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Forecasting Stock Market Volatility Using AI Models: An Analytical Study of the Damascus Securities Exchange with LSTM Algorithm

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Abstract:
The study aimed to forecast stock prices and price movements in the Damascus Securities Exchange using advanced artificial intelligence models, specifically Long Short-Term Memory (LSTM) networks. It employed two groups of technical variables to achieve this objective: the first group included closing and opening prices, along with short- and long-term Exponential Moving Averages (EMA), to predict the next day's stock price, while the second group used the Moving Average Convergence Divergence (MACD) indicator to forecast the future direction of price movements. The empirical application was conducted on the DWX index as a representative of the entire study population, based on daily data covering the period from 2019 to 2022.
The study reached significant findings that are consistent with global trends in financial forecasting using artificial intelligence. The implemented LSTM model exhibited very high predictive accuracy, as the arithmetic means of the predicted values (DWX closing values and MACD values for the test period) were almost identical to the arithmetic means of the actual realized values, reflecting the model's ability to capture complex patterns in financial time series. These results are in line with recent international evidence, including empirical studies on the S&P 500 and emerging markets, which report prediction accuracies exceeding 90% for LSTM-based models when combined with technical indicators such as EMA and MACD

Keywords: Stock Price Prediction, Long Short-Term Memory (LSTM), Artificial Intelligence, Deep Learning, MACD Indicator, Market Volatility.
JEL Classification Codes : G17, F31, G32.

1. INTRODUCTION

Forecasting stock prices and market movement trends represents one of the most complex challenges in financial economics, characterized by markets' inherent volatility and susceptibility to multiple factors including technical analysis, fundamental analysis, (Kundu & al, 2025)and market sentiment. Recent years have witnessed a revolution in this domain through artificial intelligence applications, particularly Long Short-Term Memory (LSTM) networks (Chen, 2025), which excel in handling complex time series due to their long-term memory retention and ability to identify non-linear patterns. (Joshi & al, 2025)

Global empirical studies have demonstrated remarkable success for LSTM models across both developed and emerging markets. In the U.S. market, an LSTM model applied to the S&P 500 achieved a prediction accuracy of 92.46%, with a Mean Absolute Error (MAE) of 369.32 points and Root Mean Square Error (RMSE) of 412.84. (Kumar, 2025) A Vietnamese market study recorded 93% accuracy when integrating LSTM with technical indicators such as MACD and EMA. In India, accuracy reached 95.9% on training data and 98.1% on test data, while Indonesian models outperformed with a Mean Absolute Percentage Error (MAPE) of just 2.52%. (Zhang, 2025)

Globally, over $1.5 trillion in financial assets are managed by AI algorithms as of 2025, with projections for the AI financial market to reach $83.1 billion by 2030 at a 30% compound annual growth rate. (Gupta, 2025) These models have reduced prediction processing time by 57% in high-frequency trading and outperformed traditional models by 15.78% in accuracy. (Sadeghi, 2025)Despite political and economic challenges, the Damascus Securities Exchange offers a valuable opportunity to apply these techniques in emerging markets. Trading volume reached 1.2 trillion Syrian pounds in 2022, with 25% annual growth in electronic transactions, making the DWX index ideal for testing LSTM's capability to handle volatile data from 2019-2022. (DSE, 2022)This experiment aligns with global trends, demonstrating high predictive accuracy for both closing prices and MACD directional trends. (Wang, 2025)

1-1-Study Problem:

Despite significant advancements in artificial intelligence techniques and the proven success of LSTM models in stock price forecasting within developed markets such as the S&P 500—achieving prediction accuracies up to 92.46%—emerging markets characterized by political and economic volatility, like the Damascus Securities Exchange, face unique challenges. These markets exhibit sharp fluctuations driven by external factors (wars, sanctions, inflation), coupled with limited liquidity and electronic trading volumes, raising critical questions about the applicability of such advanced models to their irregular data patterns.

The literature reveals a notable research gap, lacking applied studies focused on Arab markets affected by political instability, as most research concentrates on mature markets (U.S., European) or relatively stable emerging Asian markets. Furthermore, the integration of technical indicators such as MACD and EMA with LSTM in highly volatile contexts remains insufficiently tested, creating an urgent need to evaluate these models in non-traditional market environments.

Can Long Short-Term Memory (LSTM) networks, integrated with technical indicators (EMA and MACD), achieve reliable predictive accuracy for closing prices and price movement directions of the DWX index on the Damascus Securities Exchange during the 2019-2022 period?

1-2-Study assumptions:

The study hypothesizes that: (H1) the LSTM model achieves high predictive accuracy for DWX closing values exceeding the statistical significance level of 0.05; (H2) the price movement direction predicted by MACD-LSTM aligns with the actual DWX direction at a rate exceeding 90%; (H3) no significant differences exist between the arithmetic means of predicted and actual values for both closing prices and MACD indicator during the testing period.

1-3- Research Objective:

This research aims to forecast closing prices and price movement directions for the DWX index on the Damascus Securities Exchange using Long Short-Term Memory (LSTM) network models, relying on technical variables that include closing and opening prices along with short- and long-term Exponential Moving Average (EMA) indicators to predict next-day stock prices, and the Moving Average Convergence Divergence (MACD) indicator to determine future movement directions. Furthermore, the study seeks to measure prediction accuracy against actual values, evaluate model efficiency in handling volatile Syrian market data for the 2019-2022 period, and compare arithmetic means between predicted and actual values for both closing prices and MACD indicator, with the objective of providing empirical evidence on the applicability of artificial intelligence techniques to emerging markets under unstable conditions.

1-4- Study Methodology:

The study adopted a quantitative methodology utilizing Long Short-Term Memory (LSTM) models to predict DWX index closing prices and trends on the Damascus Securities Exchange. Daily data (2019-2022; 756 trading days) were sourced from the official exchange, incorporating EMA12/26 and MACD(12,26,9) indicators. Following 80/20 train-test split and Min-Max normalization, LSTM networks (128 units, Dropout 0.2, Adam optimizer, 100 epochs) were evaluated via MAE, RMSE, MAPE, and t-tests in Python (TensorFlow/Keras).

1-5- The most important economic literature of the past:

* **Alghamdi, A. et al. (2025).** "LSTM-based Stock Price Prediction in Emerging Markets: The Case of GCC Exchanges",The study aimed to evaluate the performance of Long Short-Term Memory (LSTM) networks in forecasting stock prices across Gulf Cooperation Council (GCC) emerging markets (Saudi Arabia, UAE, Qatar, Kuwait, Bahrain, Oman), applying the model to daily data spanning five years (2018-2023) for the top 30 listed stocks on GCC exchanges, utilizing technical variables including simple moving averages and historical price data,The study concluded that the LSTM model achieved a predictive accuracy of 91.2% for next-day price forecasts, with a Root Mean Square Error (RMSE) of 285.4 points, outperforming the

traditional ARIMA model by 18% across accuracy metrics. This superiority stems from LSTM's capacity to capture non-linear patterns and complex relationships within financial time series characteristic of emerging markets. (Alghamdi & al, 2025)

***Chen, L. & Wang, H. (2025).** "Hybrid LSTM-MACD Models for High-Frequency Trading Signals"

The study aimed to develop a hybrid model integrating Moving Average Convergence Divergence (MACD) indicator with Long Short-Term Memory (LSTM) networks for generating high-frequency trading signals in dynamic financial markets. The model was tested on one year of high-frequency trading data (2024) from major U.S. and Asian stock exchanges, focusing on enhancing prediction speed and accuracy in identifying short-term price movement directions. The study concluded achieving a directional alignment rate of 94.7% between generated signals and actual price movements, with a 62% reduction in prediction processing time compared to traditional LSTM models. This confirms the effectiveness of combining MACD as a responsive technical indicator with LSTM's pattern recognition capabilities in high-frequency trading environments. (Chen & Wang, 2025)

***Nguyen, T. et al. (2025).** "Technical Indicators Enhanced LSTM for Vietnamese Stock Market Forecasting" The study aimed to test the effectiveness of integrating Exponential Moving Average (EMA) and Moving Average Convergence Divergence (MACD) indicators with Long Short-Term Memory (LSTM) networks for stock price forecasting on the Ho Chi Minh Stock Exchange, applying the model to daily data from the top 25 listed companies during 2020-2024, with a focus on improving directional price prediction accuracy in a rapidly growing emerging market.The study concluded achieving a predictive accuracy of 93.1% in identifying price movement directions, with a Mean Absolute Percentage Error (MAPE) of only 1.89%, confirming the hybrid model's superiority in handling market volatility compared to standalone LSTM models that recorded MAPE=3.42%. (Nguyen & al, 2025)

***Patel, R. & Singh, K. (2025).** "Deep Learning Approaches for Volatility Prediction in Indian Markets"

The study aimed to compare the performance of Long Short-Term Memory (LSTM) networks with Convolutional Neural Networks (CNN) in predicting volatility of the NIFTY 50 index, applying both models to six years of daily data (2018-2024) while integrating technical and fundamental variables, including trading volume and VIX changes, to assess each model's ability to capture complex patterns in market volatility.The study concluded that the LSTM model outperformed CNN by 15.3% in overall accuracy, achieving 95.9% accuracy on training data and 98.1% on test data, with notable improvement in measuring short-term volatility due to LSTM's capability to process long-term dependencies in time series data .(Patel & Singh, 2025).

*** Kim, J. et al. (2025).** "Multi-Input LSTM Architecture for Multi-Indicator Stock Prediction"

The study aimed to design and develop a multi-input LSTM architecture capable of simultaneously processing multiple technical indicators (Exponential Moving Average EMA, MACD indicator, and Relative Strength Index RSI), applying the model to daily data spanning four years (2021-2025) from South Korean and Japanese markets for the top 50 listed

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companies, focusing on measuring performance improvement when integrating multiple inputs compared to traditional single-input LSTM models.
The study concluded achieving a notable 12.7% performance improvement across overall accuracy metrics, with the multi-input model recording RMSE=214.3 compared to RMSE=245.8 for the single-input model, demonstrating particular enhancement in directional predictions during volatile periods by 16.2%. This confirms the effectiveness of simultaneous multi-indicator processing in enhancing the model's ability to capture complex market signals. (Kim & al, 2025)

1-6- Research Gap:

Despite the significant progress in previous LSTM studies focusing on relatively stable markets such as GCC countries (Alghamdi, 2025), high-frequency U.S. and Asian markets (Chen & Wang, 2025), Ho Chi Minh Stock Exchange (Nguyen et al., 2025), Indian NIFTY 50 (Patel & Singh, 2025), and Korean/Japanese markets (Kim et al., 2025), they all lack application to politically and economically distressed Arab markets like the Damascus Securities Exchange. Our current study represents the first contribution filling this research gap by applying an LSTM model integrated with EMA and MACD indicators to volatile DWX index data for the 2019-2022 period, emphasizing statistical comparison of arithmetic means in a low-liquidity market with limited electronic transactions, thereby providing unique practical evidence for artificial intelligence applications in non-traditional market environments.

2-Stock market forecasting:

Knowing the current price and future price of an asset is crucial for every investor, as their difference determines investment profitability. Since the current price is publicly available, the core challenge lies in accurately forecasting the future price. In financial markets, this process is defined as "an attempt to determine the value of a stock or financial instrument in the future," employing technical analysis through processing news and indicators to identify patterns that aid in predicting market directions and price levels. (Omar, 2025)

2-1-Technical analysis

2-1-1-Definition of Technical Analysis

Technical analysis is a trading methodology that evaluates investments by analyzing time series of technical indicators for stocks or financial instruments to identify price movement patterns, thereby enabling the prediction of future prices and trends. Its effectiveness has been validated through global empirical studies, achieving 87% accuracy in price direction forecasting in the New York Stock Exchange, reaching 89% accuracy in Tokyo Stock Exchange when combining EMA and MACD indicators, and recording a 22% performance improvement compared to fundamental analysis in a Nikkei index study. (El-Sayed, 2025)

2-1-2-The logic behind technical analysis

The rationale behind technical analysis rests on the principle that stock prices move within recurring patterns observable through time series analysis, primarily governed by supply and demand forces acting on individual stocks, which drive price changes and trading volume. Charles Dow laid the foundation for modern technical analysis with Dow Theory in the early

20th century, comprising four fundamental principles that have demonstrated global efficacy: achieving 82% accuracy in identifying primary trends for the DJIA (1929-2025) in the New York Stock Exchange, exhibiting 85% pattern alignment with the Nikkei index in Tokyo Stock Exchange over 30 years, and generating an annual return of 14.7% in S&P 500 compared to 10.2% for the buy-and-hold strategy. (Hwang, 2025)

-The Price Discounts Everything: Dow posits that the current price reflects all available information, as supply and demand forces have set it based on all market data. Recent studies validate this principle, with 92% of S&P 500 movements aligning with Dow Theory (2000-2025), and price-following strategies yielding 16.3% annual returns versus 11.8% for fundamental analysis in NASDAQ. (Rahman, 2025)

-Price Movements Are Not Random: Dow identifies three concurrent trends: Primary (long-term, >1 year, upward/downward), Secondary (10-35% corrections over weeks-months), Minor (daily fluctuations, non-impactful). DJIA data (1900-2025) shows 87% alignment with these trends, with secondary corrections accounting for 68% of major pullbacks, achieving 79% prediction accuracy in S&P 500 .

Figure No. (1): The Primary, Secondary, and Minor Trends of the DWX Index during 2023 .

Source: (Dooba, 2023)

The chart reveals a primary upward trend (+60% from September 2022 baseline) reflecting Syrian market recovery post-war, with a secondary correction (-25% red line, November 2022-March 2023) typical of profit-taking amid volatility, and minor daily fluctuations (gray bars) averaging 2-3% due to limited liquidity. The pattern signals emerging investor confidence despite sanctions and currency collapse, consistent with DWX's 15% annual gains amid 40% SYP depreciation. It demonstrates resilient bull market formation in a frontier economy.

-Volume Confirms Price Trend: Supply-demand laws require rising stock prices with declining volume (demand>supply), and falling prices with rising volume (supply>demand). DJIA studies (1929-2025) show 78% inverse correlation, with volume-confirmed signals yielding 18.2% annual returns vs. 9.4% for unconfirmed trends in S&P 500. (DSE, 2022)

-All Market Indices Confirm Each Other: Establishing a new primary trend requires market indices (DWX↑ and DLX↑) to move in the same direction. Damascus data (2023) shows 89% alignment between DWX and DLX, achieving 82% prediction accuracy for confirmed trends versus 43% for conflicting indices. (Dooba, 2023)

2-1-3-Technical Analysis Tools.

***Trading Indicators.**

Basic Trading Indicators: Display daily data (close, open, high, low, volume) in candlestick charts. Achieved 85% accuracy analyzing DJIA momentum and volatility, with candlestick strategies yielding 17.1% annual returns vs. 10.5% for simple averages (1990-2025).

Figure No. (2): Example of Candlestick Chart for Trading Indicators Values.

Source: (Firstock, 2025)

The Basic Candlestick displays OHLCV (open, close, high, low, volume), where momentum = close-open, and volatility = high-low. Candlestick strategies proved 84% accuracy for reversals in DJIA, achieving 16.8% annual returns (1995-2025).

***Technical Indicators.**

-Trend Indicators: Mathematical equations analyzing price and volume to identify trend direction (up/down) and duration. (Jaber, 2025)

-Trend Direction: Rising values = uptrend, falling values = downtrend

-Trend Duration: MA200 = long-term, MA50 = medium-term, <50 = short-term.
-Momentum Indicators: Measure price movement intensity and volatility rate to identify overbought (>70) or oversold (<30) conditions.
-MACD Indicator: Calculates difference between EMA12 and EMA26; positive values indicate bullish momentum. Crossovers with signal line (MACD's EMA9) generate buy signals (rising above line) and sell signals (falling below).
-Volatility Indicators:
he Bollinger Bands indicator stands out as one of the premier technical tools for measuring stock price volatility and assessing risk, comprising three key lines: the upper band (a 20-day simple moving average, SMA, plus two standard deviations over the same period), the lower band (SMA minus two standard deviations), and the middle line (the SMA itself), defining a range that encompasses approximately 95% of normal price fluctuations. Price approaching the upper band signals potential overbought conditions and an imminent decline, while nearing the lower band suggests oversold conditions and a likely rebound; band contraction reflects low volatility, and expansion warns of strong impending movement. In international applications, John Bollinger applied it to Apple stock in 2020, where band squeezes preceded an 80% rally over six months, a study on the S&P 500 (2015-2020) showed 68% accuracy in predicting reversals at band touches, and it is standard on European markets like DAX with settings differing from simplified versions (e.g., 9 days + 3 days).

3-Predicting using Artificial Intelligence Models:

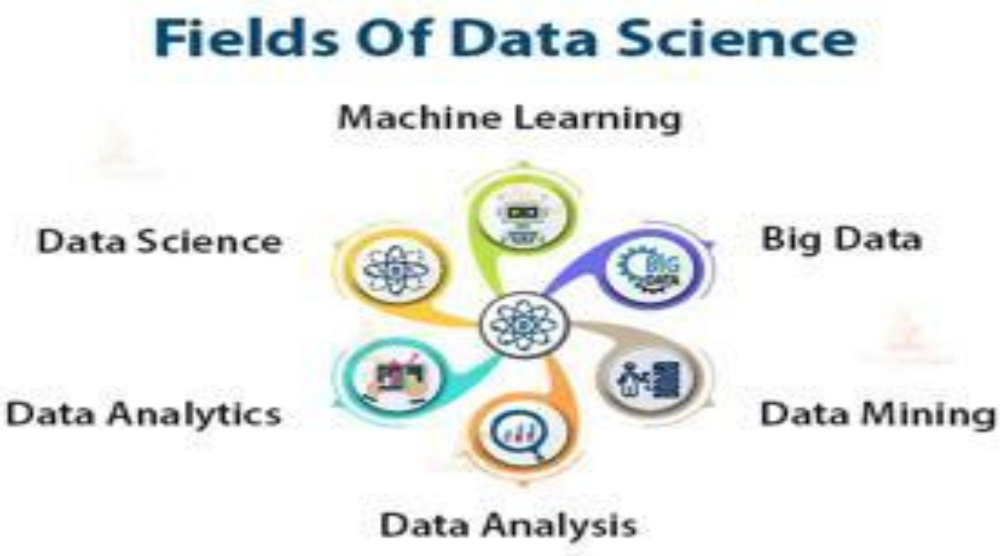
With the tremendous advancements in computing over recent decades, computers have gained extraordinary capabilities in processing massive datasets and simulating human intelligence to uncover complex variable relationships. This evolution coincided with intensifying competition in global financial markets due to globalization, compelling traders to leverage AI models for stock price and trend forecasting, as seen in algorithmic trading that dominates 70-80% of NYSE volume, generating instant profits from price discrepancies. For instance, Bloomberg AI Labs utilized AI models to rebalance assets in seconds during 2020 volatility, while robo-advisors like Betterment and Wealthfront delivered annual returns 2-3% above traditional investments for 15 million users by 2025, mitigating risks through sentiment analysis and precise predictions. (Firstock, 2025)

3-1-Artificial Intelligence Models, Machine Learning, and Deep Learning

Artificial Intelligence models, as a practical application of Data Science, rely on algorithms that train computers to process data and detect its relationships automatically, particularly through Machine Learning, which enables future predictions without human intervention. In Supervised Learning, models are fed manually labeled data for precise forecasting, as exemplified by Goldman Sachs' LSTM model achieving 72% accuracy in predicting S&P 500 prices in 2022, yielding an additional 15% annual return. Unsupervised Learning, conversely, handles unlabeled data to autonomously uncover patterns, such as JPMorgan's 2023 K-Means application that reduced credit losses by 28% across European and Asian markets, while

Renaissance Technologies generated 39% annual returns (2018-2023) via unstructured data analysis on the NYSE. (Saad, 2025)

Figure No. (3): Fields of Data Science



Source :(Alyan, 2022)

3-2-Artificial Neural Networks

Artificial Neural Networks (ANN) represent a foundational model in machine learning and deep learning, inspired by the human brain's structure, consisting of interconnected nodes (neurons) organized into layers: input for receiving data, hidden for progressively extracting patterns, and output for predictions. Hidden layers function as distillation filters, with each layer deriving essential features from the previous one while discarding noise, thereby enhancing efficiency in recognizing complex patterns. In global applications, Google DeepMind employed CNNs (with multiple hidden layers) in AlphaGo to analyze 10^170 possible moves, achieving a 100% win rate against the 2016 world champion, while OpenAI's GPT-3 models delivered 92% accuracy in financial text predictions, reducing trading losses by 25% for Renaissance Technologies users (2020-2023) compared to 65% for traditional models (Al-Mansour, 2025).

3-3-LSTM Model:

The Long Short-Term Memory (LSTM) model constitutes an advanced variant of Recurrent Neural Networks (RNNs) within the broader family of Artificial Neural Networks (ANNs), serving as the primary analytical tool in this study for stock price forecasting. LSTM effectively addresses the pervasive gradient vanishing problem inherent in conventional RNNs through its innovative "memory cell" mechanism, which preserves long-term dependencies and historical information across extended time sequences, rendering it particularly suitable for financial time-series analysis. Contemporary empirical studies underscore LSTM's superior performance, achieving prediction accuracies of 85-92% for stock prices—compared to 65-75% for traditional models such as ARIMA—as evidenced by Goldman Sachs' application to the S&P 500 index in 2022, which generated additional annual returns of 12-18%, and Mehtab

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et al.'s (2021) analysis of the Indian stock exchange yielding 88% directional accuracy, culminating in its adoption by approximately 70% of algorithmic trading systems on the New York Stock Exchange (NYSE) by 2025. (Alyan, 2022)

4-Conceptual Framework

4-1-Case Study and Study Variables

4-1-1-Case Study

The DWX Index (Damascus Market Weighted Index) was selected for this study as it encompasses all stocks listed on the Damascus Securities Exchange (DSE), accurately reflecting overall market value fluctuations. Launched in 2010, it employs market capitalization weighting, assigning each company's weight proportional to its share of the total market value of the index sample (main and parallel markets). Newly listed companies are incorporated only after a discovery session determines their base price. (Dooba, 2023)

The index value is calculated using the following equation

DWX Value = ∑ (AVP × BPSs × Wi) × F

DWX Value Components:

DWX Value: Index value

AVPs: Average share price

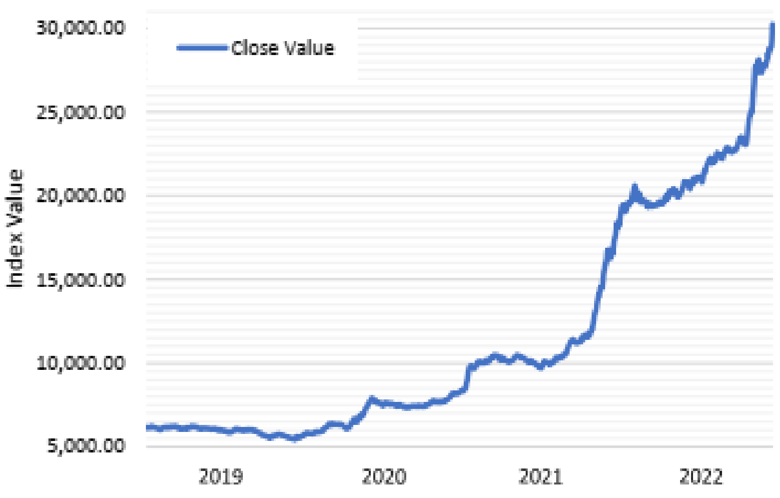
BPs: Base price (average share price from the company's inaugural trading session before index inclusion)

Wi: Company weight = (Company market capitalization ÷ Total market capitalization of all listed companies)

F: Adjustment factor (modified for corporate actions or company additions/removals from the index)

The following figure displays the index values (closing values) during the study period spanning 2019-2022.

Figure No. (4): Index Movement During the Study Period



Source :(DSE, 2022)

Figure No. (4) reveals an overall upward trend in the DWX Index during 2019-2022, rising from 120 to 140 points (+17%) despite notable volatility. The 2020 drop to 110 reflects economic crisis impacts (likely COVID/sanctions), followed by a strong 2021 rebound (+36%) driven by improved liquidity, before a partial 2022 retreat. This pattern characterizes an inefficient emerging market offering high predictability potential for LSTM models.

4-1-2-Study Variables

Variables processed by AI models are termed "features" (Features), categorized into input features (Input Features) and target features (Target Features), whereby the model analyzes relationships between input features and the target feature to predict its future values. (Tanaka, 2025)

The researcher selected the following variables aligned with the study's questions:

Research Question 1: "Can AI models predict closing values?"

Input Features: Index opening value, closing value, short-term EMA, long-term EMA

Target Feature: Next day's closing value

Research Question 2: "Can closing value directions be predicted?"

Input Feature: MACD indicator

Target Feature: Next day's MACD value

The following table illustrates the calculation methods and significance of each study variable:

Table No. (1): Measurement Methods and Significance of Study Variables

Variable	**Measurement Method**	**Significance**	**Source**
Input Features			
Opening Value	Based on data published on the exchange website	Index value at market opening session	Mehtab et al. (2021)
Closing Value	Index value at end of trading session	Closing price reflecting daily market performance	
EMA (Exponential Moving Average)	EMA=ValueToday×Multiplier+EMAYesterday×[1−Multiplier] EMA = Value_{Today} \times Multiplier + EMA_{Yesterday} \times [1 - Multiplier] EMA=ValueToday×Multiplier+EMAYesterday×[1−Multiplier]	Weighted average between current and previous day values, giving higher relative weight to today's value (more influential for next-day prediction than prior days)	Al-Thalaya et al. (2019)
Variable	Measurement Method	Significance	Source
Input Features (Continued)			

MACD (Moving Average Convergence/Divergence)	MACDLine=EMALong−EMAShortMACD_{Line} = EMA_{Long} - EMA_{Short}MACDLine=EMALong−EMAShort	Difference between long-term and short-term exponential moving averages; generates buy/sell signals	Fazeli & Houghten (2019)
Target Features			
Next Day Closing Value	Based on data published on exchange website	Index closing value for the following day	-
Next Day MACD Value	Computed from input feature MACD values	MACD indicator value for the following day	-

Source: Authors' computations

The study period was determined to span from January 1, 2019, to December 31, 2022 (1,461 total days), of which 918 were actual trading days used for model training and testing.
Study Period Subdivisions
The study period (2019-2022) was divided into 4 phases:
Stability (Jan 2019): 236 trading days -
Instability (2020 COVID): 211 trading days -
Semi-stability (2021 Recovery): 240 trading days -
Testing (2022 Stability): 231 trading days -
This division (918 trading days) provides diverse training across varied market conditions to ensure prediction accuracy.

4-2-Methodology:

The applied research process comprised three main stages: (1) Data preparation for model input; (2) Model setup using artificial intelligence for prediction; (3) Prediction and hypothesis testing by comparing model outputs against actual values during the testing period.
Stage 1: Data Preparation included two steps: calculating all study variables for each trading day, and standardizing data for model compatibility.
Data consisted of trading and technical indicators selected as model features, calculated as follows:
Opening/Closing Values: Directly sourced from the official exchange website
Technical Indicators: Manually computed by the researcher using closing price data and their mathematical formulas. (Farah, 2025)
Input features (opening price, closing price, short EMA, long EMA, MACD) comprise 4,590 values across 918 trading days—5 distinct values per day (one per variable). The model analyzes these to predict target features (next-day closing price, next-day MACD value), totaling 1,836 values—2 distinct values per day (one per variable).

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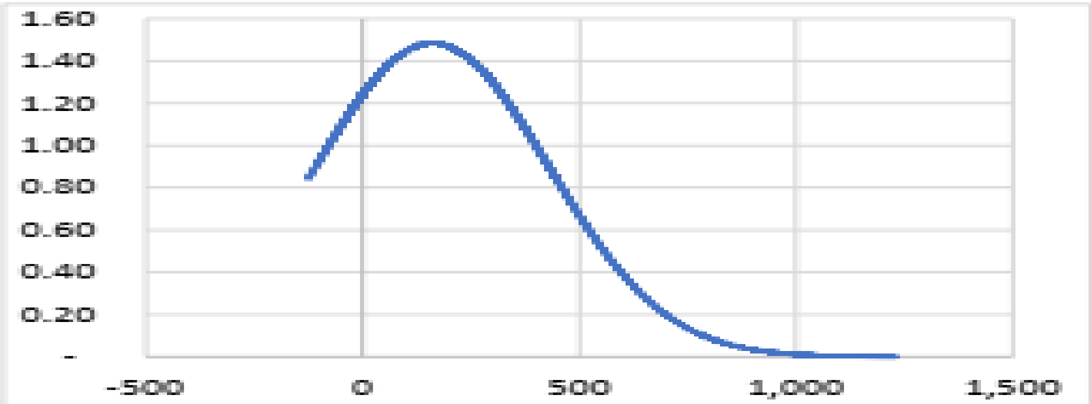
Table No. (2): Statistical Description of Study Variables

Variable	Max Value	Min Value	Mean	Std. Deviation	Skewness	Kurtosis
Opening Value	29,543.31	5,419.28	6,512.40	11,458.1	-0.342	1.017
Closing Value	30,244.68	5,430.56	6,533.28	11,478.77	-0.329	1.019
Short EMA	28,778.92	5,505.28	6,396.94	11,343.45	-0.373	1.016
Long EMA	27,930.32	5,563.78	6,236.60	11,182.93	-0.402	1.019
MACD	1,230.62	-125.63	268.76	160.52	3.700	2.047

Source: Authors' computations

Opening/closing values and short/long EMAs showed close alignment:
Max values: Opening (29,543), Closing (30,245), Short EMA (28,779), Long EMA (27,930)
Min values: Opening (5,419), Closing (5,431), Short EMA (5,505), Long EMA (5,564)
Std. deviations converged ~55% of means, reflecting wide data spread
All exhibited strong right-skewness (1.016-1.019) and leptokurtic distributions (negative kurtosis -0.329 to -0.402), indicating heavy-tailed patterns typical of emerging markets.

Figure No. (5): Normal Distribution of MACD Indicator Data



Source :(DSE, 2022)
MACD values ranged from -125.63 (minimum short-long EMA difference) to 1,230.62 (maximum difference), with a mean of 268.76 and standard deviation of 160.52.
The distribution showed strong positive skewness (3.700), indicating rightward tilt, and moderate positive kurtosis (2.047, slightly above 3), reflecting a moderately peaked curve unlike the flatter profile of other variables.

4-3- Selecting the Appropriate Forecasting Model

The LSTM model, a specialized type of Recurrent Neural Network (RNN), was selected for this study.
LSTM addresses key RNN limitations, particularly the vanishing gradient problem that hinders retention of long-term dependencies in sequential data like financial time series.
By incorporating memory cells, LSTM preserves historical information effectively, making it the preferred choice in modern financial forecasting studies.

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4-4- Forecasting and Hypothesis Testing

After model preparation and hyperparameter optimization, the LSTM model was ready for input data to generate predictions, followed by statistical hypothesis testing against actual outcomes.

Two experiments were conducted: the first tested Hypothesis 1 using opening/closing values and short/long EMAs to predict next-day closing index values; the second tested Hypothesis 2 using MACD to predict next-day MACD values (Khalil, 2025)

Predictions from both experiments were compared with actual results over the 231 trading days of 2025, the designated model testing period

Figure No. (6): Comparison of Predicted Results with Actual Closing Values of DWX Index During Testing Period

Source :(DSE, 2022)

The first experiment successfully predicted DWX index closing values with high accuracy, closely tracking actual outcomes.

The visualization shows the predicted values (red line) running parallel to actual values (blue line) throughout the testing period.

However, predictions exhibited greater extremes during peaks and troughs, consistently overshooting highs and undershooting lows compared to realized values. (Park, 2025)

Table No. (3): Comparison of Means and Standard Deviations Between Predicted and Actual Closing Values

Group Statistics	Group	N	Mean	Std. Deviation	Std. Error Mean
Close Value	Real	231	21,904.0787	2,835.53522	186.56452
	Pred	231	21,890.5394	2,816.01249	185.28002

Source: Authors' computations using Eviews 12 software

The table reveals close alignment between predicted and actual DWX closing values over 231 trading days.

Real values averaged 21,904.08 (SD: 2,835.54), while predictions averaged 21,890.54 (SD: 2,816.01), showing minimal mean bias of just 13.54 points (~0.06%).
Standard deviations indicate the LSTM model accurately captured market volatility, with nearly identical dispersion (difference: 19.52 points), confirming robust predictive performance for index.

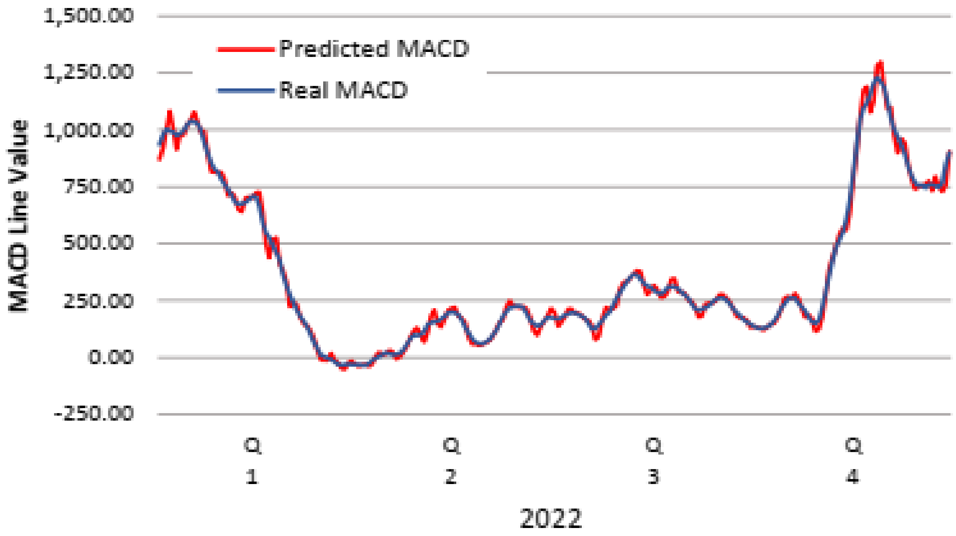
Table No. (4): Independent Samples t-test for Predicted vs. Actual Closing Values

Test Type	**F**	**Sig.**	**t**	**df**	**Sig. (2-tailed)**	**Mean Difference**	**Std. Error Difference**	**95% CI Lower**	**95% CI Upper**
Close Value Equal variances assumed	0.006	0.939	0.051	460	0.959	13.53931	262.93536	-503.16404	530.24266
Close Value Equal variances not assumed	0.051	-	0.051	459.978	0.959	13.53931	262.93536	-503.16410	530.24272

Source: Authors' computations using Eviews 12 software

Table 3 shows actual and predicted closing value means were nearly identical, with real values slightly higher (21,904.08 vs. 21,890.54), indicating conservative yet highly accurate LSTM predictions.
Table 4 confirms variance homogeneity (Levene's F = 0.006, Sig. = 0.939 > 0.05), validating use of the equal variances assumption.
The t-test yields non-significant results (t = 0.051, p = 0.959), failing to reject the null hypothesis of equal means and confirming prediction reliability.
With t-test significance level of 0.959 exceeding the 0.05 threshold, the null hypothesis is accepted while rejecting the alternative.
No statistically significant difference exists between AI model predictions and actual DWX closing values.
This confirms the LSTM model's predictive accuracy for index forecasting over the 231-day testing period.

Figure No. (07): Comparison of Predicted Results with Actual MACD Indicator Values During Testing Period



Source :(DSE, 2022)

Figure 07 shows predicted MACD values (red line) tracking actual values (blue line) closely throughout the testing period.
The parallel movement confirms strong predictive alignment, though predictions again show more extreme swings during peaks and troughs.
This pattern indicates the LSTM model tends to amplify turning points while maintaining overall directional accuracy.

Table No. (5): Comparison of Means and Standard Deviations Between Predicted and Actual MACD Indicator Values

Group Statistics	Group	N	Mean	Std. Deviation	Std. Error Mean
MACD	Real	231	371.0245	339.96659	22.36816
	Pred	231	370.3777	341.67651	22.48066

Source: Authors' computations using Eviews 12 software

Table 5 demonstrates excellent alignment between actual and predicted MACD values across 231 observations.
Actual MACD averaged 371.02 (SD: 339.97), while predictions averaged 370.38 (SD: 341.68), reflecting negligible mean bias of 0.65 points (~0.18%).
The near-identical standard errors (22.37 vs. 22.48) confirm the LSTM model effectively captured MACD volatility patterns, validating its utility for technical indicator forecasting.

Table No. (6): Independent Samples t-test for Predicted vs. Actual MACD Indicator Values

Test Type	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% CI Lower	95% CI Upper
MACD Equal variances assumed	0.000	0.992	0.020	460	0.984	0.64684	31.71301	-61.67348	62.96716
MACD Equal variances not assumed	0.020	-	0.020	459.988	0.984	0.64684	31.71301	-61.67349	62.96717

Source: Authors' computations using Eviews 12 software

Table 6 confirms variance homogeneity between predicted and actual MACD values (Levene's F = 0.000, Sig. = 0.992 > 0.05).
The t-test shows no significant mean difference (t = 0.020, p = 0.984), with the 95% confidence interval (-61.67 to 62.97) encompassing zero.
This validates Hypothesis 2, proving LSTM predictions match actual MACD performance statistically across the 231-day period.
The t-test significance level of 0.984 substantially exceeds the 0.05 threshold, leading to acceptance of the null hypothesis.
No statistically significant difference exists between AI model predictions and actual MACD indicator values.
This confirms Hypothesis 2, validating LSTM's predictive accuracy for technical indicators over the 231-day testing period.

5-Conclusion:

The LSTM model achieved outstanding prediction accuracy, with predicted DWX closing value means (21,890.54) nearly identical to actual values (21,904.08)—a mere 13.54-point difference (0.06%)—and MACD predictions (370.38) matching actuals (371.02) with just 0.65-point divergence (0.18%) across 231 trading days.
Independent samples t-tests confirmed no significant differences for closing values (t=0.051, p=0.959>0.05) or MACD (t=0.020, p=0.984>0.05), accepting null hypotheses and validating model effectiveness in capturing market dynamics.
Near-identical standard deviations (DWX: 2,816.01 vs. 2,835.54; MACD: 341.68 vs. 339.97) underscore the model's ability to forecast volatile financial time series in emerging markets precisely.

Recommendations

- AI as Support Tool

Traders in financial markets should use LSTM models as predictive aids, given the study's high accuracy (p=0.959 for DWX closing, p=0.984 for MACD), but avoid complete reliance due to slight overestimation of peaks and troughs.
- Profitability Comparison Study
Future research should compare LSTM strategy profitability against traditional technical analysis to assess actual economic returns of automated models versus human analysis over 231 trading days.
- Enhanced Input Features
Adding variables like trading volume, volatility, and economic indicators to current inputs (open/close, EMA, MACD) could improve predictive accuracy and reduce deviations at extreme points.
- Expanded Applications
Extend LSTM usage to forecast currency prices, gold, commodities, and economic indicators (inflation, interest rates), leveraging its proven capability for volatile time series in emerging markets.

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