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A Multimodal Ensemble Model for Predicting the Daily Close Price of Banking Stocks

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ABSTRACT

We introduce a multi-model lifting model for predicting the daily closing prices of major Indonesian banking stocks (BBCA, BBRI, BBNI, BMRI) that integrates quantitative market indicators and qualitative news sentiment features. The two primary data sources are daily historical stock prices (Open, High, Low, Close, and Volume) collected from Yahoo Finance and 61,173 financial news articles downloaded from popular web portals, published between 2022 and 2025. Sentiment extraction classified positive, neutral, and negative news for each headline, and content was made through the IndoBERT model, which aggregated the classification on a daily basis. Market features were augmented by a volatility measure based on daily high and low prices. The combined dataset was modeled by a Random Forest Regressor in 80:20 train-test ratio. This model had good predictive capabilities (R^2>0.89 for all stocks and a maximum of 0.9564 for BMRI). The MAPE values were always below 2.2% and it could decrease to even 1.43%, as in the case of BBCA. These findings further indicate that the fusion of market signal and news sentiment does improve the prediction of price from a psychological perspective, where both long-term trend and short-term sentiment are captured

Keywords-Ensemble Learning; Random Forest Regressor; Multimodal Data; Sentiment Analysis; Stock Price Prediction

I. INTRODUCTION

The dynamic system of the financial stock is one of the most complicated and dynamic non-linear systems and is always a topic for both investors and researchers on how to model it. Precise predictions of stock prices are usually considered to be one critical aspect in creating profitable trading strategies and improving market efficiency. Conventional analysis (such as Fundamental and Technical Analysis) is mostly based on historical price movements and public financial health information. Yet these approaches often fail to capture the quick, sometimes irrational market momentum changes that are generated by unexpected news and investor group mentality [1].

The field of Financial Data Mining (FDM) has thus resorted to more and more Machine Learning (ML), Deep Learning (DL)-techniques to deal with this complexity. They have been proven effective in finding complex patterns and non-linear relationships in large scale financial timeseries data [2, 3]. In the early ML work, most of them focused on quantitative factors including Open, High, Low and Close prices as well as trading volume (OHLCV) [4, 5]. Recent evidence indicates, however, that market shifts are also deeply conditioned by qualitative dimensions derived from financial news, social media and investor mood [6, 7]. This insight has fostered a trend towards multimodal modelling, including numerical market indicators as well as textual sentiment data to increase prediction performance. Sentiment analysis, utilizing Natural Language Processing (NLP) methods, has contributed widely in converting unstructured text e.g. news headlines and articles into measurable mental factors [8, 9]. Although global advancement has been achieved, such methods remain bounded in regional markets such as Indonesia where lack of domain-specific language models limit sentiment extraction accuracy.

To handle these problems, this study suggests a Multimodal Ensemble Model for forecasting the average daily closing prices of Indonesian main stocks (BBCA, BBRI, BBNI and BMRI). The banking industry is an important model as a result of its systemic relevance and high liquidity in the Indonesian economy. We use IndoBERT [10], a pre-trained language model tailored to Indonesian, for sentiment extraction on local financial news headlines and articles. The qualitative features are

combined with quantitative market signals (in UI applied volatility) to create a mixed-mode dataset. The fusion technique is learned using Random Forest Regressor, ensemble learning algorithm having excellent robustness and ability to model non-linear relationships over complex data structures.

The contributions of this paper are as follows. For this purpose, we also propose to model a novel multitask and multi-modal feature extractor which can fully incorporate quantitative market indicators together with qualitative sentiment information from local financial news as well, to better characterize the overall market activity in Indonesian banking sector. Second, we utilize IndoBERT to do fine-grained sentiment analysis task for large-scale financial text data to obtain precise modeling of public and investor sentiment. Third, we use the Random Forest Regressor as an ensemble learning technique to perform multimodal regression, which can model complex non-linear relationships between sentiment and technical indicators. This integrated method seeks to improve the predictive ability and consistency of short-term stock price prediction, especially in emerging markets like Indonesia.

II. METHOD

Stock market prediction has evolved from traditional technical analysis to machine learning–based modeling.

A. Ensemble Learning for Stock Prediction

The presence of non-linear and non-stationary behavior in financial time series data makes classical statistical models (e.g., ARIMA) perform not well. As a result, ML algorithms like SVM (Support Vector Machines), KNN (k-Nearest Neighbors), and ensemble methods has been increasingly used in forecasting financial markets [2, 3, 5, 11]. Of these the Random Forest Regressor (RFR) has proven to be especially successful owing to it robustness for noisy data, interpretability of feature importance and independence on data scaling [12, 13]. There are many previous studies that have validated the strong performance of RFR across different regression scenarios, including stock price and commodity prediction [14, 15]. Its variance-reducing and overlearning-tolerant properties render it as a good model for high-dimensional and volatile financial market data.

B. Sentiment Analysis and Multimodal Fusion

Purely financial metrics sometimes ignore the behavioral factors that shape market moves. Jointly exploiting investor sentiment extracted from financial news and social media can improve the predictive performance [6, 7]. On the other hand, multimodal architectures like CNN-BiLSTM ensembles and Weighted and Categorized News LSTM (WCN-LSTM), fuse numerical and textual signals to model market as well psychological aspects. Other fusion-based deep models leverage autoencoders for feature denoising along with LSTM/GRU layers for temporal modeling [7, 16, 11]. Together, the results suggest that the incorporation of sentiment leads to observable performance enhancement in stock prediction over horizons as short as 1 or 5 days.

C. NLP Challenges in Non-English Financial Texts

Many techniques for financial prediction based on sentiment analysis are built using English corpora. Applying them to different language involves difficulties in relation to syntax, idiomatic expressions and data sparsity. Parallel to, but not resulting from such initiatives is the availability of IndoLEM and IndoBERT [10], which has sidestepped such restrictions by providing large scale linguistic benchmarks and pre-trained models for Indonesia. For example, IndoBERT performs well in sentiment analysis tasks and can be used as a basis for sentiment signal extraction from Indonesian financial texts.

D. Comparison with Deep Learning Architectures

Deep learning models, including LSTM and GRU can learn long-term temporal dependencies and usually have better performance than conventional regressors [5, 17, 18]. They need quite a lot of data and computational resources, though [19]. There has also been some work on using DRL for adaptive trading [20]. By comparison, ensemble regressors such as the RFR are computationally more efficient and less prone to overfitting especially for multimodal settings which involve quantitative and sentiment-based ones [12]. This study employs such an ensemble method to balance between predictive accuracy, interpretability and scaling for Indonesian banking stock prediction.

III. PROPOSED METHOD

This research is conducted according to the Cross-Industry Standard Process for Data Mining (CRISP-DM) process model in order to keep a clear and structured approach [21]. This architecture offers a systematic and recursive flow of the development of the multimodal prediction model from data acquisition to deployment. As shown in the Figure 1, it starts with a review of literature to lay down the theoretical and empirical backdrop for the research. The subsequent Business Understanding and Data Understanding phases scope the analysis objectives and data sources (quantitative stock indicators and qualitative financial news) to be considered. The two data streams are further processed in the Data Preparation step to extract structured numerical and sentiment-based features, which can be used for machine learning. Afterward, in the Modeling phase, these features are combined using an ensemble learning, i.e., Random Forest Regressor which It utilizes IndoBERT sentiment analysis outputs.

Finally, the model is put through detailed Evaluation using statistical performance measures on predictive power. Lastly, the Deployment phase models how the model is incorporated in a web-based financial decision support application.

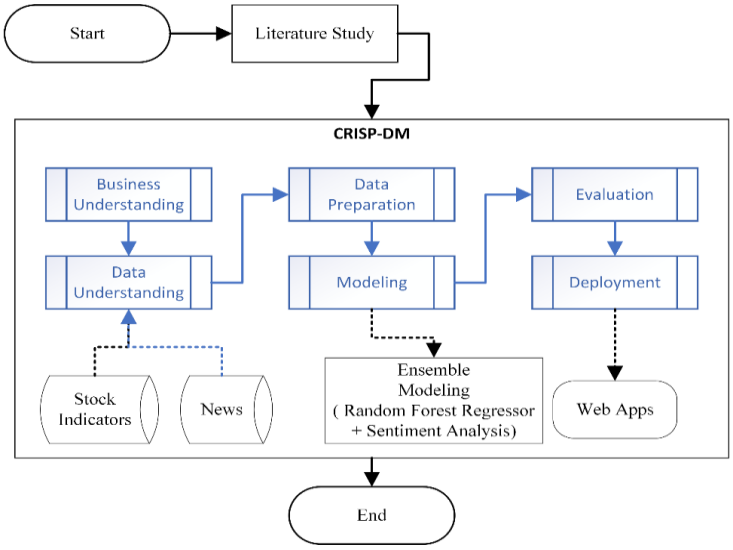

Figure. 1. Research Framework

A. Business Understanding

The key goal is to enhance the accuracy of daily close price prediction for four major Indonesian banking stocks, by using the current stock exchange index such as BBCA Stock, BBRI Stock, BBNI Stock and BMRI Stock as high-liquid cryptocurrencies of Indonesia's stock market (IDX). The research problem is cast as a multimodal time-series regression, and the task involves associating quantitative historical stock data with qualitative sentiment information extracted from financial news. The predictive accuracy is measured according to two main criteria, a very high R^2 and low MAPE covering explanatory power and prediction fitness [22].

B. Data Understanding

This study used two major categories of data, quantitative indicators derived from the market and qualitative textual information obtained from financial news (Table 1). These diverse sources are combined to obtain a more complete portrait of the market dynamics and investor sentiment crucial for precise stock price prediction.

1) Quantitative Market Data

Daily stock prices of four largest Indonesian banking stocks (BBCA, BBRI, BBNI and BMRI) were downloaded from Yahoo Finance. All the standard market indicators: Open, High, Low, Close and Volume data from January 2022 to June 2025 is provided. In this research, we use the next-day closing price as our target value to predict short-term market trend in terms of the predictive goal.

2) Qualitative News

A total of 61173 financial news were obtained from trusted Indonesian media such as Kompas.com, Republika.co.id, and CNBCIndonesia.com. Every article is available as headline and full text, permitting sufficient linguistic context for sentiment analysis. The gathered articles cover the same time range with the quantitative dataset, thus can be well synchronized for multimodal feature integration. This is qualitative aspect which would take into the real time psychological and information effects that can cause stock price changes in to the Indonesia financial market.

TABLE 1. DATASET AND FEATURES TYPES

Dataset	Variable		Types	Description
Stock Price	X_1	Open	Numeric	The opening price of the stock at the beginning of the trading day.
	X_2	Close	Numeric	The closing price at the end of the trading day
	X_3	Volume	Numeric	The total number of shares traded within the day
	X_4	Volatile	Numeric	The intraday price fluctuation calculated as the difference between the highest and lowest prices

Dataset	Variable		Types	Description
News	X_5	Avg Headline Sentiment	Numeric	The mean sentiment score of all news headlines published during the trading day
	X_6	Avg News Sentiment	Numeric	The mean sentiment score derived from full-text financial news content
	X_7	Total Positive Sentimen	Numeric	The total count of positively classified news articles on the trading day
	X_8	Total Negative Sentiment	Numeric	The total count of negatively classified news articles on the trading day

C. *Data Preparation*

This stage converted unprocessed heterogeneously structured data to a unified multimodal dataset.

1) *Feature Engineering*

Beyond the Open, Close, and Volume column values, a feature reflecting volatility (i.e., daily spread $High_t - Low_t$) was included in order to capture temporal and intra-day market dynamics.

2) *Sentiment Extraction*

Financial news were then sentiment analyzed by using IndoBERT, a pre-trained Transformer model which has been fine-tuned on Indonesian text. Both titles and article content were labeled positively, neutral or negatively overall and these labels or aggregated on a daily basis to generate sentiment-based features (daily counts of each sentiment category).

3) *Data Fusion and Normalization*

Quantitative and sentiment based features were merged on a shared daily time-line, and then normalized with the StandardScaler to avoid scale bias. The dataset was split in the ratio of 80:20 for training and testing samples per stock.

D. *Modeling*

The architectural schema, shown in Figure 2 explains in detail the multimodal data fusion procedure for incorporating quantitative stock market indicators and sentiment qualitative information to predict the daily stock close.

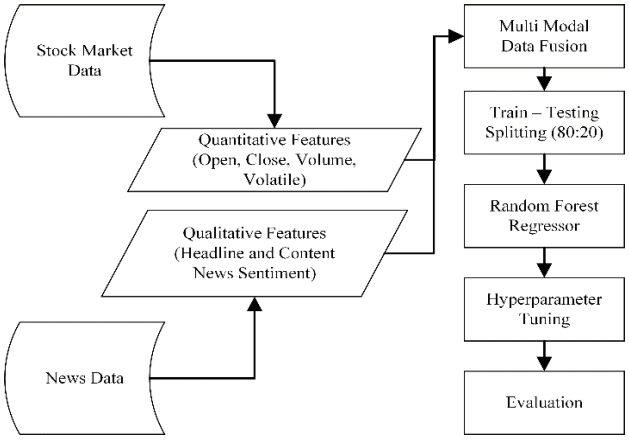

Figure. 2. Multimodal Modeling in Stock Close Prediction

Two data sources are mainly used, stock market data and financial news. The stock market datasets contained quantitative attributes such as Open, Close, Volume, and Volatile (the difference between High and Low price of the day), which represent numerical characteristics controlled by the market. Meanwhile, the news data also augmented qualitative features from headline and content-based sentiment scores by using IndoBERT model. The two sets of features were then integrated using the multimodal data fusion technique, which aligned them along a consistent daily timeline. This allowed the model to handle numerical and textual signals expressed in market dynamics and investor sentiment. The merged dataset was subsequently train-test split (80:20) for a fair and non-bias performance estimation. The underlying predictive model was a Random Forest Regressor (RFR) due to its ability to avoid overfitting, and its good accuracy for nonlinear, high-dimensional data. The model was optimized by hyperparameter tuning (Table 2) to find the best combination of estimators and tree depth. Finally, the effectiveness of the multimodal ensemble approach for predicting daily closing prices of banking stocks was validated based on statistical stability performance metrics, R^2 and MAPE.

TABLE 2. HYPERPARAMETER TUNING VALUE

Hyperparameter	Range Values
n_estimators	100, 200, 300, 500, 800, 1000
max_depth	None, 5, 10, 15, 20
min_samples_split	2, 5, 10
min_samples_leaf	1, 2, 4
max_features	sqrt, log2, None
bootstrap	True, False
criterion	squared_error, absolute_error

E. Evaluation

The test data (20%) was used to evaluate the performance of the models using two main metrics. R^2 determines the percentage of variance in actual close price explained by model and MAPE interprets prediction error in terms of the percentage.

F. Deployment

Whilst fundamentally a research contribution, the framework has application in practice and can straightforwardly be integrated within an operational financial decision support system. The model's strong predictive power and stability implicates its adequacy for generating real-time inferences, to allow investors/analysts access to timely data-driven insights about short-term dynamics impacting on value determination of Indonesian banking stocks.

IV. RESULT AND DISCUSSION

In this section, we show the empirical results and analyze their implications for the proposed multimodal stock prediction system.

A. Exploratory Data Analysis

A visualization of the trend of predictive features with regard to their quantitative and qualitative breadth is provided in Figure 3. The quantitative market-related features are: Open, Close, Volume, and Volatility, while the qualitative sentiment-based features are composed of Average Headline Sentiment, Average News Sentiment, Total Positive, and Total Negative. Open and Close prices follow a similar trend in time, they exhibit general daily market behavior for banking stocks. In both series, there is an initial upward trend from early 2022 to mid-2024, and after this date, oscillations are observed which describe cyclical market changes due to the macro-economy. As for the qualitative aspects, Both Average Headline Sentiment and Average News Sentiment alternate in the range –1.0 to 1.0, representing a variety of public sentiment from very negative sentiments to optimism ones. The high switching of polarity indication that the sentiment of investors towards Indonesian banking sector is easily influenced by short-term news or economic release. The Total Positive & Total Negative sentiment counts evidence a clear asymmetry, with negative sentiment being more prevalent and consistent with the behavioral finance literature which indicates that negative news prevails in market talk and influences short-term trading. Nonetheless, the combining of such sentiment features enriches the dataset with psychological and contextual nuances that cannot be represented by price action alone.

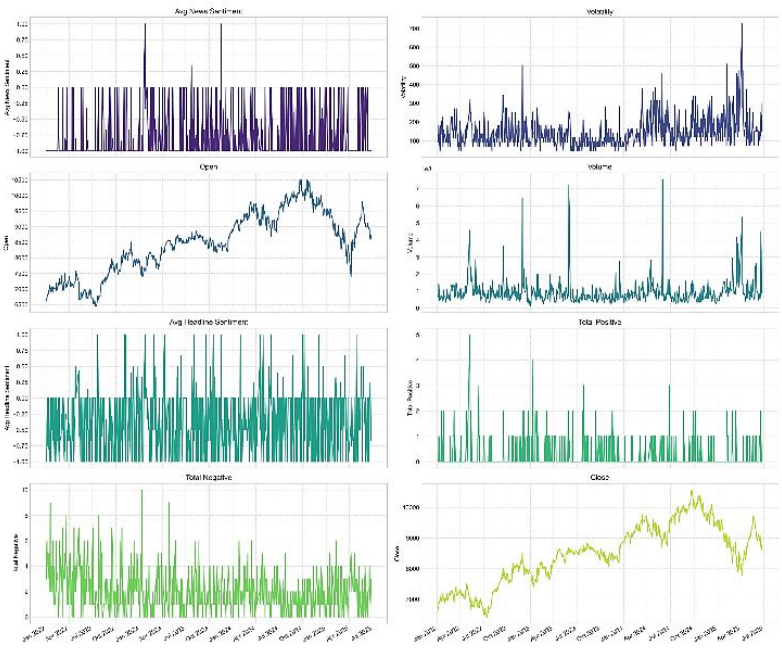

Figure. 3. Time series of Multimodal Feature

Next, it can also be seen about trading volume which is generated from the four banks selected that are BBNI, BBRI, BBCA and BMRI as shown in Figure 4. They all show quite similar time evolution, the continuous increasing trends from early 2022 up to middle of 2024, and then sliding in moderate declinations until post-2025. That indicates strong a sector-wide correlation, illustrating that market level factors such as interest rate policy, digital banking adoption and macroeconomic sentiment influences all the major banks at the same time. BBCA has the highest levels of absolute price, which reflects its status as the biggest bank in terms of market capitalization. On the other hand, BBRI and BBNI show larger short-term persistence suggesting more volatility which could be due to higher retail involvement in the stocks and exposure to MSME segments. BMRI also follows a mid-path with not too far high tails that coincide exactly to those of BBNI, showing similar institutional investor patterns.

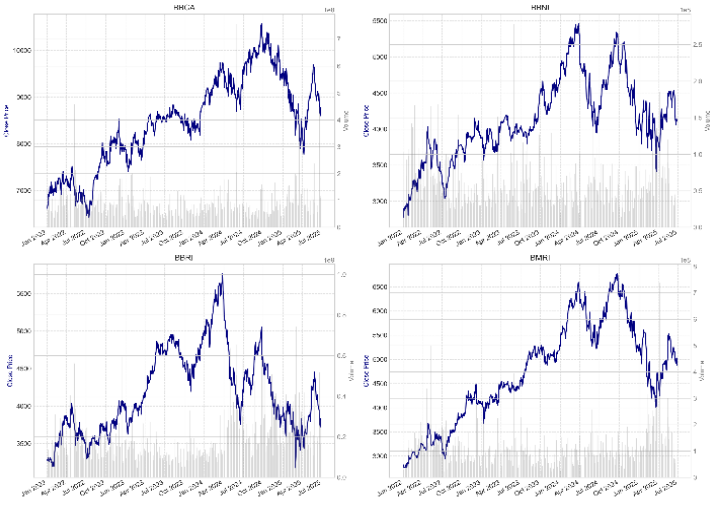

Figure. 4. Price and volume trading trends

The daily trading volume, the grey bars in each subplot of Figure 4, shows considerable stock to stock variability. Trading Volume BBRI has the highest trading volume on average with more than 800 million shares daily, reflecting high liquidity and potential of being a short-term strategy investment. BBCA, meanwhile experiences lower trade volume without random

spikes indicates a dominance of long-term followed by institutional investors. The heterogeneous behaviors among the four stocks highlight that price and sentiments features should be considered together to adequately represent behavioral and information components that drive market dynamics. On a broader scale, the exploratory analysis indicates that considering both quantitative market indicators and qualitative sentiment signals is more representative of stock behavior. This also supports the use of the proposed multimodal ensemble model, which utilizes features from both types for better prediction stability and interpretability.

B. Modeling Performance

The performance of the Random Forest Regressor model was assessed on two different feature aggregation schemes. Dataset A comprises 13 input feature, news sentiment metrics are divided according to its media sources (CNBC, Republika and Kompas). Through this design, we enable the model to embed unique sentiment nuances of each media. On the other hand, Dataset B combines all sources in a final sentiment feature (8 features for general media sentiment trends). As indicated in Table 3, both results consistently provide a strong prediction for the four banking stocks (BBCA, BBRI, BBNI and BMRI).

TABLE 3. MODEL PERFORMANCE

Stocks	Dataset	Features	R^2	MAPE
BBCA	Dataset A	13	0.92	0.015
	Dataset B	8	0.93	0.014
BBRI	Dataset A	13	0.89	0.019
	Dataset B	8	0.89	0.019
BBNI	Dataset A	13	0.90	0.021
	Dataset B	8	0.90	0.021
BMRI	Dataset A	13	0.93	0.023
	Dataset B	8	0.95	0.019

For Dataset A, the model obtained R2 between 0.89 and 0.93 and MAPE of 0.015-0.023, then we slightly enhanced the prediction performance for Dataset B with increased R2 (0.89–0.95) but lower MAPE (0.014-0.021). It shows that combining sentiment information from different media (Datasets B) can make the models generalize better and predict more accurate results.

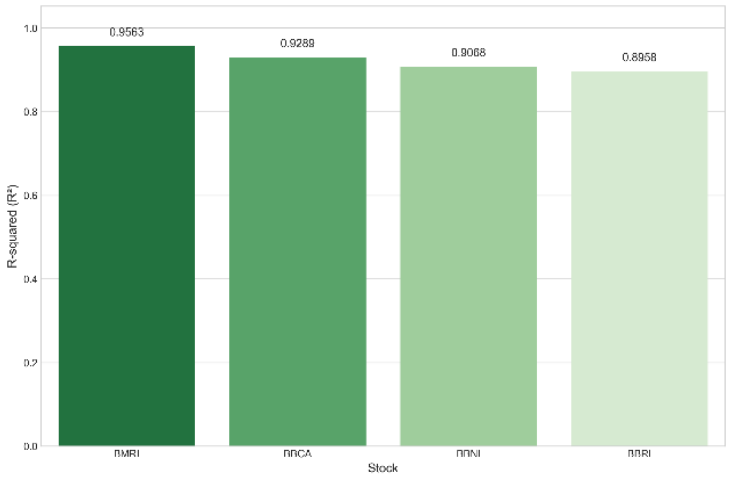

Figure. 5. R2 performance comparison

As illustrated in Figure 5, based on the comparison of R^2 values, for all models coefficient is higher than 0.89 suggesting a high fitting accuracy between predicted and actual true stock prices. Among the components, BMRI is the one with the most significant $R^2 = 0.956$, followed by BBCA ($R^2 = 0.929$), BBNI ($R^2 = 0.907$) and BBRI ($R^2 = 0.896$). This means that the BMRI model accounts for about 95.6 % of the variance in stock prices because it is a good fit for the study.

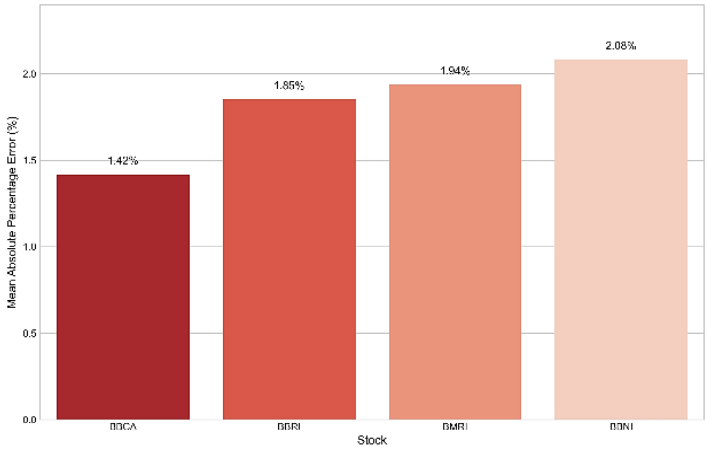

Figure. 6.MAPE performance comparison

In addition, Figure 6. reports the MAPE comparison on stocks, where we consistently achieve error rates below 2.1%. The minimum MAPE is obtained for BBCA (1.42%), meaning that this one has the highest prediction precision and steadiness in market dynamics. Meanwhile, BBNI has the highest MAPE (2.08%) indicating more price variation and perhaps noise in sentiment. This gives more evidence that multi-source sentiment enrichment would improve the performance of model, especially in the Indonesian banking sector where market movements are sensitive to public perception and investor's confidence.

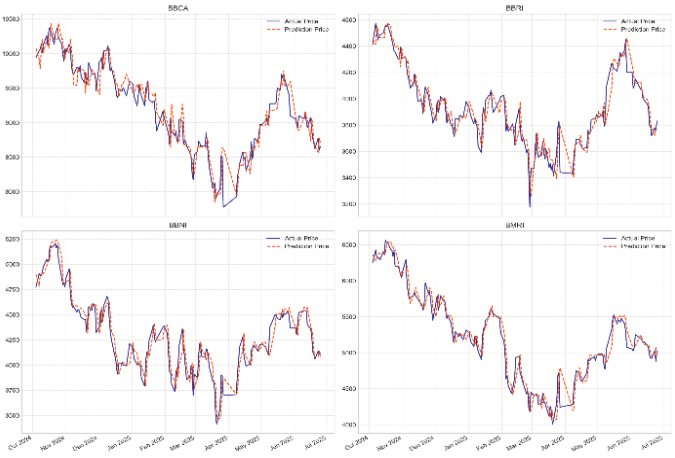

Figure. 7. Predictive and actual time series

Moreover, the real stock price and predicted stock price is compared in Figure 7, and indicates that the Random Forest Regressor is capable of capturing general moving behaviors from all four banking stocks. The orange dashed prediction lines, which closely trace the blue solid actual price trends, suggest that our model is well-generalized against temporal inconsistency. In the case of BBCA and BMRI, the predicted curve is located almost perfectly close to actual prices where it does not show high deviations both during upward and downward trends. This is consistent with the high responsiveness of the model to both quantitative gauges and sentiment aggregation dynamics. BBRI and BBNI similarly have closely matching growth paths with somewhat higher h edging during periods of severe market stress, which indicates weak level under fitting during caustic times.

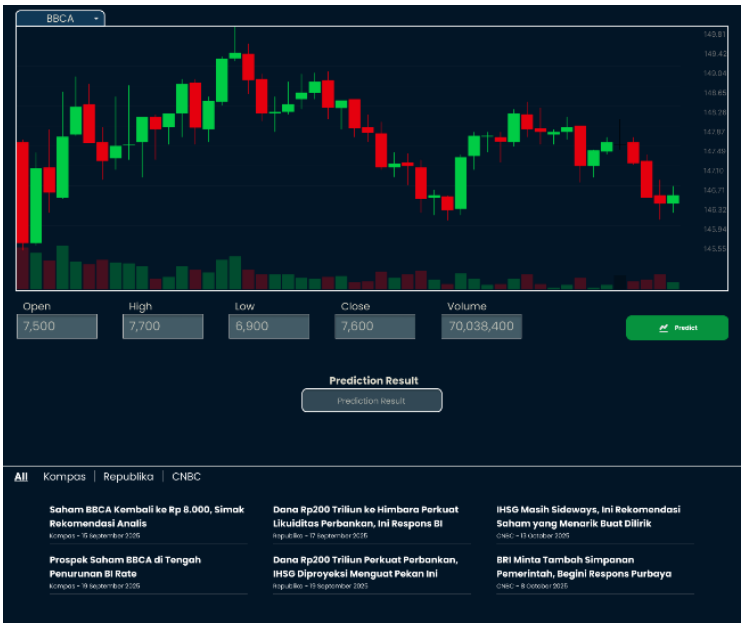

Figure. 8. Deployment mockup

An online application was created to showcase the feasibility of our model, which is as And also Figure 8. The model combines technical stock information with other features including sentiment analysis to make predictions for a selection of banking stocks.

V. CONCLUSION

The results in this work show that a novel multimodal data fusion for quantifying and stock prediction is efficient at bridging quantitative stock analysis with qualitative news sentiment. With Random Forest Regressor, High performance is obtainable in Indonesian major banking stocks (BBCA, BBRI, BBNI and BMRI) demonstrated by accuracy with R^2 more than 0.89 and MAPE less than 2.1%. The performance results suggest that market sentiment provides significant commercial value in addition to traditional trading predictors. Alternatively, a web-based predictive application enables practical access to real-time analysis and decision support. Future studies could extend the models to more sophisticated deep learning architectures and to wider sectoral data integration to improve generalization and robustness.

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