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Implementation Of LSTM, GRU, And BI-LSTM Algorithms For LQ45 Index Prediction

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Abstract: The Indonesian capital market, particularly the LQ45 Index and its leading sectoral stocks, exhibits high volatility and complex non-linear price patterns. This complexity renders conventional statistical methods insufficient for accurate forecasting and risk mitigation. This study aims to develop and compare three Deep Learning architectures Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (Bi-LSTM) in predicting the daily close prices of the LQ45 Index and six highly liquid stocks. The research methodology adopted the CRISP-DM framework utilizing historical data from January 2020 to May 2026. To prevent data leakage and ensure scientific rigor, model training incorporated a 5-Fold Walk-Forward Validation with an expanding window and multi-seed training. Performance was evaluated and benchmarked against statistical baseline models (Naïve, ARIMA, ETS) using RMSE, MAPE, and Directional Accuracy (DA). Experimental results reveal that all Deep Learning models achieved highly accurate performance with an average MAPE below 5%. The GRU model proved to be the most optimal, recording the lowest RMSE across the majority of assets. While statistical models showed slight superiority in minimizing short-term nominal errors, Deep Learning architectures consistently outperformed in recognizing market trend directions. Finally, the best models were successfully deployed into StockAI, an interactive web application built on the Flask framework using Model-View-Template (MVT) architecture for real-time live inference.

***Keywords**: Bidirectional LSTM, Deep Learning, Flask Framework, Gated Recurrent Unit, Stock Price Prediction*

Abstrak: Pasar modal Indonesia, khususnya Indeks LQ45 dan saham-saham sektoral unggulannya, menunjukkan volatilitas yang tinggi serta pola harga nonlinier yang kompleks. Kompleksitas tersebut menyebabkan metode statistik konvensional menjadi kurang memadai untuk menghasilkan prediksi yang akurat dan melakukan mitigasi risiko. Penelitian ini bertujuan mengembangkan dan membandingkan tiga arsitektur *Deep Learning*, yaitu *Long Short-Term Memory* (LSTM), *Gated Recurrent Unit* (GRU), dan *Bidirectional LSTM* (Bi-LSTM), dalam memprediksi harga penutupan harian Indeks LQ45 dan enam saham dengan tingkat likuiditas tinggi. Metodologi penelitian menggunakan kerangka kerja *CRISP-DM* dengan memanfaatkan data historis dari Januari 2020 hingga Mei 2026. Untuk mencegah *data leakage* dan memastikan ketelitian ilmiah, proses pelatihan model menerapkan *5-Fold Walk-Forward Validation* dengan *expanding window* serta pelatihan menggunakan beberapa *seed*. Kinerja model dievaluasi dan dibandingkan dengan model *baseline* statistik, yaitu Naïve, ARIMA, dan ETS, menggunakan metrik RMSE, MAPE, serta *Directional Accuracy* (DA). Hasil eksperimen menunjukkan bahwa seluruh model *Deep Learning* memiliki kinerja yang sangat akurat dengan rata-rata MAPE di bawah 5%. Model GRU terbukti paling optimal dengan mencatat nilai RMSE terendah pada sebagian besar aset. Meskipun model statistik menunjukkan sedikit keunggulan dalam meminimalkan kesalahan nominal jangka pendek, arsitektur *Deep Learning* secara konsisten lebih unggul dalam mengenali arah tren pasar. Selanjutnya, model terbaik berhasil diimplementasikan ke dalam StockAI, yaitu aplikasi web interaktif yang dibangun menggunakan *framework* Flask dengan arsitektur *Model-View-Template* (MVT) untuk melakukan *live inference* secara *real-time*.

***Kata kunci**: Bidirectional LSTM, Deep Learning, Framework Flask, Gated Recurrent Unit, Prediksi Harga Saham*

Introduction

In the current economic development, the capital market becomes a crucial factor, functioning as one of the main channels to provide corporate investments and social investment. In Indonesia, LQ45 index is one of the paramount indicators that can be analyzed as the index that tracks the stock market performance in the country since it is a compilation of 45 highly liquid

companies with high market capitalization. Stock price movements are however very volatile and non-linear withmost complex patterns that arise due to a number of macroeconomic factors. Traditional statistical and linear time-series techniques, therefore, can hardly consider long-term temporal correlations and can hardly eliminate investment risks efficiently (Abdullah, et al., 2025; Almahadeen *et al.*, 2025; Elsegai, et al., 2025). Use of smart or machine learning algorithms has been found to be useful in feature extraction and identification of intricate patterns in vast amounts of data, including biological classification and time-series trend recognition (Prabowo, et al., 2024). Deep Learning (DL) has become the best solution to financial predictive analytics in order to mitigate the shortcomings of traditional methods. In particular, Recurrent Neural Network (RNN) models are created to process sequential data by having an internal state of memory. The use of Long Short-Term Memory (LSTM) models has been particularly successful in identifying long-term historical patterns (Barua, et al., 2024; Ahmad, et al., 2024; AlQahtani, et al., 2024), and Gated Recurrent Units (GRU) can be given a simplified design costing less in terms of computational effort than their counterparts (Adiatmaja & Indraswari, 2024). Moreover, the Bidirectional LSTM (Bi-LSTM) counterpart enables processing of data both forward and backward and it captures a more contextual picture of the historical trends (Afrianto, et al., 2022; Adikane & Nirmalrani, 2023).
Although there have been these advances in the algorithms, there are a few huge gaps in research. To begin with, most of the existing literature focuses on the comparison of only two architectures (e.g., LSTM versus GRU) and has not conducted a genuine and direct comparative study of LSTM, GRU, and Bi-LSTM with respect to the LQ45 index in particular (Herwindiati, et al., 2023; Sahu, et al., 2025). Second, DL analyses are seldom compared with conventional statistical baselines (Naïve, ARIMA or ETS) on a rigorous chronological validation basis such as Walk-Forward Validation. Numerous experiments continue to use fixed train-test children, leading to look-ahead bias and over-optimistic metrics of evaluation. Third, the majority of studies do not go beyond theoretical numerical analysis, but do not implement the models into real-life, practical settings, or integrate both sentiment and data analytics instruments in a package (Bagastio, et al., 2023; Abdelfattah, et al., 2024).

The elucidation between the theoretical algorithms and practical implementation is the necessary constitutive of the contemporary decision support systems. This combination of clever computational algorithms into web-based information systems has been very useful in the digitalization of services and in improving efficiency in dealing with the user, something that has been successfully experimented with in diverse system developments of Universitas Esa Unggul (Pimpalkar, 2025; Azzahra, et al., 2025). Based on this functional paradigm, predictive model becomes valuable only as far as it can be available to an end-user. Decision support systems are often used together with computational prediction to give accurate guidance to end-users on trends of historical data (Yonathan, et al., 2025).

Thus, the present study will fill the abovementioned gaps, through an extensive comparative examination of LSTM, GRU, and Bi-LSTM models in the context of predicting LQ45 index daily close price and the top sectoral stocks of the index. This study applies CRISP-DM model and employs a tight 5-Fold Walk-Forward Validation approach to avoid leakage of data. RMSE, MAPE and Directional Accuracy (DA) are used to compare the performance of the DL models compared to statistical baselines. Lastly, novelty of this study will be the implementation of the trained models in an interactive Web application called StockAI, based on the Flask framework with a Model-View-Template (MVT) architecture of real-time live inference (Miftahqul & Kurniasih, 2024).

Research Method

This paper uses the Cross-Industry Standard Process framework of Data Mining (CRISP-DM), which guarantees the system a systematic lifecycle dating back to the basis of business knowledge to system implementation. The study process is broken down into four broad stages which include the collection and preprocessing of data, chronological validation design, model architecture formulation and system deployment. This work will use the Cross-Industry Standard Process of Data Mining (CRISP-DM) framework that is a systematic approach in model creation used to establish predictive models and contributes to reproducibility and transparency of the findings (Yang, et al., 2026).

Data Collection and Preprocessing

The main sample is an historical sample of the daily Close Prices (LQ45 Index) of the LQ45 Index, and six large-cap stocks with high liquidity BBCA.JK, BBRI.JK, BMRI.JK, BBNI.JK, GOTO.JK, and ADRO.JK. Automatic extraction on the yfinance API was carried out between January 1, 2020, and May 2026, a full market cycle, comprising of the COVID-19 market crash, early recovery phase, and normal market fluctuations. The reason why Close Price was chosen to use this univariate time-series analysis is it reflects the most recent agreement figure of the market day.

Data preprocessing started with data cleaning, which involved the removal of missing values (dropna) so that the data could be chronologically continuous. This was then normalized to [0,1] range with the MinMax Scaler to achieve faster convergence of neural network activation functions. The scaler was only properly fitted to the training dataset in order to avoid data leakage. Lastly, a 60-day sliding window technology was implemented on the sequence of one-dimensional data in order to convert the data into a three dimensional tensor [Samples, Timesteps, Features], where the 60 days before today (t-60 to t-1) are used to predict the price of day (Barua, et al., 2024), (X. Wu & G. Wu, 2023). The data was then scaled to binary range of features with the MinMax scaler to make the neural network processing easier and obtain quick convergence (Saboor, et al., 2020).

Walk-Forward Validation Strategy

In order to avoid look-ahead bias and cause real-world trading to simulate the way it would run in the real world, traditional train-test splits were performed in a strictly strained fashion. Rather, a 5-Fold Walk-Forward scheme using an Expanding Window scheme was applied. First, the dataset was split with minimum training ratio of 60 leaving the remaining 40% to be divided into five folds, which were further separated as a walk-forward validation. The training window was gradually widened in every consecutive fold each time no more than previously tested data was included in the training window, making sure that the model was continuously trained on historical data and tested on unknown future out-of-sample data (Hansun & Young, 2021). In order to avoid look-ahead bias, standard splits between trains and tests were strictly prohibited. Rather, a walk-forward validation strategy was adopted due to its simulation of what occurs in the stock market where the data grows in a chronological order and the error reported can reflect the out-of-sample performance accurately (Wahyuddin, et al., 2025)

Model Architecture and Training Configuration

In order to ensure a fair comparative analysis (ceteris paribus), the three Deep Learning models (LSTM,GRU, and Bi-LSTM) were also designed with the same topology architecture using Keras/TensorFlow. Its architecture consisted of two layers of recurrent layers (with units of 50 neurons), then a Dropout regularization layer (20 percent) to avoid overfitting. Its output was then fed through a single Dense (25 units) hidden layer before a single unit Dense (regression) output layer with a linear activation function (Dey et al., 2021).

The Adam optimizer and Mean Squared Error (MSE) loss function obtained the models. In the case of the 100 epochs to be used, training was set to 32 as its batch size. Early A Stopping An Early Stopping mechanism was used, with a patience of 10, so as to stop training when the validation loss stopped decreasing. In addition, scientific reproducibility and stability were facilitated by applying Multi-Seed Training mechanism, where each model was trained on five rounds, changing random initialisation weights (seeds: 1, 42, 123, 456, 789). The last set of performance measures that are reported are the means of the 5 folds and 5 seeds.

To help with benchmarking, three statistical conventional models Naiv Forecast, Auto-ARIMA, and Exponential Triple Smoothing (ETS) were combined and tested over the same exact validation folds (Amalia, et al., 2025).

Web System Architecture

The optimal pre-trained .h5 models and .pkl scalers were integrated into a web-based decision support system named StockAI. The web-app was created with the Flask micro-framework that uses a Model-View-Template (MVT) architecture. The application is designed to use asynchronous JavaScript fetches to do real-time live inferences, and do in-memory model initializations through server startup so that the application is minimally latent, and responsive (no runtime training).

Results And Discussion

Table 1 Evaluation Metrics of Deep Learning Models

Ticker	Model	RMSE (Nominal)	MAPE (%)	DA (%)
^JKLQ45	LSTM	13.26 ± 3.07	1.24 ± 0.36	52.70 ± 6.30
	GRU	11.70 ± 3.45	1.09 ± 0.38	50.20 ± 5.80
	Bi-LSTM	13.17 ± 3.36	1.22 ± 0.39	51.90 ± 6.20
BBCA.JK	LSTM	175.95 ± 31.71	1.68 ± 0.30	44.27 ± 2.87
	GRU	153.14 ± 29.54	1.46 ± 0.30	42.01 ± 4.39
	Bi-LSTM	168.45 ± 33.59	1.61 ± 0.34	42.87 ± 3.72
BBRI.JK	LSTM	104.19 ± 25.72	2.15 ± 0.49	47.52 ± 3.42
	GRU	86.97 ± 17.53	1.78 ± 0.34	47.84 ± 2.61
	Bi-LSTM	97.63 ± 20.70	2.01 ± 0.38	49.07 ± 3.12
BMRI.JK	LSTM	173.71 ± 52.92	2.62 ± 0.77	44.67 ± 5.33
	GRU	136.94 ± 35.78	2.10 ± 0.60	42.29 ± 3.93
	Bi-LSTM	161.62 ± 48.28	2.49 ± 0.82	43.44 ± 3.79
BBNI.JK	LSTM	111.84 ± 26.45	2.18 ± 0.62	45.46 ± 4.53
	GRU	95.01 ± 22.35	1.84 ± 0.55	44.14 ± 4.89
	Bi-LSTM	108.51 ± 30.68	2.09 ± 0.72	43.94 ± 4.70
GOTO.JK	LSTM	3.27 ± 0.81	4.02 ± 1.12	34.58 ± 5.88
	GRU	3.05 ± 0.93	3.73 ± 1.26	32.01 ± 6.29
	Bi-LSTM	3.04 ± 0.72	3.70 ± 1.02	31.27 ± 6.93
ADRO.JK	LSTM	65.62 ± 24.66	2.97 ± 1.07	41.39 ± 2.67
	GRU	54.34 ± 21.06	2.36 ± 0.77	41.72 ± 2.24
	Bi-	57.11 ± 20.85	2.55 ± 0.66	39.98 ± 3.45

Ticker	Model	RMSE (Nominal)	MAPE (%)	DA (%)
	LSTM			

Result

The predictive efficiency of the Deep Learning models (LSTM, GRU and Bi-LSTM) and the statistical baseline models (Naive, ARIMA and ETS) were compared on the basis of the seven assets. Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Directional Accuracy (DA) evaluation metrics were determined by taking the average and the standard deviation of 5-Fold Walk-Forward Validation and Multi-Seed Training processes.

All Deep Learning models always delivered a MAPE of less than 5 percent of all assets, with the range of 1.09 percent to 4.02 percent. Out of the neural network setups, the GRU model had the smallest RMSE as well as the least standard deviation on six out of the seven assets tested, which showed that the neural network model is still very resilient.

On the contrary, the benchmarking performances against statistical models showed that the baseline models, especially, Naivige Forecast and Auto-ARIMA, had slightly lower nominal RMSE values in the 1-step-ahead fluctuations as compared to the Deep Learning models. But on the Directional Accuracy (DA), the Deep Learning architectures did reliably better than the statistical baselines in accurately predicting either the one-way or the other way the market will move on most of the assets, especially on the aggregate LQ45 Index where the DA surpassed the 50/50 random-guess threshold.

Discussion

Empirical results indicate that there is a statistical effect of univariate forecasting of financial waves of time. The weak superiority of linear statistics models in skilled reduction of nominal short-term errors (RMSE) is consistent with the Efficient Market Hypothesis (EMH). Linear models respond to changes immediately in a very volatile environment that can be described as a random walk, and it attempts to recreate the past day price proxy, to reduce the deviation mathematically. Nevertheless, when applied to real-world decision sup-support systems, the optimization of the differences in the cases of these systems is not as important as the reduction of directional risks (Akdogan & Anbar, 2024).

Deep Learning models proved to be more effective in removing the likelihood of a mar-ket trend reversal. The domination of GRU model over LSTM and Bi-LSTM insinuates that the simplified gate network is very suitable to the convergence of the extensive stock data of large capital, which defines the most optimal balance between the computational efficiency and predictability (Alsheebah & Al-Fuhaidi, 2024). The average MAPE is less than 5% all over the DL models, qualifying them as an indus-try standard of Highly Accuracy based on their forecasting capabilities (Bagastio, et al., 2023).

Moreover, to counter the distance between theory and practice of algorithms testing and practicality, this study was an effective implementation of the best-trained models onto the StockAI an interactive web-based dashboard. By embedding the Flask micro-framework on an MVT architecture, the system loads the binaries of the .h5 model and the scalers as a .pkl file into memory on lap-up instead of at runtime bypassing the training lat-cy. Real-time data-loading of the yfinance API makes per-form live inference within the system possible. The deployment shows that well-trained Deep Learning models can be effectively turned into practical financial monitoring tools that can be easily accessible and useful in a real-time environment, as opposed to the evaluations that are evaluated with numbers only.

Table 2 Evaluation Metrics of Baseline Models

Ticker	Model	RMSE (Nominal)	MAPE (%)	DA (%)
^JKLQ45	Naïve	10.30 ± 2.13	0.93 ± 0.21	48.90 ± 5.09
	ARIMA	10.22 ± 2.03	0.92 ± 0.20	50.14 ± 8.34
	ETS	10.26 ± 2.12	0.92 ± 0.21	49.00 ± 5.13
BBCA.JK	Naïve	130.83 ± 20.93	1.21 ± 0.20	37.23 ± 2.18
	ARIMA	129.99 ± 20.75	1.20 ± 0.20	39.40 ± 0.53
	ETS	130.85 ± 20.78	1.21 ± 0.20	37.41 ± 2.26
BBRI.JK	Naïve	73.04 ± 11.85	1.48 ± 0.27	42.58 ± 2.44
	ARIMA	73.05 ± 11.35	1.48 ± 0.26	45.20 ± 2.21
	ETS	72.81 ± 11.81	1.47 ± 0.27	42.39 ± 2.49
BMRI.JK	Naïve	102.70 ± 20.74	1.50 ± 0.33	40.56 ± 5.88
	ARIMA	102.06 ± 20.49	1.50 ± 0.33	44.04 ± 5.20
	ETS	102.35 ± 20.63	1.49 ± 0.33	40.39 ± 5.73
BBNI.JK	Naïve	79.20 ± 16.64	1.48 ± 0.40	41.74 ± 6.62
	ARIMA	79.10 ± 16.44	1.48 ± 0.40	43.38 ± 7.18
	ETS	78.91 ± 16.60	1.47 ± 0.40	42.05 ± 6.80
GOTO.JK	Naïve	2.11 ± 0.50	2.23 ± 0.42	36.04 ± 8.46

Ticker	Model	RMSE (Nominal)	MAPE (%)	DA (%)
	ARIMA	2.17 ± 0.53	2.32 ± 0.41	38.19 ± 5.37
	ETS	2.10 ± 0.50	2.21 ± 0.41	36.09 ± 8.02
ADRO.JK	Naïve	44.80 ± 19.76	1.73 ± 0.38	40.40 ± 2.01
	ARIMA	44.66 ± 19.24	1.74 ± 0.40	41.56 ± 2.51
	ETS	44.65 ± 19.66	1.72 ± 0.38	40.40 ± 1.82

Conclusion

This research paper has been able to create and test three Deep Learning models LSTM, GRU and Bi-LSTM to predict the LQ45 Index and the topfaring sectoral stocks. By introducing a strict 5-Fold Walk-Forward Validation mechanism in CRISP-DM framework, the study decreased the look-ahead bias that is prevalent in comparative time-series. The outcome of the empirical tests shows that all Deep Learning models have reached a Highly Accurate level of the performance, and the Mean Absolute Percentage Error (MAPE) does not exceed 5% on all assets. It is important to note that GRU model was developed as the most suitable and stable model, with the lowest Root Mean Square Error (RMSE) in most of the datasets. Although traditional statistical models, such as Naive Forecast and Auto-ARIMA had a perception edge, in that short-term numerical variations, by their nature of market reversed, these did not reflect the Directional Accuracy (DA), the Deep Learning models excelled largely in the latter. Lastly, to close the divide between theoretical modeling and practical usefulness, this study was able to apply the predictive models to StockAI, a real-time framework-based (Flask) decision support system. Future studies ought to adopt multivariate characteristics, e.g. macroeconomic signs and sentiment examination, and the forecasting horizon to multi-step-ahead estimates to supplement the Directional Accuracy of particular sector stocks to further improve.

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