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Enhancing Stock Price Prediction in the Indonesian Market: A Concave LSTM Approach with RunReLU

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Mohammad Diqi, I Wayan Ordiyasa

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Abstract:
This study addresses the pressing need for improved stock price prediction models in the financial markets, focusing on the Indonesian stock market. It introduces an innovative approach that utilizes the custom activation function RunReLU within a concave long short-term memory (LSTM) framework. The primary objective is to enhance prediction accuracy, ultimately assisting investors and market participants in making more informed decisions. The research methodology used historical stock price data from ten prominent companies listed on the Indonesia Stock Exchange, covering the period from July 6, 2015, to October 14, 2021. Evaluation metrics such as RMSE, MAE, MAPE, and R2 were employed to assess model performance. The results consistently favored the RunReLU-based model over the ReLU-based model, showcasing lower RMSE and MAE values, higher R2 values, and notably reduced MAPE values. These findings underscore the practical applicability of custom activation functions for financial time series data, providing valuable tools for enhancing prediction precision in the dynamic landscape of the Indonesian stock market.

Keywords: *stock price prediction, concave LSTM, RunReLU, Indonesian stock exchange, financial forecasting*

1. Introduction

The prices of stocks are intricate and ever-changing variables impacted by many external elements, including political occurrences, economic indicators, natural calamities, and internal factors. These factors make stock price movements challenging to predict accurately [1]. The stock market is a nonlinear and highly unpredictable environment, affected by numerous elements [2]. The future price of stocks depends on many factors, making it elusive to predict based solely on available information [3]. However, researchers have explored methods and techniques, such as artificial intelligence models, deep learning, and mathematical analysis, to improve stock price prediction accuracy [4, 5]. Accurate forecasting of stock prices is crucial for investors to make informed decisions and increase their returns [6]. While no method can guarantee perfect predictions, technological advancements and data analysis have provided tools to enhance prediction models and develop effective trading strategies [7].

The unique characteristics of stock price movements in Indonesia, which differentiate them from other countries, can be attributed to several factors. Firstly, the Indonesian stock market is highly dynamic and nonlinear, making it challenging to predict future stock prices accurately [7]. Additionally, the stock market is influenced by various external factors, such as political events, natural disasters, and financial crises, which can cause sharp and unpredictable fluctuations in stock prices [8]. Moreover, the use of advanced techniques in deep learning, such as LSTM and GRU, in stock price prediction has gained popularity in Indonesia, indicating a shift towards more sophisticated modeling approaches [9]. These factors contribute to the unique characteristics of stock price movements in Indonesia, highlighting the need for specialized prediction models and strategies tailored to the Indonesian market.

For several reasons, investors, traders, companies, capital market regulators, and financial analysts need accurate stock price prediction information. Firstly, accurate predictions can help investors make informed decisions about buying or selling stocks, potentially resulting in significant profits [10]. Secondly, traders can use stock price predictions to identify trends and patterns in the market, allowing them to make timely and profitable trades [11]. Companies can benefit from accurate stock price predictions by adjusting their strategies and making informed financial decisions [1]. Capital market regulators rely on accurate predictions to monitor and regulate the market effectively, ensuring fair and transparent trading practices [12]. Finally, financial analysts use stock price predictions to provide valuable insights and recommendations to investors and companies, helping them navigate the complex and volatile stock market [4].

Conventional methods like Autoregressive Integrated Moving Average (ARIMA), machine learning, and deep learning techniques are widely employed in predicting stock prices. ARIMA models are parametric statistical models commonly used in time series analysis, including stock price prediction [10]. Machine learning methods, such as k-nearest neighbor algorithm (KNN), artificial neural networks (ANNs), support vector machines (SVMs), and random forest (RF), have also been applied to learn the relationship between technical analysis features and price movement [13].

The popularity of deep learning techniques, including convolutional neural networks (CNN), long short-term memory (LSTM) networks, and gated recurrent units (GRU), has increased in the field of stock price forecasting because of their capability to address nonlinear and multi-dimensional challenges [11]. These models have shown promising results in forecasting stock prices by considering various factors and features, including historical stock data, technical indicators, and external factors like COVID-19 cases [12].

The uncertainty of the direction of movement and the accuracy of future stock prices remain issues in stock price predictions due to several factors [14]. Firstly, stock markets are influenced by various complex factors such as politics, economic growth, and interest rates, making it challenging to predict their movements [10] accurately. Additionally, the stock market is highly volatile and subject to sudden changes, making it challenging to forecast altogether [11]. Moreover, using different prediction models and techniques introduces variations in the accuracy of forecasts, leading to uncertainty in the direction of stock price movement [1]. Lastly, the availability of vast amounts of data, including social media sentiments, introduces challenges in effectively analyzing and incorporating these data sources into prediction models [3]. Therefore, despite advancements in prediction models, the stock market's inherent complexity and dynamic nature contribute to the ongoing uncertainty in predicting stock price movements [14].

The activation function in deep learning can leave weaknesses in stock price prediction due to stock markets' complex and volatile nature [15]. Stock prices are influenced by various unpredictable external factors such as financial news, sociopolitical issues, and natural calamities [16]. Activation functions are crucial in deep learning models utilized in stock price prediction by introducing non-linearity to capture intricate data patterns effectively [17]. Nevertheless, selecting an activation function can influence the model's capacity to make precise stock price predictions. Various activation functions possess distinct characteristics and may not be appropriate for capturing the intricate non-linear connections within stock market data [18]. Therefore, selecting a proper activation function is crucial for improving the accuracy of stock price prediction models.

Addressing the challenge of handling intricate temporal patterns within stock price data remains an issue in stock price prediction for various reasons. Firstly, conventional approaches that rely solely on time-series data for individual stocks are insufficient, as they lack a comprehensive view of the situation [19]. Secondly, the intricacy of multiple elements affecting stock prices calls for the utilization of more expansive datasets, which should encompass information regarding stock relationships [10]. Thirdly, obtaining precise and up-to-date information about stock relationships is challenging since industry classification data from third-party sources is frequently approximated and may be delayed [11]. Lastly, predicting stock prices involves integrating temporal information and relationships among stocks, which requires advanced models such as deep learning methods [1]. Therefore, the problem of responding to complicated temporal signals in stock price data persists due to the limitations of traditional methods and the need for more comprehensive and accurate data and advanced prediction models [3].

The characteristics of the Indonesian stock market differ from other global stock markets, creating a gap in the development of stock price prediction models. The Indonesian stock market is influenced by politics, economic growth, and interest rates [20]. These factors and the market's volatility make accurate forecasting challenging [19]. Additionally, the complexity of the stock market and the interdependence of stocks within the market require more comprehensive data and models [21]. Conventional approaches that exclusively depend on time-series data for an individual stock are inadequate [16]. Therefore, there is a need for models that integrate time series information, relationship information, and sentiment analysis from social media [4]. By incorporating these factors, stock price prediction models can provide more accurate forecasts for the Indonesian stock market.

This research is highly significant as it introduces an innovative approach to stock price prediction in the Indonesian stock market, aiming to enhance prediction accuracy and assist investors and market participants in making more informed decisions. The novelty of this research lies in utilizing the custom activation function, RunReLU, within a concave LSTM model that combines various LSTM types for stock price prediction in the Indonesian stock market. The research seeks to create and assess a novel stock price forecasting model utilizing the concave LSTM architecture, incorporating the customized RunReLU activation function, to improve prediction accuracy within the Indonesian stock market.

2. Basic Theory

This section delves into the foundational theories underpinning our research, focusing on long short-term memory (LSTM) networks and the innovative concave LSTM architecture, including the introduction of the RunReLU activation function.

2.1. Long Short-Term Memory (LSTM)

LSTM, classified as a recurrent neural network (RNN), was developed to address the vanishing gradient challenge present in conventional RNNs. Its intricate architecture enables it to grasp and retain extended patterns of reliance in sequential data. The LSTM cell consists of three gates: input gate i_t, forget gate f_t, and output gate o_t, along with a cell state C_t [22], as formulated in Equations (1)–(6).

2.1.1. Input Gate

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \quad (1)$$

2.1.2. Forget Gate

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \quad (2)$$

2.1.3. Output Gate

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \quad (3)$$

2.1.4. Candidate Cell State

$$\widetilde{C}_t = \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (4)$$

2.1.5. New Cell State

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C}_t \quad (5)$$

2.1.6. Hidden State

$$h_t = o_t \cdot \tanh(C_t) \quad (6)$$

Where x_t is the input at time step t, h_{t-1} is the hidden state from the previous time step, W and b are weight matrices and bias terms, σ is the sigmoid activation function, $tanh$ is the hyperbolic tangent activation function.

2.2. Concave LSTM

Building upon the standard LSTM framework, the Concave LSTM integrates both stacked and bidirectional LSTM layers to enhance model performance for complex time-series predictions. This hybrid model is particularly adept at capturing nuanced patterns in financial markets, offering a robust foundation for stock price forecasting.

A pivotal enhancement in our concave LSTM model is the incorporation of the RunReLU activation function [23]. Designed to optimize the model's learning process, RunReLU introduces a dynamic, data-driven approach to activation, allowing for adaptive thresholding based on the distribution of inputs. This flexibility enhances the model's ability to model nonlinear relationships in the data, a common characteristic of financial time series.

2.3. RunReLU

Activation functions play a pivotal role in neural networks, introducing non-linearity and enabling the model to learn complex patterns in data. Traditional activation functions, such as the Rectified Linear Unit (ReLU), have been widely adopted due to their simplicity and effectiveness in various tasks. However, the static nature of these functions can limit their adaptability, especially in the volatile and non-linear domain of financial markets.

RunReLU is designed to overcome these limitations by incorporating a dynamic element into the activation process. It modulates the activation threshold based on a Gaussian distribution, with parameters μ (mean) and σ (standard deviation) tailored to the specific characteristics of the input data, as shown in Equation (7). This randomization allows for a more flexible response to the input features, enhancing the model's ability to capture the intricate dependencies within financial time series.

$$CommonReLU = max(0, x) \quad (7a)$$

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad (7b)$$

$$RunReLU = max[ReLU * f(x)] \quad (7c)$$

The primary advantage of RunReLU lies in its unparalleled adaptability, which dynamically adjusts the activation threshold for each input, allowing it to handle adeptly the volatility and non-linearity typical of financial data. This adaptability not only enhances feature representation by dynamically emphasizing or deemphasizing features based on their relevance to the task at hand, leading to a richer and more nuanced understanding of the data, but also significantly improves model generalization. By introducing variability in the activation process, RunReLU mitigates overfitting, enhancing the model's ability to perform well on unseen data. Furthermore, its capacity to adjust activation thresholds contributes to increased robustness, making the model more resilient to the noise and anomalies that frequently occur in financial datasets. This suite of benefits underscores RunReLU's critical role in refining predictive accuracy and reliability in financial modeling.

3. Research Method

3.1. Research Design

The research design involves developing and evaluating a hybrid model, concave LSTM, that combines stacked and bidirectional LSTM [12] with custom RunReLU activation for stock price prediction on data from the Indonesian stock exchange. The stacked LSTM model utilizes the RunReLU activation function, while the bidirectional LSTM model uses the ReLU activation function. Figure 1 illustrates the architecture of concave LSTM.

3.2. Dataset

The dataset used in this study is obtained from Yahoo Finance and includes the stock price information of the ten highest-ranked stocks on the Indonesia Stock Exchange. This dataset covers the period from July 6, 2015, to October 14, 2021. The stock symbols and company names analyzed in this research are detailed in Table 1.

3.3. Research Procedure and Data Analysis

The research methodology employed in this study revolves around analyzing and predicting stock prices using a dataset spanning from July 6, 2015, to October 14, 2021. The dataset encompasses daily stock price data and consists of five primary features: Open, High, Low, Close, and Volume [7, 16]. Records with a volume greater than zero were retained to ensure data quality, resulting in 1269 records. The study focuses exclusively on the Close feature for price prediction.

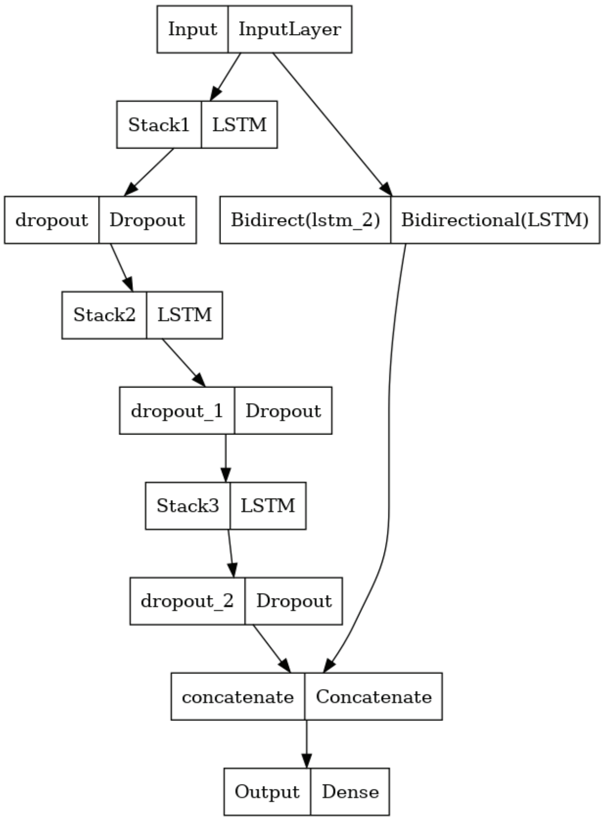

Figure 1. Concave LSTM architecture

Table 1. Ten Indonesian stocks

Symbol	Company
ACES	Ace Hardware Indonesia Tbk.
ADRO	Adaro Energy Tbk.
AKRA	AKR Corporindo Tbk.
JPFA	JAPFA Comfeed Indonesia Tbk.
MIKA	Mitra Keluarga Karyasehat Tbk.
PTBA	Tambang Batubara Bukit Asam (Persero) Tbk.
TKIM	Pabrik Kertas Tjiwi Kimia Tbk.
TLKM	Telkom Indonesia (Persero) Tbk.
TPIA	Chandra Asri Petrochemical Tbk.
WIKA	Wijaya Karya (Persero) Tbk.

Normalization was performed using the MinMax Scaler to prepare the data for modeling, ensuring that all values fall within a specified range [24]. The last 50 data points were set aside for reference to actual data.

Of the 1219 data points, 975 were designated for training the predictive model, leaving the remaining 244 for validation. The training and validation stages encompassed 100 epochs, allowing for gradual enhancements in the model's performance.

Following that, forecasts were generated for the stock prices over the forthcoming 50 days, utilizing the testing dataset. To evaluate the model's effectiveness, a range of metrics was used, encompassing root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and R-squared (R2) [25, 26].

Table 2. Performance metrics of ReLU-based model

Company	RMSE	MAE	MAPE	R2
ACES	0,01034	0,00849	0,01352	0,95084
ADRO	0,01817	0,01390	0,02792	0,96745
AKRA	0,00795	0,00760	0,02094	0,96510
JPFA	0,00585	0,00518	0,00948	0,97684
MIKA	0,00700	0,00628	0,01208	0,96692
PTBA	0,01047	0,00978	0,02689	0,96989
TKIM	0,02158	0,02142	0,05552	0,46965
TLKM	0,02194	0,02156	0,05336	0,89861
TPIA	0,01760	0,01709	0,02553	0,95579
WIKA	0,01354	0,01202	0,12252	0,96019

Furthermore, this research introduced a comparative analysis between models based on two activation functions: RunReLU and ReLU. The predictive results of both models and the actual data were graphically represented, providing a visual illustration of the model's performance in predicting stock prices.

4. Results and Discussion

4.1. Model Performance

In Table 2, we present the performance metrics of our model utilizing the ReLU activation function to predict stock prices for ten prominent companies in the market. These performance metrics, comprising RMSE, MAE, MAPE, and R2, provide valuable insights into the precision and efficiency of our model's forecasts for each company's stock. The results displayed in the table underscore the model's ability to provide precise predictions, with low RMSE and MAE values and high R2 values, demonstrating its potential as a valuable tool for investors and market analysts in the assessment of stock performance.

In Table 3, we present the performance metrics of our model utilizing the innovative RunReLU activation function to predict stock prices for ten leading companies in the market. These performance indicators, encompassing RMSE, MAE, MAPE, and R2, supply vital information regarding the accuracy and efficiency of our model's forecasts for individual company stocks. The results displayed in this table underscore the remarkable accuracy achieved by our model with the RunReLU activation function, showcasing low RMSE and MAE values, high R2 values, and minimal MAPE values. These findings affirm the potential of our novel approach to significantly benefit investors and market analysts in making informed decisions and assessing stock performance with greater accuracy and reliability.

In Figures 2 through 11, we provide a comprehensive visual representation of the predicted and actual stock prices for each of the selected ten companies over a 50-day horizon. The blue line depicts the stock prices, offering a reference point for market performance.

Table 3. Performance metrics of RunReLU-based model

Company	RMSE	MAE	MAPE	R2
ACES	0,00760	0,00588	0,00918	0,97343
ADRO	0,00727	0,00379	0,00777	0,99479
AKRA	0,00318	0,00228	0,00627	0,99441
JPFA	0,00289	0,00220	0,00405	0,99434
MIKA	0,00227	0,00189	0,00363	0,99651
PTBA	0,00434	0,00320	0,00831	0,99482
TKIM	0,00835	0,00776	0,02007	0,92064
TLKM	0,00562	0,00444	0,01190	0,99335
TPIA	0,01163	0,01049	0,01565	0,98070
WIKA	0,00703	0,00567	0,05609	0,98925

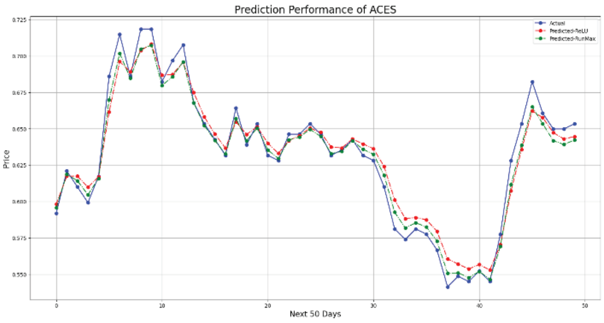

Figure 2. Performance of ACES

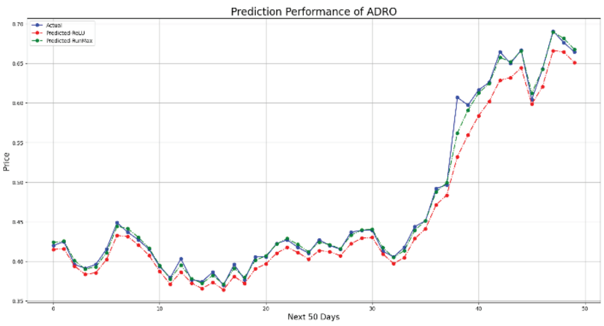

Figure 3. Performance of ADRO

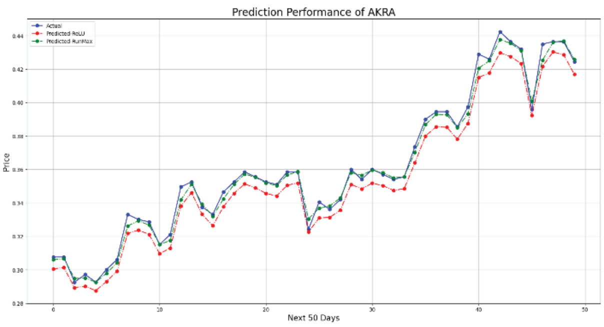

Figure 4. Performance of AKRA

Concurrently, the red line corresponds to the stock price predictions generated by our ReLU-based model, while the green line represents predictions derived from our RunReLU-based model. Closer proximity between the predicted and actual data points signifies higher accuracy in our models.

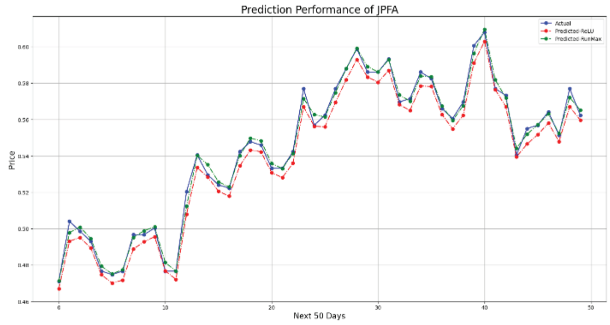

Figure 5. Performance of JPFA

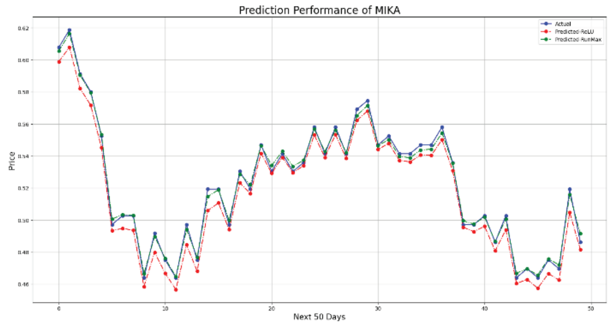

Figure 6. Performance of MIKA

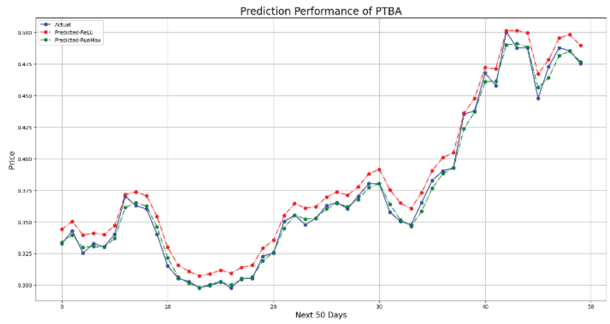

Figure 7. Performance of PTBA

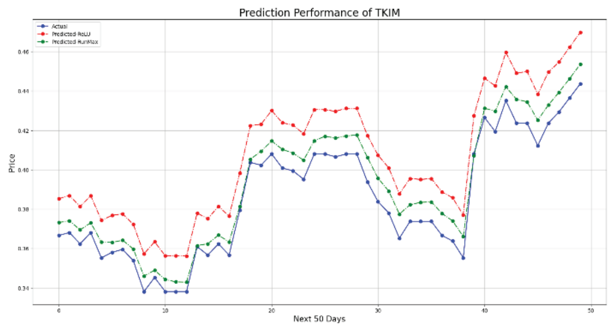

Figure 8. Performance of TKIM

The above research outcomes are instrumental in addressing our study's primary research questions and objectives. The performance metrics of our models, both based on ReLU and RunReLU activations, shed light on their efficacy in predicting stock prices in the Indonesian stock market. These findings have crucial implications for investors and market participants seeking to make more informed decisions.

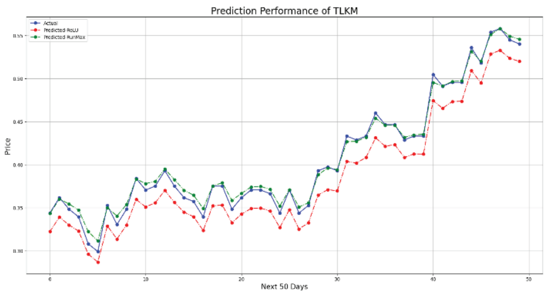

Figure 9. Performance of TLKM

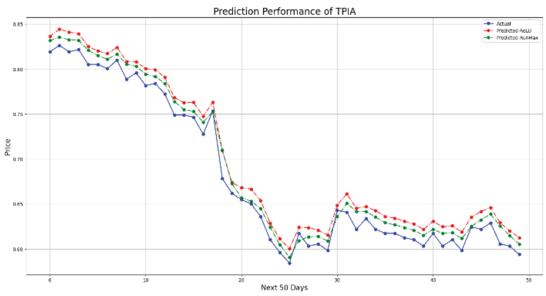

Figure 10. Performance of TPIA

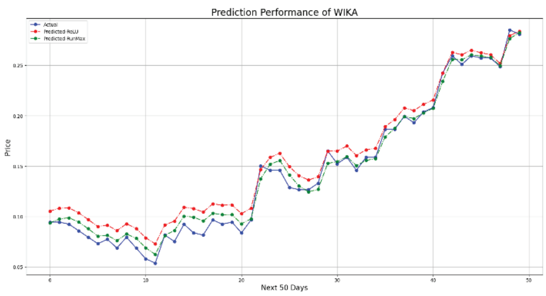

Figure 11. Performance of WIKA

Firstly, the results highlight the potential of our innovative approach, leveraging the RunReLU activation function within a concave LSTM model, to significantly enhance prediction accuracy. The lower RMSE and MAE values and higher R2 values indicate higher precision and reliability in the predictions. This aligns with our research objective to improve prediction precision in the Indonesian stock market, which is crucial for effective investment strategies.

Furthermore, the substantial reduction in MAPE values, particularly evident in the RunReLU-based model, suggests that our approach reduces prediction errors, enhancing the models' practical utility. These findings directly address the need for more accurate prediction models, as identified in our research motivation.

In summary, the research outcomes demonstrate that our innovative models, especially the RunReLU-based model, offer promising avenues for stock price prediction in the Indonesian stock market. This research contributes significantly to the field, providing investors and market analysts with enhanced tools for making well-informed decisions and improving the overall accuracy of stock price predictions in this dynamic financial landscape.

4.2. Summarization of Key Findings

This research tackles the challenge of enhancing stock price prediction accuracy in the Indonesian stock market by introducing a pioneering approach that leverages custom activation functions, including RunReLU, within concave LSTM models. The research addresses the critical need for more precise prediction models in the complex and volatile financial market context. The significant findings reveal that the RunReLU-based model outperforms the ReLU-based counterpart, showcasing lower RMSE and MAE values, higher R2 values, and significantly reduced MAPE values, demonstrating substantial improvements in prediction precision. These outcomes mark a significant contribution to the field and offer investors and market analysts valuable tools for making more informed decisions in the dynamic landscape of the Indonesian stock market.

4.3. Interpretations of the Results

The results revealed a consistent and notable pattern wherein the RunReLU-based model consistently surpasses its ReLU-based counterpart across multiple evaluation metrics, including RMSE, MAE, MAPE, and R2, signifying enhanced prediction accuracy. These outcomes align with the research's expectations, as the novel utilization of the RunReLU activation function was anticipated to improve precision in stock price prediction. The findings are consistent with prior research emphasizing the significance of custom activation functions and hybrid models in refining deep learning models' performance in financial prediction tasks.

An unexpected observation is the relatively low R2 value for TKIM in the RunReLU-based model, indicating potential external factors influencing its stock behavior that necessitate further investigation. The investigation into TKIM's anomaly reveals that its lower R2 value, indicative of a mismatch between the model's predictions and actual stock performance, may stem from a confluence of external factors specific to TKIM and its industry. The sensitivity of TKIM, a key player in the paper and pulp sector, to market dynamics like raw material costs and international trade policies potentially exacerbates this divergence. Additionally, sector-specific volatility, driven by environmental regulations, sustainability trends, and the pivot towards digital mediums, could introduce unpredictability not accounted for by the model. Moreover, unforeseen events—operational, regulatory, or corporate—might have precipitated stock price fluctuations beyond the model's predictive capacity based on historical data. This anomaly underscores the necessity of integrating external factor analysis and sector-specific considerations to enhance model accuracy and reliability.

4.4. Implications of the Research

The results obtained in this research hold significant relevance and implications for both stock price prediction and financial markets. Firstly, the consistent superiority of the RunReLU-based model in terms of lower RMSE, MAE, MAPE, and higher R2 values emphasizes its practical applicability in enhancing prediction accuracy.

These findings align with the existing literature that underscores the importance of custom activation functions and innovative model architectures for improving deep learning models' performance in financial prediction tasks. Furthermore, the research contributes new insights by introducing the RunReLU activation function as a valuable tool for stock price prediction, offering a practical alternative to standard activation functions. The unexpectedly lower R2 value for TKIM highlights the need for further research into company-specific external factors affecting stock performance. Overall, this research enhances our understanding of the potential of custom activation functions and innovative model approaches to refine stock price prediction accuracy, providing valuable insights for investors and market analysts.

4.5. Market Specificity and Generalizability

The concave LSTM model, enhanced with the RunReLU activation function, has shown notable success within the Indonesian stock market, showcasing its capability to navigate the market's unique volatility, economic policies, and investor behaviors. These specific attributes of the Indonesian market played a pivotal role in the model's initial development and subsequent refinement, ensuring it was well-suited to manage the pronounced fluctuations and unpredictability typical of emerging markets. The adaptability of the RunReLU function, in particular, was key in addressing these market characteristics, allowing for a nuanced approach to the nonlinear dynamics encountered.

Despite its optimization for the Indonesian context, the foundational principles of the concave LSTM model hold potential applicability across a broad spectrum of financial environments. The model's architecture, which emphasizes the processing of long- and short-term memory through LSTM layers, coupled with the dynamic nature of the RunReLU activation function, is designed to universally capture complex temporal relationships inherent in stock data. However, to effectively extend its application to other markets, considerations around market volatility, regulatory and economic factors, and the quality and availability of data must be thoroughly addressed. This suggests a theoretical and practical flexibility in the model's application, indicating that, with appropriate adjustments, the concave LSTM model could serve as a powerful tool for financial analysis and prediction on a global scale, offering insights into the intricacies of various stock markets around the world.

4.6. Limitations of the Research

The study's conclusions underscore the substantial benefits of employing the custom activation function RunReLU within concave LSTM models to enhance stock price prediction accuracy in the Indonesian stock market. These findings are robust, with consistent patterns of lower RMSE, MAE, MAPE, and higher R2 values compared to standard ReLU activation function models. The research introduces the valuable insight that custom activation functions, tailored to specific prediction tasks like stock prices, can be practical alternatives to standard activations.

While offering significant insights into stock price prediction using the concave LSTM model within the Indonesian market, this study presents limitations tied to the dataset's scope and the market's distinctive characteristics. The analysis is rooted in data from ten leading Indonesian companies, reflecting the market's volatility, trends, and sectoral idiosyncrasies. Such depth provides a fertile testing ground, yet the market's emerging status, unique regulatory landscape, and the economic backdrop could hinder the direct transposition of these findings to dissimilar, particularly developed, markets. The tailored calibration of the model's parameters and the RunReLU function to the Indonesian context underscores a potential challenge in generalizing these results across markets with divergent characteristics in terms of volatility, liquidity, and investment patterns, highlighting areas for future research to expand the model's global relevance and applicability.

Despite these limitations, the results remain valid, supported by a rigorous research design, statistical analysis, and the consistent performance of the RunReLU-based model, offering valuable insights for stock market participants and financial analysts.

4.7. Recommendations for Future Research

As we anticipate advancements in financial modeling and the prediction of stock prices, the enhancement of tools like the concave LSTM model becomes paramount. Our recommendations aim to navigate the intricacies of financial markets, augment the interpretability of complex models, and solidify their reliability across varied market scenarios. Enhancing model interpretability is crucial, as the intricate nature of deep learning often obscures the model's decision-making process. By implementing feature importance analysis techniques such as SHAP or LIME, we can elucidate the influence of specific inputs on predictions, offering tangible insights into the driving factors behind stock movements. Additionally, leveraging visualization tools to illustrate the model's internal mechanics demystifies its operations, aiding both developers and stakeholders in understanding its functionality.

Furthermore, integrating external factors like economic indicators and geopolitical events can significantly refine the model's predictive precision. Developing a comprehensive framework to incorporate a diverse array of data sources—including news feeds and social media sentiment—into the training dataset will allow for a nuanced understanding of stock price influencers. Adopting event-driven modeling techniques, supported by NLP analysis of financial reports and news articles, can capture the market's reaction to unforeseen events. Moreover, exploring ensemble methods and sentiment analysis promises to enhance accuracy by amalgamating predictions from various models and integrating market sentiment. Conducting comparative studies across different markets and devising adaptation strategies for the model will ensure its applicability and robustness, making it a versatile tool for global financial analysis.

5. Conclusion

The research's objective was to develop and assess an innovative stock price prediction model based on a hybrid LSTM architecture with the custom RunReLU activation function to enhance prediction accuracy in the Indonesian stock market. The supporting evidence for this objective lies in the research outcomes, which consistently demonstrate that the RunReLU-based model outperforms the ReLU-based model across various evaluation metrics, including RMSE, MAE, MAPE, and R2. These findings validate the effectiveness of the innovative approach in improving the accuracy of stock price predictions within the Indonesian market context. Consequently, the research's contribution is introducing and validating the RunReLU activation function as a valuable tool for stock price prediction, offering a practical alternative to conventional activation functions and enhancing the precision of predictions for investors and market analysts.

AUTHORS

Mohammad Diqi* – Dept. of Informatics, Universitas Respati Yogyakarta, Yogyakarta, 55281, Indonesia, e-mail: diqi@respati.ac.id.

I Wayan Ordiyasa – Dept. of Informatics, Universitas Respati Yogyakarta, Yogyakarta, 55281, Indonesia, e-mail: wayanordi@respati.ac.id.

*Corresponding author

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