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FORECASTING BANK STOCK TRENDS USING ARTIFICIAL INTELLIGENCE: A DEEP DIVE INTO THE NEURAL PROPHET APPROACH

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ABSTRACT

This research aims to use Neural Prophet, a deep learning tool, to predict stock prices in the banking sector with high accuracy and useful insights. The model's capability in managing intricate temporal patterns differentiates it, garnering attention from researchers. The significance of this research lies in its potential to enhance stock price prediction precision, especially in the context of banking stocks, offering stakeholders' deeper insights. The model's efficacy spans stable and volatile market behaviours, making it a valuable tool for informed decision-making in finance. Accurate predictions benefit risk management, facilitating well-informed investment choices in dynamic markets.

Keywords : Stock Price Prediction, Banking Sector, Financial Markets, Risk Management, Decision-Making.
JEL : C22; D53; G21

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I. INTRODUCTION

Banking in Indonesia is a crucial and rapidly growing sector that plays a vital role in the country's economy. The banking sector in Indonesia makes significant economic contributions to the country's growth and development. By acting as intermediaries between savers and borrowers, banks facilitate business transactions and provide essential financial services, such as loans and credit lines, which enable businesses to invest and expand (Hardi et al., 2023; Mala et al., 2021). Moreover, banks play a crucial role in supporting small and medium enterprises (SMEs), which are vital contributors to employment and GDP growth. The sector also encourages savings and investments through various deposit products, contributing to capital formation and economic stability (Abora et al, 2014). With the increasing adoption of digital technologies and a focus on financial inclusion, the banking industry is poised for further expansion and innovation in the years to come (Bhegawati & Utama, 2020; Karamoy & Tulung, 2020; Noviandy et al., 2023).

Additionally, a well-developed banking sector attracts foreign direct investment (FDI), while efforts in promoting financial inclusion bring the unbanked population into the formal financial system, supporting corruption-free human development, poverty reduction, and environmentally friendly economic participation with low carbon pollution (Akbar & McBride, 2004; Hardi et al,. 2023; Idroes et al., 2021; Idroes et al., 2023; Idroes et al., 2023). Furthermore, banks' involvement in trade finance and infrastructure development enhances Indonesia's trade relations, export activities, and overall economic progress (Idroes et al., 2024; Idroes et al., 2024; Noviandy et al., 2024). Overall, the banking sector's contributions encompass job creation, government revenue generation, and crucial support for economic policies and initiatives (Abduh & Omar, 2012; Hardi et al., 2023).

Financial markets epitomise a captivating and transformative innovation within contemporary society, yielding profound ramifications across sectors such as commerce, education, labour, technology, and the overarching economy (Hiransha et al., 2018). The intricate analysis of stock market dynamics and pricing behaviours is beset by formidable challenges stemming from the inherently dynamic, nonlinear, nonstationary, nonparametric, noisy, and chaotic nature intrinsic to these financial landscapes (Abu-Mostafa & Atiya, 1996). As expounded upon by Zhong & Enke (2017), stock markets resemble intricately woven tapestries influenced by a nexus of interrelated factors spanning economic, political, psychological, and firm-specific variables. Within the realm of financial inquiry, the dominant methodological paradigms encompass technical and fundamental analyses (Nguyen et al., 2015; Park & Irwin, 2007) which discerning investors adeptly wield to navigate the labyrinthine expanse of stock investments, endeavouring to harness optimal gains while prudently mitigating associated risks (Arévalo et al., 2017).

In Indonesia, the banking and stock market sectors have encountered several challenges. First, the regulatory environment and government policies can impact the operations and profitability of financial institutions and stock market activities. Economic volatility, including currency fluctuations, inflation, and changes in interest rates, also poses significant risks to these sectors. Additionally, managing asset quality and non-performing loans remains a concern for banks, particularly during economic downturns. Improving financial inclusion, addressing infrastructure development challenges, and ensuring strong corporate governance practices are also essential to sustain the growth and stability of the banking and stock market sectors (Hadad et al., 2011).

The overall macroeconomic factors and economic stability of Indonesia can impact the prices of banking stocks (Hardi et al., 2023). A robust economy generally leads to higher consumer and business lending, consequently boosting bank profits and stock prices. Changes in interest rates set by the central bank (Bank Indonesia) can affect the banks' net interest margins and, in turn, their profitability. Banking regulations and policies can also impact banks' operations, capital requirements, and potential for expansion in the international market, thereby influencing their stock performance (Bouwman et al., 2018; Hardi et al., 2021). The health of a bank's loan portfolio and its ability to manage non-performing loans can also significantly impact its financial performance and stock prices (Baele et al., 2007).

Forecasting trends in stock prices for banking companies is a challenging task that typically involves the use of various analytical and statistical techniques (Sen & Chaudhuri, 2017). Stock markets are influenced by unpredictable events, such as geopolitical issues, economic changes, and unexpected news. As a result, even the best forecasting models may not be entirely accurate in predicting future stock prices. Utilising machine learning algorithms like linear regression, time series models, or more advanced techniques such as neural networks allows for predictions based on historical data and relevant features (Tsai & Wang, 2009)

Forecasting stock prices and understanding their causal relationships with other variables are essential tasks in the field of economics. Various econometric methods, such as Autoregressive Distributed Lag (ARDL), Quantile Regression, Generalised Autoregressive Conditional Heteroscedasticity (GARCH) and Granger Causality Test, have been widely utilised for these purposes. Researchers have made significant contributions to this area, and several noteworthy studies, such as (Alomari et al., 2022; Civcir & Akkoc, 2021; Ghosh et al., 2021; Peng et al., 2020; Ruslan & Mokhtar, 2021; Torbat et al., 2018) have shed light on the application of these methods by exploring the intricacies of forecasting stock prices and assessing causal relationships with comprehensive econometric analyses. Notably, these studies have leveraged lagged values of respective variables and technical indicators as explanatory variables in their models, enabling a deeper understanding of the dynamics involved and providing valuable insights into the predictive power of these econometric methods.

Traditionally, forecasting in banking sector predominantly relied on statistical methods like Auto-Regressive Integrated Moving Average (ARIMA) (Ahmed et al., 2017; Almasarweh & Alwadi, 2018; Mondal et al., 2014; Syarif, 2020) and Exponential Smoothing (Arisoma et al., 2019; Zaini et al., 2020). However, these approaches have their limitations in real-world scenarios because they heavily rely on strict assumptions and specific parameters (Maria & Eva, 2011). To improve the accuracy of forecasting, it is essential for an expert with profound domain knowledge and expertise in classical time series modelling to be involved in the process.

Recently, there has been a rising trend in utilising deep learning approaches for forecasting (Rezaei et al., 2022; Sarveswararao et al., 2023; Vangala & Vadlamani, 2020). In contrast to conventional statistical methods, deep learning offers the advantage of automatically extracting meaningful features without the need for extensive domain knowledge or manual intervention (Idroes et al., 2023; Pouyanfar et al., 2019). There has been rapid development in fundamental deep learning tools and new prediction models, along with increased use of online news and Twitter data for stock market prediction. Moreover, the rise of graph neural networks incorporating knowledge graph data has brought innovative ideas to this field, while asset management companies and investment banks are allocating research grants to artificial intelligence, particularly deep learning models, drawn by the potential profits they offer in stock trading (Jiang, 2021).

Our primary focus is on the application of machine learning and deep learning methods in the stock market. Nevertheless, it is important to acknowledge that these methods have been widely employed in various financial problems beyond the scope of this research. The insights presented here can also be valuable for other time series prediction challenges in the finance domain, including exchange rate or cryptocurrency price prediction (Noviandy et al., 2023).

Deep learning has witnessed tremendous success in recent years, thanks to the availability of big data from the Web, the parallel processing capabilities of graphics processing units (GPUs), and advancements in convolutional neural networks. This success has been evident in diverse applications, including image classification (Jiang & Zhang, 2020; Rawat & Wang, 2017), object detection (Zhao et al., 2019), and time series prediction (Brownlee, 2018; Jiang & Zhang, 2018). Deep learning models excel at handling large datasets and capturing nonlinear relationships between input features and prediction targets, surpassing the performance of both linear and traditional machine learning models, especially in tasks such as stock market prediction.

Nonetheless, these methods have faced criticism due to their opaque nature, and the challenge of explaining their decision-making processes remains a prominent research area in the field of forecasting (Sezer et al., 2020). Furthermore, employing these models often necessitates significant engineering efforts for data preprocessing and fine-tuning hyperparameters (Almalaq & Edwards, 2017). Consequently, many non-expert forecasters in various industries have favoured simpler statistical techniques, which may not be as precise but are easier to comprehend, scalable, and require less adjustment. This has led to a divergence between traditional forecasting methods and deep learning-based approaches.

Given the challenges and opportunities presented by advanced forecasting techniques, this study aims to utilise the Neural Prophet model for precise prediction of banking stock prices by examining past data to understand intricate correlations and patterns within Indonesia's banking sector. This study first explores how effective the Neural Prophet model is in predicting stock prices in Indonesia's banking sector. Second, it investigates the specific challenges that arise when applying machine learning techniques to the Indonesian banking stock market. Third, it compares the performance of traditional econometric models to deep learning models in forecasting stock prices. By addressing these research questions, this investigation offers significant contributions to the field of stock market prediction, particularly within the banking industry, providing investors and analysts with essential perspectives and predictive frameworks to make well-informed decisions in the complex landscape of financial markets.

This study reveals several key findings. The Neural Prophet model demonstrated a high level of accuracy in predicting stock prices, particularly in capturing subtle fluctuations and trends within the banking sector. Notably, the Neural Prophet was able to anticipate market movements with greater precision, providing valuable foresight into the future trends of banking stocks. These findings underscore the model's potential as a powerful tool for financial forecasting and risk management within the banking sector.

The remainder of this paper is structured as follows: Section II presents a comprehensive review of the relevant literature on stock market prediction and the use of machine learning models. Section III describes the data and methodology employed in the study, including the Neural Prophet model and its implementation. Section IV discusses the results and provides a detailed analysis of the model's performance. Finally, Section V concludes the paper by summarising the key findings and offering policy recommendations based on the study’s insights.

II. LITERATURE REVIEW

Stock market prediction has been a subject of research for a considerable period, and preceding our work, several review papers have delved into the development and flourishing of deep learning methods. Although these reviews may touch upon the application of deep learning in stock market prediction, they also encompass a wide range of other financial problems, as observed in the work by (Jiang, 2021). In this section, we provide a chronological list of some of these problems and offer insight into our motivations and unique perspectives for conducting this research.

Technical analysis asserts that the entirety of information pertaining to the stock market is mirrored in its price movements. The task of modelling and predicting stock prices becomes comprehensive through direct engagement with these movements. The utilisation of deep learning methodologies offers an effective approach to forecasting forthcoming values, as it extracts underlying historical patterns through learning processes (Long et al., 2019).

Aguilar-Rivera et al (2015) extensively assess how evolutionary computation techniques have been employed to tackle financial challenges. Their study covers a range of methods, including genetic algorithms, genetic programming, multi-objective evolutionary algorithms, learning classifier systems, co-evolutionary approaches, and estimation of distribution algorithms. Similarly, Cavalcante et al., (2016) summarise key primary research conducted between 2009 and 2015. These studies primarily delve into financial domains, encompassing tasks like preprocessing and clustering financial data, predicting future market trends, and extracting information from financial text. Additionally, Tkáč & Verner (2016) conducted a systematic investigation into the use of neural networks in business between 1994 and 2015. Their analysis indicates a predominant focus on concerns like financial distress and bankruptcy prediction, stock price forecasting, and decision support, with a specific emphasis on classification tasks.

While some recent reviews aim to cover a broader spectrum of topics, such as Shah et al. (2019) delving into machine learning techniques for forecasting financial market prices, and (Sezer et al., 2020) encompassing a wider array of financial instruments, the motivation of this paper is to align with the current research trend of implementing deep learning methodologies. These techniques have consistently demonstrated superior performance compared to traditional machine learning approaches, notably surpassing support vector machines in the majority of literature. A few exceptions exist, such as the findings of (Ballings et al., 2015) , who identify Random Forest as the foremost algorithm, followed by Support Vector Machines, Kernel Factory, AdaBoost, Neural Networks, K-Nearest Neighbours, and Logistic Regression.

Similarly, Ersan et al., (2020) determine that both K-Nearest Neighbour and Artificial Neural Network outperform Support Vector Machines, yet a clear advantage between their performances remains elusive. Given the accumulation of historical pricing data and diverse input sources like financial news and Twitter, we anticipate that the strengths of deep learning techniques will persist. Thus, staying abreast of this evolving trend for future research endeavours is imperative.

Neural Prophet is another forecasting tool developed by Facebook that utilizes neural networks to model and forecast time series data. Unlike Facebook Prophet, Neural Prophet aims to capture more complex patterns and relationships in the data through the use of neural networks, making it potentially more powerful for certain types of data (Shehzad et al., 2022). The main difference between Facebook Prophet and Neural Prophet lies in their underlying methodologies. Facebook Prophet uses a curve-fitting approach based on additive components, making it suitable for datasets with strong seasonality and holidays. Neural Prophet, on the other hand, employs neural networks to capture complex patterns and relationships, making it more suitable for datasets with nonlinear patterns or irregular changes (ChikkaKrishna et al., 2022).

Built on PyTorch (Imambi et al., 2021), Neural Prophet incorporates cutting-edge techniques like automatic model selection, feature engineering, and uncertainty estimation, making it a robust tool for precise and dependable predictions (Triebe et al., 2021). Its versatility and capability to handle intricate temporal patterns have attracted considerable interest, positioning Neural Prophet as a promising framework for forecasting time series data (Khurana et al., 2022; Velásquez, 2022; Yu et al., 2022).

III. DATA AND METHOD

A. Population and Sample

The population in this research consisted of all conventional commercial banks operating in Indonesia as of 31 May 2023, totalling 92 units. Indonesia was chosen for this analysis because of its rapidly growing and dynamic banking sector, which plays a pivotal role in the country's economic development. As an emerging market, Indonesia presents unique financial challenges and opportunities, making it an ideal case for applying and testing advanced predictive models like Neural Prophet. Sample determination used the non-probability sampling type with a purposive sampling technique. The main characteristic of this sampling technique is that the sample is specifically selected based on the research objectives (Etikan et al., 2016). The sample criteria set in this research were the top 5 banks with the largest total assets.

The top five conventional banks in Indonesia based on total assets (OJK, 2023) are: PT Bank Rakyat Indonesia Tbk. (BBRI) with IDR 1,631.18 trillion, PT Bank Mandiri Tbk. (BMRI) with IDR 1,519.98 trillion, PT Bank Central Asia Tbk. (BBCA) with IDR 1,296.52 trillion, PT Bank Negara Indonesia Tbk. (BBNI) with IDR 967.52 trillion, and PT Bank Tabungan Negara Tbk. (BBTN) with IDR 400.49 trillion. The historical closing price of these banks in IDR for each trading day were retrieved from Yahoo Finance [28]. The data was retrieved in a comma-separated values (CSV) format, featuring two columns: the date of the trading day and the corresponding closing price of the bank's stock. The time range for each bank data is presented in Table 1.

Table 1: The Time Range for Each Bank

Ticker	Time Range
BBRI	11 November 2003 – 11 August 2023
BMRI	15 July 2003 – 11 August 2023
BBCA	9 June 2004 – 11 August 2023
BBNI	17 April 2013 – 11 August 2023
BBTN	21 December 2009 – 11 August 2023

For Neural Prophet modelling, the data used was divided into two subsets: 90% for training and 10% for testing. This split was employed to facilitate the development and evaluation of a predictive model for stock prices. The rationale behind the 90%-10% data split is implemented to simulate a real-world scenario where the model is trained on historical data and then tested on unseen future observations (Noviandy et al., 2024). Time series data involves a temporal sequence of observations, and it's crucial to assess how well a predictive model can forecast future values based on past patterns.

The 90% training subset comprises historical closing prices, allowing the model to learn from past trends, seasonality, and other temporal patterns inherent in the data. The temporal ordering is essential because it reflects the chronological progression of the stock prices. The 10% testing subset is reserved for evaluating the model's performance on unseen future data points. This configuration aligns with the goal of assessing the model's forecasting capabilities, providing insights into how well it generalises to new time points. The separation into training and testing sets is crucial in time series analysis to avoid data leakage and to ensure that the model's effectiveness is not solely due to memorising the historical data.

B. Neural Prophet

The Neural Prophet brings a significant advancement to the field of time series forecasting. It stands out by incorporating advanced features like automated differencing, inspired by Facebook's Prophet (Jha & Pande, 2021). Its modular architecture provides a solid base for effectively handling large datasets and seamlessly integrating future updates. What sets the Neural Prophet apart is its comprehensive forecasting approach. It takes into account various temporal complexities such as trends and seasonality, resulting in more accurate predictions. Moreover, the Neural Prophet uses external variables to boost its forecasting accuracy (Triebe et al., 2021).

C. Loss Function

The Neural Prophet model uses a loss function to evaluate its performance in forecasting stock prices during training phase. The loss function used is Huber loss, which is a combination of Mean Absolute Error (MAE) and Mean Squared Error (MSE). MAE is a loss function that measures the average absolute difference between the predicted and actual values. It is less sensitive to outliers than MSE, but it can be less accurate for small errors, and MSE is a loss function that measures the average squared difference between the predicted and actual values. It is more sensitive to outliers than MAE, but it is more accurate for small errors. Huber loss is less sensitive to outliers than MSE, which makes it a more robust measure of the model's performance. The formula for Huber loss is shown in Equation 1 (Hastie et al., 2009).

$$
\begin{aligned}
Huber\ Loss &= \frac{1}{n}\sum_{i=1}^{n}\frac{1}{2}(y_i - \hat{y}_i)^2 \qquad\qquad |y_i - \hat{y}_i| \le \delta \\
Huber\ Loss &= \frac{1}{n}\sum_{i=1}^{n}\frac{1}{2}\delta(|y_i - \hat{y}_i| - \frac{1}{2}\delta) \quad |y_i - \hat{y}_i| > \delta
\end{aligned} \tag{1}
$$

Where n symbolises the overall number of data points, y stands for the real value of the data point, $\hat{y}$ represents the anticipated value of the data point, and δ determines the distinct points at which the Huber loss function shifts from being quadratic to becoming linear.

D. Optimiser

An optimiser functions as a strategic algorithm employed to improve the performance of the Neural Prophet model during its training phase. In this research, we used the AdamW optimiser, a sophisticated optimisation technique that combine the weight decay regularisation with the optimisation process to effectively avoid overfitting. Overfitting is a circumstance in machine learning where a model becomes excessively attuned to the training data, resulting in a compromised ability to generalise to unseen data (Llugsi et al., 2021).

$$\Delta w_t = -\frac{\eta}{\sqrt{\hat{v}_t + \epsilon}}\left(\frac{m_t}{\sqrt{\hat{u}_t + \epsilon}} + \lambda w_t\right) \tag{2}$$

Where Δw_t for the change made to the weights during a particular time step t, η represents the learning rate, m_t estimate of how the gradients change at that time step t, $\hat{u}_t$ denotes the exponentially decaying average of squared gradients at time step $t, \hat{v}_t$ track of how quickly the weights themselves are changing at that time step t, λ represents the weight decay coefficient, and ϵ is a tiny number added to the calculations to keep everything stable and avoid any potential math glitches.

E. Model Evaluation

In this research, the performance evaluation of our Neural Prophet models is conducted using three metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics collectively provide a comprehensive assessment of the models' predictive capabilities and provides insights into the models' overall performance and their suitability for the task at hand. The Equation for RMSE, MAE, and MAPE can be seen in Equation 3, 4, and 5, respectively (Kramer, 2016).

$$RMSE(y, \hat{y}) = \sqrt{\frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} (y_i - \hat{y}_i)^2} \tag{3}$$

$$MAE(y, \hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} |y_i - \hat{y}_i| \tag{4}$$

$$MAPE(y, \hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} \frac{|y_i - \hat{y}_i|}{\max(\epsilon, |y_i|)} \tag{5}$$

IV. RESULTS AND DISCUSSION

In this research, we used Neural Prophet to forecast the stock price of the top five conventional banks in Indonesia based on their total assets. After that, we iteratively train the model using 100 epochs to ensure that the model can learn the complex relationship withing the data, allowing the model to generalise and minimising the prediction error. Prior to training process, we scaled the data using the min-max method which transform the stock price variable in a range between 0 and 1. This was done to improve model convergence time and increase model stability. The scaled data is automatically restored to original scale after the training process.

The models' performance is presented in Table 2. These results indicate that the models produced accurate predictions for the banks' financial data. It is evident that each model has varying degrees of predictive accuracy for the financial data of the listed banks. For BBRI, the model achieved an RMSE of 367.884 and an MAE of 311.046 on the testing set, with a MAPE of 7.0%, which indicates a moderate level of accuracy in its predictions. In the case of BMRI, the model exhibited a significantly higher RMSE of 1156.780 on the testing set, which is the highest among the banks, suggesting less precision in its predictions. The MAE was also quite high at 955.535, but its MAPE of 20.3% is noteworthy, as it implies a larger relative error in prediction. The higher MAPE for BMRI likely results from greater market sensitivity, more irregular data patterns in capturing BMRI's unique stock dynamics. These factors contribute to less accurate predictions for BMRI, making its stock price behaviour more complex and unpredictable compared to the other banks.

BBCA's model, while not the best, still showed reasonable accuracy with an RMSE of 460.896 and an MAE of 393.440 on the testing set. Its MAPE stood at 4.8%, which is the lowest among the banks, indicating that the percentage deviation of its predictions from the actual values is comparatively minimal. BBNI, on the other hand, demonstrated an interesting mix of results. With an RMSE of 533.486 and an MAE of 470.368 on the testing set, its absolute errors were not the lowest. However, its MAPE of 5.2% signals that the percentage difference between its predictions and actual values was relatively modest, making it a noteworthy model in terms of relative accuracy. Finally, BBTN's model outperformed others on the testing set, with the lowest RMSE of 138.764 and the lowest MAE of 117.029, indicating a high precision in its predictions. Its MAPE of 8.2% also signifies a smaller percentage error, which further corroborates the model's reliability. Overall, while each bank's model has unique strengths, BBTN's model emerges as the most accurate in testing, followed closely by BBNI in terms of percentage accuracy.

Table 2: The Performance of Neural Prophet Models

Ticker	RMSE		MAE		MAPE	
	Training Set	Testing Set	Training Set	Testing Set	Training Set	Testing Set
BBRI	279.566	367.884	188.039	311.046	12.5%	7.0%
BMRI	311.517	1156.780	221.225	955.535	12.8%	20.3%
BBCA	262.608	460.896	176.568	393.440	9.8%	4.8%
BBNI	622.885	533.486	477.321	470.368	8.1%	5.2%
BBTN	239.099	138.764	184.697	117.029	12.0%	8.2%

In order to evaluate the effectiveness of our approach, the comparison between actual stock values and the values predicted by our models for various banks is examined. This is accomplished by visualising the actual versus predicted stock prices (Figure 1, 2, 3, 4, and 5). The visualisation demonstrates that the general trend exhibited by the actual stock values is successfully captured by each model. From this observation, it can be inferred that the Neural Prophet model generally forecasts bank stock prices with a high degree of accuracy, effectively capturing trends and moderate fluctuations in the data. However, it is important to acknowledge the model's limitations during periods of extreme volatility, such as the global outbreak of the COVID-19 pandemic in 2020-2021. The pandemic introduced unprecedented market conditions, characterised by sudden and severe disruptions, which the model struggled to predict accurately.

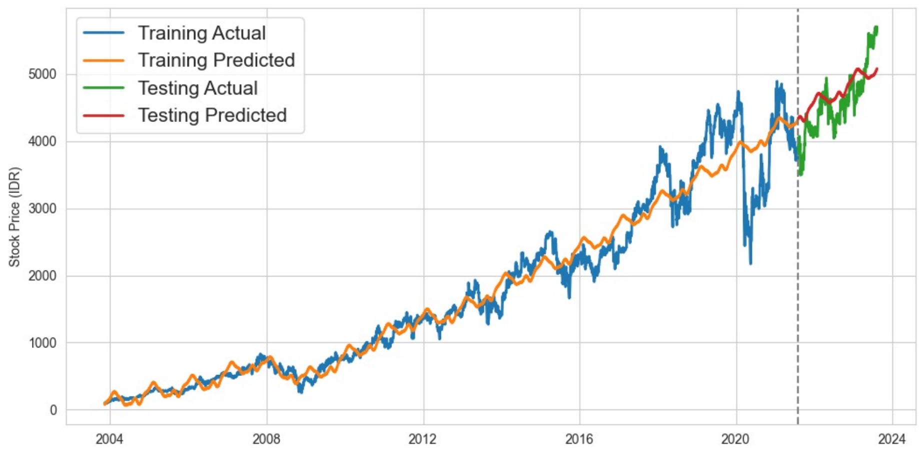

Figure 1: Actual vs predicted plot of BBRI

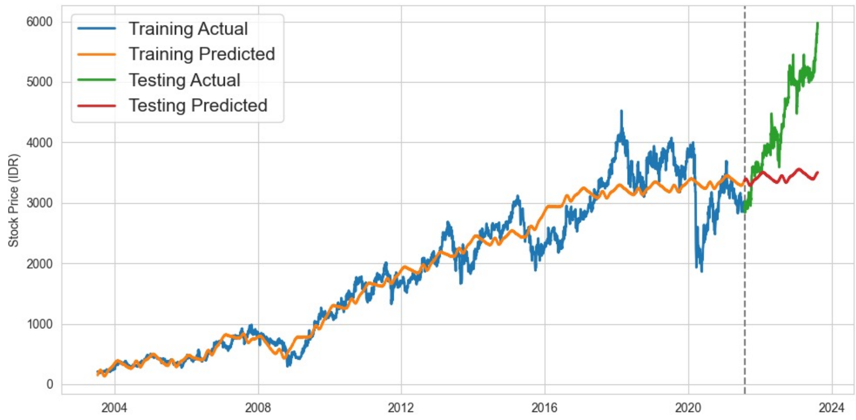

Figure 2: Actual vs predicted plot of BMRI

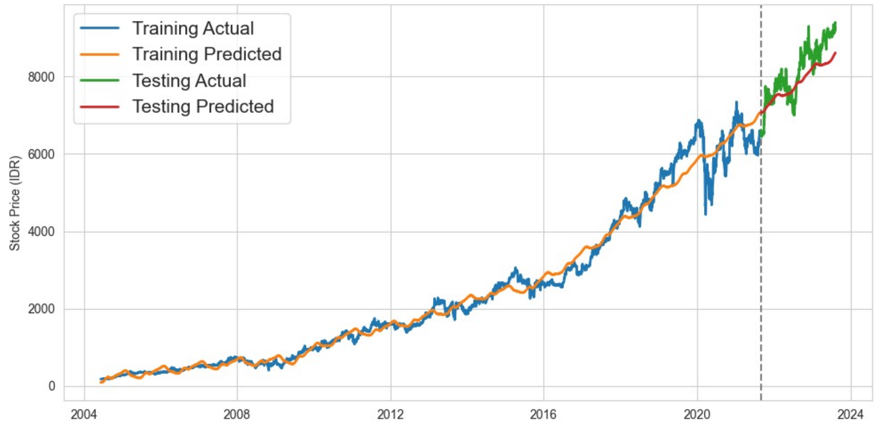

Figure 3: Actual vs predicted plot of BBCA

Figure 4: Actual vs predicted plot of BBNI

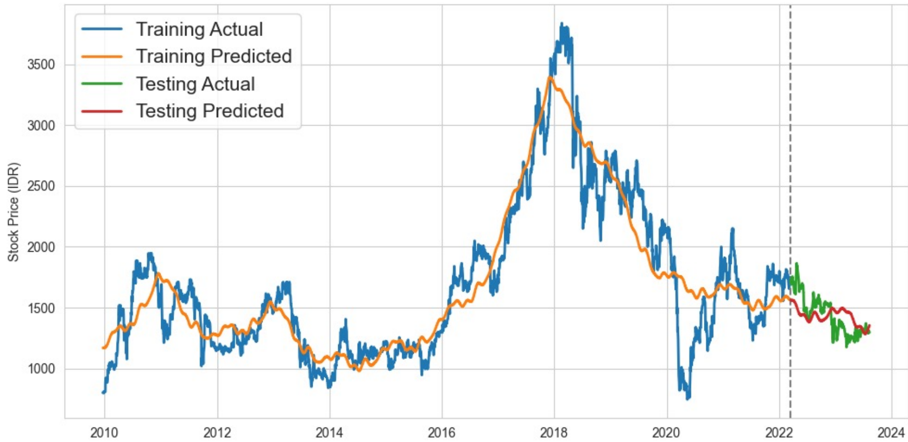

Figure 5: Actual vs predicted plot of BBTN

Displayed in Figure 1 is a comprehensive representation of the stock price movement of BBRI, spanning an extensive timeline from 11 November 2003 to 11 August 2023. The visual reveals a prevailing trend characterised by a steady and upward trajectory, indicating a sustained growth pattern over the years. However, within this otherwise stable progression, a notable deviation emerges during the period of 2020-2021. This specific time frame corresponds to the global outbreak of the COVID-19 pandemic, a phenomenon that sent shockwaves through various sectors, including financial markets. The stock prices of BBRI experienced a discernible dip during this interval, underlining the pandemic's impact on even the most established market trends. While the model performed well under typical market conditions, its predictive power diminished in the face of such extreme volatility. This observation underscores the need for caution when relying on AI models during extraordinary events and suggests potential areas for further model refinement to better handle extreme market shocks.

Similar to the BBRI stock price trend, Figure 2 illustrates the movement of BMRI stock prices, encompassing the period from 15 July 2003 to 11 August 2023. The visual presentation highlights a consistent and upward trajectory, echoing the characteristics of sustained growth. Notably, the BMRI stock price graph reveals a parallel experience with BBRI during the COVID-19 pandemic. A dip in stock prices is discernible within the same pandemic-related timeframe, underscoring the widespread influence of this global event on the financial landscape.

Moreover, as depicted in Figure 3, it becomes evident that the stock price movement of BBCA from 9 June 2004 to 11 August 2023 also showcases a notable and consistent upward and stable trajectory. This enduring trend is further accentuated by the fact that, despite encountering a slight downturn during the COVID-19 pandemic, the stock quickly recuperated and resumed its upward momentum. Throughout this extensive period, the stock's performance mirrors a robust pattern of growth and resilience. Notably, the analysis indicates that BBCA has effectively weathered various market challenges, reinforcing its reputation as a stable and promising investment option.

In sharp contrast to the trajectories of BBRI, BMRI, and BBCA stock prices, the price movement of BBNI stock tells a remarkably distinct tale. Spanning the period from 17 April 2013 to 11 August 2023, the BBNI stock price exhibited a series of fluctuating movements that stood out conspicuously. Illustrated vividly in Figure 4, the BBNI stock price's journey was characterised by extreme volatility, marked by no less than four significant declines. Notably, among these downturns was a sharp plunge experienced during the early days of the COVID-19 pandemic, which left an indelible mark on the stock's trajectory.

Much like the trajectory observed in BBNI's stock price movement, the pattern displayed by BBTN's stock price movement over the period from 21 December 2009 to 11 August 2023 also demonstrates striking similarities, marked by considerable fluctuations. As visually depicted in Figure 5, an interesting narrative unfolds for BBTN's stock price dynamics. In the year 2018, BBTN's stock price soared to impressive heights, signifying optimism and market confidence during that period. However, the optimism was short-lived as the subsequent years brought forth a contrasting narrative. Following the peak in 2018, the stock price embarked on a pronounced downward trajectory, descending sharply until the year 2020. This decline was particularly accentuated by the outbreak of the COVID-19 pandemic, which wreaked havoc on global financial markets.

The primary goal of this research endeavour is to effectively leverage the capabilities inherent in the Neural Prophet model to achieve a new level of precision in predicting the stock prices within the banking sector. Illustrated vividly through the visual representations presented in Figures 1-5, the Neural Prophet model emerges as an extraordinary tool, showcasing its exceptional prowess not solely in predicting forthcoming trends but also in adeptly foreseeing even the most nuanced undulations within the intricate landscape of banking stock prices. The orange line, meticulously derived from the predictive prowess of the Neural Prophet, remarkably emulates the undulations showcased by the blue line—symbolising the true trajectory of the banking stock price. This synchronisation between the orange and blue lines underscores the Neural Prophet's efficacy in not just predicting, but faithfully mirroring the intricate fluctuations inherent to the actual dynamics of banking stock prices. This capability underscores its potential as an invaluable tool for understanding and predicting intricate patterns within the dynamic realm of financial markets.

Neural Prophet also visualises the trend of bank stock prices and their rate changes. These rate changes hold significant implications. They could potentially denote shifts in market sentiment, economic dynamics, or industry-specific occurrences. As such, Neural Prophet's ability to visualise not only the trends themselves but also the changes in their rates adds a new layer of insight to the interpretation of financial data. Neural Prophet adopts a classical method as depicted in Equation 6, wherein an offset (m) and a growth rate (k). are combined. The influence of the trend at a specific time point $(t1)$ is computed by multiplying the growth rate (k). by the time difference $(t1 - t0)$ since the starting point $(t0)$, and then adding the offset (m). This approach empowers us to capture and visualise the underlying trend in bank stock prices, incorporating both the offset and growth rate components.

$$T(t1) = m + k \cdot (t1 - t0) = T(t0) + k \cdot (\Delta t) \quad (3)$$

Figure 6 displays the variations in the trend patterns of BBRI stock prices. Although there's a prevailing upward direction, the pace of this upward movement has considerably slowed down after 2018, a phenomenon potentially influenced by the effects of the COVID-19 pandemic. A similar decelerating trend is observable in the stock price of BMRI, as portrayed in Figure 7, specifically during the year 2018. This deceleration could also be partially attributed to the disruptions caused by the pandemic, which had rippling effects on the financial markets. Likewise, Figure 8 exhibits a comparable slowing down of the trend in BBCA stock prices, notably occurring in 2019. This period coincides with the initial stages of the COVID-19 pandemic, which had a significant impact on global economic activities and consequently influenced stock prices. It is noteworthy that BBNI stock prices, illustrated in Figure 9, underwent a rapid change in trend rate, shifting towards a steep increase after experiencing a substantial decline in 2019. This noteworthy change might be linked to a series of events, including the COVID-19 aftermath, fiscal policies, and market sentiment. Similarly, BBTN stock prices depicted in Figure 10 display a moderation in their downward trend, accompanied by an escalating trend rate since 2020. This change could also be influenced by various factors, including the evolving response to the pandemic, economic recovery efforts, and investor behaviour adjustments.

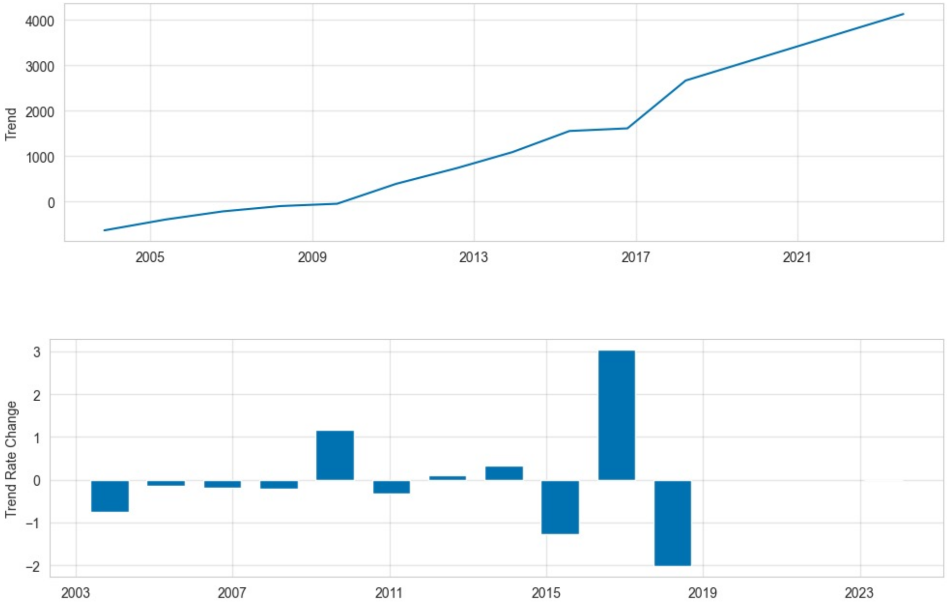

Figure 6: Trend rate change of BBRI

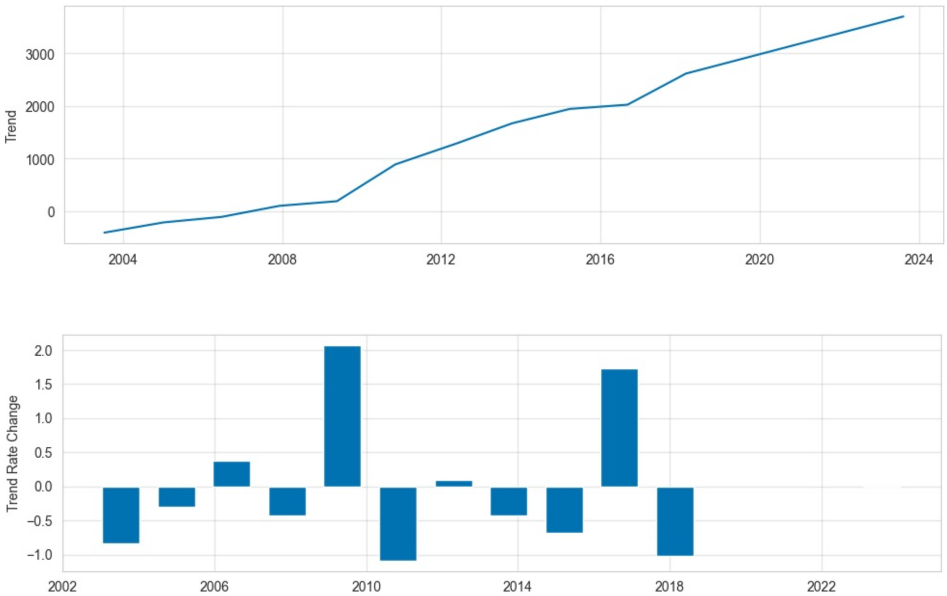

Figure 7: Trend rate change of BMRI

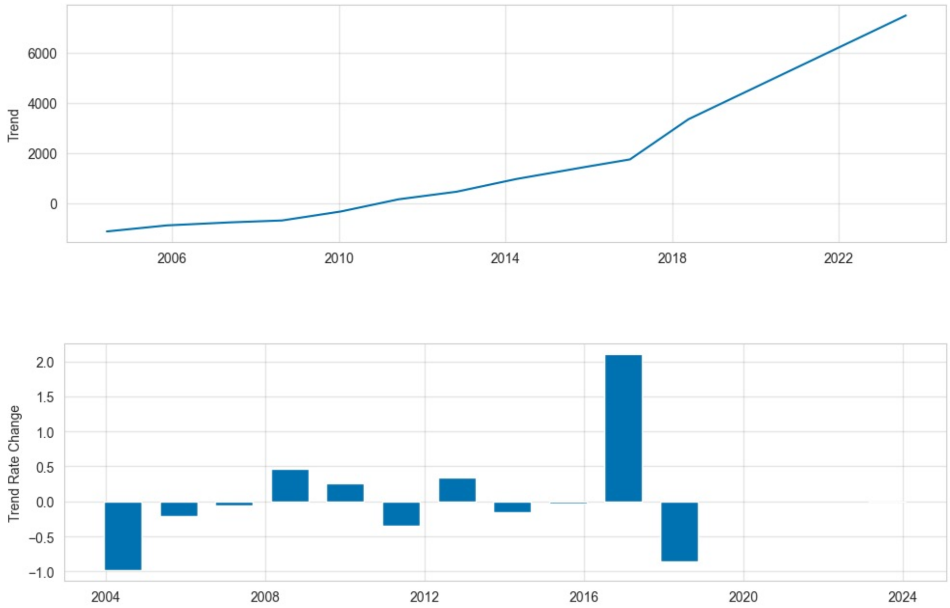

Figure 8: Trend rate change of BBCA

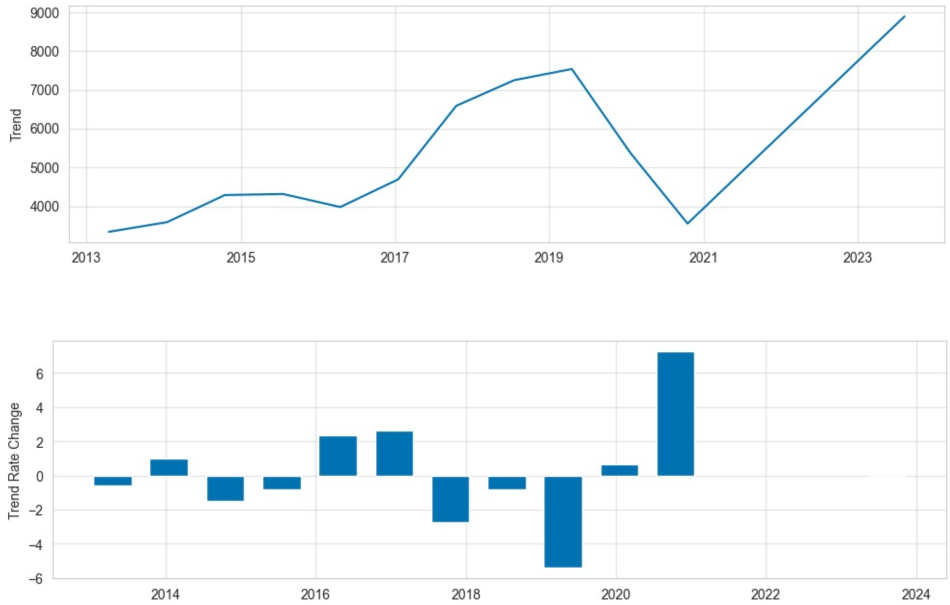

Figure 9: Trend rate change of BBNI

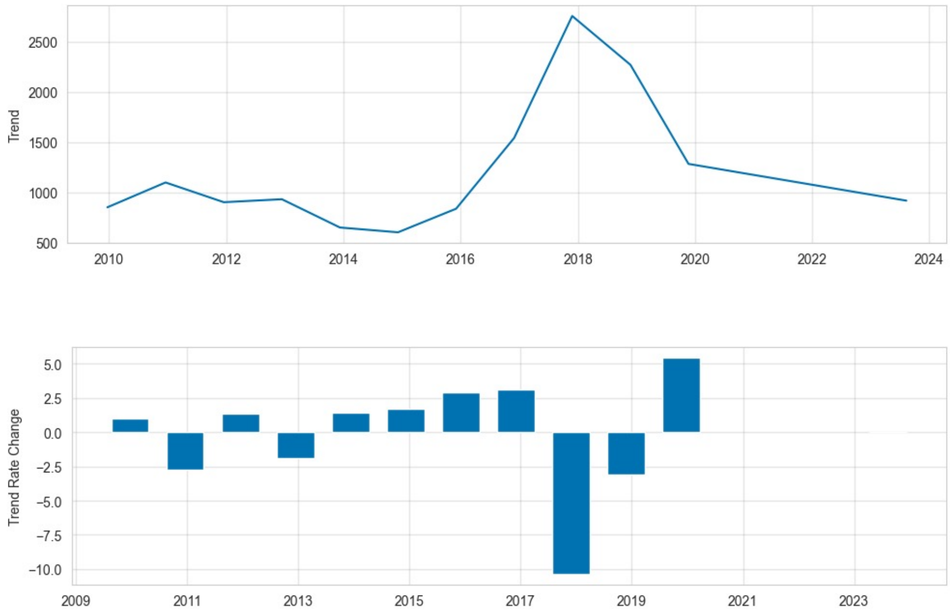

Figure 10: Trend rate change of BBTN

The unique capability of the Neural Prophet model goes beyond simple prediction and expands into proactive foresight, which is a crucial feature that distinguishes it from traditional forecasting models. This quality, as highlighted by Khurana et al. (2022); Velásquez (2022); and Yu et al. (2022) in their prior research, sets Neural Prophet apart due to its adaptability and proficiency in managing complex temporal patterns. As a result, Neural Prophet has garnered significant attention and is emerging as a prospective approach for predicting time series data.

The significance of this research lies in its pursuit of enhancing the accuracy and reliability of stock price predictions, particularly within the dynamic and intricate field of banking stocks. By harnessing the unique strengths of the Neural Prophet model, which exhibits an inherent aptitude for capturing intricate patterns and subtle variations, this research seeks to provide investors, financial analysts, and stakeholders with a more profound understanding of the future trajectory of banking stock prices.

The capability of Neural Prophet to decipher patterns in stock price movements is not confined to the serene waters of stable trends exhibited by BBRI, BMRI, and BBCA. Instead, it fearlessly navigates the stormy seas of erratic price variations in BBNI and BBTN. This striking revelation of Neural Prophet's adaptability and accuracy underscores the assertion that it is a stalwart and reliable methodology in the field of artificial intelligence, particularly for predicting intricate and ever-shifting time-series data linked to bank stocks.

Neural Prophet reaffirms its proficiency in handling the intricate dynamics of financial markets by consistently capturing both the nuances of stable and erratic market behaviours. Its ability to adapt and provide accurate forecasts across such diverse scenarios underscores its potential to play a pivotal role in informed decision-making within the finance sector. As institutions grapple with the challenges of uncertainty, Neural Prophet emerges as a valuable tool that empowers stakeholders to proactively manage risk, optimise investment strategies, and seize opportunities with a greater degree of confidence.

Our Neural Prophet models make highly accurate predictions about stock prices, which can be valuable for handling financial risks. A significant area that reaps the rewards of these precise stock price predictions is market risk. Neural Prophet's forecasts allow banks and investors to gain improved insights into potential market changes. This, in turn, enables risk managers to make informed decisions about where to invest and how to diversify their investments. Consequently, they can navigate the market's fluctuations with greater caution.

Furthermore, Neural Prophet excels in identifying periods when the market might become more turbulent. This capability assists in managing volatility, the significant price swings. With this foresight, individuals can plan ahead and implement strategies to safeguard their interests during highly unpredictable market conditions. Additionally, Neural Prophet enhances the optimisation of investment mixes for effective risk management. Risk managers can rely on its accurate predictions to identify investments that are likely to perform well even amidst changing circumstances. This approach ensures the resilience of investments, even in adverse scenarios, and facilitates the expectation of positive outcomes over time.

Neural Prophet also plays a crucial role in adhering to regulations and standards for risk management. It aids financial institutions in meeting compliance requirements by providing clear risk assessments, evaluating performance under challenging conditions, and examining diverse potential scenarios. This comprehensive analysis ensures that institutions are diligently addressing risks as required.

While the research's utilisation of Neural Prophet to predict stock prices based on total assets for Indonesian banks offers valuable insights, it is important to recognise that the analysis is confined to a specific time range. This limitation restricts the model's ability to account for broader market trends, potential economic shifts, or long-term fluctuations that might impact stock prices. Also, it is worth noting that the hyperparameter optimisations have not been implemented, potentially limiting its accuracy and generalisation to different market conditions.

V. CONCLUSION AND RECOMMENDATIONS

A. Conclusion

This research aims to utilise the Neural Prophet model for highly accurate stock price predictions in the banking sector. The model demonstrates remarkable proficiency not only in forecasting trends but also in capturing subtle fluctuations within banking stock prices. Visual representations illustrate the model's alignment with actual trajectories, showcasing its adaptability and proactive insight compared to traditional models. Neural Prophet's ability to handle intricate temporal patterns sets it apart, drawing attention from researchers.

The significance of the research lies in enhancing stock price prediction accuracy, particularly in banking stocks, providing stakeholders with deeper insights. The model's effectiveness is evident across stable and erratic market behaviours, making it a valuable AI tool for decision-making in finance. Precise predictions benefit risk management, enabling well-informed investment decisions in dynamic markets.

B. Recommendations

Based on the demonstrated efficacy of the Neural Prophet model in accurately predicting stock prices within the banking sector, it is strongly advised that financial institutions embrace the integration of this advanced predictive tool into their decision-making frameworks. However, such integration should be accompanied by stringent regulatory and supervision to ensure transparency and compliance with industry standards. This precautionary measure is essential to guarantee that the incorporation of artificial intelligence aligns with ethical practices and legal requirements, mitigating potential risks.

In parallel, fostering collaboration between academia and industry is predominant for refining and advancing the Neural Prophet model. Continued joint research and development initiatives not only enhance the model's capabilities but also address emerging challenges and biases. Concurrently, educational initiatives must be prioritised to train financial professionals in effectively leveraging AI-generated insights. By investing in these programs, stakeholders can ensure that decision-makers possess the necessary knowledge to harness the potential of AI while minimising risks. Additionally, incentivising innovation within the banking sector by promoting the use of Neural Prophet for risk management and strategic investments can significantly enhance predictive accuracy, empowering institutions to make informed decisions that contribute to overall market stability.

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