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# HYBE Corporation Stock Price Prediction Using CNN-LSTM with CRISP-DM Framework

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***Abstract*** - *Digital transformation in financial analysis requires the application of computational models that can handle the complexity of the stock market efficiently and objectively. This study aims to predict the stock price of HYBE Corporation using the Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model within the CRISP-DM (Cross Industry Standard Process for Data Mining) framework. The data used consists of daily stock prices of HYBE Corporation obtained from Yahoo Finance. The research process includes the main stages of CRISP-DM, namely business understanding, data understanding, data preparation, modeling, evaluation, and presentation of results. The CNN-LSTM model is designed to combine the ability of CNN to extract local patterns from time series with the advantage of LSTM in capturing long-term dependencies. To maximize the parameters used, this study also performed hyperparameter tuning using GridSearchCV on several key parameters. This process aimed to obtain the best combination of parameters capable of improving prediction accuracy and reducing the error value in the CNN-LSTM model. The evaluation results show that the CNN-LSTM model is capable of providing predictions with a very high level of accuracy. The Mean Squared Error (MSE) value is 0.00029, the Root Mean Squared Error (RMSE) is 0.01704, the Mean Absolute Error (MAE) is 0.01346, and the Mean Absolute Percentage Error (MAPE) is 2.15%. These low evaluation values demonstrate the model's effectiveness in handling stock market volatility while maintaining stability in predicting both short-term and long-term patterns.*

***Keywords***: *Stock; Prediction; CNN-LSTM; CRISP-DM; HYBE.*

## 1. INTRODUCTION

The capital market is one of the fundamental elements in the global financial system that serves as a means of long-term investment and a reflection of the economic dynamics of a country. One of the main instruments in the capital market is stocks, which reflect the value of a company based on economic factors, policies, and investor expectations of the company's future performance [1]. Global market capitalization has experienced significant growth in recent decades. According to World Bank data in 2022, global market capitalization reached USD 93.68 trillion, with the largest contribution coming from the technology and financial sectors which are very sensitive to changes in information, both from financial reports and public news [2]. Stock price movements are influenced by various factors such as public information, social conditions, macroeconomic policies, and political dynamics.

The entertainment industry, particularly in South Korea, represents a distinctive segment of the capital market characterized by high sensitivity to information flows and public perception. In this context, companies such as HYBE Corporation exhibit stock price dynamics that are not solely driven by fundamental financial performance, but also by non-fundamental volatility, defined as price fluctuations triggered by exogenous and sentiment-driven factors such as artist-related rumors, management controversies, and shifts in public image. The global expansion of Korean popular culture, with an estimated 89.19 million fans worldwide, amplifies information diffusion intensity and accelerates market reactions to non-financial events [3][4][5]. Empirical evidence by [6] further indicates that HYBE demonstrates higher volatility compared to its industry peers, reflecting its vulnerability to sentiment shocks. This phenomenon was evident in August 2024, when HYBE’s stock price declined by 11.2% within two weeks despite reporting record-breaking quarterly earnings, highlighting a clear disconnect between firm fundamentals and market behavior driven by negative sentiment surrounding internal issues and artist controversies [6][7].

Conventional prediction methods such as ARIMA, GARCH, and linear regression have limitations in capturing non-linear patterns in stock data, especially during high volatility such as in the entertainment sector [8][9]. These models often fail to capture complex, nonlinear interactions and abrupt structural breaks caused by sentiment shocks. In contrast, *deep learning* approaches offer a more flexible framework capable of modeling nonlinear dependencies, high-dimensional feature interactions, and dynamic temporal patterns. From a theoretical perspective, neural network-based models approximate complex functions through hierarchical feature learning, enabling the extraction of latent representations from noisy and sentiment-influenced financial data. This capability is particularly relevant in the presence of *non-fundamental volatility*, where price movements are influenced by unstructured information and behavioral responses rather than purely quantitative indicators.

Among various deep learning architectures, the hybrid Convolutional Neural Network–Long Short-Term Memory (*CNN-LSTM*) model has demonstrated strong performance in time series forecasting tasks. The CNN component functions as an automatic feature extractor that identifies local patterns and short-term fluctuations in sequential data, while the LSTM component captures long-term dependencies and temporal relationships through memory cells and gating mechanisms [10][11][12]. This integrated architecture allows the model to respond adaptively to both gradual trends and sudden sentiment-driven shocks. Unlike purely general-purpose implementations, the CNN-LSTM model in this study is conceptually aligned with the characteristics of entertainment stock data, where abrupt volatility spikes require both local pattern sensitivity and temporal memory retention.

Deep learning is a branch of machine learning that uses layered artificial neural networks to automatically learn complex data patterns. Deep learning is an algorithm that uses artificial neural networks as an architecture for understanding and learning data, which originated from artificial neural network research with multilayer perceptron as its structure [13][14]. In the context of time series-based stock prediction, deep learning is able to recognize non-linear patterns and capture long-term dependencies. These capabilities make deep learning a promising approach to improve the accuracy of stock price prediction. This capability makes deep learning a promising approach to improve stock price prediction accuracy. There are 5 generals deep learning models, including CNN-LSTM, LSTM, CNN, MLP and GRU [15]. The study by Zhang & Li, showed that CNN-LSTM can improve prediction accuracy by up to 8.45% compared to conventional deep learning models [16].

Although the CNN-LSTM model has been widely applied across various domains, including food commodities and general financial markets, these applications are predominantly situated within structured and fundamentally driven environments. For instance, [15] demonstrated the effectiveness of CNN-LSTM in predicting salmon market prices, where price movements are largely governed by supply-demand mechanisms, seasonal patterns, and relatively stable economic factors. However, such characteristics differ significantly from the data structure observed in the entertainment industry. In contrast, entertainment sector stocks, particularly those of HYBE Corporation, are highly influenced by unstructured and sentiment-driven information, such as artist-related rumors, public controversies, and media exposure. These factors generate non-fundamental volatility characterized by abrupt, nonlinear, and irregular price movements, which are difficult to model using approaches designed for structured data. Despite these distinct characteristics, the application of CNN-LSTM in capturing sentiment-driven dynamics within the entertainment sector remains limited, indicating a clear research gap.

To address this gap, this study employs the CRISP-DM (*Cross-Industry Standard Process for Data Mining*) framework to ensure a systematic and structured analytical workflow, encompassing business understanding, data understanding, data preparation, modeling, and evaluation. The deployment phase is excluded due to the research-oriented scope of this study; however, its potential implementation is discussed as a future direction, particularly in the development of decision-support systems. This framework facilitates an iterative and exploratory process, making it well-suited for time series prediction based on historical stock data.

Based on this background, this study aims to evaluate the performance of the CNN-LSTM model in predicting the daily stock price of HYBE Corporation using the CRISP-DM approach. Beyond assessing predictive accuracy, this research contributes to the field of financial technology by proposing an adaptive forecasting framework capable of capturing nonlinear patterns and sentiment-driven volatility in high-volatility cultural industries. The findings are expected to provide empirical insights into the robustness of hybrid deep learning models in environments characterized by rapid information diffusion and behavioral-driven market dynamics, thereby supporting more informed and context-aware investment decision-making.

## 2. RESEARCH METHODOLOGY

This research uses a quantitative empirical approach based on the time series forecasting method to predict the stock price of HYBE Corporation by combining the CNN-LSTM deep learning model. The research process follows the CRISP-DM framework as a systematic standard in data processing. Cross Industry Standard Process for Data Mining (CRISP-DM) is a systematic and widely used data analysis framework in data science projects. The CRISP-DM framework divides the data mining project life cycle into six phases there are business understanding, data understanding, data preparation, modelling, evaluation, and deployment [17]. Figure 1 shows the life cycle of a data mining process in CRISP-DM. This research only uses 5 stages of crisp-dm without implementing the deployment phase and aims to explore the prediction accuracy performance of CNN-LSTM hybrid deep learning model for Hybe stock price with CRISP-DM for the framework.

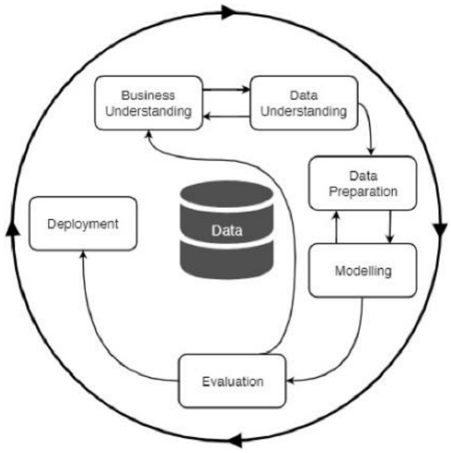


Figure 1. CRISP-DM framework.

The exclusion of the deployment phase is therefore methodological rather than conceptual. This study focuses on model development, validation, and performance assessment, rather than integrating the model into a real-world production system. Nonetheless, the deployment phase remains highly relevant as a potential extension of this research. In practice, the developed model could be deployed as part of a decision-support system for retail investors, for example through integration into web-based or mobile investment platforms. Such a system could provide real-time or near real-time stock price predictions, enabling more informed, data-driven investment decisions. Thus, while deployment is not implemented in this study, its strategic potential is acknowledged as an important direction for future work, particularly in supporting practical applications in financial analytics and retail investment environments. We illustrate our research framework in Figure 2.

This study began with the business understanding stage. Business Understanding is a phase in understanding the objectives of the analysis based on the business context or predictive needs which then results in the formulation of data mining problems and plans to achieve these business goals. Data Understanding is the phase after business understanding. In this phase, data collection is carried out, then the data is explored, described, and the quality and integrity of the data is prepared. This study was extract dataset daily stock prices HYBE at yahoo finance from October 15, 2020 to December 28, 2024. After that, proceed to the data preparation stage. Data preparation is an advanced phase of the data understanding phase, where data processing is performed. This phase includes all activities in dataset building, such as data cleaning, splitting data, transformation, and normalization processes to make it ready for modeling before being applied to the modeling phase [18][19][20]. Modeling is the phase where modeling and model testing techniques are selected and applied. In this research, CNN-LSTM predictive algorithm will be applied as well as tuning the model parameters using grid search.

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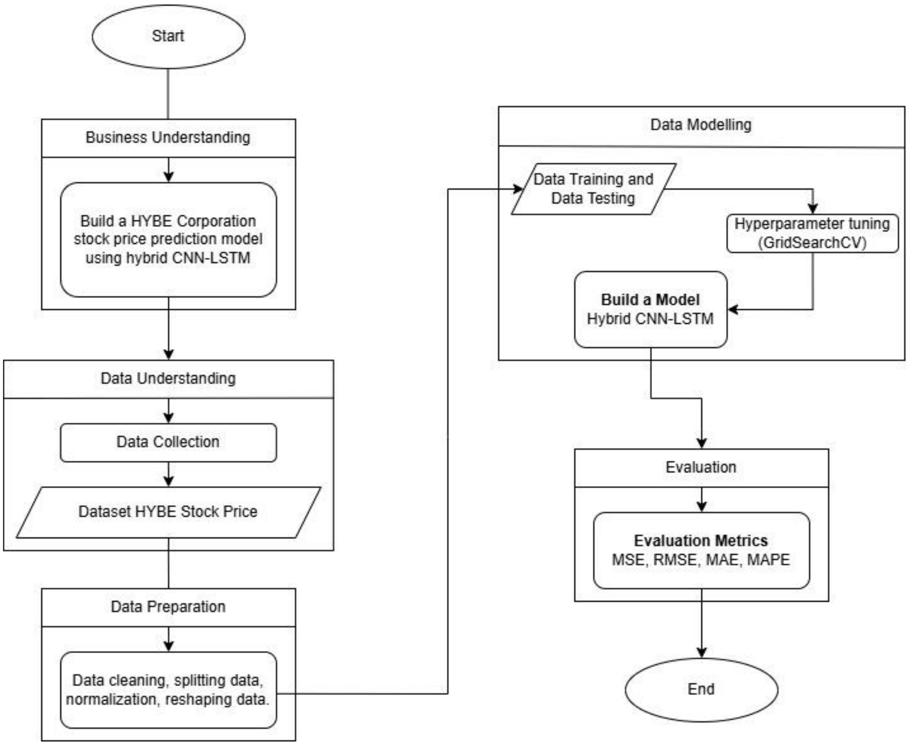


Figure 2. Research framework.

The CNN-LSTM hybrid algorithm is a combined algorithm between Convolutional Neural Networks (CNN) and Long-Short Term Memory (LSTM). In this research, CNN acts as a spatial information extractor from input data, while LSTM plays a role in capturing temporal patterns or data sequences. The convolution layer and the LSTM layer are the main parts of this model architecture. In other words, CNN processes the data within a specific time window to find important signals, and then LSTM analyzes the sequential dynamics of those features. This hybrid model has been shown to provide superior prediction performance in various financial and investment studies.

CNN is a network model proposed by LeCun and friends at 1998 [21]. CNN is a form of feedforward neural network that has been known to be effective in the application of time series data prediction, image processing and natural language. CNN excels at local perception and weight sharing capabilities, which can significantly reduce the number of parameters and improve model learning efficiency. CNN is divided into three main layers, namely convolutional layer, pooling layer, and fully connected layer [23][24][25].

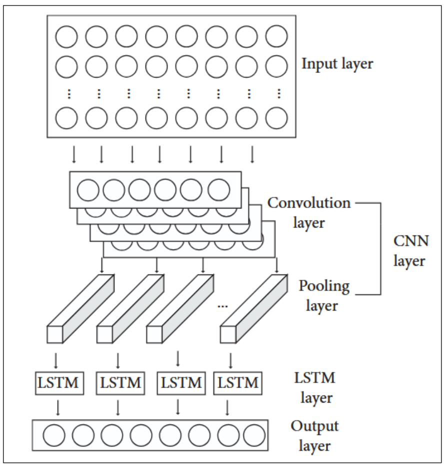


Figure 3. Architecture of CNN-LSTM model [25].

Long Short-Term Memory (LSTM) is a neural network architecture derived from RNN introduced by Hochreiter and Schmidhuber at 1997 to overcome the limitations of Recurrent Neural Network (RNN) in learning long-term dependencies, specifically the vanishing gradient problem [26]. With its complex gating mechanism, LSTM allows important information to be retained over a longer period of time, thus improving the model's ability to understand patterns hidden in sequential data [27]. LSTM memory cell consists of three elements, forget gate, input gate, and output gate [28][29].

Evaluation is the next phase after modeling is done. In this phase, the process of testing the performance of the model using certain evaluation metrics is carried out, namely checking the results to ensure that no phase is missed so that it remains on the path of the business goals that have been set. This study select 4 metrics to evaluated prediction accuracy of models, following the previous studies [15]. Mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are these metrics [30]. The calculation formula follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|X_i - Y_i| \tag{1}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2 \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2} \tag{3}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{X_i - Y_i}{Y_i}\right| \times 100 \tag{4}$$

Where $n$ is a symbol for number of test sets, $Y_i$ is the actual value and $X_i$ is the predicted value.

## 3. RESULTS AND DISCUSSION

### 3.1. Business Understanding

Volatile stock price movements pose a challenge for investors in making timely and data-driven investment decisions. HYBE Corporation, as one of the major entertainment companies in South Korea, has high market exposure, including significant stock volatility due to internal and external factors such as artist releases, market sentiment, and macroeconomic factors. This research aims to build a HYBE Corporation stock price prediction model using a deep learning approach, specifically the CNN-LSTM model. By utilizing historical daily stock price data, this model is expected to recognize complex and nonlinear price movement patterns and trends. Practically, the results of this research are expected to help retail investors and market analysts in understanding the dynamics of HYBE shares and provide predictive information for consideration in making investment decisions. From an academic perspective, this research also contributes to the development of hybrid deep learning methods as a part of time-series data based on stock price prediction.

### 3.2. Data Understanding

The data used in this study is historical daily stock price data of HYBE Corporation with stock code (352820.KS). The dataset daily stock prices HYBE was extract at yahoo finance from October 15, 2020 to December 28, 2024 using web scrapping method. There have been many related studies that extract historical stock price data from yfinance [31]. Figure 4 shows visualization the movement of HYBE stock price. This study's find that HYBE stock price fluctuated from the end of 2020 to 2022. HYBE stock price went to a historic low in the second half of 2022 and then returned to relatively high level at the beginning of 2023.

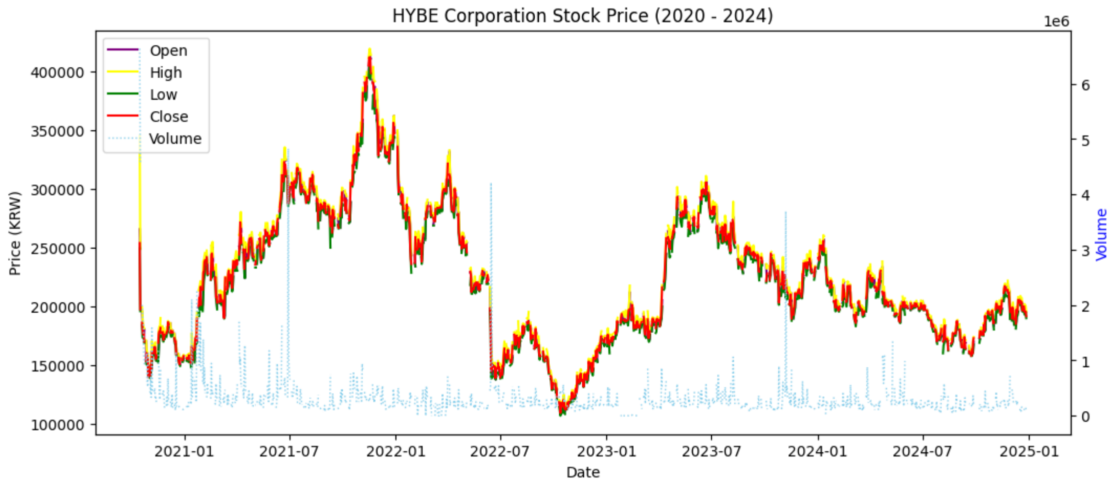


Figure 4. HYBE stock price movement.

The main attribute obtained from the extract process is Date, which is the date the stock price was recorded. Open is the price at the opening of trading day. High is the highest stock price in one trading day. Low is the lowest price on a trading day. Close is the share stock price at the close of trading day. Volume is the number of shares trade in one day. In this study, the Close price attribute is used as the target variable because it reflects the actual value that is often used as a reference in making investment decisions.

### 3.3. Data Preparation

The data preparation stage aims to prepare the daily stock price data of HYBE Corporation to match the input format of the deep learning model. The data preparation stage is a crucial stage to ensure the quality of data that will be used in training the stock price prediction model. The first step is to check the data type and the presence of missing values. The total dataset taken from yfinance amounted to 1536 rows of data before cleaning. There are 502 rows of data that contain null values because the Korean stock market does not operate every day. The process of cleaning the null data was done using the drop.na function so that the final data amounted to 1034 rows of data. Table 1 shows the descriptive statistics HYBE stock price of residence (e.g. University of Lampung, Indonesia).

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{5}$$

Where the symbols of $X_{max}$ and $X_{min}$ are the features maximum and minimum value, respectively.

To ensure that there is sufficient training data and sample data to train and evaluate the prediction results of the CNN-LSTM model, in this study the data was divided into time series based on the 9:1 rules in accordance with the research [15]. The first 90 percent of data is placed in to the training set data, and 10 percent data is placed in to the test set data. This ratio was selected to maximize the amount of training data, which is essential for deep learning models to effectively capture temporal dependencies, while still maintaining a sufficient portion for reliable evaluation. Compared to more common splits such as 8:2 or 7:3, a larger training proportion is considered more appropriate for time-series data with limited size, as reducing the training set may weaken the model's ability to learn underlying patterns. To eliminate the different in the variable dimensions, the data was normalized in the range [0,1]. The formula for dataset normalization follows Equation 5.

Furthermore, the data is transformed into a 3-dimensional format suitable for CNN-LSTM model input using a sliding window approach with time steps of 32. Each input sequence consists of 32 previous closing prices, which are used to predict the price on the following day. The *prepare_data()* function is utilized to generate input-output pairs (X, y), which are then reshaped into the format (samples, time steps, features), as illustrated in Figure 5.

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Table 1. Descriptive statistics.

| Statistics | Count | Mean | Std | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| **Value** | 1034 | 223.797,01 | 56.930,46 | 109.067,89 | 180.345,07 | 214.649,59 | 263.331,71 | 412.366,28 |

Source: data processing Notes: Values in KRW (₩)

```
X_train, y_train = prepare_data(train_scaled, time_steps)
X_test, y_test = prepare_data(test_scaled, time_steps)
X_train = X_train.reshape((X_train.shape[0], time_steps, 1))
X_test = X_test.reshape((X_test.shape[0], time_steps, 1))
```

Figure 5. Prepare data process in Python.

The selection of time_steps = 32 was determined empirically as a balance between capturing sufficient historical context and maintaining model efficiency. This value allows the model to learn short to medium term temporal patterns without introducing excessive sequence length that could increase computational complexity or noise. It was not directly determined by the 10% test set size (72 days), although the chosen window size remains proportionally appropriate to ensure adequate context within the available data. Preliminary experiments with smaller and larger window sizes showed that 32 provided more stable and accurate predictions, indicating that it is sufficient to capture the underlying temporal dependencies in the dataset.

### 3.4. Data Modeling

Modeling was performed using a hybrid Convolutional Neural Network - Long Short-Term Memory (CNN-LSTM) architecture specifically designed to handle stock time series data. CNN was used to extract spatial patterns from historical stock price data windows, while LSTM played a role in capturing long-term dependencies between time periods. The modeling was built using the Keras Sequential API with the KerasRegressor wrapper from the SciKeras library, which facilitates integration with GridSearchCV for hyperparameter tuning. The model consists of several main layers, namely Layer Conv1D for spatial feature extraction, Layer MaxPooling1D for dimension reduction, Layer LSTM for handling temporal relationships, and two Dense layers for mapping regression prediction results.

In this paper, hyperparameter tuning was also performed to optimize the parameters to be used in the model. Hyperparameter tuning was performed using the Grid Search approach with 3-fold cross-validation. The optimized parameters include the number of filters (CNN filters [32, 64]), kernel_size in Conv1D (CNN kernel_size [2, 3]), pooling size (CNN pooling size [2, 3]), number of units in LSTM (LSTM units [32, 64]), and Dense (Dense LSTM units [32, 64]). The LSTM unit range was limited to [32, 64] to balance model complexity and computational efficiency, considering the relatively limited and volatile dataset. Expanding to larger units (e.g., 128 or 256) may increase overfitting risk and training cost. The tuning process produces the best combination of hyperparameters used to build the final model. The final model is then trained for a maximum of 100 epochs with early stopping to prevent overfitting, with val_loss monitoring. Performance evaluation is carried out by observing the Mean Squared Error (MSE) metric against the validation data. The training process shows stable convergence with a decrease in loss on the training and validation data.

Figure 6 show of a steady downward trend in the training loss and validation loss for CNN-LSTM models after 20 epoch, indicating that the training process is running effectively without signs of overfitting or underfitting. Although 100 epochs were set, training was stopped at epoch 90 due to the early stopping mechanism, which halts the process when there is no significant improvement in validation loss, to maintain optimal model performance. To further prevent overfitting, a dropout layer with a rate of 0.2 was applied between the LSTM and Dense layers, enhancing the model's generalization capability. It should also be noted that the loss values (MSE) presented in Figure 6 are calculated on normalized data rather than the original KRW scale; therefore, the Y-axis represents a dimensionless error value.

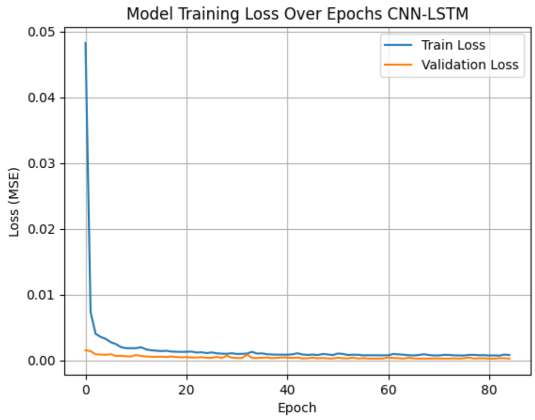


Figure 6. Train and validation loss graph.

### 3.5. Evaluation

The evaluation was conducted to measure the performance of the CNN-LSTM model in predicting HYBE Corporation's stock price based on historical data. This evaluation used four main metrics, MSE, RMSE, MAE, and MAPE. These four metric are widely used in time series research to quantitatively evaluate the prediction error rate of a model [32]. Figure 7 presents the evaluation metrics of CNN-LSTM model for predicting HYBE Corporation's stock price. The results show that the CNN-LSTM model achieves a very small error rate, with MSE of 0.00029, RMSE of 0.01704, MAE of 0.01346, and MAPE of 2.15% 0r 0.02150. These values indicate that the model produces highly accurate predictions with only minimal deviations from the actual stock price values.

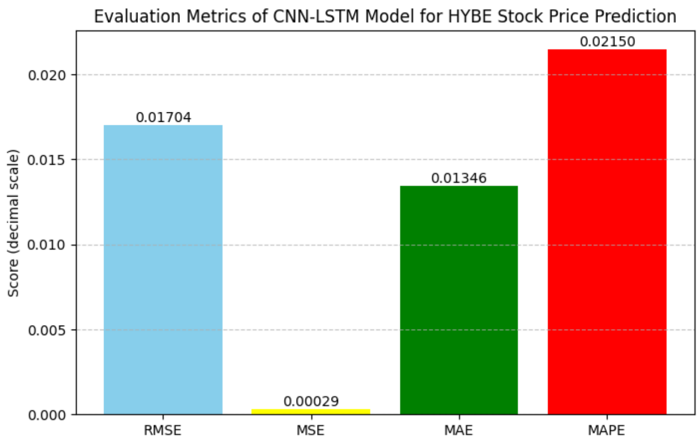


Figure 7. Evaluation result.

Figure 8 illustrates the comparison between the predicted values and the actual stock prices in the test set for 72 days ahead from 2024-09-10 to 2024-12-27. The results demonstrate that the CNN-LSTM predictions closely follow the actual movement of HYBE Corporation's stock price. The model can capture both the short-term fluctuations and long-term upward and downward trends. This alignment between predicted and actual values suggests that the hybrid structure of CNN-LSTM, which combines the feature extraction capability of Convolutional Neural Networks (CNN) with the sequential learning ability of Long Short-Term Memory (LSTM), is effective for stock price forecasting.

In particular, the CNN component enhances the model's ability to detect local temporal patterns within the stock price data, while the LSTM component captures long-term dependencies. This synergy enables the model to achieve higher prediction accuracy compared to single deep learning models reported in prior studies. The low error metrics and the close fit in the prediction visualization provide strong evidence of the CNN-LSTM model's reliability in stock price prediction tasks.

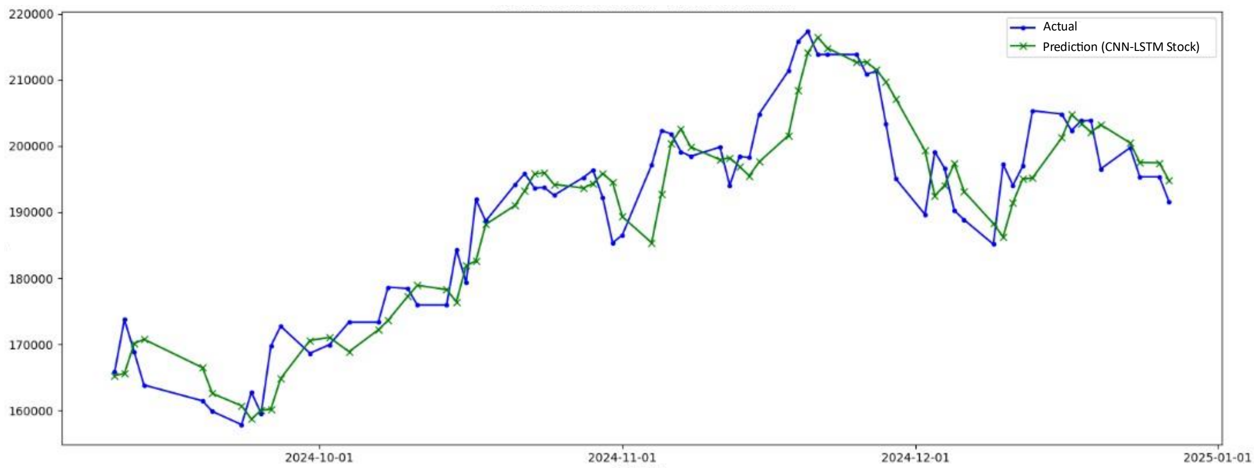


Figure 8. Visualization of prediction.

Compared to conventional methods that tend to be less adaptive to non-linear stock market patterns, the CNN-LSTM model within the CRISP-DM framework offers a more transparent, replicable, and evidence-based approach. This is important in the era of financial digital transformation, where accountability and traceability of prediction results are key prerequisites for investment decision-making [33][34]. Theoretically, this research expands the use of hybrid deep learning architecture previously widely used in the fields of imaging and text to the realm of stock price prediction. Practically, the results with low error rates confirm that CNN-LSTM not only provides accurate technical solutions but also drives a paradigm shift in investment decision-making from intuition to efficient, data-driven systems. Overall, the evaluation results confirm that the CNN-LSTM model is effective in forecasting the stock price of HYBE Corporation. By capturing both short-term and long-term dependencies, the model demonstrates the potential of hybrid deep learning approaches within the CRISP-DM framework for financial time series prediction.

## 4. CONCLUSIONS

This study successfully demonstrates that the implementation of the CNN-LSTM model within the CRISP-DM framework can be used effectively to predict the stock price of HYBE Corporation. By utilizing historical stock price data and transforming it through systematic preprocessing, the model is able to capture both short-term fluctuations and long-term dependencies in financial time series. The results of the evaluation show that the model of CNN-LSTM achieves highly accurate for prediction, with very low error values across MSE, RMSE, MAE, and MAPE metrics. This confirms the stability and reliability of the hybrid architecture in handling the inherent complexity and volatility of stock market data. Theoretically, this study expands the application of hybrid deep learning models, which have been widely applied in domains such as image and text processing, into the field of financial time-series forecasting. In practice, the CNN-LSTM model provides a data-driven alternative for investors and financial analysts to support more strategic, transparent, and accountable decision-making in stock trading and investment management. Thus, this study not only presents an effective technical solution for stock price forecasting but also contributes to the ongoing digital transformation in financial analytics, where accuracy, adaptability, and evidence-based decision-making are becoming increasingly critical.

However, it is important to note that the stability and reliability demonstrated in this study are based on a specific testing period of 72 days, which may not fully represent extreme market conditions. In the event of a prolonged market downturn, characterized by heightened volatility, structural breaks, and significant shifts in data distribution, the model's performance may be challenged due to its reliance on historical patterns learned during training. Although CNN-LSTM has the capability to model complex and nonlinear relationships, its generalization ability may decrease when facing unseen extreme scenarios. Therefore, while the model shows strong performance under normal market conditions, its effectiveness during extended periods of extreme market stress cannot be fully guaranteed. Future research is thus recommended to evaluate the model across longer time horizons, incorporate adaptive learning mechanisms such as dynamic retraining, and integrate external factors like market sentiment and macroeconomic indicators to enhance robustness and resilience.

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