

Sentiment Analysis Using Bidirectional Encoder Representations from Transformers for Indonesian Stock Price Prediction with Long Short-Term Memory and Gated Recurrent Unit Models

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Abstract

The advancement of artificial intelligence based market analytics has driven the need for stock price prediction models capable of representing market behavior both technically and psychologically. This study aims to improve stock price forecasting in the Indonesian capital market by integrating sentiment analysis with deep learning time-series models. It evaluates whether public sentiment can contribute to enhancing prediction accuracy when combined with historical stock data. Textual sentiments were extracted using IndoBERT and converted into positive, negative, and neutral scores, which were then merged with historical stock prices. These data were modeled using LSTM, GRU, and a hybrid LSTM–GRU architecture. Model evaluation was conducted using MSE, MAE, RMSE, and MAPE metrics across six Indonesian stocks ANTM, BBCA, BBRI, SCMA, TLKM, and UNVR. The hybrid LSTM–GRU model produced the lowest prediction errors for BBCA and BBRI, with MSE scores of 0.151 and 1022.062, respectively. GRU delivered the best performance for highly volatile stocks, such as SCMA MAPE 1.65% and UNVR MAPE 0.51%, while LSTM demonstrated the most stable performance for TLKM with an MSE of 606.93 and RMSE of 24.63. Across all cases, sentiment scores improved model responsiveness, particularly during price spikes ANTM mid-2025 and price declines BBRI early year. The integration of sentiment significantly enhances prediction relevance by combining psychological market indicators with technical price trends. This framework provides more reliable decision-making support for investors, strengthens algorithmic trading strategies in Indonesia, and contributes to intelligent financial analytics that reflect local market behavior.

Keywords : *indobert, sentiment analysis, stock price prediction, lstm–gru, natural language processing, financial technology.*

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1. INTRODUCTION

Stock price prediction represents one of the major challenges for economists, statisticians, and financial practitioners, as stocks play a crucial role in a country's economy [1]. The stock market serves as a medium for trading, distributing, and transferring corporate ownership, while also enabling companies to obtain capital through Initial Public Offering (IPO) mechanisms [2]. Investors may generate profits if they are able to determine the optimal timing for transactions; however, stock prices are highly volatile and influenced by a variety of internal and external factors, such as macroeconomic conditions, national policies, and investor psychological dynamics [3]. In the context of Indonesia as an emerging market, the capital market exhibits high sensitivity to global shocks such as changes in international interest rates, geopolitical events, and currency exchange volatility, all of which may affect domestic market stability [4],[5]. Moreover, public opinion and investor perceptions formed through media coverage also contribute to stock price movements [6]. This complexity necessitates the use of more adaptive technology-based approaches compared to conventional forecasting methods [7].

Traditional analytical methods commonly used in stock forecasting include fundamental analysis, which evaluates internal company conditions such as revenue, dividends, and market position, as well as technical analysis, which utilizes historical data to identify stock price movement patterns [8]. Although both approaches have been widely implemented, technological advancements have encouraged their integration with artificial intelligence and machine learning techniques [9]. Various algorithms, such as Artificial Neural Networks (ANN) [10], Bayesian Networks [11], Support Vector Machines (SVM) [12], Multi-Layer Perceptron (MLP) [13], and Recurrent Neural Networks (RNN) based on Long Short-Term Memory (LSTM), have been extensively applied to predict stock prices and their trends using historical market data, financial news, and social media content [14], [15]. Traditional algorithms have limitations because they rely solely on static features, making them less capable of capturing the linguistic context comprehensively [16]. This limitation is reinforced by the findings of Mandviwala et al. [17], who compared traditional classification models Support Vector Machine (SVM) and Random Forest with a deep learning model, Long Short-Term Memory (LSTM), for sentiment analysis in stock market prediction. The evaluation results showed that LSTM achieved the lowest RMSE of 364.11 and a positive R^2 value of 0.43, indicating a better ability to explain data variance. In contrast, Random Forest recorded an RMSE of 1,202.9 and an R^2 of 5.24, while SVM produced the poorest performance with an RMSE of 1,954.40 and an R^2 of 15.46, demonstrating their inability to capture the time-series nature of stock data. Thus, LSTM proves to be more superior than traditional models in forecasting stock price movements.

Although LSTM demonstrates superior performance in understanding word sequences and contextual relationships, it still faces limitations when processing long text and remains prone to vanishing gradient problems. These limitations have encouraged the development of more adaptive approaches, one of which is transfer learning based on Bidirectional Encoder Representations from Transformers (BERT), which is considered more accurate due to its ability to understand bidirectional context and leverage linguistic knowledge from large-scale pre-trained models [18]. Through its self-attention mechanism, BERT can capture global text context, thereby improving sentiment classification performance, including within stock market analysis. In the Indonesian context, IndoBERT was developed using a large Indonesian-language corpus, making it more sensitive to local linguistic structures and nuances [19]. Studies have shown that IndoBERT can achieve accuracy rates exceeding 95% in sentiment classification, significantly outperforming traditional models and even LSTM-based architectures [20]. With these advantages, IndoBERT stands as a strong candidate for supporting stock price prediction through more accurate, relevant, and contextually aware sentiment analysis.

Nevertheless, the application of IndoBERT within the Indonesian financial context remains limited, whereas most prior studies tend to utilize FinBERT, which is designed for English-language financial texts and is less optimal in capturing Indonesian syntactic and semantic structures. This creates a research gap concerning the need for sentiment-based stock prediction models that align more closely with Indonesian linguistic characteristics. Referring to the findings of Yulianti et al. [21], IndoBERT achieved 96% accuracy and a 91% F1-score in sentiment classification, demonstrating substantial potential for implementation in Indonesian stock market prediction. Therefore, this study aims to integrate IndoBERT into a sentiment-based stock price prediction model in order to improve forecasting accuracy compared to traditional approaches such as SVM, Random Forest, and LSTM. The contribution of this research extends beyond academic significance and includes practical implications. For investors, the proposed model can serve as a data-driven decision-support tool that captures market sentiment more realistically. For regulators, the findings provide insights into how public opinion influences the stability of the capital market. Overall, this study has the potential to promote the development of financial technology (fintech) in Indonesia and enrich academic literature related to the application of NLP in the national financial sector

2. METHOD

This study integrates sentiment analysis with stock price prediction through the utilization of artificial intelligence models. In the text classification stage, the Bidirectional Encoder Representations from Transformers for the Indonesian language (IndoBERT) is employed to accurately label sentiments extracted from news and market opinions into positive, negative, or neutral categories [22]. The sentiment classification results are subsequently incorporated as additional input variables into time-series-based stock price forecasting models, namely Long Short-Term Memory (LSTM) [23], Gated Recurrent Unit (GRU) [24], and a hybrid LSTM–GRU model [25]. This approach enables more adaptive prediction capabilities compared to conventional methods by combining the psychological context of public sentiment with the historical pattern characteristics of stock price movements. The complete research workflow is illustrated in Figure 1.

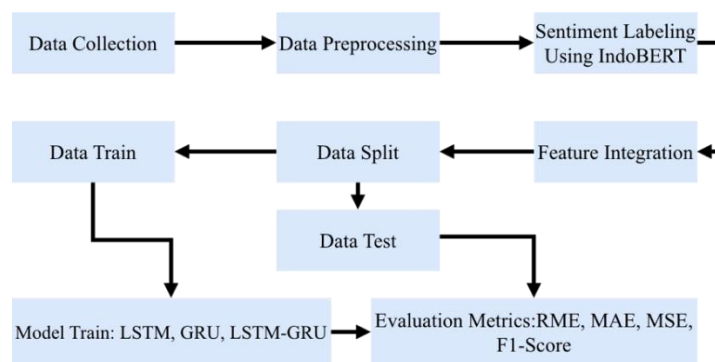


Figure 1. Research Methodology Stage

2.1. Data Collection

The dataset used in this study was obtained from publicly accessible sources; however, its extraction requires the Application Programming Interface (API) technology to automate the retrieval process using Python [26]. The time-series data were collected from Yahoo Finance over the past five years (2021–2025), covering stock indicators including Opening price (Open), Highest price (High), Lowest price (Low), Closing price (Close), and Volume for selected Indonesian blue-chip stocks, namely BBRI, BBCA, TLKM, UNVR, SCMA, and ANTM. Due to its ease of access through the yfinance library, Yahoo Finance serves as a practical choice for academic research as well as industrial implementation. Meanwhile, the sentiment text dataset was obtained from the X/Twitter platform using the Twitter API within the same period (2021–2025). The platform was chosen because it is predominantly text-based and widely utilized to express public opinions on various topics, including stock market dynamics [27]. The collection process was carried out using specific keywords and hashtags, after which the raw data underwent preprocessing that included removing URLs, irrelevant punctuation, emoticons, and performing text normalization. With its real-time data characteristics, Twitter provides a dynamic and relevant representation of public sentiment, making it highly suitable for analysis in the context of stock price prediction.

2.2. Data Preprocessing

The preprocessing stage in this study involves two separate pipelines for two different types of data, historical stock data and X/Twitter text data, each requiring distinct processing steps before being used as input for deep learning-based stock price prediction models. For stock data, the preprocessing process consists of handling missing values, transforming time-series sequences using a sliding window approach, selecting key features such as price and volume, and applying Min Max normalization to

standardize feature scales, thereby producing structured time-series data. Meanwhile, the preprocessing of X/Twitter text data includes cleaning irrelevant characters, tokenization, stop-word removal to eliminate non contribute words, and stemming to standardize word forms, resulting in clean text ready for sentiment labelling using the IndoBERT model. The complete preprocessing workflow for both pipelines is illustrated in Figure 2.

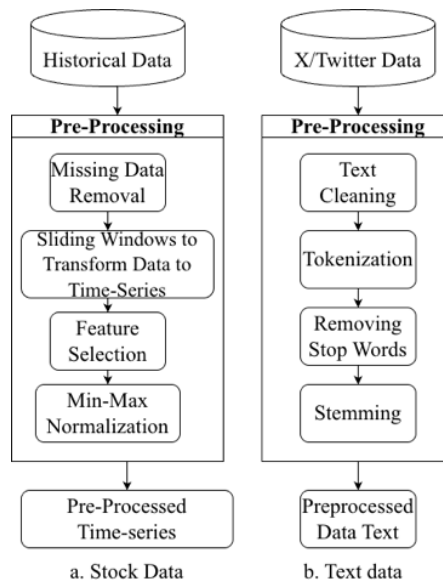


Figure 2. Preprocessing Stage[28].

2.3. Sentiment labelling using IndoBERT

Sentiment labelling in this study is performed using IndoBERT by leveraging the capability of Transformer-based language models trained on a large Indonesian-language corpus [29]. After the text data undergo preprocessing, each tweet is fed into the IndoBERT model that has been fine-tuned for sentiment classification. The model produces deep contextual representations of words and generates sentiment class predictions, namely positive, negative, or neutral. This labelling process is fully automated and more accurate than dictionary-based methods, as IndoBERT can understand contextual meaning, informal linguistic expressions, and the unique characteristics of social media text. The overall architecture of the labelling process using the IndoBERT model is illustrated in Figure 3. The final output is sentiment-labelled text data that can be used as an additional feature in deep learning-based stock price prediction.

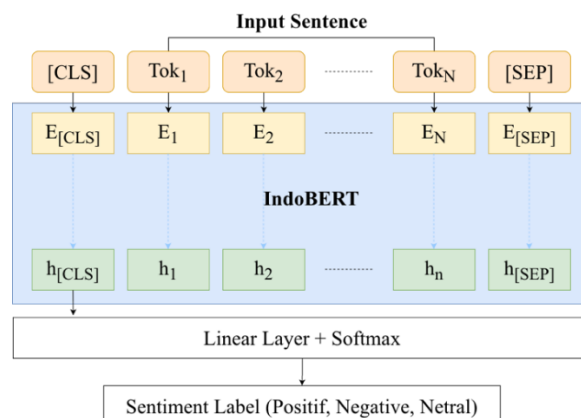


Figure 3. Architecture Labeling Using IndoBERT[21].

2.4. Feature Integration

The feature integration stage combines numerical features from historical stock market data with sentiment features obtained from social media text analysis. This integration aims to produce a more comprehensive data representation, as stock price movements are not only influenced by technical factors such as opening and closing prices, trading volume, and technical indicators (MA, RSI, MACD), but also by public sentiment reflected through opinions on social media platforms. At this stage, stock price features are structured into time-series format and subsequently merged with the daily sentiment scores generated through IndoBERT classification. The integrated data are then normalized and aligned to the same time index to ensure consistency in patterns across variables.

2.5. Model Training

In this study, the training process was conducted using three deep learning models, namely Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and a hybrid LSTM-GRU model. Prior to the training stage, the dataset was divided into two subsets, consisting of 80% for training and 20% for testing. The LSTM model processes data through three main gates, namely the Forget Gate, Input Gate, and Output Gate. The Forget Gate utilizes a sigmoid function to determine which information from the previous memory should be retained or discarded. The Input Gate combines sigmoid and tanh functions to select and generate new information to be stored in the memory cell. The Output Gate uses a sigmoid function to determine which information will be produced as the predictive output, and the resulting memory passes through a tanh function before being outputted [30]. This mechanism enables LSTM to store important information over long periods, resulting in more stable predictions. The architecture of the LSTM model is presented in Figure 4.

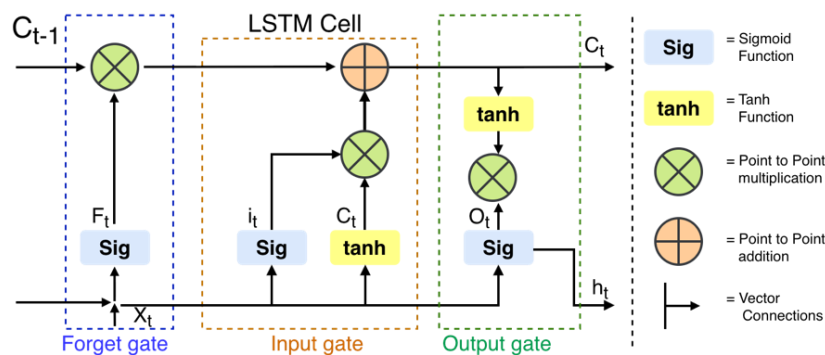


Figure 4. LSTM Model Architecture[31].

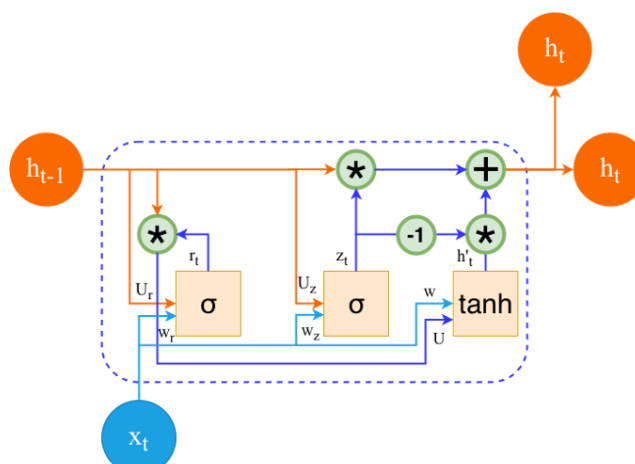


Figure 5. GRU Model Architecture[24].

The GRU model processes sequential data using two primary gates, namely the reset gate and the update gate. The reset gate determines the proportion of information from the previous hidden state that should be discarded when computing the candidate hidden state, while the update gate regulates how much prior information is retained or replaced with newly acquired information. The architectural design of the GRU model is illustrated in Figure 5.

The GRU model is capable of capturing long-term dependencies in a simpler and more efficient manner compared to LSTM [24]. The incorporation of a hybrid LSTM-GRU architecture becomes essential because LSTM excels in maintaining long-term context through its complex cell state mechanism, while GRU demonstrates faster and more computationally efficient performance. Combining both architectures enables the model to leverage their respective strengths, thereby enhancing prediction accuracy for complex sequential data such as stock prices or natural language text. The hybrid LSTM-GRU architecture is presented in Figure 6.

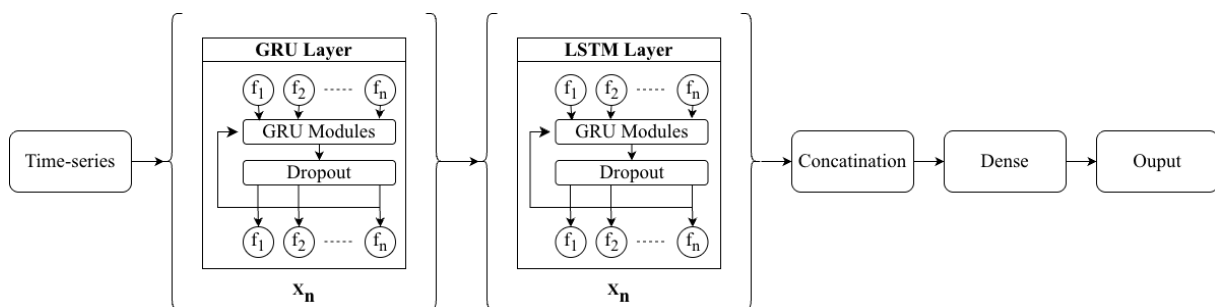


Figure 6. Hybrid Model LSTM-GRU Architecture [25].

2.6. Evaluation Metrics

The final stage of this study is model evaluation. After generating the stock price predictions, the next step is to assess the accuracy of the model in performing the forecasting task. Several commonly used evaluation metrics include Root Mean Square Error (RMSE) (Equation 1), which measures the average magnitude of prediction errors, and Mean Absolute Error (MAE) (Equation 2), which calculates the average absolute difference between actual and predicted values. In addition to numerical metrics for regression models, if the implemented model involves sentiment analysis, the evaluation can also be performed using classification metrics such as the F1-score (Equation 3).

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}} \tag{1}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \tag{2}$$

$$F1\ Score = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \tag{3}$$

3. RESULT

This section presents the experimental results that evaluate the performance of IndoBERT in sentiment labeling as well as the effectiveness of the LSTM, GRU, and hybrid LSTM-GRU models in predicting stock price movements based on market sentiment. The evaluation includes testing the

accuracy of sentiment classification, the precision of stock price forecasting, and the impact of each method on model error rates. In addition, a comparative analysis is conducted to determine which model provides the most consistent performance within the context of Indonesian stock data, which is dynamic and highly sensitive to changes in public sentiment. The findings of this study serve as a foundation for identifying the contribution of an end to end sentiment-based model in supporting investment decision making.

3.1. Dataset Validation and Label Quality

The dataset used in this study consists of two primary sources, namely Indonesian stock market data and social media sentiment data. Stock market data were obtained from the Yahoo Finance platform for a five year period, spanning from 2021 to 2025, allowing a comprehensive representation of long term stock price movements. The analysis focuses on six listed companies, namely BBRI, BBKA, TLKM, UNVR, SCMA, and ANTM, each of which represents strategic sectors in the Indonesia Stock Exchange, including banking, telecommunications, consumer goods, media, and mining. The Indonesian stock market data are presented in Table 1.

Table 1. Stock Market Indonesia data.

Date	Close	High	Low	Open	Volume	Name
2020-01-02	689.813	698.025	677.495	693.919	26829200	ANTM
2025-09-19	3450.0	3580.0	3420.0	3420.0	164297600	ANTM
2020-01-02	45.507	45.542	45.297	45.524	75200	BBKA
2025-09-19	87.900	88.050	86.959	86.970	235100	BBKA
2020-01-02	2960.843	2960.84	2927.27	2954.129	45886302	BBRI
2025-09-19	4250.0	4250.0	4180.0	4230.0	211373200	BBRI
2020-01-02	222.684	228.311	221.880	226.703	4722650	SCMA
2025-09-19	332.0	342.0	328.0	340.0	262375500	SCMA
2020-01-02	2864.55	2930.492	2857.230	2908.513	52094000	TLKM
2025-09-19	3230.0	3300.0	3160.0	3210.0	113834400	TLKM
2020-01-02	6994.39	7117.101	6953.489	6953.489	11059800	UNVR
2025-09-19	1715.0	1725.0	1700.0	1715.0	22797600	UNVR

Table 2. Dataset Sentiment Label.

No	Teks	Sentimen
1	karena hari ini bursa libur cia akan mengadakan kelas lounge live youtube umum menganalisa saham naik tinggi alert mendahului study past gainer to find next winner nanti dibagikan link	Netral
2	selama ini yang lain sih legit kalau saham nih baru semoga saja legit	Positif
3	lulus s2 pertengahan tahun mulai nabung saham bekerja profesional terima kasih telah berjuang	Positif
4	kemarin hari terakhir bursa untuk ihsg semoga porto ditutup profit yoy semoga tahun depan baik happy profit thank you	Positif
...
10044	sucor securitas memproyeksikan lima saham bersinar tahun depan	Positif

This study also utilizes a sentiment dataset obtained through social media crawling, specifically from Twitter, using keywords related to Indonesian stocks. The sentiment data collection period spans from January 1, 2024 to June 31, 2025, enabling the representation of up to date public opinion and market sentiment. The crawled text data were subsequently processed to generate positive, negative, and

neutral sentiment scores. The sentiment dataset consists of 10,044 Twitter posts related to Indonesian stocks, as presented in Table 2. The overall sentiment distribution is categorized into three classes, comprising 5,963 positive entries, 2,946 neutral entries, and 1,135 negative entries. By integrating historical stock data from Yahoo Finance with Twitter sentiment data, this study aims to analyse the relationships between public opinion and stock price movements in the Indonesian market.

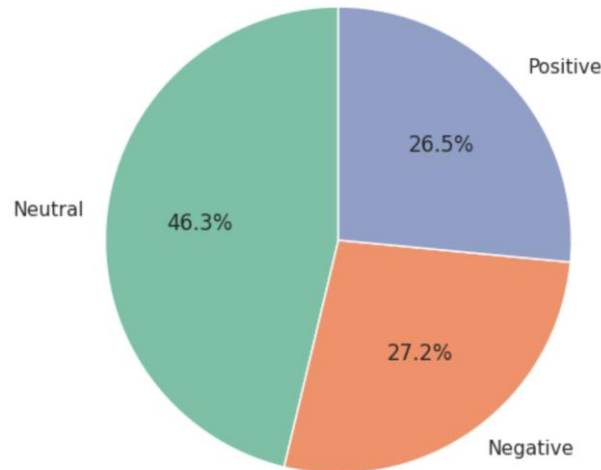


Figure 7. Distribution of Indonesian Stock Market.

Figure 7 illustrates that the distribution of sentiment labels for Indonesian stocks is relatively balanced. This indicates that there are no issues in the model training process, as the dataset used maintains a proportional class distribution. Furthermore, Figure 8 presents word cloud visualizations for each sentiment label. For the positive label, it can be observed that many Indonesian users express optimism regarding the development of the national stock market. For the negative label, the tendency toward pessimistic sentiment may be influenced by economic conditions at both national and global levels. Meanwhile, for the neutral label, the sentiment predominantly originates from individuals who are at the early stages of investing or participating in stock trading activities.



Figure 8. WordCloud.

3.2. Sentiment Analysis Model BERT Performance

This study employs BERT as the base model for sentiment classification, while SVM and Random Forest are utilized as benchmark models. The IndoBERT training process was conducted using the TrainingArguments configuration with the following parameters: model evaluation and checkpointing were performed at the end of every epoch `eval_strategy=epoch` and `save_strategy=epoch`, the learning rate was set to 2×10^{-5} , the training and validation batch sizes were both set to 16, and the training process was executed for 4 epochs. In addition, a weight decay of 0.01 was applied to prevent overfitting. The training process also included logging every 10 steps and enabled loading the best model at the end of

training based on the highest accuracy score. Based on the training results shown in Figure 9, both training loss and validation loss decreased steadily up to the 4th epoch, indicating an effective learning process without signs of overfitting. The model's accuracy also increased, with a relatively small gap between training accuracy 87% and validation accuracy 84.5%, demonstrating strong generalization capability. Furthermore, the F1-Score improved consistently, reaching 79% on the validation set, which reflects a balanced performance between precision and recall. Overall, IndoBERT demonstrated reliable and stable performance for sentiment analysis, achieving optimal results between the 3 and 4 epoch.

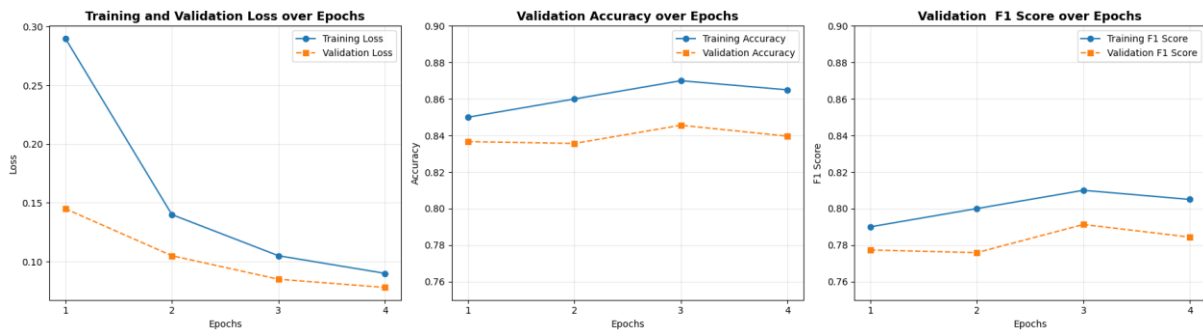


Figure 9. Model Evaluation With IndoBERT.

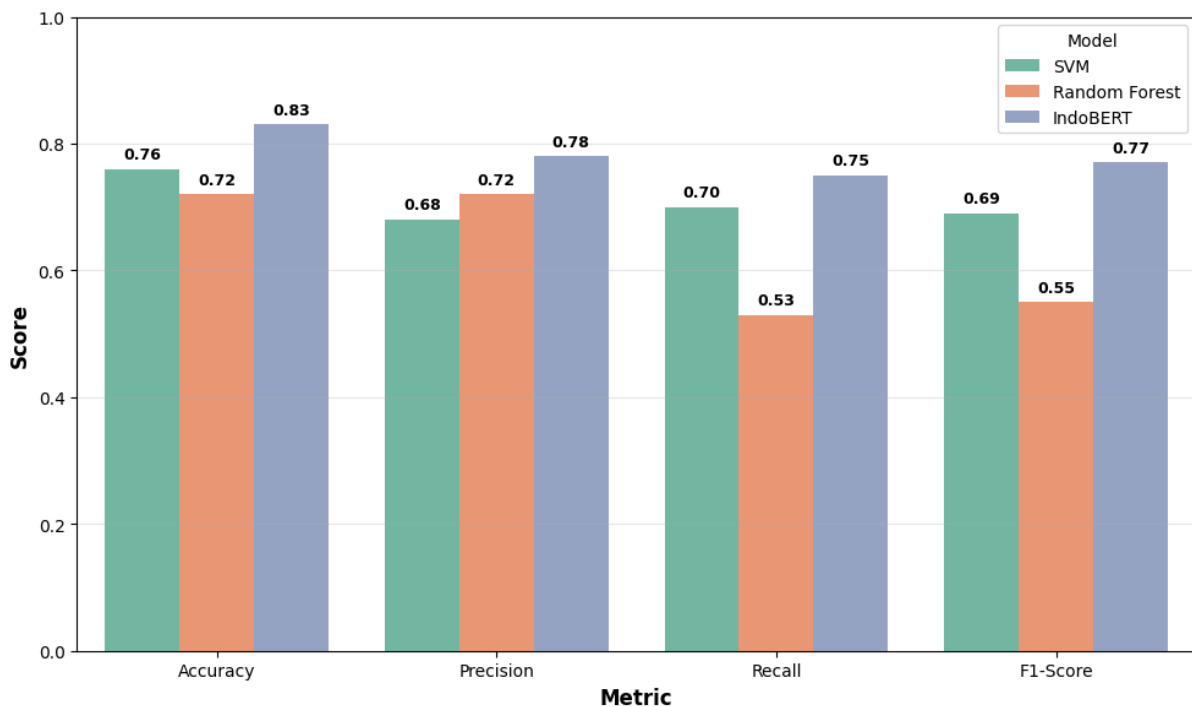


Figure 10. Evaluation Metric Comparison of Models

The performance comparison diagram in Figure 10 demonstrates that IndoBERT outperforms SVM and Random Forest across all evaluation metrics. IndoBERT achieved the highest accuracy of 83%, with a precision of 78%, recall of 75%, and an F1-score of 77%, indicating balanced classification performance for positive, negative, and neutral sentiments. Meanwhile, SVM ranked second with an accuracy of 76% and an F1-score of 69%, showing relatively stable performance but still inferior to IndoBERT. Random Forest produced the weakest results, particularly with a recall of 53% and an F1-score of 55%, making it less effective in capturing sentiment variations. Overall, these findings reinforce that transformer-based models such as IndoBERT are more effective for Indonesian sentiment analysis

than traditional machine learning approaches. Although IndoBERT demonstrated superior performance compared to SVM and Random Forest, the model requires significantly longer training time. As shown in Figure 11, IndoBERT required 417 seconds for training, whereas SVM required only 15 seconds and Random Forest 27 seconds. This difference is attributed to IndoBERT transformer architecture, which involves multi-head attention layers and bidirectional contextual modeling, resulting in intensive GPU or CPU computation. In contrast, SVM and Random Forest rely primarily on simpler mathematical operations such as hyperplane separation and decision tree construction, making their training processes faster and computationally lightweight.

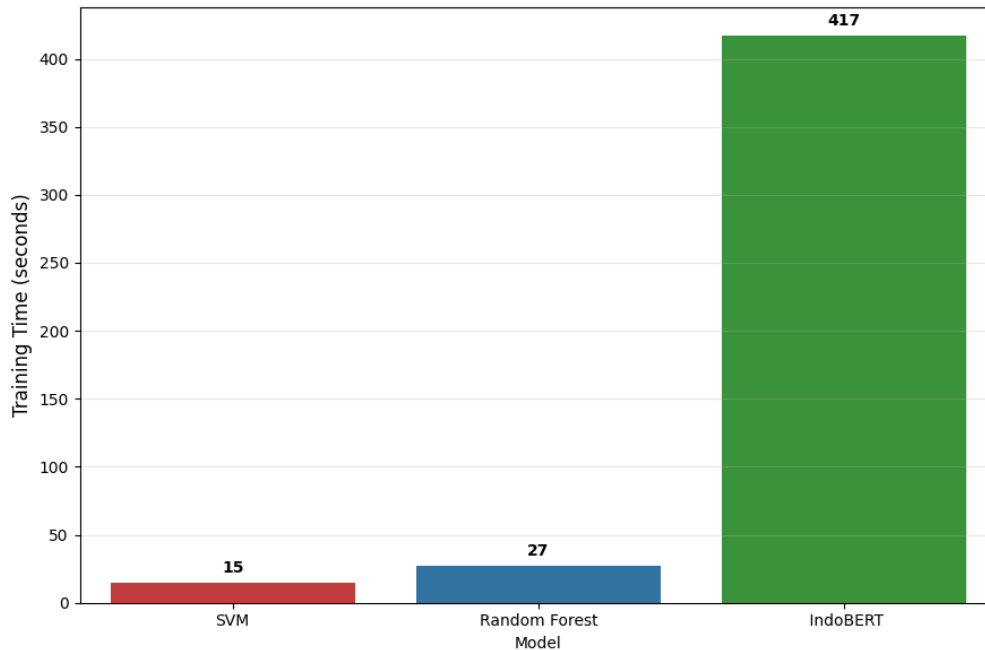


Figure 11. Comparison of Model Training Times.

3.3. Evaluation of Stock Prediction Models

After completing the sentiment analysis model training using IndoBERT, SVM, and Random Forest, the next step is to perform stock price prediction for the Indonesian market. Table 3 presents the merged dataset consisting of stock data and sentiment data. The Score column represents the numerical conversion of sentiment labels, where a value of 1 indicates positive sentiment, 0 denotes neutral sentiment, and -1 corresponds to negative sentiment. These values are then integrated with stock market data based on matching dates, allowing them to be utilized as independent variables in the subsequent stock price prediction modelling process.

Table 3. Merged dataset stock and Sentiment.

Date	Close	High	Low	Open	Volume	Name	Score
2020-01-02	689.813	698.025	677.495	693.919	26829200	ANTM	0
2025-09-19	3450.0	3580.0	3420.0	3420.0	164297600	ANTM	1
2020-01-02	45.507	45.542	45.297	45.524	75200	BBCA	1
2025-09-19	87.900	88.050	86.959	86.970	235100	BBCA	1
...
2025-09-19	4250.0	4250.0	4180.0	4230.0	211373200	BBRI	1



Figure 12. Result Models Training LSTM.



Figure 13. Result Models Training GRU.



Figure 14. Result Models Training LSTM GRU.

In this study, the stock price prediction process for the Indonesian market employed three deep learning-based models, namely LSTM, GRU, and a hybrid LSTM-GRU model. The prediction results

using the LSTM and GRU models, as illustrated in Figure 14, demonstrate strong performance in capturing actual price movements. For BBCA, both models successfully captured a steady upward trend toward the end of 2025, while for BBRI, the initial price decline followed by a recovery was accurately predicted, although a slight deviation occurred near the lowest point. For TLKM, the long-term upward trend was effectively identified, although the models tended to lag slightly during sharp price shifts. In the case of UNVR, the directional movement was well predicted, despite noticeable differences at extreme price points. Furthermore, for ANTM, the price surge occurring in mid-2025 was estimated with considerable accuracy, and SCMA yielded the most optimal prediction results, as the model closely followed the actual price movement. Overall, as shown in Figure 12, the LSTM model demonstrated superior capability in capturing long term trends, whereas the GRU model, presented in Figure 13, exhibited greater stability under fluctuating price conditions. The implementation of hyperparameter tuning was proven to enhance model sensitivity when responding to significant market changes, resulting in more accurate predictions. A comparative summary of the evaluation metrics for stock price prediction across all Indonesian stock datasets used in this study, along with the applied prediction models, is presented in Table 4

Table 4. Comparison of Evaluation Metrics with Highlights of Best Values per Dataset.

No	Dataset	Model	MSE	MAE	RMSE	MAPE (%)
1	ANTM	GRU	96.275528	7.588505	9.812009	0.389941
		LSTM	455.868064	18.524450	21.351067	0.975930
		LSTM-GRU	345.799756	12.546586	18.595692	0.573154
2	BBCA	GRU	0.368035	0.492633	0.606659	0.637941
		LSTM	0.215696	0.359025	0.464431	0.471464
		LSTM-GRU	0.151105	0.356469	0.388722	0.476391
3	BBRI	GRU + Tuning	2898.764117	51.126227	53.840172	1.263031
		LSTM	2901.139853	43.287011	53.862230	1.086325
		LSTM-GRU	1022.061956	24.563348	31.969704	0.623991
4	SCMA	GRU	15.588004	2.843005	3.948165	1.654837
		LSTM	8.875285	2.457274	2.979142	1.392885
		LSTM-GRU	8.793409	1.982664	2.965368	1.103694
5	TLKM	GRU	1592.256409	34.753921	39.903088	1.310273
		LSTM	606.932064	18.913330	24.635991	0.730966
		LSTM-GRU	570.720611	20.772487	23.889760	0.816367
6	UNVR	GRU	98.112924	7.837455	9.905197	0.511982
		LSTM	909.329327	27.696439	30.155088	1.783311
		LSTM-GRU	3851.368560	61.196250	62.059395	3.730063

The evaluation results using MSE, MAE, RMSE, and MAPE presented in Table 4 indicate that model performance varies across stocks depending on their volatility characteristics. The LSTM-GRU model for BBCA and BBRI achieved the lowest error values, particularly in terms of MSE and RMSE, demonstrating its ability to capture long term patterns while simultaneously responding to sudden fluctuations. For example, in the case of BBRI, the MSE of the LSTM-GRU model was only 1,022.06, compared to 2,898.76 for GRU and 2,901.14 for LSTM, showing a substantial improvement in accuracy due to the combination of LSTM's memory mechanism and GRU's computational efficiency. For ANTM, the GRU model exhibited the best performance compared to LSTM and LSTM-GRU, particularly in terms of MAE 7.58 and RMSE 9.81. This finding suggests that the simpler GRU architecture is more effective in handling the relatively dynamic price fluctuations of ANTM than heavier-weighted models such as LSTM. A similar pattern is observed in UNVR, where GRU again outperforms both LSTM and LSTM-GRU, with lower MSE 98.11 and RMSE 9.90, indicating that

stocks with low but irregular volatility may be better modelled using simpler architectures. SCMA and TLKM, on the other hand, show superior performance with the LSTM–GRU and LSTM models. For SCMA, LSTM–GRU yielded the lowest MAE 1.98 and MAPE 1.10%, highlighting the strong precision of the hybrid architecture in tracking real price movements. For TLKM, LSTM performed best with an RMSE of 24.63 and a MAPE of 0.73%, demonstrating the effectiveness of LSTM in learning long-term trends. Overall, these results indicate that no single model consistently outperforms the others across all stocks. However, LSTM–GRU tends to provide superior performance for stocks with strong trending behaviour, while GRU performs more reliably for stocks with high or irregular volatility. These findings emphasize the importance of selecting prediction models based on the specific characteristics of stock price movements under analysis.

4. DISCUSSIONS

The findings of this study indicate that integrating sentiment analysis with stock price prediction models provides a more comprehensive perspective on the dynamics of Indonesia’s capital market. Through text classification using IndoBERT, sentiment scores were obtained that effectively represent public perceptions of stock movements across various economic sectors. IndoBERT successfully captured linguistic nuances in the Indonesian language, including contextual meaning, irony, and opinion expressions commonly found in financial discussions on social media and online news. Positive sentiment generally reflects investor optimism and a bullish market condition, while negative sentiment illustrates selling pressure or market pessimism. Meanwhile, neutral sentiment often emerges from informative observations and passive commentary, particularly from novice investors whose influence on market direction remains limited. Therefore, sentiment analysis serves as an additional variable that influences stock price prediction, as it captures psychological aspects, collective behaviors, and social dynamics that are not reflected solely by historical price data.

The results of stock price prediction using LSTM, GRU, and hybrid LSTM–GRU models show that model performance is highly dependent on the characteristics of each stock. Stocks with high volatility, such as ANTM and SCMA, exhibited better predictive performance when using the GRU model or the LSTM–GRU hybrid. This is due to the GRU’s simpler yet responsive architecture, which adapts more efficiently to rapid price fluctuations. For banking stocks such as BBKA and BBRI, the LSTM–GRU model produced stable predictions, indicating that the combination of long term and short term memory mechanisms successfully captures consistent trends in the relatively defensive banking sector. For TLKM, the optimal performance was achieved by LSTM, which suits the long-term price behavior commonly observed in the telecommunications industry. Conversely, although UNVR experienced a notable downward trend, the GRU model performed better in adapting to its gradual decline. These findings demonstrate that deep learning models are capable of capturing nonlinear relationships between market variables, even though no model performs best under all conditions.

This study confirms that the synergy between sentiment analysis and deep learning–based prediction models produces a more effective analytical strategy to support investment decision-making in the Indonesian capital market. Sentiment acts as a psychological indicator that reflects collective market expectations, while time-series models such as LSTM and GRU capture technical dynamics and historical patterns of price movement. The integration of these two approaches not only increases predictive accuracy but also enriches the understanding of both fundamental and emotional market drivers. Therefore, this integrated approach is highly relevant for the development of investment recommendation systems, the design of algorithmic trading strategies, and data-driven risk analysis in Indonesia’s complex and dynamic stock market

5. CONCLUSION

This study concludes that integrating IndoBERT-based sentiment analysis with deep learning time-series models (LSTM, GRU, and LSTM–GRU) enhances the accuracy of stock price prediction in Indonesia by incorporating public opinion as a psychological market variable. This contribution advances the application of Informatics in the domains of Natural Language Processing and Financial Technology, demonstrating that combining natural language processing techniques with numerical predictive models can serve as a foundation for developing AI-driven investment recommendation systems and algorithmic trading. Future research is recommended to adopt aspect-based sentiment analysis, explore transformer-based time-series architectures such as TFT or Informer, and implement explainable AI to ensure that predictive models are not only accurate but also transparent and accountable for users and the financial industry.

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