

N-Beats Optimization With K-Fold Cross-Validation for Stock Market Price Prediction in Indonesia

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ABSTRACT

In the era of capital-market digitalization, stock price prediction poses a significant challenge, particularly in developing countries like Indonesia, where high market volatility is driven by political dynamics and exchange-rate fluctuations. This study aims to address these challenges by developing a stock price prediction model using the N-BEATS optimization with K-fold cross-validation for stock market price prediction in Indonesia architecture, which is designed to overcome the limitations of traditional methods such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). The dataset includes open, high, low, close, and volume from five leading Indonesian banks between 2004 and 2024. The N-BEATS optimization with K-fold cross-validation for stock market price prediction in Indonesia model is optimized using K-fold cross-validation to enhance accuracy and reduce overfitting risks. Evaluation results demonstrate that the N-BEATS optimization with K-fold cross-validation for stock market price prediction in Indonesia model gave better accuracy compared to CNN and RNN models, with a 30% improvement over CNN and 25% over RNN. Analysis of performance variability across stock symbols reveals that the intrinsic data characteristics of each stock influence prediction accuracy. The N-BEATS optimization with K-fold cross-validation for stock market price prediction in Indonesia model exhibits significant potential for stock price prediction in the Indonesian market, excelling in capturing long-term dependencies and offering better interpretability.

KEYWORDS

Stock Prediction, N-BEATS, Deep Learning, Financial Forecasting, CNN, RNN



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INTRODUCTION

In the context of capital market digitalization, stock price prediction is one of the important elements in investment decision-making, especially in developing countries such as Indonesia (Zega & Satato, 2025). The Indonesian Stock Exchange (IDX) has experienced significant growth in recent years, with market capitalization reaching IDR 9,038 trillion by the end of 2023, reflecting increased investor participation and market depth. However, this growth is accompanied by substantial challenges related to market volatility and prediction complexity.

High volatility caused by various factors, including political dynamics and exchange rate fluctuations, makes the Indonesian stock market a risky but potentially rewarding environment (Sudirman et al., 2023). The unique characteristics of emerging markets, such as Indonesia, include lower liquidity, higher transaction costs, and greater susceptibility to external shocks compared to developed markets (Indrawati, Diop, Ikhsan, & Kacaribu, 2020). These factors create distinct patterns in price movements that require specialized modeling approaches (Labys, 2017). Accuracy in stock price predictions not only affects the profitability of individual investors, but also contributes to the stability of the national financial system, given the dominance of the banking sector in the Indonesian market (Massau et al., 2021). The

banking sector accounts for approximately 40% of the total market capitalization on the IDX, making it a critical indicator of overall market health and economic stability. In this context, there is an urgent need to develop predictive models that are adaptive to dynamic changes in the market.

Various traditional machine learning methods, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), are often chosen to predict stock prices due to their ability to analyze sequential data with effective architectural patterns (Diqi & Hamzah, 2024). However, each of these methods has its drawbacks. The CNN method faces challenges in parameter optimization, given the complexity of the optimization space involving many hyperparameters, such as the number of layers, neurons, kernels, and strides, which often require large computing resources (Al-Saggaf et al., 2022). On the other hand, although RNN is capable of processing sequential data, it is susceptible to problems such as gradient loss (Vanishing Gradient) and gradient explosion (Exploding Gradient), which are caused by gradient instability in long-term assessment (Engelken, 2023).

Alternatively, Neural Basis Expansion Analysis for Time Series (N-BEATS) offers a different approach than CNN and RNN, with a unique architecture that combines forward and backward residual links as well as multiple fully connected stacks (Oreshkin et al., 2020). This approach differs from traditional deep learning models, as N-BEATS has good interpretability and can be applied directly to various domains without the need for additional modifications (Zein et al., 2024). This more efficient architecture provides a new approach to time series data prediction through a back-and-forth residual link mechanism, giving N-BEATS the advantage of predicting financial data without the need for extensive feature engineering. This method can adapt to various temporal patterns simultaneously and provide a better interpretation of the factors that affect predictions. This study shows that the N-BEATS architecture can outperform traditional deep learning methods in predicting stock prices.

The novelty of this research lies in three main contributions: First, this study represents the first comprehensive application of *N-BEATS* architecture optimized with K-Fold cross-validation specifically for Indonesian banking sector stock prediction, addressing the unique volatility patterns of emerging markets. Second, the research provides empirical evidence of N-BEATS superiority over traditional deep learning methods (CNN and RNN) in capturing both short-term fluctuations and long-term trends in Indonesian stock data, demonstrating improvements of up to 30% over CNN and 25% over RNN. Third, the study introduces a systematic analysis of how different K-Fold configurations (5, 10, 15, and 20 folds) affect model performance across stocks with varying volatility profiles, providing practical guidelines for optimal model configuration in financial forecasting applications. This study aims to explore the potential of *N-BEATS* in stock price prediction and compare it with more conventional deep learning methods. Specifically, the research objectives are: (1) to develop and optimize an *N-BEATS* model using K-Fold cross-validation for predicting Indonesian banking sector stock prices; (2) to conduct a comprehensive comparative analysis between *N-BEATS*, CNN, and RNN models using multiple evaluation metrics (MAE, RMSE, and MAPE); and (3) to analyze the impact of different K-Fold configurations on prediction accuracy across stocks with varying volatility characteristics.

The research provides significant benefits across multiple dimensions. Academically, it contributes empirical evidence on the effectiveness of *N-BEATS* architecture in emerging

market contexts, expanding the body of knowledge on deep learning applications in financial forecasting. Practically, the findings offer actionable insights for investment managers, financial analysts, and algorithmic traders seeking to improve prediction accuracy in volatile markets. For the Indonesian financial sector specifically, this research provides a robust framework for risk management and portfolio optimization, potentially improving market efficiency and investor confidence. Furthermore, the systematic analysis of K-Fold optimization strategies contributes methodological guidance for researchers applying deep learning to time series prediction problems in various domains beyond finance.

METHOD

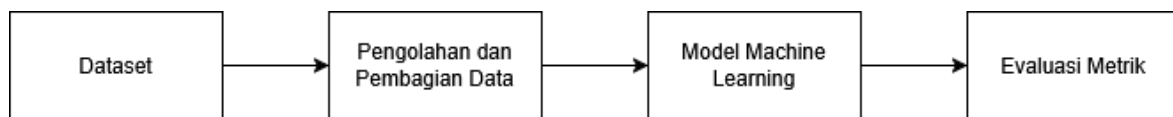


Figure 1. Research Stage Diagram

The dataset to be used in this study was obtained through the yahoo finance website (Fitriyani et al., 2021). The data used in this study consists of time series data on stock prices from five leading banks in Indonesia, namely BBKA. JK, BBRI. JK, NISP. JK, BMRI. JK, and BDMN. JK. Stock price data is taken from 2004 to 2024 which includes key attributes, such as date, opening price (Open), highest price (High), lowest price (Low), closing price (Close), and Volume. In this study, the data attribute that will be used for stock price prediction is Close data. Using data from these five banks, the study aims to evaluate how well the model is in predicting stock prices in the banking industry area.

Table 1. Stock Data Used

No.	Symbol	Amount of Data	Total Volume	Average change / year (%)
1	BBKA. JK	5079	542.520866	21.642548
2	BBRI. JK	5229	920.200486	20.171223
3	NISP. JK	5408	13.860171	13.082266
4	BMRI. JK	5314	675.262081	17.031700
5	BDMN. JK	5421	20.104527	3.902996

Data processing has several important steps that must be taken to ensure the quality and suitability of the dataset in predicting stock prices. If there is data that contains empty or incomplete values, the data is deleted to avoid errors in the analysis. The data is then processed by converting the value of the stock's closing price into a numerical format, which is then scaled using a value range between -1 and 1. This process is carried out to maintain data consistency while facilitating data processing in model training.

Normalization is performed at the closing price value using the Min-Max Scaler method to the range $[-1, 1]$. The Min-Max Scaler method was chosen because of its suitability with the characteristics of time series data such as stock prices. The Min-Max Scaler maintains the relative relationship between the original data, thus maintaining a balance between the normalized data and the data that has not. In contrast to other normalization methods such as Z-score which are suitable for data that do not have or are not known to have maximum and minimum values, the Min-Max method is more suitable for stock prices because it has

minimum and maximum value limitations (Henderi et al., 2021). Where X is the original value, X_{min} is the minimum value of the dataset, X_{max} is the maximum value of the dataset.

The dataset is divided into two main parts, namely training and validation data and testing data. The data is separated with 80% of the initial data being used for training and validation, while the other 20% is used for testing data. Data sharing aims to ensure enough training data to capture the complexity of stock price patterns, especially in deep learning models that require large amounts of data. The division is done without shuffling so that the chronological order of the data is maintained, so that the test data represents the last period that the model has not yet been "recognized" during training. This provides a real scenario where the model can predict future prices. Meanwhile, training/validation data is processed using k-fold cross-validation to maximize data usage. Each fold takes turns acting as validation data, ensuring that the model evaluation is carried out completely without any data leakage. By separating 20% of the data as test data that was completely untouched during training, the accuracy of the model evaluation was increased, as the test results reflected the generalization capabilities of the new data. This combination of proper normalization and data sharing strategies makes the dataset ready for stable and accurate model training.

Convolutional Neural Network (CNN) is a type of artificial neural network that is effective in recognizing visual patterns and processing two-dimensional data, such as images and videos. The main function of CNN lies in the use of its convolutional layer, which uses local filters on the inputs to automatically acquire important features. Each filter is applied thoroughly, so that the number of parameters studied becomes much less compared to conventional neural networks (Alshingiti et al., 2023). After the convolutional layer process, it is usually added to reduce feature dimensions, reduce sensitivity to small changes to data, and lower computational complexity. Furthermore, the fully connected layer combines all of these features for classification or prediction, with a backpropagation algorithm to adjust the filter weights and parameters in each layer so that the difference between the predicted result and the expected target is small.

On the other hand, Recurrent Neural Networks (RNNs) are a type of deep learning model designed to process sequential data. Unlike conventional feedforward neural networks that process each input autonomously, RNN maintains an internal state (memory) to process information from previous inputs. these capabilities make RNN suitable for tasks such as time series forecasting, language modeling, and speech recognition (Shiri et al., 2023).

In general, the RNN architecture consists of several layers, namely the input layer, one or more hidden layers, and the output layer. The input sequence is divided into segments (or time steps), and then processed in the form of arrays arranged sequentially (Wang et al., 2024). Table 5 describes the symbols used by the RNN. To overcome the limitations of CNN and RNN in stock price prediction, N-BEATS (Neural Basis Expansion Analysis for Time Series) comes with a new approach. N-BEATS is specifically designed to address the complexity of time series data using a forward and backward residual link mechanism and multiple fully connected stacks. Thanks to its architectural structure, N-BEATS is capable of processing and capturing Long-term data dependencies, while offering better interpretability, computational efficiency without the need for extensive feature engineering, making it a solution for long-term stock market predictions.

N-BEATS (Neural Basis Expansion Analysis for Time Series) is a deep learning architecture created for forecasting time series data with a new approach. Unlike traditional models that treat forecasting or prediction as a sequence-to-sequence problem, N-BEATS models it as non-linear multivariate regression. The basic block consists of layers of interconnected neural networks that process data to predict multiple points within the forecasting horizon. Each block not only generates a forecast, but also reconstructs the contribution of the residue to the input (backcast), allowing for a structured division of the pattern. This residue principle helps in the effective accumulation of up to hundreds of layers, increasing the capacity of the model without sacrificing generalization capabilities (Oreshkin et al., 2021).

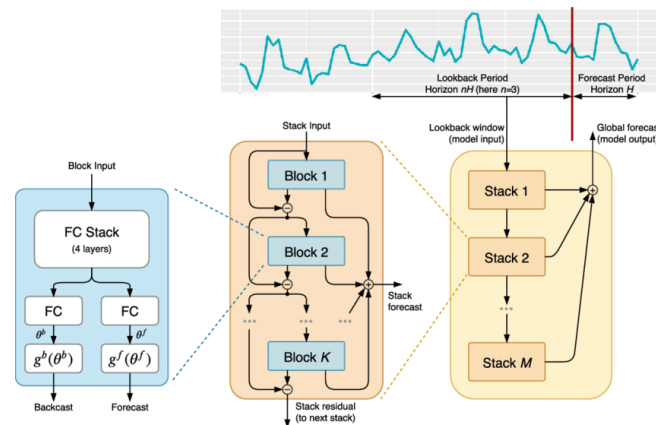


Figure 2. N-BEATS Architecture

Figure 2 illustrates the architecture of the N-BEATS (Neural Basis Expansion Analysis for Time Series) model which consists of several stacks connected in order. Each stack has several blocks, where each block processes input from the previous stack through a fully connected layer (FC) to produce two outputs: input (backcast) and prediction (forecast). The θ^b and θ^f parameters are used to calculate the inputs and predictions, while the remaining errors from the reconstruction (residual) are passed on to the next block in the same stack or to the next stack for further processing.

By collecting residual blocks, either using generic or specialized (trend/seasonal) configurations, N-BEATS is able to identify complex temporal dependencies while generating good predictions. Its architecture that uses deep residual learning can also address issues such as vanishing gradients, allowing the model to achieve the best performance on a wide range of time series prediction tasks.

The evaluation of model performance was carried out using three metric evaluations, namely Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics are widely used in the machine learning literature to measure the accuracy of model performance, where each metric is mathematically designed to compare how close the predicted results are to the original value (Geng, 2024; Plevris et al., 2022). Table 2 describes the symbols used to evaluate the metrics. Mean Absolute Error (MAE) calculates the average difference between the predicted value and the original value, the lower the MAE calculation results indicate that the model has good prediction accuracy (Sales et al., 2024). The MAE formula can be seen in table 5 number 1: Root Mean Squared Error (RMSE) used to evaluate the model's performance in predicting the outcome between the predicted

value and the original value. The lower the RMSE value indicates that the prediction is close to the original value (Julkarnaen et al., 2024). the smaller the RMSE value result, the more accurate the prediction produced. The RMSE formula can be seen in table 5 number 2: Mean Absolute Percentage Error (MAPE) calculates errors by dividing the absolute value of the difference between the predicted value and the actual value, then from the value the average of the error percentage is taken (Hajjah & Marlim, 2021). The results are in the form of percentages, making it easier to interpret the accuracy of the model independently of the data scale.

RESULTS AND DISCUSSION

The N-BEATS model will compare its performance with the CNN and RNN models. N-BEATS uses KFold with various variations in fold sizes: 5, 10, 15, 20. This is done to improve the accuracy of the model and reduce the risk of overfit during data training. The final accuracy of the model is calculated from the average result of the entire fold using three metric evaluations: MAE, MAPE, and RMSE, the measurements can be seen in table 2.

Variability of Model Performance Between Stock Symbols

The results of the evaluation showed a significant difference in the accuracy of the N-BEATS model prediction between stock markets. For example, table 2 lists BBKA shares. JK has the highest RMSE value (860.50 in the 5th fold), while NISP. JK has the lowest RMSE (85.02 in the 5th fold). This difference occurs because the data characteristics of each stock are different. Stocks with high volatility such as BBKA. JK generates greater errors because the model has difficulty capturing unstable fluctuation patterns. On the other hand, stocks with a stable trend such as NISP. JK makes it easy for models to provide accurate predictions with small errors. In addition, the amount of data also plays an important role, stocks with longer data such as BBRI. JK shows a decrease in error as the number of folds increases, indicating the model's adaptation to diverse data variations.

Effect of Number of Folds (K-Folds) on Model Accuracy

Table 2. Results of Evaluation of N-BEATS Metrics

Symbol	Fold	RMSE	MAE	MAPE
BBKA.JK	5	860.50	774.00	8.77%
	10	445.47	370.80	4.25%
	15	516.31	439.31	4.98%
	20	558.66	482.24	5.46%
BBRI.JK	5	514.31	447.30	9.28%
	10	313.00	250.96	5.18%
	15	314.16	248.94	5.15%
	20	313.05	246.07	5.03%
NISP.JK	5	85.02	64.10	5.68%
	10	91.47	68.83	6.02%
	15	85.03	63.52	5.66%
	20	94.99	70.82	6.24%
BMRI.JK	5	607.64	469.91	8.35%

Symbol	Fold	RMSE	MAE	MAPE
BDMN.JK	10	527.47	401.78	7.14%
	15	444.23	339.19	6.12%
	20	561.00	430.67	7.61%
	5	252.36	218.49	8.23%
	10	173.33	142.69	5.37%
	15	191.33	164.10	6.21%
	20	219.85	188.30	7.09%

Based on table 2 the increase in the number of folds on validation, generally related to a decrease in errors. This can be seen in BBRI shares. JK, where RMSE dropped from 514.31 in the 5th fold to 313.05 in the 20th fold. This event arises due to increased data diversity during training, thereby reducing the risk of overfitting and encouraging models to learn more common patterns. However, in some cases such as BBKA. JK, the increase in the fold actually increases the error, the error value of the RMSE BBKA. JK rose from 445.47 in the 10th fold to 558.66 in the 20th fold. This happens when the amount of data per fold is too small to understand complex patterns, causing underfitting, or when a validation subset contains many outliers. Thus, the relationship between the number of folds and the accuracy of the model is non-linear and depends on the balance of the size of the dataset, the complexity of the model, and the stability of the data.

In comparison to the results of the evaluation of the N-BEATS model, the traditional CNN and RNN models will be used using the same dataset, hyperparameters, and evaluation of metrics. The purpose of this comparison between traditional and modern models is to assess whether the latest model such as the N-BEATS is capable of delivering better results than traditional models that have been around for quite some time. The comparison between CNN, RNN, and N-BEATS can be seen in table 3.

Table 3. CNN, RNN, N-BEATS Comparison Results

Symbol	Model	RMSE	MAE	MAPE
BBKA.JK	N-BEATS	445.47	370.80	4.25%
	CNN	1085.66	887.14	9.91%
	RNN	728.08	588.39	6.46%
BBRI.JK	N-BEATS	313.05	246.07	5.03%
	CNN	437.63	373.56	7.73%
	RNN	239.65	183.75	3.69%
NISP.JK	N-BEATS	85.03	63.52	5.66%
	CNN	149.57	98.52	8.11%
	RNN	108.23	72.22	5.93%
BMRI.JK	N-BEATS	444.23	339.19	6.12%
	CNN	474.71	339.90	6.03%
	RNN	805.75	524.15	8.68%
BDMN.JK	N-BEATS	173.33	142.69	5.37%
	CNN	256.34	237.95	9.10%
	RNN	265.91	260.63	9.93%

Based on the results of the comparison of the performance of the three models on the five-stock data in the table, it shows that N-BEATS consistently provides the lowest RMSE, MAE, and MAPE values compared to CNN and RNN. On BBKA shares. JK, N-BEATS recorded an RMSE value of around 403, while CNN and RNN had an RMSE value above 700. The same is seen in other data, where N-BEATS is able to provide a lower and more stable prediction error. This shows the advantages of the N-BEATS model in capturing stock price movement patterns, both for short-term and long-term analysis, compared to the CNN and RNN models.

Comparison of CNN, RNN and N-BEATS Models

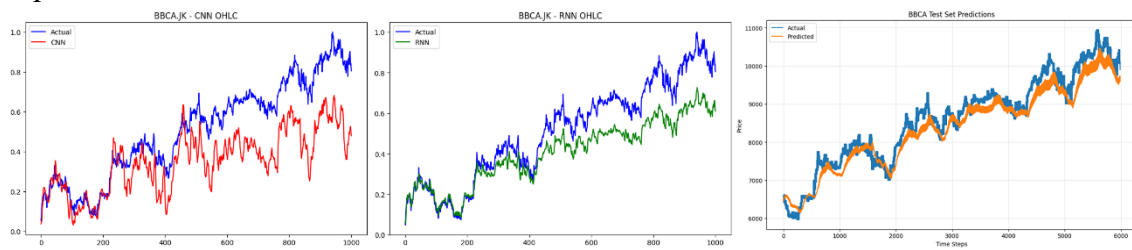


Figure 3. BBKA Data Comparison Graph. JK

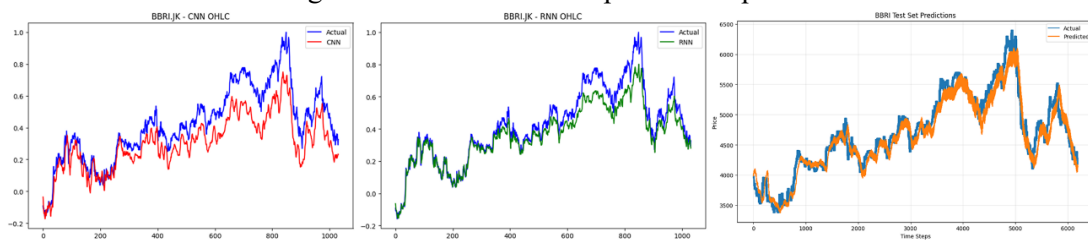


Figure 4. BBRI Data Comparison Chart. JK

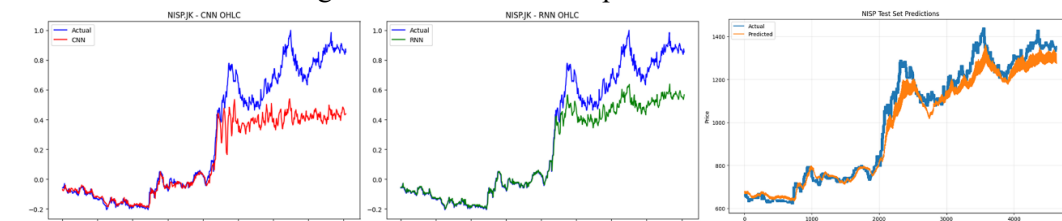


Figure 5. NISP Data Comparison Graph. JK

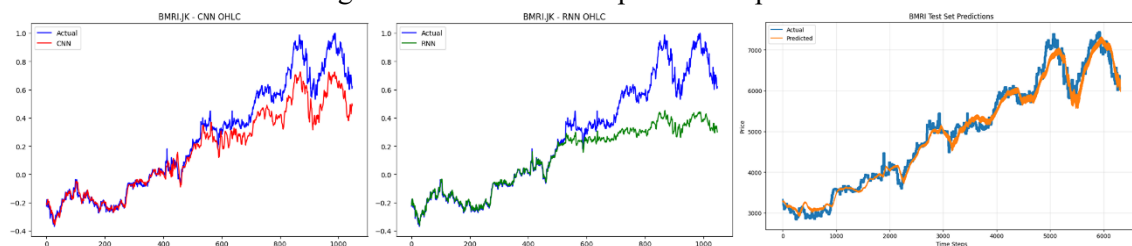


Figure 6. Data Comparison Graph BMRI.JK

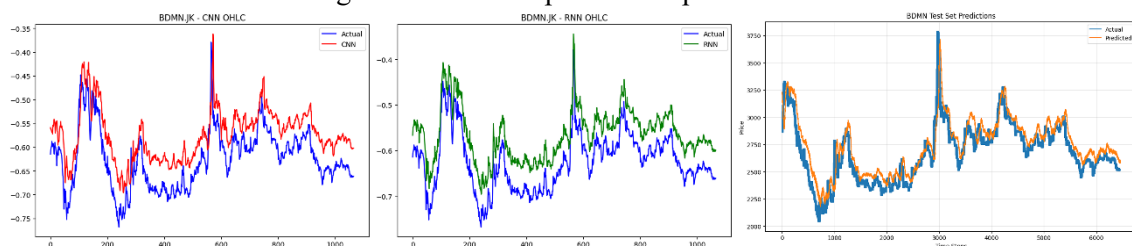


Figure 7. BDMN Data Comparison Graph. JK

As can be seen in figures 3 to 7, N-BEATS has consistently shown significant advantages over CNN and RNN on most stocks, with lower RMSE, MAE, and MAPE values. For example, in BBCA shares. JK, N-BEATS recorded an RMSE of 445.47, much better than CNN with a score of 1085.66 and RNN with a score of 728.08. This advantage is supported by the N-BEATS architecture specifically designed for time series data prediction, with the explicit decomposition capability of trending and seasonal components through residual blocks. Each block not only generates a forecast, but also reconstructs the data input (backcast), thereby improving the model's consistency and generalization capabilities. In addition, the use of interconnected layers avoids the problem of gradient loss (Vanishing Gradient) that is often encountered by RNNs, as well as the limitations of CNN in capturing long-term patterns. In stocks with a stable trend such as NISP. JK and BDMN. JK, N-BEATS recorded MAPE of 5.66% and 5.37%, outperforming CNN and RNN which tend to be affected by random data (noise).

Although N-BEATS provides better results than other methods, there are some cases where exceptions are made. In BBRI shares. JK, RNN recorded the lowest MAPE of 3.69%, outperforming N-BEATS with a value of 5.03%. This shows that BBRI. JK is dominated by short-term patterns such as daily fluctuations due to market news, which are more effectively captured by RNN's short-term memory mechanism. Meanwhile, at BMRI. JK, CNN shows a MAPE of 6.03%, slightly better than N-BEATS with a value of 6.12%. CNN's superiority can be attributed to its ability to detect local patterns, such as price reactions to specific events, through its convolutional filters. This case confirms that the performance of the model depends on the characteristics of the data. N-BEATS excels at capturing macro patterns, while CNN/RNN remains relevant for micropattern-based analysis.

The strengths of N-BEATS are not only evident in its architecture, but also in its specific design to overcome the challenges of time series forecasting. As a model developed for this purpose, the N-BEATS is equipped with built-in regularizations, such as dropout and early stoppings to reduce overfitting of unstable data. Its ability to separate trend patterns from random data (noise) through gradual decomposition makes it more palatable when compared to common approaches such as CNN or RNN. However, the weakness of N-BEATS is seen in data with extreme random (noise) data, such as BBCA. JK, where the RMSE increases with the addition of folds, indicates the need for hyperparameter adjustments.

CONCLUSION

The N-BEATS model consistently outperforms CNN and RNN in predicting stock movements, especially on data with stable trends such as NISP. JK and BDMN. JK. This advantage is supported by a particular architecture that is able to decompose trends and seasonality through residual blocks, as well as a back-and-forth mechanism that improves model generalization. Increasing the number of K-Fold folds generally improves the accuracy of the model, but at high random data (noise) such as BBCA. JK can cause underfitting. Although it excels in providing computational efficiency and interpretability, the weakness of N-BEATS is seen in extreme data that requires hyperparameter adjustments or additional techniques such as attention mechanisms. Future research include exploring hybrid models, such as the N-BEATS and Transformer models, as well as the use of temporal validation to

avoid data leaks. These findings support that N-BEATS is suitable for use in predicting the stock market, with better performance than traditional models.

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