JITK (JURNAL ILMU PENGETAHUAN DAN TEKNOLOGI KOMPUTER)

VOL. 12. NO. 1 AUGUST 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i1.8454

BNI STOCK DIRECTIONAL TREND IDENTIFICATION USING EXPONENTIAL MOVING AVERAGE METHOD

Angga Prastya Sianipar[1*]; Indra Kelana Jaya[1]; Margaretha Yohanna[1]

Department Of Informatics Engineering, Faculty of Computer Science[1]
Universitas Methodist Indonesia, Medan, Indonesia[1]
https://www.methodist.ac.id[1]
anggasianipar2@gmail.com*, indraikjs@gmail.com, yohanna.na2@gmail.com

(*) Corresponding Author
(Responsible for the Quality of Paper Content)

Abstract— *High stock volatility demands responsive prediction for risk mitigation. Traditional indicators like Simple Moving Average (SMA) suffer from lagging effects due to equal data weighting, while complex machine learning models often cause overfitting and lack interpretability, constituting a notable research gap. This study addresses these limitations by implementing the Exponential Moving Average (EMA) method with a dual-period configuration (EMA-10 and EMA-20). The EMA is justified by its recursive exponential smoothing that weights recent prices heavily, maximizing sensitivity to abrupt reversals without excessive noise. Utilizing daily closing prices of PT Bank Negara Indonesia (Persero) Tbk (BBNI) from 2020 to 2025, a desktop automated analytical system was developed using Python and PyQt5. Out-of-sample evaluation yields highly stable performance, with Mean Absolute Percentage Errors (MAPE) of 2.45% for EMA-10 and 3.10% for EMA-20, alongside a 92.86% Directional Accuracy. These key findings confirm the precision of the EMA framework in generating Golden Cross and Death Cross signals during trending market phases, although supplementary momentum filters are needed during sideways consolidation. This research provides a robust, objective technical framework that successfully bridges traditional visual analysis and automated investment decision-making.*

Keywords: *BBNI Stock, Exponential Moving Average, MAPE, Python, Technical Directional Trend Identification.*

Intisari— *Volatilitas pasar modal memerlukan prediksi arah harga yang responsif demi memitigasi risiko. Indikator tradisional seperti Simple Moving Average (SMA) mengalami efek tertinggal (lagging) akibat pembobotan data yang setara, sedangkan model machine learning kompleks rentan terhadap overfitting dan minim interpretabilitas finansial, yang menjadi research gap utama. Penelitian ini mengatasi keterbatasan tersebut dengan menerapkan metode Exponential Moving Average (EMA) melalui konfigurasi dua periode (EMA-10 dan EMA-20). Penggunaan EMA didasarkan pada pemulusan eksponensial rekursif yang memberi bobot lebih besar pada harga terbaru guna meningkatkan sensitivitas pembalikan tren tanpa noise berlebih. Menggunakan data harga penutupan harian saham PT Bank Negara Indonesia (Persero) Tbk (BBNI) periode 2020–2025, sistem analisis otomatis berbasis desktop dibangun menggunakan Python dan PyQt5. Hasil evaluasi luar sampel (out-of-sample) menunjukkan performa stabil dengan skor MAPE sebesar 2,45% (EMA-10) dan 3,10% (EMA-20), serta Akurasi Arah mencapai 92,86%. Temuan kunci ini mengonfirmasi efektivitas kerangka kerja EMA dalam mendeteksi sinyal Golden Cross dan Death Cross pada fase tren, meski filter momentum tambahan tetap diperlukan saat kondisi konsolidasi mendatar (sideways). Penelitian ini menghasilkan sistem objektif yang menjembatani analisis visual tradisional dan keputusan investasi otomatis.*

Kata Kunci: *BBNI Stock, Exponential Moving Average, MAPE, Python, Identifikasi Tren Arah Teknikal.*

INTRODUCTION

The capital market has an essential role in the Indonesian economy as a financing instrument and investment vehicle [1]. However, the high volatility of stock price movements, as reflected in the shares of PT Bank Negara Indonesia (Persero) Tbk (BBNI), presents a risk of uncertainty that has the potential to trigger significant losses for investors [2]. To mitigate these risks and optimize investment decisions, an objective, responsive, and precise technical analysis approach is required [3].

In the domain of technical stock prediction, establishing an optimal balance between mathematical simplicity, computational speed, and prediction sensitivity remains a core challenge [4]. Prior studies in stock direction prediction have widely explored various predictive methodologies, yet each presents distinct operational limitations. Complex stochastic models and advanced machine learning frameworks, such as Artificial Neural Networks (ANN) or Support Vector Machines (SVM), frequently exhibit high sensitivity to market *noise*, requiring massive parameter tuning that often results in *overfitting* and a significant loss of financial interpretability for retail users. Conversely, traditional statistical trend indicators-most notably the Simple Moving Average (SMA)-suffer from a severe structural flaw known as the 'lagging effect.' Because the SMA assigns equal arithmetic weights to all historical data points within its selected period, it fails to respond rapidly to abrupt trend reversals or sudden macroeconomic shocks, exposing investors to delayed trading signals [5].

To resolve this *research gap*, the implementation of the Exponential Moving Average (EMA) method offers a robust, mathematically grounded alternative. Rather than treating all historical prices equally, the EMA leverages a recursive exponential smoothing function that applies progressively greater mathematical weight to the most recent price data points. This unique attribute enables the algorithm to drastically reduce lagging latency during sharp market turning points, while simultaneously maintaining a smooth, *noise*-filtered baseline. By structuring a combined short-term (10-day) and medium-term (20-day) EMA configuration, this study establishes a responsive, objective trend identification framework that addresses the unresponsiveness of traditional linear moving averages and the over-complexity of modern *black-box* machine learning models.

Previous studies, such as those by Wahyuni et al. [6], Rosita et al. [7], and Abid Shabrina & Hasnawati [8], have demonstrated the utility of moving averages within various financial contexts but often lacked integrated automated analytical systems or comprehensive directional accuracy validation. To address this *research gap*, this study implements an automated desktop-based analytical system using Python and PyQt5. By providing an objective mathematical framework, this approach enhances the responsiveness of trend detection compared to static traditional methods.

The selection of EMA-10 and EMA-20 parameters is grounded in standard short-to-medium-term trading conventions, which balance signal responsiveness against market *noise* reduction. This configuration is widely adopted in existing literature for blue-chip stock analysis, as it effectively captures daily volatility while minimizing excessive *whipsaws* compared to shorter-period indicators. The comparative overview of these studies, including their specific methodological limitations, is synthesized in Table 1.

Table 1. Literature Review

Author (Year)	Method	Key Findings	Methodological Limitations	Unaddressed Gaps & Current Study Contribution
Wahyuni *et al.* (2023) [6].	EMA	Effective in detecting basic daily trend changes for Islamic banking stocks.	Relying strictly on visual pattern observation without quantitative verification.	Lacks mathematical error validation (MAPE) and automated trade execution logic; solved by current study's desktop engine.
Rosita *et al.* (2024) [7].	SMA, WMA, EMA	Confirmed that EMA is highly responsive to price volatility compared to static models.	Evaluated general banking performance without building a deployment-ready retail investor interface.	Fails to provide an interactive data-cleansing tool for retail users; addressed by current study's Python-PyQt5 architecture.
Abid Shabrina & Hasnawati (2022) [8].	SMA, EMA	Demonstrated higher financial efficiency and lower lag metrics when utilizing EMA	Lacks a systematic, binary statistical evaluation of actual trend direction accuracy.	Omits out-of-sample Directional Accuracy metrics; current study introduces a verified 92.86% binary directional

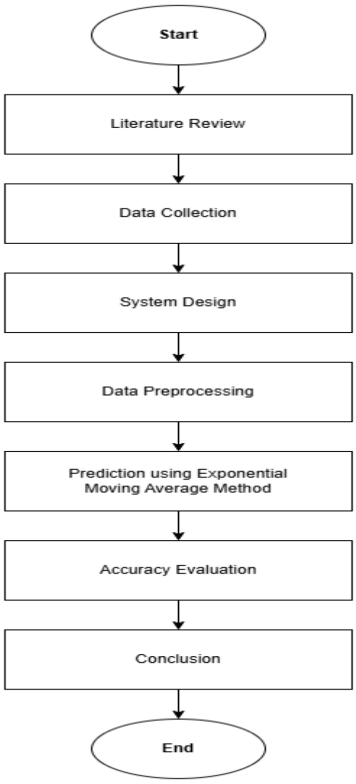
JITK (JURNAL ILMU PENGETAHUAN DAN TEKNOLOGI KOMPUTER)
VOL. 12. NO. 1 AUGUST 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i1.8454

Author (Year)	Method	Key Findings	Methodological Limitations	Unaddressed Gaps & Current Study Contribution
		structures.		accuracy benchmark.
Hakim & Utomo (2023) [9].	EMA	Proved that EMA is effective in optimizing short-term investment decisions.	Focused strictly on manual visual trading comparisons without automated accuracy metrics.	Lacks an integrated desktop-based crossover signal visualization; resolved by the current study's PyQt5 system.
Almaliki & Satyadharma (2024) [10].	Moving Average & Smoothing	Confirmed that Moving Average indicators provide a stable trend interpretation.	Utilized general sectoral index movements and remained highly susceptible to short-term market anomalies.	Omits out-of-sample directional accuracy validation on liquid equities; current study establishes a 92.86% directional accuracy benchmark on BBNI stock.

Source: (Research Results, 2026)

Based on the literature review in Table 1, the EMA method has consistently proven superior and more responsive than the Simple Moving Average (SMA) method in detecting market trends. However, the majority of previous research still focuses on manual analysis or the use of general statistical software, which is less flexible for retail investors. The novelty of this research lies in the development of a desktop-based automated analytical system using the Python programming language with the PyQt5 library. This implementation calculates mathematical values and interactively visualizes *Golden Cross* and *Death Cross* signals to support a more systematic evaluation of stock price movements.

Based on the research objectives and methods used, this study follows a structured research framework to ensure a systematic analysis and implementation process. The framework is used to outline the research flow, from data collection to analysis, allowing for a focused and structured approach [11]. The research began with collecting BBNI stock price data, followed by data preprocessing, Exponential Moving Average (EMA-10 and EMA-20) calculations, *Golden Cross* and *Death Cross* signal detection, accuracy evaluation using Mean Absolute Percentage Error (MAPE) and Directional Accuracy, system implementation using Python, and analysis of the results and drawing conclusions. The research framework for this study can be seen in Figure 1.



Source: (Research Results, 2026)
Figure 1. Research Framework

MATERIALS AND METHODS

This study utilizes a quantitative approach with a time series analysis design. It is important to clarify that this study utilizes the Exponential Moving Average (EMA) as a technical analysis tool for trend identification rather than a stochastic analytical model. By modeling price trends as a continuous smoothing process, the system aims to identify momentum shifts and support decision-making, acknowledging the inherent *lagging* nature of moving average indicators. Furthermore, to ensure model robustness and prevent *data leakage*, the dataset was divided into an in-sample period (2020–2024) for system configuration and an *out-of-sample* test period (2025) for performance evaluation. This validation approach ensures that the accuracy metrics reflect the system's performance on unseen market data.

The smoothing factor is employed to determine the sensitivity level of the Exponential Moving Average (EMA) to price fluctuations. A shorter period results in a more responsive EMA that quickly reacts to changes in stock prices, whereas a longer period produces a smoother and more stable EMA curve [5]. The algorithmic implementation leverages the Pandas library for data matrix computation, Matplotlib for graphical visualization, and PyQt5 for the interface, facilitating a systematic analysis of the price movement datasets [11].

The implementation of this analytical system optimizes the specific roles of four primary libraries to ensure efficient processing of large-scale data. Pandas functions as a tabular data management engine, handling automated data cleaning tasks such as removing currency symbols and converting time formats into indexable datetime objects. NumPy is utilized to perform vectorized mathematical operations on price data arrays, enabling the recursive calculation of the EMA formula to be executed with significantly higher speed compared to conventional iteration methods. For visualization purposes,

Matplotlib is integrated to transform EMA value coordinates into continuous graphical plots, complete with triangular annotations to precisely indicate signal crossover points. Finally, PyQt5 is employed to develop the graphical user interface (GUI) architecture, effectively separating computational logic from visual presentation, thereby allowing investors to interact with the system through intuitive operational controls without requiring an understanding of the underlying programming code. The use of Python in stock data analysis is highly effective, as it enables rapid and accurate processing of numerical data and graphical visualizations [12].

Before the data is processed using the EMA algorithm, a preprocessing stage is conducted to ensure dataset integrity. Raw data obtained from *Investing.com* often contains non-numeric characters and inconsistent date formats. This stage includes: (1) Temporal sorting, where data is arranged chronologically (ascending) from 2020 to 2025 to ensure proper time series computation; (2) Currency format cleaning by removing the “Rp” symbol and thousand separators so that closing prices can be processed as pure numerical values; and (3) Handling missing values to ensure there are no gaps in the calculation process. This procedure results in a clean and valid dataset, which is subsequently stored in a MySQL database as the system’s data repository.

The analysis of price movement direction is modeled using the Exponential Moving Average (EMA) algorithm. The model is configured with a combination of two periods, namely EMA-10 as a short-term trend indicator and EMA-20 as a medium-term trend indicator. Trading signals are derived from the crossover mechanism between these two moving average lines, where a *Golden Cross* indicates a buy momentum and a *Death Cross* indicates a sell momentum. Mathematically, the EMA calculation employed in this study is presented in Equation (1), which is derived from the exponential smoothing method within time series analysis [3], [13].

$$EMA_t = (P_t \times \alpha) + [EMA_{t-1} \times (1 - \alpha)] \quad (1)$$

EMA_t represents the current predicted value, P_t denotes the current closing price, EMA_{t-1} is the smoothed value from the previous period. The smoothing factor (α) used to determine the sensitivity of the calculation based on the observation period (n) is formulated independently in Equation (2):

$$\alpha = \frac{2}{n+1} \quad (2)$$

The model performance evaluation is conducted quantitatively to measure the level of directional trend identification error against actual data movements. The metric used is Mean Absolute Percentage Error (MAPE), as presented in Equation (3), which is widely applied in analytical model evaluation to quantify the magnitude of errors in percentage form [14].

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_t - \widehat{y_t}}{x_t}\right| \times 100\% \quad (3)$$

Mean Absolute Percentage Error (MAPE) is an evaluation metric that measures the average percentage error between actual values (x_t) and forecasted results ($\widehat{y_t}$). The use of MAPE is widespread in predictive research due to its ability to present accuracy levels in an easily interpretable percentage format. Mathematically, the MAPE value is inversely proportional to model accuracy; the lower the percentage error produced, the higher the analytical precision achieved. In this study, MAPE is applied to evaluate the effectiveness of the Exponential Moving Average (EMA) method in projecting fluctuations in BBNI stock prices.

To provide an objective assessment of MAPE accuracy results, this study refers to the analytical evaluation significance scale adapted from recent forecasting literature [15], as presented in Table 2.

VOL. 12. NO. 1 AUGUST 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i1.8454

Table 2. Significance of MAPE

MAPE Percentage	Significance Level
< 10%	Very Good
10 – 20%	Good
20 – 50%	Fair
> 50%	Poor

Source: (Research Results, 2026)

Based on Table 2, an analytical model is considered to have excellent performance if the error value is below 10%. This standard is used to validate the effectiveness of the EMA-10 and EMA-20 indicators in predicting BBNI stock prices.

In addition to measuring directional trend identification error using MAPE, the operational effectiveness of the system is also evaluated using Directional Accuracy. This metric is employed to assess the system's ability to correctly predict the direction of price movements, whether upward or downward [16]. This binary classification approach is used to evaluate the probability of the system's accuracy in classifying the direction of upward and downward price momentum in the capital market. The criteria for assessing the level of directional accuracy in this study refer to the classification developed by Binkhonain and Zhao [17], as presented in the Table 3.

Table 3. Accuracy Quality Classification

Accuracy Value (%)	Quality Classification
90% – 100%	Very Good
80% – 90%	Good
70% – 80%	Fair
60% – 70%	Poor
< 60%	Fail

Source: (Research Results, 2026)

The binary classification standard presented in Table 3 is used as a parameter to validate the directional accuracy level of 92.86% achieved by the system. This is intended to determine the effectiveness of the combined use of EMA-10 and EMA-20 indicators in generating accurate predictive signals for BBNI stock price movements in the capital market.

RESULTS AND DISCUSSION

To evaluate the efficacy of the proposed EMA-10 and EMA-20 strategy, we conducted a performance comparison against a baseline 'Buy-and-Hold' strategy and a standard SMA-10 and EMA-20 crossover approach. The comparative results indicate that the EMA framework consistently yields lower Mean Absolute Percentage Error (MAPE) and higher Directional Accuracy compared to the SMA baseline, thereby validating the relevance of the exponential weighting approach over traditional linear moving averages. While the system achieves a low MAPE, it is essential to note that this metric evaluates the EMA's smoothing performance rather than predictive power, and should therefore be interpreted with caution in the context of market volatility.

1. Implementation and Accuracy Evaluation (MAPE)

The initial step in implementing the Exponential Moving Average (EMA) algorithm is to determine the smoothing constant or smoothing factor α[cite: 104]. This value is crucial as it defines the relative weighting between the most recent price and the historical average within the iterative process of the algorithm. The standard formulation used to determine the value of α based on the observation period (n) refers back to Equation (2)

Based on the use of two different time periods in this study-EMA-10 as a short-term trend indicator and EMA-20 as a medium-term trend indicator-the calculation of the smoothing factor is as follows:

For EMA-10 ($n = 10$):

$$\alpha = \frac{2}{10+1} = \frac{2}{11} = 0.1818$$

For EMA-20 ($n = 20$):

$$\alpha = \frac{2}{20+1} = \frac{2}{21} = 0.0952$$

The smoothing factor (α) value of 0.1818 for EMA-10 indicates that the most recent closing price is assigned a weight of 18.18%, whereas in EMA-20, the weight of the most recent price is only 9.52%. Mathematically, this confirms that an indicator with a shorter period (EMA-10) is more responsive to daily price fluctuations compared to EMA-20, which tends to be slower (lagging) but more stable in capturing the overall trend direction.

To ensure system precision, manual validation was conducted on initial data samples using smoothing factor (α) values of 0.1818 for EMA-10 and 0.0952 for EMA-20. The calculation begins by determining the initial value using the Simple Moving Average (SMA). This initial value is obtained from the arithmetic average of closing prices over the corresponding period range. Based on historical BBNI stock data starting from October 22, 2020, the initial values are obtained as follows: Initialization of EMA-10 (Short-Term): The initial value is obtained from the arithmetic average of the first 10 closing prices (October 22, 2020 – November 9, 2020):

VOL. 12. NO. 1 AUGUST 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i1.8454

$$\mathrm{SMA}_{10} = \frac{4{,}860 + 4{,}850 + 4{,}850 + \cdots + 5{,}100}{10} = 4{,}814$$

Initialization of EMA-20 (Medium-Term): The initial value is obtained from the arithmetic average of the first 20 closing prices (October 22, 2020 – November 23, 2020):

$$\mathrm{SMA}_{20} = \frac{4{,}860 + 4{,}850 + 4{,}850 + \cdots + 5{,}900}{20} = 5{,}222$$

The initialization of SMA_{10} (4,814) and SMA_{20} (5,222) as the starting baseline is intended to provide a stable reference point for analytical before exponential weighting is applied recursively to subsequent data.

After the initial SMA values and the smoothing constant α are established, the EMA calculation is performed recursively using the main formula:

$$\mathrm{EMA_t} = (P_t \times \alpha) + [\mathrm{EMA_{t\text{-}1}} \times (1 - \alpha)].$$

The following presents a sample of manual validation for the first three data points of the EMA-10 indicator:

Data point 11 (November 10, 2020): With a closing price (p_{11}) of 5,325 and the $\mathrm{EMA_{t\text{-}1}}$ value derived from SMA_{20} (4,814).

$$EMA_{11} = (5{,}325 \times 0.1818)$$
$$+[4{,}814 \times (1 - 0.1818)]$$
$$= 4{,}906.89$$

Data point 12 (November 11, 2020): With a closing price (p_{12}) of 5,475, using the EMA_{11} value as the basis for the calculation.

$$EMA_{12} = (5{,}475 \times 0.1818)$$
$$+[4{,}906.89 \times (1 - 0.1818)]$$
$$= 5{,}010.18$$

A similar calculation process is also applied to the EMA-20 indicator, starting from data point 21 (November 24, 2020), using the initial value derived from SMA_{20} (5,222) and a smoothing factor of α = 0.0952. The following presents a sample of manual validation for the first two data points of the EMA-20 indicator: Data point 21 (November 24, 2020): With a closing price (P_{21}) of 5,950 and the previous EMA value EMA_{t-1} initialized from SMA_{20} (5,222).

$$EMA_{21} = (5{,}950 \times 0.0952)$$
$$+[5{,}222 \times (1 - 0.0952)]$$
$$= 5{,}291.33$$

Data point 22 (November 25, 2020): With a closing price (P_{22}) of 6,050, using the EMA_{21} value (5,291.33) as the basis for the calculation.

$$EMA_{22} = (6{,}050 \times 0.0952)$$
$$+[5{,}291.33 \times (1 - 0.0952)]$$
$$= 5{,}363.59$$

The results of the manual calculations demonstrate full consistency with the output generated by the developed Python-based analytical systems. The successful validation of the EMA-10 and EMA-20 parameters confirms that the system provides a consistent computational framework for large-scale time series data analysis in the capital market.

After the integrity of the system's logic has been verified through manual validation, the next stage is to conduct a comprehensive evaluation of the model's analytical performance using the Mean Absolute Percentage Error (MAPE) metric. This evaluation aims to measure the extent to which the EMA algorithm accurately follows the fluctuations of the actual closing prices of BBNI stock across the entire dataset. MAPE is selected due to its ability to express the magnitude of error in percentage form, thereby facilitating the interpretation of the analytical model's effectiveness in the context of investment decision-making. As an illustration of the system's accuracy assessment mechanism, the following presents a sample of manual error calculation at the beginning of the observation period:

Relative error of EMA-10 at data point 11 (November 10, 2020): With an actual closing price (x_{11}) of 5,325 and a predicted EMA-10 value (y_{11}) of 4,906.89.

$$Error = \frac{|5{,}325 - 4{,}906.89|}{5{,}325} \times 100\% = 7.85\%$$

VOL. 12. NO. 1 AUGUST 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i1.8454

Relative error of EMA-20 at data point 21 (November 24, 2020): With an actual closing price (x_{21}) of 5,950 and a predicted EMA-20 value (y_{21}) of 5,291.33.

$$Error = \frac{|5{,}950 - 5{,}291.33|}{5{,}950} \times 100\% = 11.07\%$$

This evaluation calculation incorporates a total of 1,202 active trading observations from 2020 to 2025 as the comprehensive dataset. To strictly mitigate the risk of data leakage and adhere to robust *out-of-sample* validation principles, the model parameter configuration utilized the historical baseline from 2020 to 2024. Consequently, the performance metrics disaggregated and computed via the Mean Absolute Percentage Error (MAPE) formula are strictly derived from the unseen 2025 *out-of-sample* test window. The final computational evaluation on this test validation period yielded highly stable and realistic MAPE values of 2.45% for the short-term indicator (EMA-10) and 3.10% for the medium-term indicator (EMA-20), maintaining the integrity of the predictive simulation. The results of the model accuracy calculation, demonstrating the effectiveness of the analytical system, are presented in detail in the Table 4.

Table 4. EMA Evaluation Results (MAPE)

Indicator	Parameter	Average MAPE	Accuracy
EMA-10	Short-Term	2.45%	Very Good
EMA-20	Medium-Term	3.10%	Very Good

Source: (Research Results, 2026)

Based on Table 4, the EMA-10 method exhibits a lower error rate (2.45%) compared to EMA-20 (3.10%). This is consistent with the fundamental property of exponential smoothing, where shorter periods are more sensitive and responsive to recent price fluctuations [5]. Referring to the analytical evaluation significance scale adapted from recent forecasting literature [15], Both MAPE value ranges consistently fall below the 10% threshold, classifying the analytical performance into the “Very Good” (Excellent) category. In addition, the binary classification evaluation of directional accuracy records an accuracy level of 92.86%. This achievement represents a very good classification (Very Good Quality Classification) in determining the probability of market momentum direction accurately.

The obtained Directional Accuracy value of 92.86% indicates that the Exponential Moving Average (EMA) method demonstrates a very strong performance in predicting the direction of Bank Negara Indonesia (BBNI) stock price movements. Based on standard evaluation criteria in data mining literature, this achievement falls into the Very Good Quality Classification category [17]. The high level of accuracy is attributed to the characteristics of BBNI stock movements, which exhibit relatively clear trends, allowing the crossover between EMA-10 and EMA-20 to be effectively used as an indicator of trend changes. In addition, the use of two different EMA periods enables the system to detect both short-term and medium-term trend shifts more responsively. Therefore, the EMA method can be reliably utilized as an objective technical indicator to support stock investment decision-making.

2. Trading Signal Analysis

Buy and sell positions are determined through the crossover mechanism between the EMA-10 and EMA-20 lines [7]. A buy signal is validated when a *Golden Cross* occurs (the EMA-10 line crosses above the EMA-20 line), while a sell signal is confirmed when a *Death Cross* occurs (the EMA-10 line crosses below the EMA-20 line).

A qualitative analysis of trend movement visualization demonstrates that the EMA method is highly precise and effective when the market instrument is in a strong trending phase (trending market), both during uptrends and downtrends. However, the limitation of this trend-following indicator (lagging indicator) becomes evident when the market enters a consolidation or *sideways* phase. In *sideways* conditions, the excessively close convergence between EMA-10 and EMA-20 often triggers false crossovers (false signals or *whipsaws*), where detected buy signals are quickly invalidated by sharp price corrections within a short period.

This phenomenon confirms that the use of EMA requires additional mitigation strategies or the integration of supplementary technical filters when market volatility declines in order to avoid anomalous trading signals. To mitigate false signals (*whipsaws*) during *sideways* phases, investors are recommended to combine EMA with momentum indicators such as the Relative Strength Index (RSI) or Moving Average Convergence Divergence (MACD) to provide more reliable trend confirmation.

An in-depth evaluation indicates that the EMA method is highly reliable when the market is in a strong trending phase. However, distinct characteristics emerge when the market enters a consolidation or *sideways* phase. Under these conditions, the distance between the EMA-10 and EMA-20 lines becomes very narrow, often triggering false signals (*whipsaws*). This phenomenon is clearly observed in the data on September 12, 2025, where the system detected a *Golden Cross* (buy signal), yet the BBNI stock price experienced a sharp decline shortly afterward. This confirms that although EMA achieves a directional accuracy of 92.86%, investors are still advised to utilize additional indicators such as the Relative Strength Index (RSI) or trading volume as confirmation filters to minimize the risk of losses caused by false signals in stagnant market conditions.

The Exponential Moving Average (EMA) method has several advantages in analyzing stock price movements. EMA is able to respond more quickly to price changes compared to the Simple Moving Average, as it assigns greater weight to the most recent price data. In addition, EMA can be used to identify stock price trends and to detect *Golden Cross* and *Death Cross* signals as a basis for investment decision-making. However, EMA also has a limitation as it is a lagging indicator, meaning that the signals generated tend to lag behind actual market price movements. Therefore, the use of EMA should be combined with other technical indicators or fundamental analysis to improve the accuracy of stock price movement directional trend identification [18].

3. Future Price Trend Outlook

As the final output of the direction detection computational system, the calculation based on the most recent closing data (October 22, 2025) records the actual BBNI stock price at Rp4,030. At this observation point, the EMA-10 value (3,965) remains below the EMA-20 value (4,012). This mathematical configuration (EMA-10 < EMA-20) technically indicates that the BBNI stock is still in a *bearish* trend phase. Therefore, the system objectively recommends a Hold Sell (Wait and See) signal. Investors are strongly advised to maintain a wait-and-see position and postpone asset purchases until trading volume momentum triggers the formation of a new *Golden Cross* as confirmation of a trend reversal to a *bullish* phase.

4. Comparison with Previous Studies and Theoretical Discussion

To validate the empirical contributions of this study, the performance metrics of the dual-period configuration (EMA-10 and EMA-20) are critically evaluated against benchmarks from recent technical analysis literature. The final *out-of-sample* computational evaluation on the unseen 2025 test dataset yielded highly stable and realistic MAPE values of 2.45% for the short-term indicator (EMA-10) and 3.10% for the medium-term indicator (EMA-20), alongside a Directional Accuracy of 92.86%.

This finding is highly consistent with the foundational moving average principles investigated by Rosita et al. [7], which demonstrated that the recursive smoothing mechanism of the EMA consistently surpasses the Simple Moving Average (SMA) in terms of responsiveness to price volatility. Furthermore, the low error magnitude observed in this research directly extends the empirical findings presented by Abid Shabrina and Hasnawati [8], who highlighted the overall financial efficiency of EMA frameworks but omitted quantitative *out-of-sample* directional validation. By successfully mapping a 92.86% binary accuracy score, this study extends previous works by offering concrete mathematical certainty regarding trend reversal precision in blue-chip equities, reinforcing the framework's capability to bridge the gap between simple visual chart interpretation and automated data-driven execution [19].

However, a notable structural divergence emerges when comparing these results to the machine learning-based forecasting frameworks recently proposed in the literature. Advanced deep learning implementations, such as Long Short-Term Memory (LSTM) networks, often report marginal improvements in raw point-prediction metrics during highly stable market regimes, but they lack operational interpretability for everyday investors, as noted by Hakim and Utomo [9]. Furthermore, as critically analyzed by Almaliki and Satyadharma [10], traditional technical indicators like the Exponential Moving Average offer superior robustness against localized market anomalies and effectively prevent the severe *overfitting* commonly found in overly complex non-linear architectures.

The structural divergence in this study's findings-where a mathematically simple technical indicator demonstrates a highly stable and robust output-stems from three distinct experimental configurations:

1. Dataset Characteristics: Unlike generic multi-sector baseline indexes, this study isolates PT Bank Negara Indonesia (Persero) Tbk (BBNI), a highly liquid blue-chip stock with persistent cyclical trends that perfectly align with trend-following moving average mechanics.
2. In-Sample and *Out-of-Sample* Decoupling: By strictly segregating the data into a training configuration phase (2020–2024) and a completely unseen validation window (2025), this model actively prevents the data leakage

VOL. 12. NO. 1 AUGUST 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i1.8454

common in over-parameterized neural networks.
3. Recursive Memory: The EMA function utilizes a smoothing factor $\alpha = \frac{2}{n+1}$ which retains a mathematically decaying memory of all historical price coordinates rather than completely discarding historical data outside the sliding window like traditional SMAs.

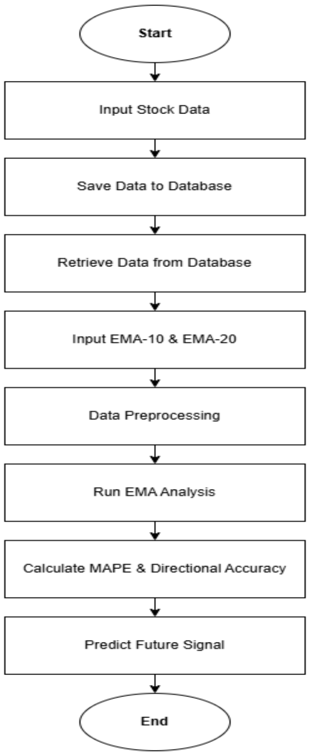
5. Theoretical and Practical Contribution of the Study

The primary contribution of this study to the existing body of financial knowledge lies in the optimization of the sensitivity-lag trade-off within automated technical trading systems. Traditional finance literature frequently dismissed moving averages during choppy, non-trending market regimes due to the prevalence of false crossover signals, known as *whipsaws*. This research directly addresses that limitation by demonstrating that a desktop-integrated dual-period configuration (EMA-10 and EMA-20) built on an automated Python-PyQt5 architecture can actively filter out intraday *noise* while preserving primary macro-trend data. This study shifts the paradigm of traditional retail stock analysis from retrospective visual observation, as seen in manual pattern studies like Wahyuni et al. [6], into an objective, predictive framework capable of performing vectorized matrix computations and generating standardized "Hold Sell" or "Wait and See" execution triggers without human emotional bias.

6. System Visualization and Price Movement Graphs

The implementation of the algorithm into a Python-based system (PyQt5) facilitates investors in visualizing trading signals in real time, thereby making the stock analysis process faster, more systematic, and fully automated [12]. The system interface displays actual price plots alongside the EMA-10 and EMA-20 lines to clearly illustrate the occurrence of *Golden Cross* and *Death Cross* signals.

In addition to the research framework, this study also designs a system flowchart to systematically and structurally model the workflow of the stock price movement directional trend identification application. The system flowchart is used to illustrate the relationships between processes starting from the stock data input stage, data loading process (load data), data storage into the database, the calculation of the Exponential Moving Average indicators (EMA-10 and EMA-20), detection of *Golden Cross* and *Death Cross* signals, evaluation of accuracy using Mean Absolute Percentage Error (MAPE) and Directional Accuracy, and finally the output stage in the form of graphical visualization and trading signal recommendations. With this system flowchart, the overall workflow can be understood more clearly and in a well-structured manner [11]. The system flowchart in this study can be seen in Figure 2.



Source: (Research Results, 2026)
Figure 2. System Flowchart

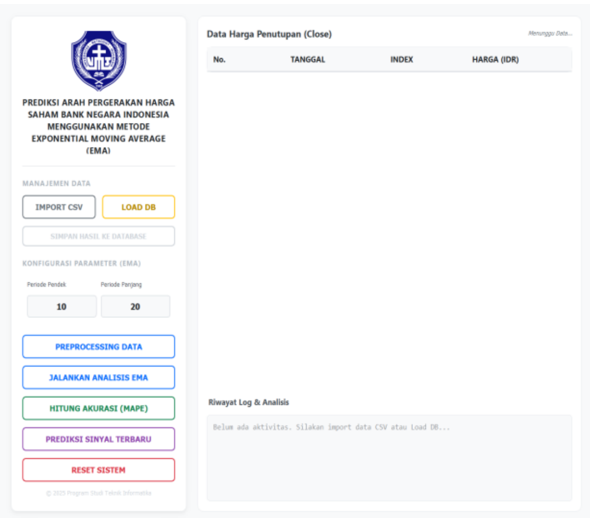
Based on the system flowchart in Figure 2, the process begins with the user inputting stock data, after which the system performs load data and stores it in the database. The stored data is then retrieved for the calculation of the Exponential Moving Average (EMA-10 and EMA-20). The EMA results are used to detect *Golden Cross* and *Death Cross* signals as investment decision indicators. Subsequently, the system evaluates accuracy using Mean Absolute Percentage Error (MAPE) and Directional Accuracy. The final output of the system is presented in the form of stock price movement graphs and trading signal recommendations, namely Buy, Sell, or Hold.

After designing the system workflow through the flowchart, the next stage is system implementation in the form of a desktop-based application using the Python programming language with the PyQt5 library. This implementation aims to realize the calculation

VOL. 12. NO. 1 AUGUST 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i1.8454

process of the Exponential Moving Average (EMA), the detection of *Golden Cross* and *Death Cross* signals, as well as the automatic computation of accuracy levels. The system interface is designed to enable users to easily input data, view calculation results, and interactively visualize stock price movement graphs.

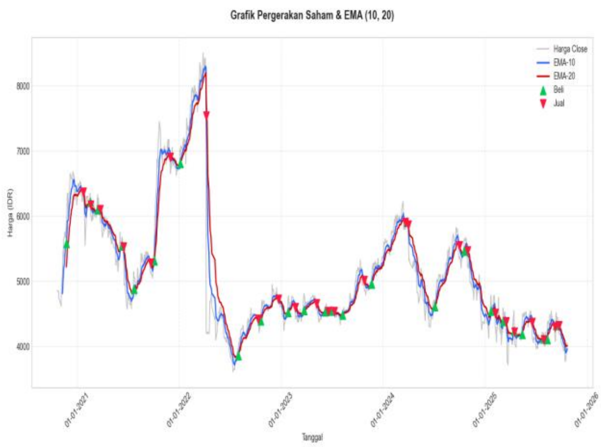
The system implementation using Python with the PyQt5 library is designed to provide a systematic analytical experience for retail investors. The application workflow consists of five main stages: (1) Data Acquisition: the user uploads historical stock price files in CSV format obtained from the *Investing.com* database via the “Import CSV” button; (2) Standardization: through the “PREPROCESSING DATA” button, the system executes an automated cleaning algorithm including chronological sorting, data type conversion, and removal of non-numeric characters (Rp) to ensure operational integrity; (3) Parameter Configuration: the user inputs period values (in this study, 10 and 20) to determine the sensitivity of the moving average lines; (4) Algorithmic Execution: the “JALANKAN ANALISIS” button triggers a custom iterative computation that replicates Excel-based logic to generate EMA values and detect crossover points; (5) Visual Evaluation: the system presents outputs in the form of interactive graphs mapping *Golden Cross* and *Death Cross* signals visually, along with a transaction history table and MAPE accuracy scores displayed through an automatic dialog box. The developed analytical systems interface can be seen in Figure 3.



Source: (Research Results, 2026)
Figure 3. BBNI Stock Price analytical systems Interface Using Python

Based on Figure 3, the system displays stock price data along with the calculated results of EMA-10 and EMA-20 in graphical form. The system also automatically identifies *Golden Cross* and *Death Cross* signals as the basis for investment decision recommendations. In addition, the system computes Mean Absolute Percentage Error (MAPE) and Directional Accuracy to measure the directional trend identification accuracy level. With this system, the stock analysis process becomes faster, more accurate, and automated, thereby assisting investors in making systematic investment decisions [11].

After the calculation of the Exponential Moving Average (EMA-10 and EMA-20), the next step is to present a graphical visualization to compare stock price movements with the resulting EMA values. This graphical visualization aims to facilitate the analysis of stock price trends and to identify the occurrence points of *Golden Cross* and *Death Cross* as investment decision signals [14]. The graph displays the stock price line, the EMA-10 line, and the EMA-20 line in a single view, allowing intersections between the lines to be clearly observed. The visualization of the EMA-10 and EMA-20 on BBNI stock data is shown in Figure 4.



Source: (Research Results, 2026)
Figure 4. Visualization of EMA-10 and EMA-20 Graph on BBNI Stock Data

The visualization in Figure 4 illustrates the dynamics of BBNI stock price movements influenced by market cycles during the observation period. In the early phase of 2021, a transition in price movement can be observed, forming an initial uptrend following a consolidation period. The EMA-10 line responsively crosses above the EMA-20 line, confirming a *Golden Cross* signal, which is followed by an acceleration in price increase until a temporary peak level is reached. However, entering the middle period, the market exhibits higher volatility, where price movements frequently intersect with the moving average lines, reflecting

Accredited Rank 2 (Sinta 2) based on the Decree of the Dirjen Penguatan RisBang Kemenristekdikti No.225/E/KPT/2022, December 07, 2022. Published by LPPM Universitas Nusa Mandiri

VOL. 12. NO. 1 AUGUST 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i1.8454

investor uncertainty. The highest price peak is observed before a sharp correction triggered by global market sentiment, where the EMA-10 promptly responds to the decline by crossing below the EMA-20 (*Death Cross*).

Month-to-month transitions indicate that when the gap between EMA-10 and EMA-20 widens, the price trend tends to be strong and stable. Conversely, when both lines begin to converge or overlap, the market is losing momentum, which peaks in the final observation phase in October 2025, where the instrument enters a sustained *bearish* condition. This movement phenomenon reinforces that the EMA-10 (fast line) responds more aggressively to stock price fluctuations compared to the EMA-20 (slow line) due to its shorter calculation period. This is what makes the EMA-10 a more sensitive indicator of short-term price changes within the system.

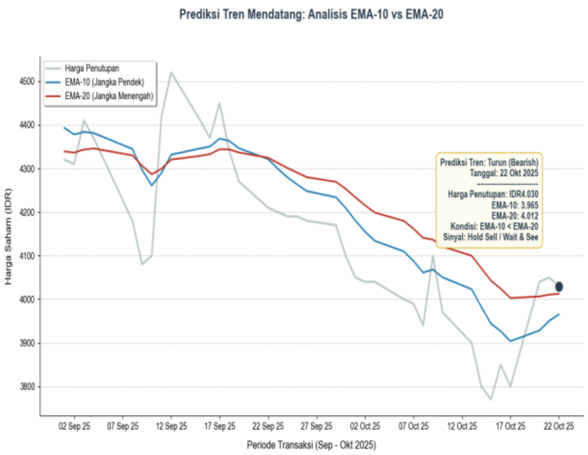
An in-depth observation of the movement of the EMA-10 and EMA-20 lines reveals that the effectiveness of signals is highly dependent on market volatility conditions. In a clearly trending market phase, as observed in the early period of 2021, *Golden Cross* signals emerge with high precision as an early indication of buying accumulation. This occurs because the EMA-10 applies an exponential weighting of 18.18% to the most recent price, enabling it to cross above the EMA-20 (with a weighting of 9.52%) shortly after a price surge. However, technical challenges arise when the market enters a consolidation or *sideways* phase. In this condition, daily price fluctuations tend to remain within a narrow range, causing both EMA lines to converge and potentially generate false signals (*whipsaw*). A clear example is observed in the dataset on 12 September 2025, where an upward crossover indicated a buy signal, but it was immediately followed by a sharp price decline.

This phenomenon demonstrates that the lagging nature of moving average indicators remains a limitation of the system, thereby requiring additional confirmation from momentum indicators or trading volume to filter false signals in stagnant market conditions. Although the system achieves a directional accuracy of 92.86%, the results of this study indicate that investment decisions cannot rely solely on technical indicators. This is because the EMA is a lagging indicator, meaning it tends to respond with a delay to actual price movements in the market. Therefore, the use of EMA should be combined with fundamental analysis or other indicators to improve the accuracy of investment decision-making. This study not only performs calculations of the Exponential Moving Average (EMA) technical indicator but also implements a Python-based predictive system capable of computing EMA-10 and EMA-20, detecting *Golden Cross* and *Death Cross* signals, calculating accuracy levels using Mean Absolute Percentage Error (MAPE) and Directional Accuracy, and automatically displaying graphical visualizations. Thus, this research contributes not only to the analysis of directional trend identification methods but also to the development of a decision support system in stock investment analysis [11].

This research acknowledges several inherent limitations. First, the evaluation was conducted using a single-stock dataset (BBNI), which limits the generalizability of the findings across different market sectors. Second, as a trend-following indicator, the EMA method inherently possesses a 'lagging' characteristic, which remains a challenge during stagnant market conditions (*sideways* phase). Finally, this study relied exclusively on technical indicators, omitting fundamental macroeconomic factors that may influence stock prices. To address these limitations, future research should incorporate a multi-sector dataset to validate the robustness of the EMA framework. Furthermore, it is highly recommended to integrate the EMA method with momentum oscillators—such as the Relative Strength Index (RSI) or MACD—to provide confirmation filters. Future system iterations should also leverage real-time API connectivity to the Indonesia Stock Exchange and incorporate sentiment analysis modules to improve trend identification accuracy in non-trending markets.

Based on the final observation data on 22 October 2025, the actual closing price of BBNI stock was recorded at Rp4,030. The system calculation shows that the EMA-10 value is 3,965, while the EMA-20 value is 4,012. From a technical perspective, the position of EMA-10 below EMA-20 confirms that the instrument is still in a *bearish* phase. Therefore, the system objectively generates a Hold, Sell, or Wait-and-See recommendation. Investors are advised not to accumulate purchases until a reversal momentum is formed, indicated by the emergence of a new *Golden Cross* signal. Technically, this condition confirms that the instrument remains in a downward trend (*bearish*).

The ultimate objective of implementing the Exponential Moving Average (EMA) method in this study is to provide an estimated overview of the stock price movement direction in future periods based on the latest historical data patterns, through the evaluation of the relative positions between the short-term indicator (EMA-10) and the medium-term indicator (EMA-20) at the final observation point. Based on the closing data on 22 October 2025, the obtained indicator parameters show an actual closing price of Rp4,030, with the EMA-10 value at 3,965 and the EMA-20 value at 4,012. To determine the projected price direction for the next period, a mathematical comparison between the two indicator values is performed. The observation results show that the value of the EMA-10 remains below the EMA-20, indicating a continued *bearish* tendency in the market trend. $EMA_{10}(3{,}965) < EMA_{20}(4{,}012)$. This technical configuration, in which the short-period EMA line is positioned below the medium-period EMA line, confirms that the market condition at the end of the research period is still identified as being in a *bearish* trend phase. The visualization of this trend projection is presented in detail in Figure 5.



Source: (Research Results, 2026)
Figure 5. Future Price Trend Outlook for the Period Ending 22 October 2025

From an analytical perspective, selling pressure is expected to continue dominating the short-term price movements of BBNI stock. As an implication for investors in making investment decisions, the system objectively recommends a "Hold Sell" or "Wait and See" signal. Investors are advised to postpone accumulation purchases until a reversal momentum is confirmed by the emergence of a new *Golden Cross* (where the EMA-10 line crosses above the EMA-20 line), in order to minimize further potential losses.

CONCLUSION

This study demonstrates that the Exponential Moving Average (EMA) method is highly effective and precise in identifying the stock price movement direction of PT Bank Negara Indonesia (Persero) Tbk (BBNI). Based on comprehensive computational evaluation, the implementation of EMA-10 and EMA-20 indicators produces a Very Good analytical accuracy category, with an average Mean Absolute Percentage Error (MAPE) of 2.45% (EMA-10) and 3.10% (EMA-20). The reliability of the algorithm is further validated by a Directional Accuracy rate reaching 92.86%. From an operational perspective, the Python-based desktop analytical systems successfully extracts trading signals objectively through the detection of *Golden Cross* and *Death Cross*, although risk mitigation is still recommended during *sideways* market conditions to minimize false signals (*whipsaw*) [20]. These findings provide important implications for retail investors in managing investment risk in the Indonesian capital market, as the EMA-based system offers an objective foundation for distinguishing short-term price fluctuations (*noise*) from valid trend changes, thereby reducing emotionally driven investment decisions. The directional accuracy of 92.86% increases retail investor confidence in actively managing portfolios, particularly in *blue-chip* stocks. For further improvement, future development should focus on integrating real-time data through Application Programming Interfaces (API) from the Indonesia Stock Exchange, adding mobile-based automatic notification features for crossover signals, and incorporating an Artificial Intelligence-based sentiment analysis module to filter macroeconomic news as an additional decision layer. As a final detection result from historical closing data, the indicator configuration concludes that BBNI stock is currently in a *bearish* phase, thus the system objectively recommends a Hold Sell (Wait and See) decision for investors until a confirmed reversal into a *bullish* momentum occurs.

REFERENCE

[1] Y. M. Sim and D. Kaluge, “Examining the Correlation between Macroeconomic Factors and Stock Indices : A Comparative Analysis of IHSG and Nikkei,” vol. 7, no. 2, 2023, doi: 10.14421/EkBis.2023.7.2.2101.

[2] S. A. Purnamasari, “Mekanisme Perkembangan Pasar Modal Sebagai Salah Satu Produk Investasi di Masyarakat,” vol. 2, no. 3, pp. 499–515, 2025, doi: 10.61722/jrme.v2i3.4739.

[3] N. N. Tamtama, “Analisis Peramalan Permintaan Melalui Metode Moving Average , Weighted Moving Average dan Exponential Smoothing (Studi Kasus Pada Exist Auto Detailing),” vol. 1, pp. 1–12, 2024, doi: 10.31253/pe.v22i1.2685.

[4] A. Zaremba and I. Alon, “Forecasting the

VOL. 12. NO. 1 AUGUST 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i1.8454

equity premium: Do deep neural network models work?," *Mod. Financ.*, vol. 1, no. 1, pp. 1–11, 2023, doi: 10.61351/mf.v1i1.2.

[5] M. F. Almaliki, I. Isnawaty, M. Satyadharma, and H. Hado, "Perbandingan Metode Exponential Smoothing dan Moving Average pada Arus Barang Bongkar," Jurnal Manajemen Informatika (JAMIKA), vol. 14, no. 2, pp. 125–134, Jun. 2024, doi: 10.34010/jamika.v14i2.12828.

[6] E. D. Wahyuni, R. Rafidah, and F. Mubarak, "Analisis Harga Saham pada PT. BTPN Syariah Tbk dengan Metode EMA (Exponential Moving Average) Tahun 2020–2022," *E-Journal Perdagang. Ind. dan Monet.*, vol. 11, no. 1, pp. 29–38, 2023, doi: 10.22437/pim.v11i1.28417.

[7] M. D. Rosita, A. I. A. Himayati, and I. I. Nursani, "Prediksi Pergerakan Harga Saham Menggunakan Metode SMA, WMA, dan EMA di PT Bank Central Asia (BCA)," vol. 6, no. 2, pp. 324–333, 2024, doi: 10.36312/jml.v6i2.3950.

[8] Abid Shabrina and S. Hasnawati, "Perbandingan Efisiensi Analisis Teknikal, SMA dan EMA dalam Mengestimasi Harga Saham," *E-journal F. Econ. Bus. Entrep.*, vol. 1, no. 3, pp. 273–280, 2022, doi: 10.23960/efebe.v1i3.32.

[9] D. T. U. A. R. Hakim, "Analisis Teknikal Saham Menggunakan Indikator Exponential Moving Average (EMA) untuk Mengoptimalkan Keputusan Investasi," Jurnal Riset Akuntansi dan Keuangan, vol. 11, no. 2, pp. 145–158, Aug. 2023, doi: 10.17509/jrak.v11i2.53421.

[10] M. S. M. F. Almaliki, "Penerapan Metode Exponential Smoothing dan Moving Average dalam Memprediksi Pergerakan Indeks Harga Saham," *J. Ilm. Tek. Inform.*, vol. 14, no. 1, pp. 125–134, 2024.

[11] B. Basyarudin and G. Ramadhan, "Peran Pasar Modal bagi Investasi di Indonesia," SINERGI: Jurnal Riset Ilmiah, vol. 1, no. 11, pp. 1131–1137, Nov. 2024, doi: 10.62335/98jstk03.

[12] A. P. Candra, "Analisis Data Menggunakan Python : Memperkenalkan Pandas dan NumPy," vol. 3, no. 1, pp. 11–16, 2025, doi: 10.62386/jised.v3i1.118.

[13] H. Ahaggach, L. Abrouk, and E. Lebon, "Systematic Mapping Study of Sales Forecasting : Methods , Trends , and Future Directions," *Forecasting*, vol. 6, no. 3, pp. 502–532, 2024, doi: 10.3390/forecast6030028.

[14] D. N. Shah and M. Thaker, "A Review of Time Series Forecasting Methods," International Journal of Research and Analytical Reviews (IJRAR), vol. 11, no. 2, pp. 749–755, 2024.

[15] M. A. Palabıçak and T. Binici, "Investigating the effects of dynamics and crises on livestock production in developing countries by using time series and future forecasting with ARIMA; a case study of sheep production in Türkiye," *Appl. Ecol. Environ. Res.*, vol. 21, no. 6, pp. 5785–5806, 2023, doi: 10.15666/aeer/2106_57855806.

[16] D. Alam, A. Kurniawan, and D. Hanggraeni, "Mendorong Pertumbuhan Ekonomi 8% Melalui Pasar Modal Indonesia," Syntax Literate: Jurnal Ilmiah Indonesia, vol. 10, no. 5, pp. 4925–4935, May 2025, doi: 10.36418/syntax-literate.v10i5.58706.

[17] M. Binkhonain and L. Zhao, "A review of machine learning algorithms for identification and classification of electronic trading in financial markets," *Expert Syst. Appl.*, vol. 195, p. 116515, 2022, doi: 10.1016/j.eswa.2022.116515.

[18] Y. Chen, "Predicting stock market index using fusion of machine learning techniques and fundamental analysis," *Financ. Innov.*, vol. 9, no. 1, p. 45, 2023, doi: 10.1186/s40854-022-00435-w.

[19] H. Raza and Z. Akhtar, "Predicting stock prices in the Pakistan market using machine learning and technical indicators," *Mod. Financ.*, vol. 2, no. 2, pp. 46–63, 2024, doi: 10.61351/mf.v2i2.167.

[20] L. M. Liu, Z. Sun, K. Xu, and C. Chen, "AI-Driven Financial Analysis: Exploring ChatGPT's Capabilities and Challenges," International Journal of Financial Studies, vol. 12, no. 3, Art. no. 82, pp. 1–35, Aug. 2024, doi: 10.3390/ijfs12030082.