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Predictive Analysis of Indonesian Stock Market Prices Using Deep Learning: An Application of Diffusion Variational Autoencoders

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ABSTRACT

This study introduces the application of the Diffusion Variational Autoencoder (D-VAE), a deep learning technique, for predicting stock prices in the Indonesian stock market. With the challenges presented by market volatility and complex data distributions, D-VAE is explored for its capability to encapsulate uncertainty and model complex distributions. This study is significant as it explores the potential of D-VAE in the context of the Indonesian stock market, which has not been widely studied before. Historical stock data from Yahoo Finance was collected over one year and preprocessed for training and validation of the model. The model is trained with an architecture designed to allow tuning of the latent space, utilising ReLU and linear activation functions for the encoder and decoder. The model's performance is evaluated using the Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared metrics, yielding results that highlight the model's capability to enhance the accuracy of stock price predictions. By leveraging machine learning techniques in stock price prediction models, this study underscores the significant contribution such approaches can make to informed and successful investment decisions underpinned by robust data.

Introduction

Stocks are financial instruments that offer investors a fraction of a company's ownership. Investors who invest in a stock have a high percentage of the profits earned by the company (Patel, Kumar, & Yadav, 2023). As a vital component in the economy, the stock market is an indicator of economic health and a platform for companies to accumulate capital. However, the high volatility of the stock market, influenced by various factors such as the economy, politics, and social issues, makes stock price prediction very complex and challenging (Farild, Sawaji, & Poddala, 2023).

The stock market not only acts as an indicator of economic health but also as an arena for investors to optimise their investment decisions (Al-Alawi & Alaali, 2023). Accuracy in stock price prediction significantly impacts companies' investment decisions.

An interesting approach in this regard is the application of the Diffusion Variational Autoencoder (D-VAE). This deep learning technique can capture uncertainty and model complex data distributions (Koa, Ma, Ng, & Chua, 2023). Although D-VAE has shown potential in other domains as an application, its use for stock price prediction in the Indonesian market has yet to be extensively explored.

Research related to stock price prediction has been growing and pushing computational intelligence to encourage the enhancement of prediction model performance further (Shen & Shafiq, 2020). Technical analysis, which predicts stock prices based on historical data such as stock trading volume and price movements, and approaches such as ARIMA (Islam & Nguyen, 2020) and Stochastic Oscillator (Alviyanil’Izzah et al., 2021), will be utilised in this research using historical stock data from companies in Indonesia.

On the other hand, the popularity of machine learning in predicting stock prices is increasing, presenting systems to learn from historical data. Techniques like LSTM (Qiu, Wang, & Zhou, 2020) and Support Vector Machine (SVM) (Madhusudan, 2020) have been widely used in stock price prediction. This research aims to bridge a gap in the literature by critically evaluating and applying D-VAE for stock price prediction in the Indonesian market, offering new insights into the potential of D-VAE in this context(Nath & Shakhari, n.d.).

Integrating machine learning, especially D-VAE, and technical analysis is expected to yield more accurate and effective stock price prediction models for the Indonesian stock market, making a valuable contribution to data-based investment decision-making.

Research Methods

This study was designed to test a stock price prediction model for the Indonesian stock market using the Diffusion Variational Autoencoder (D-VAE). This approach combines Deep Learning techniques with technical analysis to understand and predict the dynamics of stock prices in the Indonesian stock market.

Data Collection and Preparation

The data used in this study is from Yahoo Finance—the period they have taken ranges from January 1st, 2022, to January 1st, 2023. The data consists of the columns for the opening (Open), highest (High), lowest (Low), closing (Close) prices, and the trading volume (Volume) of stocks in the Indonesian stock market. The collected data was then processed to eliminate any missing data. We extracted relevant features from this data to construct the model and the target for predictions. These features include the opening, highest, lowest prices, and trading volume. Then, for the closing price, it becomes the prediction target. Before feeding the data into the mel, we normalised the feature andarget using MiMaxScaer. T steps cruciao nsmore stable d ffii earng the matheatical mode us t normalie hedta: $X_{Scaled}=\frac{X- X_{min}}{X_{max}-X_{min}}$, $y_{Scal}=\frac{y- y_{min}}{y_{max}-y_{min}}$

Where the value X represents the actual value of the feature to be normalised. For Xmin, it is the minimum value of each feature in the data, serving as the lower reference value for normalisation. Similarly, Xmax is the maximum value of each feature in the data, serving as the upper reference value for normalisation. The value Xscaled is the normalised value of the feature. The normalisation process changes the actual data to a scale from 0 to 1.

While y represents the actual value of the target to be normalised, for men, it is the smallest value among all the target values in the data. This value serves as the lower reference point for the range of normalisation. For max, it is the most significant value among all the target values in the data. This value serves as the upper reference point for the range of normalisation. Finally, scale is the normalised target value. The result of this normalisation process changes the original data into a scale from 0 to 1.

Diffusion Variational Autoencoder (D-VAE) Model Architecture

The developed D-VAE model is based on a tunable latent space architecture that consists of an encoder and a decoder. The encoder captures the complex relationships among the numerous features of the volatile stock market and outputs a prediction of the closing price. The encoder operates as a data compression mechanism, encoding the input data into a more compact representation within the latent space. This compression to a more succinct representation is accomplished through a series of hidden layers. The input layer receives the input, matching the number of features used. This serves as the entry point into the D-VAE model. As for the hidden layers, they consist of multiple layers with neuron units varying in number. These layers have the Rectified Linear Unit (ReLU) activation function. ReLU is chosen because it does not activate at negative input values, which can help mitigate the vanishing gradient problem, as the derivative of the ReLU function remains constant for all positive inputs, thus facilitating a more efficient training process.

$$f(x)=\max(0,x)$$

In the ReLU activation function used in the D-VAE architecture, the variable x represents the input for the ReLU function. The previous layer's output within the neural network is used as the input for the ReLU function. If the output (f(x)) is higher than zero, it will equal the input value; if less, it will be zero. This ensures that the output will always be non-negative. If x is positive, f(x) will be equal to x, but if x is negative, f(x) will be zero. This helps address the vanishing gradient problem because the derivative of the ReLU function is consistent for all positive values, thus ensuring efficient backpropagation during training.

The decoder layer operates as a mechanism to extract the compressed representation from the encoder and reconstruct the original expected output. This is the inverse process of the encoder. The decoder architecture mirrors that of the encoder but in reverse order. The main difference in its implementation is that it aims to gradually expand the succinct representation from the encoder back to its original form that is more detailed and specific to the prediction target.

$$f(x) = x$$

The output layer consists of a single neuron with a linear activation function. This function maintains the input value without any changes, allowing the model to predict continuous values. In the context of stock price prediction, the model can produce a prediction value that is sufficiently accurate for the stock's closing price.

Training and Evaluation of the Model

The Diffusion Variational Autoencoder (D-VAE) model is trained using normalised data to ensure all features are on the same scale. This approach can improve the model's ability to capture patterns and trends present in the data more effectively.

We employed the Adaptive Moment Estimation (Adam) algorithm to optimise. Adam is an optimisation algoriththat calculates the learning rates from the scond moment of grient using RMSPro. It computes adptive earning ratesfor eac parameter by cnsidering the firt an second estimates of the the graie.. $\theta_{t+1} = \theta_t + \frac{\eta}{\sqrt{\hat{v}_t}+\varepsilon}\widehat{m}_t$

The value θ represents the model parameters or the weights of the model. These are the values we aim to ooptimise Then, η represents the learning rate. When changing the model parameters, this scalar value adjusts the step size during each iteration. The te $\widehat{m}_t$ represents the first estimate of the gradient. It is the average of the gradient of the loss function concerning the model parameters. This helps to adjust the learning rate adaptively for each parameter. Then, the te $\hat{v}_t$ represents the second estimate of the gradient or the uncentered variance of the gradient. The average of the squared gradient provides an estimate of the gradient variability ofthe lvaluesunctilarto $\widehat{m}_t$he value $\hat{v}_t$ ed to adjust the learning rate for each parameter while considering the scale of the gradient. Finally, the value ε is a small constant added to prevent didivisiony zro when dividing b thesquare root ftthe thehe $\sqrt{\hat{v}_t}$.. e employ Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared to evaluate the model used.

$$\sum_{i=1}^{n} (y_i - \hat{y}_i)$$

MSE is calculated as the average of the squares of the differences between actual and predicted values. It measures how close the predictions are to the actual values. The value yi represents the stock's actual value being predicted. Then, yˆ_i represents the predicted value. Moreover, 'n' is the number of samples in tis experiment$\frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$.

MAE measures the average absolute error between predictions and actual values. Unlike MSE, MAE provides a more linear perspective on prediction errors. The value yi represents the stock's actual value being predicted. Then, yˆ_i represents the predicted value. Moreover, 'n' is the number of samples in this experiment.

$$eR^2 =$$

E represents the actual average value, model evaluation is performed by calculating this metric on the test dataset. It provides a comprehensive picture of the model's performance in predicting stock prices, considering various aspects of error and accuracy.

Results and Discussion

Model Evaluation Results

The Diffusion Variational Autoencoder (D-VAE) model has been tested on several Indonesian stocks. The evaluation results show that the model can follow stock price trends relatively well. The graphs presented are comparisons between the actual stock prices and the predicted stock prices. These graphs visually represent several companies' stock performance on the Indonesian stock market (Mukherjee et al., & De, 2023).

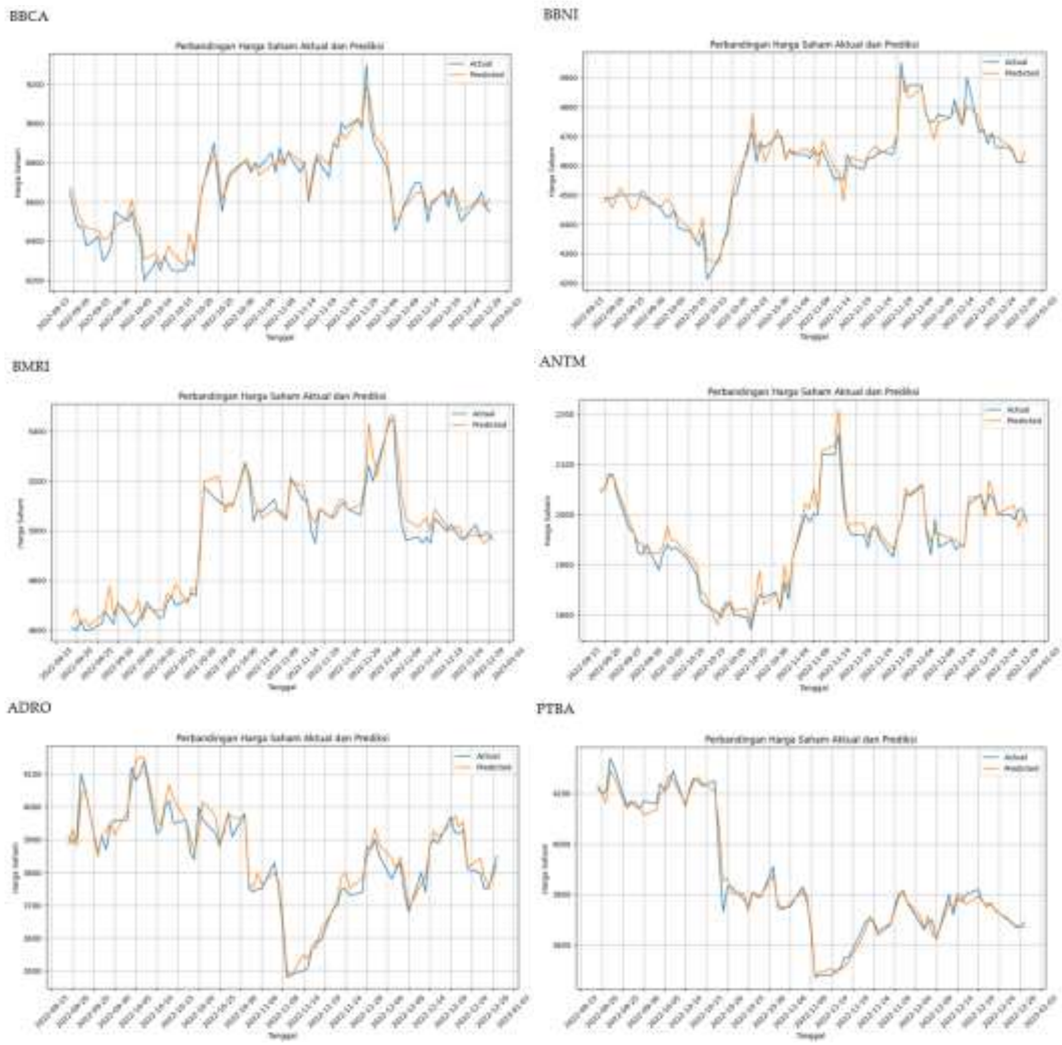

Fig 1 Comparison Chart of Actual 'Close' Stock Prices With Predicted 'Close' Stock Prices in Several Companies Stocks

The graphs displayed compare the actual stock prices and those resulting from predictions. These graphs visually represent the performance of several companies' stocks in the Indonesian stock market, such as PT Bank Central Asia Tbk (BBCA), PT Bank Negara Indonesia (Persero) Tbk (BBNI), PT Bank Mandiri (Persero) Tbk (BBNI), PT Adaro Energy Indonesia Tbk (ADRO), PT Aneka Tambang Tbk (ANTM), PT Bukit Asam Tbk (PTBA). From these graphs, the model accurately follows the general market trends. However, there are specific periods where the predictions do not align with the actual values, particularly during periods of high market volatility.

Table 1

Comparison of MSE, MAE, and R-squared Values from Several Companies

Stock	MSE	MAE	R2
🏛 PT Bank Central Asia Tbk (XIDX:BBCA)	3155,4965	46,4066	0,9364
🏛 PT Bank Negara Indonesia (Persero) Tbk (XIDX:BBNI)	1119,1449	27,0061	0,9501
🏛 PT Bank Mandiri (Persero) Tbk (XIDX:BMRI)	2824,7450	93,7510	0,9401
🏛 PT Adaro Energy Indonesia Tbk (XIDX:ADRO)	1244,5671	29,2958	0,9425
🏛 PT Aneka Tambang Tbk (XIDX:ANTM)	378,9566	15,6345	0,9497
🏛 PT Bukit Asam Tbk (XIDX:PTBA)	902,4240	21,2658	0,9847
❓ Average	1604,2223	38,8933	0,9506

The observed fluctuations in MSE and MAE values suggest that the model may require more specific adjustments or tuning for each stock. In some cases, the model predicts well, showing more minor errors and higher accuracy, while in others, more significant prediction errors indicate areas where the model can be improved. This could involve incorporating more features into the model or combining other machine-learning techniques.

Consistently high R-squared values indicate that the model can reasonably explain the variability in stock price data. Although our model is good at summarizing the data explained, there are volatility periods where the model fails to capture price movements accurately, indicating the need for more investigation into how the model can be adjusted to be more sensitive to sudden market changes.

In analyzing the evaluation metrics, we found that although there were variations in MSE and MAE among different stocks, the model consistently showed a high R2 value across all the data examined. This indicates that the model accurately captures the variances within the stock market data. However, the R-squared value does not always reflect the variability of the actual stock market values. Hence, while it indicates the model can capture the general trend, specific predictions may diverge from the actual values, particularly during periods of market volatility.

The variation in MSE and MAE values points to the need for further refinement and adjustment of the model, mainly when predicting during volatile periods, as discussed in (Gangwar, Kumar, & Bijpuria, 2021), where hyperparameter tuning improved stock price prediction accuracy. Similarly, the work by (Stoean, Paja, Stoean, & Sandita, 2019) showed that integrating additional market sentiment data and indicators could make the model more sensitive to market dynamics.

Further research by (Kumar et al., 2023) suggests that using different machine learning algorithms that account for different aspects of the data can enhance model responsiveness and improve predictions during volatile market conditions. This reinforces the idea that various machine learning techniques can provide a deeper insight into data analysis.

Given these findings, there are opportunities to further improve the D-VAE model with ensemble methods, where the prediction of several models can be combined to achieve a more robust outcome. Moreover, future studies may explore modifications in the D-VAE architecture, such as adding or reducing the number of neuron layers or applying techniques like regularization to prevent overfitting and enhance the model's generalization.

Conclusion

The application of the Diffusion Variational Autoencoder (D-VAE) technique to predict stock prices in the Indonesian stock market has demonstrated the potential of this approach. With the implementation of deep learning and machine learning methodologies, this research has contributed to exploring complex data within the volatile market. The D-VAE model has shown significant capabilities in following the stock market trends and has produced good prediction accuracy for various stocks. Evaluation metrics such as MSE, MAE, and R-squared have varied between stocks, reflecting the intrinsic stock market variability. Despite variations in MSE and MAE values across different stocks, a consistently high R-squared value suggests that the model performs well in capturing the trends within the market. However, a high R-squared value does not directly reflect the precision of the stock price predictions, especially during periods of high market volatility.

This study also identifies the need for further refinement and specificity in the model for individual stocks and market conditions. Additional factors like economic indicators and market sentiment should be integrated to enhance the model's predictions. The value of D-VAE lies in its capacity for more detailed training and its potential to provide a stronger foundation for investment decisions based on robust predictions. Despite the need for further improvements, the existing model has demonstrated the ability to provide valuable insights for financial analysts, aiding investors in making more informed and accurate investment decisions based on stock price predictions.

Bibliography

Al-Alawi, Adel Ismail, & Alaali, Yusuf Ahmed. (2023). Stock Market Prediction using

Machine Learning Techniques: Literature Review Analysis. *2023 International Conference On Cyber Management And Engineering (CyMaEn)*, 153–157. IEEE.

Alviyanil'Izzah, Nur, Martia, Dina Yeni, Imaculata, Maria, Hidayatullah, Moh Iqbal, Pradana, Andhika Bagus, Setiyani, Diyah Ayu, & Sapuri, Enes. (2021). Analisis Teknikal Pergerakan Harga Saham Dengan Menggunakan Indikator Stochastic Oscillator Dan Weighted Moving Average. *Keunis*, *9*(1), 36–53. https://doi.org/10.32497/keunis.v9i1.2307

Farild, Miftha, Sawaji, Muh Izzulhaq, & Poddala, Paramita. (2023). Analisis teknikal sebagai dasar pengambilan keputusan dalam transaksi saham. *FORUM EKONOMI: Jurnal Ekonomi, Manajemen Dan Akuntansi*, *25*(4), 734–739.

Gangwar, Abhinav, Kumar, Ayush, & Bijpuria, Eshikha. (2021). Stock Price Prediction using Machine Learning. *2021 3rd International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)*, 189–193. IEEE.

Islam, Mohammad Rafiqul, & Nguyen, Nguyet. (2020). Comparison of financial models for stock price prediction. *Journal of Risk and Financial Management*, *13*(8), 181.

Koa, Kelvin J. L., Ma, Yunshan, Ng, Ritchie, & Chua, Tat Seng. (2023). Diffusion Variational Autoencoder for Tackling Stochasticity in Multi-Step Regression Stock Price Prediction. *Proceedings of the 32nd ACM International Conference on Information and Knowledge Management*, 1087–1096. https://doi.org/10.1145/3583780.3614844

Kumar, Amodh, Hooda, Susheela, Gill, Rupali, Ahlawat, Deepak, Srivastva, Durgesh, & Kumar, Raju. (2023). Stock Price Prediction Using Machine Learning. *2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES)*, 926–932. IEEE.

Madhusudan, Desai Mitesh. (2020). Stock Closing Price Prediction Using Machine Learning SVM Model. *International Journal for Research in Applied Science and Engineering Technology*.

Mukherjee, Somenath, Sadhukhan, Bikash, Sarkar, Nairita, Roy, Debajyoti, & De, Soumil. (2023). Stock market prediction using deep learning algorithms. *CAAI Transactions on Intelligence Technology*, *8*(1), 82–94.

Nath, Om, & Shakhari, Swapan. (n.d.). *Stock Market Prediction Techniques: A Literature*.

Patel, Vikas, Kumar, Ashwani, & Yadav, Deepak. (2023). Machine Learning Techniques for Predicting Stock Closing Prices. *2023 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN)*, 447–452. https://doi.org/10.1109/ICPCSN58827.2023.00079

Qiu, Jiayu, Wang, Bin, & Zhou, Changjun. (2020). Forecasting stock prices with longshort term memory neural network based on attention mechanism. *PloS One*, *15*(1), e0227222.

Shen, Jingyi, & Shafiq, M. Omair. (2020). Short-term stock market price trend prediction using a comprehensive deep learning system. *Journal of Big Data*, *7*, 1–33.

Stoean, Catalin, Paja, Wiesław, Stoean, Ruxandra, & Sandita, Adrian. (2019). Deep architectures for long-term stock price prediction with a heuristic-based strategy for trading simulations. *PloS One*, *14*(10), e0223593.