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Forecasting electronic money trends in Indonesia using neural network models: A comparative analysis

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Abstract

Forecasting electronic money transaction values is essential for effective financial planning and decision-making in various industries. This study evaluates the performance of three neural network models, which are Extreme Learning Machines (ELM), Multilayer Perceptron (MLP), and Neural Network Auto regression (NNETAR) for forecasting electronic money transaction values in Indonesia. The study fitted each model to electronic money transaction data, incorporating features like series modeling in differences, unilabiate lags, and output weight estimation techniques. The ELM utilized 24 hidden nodes and 20 repetitions, while the MLP used 5 hidden nodes and 20 repetitions, and NNETAR employed a 2-2-1 network architecture with 9 weights. Point forecasts were generated for future transaction values using each model. The results revealed variations in the point forecasts across the three models for each respective month, highlighting the diverse methodologies employed by ELM, MLP, and NNETAR in capturing underlying patterns within the data. For instance, the point forecasts for February 2024 ranged from 182,648 for the ELM to 170,525 for the MLP and 173,468 for NNETAR. Evaluation metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Scaled Error (MASE), were employed to assess the accuracy and reliability of the point forecasts. The results indicated that MLP consistently outperformed ELM and NNETAR across all evaluation metrics.

Keywords: Electronic money, forecasting, neural network, ELM, MLP, NNETAR
MSC2020: 91B84, 68T07, 62M10

1. Introduction

E-money usage in Indonesia has surged in recent years, reflecting a shift from cash to non-cash transactions. This trend aligns with global preferences for digital payments, driven by convenience, security, and technological advancements, positioning e-money as a key player in modern financial ecosystems.

Bank Indonesia reports a significant growth trend in the value of electronic money (e-money) transactions in Indonesia from 2015 to 2023. Starting at 14.756 billion Indonesian Rupiah (IDR) in 2015, the transaction value increased steadily, reaching 1.859.951 trillion IDR in 2023. This data indicates a notable shift towards non-cash payment usage among Indonesian society, highlighting rapid growth and significant market potential for e-money services in the country [1].

Therefore, employing accurate forecasting models for e-money transactions is crucial in today's digital financial landscape. Accurate forecasts help them anticipate demand fluctuations, optimize marketing efforts, and tailor services to meet consumer needs. By leveraging appropriate forecasting models, stakeholders can make informed decisions, mitigate risks, and capitalize on opportunities in the evolving digital financial ecosystem. Therefore, the use of suitable forecasting models for e-money transactions is indispensable in navigating the dynamic financial landscape.

A significant literature fact is the underutilization of neural network models in forecasting [2]–[8]. Despite the advancements in machine learning and artificial intelligence techniques, including neural networks, their application in forecasting e-money transactions remains relatively limited. Research trends related to forecasting electronic money usage encompass various methodologies. A study employed an ARIMAX-GARCH model to forecast electronic money transaction volumes [9]. Additionally, a study conducted research forecasting the diffusion of four major electronic payment methods [10]. Furthermore, a study predicted the adoption of mobile payment implementation using SEM-PLS [11]. While these methods have demonstrated efficacy in certain contexts, they may not fully capture the non-linear and dynamic nature of e-money transactions. Consequently, there is a notable gap in the literature regarding the exploration and adoption of neural network models for e-money forecasting, despite their potential to offer more accurate predictions and insights into complex transaction patterns.

The aim of this research is to address the existing gap in the literature regarding the utilization of neural network models in forecasting e-money trends. Despite the rapid development of machine learning techniques, including neural networks, their application in predicting e-money transactions remains relatively limited. This study aims to fill this knowledge gap by investigating the effectiveness of neural network models, such as Extreme Learning Machines (ELM), Multilayer Perceptron (MLP), and *Neural Network Auto regression* (NNETAR) in forecasting e-money trends in Indonesia. By conducting comparative analyses of these models alongside traditional forecasting methods, the research aims to provide a deeper understanding of the potential and advantages of neural network models in forecasting e-money transactions. It is expected that this research will offer new insights and make a significant contribution to the literature and digital financial management practices, helping bridge the existing knowledge gap and advancing our understanding of e-money trend forecasting.

ELM is a machine learning technique that uses a simple type of neural network with only one hidden layer. Unlike traditional neural networks, which adjust all their weights through an iterative learning process, ELM randomly assigns the weights in the hidden layer and then calculates the output weights using a mathematical formula. This approach makes training extremely fast and reduces the need for complex computations, making it useful for applications where speed is important, such as real-time data processing. MLP is one of the most common types of artificial neural networks, designed to recognize patterns and relationships in data. It consists of three main types of layers: an input layer, which receives data; one or more hidden layers, where computations are performed; and an output layer, which provides the final result. Each neuron (or node) in a layer is connected to neurons in the next layer, and these connections have adjustable weights. During training, the network learns by adjusting these weights to improve its predictions. MLPs are widely used for tasks like image recognition, speech processing, and predicting trends in data. Neural Network Auto regression (NNETAR) is a specialized model that applies neural networks to time-series forecasting, meaning it predicts future values based on past data. It works by identifying patterns and dependencies in historical data and then using this knowledge to make forecasts. For example, if a company wants to predict next month's sales based on previous months, NNETAR can analyze past trends and generate an estimate. This method is useful in areas such as economic forecasting, weather prediction, and stock market analysis. These three approaches represent distinct methodologies within the realm of neural network modeling, each with its unique characteristics and applications in various fields, including time series forecasting.

This research conducts a comparative analysis to evaluate the forecasting performance of ELM, MLP, and NNETAR models for e-money transaction trends in Indonesia. Using historical data and advanced neural network architectures, it highlights the strengths and limitations of each model. The findings aim to enhance forecasting techniques in the financial sector, supporting better decision-making and strategic planning for e-money transactions both in Indonesia and globally.

2. Methods

2.1 Data

This research used a comparative analysis approach to assess the forecasting effectiveness of three neural network models: ELM, MLP, and NNETAR. Employing a quantitative research design, it utilized historical electronic money transaction data sourced from Bank Indonesia's official website. The dataset, spanning a significant period, provided a robust basis for analyzing trends and evaluating model performance.

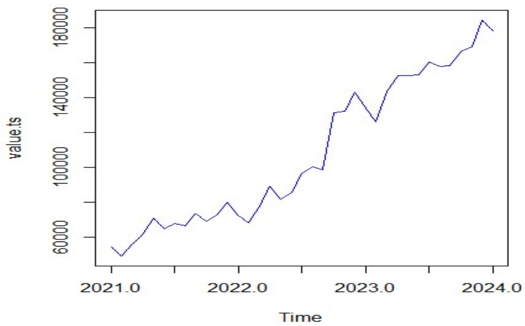


Figure 1. Plot of e-money transaction values (in billions)

Figure 1 displays monthly electronic money transaction values in Indonesia from January 2021 to January 2024, highlighting key trends and fluctuations. Transaction values showed steady growth from January 2021 to December 2022, peaking at 142,967 billion rupiahs before a slight decline. Significant surges in October and November 2022 suggest seasonal or event-driven factors. Growth continued in 2023, reaching 184,629 billion rupiahs by December. These trends provide valuable insights for optimizing electronic payment systems and enhancing financial inclusion.

The analysis focused on forecasting electronic money trends using ELM, MLP, and NNETAR models. Historical transaction data from Bank Indonesia were split into 80% training and 20% testing sets to ensure effective learning and unbiased evaluation. The training phase optimized model parameters, while the testing phase assessed performance on unseen data. Forecasting accuracy was measured using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). A comparative analysis evaluated each model's accuracy, robustness, and computational efficiency in predicting electronic money trends in Indonesia.

2.2 Extreme Learning Machines (ELM)

Extreme Learning Machines (ELM) is a concept in machine learning that involves the use of artificial neural networks with a single hidden layer, where the weights are randomly and directly assigned during the initial learning phase [3], [4]. This concept was developed as an alternative to address limitations in conventional learning methods that require lengthy iterative processes to determine weights. ELM stands as a training algorithm tailored for single hidden layer feed-forward neural networks (SLFN). It demonstrates notably accelerated convergence compared to conventional methods, delivering encouraging performance outcomes [12]. As an emerging technology, the ELM has garnered increasing interest from researchers, offering solutions to challenges encountered by alternative techniques[13].

The mathematical formulation for ELM can be written as follows. Let’s assume there is a training dataset$\{(x_i, t_i)\}_{i=1}^{N}$, where x_i is the input feature vector with length L and t_i is the target to be predicted. The goal of ELM is to learn a function f(x) that maps input **x** to output **y**, where **y** is the prediction generated by the model [13], [14].

The ELM model consists of a hidden layer with **M** neurons. The weights between input and hidden layer are given randomly and directly. Let's define the weights and biases for the hidden layer as **W** and **b**, respectively. The steps to form an ELM model are as follows [14]:

Step 1: Initialize weights **W** and biases **b** between input and hidden layer are randomly initialized with values taken from a certain distribution.
Step 2: Calculate output from the hidden layer **H** is obtained by multiplying input matrix **X** with weights **W** and adding bias **b**, then applying activation function $\boldsymbol{H} = g(\mathbf{XW} + \mathbf{b})$. Where *X* is the input matrix with dimensions $N \times L$, **H** is the output matrix from the hidden layer with dimensions $N \times M$.
Step 3: Calculate output weights by taking the pseudo-inverse of **H** and multiplying it with the target **t**; $\mathbf{W}_{output} = \mathbf{H}^{\dagger}\mathbf{t}$, where $\mathbf{H}^{\dagger}$ is the pseudo-inverse matrix of **H.**
Step 4: Predict the output of the model **y** by multiplying the output from the hidden layer **H** with the output weights; $\boldsymbol{y} = \mathbf{HW}_{output}$.

2.3 Multilayer Perceptron (MLP)

The Multilayer Perceptron (MLP) is a type of artificial neural network that consists of multiple layers of nodes, including an input layer, one or more hidden layers, and an output layer. Each node in the network, except for the input nodes, is a neuron that employs an activation function to compute its output. MLPs are widely used in various machine learning tasks, including classification, regression, and pattern recognition. The mathematical formulation for Multilayer Perceptron (MLP) can be described as follow. Let **x** be the input vector of dimension *n*, **y** be the output vector of dimension *m*, and $\mathbf{h}^{l}$ be the output vector of the l^{th} hidden layer with k_l nodes. The weight matrix connecting layer *l* to layer $l+1$ is denotedW^{l}, and the bias vector for layer $l+1$ is denoted by $\mathbf{b}^{(l+1)}$. The activation function for the neurons in the hidden layers and output layer is denoted by $f(\cdot)$.

The forward propagation of input data through the network to compute the output in MLP can be formulated as follows [15], [16]. For the first hidden layer$\mathbf{h}^{(1)} = f\left(\mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)}\right)$. Further, for $l = 2,3, \ldots, L-1$, where L is the total number of layers then $\mathbf{h}^{(l)} = f\left(\mathbf{W}^{(l)}\mathbf{h}^{(l-1)} + \mathbf{b}^{(l)}\right)$. Then, for the output layer $\mathbf{y} = f\left(\mathbf{W}^{(L)}\mathbf{h}^{(L-1)} + \mathbf{b}^{(L)}\right)$.

2.4 Neural Network Autoregression (NNETAR)

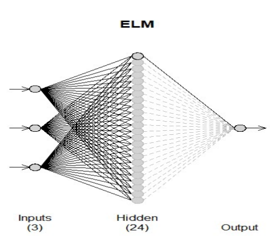
Neural Network Auto regression (NNETAR) is a method for time series forecasting that combines autoregressive (AR) modeling with neural networks to capture complex temporal dependencies in the data. It utilizes the strengths of both approaches to provide accurate predictions for time series data. The mathematical formulation for Neural Network Auto regression can be described as follows [17], [18]. Let y_t be the value of the time series at time t, and x_{t-k} represent the lagged values of the time series up to lag k. The goal of NNETAR is to predict the value of y_{t+1} based on the past values of the time series. Let the formulation of The AR component captures the linear relationship between the current value of the time series and its lagged values up to lag p can be written as $\hat{y}_{t+1} = \phi_0 + \phi_1 y_t + \phi_2 y_{t-1} + \cdots + \phi_p y_{t-p+1} + \epsilon_t$, where $\hat{y}_{t+1}$ is the predicted value at time $t+1$, $\phi_0, \phi_1, \ldots, \phi_p$ are the coefficients, and ϵ_t is the error term.

The neural network component captures non-linear patterns and dependencies in the data that may not be captured by the AR component alone can be formulated as $\hat{y}_{t+1} = f(\mathbf{W} \cdot \mathbf{x}_{t+1} + \mathbf{b})$, where $\hat{y}_{t+1}$ is the predicted value at time $t+1$, $f(\cdot)$ is the activation function, $\mathbf{W}$ is the weight matrix, $\mathbf{x}_{t+1}$is the input vector containing lagged values of the time series, and $\mathbf{b}$ is the bias vector. The final prediction is obtained by combining the predictions from the AR component and the neural network component, typically through a weighted sum or a simple averaging.

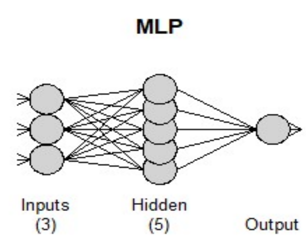
3. Results

3.1 Fitting Model Results and Network Architectures

Figure 2 displays the results of fitting the models used, illustrating how the model aligns with the available data. It is important to note that all data was analyzed using Rstudio software.



(a)



(b)

Figure 2. (a) ELM Network Architecture; (b) MLP Network Architecture

These research findings illustrate the application of the ELM model to the time series data representing electronic money transaction values in Indonesia. The model, with 24 hidden nodes and 20 repetitions, used first-order differencing to make the data stationary. It employed univariate lags at 1, 2, and 10 periods for prediction. The median of predicted values was used for final forecasts, and output weights were estimated using the Lasso method to prevent over fitting. However, the model's evaluation showed a high Mean Squared Error (MSE) of 85,280,523.7751, indicating significant prediction errors and suggesting the need for further refinement. The findings also highlight the use of the MLP model on the dataset, configured with 5 hidden nodes and 20 repetitions. The data was transformed into first-order differences (D1) to eliminate trends and make it stationary for better modeling. The model used univariate lags at lag 1, 2, and 10 as predictors, and the predictions were aggregated using the median operator. Output weights were estimated using the Lasso method to prevent overfitting. The model's performance was evaluated using Mean Squared Error (MSE), which was 1,652,919.54, indicating low error and promising predictive performance for forecasting the dataset.

Furthermore, forecasting model applied to electronic money transaction values in Indonesia uses the NNAR (1,1,2) [12] model, which includes one autoregressive term, one seasonal term, and two non-seasonal terms with a seasonal frequency of 12. The model averages results from 20 individual 2-2-1 neural networks and uses linear output units. The variance of the model residuals is 47,784,000, indicating variability around the predicted values.

Figure 2 illustrates the architecture of the ELM Network, where the hidden layer uses random projection weights, and the output layer employs LASSO for weight estimation. The hidden layer consists of 24 nodes, with each neuron receiving inputs from the input layer and generating outputs sent to the output layer. ELM assigns random weights between the input and hidden layers, allowing for quick learning without complex iterative processes. These weights remain fixed during training. The output layer has a single neuron that predicts the target variable. LASSO is used to estimate output weights, helping reduce over fitting and improve generalization by eliminating irrelevant features. Meanwhile, the MLP network architecture, consisting of 5 hidden layers designed to capture complex data patterns. While the number of hidden nodes in each layer is unspecified, each layer contains multiple neurons that perform nonlinear transformations on the input data. These transformations enable the network to learn abstract and nuanced representations, identifying intricate relationships in the data. The output layer contains a single neuron that synthesizes information from the hidden layers to generate predictions for electronic money transactions. This hierarchical structure allows the MLP to effectively model complex relationships, making it a powerful tool for forecasting and machine learning applications. The NNETAR model, specifically NNETAR (1,1,2) [12], uses a neural network architecture with one autoregressive term, one seasonal term, and two non-seasonal terms, with a seasonal frequency of 12. The MSE for the NNETAR model is 47,784,000, reflecting its ability to capture patterns within the dataset. Comparing the models, the MLP model shows the lowest MSE, indicating superior predictive performance over ELM and NNETAR. However, the choice of the best model depends on the specific analysis goals and the characteristics of the electronic money transaction dataset.

A comparison of the results from three models—ELM, MLP, and NNETAR —reveals distinct characteristics. The ELM model uses 24 hidden nodes and 20 repetitions, with first-order differences and univariate lags as predictors. Its MSE is 85,280,523.7751. The

MLP model, with 5 hidden nodes and 20 repetitions, achieves a significantly lower MSE of 1,652,919.5418. Lastly, the NNETAR model, with one autoregressive and one seasonal term, reports an MSE of 47,784,000. The MLP model performs best with the lowest MSE, suggesting superior predictive accuracy. However, the best model choice depends on the specific objectives and characteristics of the dataset.

3.2 Accuracy Measures

The following table 1 presents the results of accuracy testing for the forecasting models using ELM, MLP, and NNETAR.

Table 1. Accuracy measures

Accuracy measures	ELM	MLP	NNETAR
ME	0.000	-149.720	23.916
RMSE	9234.745	1455.447	6777.317
MAE	7237.444	993.537	4811.806
MPE	-0.396	-0.315	-0.393
MAPE	9.533	1.325	4.231
MASE	0.198	0.027	0.108

The evaluation metrics in table 1 provide valuable insights into the predictive accuracy and tendencies of the three forecasting models: ELM, MLP, and NNETAR. For Mean Error (ME), the ELM model shows no systematic bias with a value of 0.000, meaning its predictions are equally distributed around the actual values. In contrast, the MLP model has a negative ME of -149.720, suggesting a consistent underestimation of actual values, while the NNETAR model has a positive ME of 23.916, indicating a tendency to overestimate.

From table 1, in terms of Root Mean Squared Error (RMSE), the ELM model exhibits the highest value of 9234.745, indicating a relatively large deviation from the actual values. The MLP model performs better with a much lower RMSE of 1455.447, suggesting more accurate predictions. The NNETAR model falls in between with an RMSE of 6777.317, indicating moderate prediction accuracy. Similarly, for Mean Absolute Error (MAE), the ELM model shows a relatively high error of 7237.444, while the MLP model again outperforms with an MAE of 993.537, and the NNETAR model has a value of 4811.806, showing intermediate performance.

The Mean Percentage Error (MPE) for the ELM, MLP, and NNETAR models are -0.396%, -0.315%, and -0.393%, respectively, indicating that all models tend to underestimate the actual values, with the MLP showing the least underestimation. For Mean Absolute Percentage Error (MAPE), the ELM model has the highest value of 9.533%, indicating significant deviations from actual values, while the MLP model performs best with a low MAPE of 1.325%, suggesting more accurate predictions. The NNETAR model's MAPE of 4.231% places it in between the other two models.

Finally, in terms of Mean Absolute Scaled Error (MASE), the MLP model has the best relative accuracy with a value of 0.027, suggesting its performance is very close to the baseline model. The NNETAR model has a MASE of 0.108, indicating better performance than the ELM model, which has a MASE of 0.198, suggesting its predictions are relatively worse than the naive baseline.

Overall, table 1 shows the MLP model outperforms both ELM and NNETAR across most metrics, particularly in terms of accuracy and relative error, making it the most reliable model for forecasting electronic money transaction values in this study. However, these metrics should be considered alongside the models' characteristics and the specific forecasting context for a comprehensive assessment.

3.3 Forecasting Results

The forecasted values of electronic money transactions in Indonesia for the next 12 months using ELM, MLP, and NNETAR models are presented in the following Table 2.

Table 2. Point forecasts

Point forecasts	ELM	MLP	NNETAR
Feb-24	182648	170525	173468
Mar-24	186727	193864	178053
Apr-24	190805	209839	180118
May-24	194884	218528	180626
Jun-24	198962	216170	180795
Jul-24	203040	224193	180382
Aug-24	207119	223829	180775
Sep-24	211197	222652	180851
Oct-24	215276	242486	175952
Nov-24	219354	246740	165655
Dec-24	223432	259970	157239
Jan-25	227511	256664	157761

The visualization of the forecasting results is presented in Figure 3 below to quickly convey information regarding trends, patterns, and fluctuations in the predicted data over time.

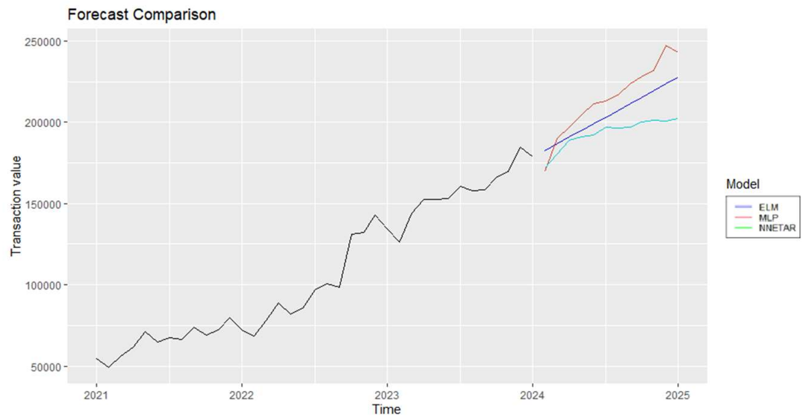


Figure 3. Plot of forecasting results

In the above Figure 3, the red line represents the forecast results using MLP, the blue line represents the forecast results using ELM, and the green line represents the forecast results using NNETAR. Table 2 and figure 3 show the point forecasts from ELM, MLP, and NNETAR models for each month from February 2024 to January 2025. The point forecasts obtained from the ELM, MLP, and NNETAR models provide valuable insights into the projected electronic money transaction values in Indonesia for the period from February 2024 to January 2025. Each model offers its unique perspective on the future trends in electronic money transactions.

The point forecasts from the ELM, MLP, and NNETAR models show variations in predicted values for each month, highlighting the different methodologies used by each model to capture underlying patterns. For example, for February 2024, the ELM model predicts a transaction value of 182,648, while the MLP model forecasts a lower value of 170,525, and the NNETAR model predicts 173,468. These differences continue across the following months, indicating that each model offers unique projections.

4. Conclusion

From the results and discussion of the research, it can be concluded that the evaluation of forecasting models for electronic money transaction values in Indonesia provides a comprehensive overview of the performance of each model. Various evaluation metrics, such as RMSE, MAE, MAPE, and MASE, were used to measure the accuracy and reliability of predictions from each model. Based on the evaluation results, it was found that the Multilayer Perceptron (MLP) model excels as the best model for predicting electronic money transaction values. MLP demonstrates superior performance compared to the Extreme Learning Machines (ELM) and Neural Network Auto regression (NNETAR) models across several evaluation metrics. With lower RMSE, smaller MAE, lower MAPE, and significantly lower MASE, MLP provides more accurate and reliable predictions. These findings offer a strong recommendation for stakeholders to utilize the MLP model in forecasting applications related to electronic money transaction values in

Indonesia. Furthermore, the analysis indicates that comparing predictions from each model provides valuable insights into the strengths and weaknesses of each approach. The differences in predictions between models highlight the diverse methodologies in capturing underlying patterns in the data. Therefore, this evaluation not only provides information about the relative performance of each model but also offers deep insights into the complexity of the data and the most effective approaches in forecasting electronic money transaction trends in Indonesia.

This research has some limitations. It is limited to a specific time frame and dataset, and the results may vary when applied to different datasets or time periods. Therefore, future research is recommended to expand the scope by including a broader range of datasets and testing the robustness of the findings across various contexts. This research contributes valuable insights into the forecasting of electronic money transaction values in Indonesia. By highlighting the superiority of the MLP model and providing recommendations for future research directions, this study informs stakeholders and researchers in making informed decisions and advancing the field of electronic money transaction forecasting.

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