et al., 2019).

To address the multifaceted challenges presented in this study, a data-driven approach through sales prediction has emerged as a promising solution. By analyzing historical sales data, management can forecast future product demand more accurately, identify purchasing trends, and support data-informed decision-making in retail planning. Technologies such as machine learning and big data analytics have been proven to enhance the precision of demand predicting while significantly improving overall operational efficiency. A study by Harvard Business Review reports that the implementation of predictive analytics can improve prediction accuracy and reduce out-of-stock incidents that lead to missed sales opportunities. Moreover, accurate sales prediction enables retailers to adjust marketing strategies, optimize promotional timing, and refine product assortments in response to evolving consumer behavior. With these predictive tools, Toko Basmalah can not only enhance sales performance but also strengthen its competitiveness and sustainability within the increasingly dynamic Sharia retail market.

However, despite the growing adoption of data-driven techniques in retail operations, research specifically examining the implementation and performance evaluation of Artificial Neural Network (ANN) models for sales prediction within the context of local retail enterprises such as Toko Basmalah in Malang Regency remains limited. Previous studies have predominantly focused on large-scale or online retail environments, leaving a gap in understanding how ANN can be effectively applied to optimize inventory management in regional retail chains. Therefore, the objective of this research is to implement and evaluate the performance of an Artificial Neural Network (ANN) model in predicting product sales at Toko Basmalah. This study aims to assess the accuracy, reliability, and practical applicability of the ANN model in supporting data-driven decision-making for retail inventory management.

METHOD

This study adopts a quantitative approach, as the entire analysis process is based on numerical data that is processed using statistical methods (Weng et al., 2018). In general, the research steps are systematically organized into six main stages (Fig. 1), starting with the collection of relevant data, followed by data engineering to ensure input quality, and then the design and implementation of the prediction system. Once the system is developed, experiments and model performance testing are conducted. The results of these tests are then evaluated to assess their effectiveness, and the process concludes with the drawing of conclusions and documentation so that the research findings can be understood and further utilized.

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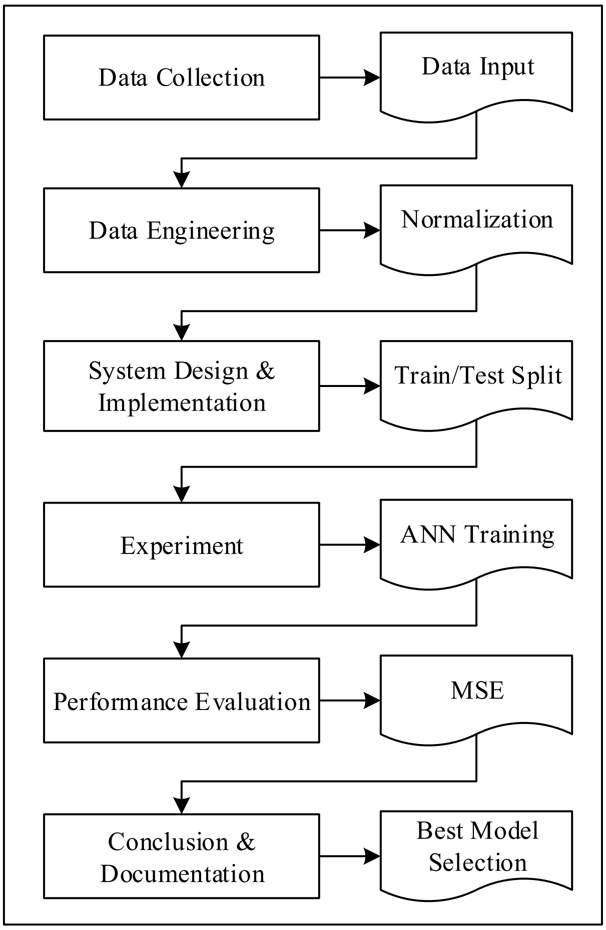

Fig. 1. Research Procedure

Data Collection

First, the data collection process was carried out by downloading primary time series data related to product sales at Toko Basmalah outlets located throughout the Malang Regency/City area. This data was obtained directly from the marketing division of PT. Sidogiri Pandu Utama, covering the period from January 1, 2023, to December 31, 2024. The data collection activity took place on January 3, 2025. In total, there are approximately 11,266 data entries for each available attribute. The collected attributes include transaction date (Date), presence of promotion (Promo), outlet location (Location), competition conditions (Competitor), customer loyalty level (Customer Loyalty/CL), product price (Price), and sales volume (Sales). This information serves as a crucial foundation for building an accurate prediction model.

Table 1. Sales Dataset of Toko Basmalah Outlet Products

Date	Promo	Location	Competitor	CL	Price	Sales
1/1/2023	1	BASMALAH CABANG JATIKERTO	3	0	157000	76
1/1/2023	1	BASMALAH CABANG PAKISAJI	2	0	413000	130
1/1/2023	1	BASMALAH CABANG KEPANJEN MALANG	4	0	349000	73
1/1/2023	1	BASMALAH CABANG LOWOKWARU	3	0	295000	154
…	…	…	…	…	…	…
12/31/2024	0	BASMALAH CABANG TALANGSUKO	5	0	355000	0

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12/31/2024	1	BASMALAH CABANG WAGIR MALANG	3	0	304000	156

Data Engineering

The second stage is data engineering, which is carried out to clean and adjust the data format so that it aligns with the needs of the research. This process is essential to ensure that the data used is truly ready for analysis and free from anomalies that could affect the results. One of the techniques applied is min-max scaling (1), a data normalization method aimed at improving model accuracy while minimizing the risk of overfitting during the prediction process. In other words, data engineering is a crucial step to ensure that the model can learn from the data optimally (Huang et al., 2023).

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (1)$$

Where:

- x' = normalized data
- x = original data
- x_{min} = minimum value in the dataset
- x_{max} = maximum value in the dataset

After the data has undergone normalization, it is then divided into two main groups: training data and testing data. The purpose of this division is to ensure that the model can learn from a portion of the data and then be tested on data it has never seen before. In this study, the data was distributed using several different compositions to explore which configuration could yield the most optimal model performance. This process is experimental in nature, meaning that each split is carried out with consideration of its impact on the final results so that the best combination can be found to enhance prediction accuracy while maintaining model reliability (Robbins et al., 2004).

System Design & Implementation

The third stage involves designing the architecture of the backpropagation ANN algorithm (Fig. 2). In this study, the architecture utilizes two hidden layers, consisting of input data (Ii) in the form of product sales figures, weight values between the input layer and the first hidden layer (Tij), output values from the first hidden layer with a predetermined number of nodes (Hj), weight values between the first and second hidden layers (Ujk), output values from the second hidden layer with a specified number of nodes (Gk), weight values between the second hidden layer and the output layer (Vkl), and the final output value in the form of sales prediction (Ol).

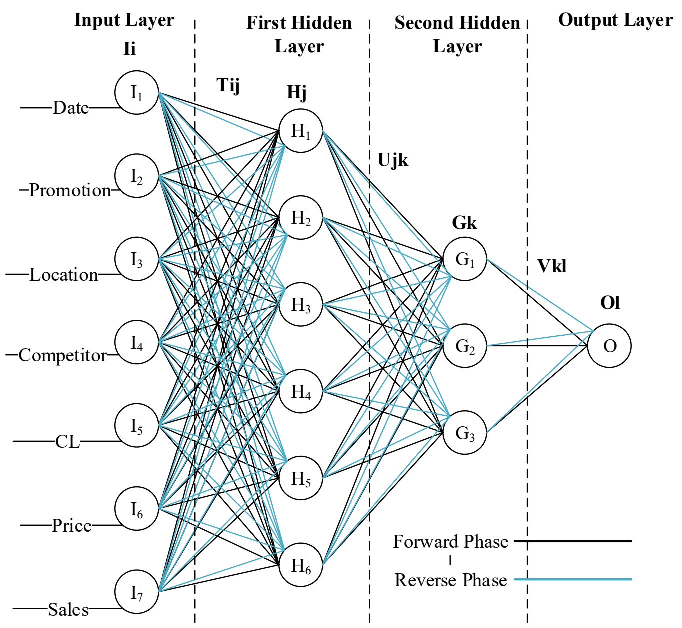

Fig. 2. Network System Architecture Design ANN Model (7-6-3-1)

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The determination of the number of nodes in each layer is based on the characteristics of the data, namely seven attributes as input, six-digit figures from the price attribute for the first hidden layer, three-digit figures from the sales attribute for the second hidden layer, and a single output value as the prediction result (Sahi, 2023). According to Thomas et al. (2017), the use of two hidden layers can enhance the model's generalization capability by allowing it to capture more complex and nonlinear relationships within the data, which leads to improved prediction performance compared to single-layer architectures. This output is calculated using the following (2):

$$net = w_0 + \sum_{i=1}^{n} x_i w_i \qquad (2)$$

Where net is the output value of the node being calculated, w_0 is the bias weight of the node, i is the index used in the summation from 1 to n, xi is the weight connecting the node with the i-th input neuron, wi is the i-th input value of the previous node, and n is the total number of features (Sahi et al., 2023).

Experiment

In the fourth stage, the experimental process was conducted by running five test iterations on the Kaggle Editor platform. Each iteration represented a different data-split scenario to evaluate the model's consistency and robustness, rather than testing multiple architectural variations. Model was implemented using Python on Kaggle Editor with TensorFlow backend. This testing aimed to assess how well the ANN model could accurately predict future product sales at Toko Basmalah in Malang Regency. Each prediction result was then analyzed in depth, particularly to evaluate the performance of each designed model architecture.

Performance Evaluation

Next, the fifth stage is performance evaluation, which focuses on selecting the best model based on the smallest error rate. This assessment uses the Mean Squared Error (MSE) as the primary evaluation metric (3). From this evaluation, the researcher can draw more accurate conclusions about which model is the most reliable and suitable for use in the context of sales prediction. The final decision is made based on the analysis results that most closely reflect the actual conditions in the field (Allen, 1971; Hodson et al., 2021).

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(\mathrm{Y_i} - \hat{\mathrm{Y}}_i\right)^2 \qquad (3)$$

Where MSE is the mean squared error, n is the number of data points, Yi is the observed value, and $\hat{\mathrm{Y}}i$ is the predicted value.

Conclusion & Documentaion

Based on all the stages that have been carried out—from the design of the ANN architecture, and selection of training parameters, to the execution of experiments and model evaluation—the sixth stage, namely conclusion and documentation, involves making the final decision regarding the product sales prediction system for Toko Basmalah in the Malang Regency area. The developed system is expected to provide relevant and accurate results in predicting future sales trends. Through repeated training and testing processes, along with performance evaluation using the Mean Squared Error (MSE) metric, the best-performing model with the highest accuracy was obtained, which can serve as a reference for making operational decisions and sales strategies in the field.

RESULT

In this study, the model was designed with two hidden layers using a 7-6-3-1 architecture, employing the ANN approach with the backpropagation algorithm. The backpropagation algorithm itself is one of the commonly used supervised learning methods for training artificial neural networks. The model training process was carried out using the MSE function as the stopping criterion, where training automatically stops once the model reaches a certain level of convergence—specifically when the error falls within an acceptable range. The performance and outcomes of the backpropagation algorithm are significantly influenced by several key parameters, such as the number of nodes in the network, the learning rate, the target error level, and the number of epochs or training cycles (Abdolrasol et al., 2021; Ghaffari et al., 2006; Shrestha & Mahmood, 2019; Takase et al., 2018). During the training process, the ReLU (Rectified Linear Unit) activation function was used, which generally produces outputs ranging from zero to positive values (Szandała, 2020; Yu et al., 2020). To test the model's performance and accuracy, a series of experiments was conducted by implementing the program code on the Kaggle Editor platform. The results of these experiments are in the form of sales predictions for products at Toko Basmalah in

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the Malang Regency/City area, determined based on the parameters designed and detailed in Table 2.

Table 2. Parameters of ANN Model

Parameters Mode	Information
network model	ann with backpropagation algorithm
activation function	relu
optimizer	adam optimizer
performance evaluation	mean square error (MSE)
input layer	7 nodes
first hidden layer	6 nodes
second hidden layer	3 nodes
output layer	1 node
learning rate	0.2
epochs	50 epochs

The model training process was conducted using input data that had been divided into training data and testing data. This division was based on previously normalized data, where the testing portion was used to evaluate the model's performance. During training, variations in data distribution were implemented, and each variation was assigned a different name: ANN-A, ANN-B, ANN-C, ANN-D, and ANN-E. Throughout the entire training process, the *Sales* attribute was used as the target variable to be predicted.

Table 3. ANN Model Testing Results

Model Name	Data Composition	Convergence Time	MSE (Testing)
ANN-A	50:50	3ms/training step	0.3952
ANN-B	60:40	3ms/training step	0.3947
ANN-C	70:30	2ms/training step	0.3989
ANN-D	80:20	3ms/training step	0.3963
ANN-E	90:10	2ms/training step	0.3438

Note: convergence time = 50th epoch

From the training results of the five ANN models shown in Table 3, which were used to predict product sales at Toko Basmalah in Malang Regency, differences in performance among the models can be observed. Two key indicators were analyzed: convergence time, which measures how quickly a model reaches stability, and the Mean Squared Error (MSE) on the testing data, which reflects the accuracy level of the prediction. In general, the smaller the MSE value, the better the model replicates actual sales patterns.

Five ANN models were tested using different data-split compositions of 50:50, 60:40, 70:30, 80:20, and 90:10 to evaluate how the proportion of training and testing data affected model performance. To ensure result consistency and avoid bias from a single data partition, each configuration was tested across multiple split scenarios through repeated runs. This approach serves as an internal validation mechanism similar to cross-validation, allowing the performance trends of each model to be observed more reliably.

Among these, the ANN-E model with a 90:10 ratio demonstrated the best predictive accuracy, achieving the lowest Mean Squared Error (MSE) of 0.3438. In contrast, the other models (ANN-A to ANN-D) produced relatively higher MSE values, averaging around 0.39. Although the ANN-E model required slightly longer training time (approximately one second per step), the improvement in prediction accuracy represents a significant advantage.

Meanwhile, models such as ANN-A to ANN-C completed training more quickly, but this came at the cost of lower accuracy. With higher error rates, these models are less suitable for decision-making scenarios that demand precise sales data. This demonstrates that speed alone is not sufficient—in practice, it is essential to strike a balance between time efficiency and result accuracy. Therefore, ANN-E can be considered the most viable model for the sales prediction system, as it delivers outcomes that more closely reflect real-world conditions.

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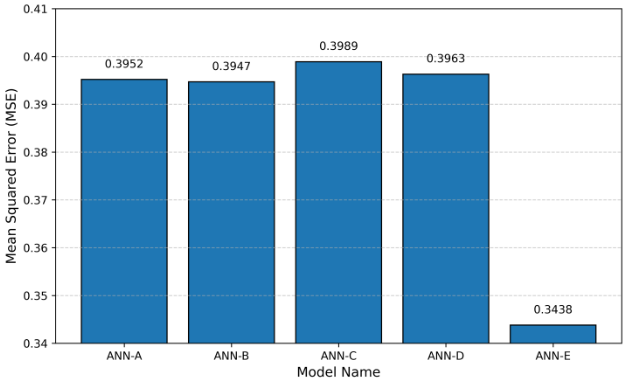

Fig. 3. Comparison of Testing MSE among ANN Models (ANN-A to ANN-E)

Effective product distribution is a crucial aspect of modern retail logistics systems, especially for companies with multiple branches such as Toko Basmalah in the Malang Regency area. In this context, the ability to accurately predict sales is essential for maintaining stock balance and avoiding both overstocking and understocking at each outlet. Therefore, the implementation of predictive models based on machine learning—particularly Artificial Neural Networks (ANN)—emerges as a promising strategic solution.

DISCUSSIONS

This study reveals that the application of ANN can significantly assist management in better understanding and projecting product demand with greater precision (Fig. 3). The ANN model employed features a 7-6-3-1 network architecture and was tested across five different data distribution scenarios. Among all tested models, ANN-E, which utilized a 90:10 split between training and testing data, demonstrated the best performance, achieving a Mean Squared Error (MSE) of 0.3438. This low prediction deviation highlights the model's accuracy and makes it a viable option for implementation in a retail environment.

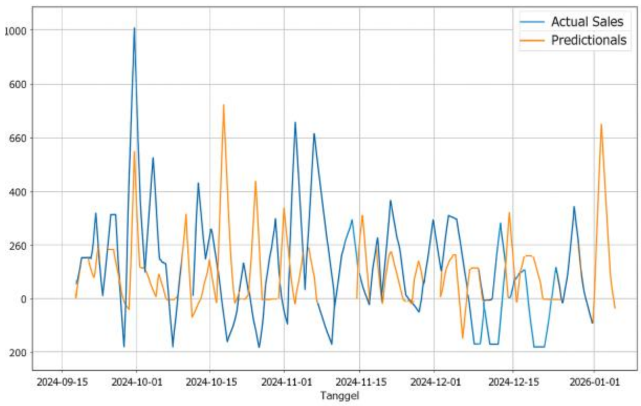

Fig. 4. Predicted vs Actual Sales for ANN-E Model (90:10 split)

The prediction accuracy of the ANN-E model is reflected in the similarity between the actual data graph and the predicted results (Fig. 4). This indicates that the ANN is capable of recognizing complex and dynamic sales patterns, even in the presence of external factors such as promotions, seasons, or shifts in consumer behavior. These findings support those of Li & Zhang (2024), who stated that ANNs are highly reliable in processing non-linear time series data. The strong performance of the ANN model in this study is also consistent with the view of Thomas et al. (2017), who explained that the use of two hidden layers can enhance the generalization ability of artificial neural networks.

Mathematically, the superior performance of the ANN-E model can be attributed to its larger training data proportion (90%), which allows the network to learn a more comprehensive representation of the underlying sales patterns. A greater amount of training data reduces estimation bias and enables the optimization algorithm to converge toward more stable weight values, minimizing generalization errors during testing. Consequently, the ANN-E model demonstrates higher predictive accuracy compared to other models with smaller training proportions or simpler architectures.

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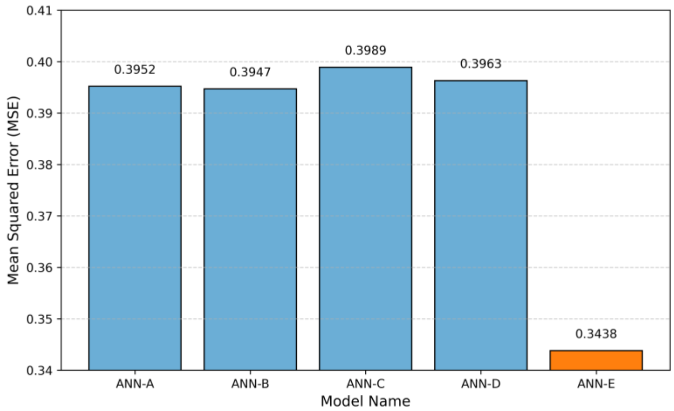

Fig. 5. Sales Prediction Test Results for ANN-E Model (90:10 split)

For retail management entities such as Toko Basmalah, the accuracy of sales predictions has a direct impact on operational decision-making. Decisions regarding supplier purchases, inter-outlet distribution, and promotional strategies become more targeted when based on accurate projections. Thus, the implementation of an ANN model serves not only as an analytical tool but also as a decision support system in the context of logistics planning. The ANN model also demonstrates adaptability to the dynamics of macroeconomic conditions. When fluctuations in product prices or shifts in consumer spending behavior occur, the ANN can adjust its predictions based on similar historical patterns. This makes ANN superior to classical statistical methods, which generally assume linear relationships. These findings are supported by Khashei & Bijari (2010), who stated that ANN excels at handling data with high levels of noise and volatility.

Furthermore, the accuracy demonstrated by the ANN-E model in Fig. 5 is not limited to identifying general patterns but also extends to detecting micro-patterns, such as weekly or seasonal sales spikes. This capability is crucial for management when developing tactical strategies, such as weekly promotions, stock increases during holiday periods, or new product launches. The model's sharpness in identifying short-term trends provides added value in the highly competitive retail environment. If directly integrated with Toko Basmalah's sales management information system, the ANN-E model can function as an intelligent analytics module that provides quantitative recommendations related to stock projections, logistics needs, and profit estimations. This advantage supports the principle of operational efficiency and enables data-driven, real-time decision-making.

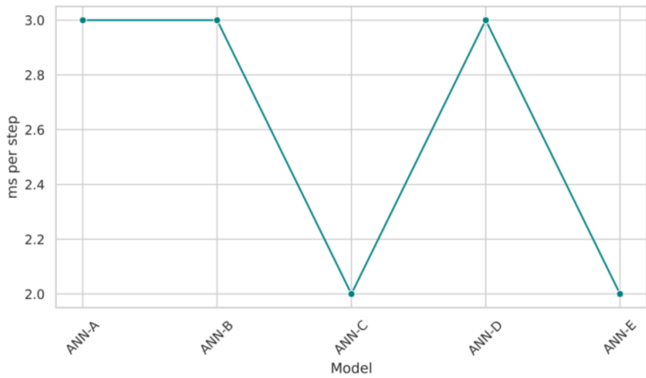

Fig. 6. Convergence Time of Training Process at Epoch 50^{th} (ANN-A to ANN-E)

From a technical standpoint, training an ANN model requires careful attention to avoid overfitting or underfitting. In Fig. 6, training was halted at the 50th epoch, indicating that the model reached convergence efficiently. The average convergence time of 2–3 ms per training step also reflects a level of computational efficiency suitable for practical implementation. Beyond its predictive capabilities, the economic benefits of implementing ANN should not be overlooked. With more accurate predictions, companies can avoid high storage costs due to overstocking and minimize lost sales due to stockouts. This aligns with the principles of agility in modern supply chain management, which emphasize the importance of rapid response to market demand.

Furthermore, the prediction graphs produced by the ANN model in this study show a high degree of alignment with actual data (Fig. 5). They not only capture overall trends but also reflect minor fluctuations caused by factors

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such as promotions, weather, or holidays. This reinforces the potential of ANN as a strategic decision-support tool for daily operations in retail management. Supporting evidence from Chen et al. (2016), also suggests that ANN models with two hidden layers deliver excellent prediction performance in the retail sector, particularly in predicting electronics sales in China. Their findings highlight that network architecture plays a crucial role in model performance and can be tailored to the specific needs of different business sectors.

With its low MSE and prediction graphs that closely mirror actual sales patterns, the ANN-E model can be concluded to be the optimal choice for predicting product sales at Toko Basmalah in the Malang Regency area. These advantages make ANN an effective and practical machine-learning approach for data-driven retail management.

CONCLUSION

This research provides one of the earliest applications of ANN-based forecasting in a Sharia retail context. The findings demonstrate that Artificial Neural Networks (ANN) offer a robust framework for capturing complex and nonlinear sales patterns, making them particularly suitable for the dynamic environment of retail operations such as Toko Basmalah in Malang Regency. Through systematic experimentation, the ANN-E architecture with a 90:10 training-to-testing data ratio emerged as the most optimal model, achieving a Mean Squared Error (MSE) of 0.3438. This low error rate indicates high predictive accuracy, as reflected in the close resemblance between predicted and actual sales trends. The model's ability to capture seasonal and weekly fluctuations further reinforces its effectiveness as a data-driven decision-support tool for retail management.

The practical implications of these findings suggest that integrating the ANN model into sales management systems can enhance responsiveness, efficiency, and accuracy in decision-making ranging from inventory planning and inter-outlet distribution to promotional strategy optimization. The results also encourage the adoption of AI-driven forecasting tools in local cooperatives to strengthen financial resilience and operational sustainability in the Sharia retail sector.

For future research, it is recommended to extend the model by incorporating external variables such as macroeconomic indicators, digital consumption behavior, or regional demand patterns to improve adaptability and predictive precision. Future studies may also compare ANN with hybrid deep learning models such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) for multi-branch demand prediction and broader generalization.

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