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Advanced Stock Price Prediction in the Indonesian Banking Sector using Sentiment Analysis and CNN-LSTM Models

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This study examines the crucial function of stocks in indicating the economic well-being of a country, with a particular emphasis on the Indonesian market. The study focuses on the relationship between the performance of the stock market and the strength of the Indonesian rupiah (IDR), explicitly showing how investor mood affects changes in stock prices. Before making investments, it is recommended that investors consider the financial conditions, management effectiveness, and the company's competitive landscape. The research focuses primarily on the Indonesia Stock Exchange (IDX), explicitly analyzing the LQ45 index using historical stock data and time series prediction algorithms. This article showcases the utilization of Long Short-Term Memory (LSTM), a Recurrent Neural Network (RNN) structure, with exceptional precision in forecasting stock prices, surpassing 90%. In addition, the study combines Convolutional Neural Network (CNN) techniques with stock time series forecasting to provide a multi-dimensional viewpoint and improve the accuracy of predictions. The study utilizes cutting-edge deep-learning methods to enhance the understanding of natural language to web news. It focuses explicitly on transfer learning utilizing Generative Pre-Training and the Bidirectional Encoder Representations from Transformer (BERT) architecture. The approach focuses on integrating BERT and LSTM models, leveraging news datasets and time series data to enhance the accuracy of predictions. Ultimately, this research highlights the efficacy of combining BERT and CNN-LSTM models for accurately forecasting stock prices. Combining the BERT and CNN-LSTM models and utilizing datasets from news and historical time series data has demonstrated a reliable method for predicting stock prices. The findings emphasize the significance of investor attitude, corporate financial well-being, and broader

economic circumstances in stock market investing. The utilization of BERT for the comprehension of natural language and analysis of sentiment, in conjunction with LSTM for the prediction of time series, has resulted in an exact model, surpassing a precision rate of 90%. The findings indicate a favorable outlook for the application of artificial intelligence in the field of finance and investing.
Keywords: Stock Price Prediction, Machine Learning, Sentiment Analysis, Deep Learning, CNN, LSTM, BERT, Indonesian Banking Sector, Time Series Analysis, Financial Markets

1. Introduction

The stock index is essential for fostering the growth of a country's capital market and assessing the performance of capital markets and investment products. An index measures market sentiment or investor confidence. Changes in the value reflected in an index can represent all market participant's aggregate opinions. As a result, the stock index serves as an assessment tool for investors and other stakeholders to evaluate the capital market's overall health and potential. Furthermore, the stock index can track market patterns and help investors make more educated selections.

The global expansion of passive investing has been notable, with passive investment vehicles like index funds and ETFs in the United States experiencing a $1.8 trillion increase from 2010 to 2019. In contrast, active investments, such as non-index mutual funds, saw a decline of $1.7 trillion over the same timeframe. Using Indonesia Stock Exchange (IDX) indices as investment products has seen substantial growth in Indonesia. The value of managed funds increased from IDR 2.72 trillion in 2015 to IDR 15.88 trillion in 2020, indicating a growth rate of 42% over the five years [1].

Investor sentiment also affects stock price fluctuations. In Indonesia, the LQ45 index encapsulates 45 companies listed on the Indonesia Stock Exchange (IDX), chosen based on their market capitalization and liquidity [2]. Stock indexes like IDX, S&P 500, CSI 300, TOPIX Core 30, and Eastern Stock Exchange are employed in other research. This study focuses on the Indonesia Stock Exchange (IDX).

The importance of historical stock data is underlined when employing time series prediction models. Previous studies have successfully predicted stock prices by integrating a machine learning approach with data from the internet, such as social media [3], [4], [5], [6], forums [7], and online news [4], [5], [6], [7], [8], [9], [10], [11]. Stock prediction studies are instrumental in aiding investors, employing two main techniques: machine learning models like classification and statistical models like regression. The most widely used stock price forecasting research employs Short-Term Long Memory (LSTM), a type of Recurrent Neural Network (RNN) architecture, which is preferred over uni-method models such as Linear Regression, Random Forests, Fast Forward Neural Networks, etc. [11]. LSTM has proven to be an effective method for time series analysis and predicting stock prices, boasting an accuracy rate of over 90% [2,4,5,6,7,8][2], [3], [4], [8], [9], [10].

Several studies about stock time series prediction with natural language processing techniques offer an additional perspective and enhance accuracy. Sentiment analysis, a factor that can influence stock prices from a public perspective, can be automated with the help of artificial intelligence. There have been several findings in text classification that analyze online news using keywords or lexicons [12], and some researchers have utilized financial information as a dataset [2], [4], [5], [10], [11]. The latest findings in deep learning for natural language comprehension have improved classification through transfer learning by the Generative Pre-Training [13] and further enhancement using the Bidirectional Encoder Representations from the Transformer Architecture [14]. Prior research has merged BERT, operating a news dataset, and LSTM [2], [6], [15].

2. Related Works

A. BERT and Sentiment Analysis

BERT, developed by Google, has transformed the field of Natural Language Processing (NLP) with its innovative approach to language understanding. Its bidirectional nature allows BERT to grasp the context of a word by considering all surrounding words. Sentiment analysis, used to understand context, is crucial for determining sentiment in text Fields [14]. Pre-training involves the Masked Language Model (MLM) and Next Sentence Prediction (NSP). MLM helps BERT handle words based on sentence context, while NSP aids in understanding relationships between sentences [13]. This deep comprehension makes BERT highly effective in Sentiment Analysis. Fine-tuning BERT for specific tasks like Sentiment Analysis can achieve state-of-the-art results. This involves training the model on a large text corpus and adjusting parameters in the particular task. This combination of pre-training and fine-tuning allows BERT to understand and categorize sentiments effectively.

BERT's strength in Sentiment Analysis lies in its ability to capture complex language nuances, such as sarcasm and contextual meaning. Traditional methods often struggle in complex scenarios, while BERT excels due to its deep contextual understanding. BERT models can be used for binary (positive/negative) and multi-class (positive/ negative/neutral) sentiment analysis [16] [15]. When fine-tuned for a specific Sentiment Analysis task, BERT learns from task-specific annotations in the training data, resulting in more accurate predictions. In conclusion, BERT has significantly advanced Sentiment Analysis by classifying sentiments. As research progresses and computational resources become more accessible, further advancements in applying BERT and other transformer-based models to Sentiment Analysis are expected.

Transformer models, particularly BERT, have been increasingly applied in stock price prediction, especially in the context of sentiment analysis. Sulistyo and Suhartono [3] demonstrated that combining CNN-LSTM with BERT for social media data sentiment analysis provided a robust framework for stock price prediction. BERT's ability to understand contextual relationships in text significantly improved prediction performance, especially when combined with traditional time-series models like LSTM.

B. Stock Prediction

In recent years, integrating Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) has become a popular trend in stock price prediction, particularly when combined with sentiment analysis from various data sources, including financial news and social media. Halder (2022) explored a model that utilizes LSTM networks and FinBERT, a variant of BERT fine-tuned for financial contexts, to analyze sentiment in financial news for stock price predictions. This approach leverages LSTM's ability to handle sequential time-series data and BERT's advanced capabilities in processing textual sentiment, demonstrating improved prediction accuracy by considering the nuances of market sentiment [2]. Further, Sulistyo and Suhartono [3] proposed a novel application combining CNN-LSTM for technical stock analysis with BERT for sentiment analysis derived from social media data. This dual approach minimizes prediction errors by extracting detailed features from time-series data using CNNs while capturing temporal dependencies through LSTMs. The integration of sentiment analysis further enriches the model by incorporating the emotional and psychological states of the market, reflected in social media discussions, into the prediction mechanism.

A comparison of CNN and LSTM architectures for stock prediction was also explored [7], and it was found that while CNNs are powerful for capturing spatial patterns in stock price data, LSTMs are more adept at learning temporal patterns and trends. In cases where both spatial and temporal relationships are crucial, hybrid models like CNN-LSTM are more effective than standalone CNN or LSTM models. Integrating both architectures allows for a more comprehensive understanding of stock price dynamics. Overall, the convergence of CNNs, LSTMs, and sentiment analysis tools marks a compelling trend toward more sophisticated, multifaceted models in stock market forecasting. These models address the quantitative aspects of stock data and the qualitative sentiments that significantly sway market dynamics.

3. Research Methodology

A. Architecture

In the proposed system in Figure 1, the data source layer comprises online news gathered through news crawling and stock index data for LQ45 obtained from Yahoo Finance.

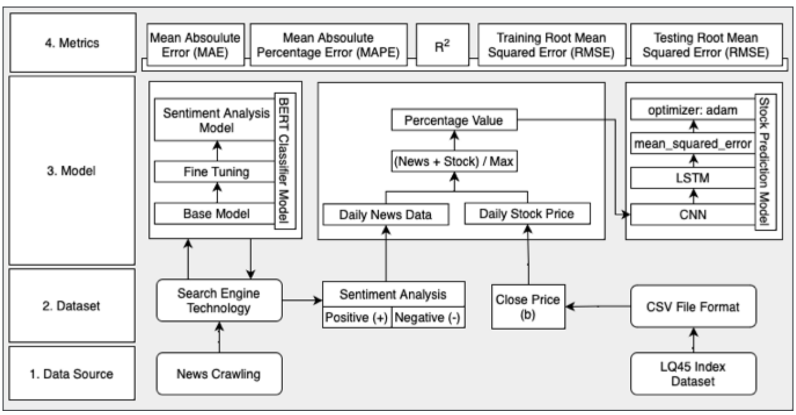

Figure 1. Baseline Architecture

The stock date range encompasses daily data from November 2021 to February 2023. In the dataset layer, CSV files are maintained for the LQ45 Index, and online news assists in searching for company names or stock index codes using a search engine. Each archived online news document will be tagged with sentiment analysis using the BERT Classifier Model.

The BERT architecture, initially a general-purpose model, can be fine-tuned to specialize in the Indonesian language for sentiment analysis tasks. This involves adapting the model to incorporate specific domain knowledge, ensuring that the sentiment analysis aligns with the researcher's perspective and accurately categorizes sentiments as positive or negative.

The dataset used in this analysis includes daily closing prices of stock data, each representing the end-of-day price for a specific trading day. Before analysis, the data undergoes normalization to ensure it is appropriately scaled, which is crucial for accurate predictive modeling. The models employed include Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, chosen for their effectiveness in capturing complex patterns and temporal dependencies in financial data.

B. Stock Prediction using Sentiment Analysis & CNN-LSTM

The diagrams in Figure 2 provide a detailed overview of a stock prediction model, highlighting two essential components: the data normalization process and the stock prediction model itself. The initial phase, shown on the left side of the diagrams, involves collecting daily news data and daily stock prices. These datasets are combined and normalized by dividing by their maximum value, resulting in percentage values scaled between 0 and 1. This normalization is critical as it ensures that both datasets are on a comparable scale, essential for accurate analysis and modeling. By standardizing the data, the model can more effectively interpret the influence of news on stock prices, allowing for a more integrated approach to prediction.

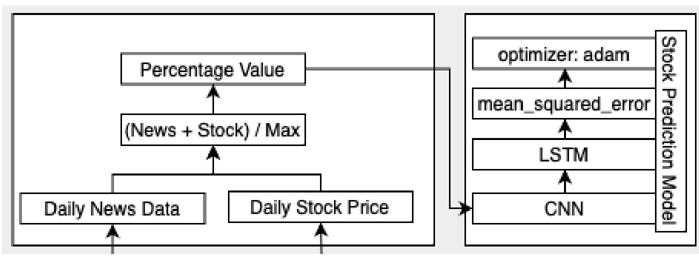

Figure 2. Prediction Model

The second phase, depicted on the right side of the diagrams, involves the stock prediction model, which utilizes advanced deep learning techniques. The model implements Long Short-Term Memory (LSTM) networks to handle time-series data, capturing long-term dependencies crucial for understanding trends and patterns in stock prices. Convolutional Neural Networks (CNN) are used for feature extraction, enabling the model to identify significant patterns and features within the data. The model's optimization uses the Adam optimizer, known for its efficiency in training deep learning models, while prediction errors are measured using the mean squared error loss function. This combination of techniques allows the model to accurately predict stock prices by leveraging historical data and current news.

Table 1. Parameter & Configuration

Seq	Model	SENT	Epoch	Neuron	DO-Rate	Dense	Activation	Optimizer	Metric
1	CNN	No	50	{64,32}			relu	adam	mean_squared_error
2	CNN-do	No	50	{64,32}	{0.1,0.1}		relu	adam	mean_squared_error
3	LSTM	No	50	{128,192}	{0.2,0.1}	{128,32}	relu	adam	mean_squared_error
4	CNN-LSTM	No	50	{64,32,128,192}	{0.1,0.1,0.2,0.1}	{128,32}	relu	adam	mean_squared_error
5	CNN-do-LSTM	No	50	{64,32,128,192}	{0.1,0.1,0.2,0.1}	{128,32}	relu	adam	mean_squared_error
6	BERT-CNN	Yes	50	{64,32}			relu	adam	mean_squared_error
7	BERT-CNN-do	Yes	50	{64,32}	{0.1,0.1}		relu	adam	mean_squared_error
8	BERT-LSTM	Yes	50	{128,192}	{0.2,0.1}	{128,32}	relu	adam	mean_squared_error
9	BERT-CNN-LSTM	Yes	50	{64,32,128,192}	{0.1,0.1,0.2,0.1}	{128,32}	relu	adam	mean_squared_error
10	BERT-CNN-do-LSTM	Yes	50	{64,32,128,192}	{0.1,0.1,0.2,0.1}	{128,32}	relu	adam	mean_squared_error

The following model configurations, shown in Table 1, were used in this study to predict stock prices using sentiment analysis and machine learning techniques. Each configuration combines different architectures to leverage their strengths in capturing various aspects of the data.

1) BERT-CNN: This model integrates BERT with a CNN architecture to capture local patterns in data, which helps identify short-term trends in stock prices.

2) BERT-CNN-do: This variation of the BERT-CNN model includes dropout layers to prevent overfitting and improve the model's generalization.

3) The BERT-LSTM model combines BERT and LSTM. It utilizes LSTM to effectively capture long-term dependencies in sequential data, which proves advantageous in modeling the temporal dependencies in stock price movements.

4) BERT-CNN-LSTM: This hybrid model leverages the strengths of both CNN and LSTM architectures, using CNN to capture local features and LSTM to model long-term dependencies.

5) BERT-CNN-do-LSTM: Similar to the BERT-CNN-LSTM model, this configuration includes dropout layers to enhance generalization capabilities further.

Table 2. Experiment Sample with BERT

Index	Predict Range	BERT-CNN	BERT-CNN-do	BERT-LSTM	BERT-CNN-LSTM	BERT-CNN-do-LSTM
BBCA	1 day	sample-1	sample-21	sample-41	sample-61	sample-81
BBCA	3 days	sample-2	sample-22	sample-42	sample-62	sample-82
BBCA	7 days	sample-3	sample-23	sample-43	sample-63	sample-83
BBCA	30 days	sample-4	sample-24	sample-44	sample-64	sample-84
BBNI	1 day	sample-5	sample-25	sample-45	sample-65	sample-85
BBNI	3 days	sample-6	sample-26	sample-46	sample-66	sample-86
BBNI	7 days	sample-7	sample-27	sample-47	sample-67	sample-87
BBNI	30 days	sample-8	sample-28	sample-48	sample-68	sample-88
BBRI	1 day	sample-9	sample-29	sample-49	sample-69	sample-89
BBRI	3 days	sample-10	sample-30	sample-50	sample-70	sample-90
BBRI	7 days	sample-11	sample-31	sample-51	sample-71	sample-91
BBRI	30 days	sample-12	sample-32	sample-52	sample-72	sample-92
BBTN	1 day	sample-13	sample-33	sample-53	sample-73	sample-93
BBTN	3 days	sample-14	sample-34	sample-54	sample-74	sample-94
BBTN	7 days	sample-15	sample-35	sample-55	sample-75	sample-95
BBTN	30 days	sample-16	sample-36	sample-56	sample-76	sample-96
BMRI	1 day	sample-17	sample-37	sample-57	sample-77	sample-97
BMRI	3 days	sample-18	sample-38	sample-58	sample-78	sample-98
BMRI	7 days	sample-19	sample-39	sample-59	sample-79	sample-99
BMRI	30 days	sample-20	sample-40	sample-60	sample-80	sample-100

The experiment sample scenarios are structured to evaluate the performance of different model architectures in predicting stock prices over various time horizons (1 day, 3 days, 7 days, and 30 days). The models tested include combinations of BERT with CNN and LSTM, both with and without dropout layers, which are used to prevent overfitting results. The samples can be seen in Table 2.

Table 3. Experiment Sample without BERT

Index	Predict Range	CNN	CNN-do	LSTM	CNN-LSTM	CNN-do-LSTM
BBCA	1 day	sample-1	sample-21	sample-41	sample-61	sample-81
BBCA	3 days	sample-2	sample-22	sample-42	sample-62	sample-82
BBCA	7 days	sample-3	sample-23	sample-43	sample-63	sample-83
BBCA	30 days	sample-4	sample-24	sample-44	sample-64	sample-84
BBNI	1 day	sample-5	sample-25	sample-45	sample-65	sample-85
BBNI	3 days	sample-6	sample-26	sample-46	sample-66	sample-86
BBNI	7 days	sample-7	sample-27	sample-47	sample-67	sample-87
BBNI	30 days	sample-8	sample-28	sample-48	sample-68	sample-88
BBRI	1 day	sample-9	sample-29	sample-49	sample-69	sample-89
BBRI	3 days	sample-10	sample-30	sample-50	sample-70	sample-90
BBRI	7 days	sample-11	sample-31	sample-51	sample-71	sample-91
BBRI	30 days	sample-12	sample-32	sample-52	sample-72	sample-92
BBTN	1 day	sample-13	sample-33	sample-53	sample-73	sample-93
BBTN	3 days	sample-14	sample-34	sample-54	sample-74	sample-94
BBTN	7 days	sample-15	sample-35	sample-55	sample-75	sample-95
BBTN	30 days	sample-16	sample-36	sample-56	sample-76	sample-96
BMRI	1 day	sample-17	sample-37	sample-57	sample-77	sample-97
BMRI	3 days	sample-18	sample-38	sample-58	sample-78	sample-98
BMRI	7 days	sample-19	sample-39	sample-59	sample-79	sample-99
BMRI	30 days	sample-20	sample-40	sample-60	sample-80	sample-100

Unlike the previous scenario, this is without BERT. The experiment assessed how well different model architectures can predict stock prices over multiple timeframes, including 1 day, 3 days, 7 days, and 30 days. The tested models consist solely of combinations of CNN and LSTM architectures, both with and without dropout layers. Dropout layers mitigate the problem of overfitting by stochastically deactivating a portion of input units during the training stage. Table 3 displays the sample that does not utilize BERT.

C. Infrastructure

The infrastructure for this study was designed to handle large datasets and complex model training processes efficiently. The following components were integral to the research:

1) Data Storage and Search: Elasticsearch was the primary search engine and data storage solution [17]. Its robust capabilities in handling large volumes of data and providing fast retrieval times were crucial for managing the extensive datasets used in this study, including historical stock data and online news articles.

2) Computational Resources: The trials were carried out using a high-performance computing infrastructure. The system had a CPU Intel Core i5-13400F, 64GB DDR4 RAM, and GPU NVIDIA GeForce RTX 3080 Ti 12GB VRAM. Utilizing this architecture was crucial for training complex deep learning models like CNN-LSTM and BERT, which demand substantial processing capacity and memory resources.

3) Software and Libraries: The research utilized Python as the primary programming language, leveraging libraries such as TensorFlow and PyTorch for deep learning model development. Pandas and NumPy were used for data manipulation and analysis, while Scikit-learn facilitated the implementation of machine learning algorithms.

D. Materials (Experimental Data for Testing)

Data shown in Table 4 is a structured dataset containing stock market information. It includes columns for time, open, high, low, and close prices, trading volume, and a moving average of the volume. Each column is represented as an integer data type, indicating numerical values for each attribute. This dataset is organized in a tabular format, typically used for analyzing stock performance over a specified period.

Table 4. Raw Data Stock Format

Datetime	Open	High	Low	Close	Volume	Volume MA
1637892000	7400	7450	7250	7275	113288400	65576390
1638151200	7275	7425	7175	7400	87907900	68042115
1638237600	7325	7425	7275	7275	144923700	70761530
1638324000	7275	7450	7275	7300	76538100	71507360
1638410400	7375	7500	7300	7500	66831000	71794840
1638496800	7525	7525	7350	7375	63283700	72803005
1638756000	7450	7475	7350	7350	56944100	71378125
1638842400	7450	7475	7350	7350	51258200	68851745
1638928800	7450	7475	7400	7425	74775000	70215300

The image showcases a series of line charts, each depicting the closing prices of different stocks over time. These charts are labeled with stock names and display the dates on the x-axis and closing prices on the y-axis. This visualization provides an overview of the available data for research, illustrating the stock price movements across various periods. Table 4 contains daily stock prices, as shown in Figure 3.

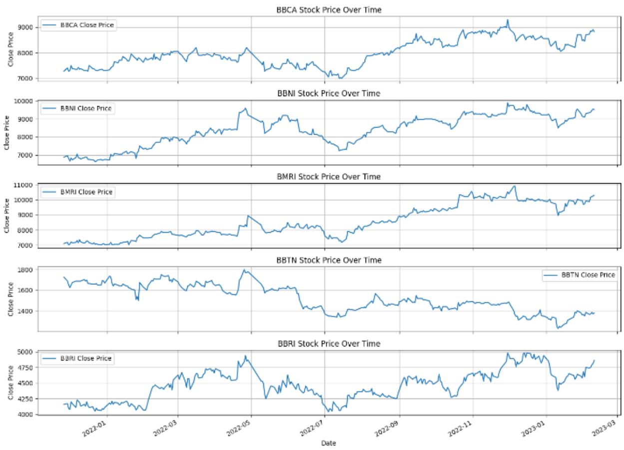

Figure 3. Daily Stock Movement

The data Table 5 represents metadata from online news articles. It comprises four fields: datetime_ms (datetime millisecond), content, title, and analysis_sentiment. The datetime_ms field is a JSON integer that records the timestamp of the news article in milliseconds. The content and title fields are JSON strings that contain metadata for the news article and title. Lastly, the analysis.sentiment field is a JSON string that indicates the sentiment of the article, which can be either positive ("pos") or negative ("neg").

Table 5. News Online Table

No	Field	Sample Output	Data Type
1	datetime_ms	1722646802205	json integer
2	content	text….	json string
3	title	title….	json string
4	analysis.sentiment	pos/neg	json string

The final stock prediction data comprises several fields, as seen in Table 6. The Timestamp is recorded as 45061.55947, representing the date of the prediction. The stock being analyzed is for the issuer BBCA, denoted by a four-character string. The Dataset Stock file is located at "LQ45-1D-1Y/IDX_DLY_BBCA, 1D.csv," with a maximum string length of 255 characters. The dataset query includes the search terms "bank bca" or "bank central asia," each with a string length of up to 255 characters. A total of 17,971 queries were made, as indicated by the Total Dataset Query. The Delay in processing is noted as 1, and the model underwent 50 epochs during training. The Prediction Day is set to 1, meaning the prediction is for the next day. The model's performance metrics include a Mean Absolute Error (MAE) of 0.23456 and a Mean Absolute Percentage Error (MAPE) of 0.12345. The R Square value is not available, indicated by "nan." The Train Score RMSE is 0.04567, while the Test Score RMSE is 0.01234, reflecting the model's accuracy in the training and testing phases. A UniqueHashID is assigned to this prediction, and the entire process took 400 units of time, as noted in TimeProcess.

Table 6. Output Format

No	Field	Sample Output	Data Type
1	Timestamp	45061,55947	Date
2	Emiten	BBCA	string(4)
3	Dataset Stock File	LQ45-1D-1Y/IDX_DLY_BBCA, 1D.csv	string(255)
4	Dataset Query	query:("bank bca" OR "bank central asia")	string(255)
5	Total Dataset Query	17971	int
6	Delay	1	int
7	Epochs	50	int
8	Prediction Day	1	int
9	MAE	0.23456	float
10	MAPE	0.12345	float
11	R Square	nan	float
12	Train Score RMSE	0.04567	float
13	Test Score RMSE	0.01234	float
14	UniqueHashID	c033df87512c69bfc61629df0251859b	string(32)
15	TimeProcess	400	int

4. Results and Discussion

A. Experiment 1 – Bank BCA (BBCA)

When predicting stock indices for a single day, as in Figure 4, the models yielded an undefined R2 value, represented as NaN (Not a Number). For a 30-day prediction (green line), the most noteworthy R2 value attained was 0.655. However, this was accompanied by a high Testing Score RMSE of 134.86 when employing the CNN model. The most favorable result was observed with the BBCA Index, in which the BERT-CNN model achieved an R2 of 0.628 and a Testing Score RMSE of 0.011 for a 30-day.

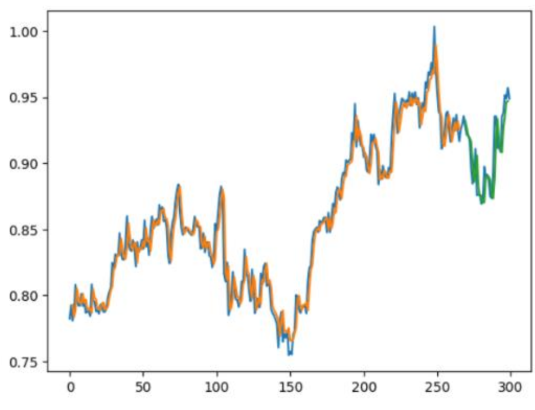

Figure 4. BBCA Stock Price

B. Experiment 2 - Bank BNI (BBNI)

When predicting stock indices for a single day, as in Figure 4, the models resulted in an undefined R2 value, indicated as NaN (Not a Number). For a 30-day prediction (green line), the highest R2 value observed was 0.722, although this came with a high Testing Score RMSE of 142.70 when using the CNN model. The most effective outcome was achieved with the BBNI Index, where the BERT-CNN model attained an R2 of 0.710 and a Testing Score RMSE of 0.014 for a 30-day prediction.

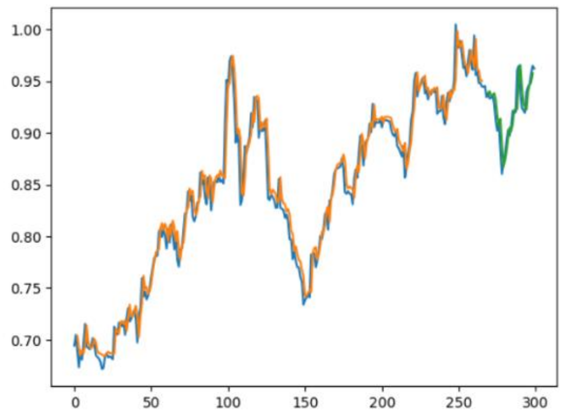

Figure 5. BBNI Stock Price

C. Experiment 3 - Bank BRI (BBRI)

When predicting stock indices for a single day, as in Figure 4, the models resulted in an undefined R2 value, indicated as NaN (Not a Number). For a 30-day prediction (green line), the highest R2 value observed was 0.701, accompanied by a Testing Score RMSE of 73.14 when employing the CNN-LSTM model. The most effective outcome was found in the BBRI Index, where the BERT-CNN model achieved an R2 of 0.543 and a Testing Score RMSE of 0.017 for a 30-day prediction.

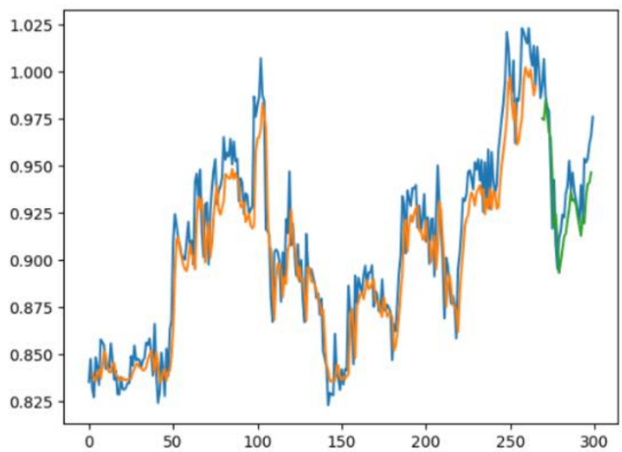

Figure 6. BBRI Stock Price

D. Experiment 4 - Bank BTN (BBTN)

When predicting stock indices for a single day, as in Figure 4, the models resulted in an undefined R2 value, indicated as NaN (Not a Number). For a 30-day prediction (green line), the highest R2 value achieved was 0.736, accompanied by a Testing Score RMSE of 24.6 when using the LSTM model. The best outcome was observed with the BBTN Index, where the BERT-LSTM model yielded an R2 of 0.512 and a Testing Score RMSE of 0.015 for a 30-day prediction.

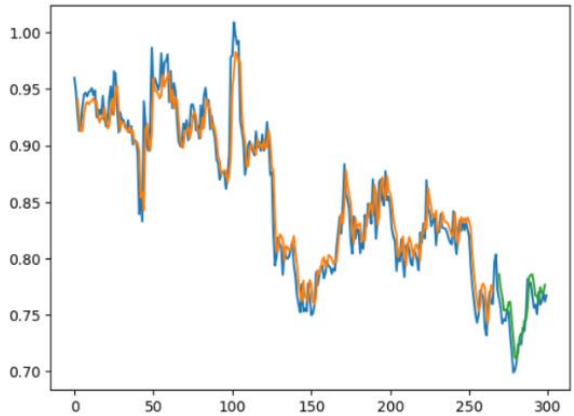

Figure 7. BBTN Stock Price

E. Experiment 5 – Bank Mandiri (BMRI)

When predicting stock indices for a single day, as in Figure 4, the models resulted in an undefined R2 value, indicated as NaN (Not a Number). For a 30-day prediction (green line), the highest R2 value recorded was 0.610, accompanied by a Testing Score RMSE of 192.88 when using the LSTM model. Interestingly, the best result was achieved with the BBTN Index, where the BERT-CNN-LSTM model attained an R2 of 0.587 and a Testing Score RMSE of 0.017 for a 30-day prediction.

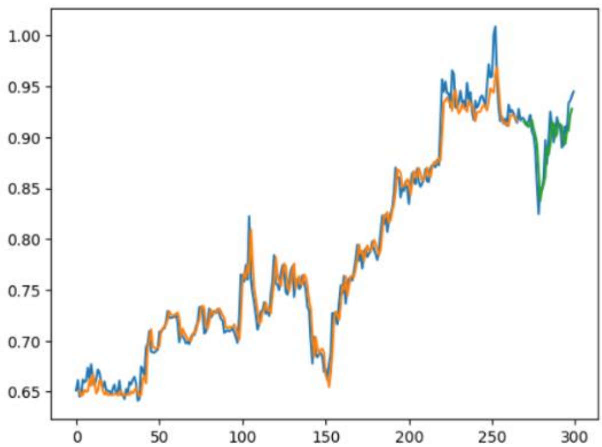

Figure 8. BMRI Stock Price

The dataset contains detailed information on the performance of various stock prediction models applied to five stock indices: BBCA, BBNI, BBRI, BBTN, and BMRI. Table 1 Display Comparison Each entry in the dataset includes key fields such as Index, Total Dataset Data, BERT, Epochs, and Prediction Day. Performance metrics encompass Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), R-squared (R2), Train Score RMSE, Test Score RMSE, and Time Process (s). The Model field specifies the type of model used, such as CNN, LSTM, or a combination like CNN-LSTM. This dataset offers a comprehensive overview of the model performance metrics that predict stock movements.

Table 7. Experiment Results

Index	Total Dataset Data	BERT	Epochs	Prediction Day	MAE	MAPE	R^2	Train Score RMSE	Test Score RMSE	Time Process	Model
BBCA	17971	0	50	30	103,15509	1,2193821	0,6550444	109,6812715	134,866528	4,10s	cnn
BBCA	17971	1	50	30	0,0113849	1,2508318	0,6280349	0,011981095	0,01587810	3,95s	cnn
BBNI	24266	0	50	30	104,18835	1,1491261	0,7222871	147,4829077	142,705429	3,57s	cnn
BBNI	24266	1	50	30	0,01068	1,1645639	0,7100253	0,015300306	0,01444609	4,15s	cnn
BBRI	48257	0	50	30	60,511702	1,30109	0,7012684	70,74588898	73,1433593	4,96s	cnn-lstm
BBRI	48257	1	50	30	0,015219	1,6101085	0,5340776	0,018041749	0,01792817	4,59s	cnn
BBTN	10441	0	50	30	18,144466	1,3764194	0,7360184	30,36420311	24,6448822	4,61s	lstm
BBTN	10441	1	50	30	0,0129459	1,7399009	0,5121142	0,019707524	0,01546428	4,54s	lstm
BMRI	36815	0	50	30	143,05319	1,4808416	0,6103477	148,6052612	192,881839	5,43s	lstm
BMRI	36815	1	50	30	0,0131918	1,481201	0,5873573	0,014647606	0,01767111	4,62s	cnn-lstm

From the experimental results, we explored the application of a CNN-LSTM model for predicting stock prices within the Indonesian banking sector, focusing on prominent institutions such as Bank Central Asia (BBCA), Bank Negara Indonesia (BBNI), Bank Rakyat Indonesia (BBRI), Bank Tabungan Negara (BBTN), and Bank Mandiri (BMRI). The CNN-LSTM model synergistically combines the capabilities of CNN and LSTM networks, allowing it to capture spatial and temporal patterns in historical stock data effectively. This dual capability is essential for accurately forecasting stock prices, enabling the model to discern long-term trends and short-term fluctuations. The empirical results indicate that the CNN-LSTM model achieves promising accuracy in stock price prediction, as evidenced by evaluation metrics such as Root Mean Square Error (RMSE) to measure error threshold and Mean Absolute Percentage Error (MAPE). These metrics underscore the model's proficiency in minimizing prediction errors and delivering reliable forecasts for stock prices in the banking sector.

Integrating BERT (Bidirectional Encoder Representations from Transformers) into the stock prediction model enhanced prediction accuracy by incorporating sentiment analysis. BERT's advanced ability to comprehend the context and subtleties of text was utilized to analyze sentiment from textual data sources, including news articles and social media, which are known to influence stock prices. The model could account for market sentiment factors extracted from textual data by incorporating BERT. Sentiment analysis offered additional insights into market dynamics, where positive sentiment towards a bank could increase its stock price. In contrast, negative sentiment could have the opposite effect. The study found that incorporating sentiment analysis using BERT improved the model's prediction accuracy from 73.41% to 77.75%.

The processing time for models with BERT integration remained relatively high compared to those without it. The average processing time for models without BERT was approximately 4.534 seconds, whereas models with BERT averaged around 4.370 seconds. This indicates that including BERT does not substantially heighten computational demands, making it a feasible enhancement for real-time applications. For specific banks, the model configurations that yielded the best performance varied. For BBCA, BBNI, and BBRI, the optimal model was a combination of BERT and CNN, which provided the most accurate predictions for these institutions. In contrast, for BBTN, the best-performing model was a combination of BERT and LSTM, demonstrating LSTM's effectiveness in capturing temporal dependencies specific to BBTN's stock data. Notably, BMRI benefited most from a combination of BERT and CNN-LSTM, suggesting that the hybrid approach of CNN-LSTM was particularly well-suited to the unique characteristics of BMRI's data.

Overall, integrating BERT within the CNN-LSTM framework enhanced the accuracy of stock price predictions and provided valuable insights into how public sentiment can influence stock market movements. This underscores the significant potential of sentiment-based approaches in financial market prediction and decision-making strategies. The findings suggest that models incorporating sentiment analysis can offer a competitive advantage in understanding and forecasting stock market trends, particularly in dynamic and sentiment-driven financial markets.

5. Conclusion

In this experiment, we successfully applied a CNN-LSTM model to predict stock prices in the Indonesian banking sector, focusing on significant banks such as BBCA, BBNI, BBRI, BBTN, and BMRI. The model effectively captured spatial and temporal patterns in historical stock data, demonstrating promising accuracy as metrics like RMSE and MAPE indicated. Integrating BERT for sentiment analysis enhanced prediction accuracy by incorporating contextual understanding from textual data sources such as news articles and social media. This integration improved the model's prediction accuracy from 73.41% to 77.75%, highlighting the value of sentiment analysis in understanding market dynamics. Overall, this study underscores the significant potential of combining CNN-LSTM with BERT to enhance financial market predictions and provides valuable insights into the influence of public sentiment on stock market movements.

Future research could explore several avenues to build on the findings of this study. One potential direction is to expand the dataset to include more diverse textual data sources, such as financial reports and analyst opinions, to refine sentiment analysis further. Additionally, experimenting with other advanced NLP models, such as GPT from the OpenAI Field [17] or LLAMA from the Meta [18], could provide comparative insights into their effectiveness in sentiment analysis for stock prediction. Another area of interest could be developing hybrid models that integrate other machine learning techniques, such as reinforcement learning, to adjust predictions based on real-time market changes dynamically. Finally, applying this approach to other sectors beyond banking could validate the model's versatility and effectiveness in different financial contexts.

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