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Stock Price Prediction Using the ETSFormer Model Case Study: PTBA

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ABSTRACT

The capital market in Indonesia is currently experiencing very rapid development. This growth is significantly evidenced by the increasing number of investors, especially from the millennial and Gen Z demographics. However, this growing investor base also faces a major challenge: high stock price volatility. These fluctuations are triggered by various factors, ranging from domestic economic policies and global geopolitical conditions to rapidly changing market sentiment. This research aims to build a stock price prediction model for PT Bukit Asam Tbk (PTBA) using the ETSFormer architecture, a modern Transformer-based method designed for time-series data. The historical stock price data used in this study covers a five-year period from 2020 to 2025. To ensure optimal model performance, the best model was identified using the Grid Search technique to find the most effective combination of hyperparameters. The results of this study determined that the best model was achieved with the hyperparameters model dimension = 16, batch size = 16, and a learning rate = 0.01, which yielded a validation loss of 0.0074. In the evaluation phase, this model demonstrated solid performance with a MAPE score of 3.28%, an MAE of 86.76, and an RMSE of 117.2. Although the resulting model is quite good at reading long-term trend directions, observations indicate limitations in capturing short-term price volatility. This implies that the model is more suitable for strategic trend analysis than for predicting daily fluctuations.

INTRODUCTION

The stock market is one of the main pillars of a country's economic system, serving as both a measure of economic health and an important means for companies to raise funds and for investors to seek profits (Istinganah & Hartiyah, 2021). In Indonesia, the stock market, represented by the Indonesia Stock Exchange (IDX/BEI), plays a crucial role in supporting the development of financial infrastructure that creates an efficient and secure trading system (Anas et al., 2020). Since its establishment in 1912 and reactivation in 1977, the IDX has grown rapidly, especially in the last two decades. The Jakarta Composite Index (JCI/IHSG), as the main indicator of the Indonesian stock market's performance, has recorded significant growth, although it has experienced fluctuations caused by various factors along the way (Istinganah & Hartiyah, 2021).

However, this growth is accompanied by a major challenge: high stock price fluctuations. Internal factors like company performance and investor perceptions of specific issues amplify this uncertainty. In this environment, volatility—the rate of variability in stock prices over a specific period—becomes a reflection of high market uncertainty (Nurjanah et al., 2024). This phenomenon is reflected in various real-world events. In a global context, the US Federal Reserve's decision to raise interest rates in 2022 triggered a sharp decline in global stock markets (M et al., 2024). Meanwhile, the Indonesian stock market has also shown its vulnerability to global dynamics, for example, through commodity price fluctuations that directly impact the performance of stocks in the energy and mining sectors (Artiani & Sari, 2019). Additionally, domestic political stability and government policies also contribute to the volatility of the JCI (Hidayati, 2024).

A clear example is the drastic decline of the JCI during the COVID-19 pandemic in March 2020, where the index plummeted from around 6,300 points to below 4,000 in less than two months. However, as the economy recovered, the JCI rebounded and reached a level of 7,200 by the end of April 2022. These fluctuations show that stock prices are not only influenced by a company's fundamental performance but also by market sentiment and unexpected events (Nurjanah et al., 2024).

Amid these dynamics, the ability to predict stock prices becomes crucial. Stock price prediction is the effort to forecast future price movements to formulate investment strategies. The ability to predict accurately can give investors an edge in managing risk and maximizing returns(Shah et al., 2023). For the growing number of retail investors, unexpected fluctuations can make it difficult to develop investment strategies, and without accurate predictions, they are prone to making impulsive decisions (Jati & Indriastuti, 2024).

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Stock price prediction is a complex challenge as it is influenced by many factors. The main challenge lies in the characteristics of the stock price data itself, which is non-stationary, non-linear, and full of noise (Shah et al., 2023). The non-stationary nature means that the data's statistics continuously change over time. The non-linear nature means the relationship between the price and its influencing factors cannot be explained simply. Meanwhile, noise refers to random fluctuations originating from imperfections in the trading mechanism.

In line with the importance of accuracy in developing prediction models, this research adopts ETSFormer due to its superior ability to handle complex and dynamic time-series data. To test this model's performance in the real context of the Indonesian stock market, a relevant study object that reflects challenging data characteristics is needed. The issuer selected as the case study for this research is PT Bukit Asam Tbk (PTBA), a state-owned enterprise in the coal mining sector. As one of the main issuers in the mining sector, PTBA's stock price movement is highly influenced by global commodity price fluctuations, especially coal. This volatility is also amplified by global demand dynamics, export policies, and energy transition issues that affect the prospects of the mining industry. These characteristics make PTBA a representative example of a mining sector stock with high sensitivity to both external and internal factors.

Therefore, this research is expected to provide a new contribution to creating a more accurate and adaptive stock price prediction model for the Indonesian capital market.

LITERATURE REVIEW

The prediction of stock price movements stands as one of the most compelling and complex challenges in the worlds of finance and data science. Accuracy in forecasting stock prices can minimize the risk of loss and maximize profits for investors (Shah et al., 2023). Given the volatile nature of stock prices, which are influenced by a multitude of factors, both internal to the company and external, the study of prediction methods continues to evolve rapidly.

Historically, early approaches to stock analysis were divided into two main camps: fundamental analysis and technical analysis. Fundamental analysis focuses on the financial health and business prospects of a company, whereas technical analysis utilizes historical price movement and trading volume data to identify patterns and trends (Triya et al., 2024).

With advancements in computation, statistical models such as the Autoregressive Integrated Moving Average (ARIMA) and its variants became popular. These models work by analyzing time series data to make forecasts. Faisal (2021) employed the ARIMA model to predict the TLKM stock price. However, ARIMA models have significant limitations, particularly in handling the non-linear and non-stationary nature of stock price data (Minhaj et al., 2022).

The era of machine learning brought a breath of fresh air by introducing more sophisticated and flexible algorithms. Methods like Linear Regression, Support Vector Machines (SVM), and Random Forest demonstrated superior capabilities in handling the complex relationships within financial data. According to Wang et al., (2017), the SVM algorithm is less effective when applied to data containing significant noise.

The current peak of this evolution lies in the application of deep learning. Artificial neural network architectures such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) are specifically designed to process sequential or time series data, making them highly suitable for stock price prediction. However, according to Wen & Li, (2023) LSTM has low accuracy when dealing with non-stationary multivariate data.

The quest for greater predictive accuracy has driven the evolution beyond standalone deep learning models, leading to the emergence of hybrid architectures. This trend is exemplified by the ETSformer, a novel model that merges two powerful but distinct approaches: the attention-based Transformer model and the classical Exponential Smoothing (ETS) method (Woo et al., 2022). By embedding the classical decomposition principles of ETS directly into the powerful Transformer framework, the ETSformer is specifically designed to overcome the weaknesses of its predecessors in handling non-stationary and noisy time-series data (Woo et al., 2022).

METHOD

In this research, there are five stages in general, namely data collection, data preprocessing, training and hyperparameter tuning, and testing (Hanafiah et al., 2023).

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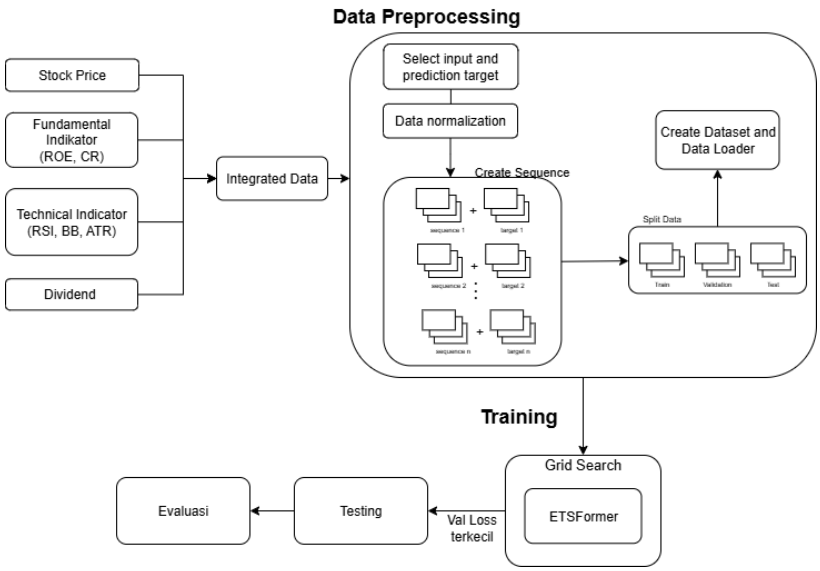

Fig. 1 Computational Model

Data Collection

The data in this study consists of five types of data: daily stock prices, daily dollar exchange rates, daily coal prices, fundamental company indicators, and technical indicators. The data used in this study covers a five-year period, from June 2, 2020, to May 28, 2025.

Daily stock price data was taken from the website id.investing.com. This data consists of several columns: date, opening price, last price, highest price, and lowest price. The resulting row count is 1236.

The US dollar price data against the Indonesian rupiah was taken from the website id.investing.com. This data consists of several columns: date, opening price, last price, highest price, and lowest price. This data is daily, including public holidays. The total number of rows in the data is 1,258. In the next step, the columns used in this data are the date and last price columns.

Daily coal price data was obtained from the markets.businessinsider.com website. The dataset consists of 1,258 rows and includes columns for Date, Opening price, Last price, Highest price, and Lowest price. In the subsequent stage of analysis, only the 'Date' and 'Last price' columns were utilized.

The company's fundamental indicators were sourced from the Stockbit application. For this study, the selected metrics were Return on Equity (ROE) and Current Ratio (CR), both of which are derived from the company's quarterly financial reports. To align with the daily frequency of other data, these quarterly indicators were converted to a daily series using the same methodology applied to the interest rate and inflation data.

In addition to these quarterly metrics, dividend data was also incorporated as a fundamental indicator. Unlike ROE and CR, dividend information is typically released annually. The collected dividend dataset includes key information such as the dividend amount, ex-date, and cum-date.

Technical indicators were derived from the PTBA stock data by utilizing the ta Python library. The calculation of these indicators, which often requires a look-back period, resulted in initial rows containing null values. These rows were subsequently removed to ensure data validity, reducing the final dataset to 1,202 rows. The specific indicators selected for this study include the Relative Strength Index (RSI), Bollinger Bands, and the Average True Range (ATR).

Data Preprocessing

All collected datasets were integrated into a single comprehensive dataset using the 'Date' column as the primary key. For the stock price, dollar exchange rate, and coal price data, this integration was straightforward as they all shared a daily frequency.

However, a different approach was required for the fundamental indicators due to their lower-frequency reporting. To handle this discrepancy, a forward-fill method was applied. With this method, a given value is held constant and propagated forward daily until a new value is reported.

The data preparation process began by defining all columns, excluding the date, as input features and the PTBA stock's closing price as the target variable. Both the input and target data were then normalized using a MinMaxScaler to bring them to a common scale. Subsequently, the data was transformed into sequential input-target pairs and split into training (90%) and testing (10%) sets. This division was performed chronologically, without shuffling, to maintain the temporal integrity of the time-series data.

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To make the data compatible with the model, these sequences were converted into the torch.tensor format and organized into a custom Dataset. A Data Loader was then utilized to load the data incrementally in batches, which is an efficient method for the model training process.

Training

To optimize the hyperparameters, this study implemented a Grid Search coupled with 5-fold Time Series Cross-Validation (TSCV) to ensure a robust and generalized evaluation. The grid search tested combinations of three values for each of the following hyperparameters: model dimension, learning rate, and batch size.

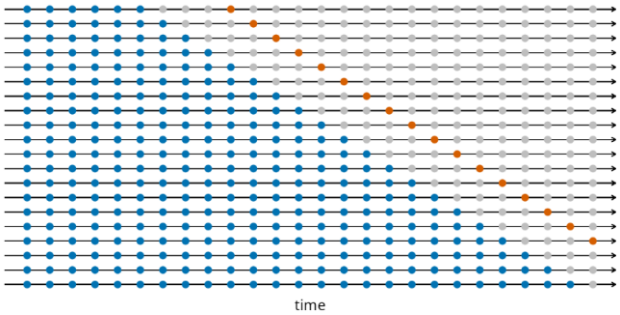

Fig. 2 TSCV Process

Unlike standard cross-validation, the TSCV method preserves the chronological order of the data in each fold, as illustrated in Figure 2. For each hyperparameter combination, the validation loss values from the five folds were averaged to produce a single performance score, which was subsequently used to identify the optimal combination.

Testing

The final stage of the research was the testing phase. In this phase, the optimal model identified during training and hyperparameter tuning was evaluated on a hold-out test set, which comprised 10% of the total dataset and consisted of data previously unseen by the model. The output of this stage includes the evaluation metrics MAPE (Mean Absolute Percentage Error), MAE (Mean Absolute Error), and RMSE (Root Mean Squared Error). Additionally, a graphical comparison between the actual and predicted values was generated to visually assess the model's performance.

RESULT

Experiment Scenario

The experimental design involved partitioning the data into a 90% training set and a 10% test set. The training data was used for the grid search procedure, where each potential model was evaluated using 5-fold cross-validation. The test data was held out and used only once to evaluate the final, optimal model selected from the grid search.

Table 1. Hyperparameter Grid Search

Input	Target
Batch Size	16, 32, 64
Learning Rate	0.01 ,0.05, 0.1
Model Dimension	16, 32, 64

Each training run was set for a maximum of 1,000 epochs, with an early stopping patience of 10. This would terminate the training if no improvement in validation loss was observed for 10 epochs. As shown in Table 1, the grid search tested three values for each hyperparameter, leading to a total of 27 distinct combinations

Experiment Results

Based on the experimental scenario, the experiment was conducted using a grid search technique based on predetermined hyperparameters, namely batch size, learning rate, and model dimension. The experimental results can be seen in Table 2.

Table 2. Top Ten Experimental Results

Model Dimension	Batch Size	Learning Rate	Average Loss Validation
16	16	0.01	0.00744
16	16	0.05	0.00746
16	16	0.1	0.00755
16	32	0.1	0.00767
16	32	0.05	0.00783
32	32	0.05	0.00786

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16	32	0.01	0.0083
16	64	0.1	0.00893
32	64	0.05	0.00894
16	64	0.05	0.00914

Grid search results for the ETSFormer model were obtained with the best combination of model dimension of 16, batch size of 16, and learning rate of 0.01, with a validation loss value of 0.00744.

DISCUSSION

To ensure an unbiased evaluation, the model was assessed on a hold-out test set. This testing process was conducted once using data previously unseen by the model during training, with the primary goal of evaluating the model's generalization capability on new data. The evaluation results are presented through performance metrics and a visual comparison of the model's predictions.

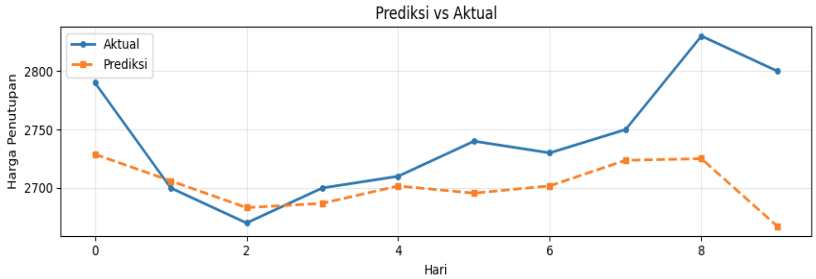

Fig. 3 Best Model Prediction Results

Figure 3 illustrates the prediction results from the model configured with the optimal hyperparameters: a model dimension of 16, a batch size of 16, and a learning rate of 0.01. Visually, the model effectively captures the overall pattern or trend of the actual price movement. Furthermore, it demonstrates a reasonable ability to identify turning points. When the actual price rises, the model's prediction follows suit, despite a prediction error in the trend on the 5th and 6th days.

Despite the positive trend alignment, the model's predictions are consistently lower than the actual values. Moreover, the model struggles to capture price volatility. This limitation is particularly evident in the transition from the 7th to the 8th day, where the actual price shows a significant increase, yet the model predicts a relatively flat trend for that period.

Table 3. Best Model Evaluation Matriks

Evaluation Matriks	Results
MAPE	3.28%
MAE	86.76
RMSE	117.20

Table 3 presents the model's evaluation results, which indicate a solid predictive performance. The MAPE of 3.28% suggests a high level of accuracy. An MAE of 86.76 signifies that, on average, the predictions deviate by 86.76 points from the actual price. The higher RMSE value of 117.2, compared to the MAE, implies that while most errors are small and consistent, the model occasionally produces larger, more significant prediction errors.

CONCLUSION

This research successfully constructed a predictive model for PTBA stock prices by leveraging a five-year historical dataset augmented with technical, fundamental, and external indicators. A Grid Search across 27 hyperparameter combinations determined the optimal configuration—a model dimension of 16, a batch size of 16, and a learning rate of 0.01—which produced a validation loss of 0.0074. Subsequent evaluation on the test set demonstrated the model's performance, with a MAPE of 3.28%, an MAE of 86.76, and an RMSE of 117.2. It is concluded that while the model is proficient at identifying price trends, it struggles to capture periods of high volatility

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