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A MULTI-LAYER PERCEPTRON NEURAL NETWORK FOR PREDICTING MOBILE BANKING TRANSACTION

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Abstrak

Perbankan mobile semakin marak di era digital saat ini, memberikan kemudahan dan aksesibilitas dalam melakukan transaksi keuangan bagi para pengguna. Penelitian ini menggunakan model jaringan saraf tiruan multi-layer perceptron (MLP) *untuk melakukan peramalan volume transaksi* mobile banking *di Indonesia. Dengan memanfaatkan data sekunder yang bersumber dari situs resmi Bank Indonesia, digunakan* dataset *yang terdiri atas 133 observasi deret waktu dari Januari 2013 hingga Januari 2024. Data dibagi menjadi* training set *dan* testing set *dengan proporsi masing-masing 80% dan 20%. Analisis dilakukan menggunakan* RStudio. MLP *dikonfigurasi dengan 5* hidden nodes *dan 20* repetitions.*Evaluasi hasil menunjukkan adanya perbedaan kinerja model yang cukup mencolok antara* training set *dan* test set. *Model* MLP *menghasilkan akurasi peramalan yang tinggi dengan tingkat kesalahan yang minimal, yang ditunjukkan oleh nilai* Mean Absolute Error (MAE) *sebesar 754,294,* Mean Absolute Percentage Error (MAPE) *sebesar 1,163, dan* Mean Absolute Scaled Error (MASE) *sebesar 0,027. Hasil ini menegaskan keandalan model* MLP *sebagai alat yang efektif untuk peramalan deret waktu.Hasil peramalan menunjukkan adanya tren peningkatan yang signifikan pada volume transaksi* mobile banking *selama 24 bulan ke depan (Februari 2024–Januari 2026). Volume tertinggi diproyeksikan terjadi pada Desember 2025, yaitu mencapai 2.065.309 transaksi, dengan fluktuasi kecil pada beberapa bulan tertentu. Temuan ini memberikan wawasan berharga bagi lembaga keuangan dalam merancang strategi dan mengalokasikan sumber daya secara efektif untuk mengantisipasi pertumbuhan* mobile banking *yang diperkirakan.*

Abstract

Mobile banking has become increasingly prevalent in today's digital age, providing convenient and accessible financial transactions for users. This research used a multi-layer perceptron (MLP) of neural network model for forecasting mobile banking transaction volumes in Indonesia. Utilizing secondary data sourced from Bank Indonesia's official website, a dataset comprising 133 time series observations from January 2013 to January 2024 was analyzed. The data was divided into training and testing sets, with proportions of 80% and 20%, respectively. Analysis was conducted using RStudio. The MLP was configured with 5 hidden nodes and 20 repetitions. The evaluation of results revealed noteworthy differences in model performance between the training and test sets. The MLP model delivered high forecasting accuracy with minimal error, evidenced by a Mean Absolute Error (MAE) of 754.294, a Mean Absolute Percentage Error (MAPE) of 1.163, and a Mean Absolute Scaled Error (MASE) of 0.027. These results confirm the MLP model's reliability as an effective tool for time series forecasting. Forecasting results indicate a significant upward trend in mobile banking transaction volumes over the next 24 months (February 2024–January 2026). The highest volume is projected in December 2025, reaching 2,065,309 transactions, with minor fluctuations observed in some months. These findings provide valuable insights for financial institutions to strategize and allocate resources effectively to accommodate the anticipated growth in mobile banking

Keywords: *mobile banking transaction, forecasting, neural network, multi-layer perceptron*

INTRODUCTION

The emergence of mobile technology has brought about significant transformations across various aspects of daily life, notably impacting the realm of financial transactions. In Indonesia, the widespread adoption of mobile banking has reshaped the landscape of financial services, providing unparalleled convenience and accessibility to a diverse range of users. However, amidst the rapid expansion of mobile banking usage, financial institutions encounter the pressing challenge of accurately forecasting transaction volumes. This task is essential for effectively managing resources, mitigating risks, and optimizing service delivery to meet the evolving needs of customers. Thus, the ability to predict mobile banking transaction volumes reliably holds paramount importance in ensuring the sustainability and efficiency of banking operations in Indonesia's dynamic financial environment.

The data from Bank Indonesia (2024) illustrates a clear upward trend in mobile banking transaction volumes in Indonesia over the years. From 2020 to 2023, there is a consistent increase in transaction volumes month by month, indicating a growing preference for mobile banking services among Indonesians. The trend suggests a sustained and robust adoption of mobile banking technology in the country's financial ecosystem. Several significant increases in transaction volumes stand out within the dataset. For instance, in August 2023, there is a substantial surge in transaction volumes compared to previous months, with transaction volume reaching 1,219,044 (in thousand).

Previous research has extensively investigated predictive modeling techniques for forecasting financial transaction volumes, particularly in the realm of time series analysis. One prediction tool that is believed to provide high accuracy results is a multi-layer perceptron (MLP) based on artificial neural networks (Al-Dahhan et al., 2023; Yan et al., 2023). The MLP is a basic feed-forward neural network that helps illustrate the traditional architectures of most deep learning models. It consists of multiple layers of neurons, typically structured into three primary types of layers: It is composed of an input layer, one or multiple hidden layers, and the output layer (Park & Lek, 2016). Each neuron in the MLP is connected to every neuron in adjacent layers, with weights adjusted during training to approximate complex non-linear functions (Park & Lek, 2016).This makes it possible for the MLPs to decode and encode information through multiple layers meaning that each layer contributes to the accuracy of the overall network in terms of making predictions or classifications of the data.

Several investigations have examined the use of MLP in various fields, demonstrating their capacity for precise forecasting. The capacity of the MLP models to employ multi-layered neural network architectures to capture intricate correlations within data has drawn attention. In a study, the MLP is used to forecast currency rates (Maté & Jimeńez, 2021). The MLP is a prediction model used in research by Mahmudah et al. (2022) to evaluate academic resilience. The MLP model's predictions show a high degree of accuracy. Additionally, bankruptcy is predicted by the MLP model (Brenes et al., 2022). MLP models have garnered attention for their ability to capture complex relationships within data through the use of multi-layered neural network architectures. A research apply the MLP for forecasting exchange rates (Maté & Jimeńez, 2021). Research by Mahmudah et al. (2022) employs the MLP as a predictive model to assess academic resilience. The predictions made by the MLP model exhibit a high level of accuracy. The MLP model also uses to predict bankruptcy (Brenes et al., 2022).

Furthermore, forecasting mobile banking transactions using a MLP neural network can be a powerful tool in enhancing security and efficiency in financial transactions. Studies have shown the increasing importance of safe financial transactions in mobile banking (Oguntimilehin et al., 2022; Shrivastava & Johari, 2022), with a focus on authentication solutions using Convolutional Neural Networks (CNN) and facial recognition models (Oguntimilehin et al., 2022). Additionally, research has highlighted the significant predictors influencing mobile banking acceptance, such as autonomous motivation and perceived ease of use (Akgül, 2020). Understanding customers' reasons for non-usage of mobile banking apps in developing countries like Nigeria is crucial, with AI-based models identifying dominant parameters affecting mobile banking growth, including risk, trust, and digital laws (Cavus et al., 2021). By leveraging MLP neural networks, financial institutions can improve forecasting accuracy and enhance the overall mobile banking experience.

However, predictions of mobile banking transactions in Indonesia using MLP have not been widely analysed. The novelty of this research lies in its exploration of mobile banking transaction predictions specifically within the context of Indonesia, utilizing the MLP neural network. In spite of Indonesia's extensive use of mobile banking, there is a noticeable lack of information in the literature about the use of MLP for transaction forecasting in this specific market. By filling this gap, the research hopes to provide insightful information about the dynamics of mobile banking transactions in Indonesia, providing a fresh viewpoint that hasn't been thoroughly examined before. With a localized focus, forecasting may be done more precisely and contextually, taking into account the unique features and subtleties of the Indonesian banking environment.

Furthermore, this research adds contextual information to the predictive model, enabling more precise and flexible forecasts, by utilizing past transaction data as well as external variables like economic and demographic aspects. Furthermore, this demonstrates the precision and dependability of the model through thorough optimization and performance assessment. Its ramifications reach into managerial and business contexts, providing guidance on risk management, financial planning, and strategic decision-making. Therefore, it makes a substantial contribution to more effective and economical prediction algorithms with wider applicability in financial analytics and banking by improving understanding of mobile banking transaction trends.

LITERATURE REVIEW

Mobile Banking Transaction

Mobile banking transactions involve the execution of financial activities via mobile devices, enabling users to access banking services such as account monitoring, money transfers, bill payments and remote cheque deposits (Weber & Darbellay, 2010). Mobile banking adoption has been extensively studied using various theoretical frameworks to understand user acceptance and behavior (Baptista & Oliveira, 2015). Prominent among these is the Technology Acceptance Model (TAM), which posits that perceived ease of use and perceived usefulness are critical determinants of technology adoption.

Further research has extended these models by integrating variables such as trust, perceived risk, and transaction convenience to provide a more comprehensive understanding of mobile banking adoption. For example, a conceptual framework that extends TAM includes transaction convenience and perceived risk as significant factors affecting user acceptance of mobile banking services (Sulistyowati et al., 2021). This approach recognizes that while users may recognize the benefits and ease of use of mobile banking, concerns about security and trustworthiness may significantly influence their decision to adopt such technologies.

Multilayer Perceptron (MLP)

The forecasting analysis step of the data analysis involves applying the MLP model to the time series dataset. In this investigation, past mobile banking transaction data is used to train the models, and their accuracy in forecasting future transaction volumes is evaluated. Because it is one of the most widely used varieties of artificial neural networks and has the ability to understand intricate correlations between input and output, the MLP was selected. The 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 (Dawson, 2018; Kuvvetli et al., 2021). 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 (El hlouli et al., 2020; Lima-Junior & Carpinetti, 2019).

The mathematical formulation for MLP can be described as follow. Let $\mathbf{x}$ be the input vector of dimension n, $\mathbf{y}$ 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 (Rumelhart et al., 1986, 2019). For the first hidden layer $\mathbf{h}^{(1)} = f\left(\mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)}\right)$. Further, for $l = 2,3, \dots, L-1$, 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 $\mathbf{y} = f\left(\mathbf{W}^{(L)}\mathbf{h}^{(L-1)} + \mathbf{b}^{(L)}\right)$.

METHODS

The selection of mobile banking transaction in Indonesia as the focus of this research stems from its increasing significance in the country's financial landscape. With the rapid growth of mobile technology and internet accessibility, mobile banking has emerged as a prominent channel for financial transactions among Indonesian consumers. This trend aligns with the broader global shift towards digital banking services. This research adopts a quantitative design through forecasting analysis to compare the efficacy of extreme learning machine and MLP models in predicting mobile banking transactions in Indonesia. Quantitative research allows for the systematic examination and comparison of numerical data, providing empirical evidence to support research hypotheses. By employing quantitative methodologies, this study aims to quantify the predictive accuracy, reliability, and computational efficiency of MLP model in forecasting mobile banking transaction volumes.

The secondary data utilized in this research consists of a time series dataset comprising mobile banking transaction volumes recorded from January 2013 to January 2024. Data collection involves the retrieval of secondary data published by Bank Indonesia through their official website. By accessing data from the primary regulatory authority overseeing the banking sector in Indonesia, this research ensures the reliability, accuracy, and integrity of the dataset. The utilization of secondary data from a reputable source enhances the validity of the findings and facilitates meaningful comparisons between different prediction models.

Figure 1 below illustrates the trend of the time series data for mobile banking transaction volume spanning from January 2013 to January 2024.

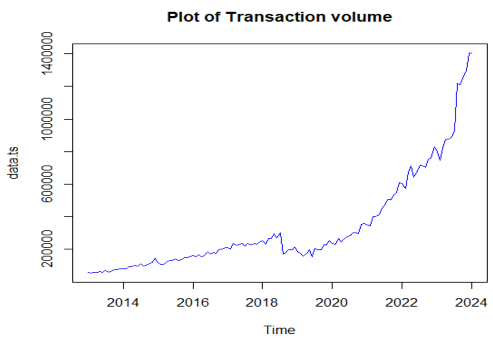
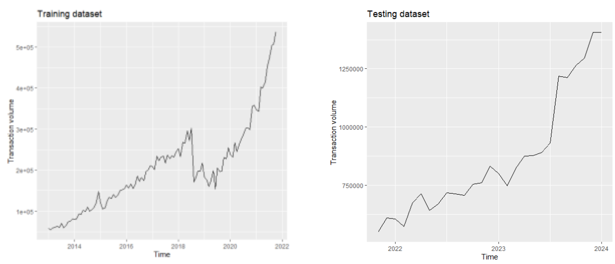


Figure 1: Plot of Mobile Banking Transaction Volume (in Thousand)

The figure 2 below illustrates the training and testing datasets sequentially, adhering to the 80-20 split criterion. Training data comprises 80% of the dataset, while testing data consists of the remaining 20%.



(a) Plot of Training Dataset

(b) Plot of Testing Dataset

Figure 2: Plot of Training and Testing Datasets

Training data is used to train the neural network model. The training process involves presenting historical transaction data to the model, allowing it to learn patterns within the data. Training data is used to adjust the weights connecting the neurons in the neural network. Testing data is used to evaluate the performance of the trained model. Testing data should not be used in the training process, thus providing an independent evaluation of the model's ability to predict new data. After the model is trained using the training data, testing data is then presented to the model to generate predictions. Subsequently, the predicted results are compared with the actual values in the testing data. Model performance evaluation is conducted based on metrics such as ME (Mean Error), RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), MPE (Mean Percentage Error), MAPE (Mean Absolute

Percentage Error), MASE (Mean Absolute Scaled Error), and ACF1 (Autocorrelation Function).

RESULT AND DISCUSSION

Model Fitting

The fitting of the models is a critical activity in the assessment of the mobile banking transaction volume forecast using the MLP. Thus, by fine-tuning the model parameters successfully we achieve the best performance, which increases the predictability of mobile banking transactions to overcome the challenges of the complex nature of the transaction data set. This makes certain that the MLP model would be capable of learning complex structures within the data hence providing the necessary and accurate predictions that the financial institutions need for proper planning and decision making. Based on the MLP model, the training data has been fitted. The Figure 3 provided illustrates the architecture of the MLP Network.

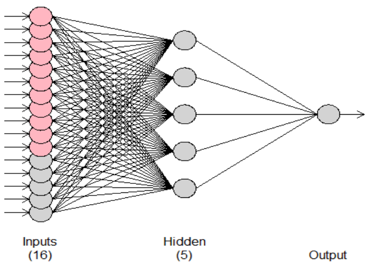


Figure 3 MLP Network Architecture

Accompanying figure 3, the output details the specific configuration and settings used during the model fitting process. the MLP model trained with 5 hidden nodes and 20 repetitions, models the series in differences (D1) with univariate lags at intervals of 1, 5, 7, 10, and 12, alongside deterministic seasonal dummies. Utilizing the median operator for forecast combination, the model exhibits a Mean Squared Error (MSE) of 12,691,303.21.

Forecasting Results

This section discusses the forecasting results for mobile banking transaction volumes in Indonesia using time series data spanning from January 2013 to January 2024. The forecasting exercise provides insights into the anticipated trends and patterns in mobile banking transaction volumes over the forecast horizon. The table below displays the accuracy measure values from the MLP model.

Table 1: Performance of Forecasting Results

Accuracy measures	**Measure error**
ME	46.518
RMSE	1172.287
MAE	754.294
MPE	0.061
MAPE	1.163
MASE	0.027
ACF1	0.1754

The Multi-Layer Perceptron (MLP) model forecasting results show a passably excellent performance in predicting the time series data. The model's Mean Error (ME) of 46.518, as indicated by the error measurements, indicates a minor propensity to under-predict on average. The average size of prediction mistakes is indicated by the Mean Absolute Error (MAE) of 754.294 and the Root Mean Squared Error (RMSE) of 1172.287. Both the mean and the relative percentage errors of the model's predictions—the mean percentage error (MPE) is 0.061, and the mean absolute percentage error (MAPE) is 1.163—show that the model's forecasts are accurate. Furthermore, the model performs noticeably better than a naive forecasting strategy, as evidenced by the Mean Absolute Scaled Error (MASE) of 0.027. The residuals' autocorrelation at lag 1 (ACF1) is 0.175, indicating that the forecast errors' autocorrelation is within reasonable bounds. All things considered, these measures show that the MLP model is a trustworthy forecasting tool that produces precise predictions with minimal levels of error.

Figure 4 presents the point forecasts derived from the ELM and MLP models, showcasing the projected transaction volumes for each month within the forecast period.

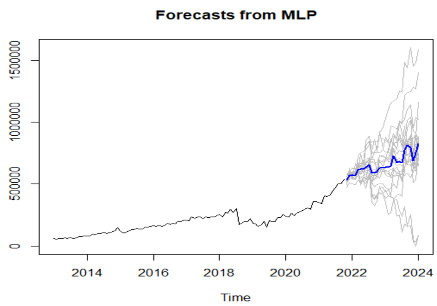


Figure 4: forecast results from MLP

From figure 4 can be seen clearly that the forecast highlights seasonal fluctuations in mobile banking transaction volumes across different months and years. Notable increases in transaction volumes during certain months are followed by periods of relatively lower activity. This seasonal pattern suggests the influence of external factors such as holidays, economic cycles, or promotional activities on mobile banking usage. Despite seasonal variations, the forecast indicates an overall upward trend in mobile banking transaction volumes over the forecast horizon. The projected volumes show a gradual increase from year to year, reflecting the growing adoption of mobile banking services among Indonesian consumers. This trend aligns with the broader shift towards digital banking channels and the increasing reliance on mobile devices for financial transactions.

The finding in Figure 4 indicate that the MLP model produces predictions closer to the testing data underscores its superior capability in capturing complex data patterns. This suggests that the MLP model has a higher degree of flexibility and adaptability, allowing it to better adjust to the nuances of the data and produce more accurate forecasts. The practical significance of this observation is substantial, particularly within the banking sector. Accurate predictions of mobile banking transaction volumes are crucial for banks in various aspects of their operations, including resource allocation, risk management, and strategic decision-making. By utilizing the MLP model, banks can make more informed decisions based on forecasts that closely resemble real-world scenarios. This can lead to more effective strategic planning, such as optimizing marketing campaigns, adjusting service offerings, or managing cash flow more efficiently.

The figure 5 illustrates the forecasted volume of mobile banking transactions for the next 24 months using the MLP model.

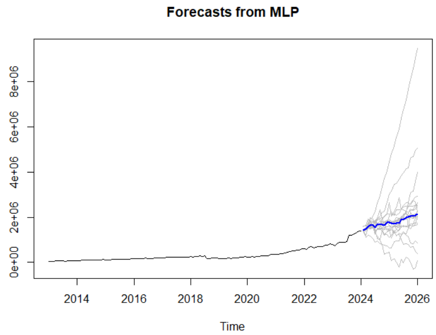


Figure 5: Forecasting Results using MLP Model

The point forecast results for mobile banking transaction volumes over the next 24 months, using the best model, MLP, reveal a significant upward trend month by month. In this depiction, it is evident that transaction volumes are expected to continue increasing from February 2024 to January 2026. The highest peak is projected to occur in December 2025, with transaction volumes reaching 2,065,309. Other periods also indicate a consistently rising trend, except for a few months experiencing minor fluctuations. These projections offer valuable insights for financial institutions in planning strategies and resource allocation to anticipate the growth of mobile banking transaction volumes in the future.

The analysis of the forecast conducted using the MLP model unveils significant insights into mobile banking transaction volumes in Indonesia. Three key observations emerge from the forecast, providing valuable understanding of the trends and patterns in the data. Firstly, the forecast illustrates pronounced seasonal fluctuations in transaction volumes across various months and years. This pattern suggests the impact of external factors such as holidays, economic cycles, or promotional activities on mobile banking usage. Secondly, despite these seasonal variations, the forecast indicates a consistent upward trend in transaction volumes over the forecast period. This reflects the ongoing adoption of mobile banking services among Indonesian consumers, aligning with the broader transition towards digital banking channels and increased reliance on mobile devices for financial transactions. Lastly, the graphical representation of the forecasted volumes offers stakeholders insights into the accuracy and reliability of the MLP model's predictions. By comparing forecasted values with historical data, stakeholders can assess the model's performance and make informed decisions regarding resource allocation, operational planning, and strategic initiatives in the mobile banking sector. These observations not only provide strategic insights for decision-making but also enable stakeholders to assess the model's performance and identify areas for improvement, ultimately contributing to the advancement of the mobile banking landscape in Indonesia.

From figure 5, the comprehensive analysis of the forecasting results from the MLP model as the best model for mobile banking transaction volumes over the next 24 months reveals several important insights. Firstly, there is a consistent and steady growth trend projected, indicating an ongoing increase in mobile banking usage among consumers. This suggests a sustained shift towards digital banking services, reflecting evolving consumer preferences and technological advancements. Secondly, December 2025 emerges as a peak period with the highest anticipated transaction volume, likely driven by seasonal factors and end-of-year financial activities. Despite this overall upward trend, minor fluctuations are observed in certain months, possibly influenced by seasonal spending patterns or economic conditions. These fluctuations underscore the dynamic nature of mobile banking usage and the need for adaptive strategies by financial institutions. Moreover, these forecasts offer strategic planning implications for banks, enabling them to allocate resources effectively, optimize digital infrastructure, and tailor marketing strategies to accommodate the expected growth in mobile banking transactions. Additionally, the projected increase in transaction volumes presents opportunities for banks to enhance customer engagement through innovative mobile banking features and personalized services. However, alongside these opportunities, banks must also prioritize risk management strategies to safeguard customer data, prevent fraudulent activities, and ensure the security of mobile banking platforms. Furthermore, the implications extend beyond individual banks to the industry as a whole. The adoption of advanced prediction models like MLP can enhance the overall efficiency and competitiveness of the banking sector. Banks that leverage sophisticated forecasting techniques are better positioned to anticipate market trends, mitigate risks, and capitalize on emerging opportunities. This not only benefits individual institutions but also contributes to the stability and innovation within the banking industry.

CONCLUSIONS

In conclusion, this research has successfully demonstrated the MLP model's robust capability in accurately forecasting transaction volumes in the mobile banking sector. The findings from the study reveal that the MLP model consistently produces predictions that align closely with actual testing data, highlighting its superior ability to capture complex data patterns and adapt to nuanced changes. This adaptability makes it a valuable tool for financial institutions, which require precise forecasts to optimize operations, manage risks, and guide strategic decision-making effectively. The finding, particularly evident in the projections for the next 28 months, indicates a significant and continuous upward trend in mobile banking transaction volumes. This trend suggests not only an increase in mobile banking transactions but also reflects a broader consumer shift towards digital banking solutions, driven by evolving preferences and technological advancements.

The practical contribution of this research lies in providing valuable insights for the banking industry, particularly in developing prediction models for estimating mobile banking transaction volumes. With a better understanding of prediction model performance, banks can choose the most suitable models, enhancing prediction accuracy, and optimizing their business strategies. However, limitations may lie in the specific focus on mobile banking transaction data in Indonesia, potentially limiting direct applicability to other countries' mobile banking contexts. Recommendations for future research include expanding the study scope to involve data from various countries or regions and exploring the use of alternative prediction techniques or models to improve the prediction performance of mobile banking transaction volumes globally.

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