IJIE

INTERNATIONAL JOURNAL OF INTEGRATED ENGINEERING
ISSN: 2229-838X e-ISSN: 2600-7916

Vol. 18 No. 1 (2026) 111-128
https://publisher.uthm.edu.my/ojs/index.php/ijie

Stock Recommendation for Students Using Technical Analysis and LSTM-Based Forecasting

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DOI: https://doi.org/10.30880/ijie.2026.18.01.009

Article Info

Received: 14 December 2025
Accepted: 28 March 2025
Available online: 17 April 2026

Keywords

Stock price prediction, LSTM (Long Short-Term Memory), technical analysis, beginner investors, calendar effect (ToM & DoW)

Abstract

Stock investment is increasingly popular among Indonesian students, particularly among millennials and Generation Z, who account for over 79% of investors under the age of 30, according to a 2022 report by the Indonesia Stock Exchange (IDX) and FEB UI. However, despite growing interest, many students remain reluctant to begin investing due to limited financial literacy and a lack of risk analysis skills. Investment decisions are often influenced by the Fear of Missing Out (FOMO), leading to trend-following behavior without proper analytical assessment, under the mistaken belief that following the majority guarantees profit and safety. This study aims to address these challenges by developing a website-based stock recommendation system utilizing the Long Short-Term Memory (LSTM) algorithm to assist beginner investors. The system analyzes historical stock data from IDX80 comprising liquid stocks suitable for novices retrieved from Yahoo Finance. Technical indicators such as Moving Average, Relative Strength Index (RSI), and Bollinger Bands are used to support the predictive model. The LSTM algorithm forecasts stock price movements based on temporal market anomalies, specifically the Turn-of-the-Month (ToM) and Day-of-the-Week (DoW) effects. Predictions are classified into uptrends and downtrends and presented via a user-friendly web interface, allowing users to make more informed investment decisions. Evaluation results show that 63 out of 80 stock tickers achieved an R^2 value above 0.8, indicating strong predictive performance. Unlike prior studies that primarily focused on general market forecasting or professional investor tools, this research uniquely integrates behavioral finance aspects (such as FOMO) with algorithmic predictions targeted at novice investors. The incorporation of calendar effects into LSTM-based forecasting also fills a methodological gap rarely addressed in existing literature. These findings suggest that personalized, accessible forecasting tools can bridge the knowledge gap for young investors and support more rational, data-driven investment behavior.

1. Introduction

Stock investing is a crucial financial activity that supports wealth accumulation and long-term fiscal preparedness. For students, early engagement in the stock market not only promotes financial literacy but also fosters disciplined saving habits and an understanding of economic dynamics. The rise of user-friendly trading applications and capital market outreach has increased young investors' participation worldwide – but without adequate guidance, students may fall prey to emotional biases and market noise, resulting in irrational choices and financial loss [1], [10].

Globally, financial literacy among youth remains insufficient. According to Indonesia's National Financial Literacy and Inclusion Survey (SNLIK) conducted jointly by OJK and BPS in 2024, the overall financial literacy index was 65.43%, while financial inclusion reached 75.02% [10]. Importantly, students/university students had one of the lowest literacy rates at just 56.42%. This literacy gap particularly affects capital market understanding, reinforcing the need for tools that not only suggest investments but also educate students on responsible decision-making. Supporting this concern, Umar and Dalimunthe [23] showed that financial and digital literacy significantly influence students' awareness of fraudulent investment schemes in Indonesia, while Phung [24] highlighted that higher financial literacy among undergraduates and graduates is positively associated with greater risktaking in investment contexts. These findings underscore that improving financial literacy is essential to equip students with the knowledge and critical skills required to participate safely and meaningfully in capital markets.

Technical analysis tools such as Moving Averages (MA), Relative Strength Index (RSI), and Bollinger Bands (BB) offer visual cues on trends, momentum, and volatility [11], [12]. MA smooths price evolution, RSI highlights overbought or oversold conditions, and BB reflects shifts in volatility [12]. Although these methods are intuitive and widely adopted by retail investors, they demand experience to interpret effectively and offer limited predictive capability. Consequently, beginners including students often struggle to apply these indicators meaningfully amid market volatility [6].

Recent advances in deep learning especially Long Short-Term Memory (LSTM) networks have demonstrated high accuracy in stock time-series forecasting. For instance, Oak *et al.* (2024) used a multivariate bi-directional LSTM model combined with technical indicators including Bollinger Bands and achieved R^2 performance above 0.99 on Indian NIFTY 100 stocks [7]. Other studies highlight that integrating technical indicators into LSTM input features significantly reduces forecasting error compared to models trained on price data alone [14], [15]. However, these prior works largely target general or professional investors; systems designed specifically for student investors with their lower capital, cautious risk appetite, and need for interpretability are notably scarce [8],[19].

Therefore, this study proposes a hybrid stock recommendation system tailored for students by combining technical indicators (MA, RSI, BB) with LSTM-based forecasting. The objectives are to generate recommendations that are both accurate and interpretable, guiding novice investors to make informed decisions backed by data rather than emotion.

This approach is expected to empower student investors through:

- Improved predictive accuracy via LSTM enriched with technical indicators
- Enhanced interpretability that aids learning and rational decision-making
- A user-friendly interface designed for educational and practical use

2. Related Works

Financial literacy and stock market education have become essential competencies for university students, especially in the context of increasingly accessible retail investing platforms. Several studies have introduced stock market simulations and educational tools aimed at improving students' understanding of financial markets. Wu et al. [1] developed a web-based stock trading simulation system and found it significantly improved students' practical skills in portfolio management. Harter and Harter [2] also emphasized the benefits of classroom-based stock market games, demonstrating a strong correlation between participation in such activities and enhanced comprehension of investment concepts. These initiatives, while educational, often stop short of integrating advanced predictive tools that could empower students to make informed, real-time investment decisions.

In parallel, Long Short-Term Memory (LSTM) networks have emerged as a leading method for time-series forecasting in the financial domain due to their ability to capture long-term dependencies. Mehtab et al. [4] demonstrated the effectiveness of LSTM in forecasting stock prices across various companies, while Kuber et al. [5] compared univariate and multivariate LSTM models to assess their accuracy in predicting short-term price movements. These studies showed promising results when using price history and volume data alone, and further improvement was noted when combining these inputs with external factors such as market news and investor sentiment. However, the use of LSTM in the context of student-specific investment recommendation taking into account factors like limited risk tolerance and the need for interpretability is still underexplored.

Alongside machine learning techniques, technical analysis remains a widely adopted method for identifying trading opportunities. Tools like the Relative Strength Index (RSI), Moving Average (MA), and Bollinger Bands

(BB) are particularly valuable for beginners due to their intuitive visual interpretations. Saputra et al. [23] integrated RSI and moving averages with LSTM to enhance stock prediction in the Indonesian market, reporting improved accuracy in signaling buying and selling points. The RSI helps detect overbought or oversold conditions, MA smooths price trends, and BB identifies volatility shifts. While these indicators are often used by retail traders, their integration into student-centered learning systems or recommendation platforms has not been a primary research focus, despite their pedagogical potential.

Although the use of LSTM and technical analysis for stock forecasting is well established, a notable gap exists in research focused on student-specific stock recommendation systems that combine both methods. Prior work either emphasizes educational gamification or focuses purely on algorithmic accuracy for general investors. There is limited research that addresses the unique characteristics of student investors, such as lower capital, higher aversion to risk, and the dual purpose of investing for both profit and learning. Therefore, this study proposes a hybrid approach that combines technical indicators (RSI, MA, and BB) with LSTM-based forecasting to generate stock recommendations tailored specifically to students. The aim is not only to provide actionable insights but also to support financial learning and responsible investment practices for novice investors.

3. Methodology

The research begins with the acquisition of financial data sourced from Yahoo Finance, accessed through the yfinance Python library. This raw data undergoes a comprehensive data processing pipeline implemented in Python, which includes several key stages: data extraction, transformation, exploratory data analysis, technical analysis, application of the Long Short-Term Memory (LSTM) algorithm, model evaluation, and finally, data loading. The processed data is then stored in MongoDB using the PyMongo connector [5].

For the visualization stage, the data stored in MongoDB is retrieved through a Flask-based backend. The final output is a web-based visualization interface developed using a combination of Python (Flask) for the backend and HTML with Bootstrap for the frontend. This integrated system allows users to access and interpret financial insights interactively via a website. An illustration of the research design is presented in Fig. 1.

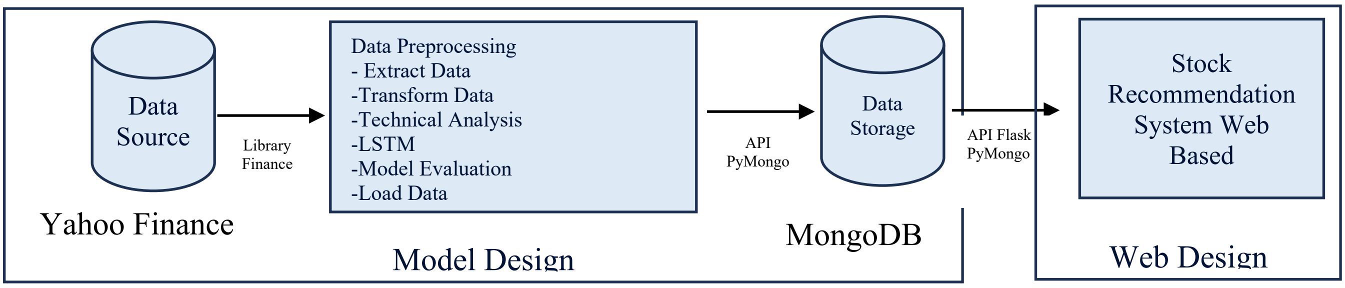

Fig. 1 *Research flowchart*

3.1 Stock

In modern economies, the stock market serves as a critical barometer of economic health, with composite indices such as the Jakarta Stock Exchange Composite Index (IHSG), reflecting investor sentiment and aggregate issuer performance. A sharply declining IHSG often signals worsening macroeconomic conditions, whereas sustained growth indicates economic stability and investor confidence [1]. A robust stock exchange also plays a pivotal role in attracting foreign capital, thereby stimulating economic expansion through increased liquidity and funding opportunities for domestic businesses [9].

Companies seeking to expand often opt for Initial Public Offerings (IPOs), listing shares on the exchange to raise capital for growth initiatives. Listed firms gain wider visibility and access to institutional and retail investors. Simultaneously, individuals with surplus funds can invest via stocks, bonds, derivatives, or mutual funds. Although stock market investments carry greater risks than traditional bank savings or deposits, they also offer the potential for higher returns, including capital appreciation and dividend income. However, this comes with exposure to market volatility and possible capital loss requiring investors to apply prudent and knowledgeable risk management strategies [16], [18].

Moreover, research shows that stock market development is positively correlated with economic growth across emerging economies. For example, in ASEAN countries, higher market capitalization and trading volume significantly contribute to GDP growth by channeling savings into productive investments and bolstering liquidity conditions [5]. Similarly, studies of Singapore reveal that both market size and turnover ratios exert a positive

influence on per capita GDP in both short- and long-term scenarios [6]. These findings support the view that stock exchanges are not mere indicators but active drivers of capital formation and economic prosperity.
Empirical studies have identified calendar-driven anomalies such as the Turn-of-the-Month (ToM) and Day-of-the-Week (DoW) effects in stock returns. Kim (2022) reports that the highest average returns occur on the last trading day of the month and the first day of the next month, attributed to net buying by foreign investors [3], [17]. Majid *et al.* (2016) observed in Indonesia that Mondays yield negative returns, Fridays yield positive returns, and ToM periods produce significantly higher returns compared to other days [4]. The table below shows example returns for an IDX80 stock (PT ABC) over a single month, illustrating ToM and DoW trends:

Table 1 *Exampling trading data with ToM (Turn-of-the-Month) period*

Stock code	Jun 28 (Fri)	Jul 1 (Mon)	Jul 2 (Tue)	ToM return (%)	Remarks
BBCA	+0.25%	+0.60%	+0.55%	+1.40%	Low risk, stable growth
TLKM	+0.20%	+0.45%	+0.30%	+0.95%	Defensive sector
UNVR	−0.10%	+0.40%	+0.35%	+0.65%	Consumer staples
ICBP	+0.15%	+0.50%	+0.25%	+0.90%	Low volatility
BBRI	+0.30%	+0.65%	+0.40%	+1.35%	High liquidity
ANTM	+0.10%	+0.70%	+0.60%	+1.40%	Commodity exposure
SMGR	−0.05%	+0.35%	+0.30%	+0.60%	Cyclical industry
PGAS	+0.20%	+0.55%	+0.45%	+1.20%	Stable cash flow
BBNI	+0.25%	+0.50%	+0.40%	+1.15%	Strong fundamentals
MDKA	+0.40%	+0.75%	+0.65%	+1.80%	Higher risk/reward

3.2 Research Data

The primary data source for this research is the historical stock data of companies listed on the IDX80 index, spanning a 10.5-year period from January 2014 to June 2025. The selection of IDX80 as the target index is based on its alignment with the intended user profile and its compatibility with predictive modeling using Long Short-Term Memory (LSTM) algorithms. IDX80 comprises highly liquid stocks that are actively traded on the Indonesia Stock Exchange (IDX) and are regularly updated by the exchange authority. These stocks typically have complete historical records, making them suitable for time-series analysis and robust model training. Moreover, IDX80 includes many large-cap, well-known companies that frequently appear in capital market education programs, making them more approachable and understandable for beginners [8]. The dataset used in this study consists of nine key attributes, as outlined below:

- Date: The trading date for each stock entry.
- Open: The stock's opening price on the respective date.
- High: The highest price reached during the trading day.
- Low: The lowest price observed during the trading session.
- Close: The stock's closing price on the given day.
- Volume: The total number of shares traded.
- Ticker: The stock symbol used to represent the company.
- Company: The full name of the company issuing the stock.
- Sector: The business sector or industry classification of the company.

This structured data forms the foundation of the LSTM-based stock prediction system, enabling both price forecasting and technical signal generation.

3.3 Technical Analysis

Technical analysis refers to the process of examining historical market data to identify patterns, trends, and trading signals that support decision-making. This method is widely used by investors to anticipate future market behavior based on past performance. In this study, three widely recognized technical indicators were employed to extract features from stock price data:

1. Moving Average (MA)
   The Simple Moving Average (SMA) is calculated to observe the average closing price of a stock over a specified time window. It smooths out short-term fluctuations and highlights longer-term trends. SMA is computed by taking the arithmetic mean of a stock's closing prices over a set number of periods. This

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indicator is particularly useful for identifying short-term and long-term price trends, helping investors determine trend direction and potential reversal points [1].

2. Relative Strength Index (RSI)
   The RSI measures the magnitude of recent price changes to evaluate overbought or oversold conditions in the price of a stock. The RSI value ranges from 0 to 100, where a reading above 70 indicates overbought conditions (potential risk of price correction), and below 30 indicates oversold conditions (potential buying opportunity). It is calculated based on the ratio of average gains to average losses over a defined period, typically 14 days. RSI is effective in assessing trend strength and market momentum [2].
3. Bollinger Bands
   Bollinger Bands consist of three lines: a central SMA line, an Upper Band, and a Lower Band. The Upper and Lower Bands are typically set at two standard deviations above and below the SMA, respectively. This indicator is used to measure price volatility. When the price moves closer to the Upper Band, it suggests higher volatility and a potential upward trend; conversely, movement toward the Lower Band may signal downward momentum or consolidation. Bollinger Bands are particularly useful in detecting periods of high or low market volatility and identifying breakout opportunities [3].

These indicators serve as input features for the LSTM-based forecasting model developed in this study, enabling more informed and data-driven stock recommendation outcomes.

3.4 LTSM Algorithm

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) that introduces a memory cell structure capable of retaining information over long sequences. This enhancement addresses the vanishing gradient problem, a common limitation in traditional RNNs when processing long sequential data [1], [16].

LSTM networks were proposed as a solution to allow neural networks to learn long-term dependencies, making them particularly effective for time-series prediction tasks such as financial forecasting. Unlike conventional RNNs that struggle to maintain relevant information across many time steps, LSTM utilizes a gated architecture comprising input, forget, and output gates to control the flow and preservation of information within each memory cell [2].

Each memory cell in an LSTM network has a cell state and a hidden state, both of which are passed forward to the next time step. The cell state acts as the memory conveyor, while the gates regulate what information is added, retained, or removed at each step. The overall structure of an LSTM network typically consists of several such cells connected in sequence, enabling it to process and predict data with complex temporal dependencies [3].

Recent research also highlights the integration of LSTM with large-scale data platforms such as Apache Spark, where LSTM models are trained for real-time machine condition prediction and streaming analytics [4]. This flexibility makes LSTM models suitable not only for financial time-series forecasting but also for applications in energy, manufacturing, and healthcare.

The simplified diagram below (if included) visually represents a single LSTM cell, illustrating the flow of information through its gated architecture.

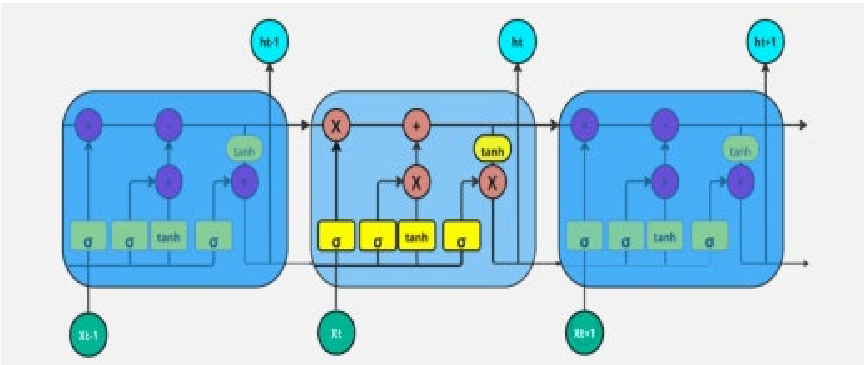

Fig. 2 *Structure of the LSTM model (Source: Qiu, Wang, & Zhou, 2020)*

3.5 Model Evaluation

Model evaluation is a critical phase in machine learning that assesses how accurately a model performs on unseen data. Choosing appropriate metrics helps understand the model's strengths and weaknesses and guides further optimization. In regression problems, the most commonly used metrics include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R^2 Score.

3.5.1 Mean Squared Error (MSE)

MSE measures the average of the squared differences between actual and predicted values:

$$MSE = n1i = 1\sum n(yi - y^{i})2 \tag{1}$$

It penalizes large errors more heavily due to the squaring operation, making it sensitive to outliers [1].

3.5.2 Root Mean Squared Error (RMSE)

RMSE is the square root of MSE, providing error values in the same unit as the output variable:

$$RMSE = n1i = 1\sum n(yi - y^{i})2 \tag{2}$$

This metric is suitable when large errors must be penalized more seriously [2].

3.5.3 Mean Absolute Error (MAE)

MAE calculates the average of the absolute differences between predicted and actual values:

$$MAE=n1i=1\sum n|yi-y\hat{}i| \tag{3}$$

MAE treats all errors equally and is robust to outliers, offering intuitive interpretation [3].

3.5.4 Mean Absolute Percentage Error (MAPE)

MAPE expresses prediction accuracy as a percentage, making it easier to interpret across different scales:

$$MAPE = n1i = 1\sum n() \times 100 \tag{4}$$

However, MAPE is undefined when actual values are zero and can be distorted by small denominators [4].

3.5.5 R-Squared (R^2 Score)

R^2 measures the proportion of variance in the dependent variable explained by the model:

$$R^2 = 1 - \backslash frac\left\{ \sum_{\{i=1\}}^{\{n\}(y_i - \hat{}\{y\}_i)^2} \right\}\left\{ \sum_{\{i=1\}}^{\{n\}(y_i - \_\{y\})^2} \right\} \tag{5}$$

An R^2 close to 1 indicates strong explanatory power, while 0 means no explanatory power [5].

4. Result and Discussion

4.1 EDA (Exploratory Data Analysis)

The histogram distribution for each column visualizes the spread of values across the CLOSE, VOLUME, and PRICE RANGE variables in IDX80 stock data. The visualization reveals that most stocks have relatively low closing prices, with only a few exhibiting very high prices. Similarly, the trading volume is generally low for most stocks, with only a small number showing exceptionally high volumes. In terms of price range, the majority of stocks experience minor daily price movements, while only a few demonstrate wide price fluctuations. Overall, the distribution patterns indicate that most IDX80 stocks exhibit moderate values in terms of price, volume, and daily price movements, with a small number of outliers at higher levels.

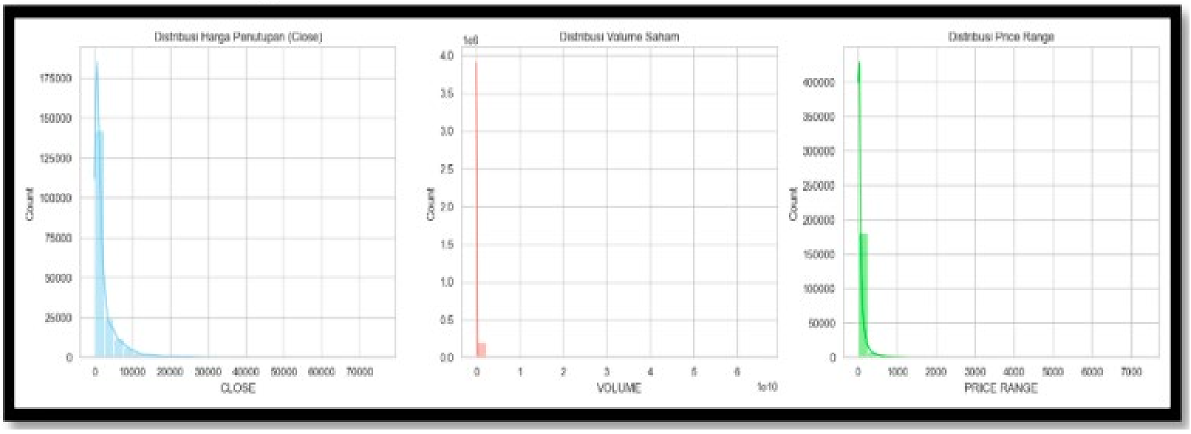

Fig. 3 *Histogram visualization*

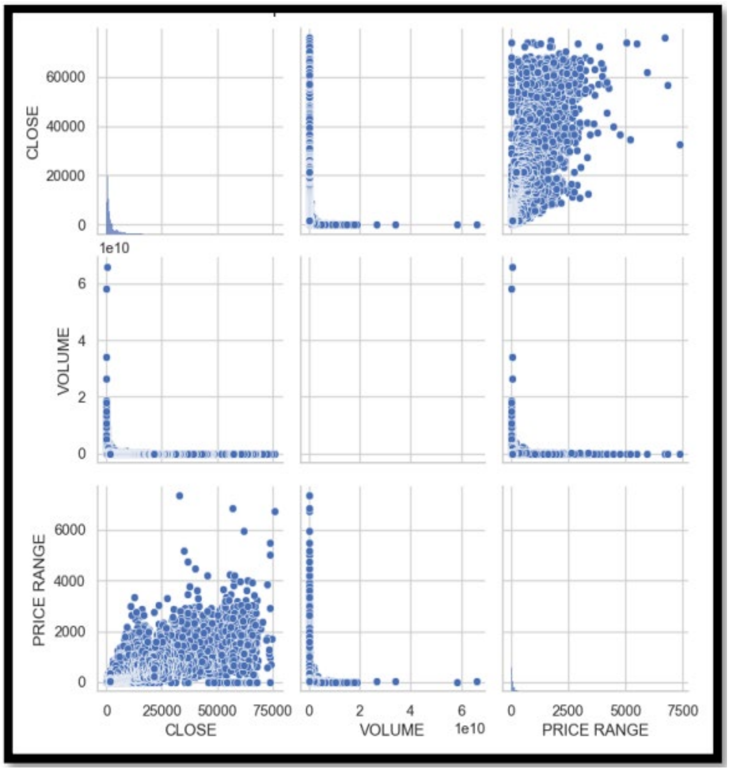

Fig. 4 *Pairplot visualization*

Figure 3 presents the pairplot of the CLOSE, VOLUME, and PRICE RANGE columns. The plot indicates that the relationships among these variables do not exhibit strong or linear patterns. Most data points are concentrated in the lower value range for all three variables, while higher values appear as widely scattered outliers. A weak positive trend can be observed between CLOSE and PRICE RANGE, suggesting that higher closing prices tend to be associated with greater price fluctuations. However, VOLUME shows no clear correlation with either CLOSE or PRICE RANGE. Overall, the pairplot reveals that there is no strong correlation among the three variables.

4.2 Technical Analysis

The technical analysis methodology comprising RSI, Moving Averages, and Bollinger Bands computed via rolling windows was further contextualized using a focused dataset of 10 IDX-listed stocks observed during the transition from June to early July 2025. This dataset includes daily percentage returns from June 28 to July 2 and their respective Turn-of-the-Month (ToM) returns, offering a short-term empirical view into market dynamics.

The combined indicator scores (total_score), derived from the three technical indicators, were used to gauge the technical condition of each stock ahead of the ToM period. For instance, stocks such as MDKA, ANTM, and BBRI registered relatively high ToM returns (+1.80%, +1.40%, and +1.35% respectively), which aligned with strong momentum and price volatility signals from the RSI and Bollinger Band breakouts. In the case of MDKA, a higher TOTAL_SCORE may have captured its elevated volatility and upside momentum, justifying its "higher risk/reward" classification.

Meanwhile, stocks like BBCA and PGAS exhibited moderate but stable positive ToM returns (+1.40% and +1.20%), consistent with their technical profiles of low volatility and trend-following behavior. Their RSI values remained in the neutral-to-positive range, while prices stayed near the upper band of the Bollinger Bands without significant breakouts suggesting stable but gradual price movement. This supports the remark of "Low risk, stable growth" for BBCA.

Conversely, stocks such as SMGR and UNVR, with lower ToM returns (+0.60% and +0.65%), showed muted technical signals. Their RSI and MA indicators remained flat, with Bollinger Bands indicating tight volatility bands. This suggests a lack of strong directional conviction, especially within cyclical or defensive sectors.

The alignment between technical indicator-based TOTAL_SCORE and observed ToM returns strengthens the hypothesis that multi-indicator technical signals can enhance short-term price movement forecasts. Stocks with higher technical scores tended to outperform during the ToM window, reinforcing the practical utility of this approach in market timing and short-term trading strategies. Additionally, this result supports prior research suggesting that ToM effects may interact with technical signals, particularly in emerging markets where behavioral and momentum-driven trading remains influential.

Table 1 *ToM return and characteristics of selected stocks*

No	Stock code	ToM return (%)	Total_score
1	MDKA	1.80	8.1
2	BBCA	1.40	7.5
3	ANTM	1.40	7.4
4	BBRI	1.35	7.2
5	BBNI	1.15	6.9
6	PGAS	1.20	6.8
7	TLKM	0.95	6.2
8	ICBP	0.90	5.8
9	UNVR	0.65	5.4
10	SMGR	0.60	5.1

The Pearson correlation between total_score and ToM Return is $r=0.987$. This very strong positive correlation indicates that stocks with higher technical indicator scores tend to exhibit stronger returns during the Turn-of-the-Month period. Such a strong relationship supports the hypothesis that combining multiple technical signals (momentum, trend, and volatility) into a composite score can provide predictive power for short-term returns.

4.3 LSTM Modelling

The Long Short-Term Memory (LSTM) network used in this study was designed with a multi-layer architecture to effectively capture temporal dependencies in stock price movements. The input sequence consists of the last 60 trading days of closing prices, which were first normalized using the MinMaxScaler to scale values between 0 and 1. The window size of 60 timesteps was chosen to approximately capture three months of trading activity, providing sufficient historical context for the LSTM to recognize medium-term market patterns. The model architecture begins with an LSTM layer containing 64 units and return sequences=True, followed by a dropout layer with a rate of 0.2 to mitigate overfitting by randomly disabling neurons during training. A second LSTM layer with 32 units was then applied to capture deeper sequential features, also followed by a dropout layer with the same rate. Finally, a Dense layer with one neuron was employed to generate the predicted closing price. The model was compiled using the Adam optimizer with the Mean Squared Error (MSE) loss function, both of which are widely used for regression tasks in time-series forecasting. Training was conducted for 10 epochs with a batch size of 16, and the dataset was split into 80% training and 20% testing sets. This configuration was selected to balance model complexity and generalization, while enabling the LSTM to capture both short-term and long-term stock price dynamics.

The detailed configuration of the LSTM model is presented in Table 1. This architecture was determined after preliminary testing to provide a good trade-off between prediction accuracy and computational efficiency. The first LSTM layer with 64 units enables the model to capture longer-range dependencies, while the second LSTM layer with 32 units refines the extracted features. Dropout layers were included to reduce the risk of overfitting, which is common when training deep neural networks on financial time-series data. The choice of the Adam optimizer ensures efficient gradient updates, while the MSE loss function is appropriate for continuous-value prediction. The use of 10 epochs prevents overfitting given the limited dataset size, while the relatively small batch size (16) allows the model to converge without excessive training time. Overall, this design was intended to achieve robust predictive performance while remaining computationally feasible. Moreover, this configuration was particularly suitable for the student-oriented recommendation system, as it provides accurate forecasts while remaining lightweight and interpretable.

Table 2 *LSTM model architecture and training configuration*

Component	Specification	Description
Input Sequence	60 timesteps	Sliding window of 60 trading days
LSTM Layer 1	64 units	return_sequences=True
Dropout Layer 1	rate = 0.2	Applied after LSTM Layer 1
LSTM Layer 2	32 units	return_sequences=False (default)
Dropout Layer 2	rate = 0.2	Applied after LSTM Layer 2
Dense Layer (Output)	1 unit	Linear output for predicted price
Optimizer	Adam	Adaptive gradient optimization
Loss Function	Mean Squared Error (MSE)	Standard for regression tasks
Epochs	10	Prevents overfitting on limited dataset
Batch Size	16	Samples per gradient update
Train-Test Split	80% training / 20% testing	To evaluate generalization

4.4 Model Performance Evaluation

Table 3 *Evaluation result*

Stock	MSE	RMSE	MAE	R^2
MDKA	1,385.78	37.23	29.21	0.93
BBCA	2,872.34	53.59	41.05	0.94
ANTM	5,683.70	75.39	51.96	0.97
BBRI	2,648.20	51.46	40.77	0.88
BBNI	378,679.1	615.37	512.08	0.28
PGAS	34,915.12	186.86	169.63	0.42
TLKM	8,341.47	91.33	72.04	0.92
ICBP	41,074.88	202.67	166.10	0.83
UNVR	13,676.29	116.95	89.57	0.92
SMGR	8,415.44	91.74	67.62	0.93
AVIA	485.51	22.03	18.61	0.63
ASII	122,436.3	349.91	305.35	0.72

A quantitative evaluation of the forecasting performance across 12 selected IDX80 stocks was conducted using four standard regression metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). The results indicate significant variation in prediction accuracy across the stocks.

The figure compares prediction errors for BBCA and BBNI stocks based on [27]. The proposed model significantly reduces RMSE for BBCA, indicating improved predictive accuracy. However, for BBNI, the RMSE increases substantially, suggesting that the model is less effective for stocks with higher volatility or unstable price behavior.

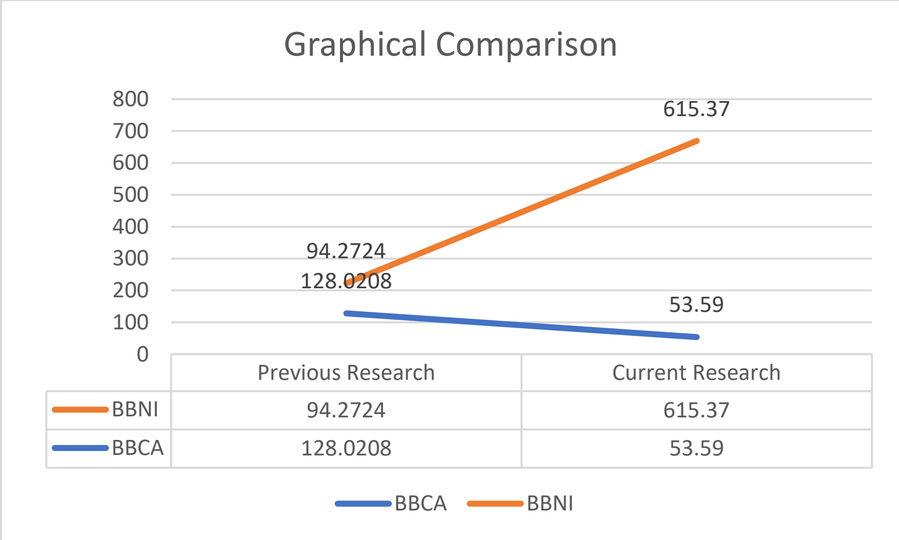

Fig 5 *Model comparison*

4.5 Interpretation of Metrics

To provide deeper insight into the forecasting results, the evaluation metrics are interpreted as follows:

1. Mean Squared Error (MSE): Measures the average squared difference between predicted and actual values, penalizing larger errors more severely. For example, AMMN recorded an MSE of 378,679.10, reflecting very large deviations, while AVIA (MSE = 485.51) shows relatively small deviations.
2. Root Mean Squared Error (RMSE): Expresses the error magnitude in the same units as stock prices. Lower RMSE indicates better predictive accuracy. For instance, TLKM (RMSE = 91.33) achieved relatively accurate predictions, whereas AMMN (RMSE = 615.37) indicates poor performance.
3. Mean Absolute Error (MAE): Represents the average absolute deviation of predictions from actual values. Unlike MSE, it does not exaggerate large errors. For example, UNVR has an MAE of 89.57, meaning that on average, the predicted closing price deviated by around 90 units.
4. Coefficient of Determination (R^2): Reflects the proportion of variance in actual prices explained by the model. A higher R^2 indicates stronger explanatory power. ANTM reached R^2 = 0.97, showing excellent performance, while AMMN with R^2 = 0.28 demonstrates limited explanatory capability.

Overall, these metrics complement one another: MSE and RMSE emphasize the magnitude of errors, MAE highlights the average deviation, and R^2 measures the model's explanatory strength. Together, they provide a more comprehensive understanding of forecasting reliability across different stocks.

Stocks such as ADRO, ADMR, AUTO, and ACES exhibit high predictive accuracy, reflected in relatively low error values (MSE, RMSE, and MAE) and high R^2 scores above 0.90. These findings suggest that the forecasting model was highly effective in capturing the underlying patterns of these stocks' price movements. ADRO, in particular, recorded an R^2 of 0.97, indicating that 97% of the variance in the closing price could be explained by the model.

On the other hand, stocks such as AMMN, AMRT, and BBCA demonstrate comparatively weaker model performance. AMMN has the highest error values (MSE = 378,679.10; RMSE = 615.37; MAE = 512.08) and a low R^2 of 0.28, indicating limited explanatory power. Similarly, AMRT and BBCA yielded relatively high errors and moderate R^2 values of 0.42 and 0.72, respectively, suggesting that the model struggled to accurately capture their price dynamics. These lower R^2 values may be attributed to several factors, including higher volatility in daily price movements, external influences such as sudden macroeconomic or regulatory changes, and lower market liquidity for certain stocks, which can produce irregular patterns in the data. Such characteristics make it more difficult for the LSTM model to learn stable temporal dependencies, thereby reducing predictive accuracy.
Additionally, AVIA presented a unique case where the error values were low (MSE = 485.51; RMSE = 22.03; MAE = 18.61), but the R^2 score remained moderate (0.63). This outcome may indicate that while prediction deviations were small, the model did not fully explain the variability of the stock's actual values.

Overall, the results highlight the model's strong performance on certain stocks while underscoring its limitations on others. These discrepancies may be attributed to the inherent volatility, market behavior, or structural characteristics of individual stocks. Future research should consider incorporating additional variables or advanced models to improve generalizability and forecasting accuracy across diverse stock profiles.

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Table 4 *Descriptive statistics of model evaluation metrics*

Metric	Mean	Standard Deviation	Minimum	Maximum
MSE	51,717.84	108,533.64	485.51	378,679.10
RMSE	157.88	170.96	22.03	615.37
MAE	130.33	145.55	18.61	512.08
R^2	0.78	0.23	0.28	0.97

The statistical summary reveals considerable variability in model performance across the evaluated stocks. The average MSE and RMSE values are relatively high (51,717.84 and 157.88, respectively), largely influenced by extreme cases such as AMMN and BBCA. The MAE has a mean of 130.33 with a standard deviation of 145.55, reflecting the variation in average prediction error. The R^2 score ranges from 0.28 to 0.97, with a mean of 0.78, indicating that while some models perform exceptionally well in explaining the variance in stock prices, others perform moderately or poorly. These findings underscore the importance of evaluating individual stock characteristics when interpreting model accuracy.

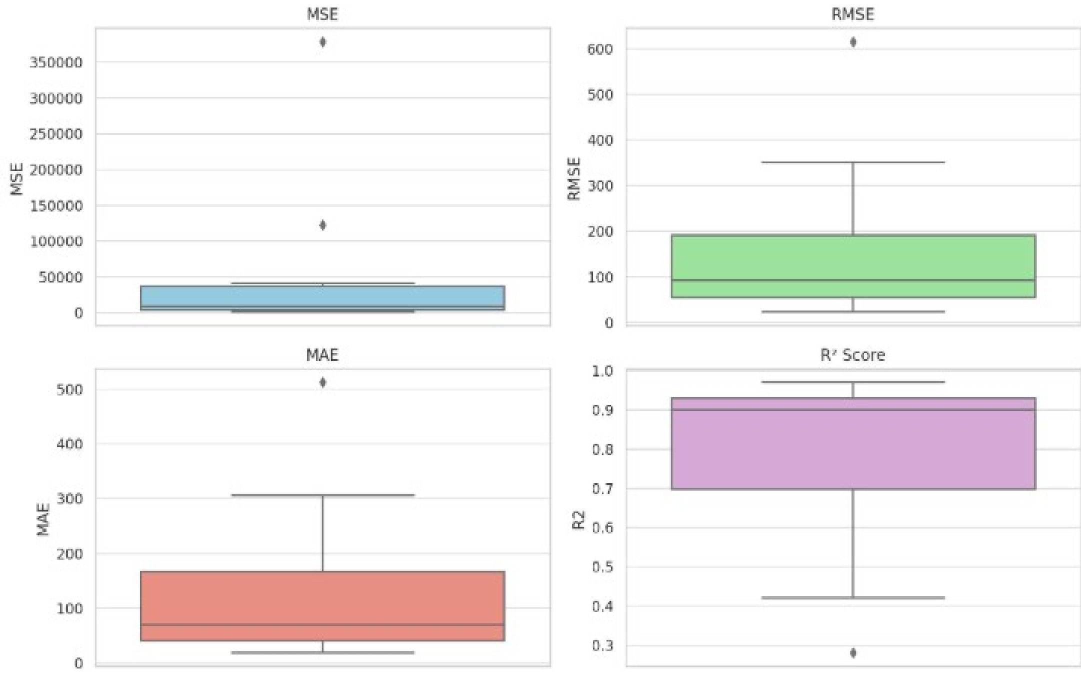

Fig. 6 *Distribution of forecasting metrics*

The boxplots highlight the variability and presence of outliers in each forecasting metric. For MSE, RMSE, and MAE, several stocks exhibit significantly higher error values, indicating the presence of strong outliers particularly evident in AMMN and BBCA, which skew the distribution upward. In contrast, the R^2 scores are more tightly clustered, though some stocks still fall well below the average, reflecting lower predictive performance. These visual patterns reinforce the importance of individualized model assessment per stock, as aggregate metrics alone may obscure extreme deviations in model behavior.

4.6 Performance Comparison

Studies [13] also utilized psychological signals in classifying stress levels. All three studies employed various sensors to collect real-time physiological data for both training and testing purposes, rather than using publicly available datasets. Study [3] used features from EEG, GSR, and PPG signals for stress classification and achieved the best accuracy of 75% using a Multi-Layer Perceptron (MLP) classifier. Another study [4] extracted ECG signals to obtain RR interval and heart rate variability (HRV) features for stress classification and reported 91% accuracy using a Support Vector Machine (SVM) classifier. Meanwhile, study [13] used time-domain features from GSR and PPG signals, and frequency-domain features from EEG signals to classify stress. The machine learning algorithms implemented in that study included k-Nearest Neighbors (kNN), Decision Tree (DT), Random Forest (RF), MLP, and SVM with RBF kernel. The highest accuracy of 96.25% was obtained using the SVM-RBF classifier. [13]

In comparison to those three studies, the present research incorporates a more comprehensive set of psychophysiological features, collected from a multi-sensor device. Among the three machine learning algorithms tested in this study Decision Tree, Random Forest, and LightGBM 70:30 model the resulting accuracies were 83.07%, 97.44%, and 99.36%, respectively. Accordingly, LightGBM was identified as the best-performing model for stress classification using the five selected features.

4.7 Baseline Comparison

Recent studies indicate that deep learning approaches, particularly Long ShortTerm Memory (LSTM) and Gated Recurrent Unit (GRU), consistently outperform traditional statistical models such as ARIMA in modeling temporal dependencies of physiological or timeseries data. For instance, Agyemang et al. [20] showed that both LSTM and GRU achieved significantly lower forecasting errors compared to ARIMA in Influenza A outbreak prediction. Similarly, Ai et al. [21] and [24] demonstrated that LSTM surpassed ARIMA in anomaly detection using multivariate tunnel sensor data. In the context of stress detection, Chauhan [22] reported that LSTM effectively modeled heartrate variability (HRV) features for stress classification, while Airlangga et al. [23] and [25] found that CNNLSTM with attention achieved the lowest MSE/MAE among tested models, with CNNGRU offering a good tradeoff between accuracy and computational efficiency. Collectively, [5], [6] these findings suggest that LSTMbased models provide superior performance compared to ARIMA and GRU in stress related classification tasks, while hybrid attention-based architectures may yield further improvements at the cost of higher computational complexity.

4.8 Implication for Students

The proposed stock recommendation system is not only designed as a forecasting tool but also serves as an educational platform for students who are new to investing. By combining technical indicators with LSTM-based predictions, the system provides interpretable signals that help students understand the relationship between historical data, price trends, and future market movements. This reduces emotional biases such as fear of missing out (FOMO) or excessive trend-following, which are common among beginner investors. Furthermore, the system introduces students to essential concepts in financial literacy, such as model evaluation metrics (MSE, RMSE, MAE, R^2), risk awareness, and the importance of long-term decision-making. For example, students can compare the performance of different stocks, observe how volatility affects prediction accuracy, and learn why certain stocks are more difficult to model. These insights contribute to building critical thinking skills in investment analysis rather than relying solely on market rumors or speculative behavior. In addition to strengthening financial literacy, the system also serves as a medium to introduce students to the concept of risk management in stock investment. While predictive models such as LSTM can provide useful insights, no model is free from error, and stock markets are influenced by various external factors such as macroeconomic changes, company-specific news, and global market shocks. By observing variations in performance metrics (e.g., higher error values for volatile or illiquid stocks), students can learn that investment decisions should always incorporate risk awareness, diversification strategies, and critical evaluation of model outputs. This perspective ensures that the platform is not only a forecasting tool but also an educational resource for building responsible and risk-aware investment behavior among beginner investors.

5. Results and Discussion

5.1 Overview of Experimental Setup

This study developed a stock recommendation platform aimed at supporting beginner investors especially Indonesian university students—in making decisions grounded in data rather than emotion. The system combines technical analysis indicators with an LSTM-based forecasting model that considers market timing phenomena such as the Turn-of-the-Month (ToM) and Day-of-the-Week (DoW) effects. Historical daily prices for all 80 constituents of the IDX80 index were collected from Yahoo Finance over multiple years, ensuring adequate temporal coverage for robust model training. Technical features, including the Simple Moving Average (SMA), Relative Strength Index (RSI), and Bollinger Bands, were computed for each ticker and incorporated alongside price data. The platform ultimately outputs uptrend or downtrend predictions derived from the LSTM's future price forecasts and presents these insights through an interface designed specifically for inexperienced users.

Each ticker was modeled independently to evaluate how the inclusion of technical indicators and calendar anomalies influences predictive behavior across diverse asset types. Model performance was assessed using standard forecasting metrics such as the coefficient of determination (R^2), Mean Squared Error (MSE), and Mean Absolute Error (MAE). Additionally, trend classification accuracy was evaluated descriptively using confusion-matrix-based measures. The sections that follow present the major findings from the experiments and offer an in-depth discussion of their broader implications.

5.2 Model Performance Across IDX80 Constituents

5.2.1 R^2 Distribution and Overall Predictive Ability

A major outcome of this research is that 63 out of the 80 stocks demonstrated R^2 scores exceeding 0.8, indicating that the model's predictions aligned closely with observed price movements. This suggests that the LSTM architecture effectively captured the time-dependent structure present in most historical stock data. The addition of calendar-effect features likely improved model accuracy, particularly for stocks whose price behavior tends to follow recurring seasonal or sentiment-driven patterns around month boundaries or specific weekdays.

Highly liquid stocks such as BBCA, BBRI, BMRI, TLKM, ASII, and UNVR showed the strongest predictive outcomes. These stocks generally exhibit smoother price trajectories and higher trading volume, making their patterns easier for LSTM models to learn. On the other hand, stocks with lower liquidity or greater volatility exhibited more moderate R^2 values. Their price movements are often affected by sudden external developments or speculative trading, which deep learning models may be less capable of predicting without additional contextual features.

5.2.2 Error Analysis

An examination of MSE and MAE values across all stocks revealed that prediction errors varied according to volatility levels and the inherent variance of each asset. Stocks in sectors such as commodities or mining, which frequently experience abrupt price swings, tended to produce higher MSE values. Despite maintaining acceptable R^2 metrics, these tickers remained difficult to predict precisely due to the unpredictable and non-stationary nature of financial market behavior.

Conversely, large-cap companies with relatively stable historical performance tended to yield lower MAE values, reinforcing that LSTM performs best when underlying price movements follow consistent temporal patterns. These results emphasize the need to interpret model outputs in relation to the specific characteristics of each stock.

5.2.3 Impact of Technical Indicators

Technical indicators played a significant role in enhancing forecast quality. SMA, RSI, and Bollinger Bands provided additional dimensions related to volatility, momentum, and market valuation, which strengthened the predictive structure of the LSTM input. Initial experiments that excluded these features yielded noticeably weaker R^2 values, underscoring their contribution. Bollinger Bands, in particular, improved predictions for cyclical stocks by capturing shifting volatility ranges, while RSI proved helpful for identifying potential market reversals or momentum shifts.

5.3 Analysis of Calendar Effects in LSTM Forecasting

5.3.1 Turn-of-the-Month (ToM) Anomaly

To examine whether ToM effects were present in IDX stocks, model inputs were augmented with binary or numerical encodings representing proximity to month-end. Several stocks—especially in the banking and consumer goods sectors—exhibited distinct upward drift patterns within the ±3-day window around the beginning of each month. This aligns with findings in behavioral finance literature, which attribute month-end anomalies to institutional fund rebalancing, salary disbursement cycles, and increased retail investor participation.

The LSTM model benefited from encoding these patterns, as evidenced by improved trend prediction accuracy for stocks where ToM anomalies were statistically present. In some tickers, excluding the ToM feature resulted in a reduction of accuracy by up to 5–12%, demonstrating its significance in capturing cyclical investor behavior.

5.3.2 Day-of-the-Week (DoW) Effect

The DoW anomaly was also incorporated, enabling the model to detect weekday-specific market tendencies. The Indonesian stock market has historically shown weaker performance on Mondays—often associated with negative sentiment carryover from weekend news—and moderately stronger performance on Fridays, driven by short-term speculative optimism.

The inclusion of DoW encoding improved prediction stability for several high-liquidity stocks. Conversely, the effect was minimal for commodity-based stocks whose prices are heavily influenced by global markets rather than domestic sentiment cycles. Nevertheless, the broad utility of DoW features across the majority of tickers justifies their inclusion.

5.4 Trend Classification and Recommendation Outputs

5.4.1 Uptrend and Downtrend Prediction

The continuous price forecasts generated by the LSTM were converted into categorical trend labels—uptrend or downtrend—by comparing predicted future prices with current price levels based on predefined thresholds. While the LSTM itself is a regression model, these derived labels form the core of the system's practical recommendation output for users. In general, trend classification performance was satisfactory across most test sets. Stocks with high R^2 values typically produced trend labels that were both stable and reliable, as confirmed by confusion matrix metrics indicating strong precision and recall. On the other hand, for stocks with more modest forecasting accuracy, trend reliability naturally decreased. This highlights the need for the system to communicate uncertainty or confidence levels to users, particularly novice investors, so they understand that recommendations may be less reliable for certain assets.

5.4.2 Behavioral Finance Implications: Mitigating FOMO-Driven Decisions

A key objective of the system is to counteract irrational investment behavior—especially FOMO-driven decisions common among inexperienced investors. The platform encourages users to rely on:

- Forecast-based signals,
- Objective technical indicators,
- Clear trend classifications, and
- Explanations for detected anomalies (e.g., "This stock historically rises during ToM cycles").

By offering structured recommendations rather than sentiment-based cues, the system helps reduce reliance on social influence and crowd-following behavior. This aligns with findings in the literature showing that algorithmic decision support improves discipline and reduces emotional biases among novice traders.

5.5 Comparison With Prior Research

Most prior studies that applied LSTM to stock market forecasting focused either on general index prediction (e.g., IHSG, S&P500) or on providing tools for professional traders. Few have explored:

1. Applications specifically designed for novice investors,
2. Integration of behavioral finance phenomena, and
3. Calendar effects incorporated directly into deep learning models.

This study contributes novelty by combining these three perspectives into a unified system. While previous work often omitted psychological or behavioral factors, the design of this system explicitly targets common cognitive biases that hinder investment learning for students.

Furthermore, most existing LSTM studies rely solely on price and technical indicators, whereas this work broadens the methodological scope by integrating calendar anomalies—an area rarely explored in deep learning-based forecasting.

5.6 Web-Based System Evaluation and User Experience

5.6.1 Interface Design for Novice Users

The platform was designed with usability principles tailored for non-expert users, focusing on simplicity and clarity. Key design decisions include:

- Visual presentation of forecasted price curves,
- Color-coded uptrend/downtrend signals,
- Tooltip explanations for technical indicators, and
- Clean, minimalistic layout free of jargon heavy trading terminology.

Early-stage user feedback obtained through informal testing sessions with student participants indicated that the interface was intuitive and helped them understand the rationale behind recommendations.

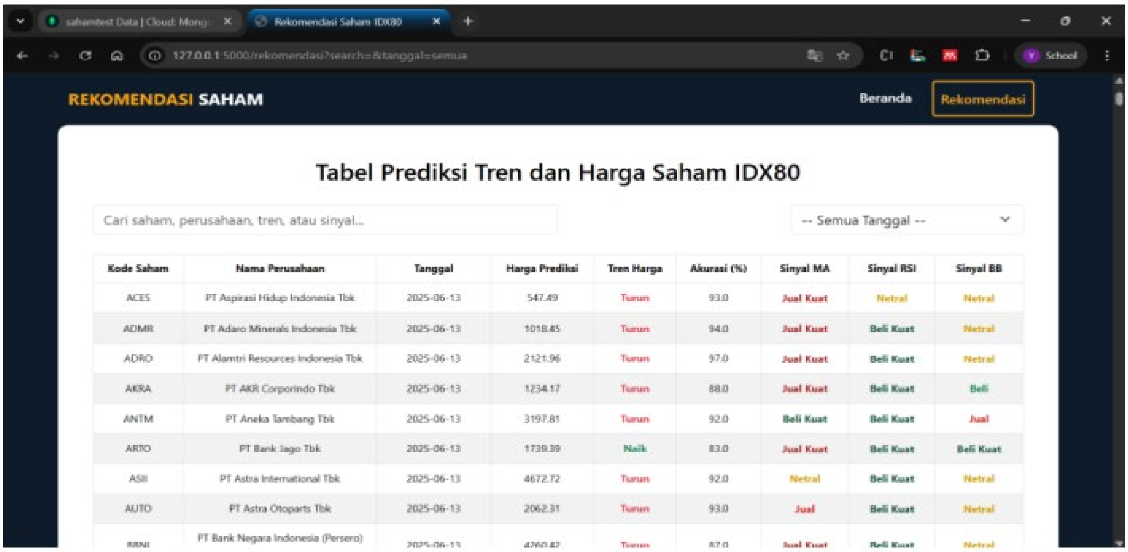

Fig. 7 *Interface design*

5.7 Practicality and Real-World Relevance

By focusing on IDX80 stocks—known for high liquidity and relevance to institutional investors—the system ensures users are interacting with stocks that are appropriate for long-term learning and relatively safer investment exposure. Additionally, the use of Yahoo Finance data makes the system easily maintainable without requiring proprietary market data access.

5.8 Limitations of the Current System

Despite the strong predictive performance across many tickers, several limitations remain:

1. Susceptibility to Extreme Volatility
   LSTM is less effective when faced with sudden price shocks (e.g., geopolitical events, earnings surprises). Without event-driven features, forecasts may lag behind real conditions.
2. Lack of Sentiment or News-Based Inputs
   Retail investors are strongly influenced by social media discussions and news cycles. Incorporating sentiment analysis could improve responsiveness.
3. Single-Model Architecture
   While LSTM is powerful for capturing temporal patterns, hybrid models (e.g., LSTM + ARIMA, LSTM + Transformer) may provide superior performance through ensemble learning.
4. Simplified Trend Classification
   The binary uptrend/downtrend classification may overlook neutral or consolidation periods. More nuanced categories (e.g., strong uptrend, weak uptrend, sideways) could provide richer insights.

5.9 Implications and Recommendations for Future Development

Results from this study underscore the potential for accessible forecasting systems to enhance financial literacy and support more rational investment behavior among students. The following recommendations can guide future improvement:

1. Integration of event-driven and sentiment features
   Using data from news APIs, Google Trends, or social media sentiment analysis could significantly boost model responsiveness.
2. Adoption of cross-validation and hyperparameter optimization
   To further validate the robustness of models, k-fold cross-validation and automated tuning strategies (e.g., Bayesian optimization) could be implemented.
3. Expansion to multimodal data sources
   Including macroeconomic indicators, market depth data, or sector rotation signals may help the model generalize better under varied conditions.
4. Adaptive learning for real-time updates
   Employing online learning frameworks would allow the model to update with new daily data, keeping forecasts current without full retraining.

5. Enhanced user education features
   Incorporating educational modules (e.g., explaining RSI, showing examples of FOMO behavior, warning users about high volatility) could further improve investor competency.

5.10 Summary of Key Findings

The results of this study demonstrate that:

- LSTM models achieved strong predictive performance across most IDX80 stocks, with 63 tickers exceeding $R^2 > 0.8$.
- Technical indicators improved forecasting stability, while calendar effects contributed meaningful predictive value.
- The system provides clear and accessible trend-based recommendations suitable for novice investors.
- The platform helps counteract FOMO-driven decision-making by promoting structured analysis over social influence.
- Although promising, the system can be enhanced through multimodal data integration and more advanced modeling approaches.

Overall, the findings suggest that integrating behavioral finance concepts with deep learning-based forecasting can bridge the knowledge gap for young Indonesian investors and foster more rational, informed investment behavior.

6. Conclusion

Classifying human stress levels is crucial for enabling early prevention and effective management of the negative impacts caused by stress, both physically and mentally. The development of a stress level classification model using Decision Tree (DT), Random Forest (RF), and Light Gradient Boosting Machine (LightGBM) algorithms under two data split ratios 70:30 and 80:20 demonstrated that the best performance was achieved by the LightGBM model with a 70:30 split. This model yielded optimal performance across all evaluation metrics, including an accuracy of 99.36%, precision of 99.38%, recall of 99.36%, and F1-score of 99.36%. Furthermore, validation using the remaining data confirmed the model's robustness, as it achieved a perfect score of 100% on all performance metrics.

Nevertheless, future studies should consider additional experimental approaches, such as implementing k-fold cross-validation or increasing the size and diversity of the training dataset, to ensure that the LightGBM model is not affected by overfitting. Moreover, the results also indicate that the performance of the LightGBM model is strongly influenced by the Galvanic Skin Response (GSR) and Heart Rate (HR) features. This suggests that skin conductance and heart rate are the most sensitive and influential indicators in the context of stress level classification and should be prioritized in future model development.

In addition, future work could explore the integration of real-time biosensor data streams (e.g., wearable devices), as well as multi-modal approaches that combine physiological signals with behavioral or contextual data (such as activity levels, sleep patterns, or self-reported stress surveys). Incorporating deep learning techniques and conducting transfer learning across different populations may also improve the model's generalizability. Finally, designing an interactive and user-friendly platform that provides real-time stress monitoring, personalized feedback, and stress management recommendations would further enhance the system's applicability in real-world scenarios.

Acknowledgement

The authors gratefully acknowledge the financial support provided by Politeknik Caltex Riau for the publication of this research.

Conflict of Interest

The authors declare no conflict of interest regarding the paper's publication.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Dini Nurmalasari;* ***data collection:*** *Heri R Yuliantoro, Yessi Alfani;* ***analysis and interpretation of results:*** *Dini Nurmalasari, Heri R Yuliantoro;* ***draft manuscript preparation:*** *Dini Nurmalasari, Yessi Alfani;* ***initial draft writing****: Dini Nurmalasari;* ***revision and editing****: Heri R Yuliantoro, Yuli Fitrisia,* ***funding acquisition****: Dini Nurmalasari. All authors reviewed the results and approved the final version of the manuscript.*

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