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Stock Price Prediction and Loss Risk Analysis of PT Sawit Sumbermas Sarana Tbk Using a Hybrid TCN-GAN Model

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ABSTRACT

The Crude Palm Oil (CPO) industry is a strategic sector for the Indonesian economy. Yet, stock prices of companies in this sector tend to be highly volatile due to global market dynamics and export policies, increasing investment risk. Conventional models, such as ARIMA, rely on linearity assumptions that limit their ability to capture nonlinear dynamics, while deep learning models, such as RNN, GRU, and LSTM, still suffer from vanishing-gradient problems. Therefore, this study proposes a hybrid Temporal Convolutional Network–Generative Adversarial Network (TCN-GAN) model for stock price prediction and investment risk analysis using the Value-at-Risk (VaR) method with Historical Simulation. The TCN-GAN combines TCN's ability to capture long-term temporal patterns with the adversarial mechanism of GAN to improve prediction accuracy. The data consist of daily closing prices of PT Sawit Sumbermas Sarana Tbk (SSMS.JK) from Yahoo Finance, covering January 1, 2020, to September 30, 2025. A sensitivity analysis on sliding window lengths of 10, 20, and 30 days was conducted to validate model robustness, with window 20 identified as optimal. The TCN-GAN model significantly outperforms the ARIMA baseline, which yielded a MAPE of 18.12% and RMSE of 368.68, by achieving a MAPE of 3.22% and RMSE of 84.23. The model was further used to predict stock prices for the next five periods, yielding an average of IDR 1,647.82. The VaR analysis at a 95% confidence level with a five-day holding period indicates a maximum potential loss of IDR 146,204.

1. Introduction

The Crude Palm Oil (CPO) industry is one of the strategic sectors in the Indonesian economy, with export revenues recorded at USD 17.277 billion in 2025 [1]. Stocks of companies operating in this sector tend to exhibit high volatility driven by global market dynamics and export policies. PT Sawit Sumbermas Sarana Tbk. (SSMS) recorded a volatility level of 52.38%, classified as high volatility based on the LiteFinance benchmark [2]. This condition reflects a substantial level of investment risk, underscoring the need for analytical approaches that can accurately model stock price movements while also estimating the potential losses faced by investors.

Accurate stock price prediction in highly volatile markets remains a significant challenge in financial time series analysis. Conventional statistical models such as ARIMA rely on linearity assumptions that limit their ability to capture the complex nonlinear dynamics of stock price data [3]. Deep learning models such as RNN and LSTM were developed to overcome this limitation, yet both still suffer from vanishing gradient problems and computational inefficiency on long sequences, as evidenced by an MAPE of 18.66% in a Tesla stock price prediction study [4]. GRU offers a simpler architecture than LSTM but delivers comparable performance and shares the same limitations in capturing multi-scale patterns [5]. CNN-LSTM combines local feature extraction with sequential modeling but inherits LSTM's computational constraints [6]. These limitations have driven the development of more advanced architectures capable of handling the nonlinear and volatile nature of financial time series data.

Temporal Convolutional Network (TCN) addresses these shortcomings through dilated causal convolution, enabling parallel computation and more stable gradient flow. TCN has been shown to outperform LSTM, achieving a MAPE of 2.58% compared to 7.05% obtained by LSTM [7]. A further development integrated TCN with a Generative Adversarial Network (GAN) into a hybrid TCN-GAN model. In this model, the TCN-based Generator learns temporal patterns in stock price data, while the MLP-based Discriminator evaluates the conformity of predictions with actual data through an adversarial training mechanism. This hybrid approach achieved a MAPE of 2.16% on high-risk stocks, outperforming the standalone TCN model, which obtained a MAPE of 4.12% [8].

Despite its promising performance, several research gaps remain in the existing literature. ARIMA and other linear models fail to capture nonlinear patterns in highly volatile financial data [9]. RNN, LSTM, and GRU-based models remain prone to vanishing gradients and computational inefficiency [10]. Most prior studies have focused solely on improving prediction accuracy without utilizing the results for formal investment risk quantification. Furthermore, the influence of sliding window length on model robustness has not been systematically analyzed. TCN-GAN addresses all of these gaps by combining the strength of TCN in capturing long-term temporal patterns with the adversarial mechanism of GAN that produces predictions with more realistic distributions, making it the making it a promising approach for nonlinear and highly volatile stock data.

Model robustness against input configuration variations is also an important aspect in time series prediction. The sliding window length used as model input can influence the model's ability to capture temporal patterns in stock price data. A window that is too short risks losing relevant historical information, while a window that is too long may introduce noise that disrupts the learning process. Therefore, the novelty of this study lies in conducting a sensitivity analysis on sliding window lengths of 10, 20, and 30 days to identify the optimal input configuration and validate the robustness of the TCN-GAN model.

This study focuses on a CPO issuer listed on the Indonesia Stock Exchange, namely PT Sawit Sumbermas Sarana Tbk. (SSMS.JK). SSMS was selected due to its strong market position in the palm oil plantation sector and the absence of prior studies applying the TCN-GAN model to CPO sector stocks. This study makes three main contributions. First, the hybrid TCN-GAN model is systematically compared against an ARIMA baseline to validate its superiority. Second, a sliding window sensitivity analysis is conducted to validate model robustness. Third, the prediction results are integrated into an investment risk analysis framework using the Value-at-Risk (VaR) method with the Historical Simulation approach. The data were obtained from Yahoo Finance in the form of daily closing prices of SSMS.JK for the period from January 1, 2020, to September 30, 2025. Through this integrated approach, this study not only produces accurate stock price estimates but also delivers more informative measurements of potential investment losses to support better investment decision-making.

2. Methods

This study utilizes daily closing price data of SSMS.JK obtained from Yahoo Finance for the period from January 1, 2020, to September 30, 2025, consisting of 1,384 observations with an 80:20 train-test split. The stages of this research describe the process of data processing, stock price modeling using ARIMA as the baseline model and TCN-GAN as the proposed model, and investment risk analysis using the Value-at-Risk approach.

2.1. Research Process

The stages of this research describe data processing, stock price modeling using ARIMA as the baseline model and TCN-GAN as the proposed model, and risk analysis using the VaR approach.

a. The research process begins with the collection of daily closing price data of SSMS.JK obtained from Yahoo Finance.
b. The collected data are then analyzed through Exploratory Data Analysis (EDA) to understand the characteristics of stock price data before modeling, which includes:

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    i. Descriptive analysis, which is used to describe the statistical characteristics of stock price data, such as minimum, maximum, mean values, and data dispersion.
    ii. Data visualization, which is used to observe stock price movement patterns, trends, and volatility levels during the observation period.
c. The dataset is then split, with 80% allocated for model training and the remaining 20% used for testing.
d. The ARIMA model is applied as a statistical baseline using the same training and testing split. The optimal order (p,d,q) is determined through stationarity testing and identification of the ACF and PACF plots, followed by parameter significance testing and residual assumption verification.
e. The training data are used in the training process of the hybrid TCN-GAN model.
    i. The Generator architecture employs a Temporal Convolutional Network (TCN) to learn the temporal patterns of stock prices.
    ii. The Discriminator utilizes a Multilayer Perceptron (MLP) architecture to distinguish between actual stock price data and the Generator's predicted outputs.
    iii. The trained TCN-GAN model is then used to generate stock price predictions on the testing data.
f. A sliding window sensitivity analysis is conducted using window lengths of 10, 20, and 30 days to identify the optimal input configuration and validate the robustness of the TCN-GAN model.
g. The prediction results of both ARIMA and TCN-GAN are evaluated and compared using MAPE and RMSE to assess the superiority of the proposed model.
h. After evaluation, the best-performing TCN-GAN model is used to predict the closing price of SSMS.JK for the next five periods.
i. The prediction results on the testing data are combined with the five-period-ahead forecasts as inputs for the Value-at-Risk (VaR) analysis.
    i. The combined data are converted into stock returns as inputs for risk analysis.
    ii. The risk analysis is conducted using the Value-at-Risk (VaR) method with the Historical Simulation approach based on the distribution of stock returns.
j. The research process concludes with the estimation of the maximum potential loss as the basis for investment risk analysis.

2.2. ARIMA

The Autoregressive Integrated Moving Average (ARIMA) model is a statistical approach widely used in time series modeling due to its ability to capture dependencies between past observations and previous error terms [9]. ARIMA consists of three components represented by parameters (p,d,q): the autoregressive (AR) component captures the linear relationship between the current value and its past lags, the integrated (I) component applies differencing to remove trends and achieve stationarity, and the moving average (MA) component models the effect of past residuals on the current value [11]. The ARIMA(p,d,q) model is mathematically expressed as follows [12]:

$$\Phi_p(B)D^d Z_t = \mu + \theta_q(B)a_t \tag{1}$$

where B denotes the backshift operator, D represents the differencing process, p is the order of the autoregressive component, d is the degree of differencing, and q is the order of the moving average component.

Model identification is carried out through a stationarity test using the Augmented Dickey-Fuller (ADF) test, followed by differencing if required, and selection of (p, d, q) based on the ACF and PACF plots. The identified model is then evaluated through residual assumption tests covering white noise, normality, and heteroscedasticity to confirm its validity as a baseline model for comparison in this study.

2.3. TCN-GAN

A Generative Adversarial Network (GAN) is a deep learning model consisting of a Generator and a Discriminator that compete with each other [13]. In this study, GAN is adapted for time series prediction by employing a Temporal Convolutional Network (TCN) as the Generator, which is wellsuited for learning sequential structures across long time spans [14]. Meanwhile, a Multilayer Perceptron (MLP) is used as the Discriminator to distinguish between real data and predicted data [15].

In the proposed model, the TCN-based Generator undergoes adversarial training alongside a Discriminator. Historical stock price sequences are fed into the Generator to produce forecasts, and the Discriminator assesses these outputs by comparing them with actual data. The convolution operation in the TCN employs dilated causal convolution, enabling the model to capture long-term temporal dependencies without significantly increasing network complexity. This operation can be generally formulated as follows [8]:

$$y(t) = \sum_{k=0}^{K-1} f(k)x(t - d \cdot k) \tag{2}$$

where (d) denotes the dilation factor, which allows the model to capture long-term temporal dependencies without significantly increasing network complexity. The following table presents the TCN parameters used as the Generator in this study.

Table 1. TCN-Generator Description

Parameter	Description
TCN Structure	Captures multi-scale temporal dependencies
Activation	Activation function applied in each convolutional layer
Batch Size	Number of samples per training batch
Epoch	Number of complete training iterations over the dataset
Generator Update / Epoch	Number of Generator updates per epoch
Learning Rate	Learning rate of the Generator

The Discriminator is formulated as a binary classifier tasked with distinguishing between actual data and predicted data, where real data are assigned a label of 1 and synthetic data are assigned a label of 0. The training process of the Discriminator is optimized using Binary Cross-Entropy (BCE) as the loss function to maximize its classification capability between the two data types. The loss function is formulated as follows [16]:

$$Loss = -(y \log(\hat{y}) + (1 - y)\log(1 - \hat{y})) \tag{3}$$

As shown in Equation (3), $\hat{y}$ corresponds to the output probability generated by the Discriminator, indicating whether the input sample is classified as real, whereas y refers to the corresponding ground-truth label. Table 2 summarizes the configuration of the multilayer perceptron (MLP) employed as the Discriminator in this research.

Table 2. MLP-Discriminator Description

Parameter	Description
MLP Structure	Discriminator architecture
Activation Function	Activation function in the hidden layers
Loss Function	Discriminator loss function
Learning Rate	Discriminator learning rate

The objective function of the GAN is formulated to represent the adversarial process between the generator and the discriminator in distinguishing real data from generated data.

$$V(G, D) = \mathbb{E}_{x\sim P_{data}(x)}[\log D(x)] + \mathbb{E}_{x\sim P_g}\left[\log\left(1 - D\big(G(x)\big)\right)\right] \tag{4}$$

Referring to Equation (4), the first component describes the expected output of the Discriminator when evaluating authentic samples x through $D(x)$. The second component corresponds to the expectation computed from the Generator's outputs, where $D(G(x))$ indicates the likelihood that the generated samples are recognized as real by the Discriminator. The TCN-GAN model qualifies as a hybrid model in the form of a sequential pipeline, which can be expressed as:

$$\hat{y} = G_{TCN}(x; \theta_G), \text{ where } \theta_G = \arg\min_{G}\max_{D} V(G, D) \tag{5}$$

where the final prediction $\hat{y}$ is produced by the TCN-based Generator G, whose parameters θ_G are optimized through adversarial interaction with the MLP-based Discriminator D. This confirms the hybrid nature of the model, as two architecturally distinct components operate under a unified training objective.

2.4. Value at Risk with Historical Simulation

Value-at-Risk (VaR) was first introduced by J.P. Morgan in the early 1990s through the RiskMetrics system as a standard measure for assessing market risk in financial activities [17]. Over time, VaR has become a global benchmark in risk management due to its ability to condense potential losses into a single, easily interpretable value, making it widely used by financial institutions, banks, and investors. In general, VaR is a statistical approach used to estimate the maximum potential loss of a portfolio over a specific period at a given confidence level, providing insight into the risks arising from market fluctuations and assisting investors in designing appropriate mitigation strategies [18].

The Historical Simulation (HS) method is a technique for estimating Value-at-Risk (VaR) that uses historical data to forecast potential future losses. The advantage of this method lies in its non-parametric nature, meaning it does not require any assumptions regarding the probability distribution of returns [18]. HS calculates risk by directly observing actual market value changes in previous periods, thereby providing a realistic representation of potential losses that investors may experience [19]. The VaR value using Historical Simulation is calculated based on the percentile of returns as follows [20].

$$VaR_{\alpha,T}^{HS}(X) = V_0 \delta \sqrt{T} \tag{6}$$

where X represents the stock returns, and α is the confidence level used in the risk estimation. The parameter T denotes the holding period, and V_0 is the initial investment value. Meanwhile, δ is the $(1-\alpha)$ th percentile of the ordered returns, which serves as the basis for determining the magnitude of the potential loss.

2.5. Model Evaluation

To examine the accuracy of the proposed model, a performance assessment is carried out by comparing predicted outcomes with actual observations. The assessment utilizes Mean Absolute Percentage Error (MAPE) to quantify relative error and Root Mean Square Error (RMSE) to measure absolute deviation.

a. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is a commonly used evaluation metric that quantifies prediction accuracy by averaging the percentage-based absolute errors between forecasted outputs and their corresponding actual values. Mathematically, MAPE can be expressed as follows [21]

$$MAPE = \frac{100\ \%}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{7}$$

Forecasting accuracy improves as the MAPE value decreases, indicating a closer alignment between predictions and actual data. The interpretation of MAPE in this study follows the classification ranges shown in Table 3 [22]

Table 3. MAPE Value Ranges

MAPE	Description
$< 10\%$	Highly accurate prediction
$10\% - 20\%$	Good prediction accuracy
$20\% - 50\%$	Fair or acceptable prediction
$> 50\%$	Poor prediction accuracy

b. Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is an evaluation metric that measures the absolute prediction error by considering the squared differences between actual and predicted values. RMSE places greater emphasis on large forecasting errors, thereby reflecting the magnitude of discrepancies between the model outputs and the observed data. The mathematical formulation of RMSE is given as follows [23]:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{8}$$

A lower RMSE value indicates smaller prediction errors and better model performance.

3. Results and Discussions

3.1. Descriptive Analysis

The closing price data of SSMS.JK stocks used in this study were obtained from Yahoo Finance for the period from January 1, 2020, to September 30, 2025. To understand the data characteristics before modeling, an initial analysis was conducted on the stock price movement patterns and descriptive statistics of each company.

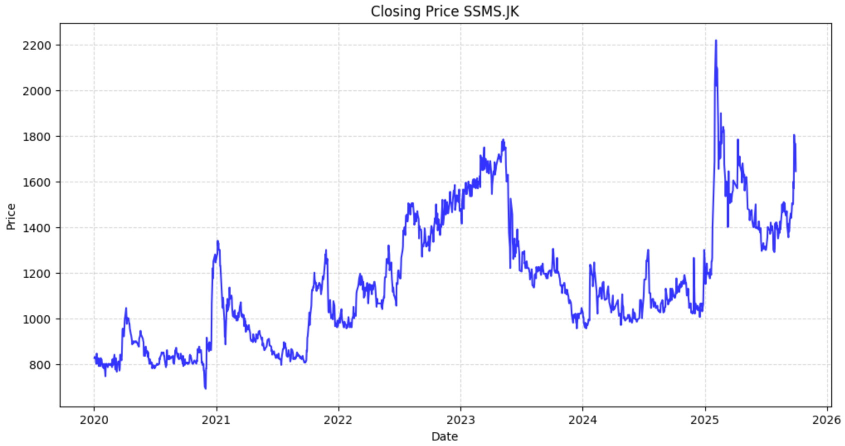

Figure 1. Closing Price SSMS.JK

Figure 1 illustrates the closing price movement of PT Sawit Sumbermas Sarana Tbk. (SSMS.JK) during the observation period. The stock price of SSMS.JK exhibits sharp fluctuations in several periods, reflecting a relatively high level of volatility.

Table 4. Descriptive Statistic

Count	Mean	Std	Min	25%	50%	75%	Max
1,384	1,152.69	270.50	690.00	955.00	1,105.00	1,341.00	2,220.00

Table 4 presents the descriptive statistics of the closing prices of PT Sawit Sumbermas Sarana Tbk. (SSMS.JK). The SSMS.JK stock has an average price of 1,152.69 with a standard deviation of 270.50, indicating a relatively high price variation. The minimum and maximum prices during the observation period were 690.00 and 2,220.00, respectively, reflecting a wide price range and suggesting that SSMS.JK exhibits relatively high volatility and risk.

Table 5. Splitting Data

	Total Data	Periode Data
Train	1,107	January 2020 – July 2024
Test	277	August 2024 – September 2025

Table 5 presents the division of SSMS.JK stock price data into training and testing sets with an 80:20 ratio. Out of a total of 1,384 observations, 1,107 observations are used for training and 277 for testing.

3.2. ARIMA Baseline Model

a. Stationer Test

Before model identification, a stationarity test was conducted on the SSMS.JK closing price data using the Augmented Dickey-Fuller (ADF) test.

Table 6. ADF Test Results

Condition	ADF Value	P-value
Original Data	-2,1740	0,2158
1st Differencing	-35,4753	0,00

The results indicated that the original data were not stationary, as the p-value of 0.2158 exceeds the significance level of 0.05. After applying first-order differencing (d=1), the ADF value decreased to -35.4753 with a p-value of 0.00, confirming that the data achieved stationarity and is ready for further model identification.

b. Model Identification

Model identification was carried out by examining the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots at each differencing order, as presented in Figure 2.

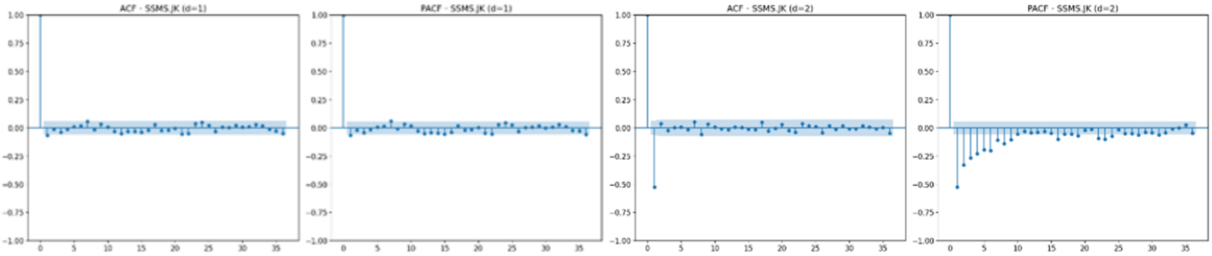

Figure 2. Plot ACF and PACF

Based on the ACF and PACF plots at d=1, no clear pattern was observed, indicating that the differencing order was insufficient to reveal the underlying temporal structure of the data. Therefore, second-order differencing (d=2) was applied. The ACF and PACF plots at d=2 show a significant spike at lag 1 followed by a sharp cutoff on the ACF plot, while the PACF plot shows a gradual decay. This pattern suggests a Moving Average component of order q=1 and an autoregressive component of order p=0, leading to the selection of ARIMA(0,2,1) as the candidate model.

c. Parameter Significance Test

The estimated parameters of the ARIMA(0,2,1) model for SSMS.JK is presented in Table 7.

Table 7. Parameter Significance Test Results

Model ARIMA	Coefficient	P-value	Description
ARIMA (0,2,1)	-0,9997	0,00	Significant

The MA(1) coefficient of −0.9997 is statistically significant (p-value = 0.00 < 0.05), indicating that the model parameter is valid and contributes meaningfully to the prediction.

d. Residual Assumption Test

The white noise assumption was examined using the Ljung-Box test, yielding a test statistic of 48.52 with a p-value of 5.00, indicating that the residuals satisfy the white noise assumption and no significant autocorrelation remains.

Table 8. Residual Assumption Test Results

Test	Test Statistic	P-Value	Description
White Noise	3,56	0.9650	White Noise
Normality	0,1209	0,00	Not Normally Distributed
Heteroscedasticity	61,77	0,00	Heteroscedastic

The normality test shows that the residuals are not normally distributed (p-value = 0.00 < 0.05). However, this violation is common in financial time series data due to extreme price movements and market shocks, and does not invalidate the model given the sufficiently large sample size based on the central limit theorem. The heteroscedasticity test further indicates the presence of non-constant variance in the residuals, consistent with the high volatility characteristics of CPO sector stock prices. While these violations suggest that ARIMA alone is insufficient for capturing the full dynamics of the data, they further reinforce the need for a more advanced model such as TCN-GAN.

3.3. TCN-GAN Model Prediction

a. Model Training Workflow

The training workflow of the TCN-GAN model illustrates the learning process, from data input to generating predictions. Figure 3 presents the workflow of the model training process.

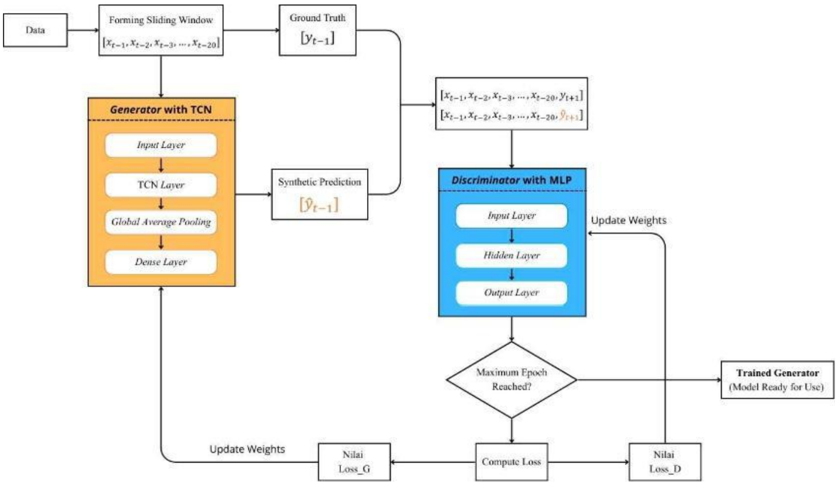

Figure 3. Training Flow

The training process of the TCN-GAN begins with the formation of sliding windows from historical data, which serve as input for the TCN-based Generator to produce stock price predictions. The generated predictions are then evaluated by a Multilayer Perceptron (MLP)-based Discriminator by comparing them with the actual data. Both networks are trained adversarially until the Generator can produce predictions that closely resemble the patterns of the real data. Once the training is complete, the trained Generator is used as the prediction model. During the prediction phase, only the TCN Generator is used without involving the Discriminator. Five-day-ahead forecasts are generated using a recursive forecasting approach, where each one-step-ahead prediction is fed back as input for the next step until the desired prediction horizon is reached.

b. Parameter Selection

The initial stage in applying the TCN-GAN model is parameter selection, which aims to obtain a model configuration that delivers optimal prediction performance. The parameters used in this study, with a TCN-based Generator and an MLP-based Discriminator, are presented in Tables 9 and 10.

Table 9. TCN-Generator Parameters

Parameter	Value
TCN Structure	Conv1D dilasi (1,2,4)
Activation	ReLu
Epoch	500
Batch Size	128
Generator Update / Epoch	2
Learning Rate	0,0004

The hyperparameter settings of the TCN-Generator are detailed in Table 9. This includes the use of dilated one-dimensional convolutions, ReLU activation, average pooling, a mini-batch size of 128, a learning rate of 0.0004, and a double update of the Generator per epoch, following parameter choices reported to yield stable training in earlier research.

Table 10. MLP-Discriminator Parameters

Parameter	Value
MLP Structure	Dense 128–64–32
Activation Function	ReLu
Loss Function	Binary Cross-Entropy
Learning Rate	0,0001

Table 10 shows the parameters of the MLP-Discriminator used in this study. The Dense layer structure of 128–64–32, ReLU activation function (α = 0.2), Binary Cross-Entropy as the loss function, and a learning rate of 0.0001 were chosen to ensure training stability and efficiency, referring to configurations that have been demonstrated to be effective in prior studies.

c. Sliding Window Sensitivity Analysis

To evaluate the robustness of the TCN-GAN model, a sensitivity analysis was conducted on three sliding window lengths: 10, 20, and 30 days while keeping all other hyperparameters constant.

Table 11. Sliding Window Sensitivity Analysis Results

Window	Epoch	Generator LR	Discriminator LR	Generator Updates/Epoch	MAPE	RMSE
10	500	0.0003	0.0001	2	5.02%	192.55
20	**500**	**0.0003**	**0.0001**	**2**	**3.36%**	**89.92**
30	500	0.0003	0.0001	2	4.43%	116.98

Based on Table 11, window 20 yields the best performance with an MAPE of 3.36% and RMSE of 89.92. Windows 10 performs worse as the short historical range is insufficient to capture long-term temporal patterns, while window 30 introduces noise from less relevant historical data, reducing model performance. Window 20 provides the optimal balance between historical coverage and data relevance, and is therefore selected as the final configuration. All window variants achieve MAPE below 20%, confirming the robustness of the TCN-GAN model across different input configurations.

d. Training Loss Graph

The training loss plot is used to evaluate the training process of the TCN-GAN model and to observe the stability of the interaction between the Generator and Discriminator during learning. Figure 4 presents the TCN-GAN training loss for SSMS.JK stocks.

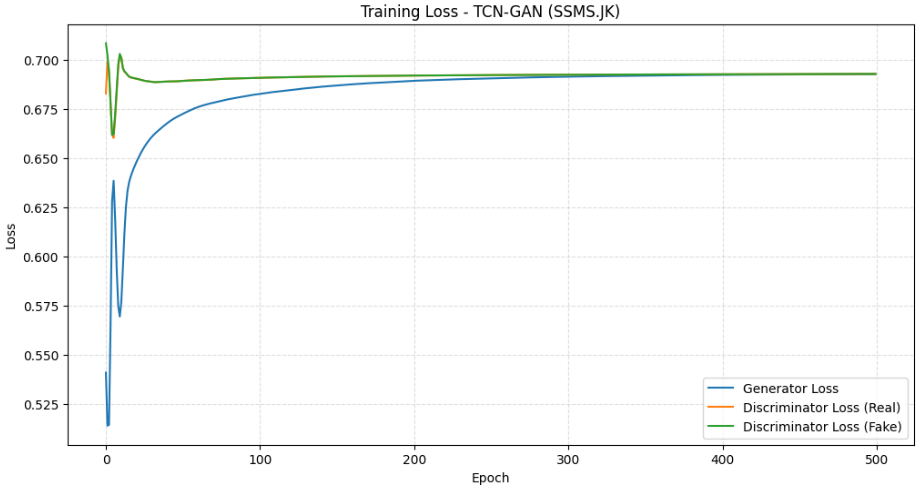

Figure 4. Training Loss

Based on the TCN-GAN training loss plot, the initial epochs show fluctuations in the loss values, indicating the adjustment process between the Generator and Discriminator. As the number of epochs increases, the loss values of both networks decrease and tend to stabilize, demonstrating that the training process has converged.

e. TCN-GAN Model Prediction Results

This section presents the stock price predictions generated by the TCN-GAN model on the test data, displayed in a plot comparing actual and predicted prices to assess the alignment of price movement patterns.

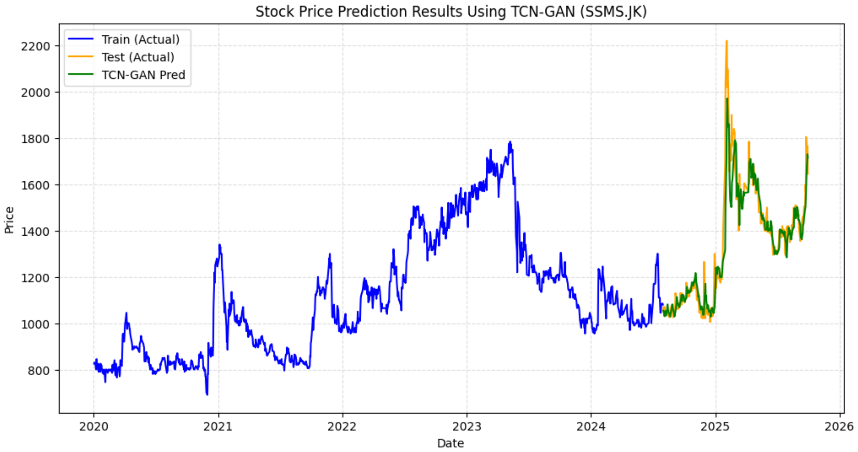

Figure 5. Stock Price Prediction

Figure 5 shows that the TCN-GAN model predictions on the test data closely follow the stock price movements, with the predicted line remaining near the actual price line. These findings imply that the model successfully learns both directional movements and variability in stock prices during the evaluation period, yielding more accurate representations than conventional models.

3.4. Model Performance Comparison

To quantitatively assess predictive performance, a comparison between the ARIMA baseline model and the hybrid TCN-GAN model was conducted using MAPE and RMSE metrics on the test data covering the period from August 1, 2024, to September 30, 2025.

Table 12. Model Performance Comparison

Evaluation Metric	ARIMA	TCN-GAN
MAPE	18.12%	3.22%
RMSE	368.68	84.23

Based on Table 12, the TCN-GAN model significantly outperforms the ARIMA baseline across both evaluation metrics. The TCN-GAN model achieved an MAPE of 3.22% and an RMSE of 84.23, compared to 18.12% and 368.68 obtained by ARIMA, representing an error reduction of approximately 82.2% in terms of MAPE and 77.2% in terms of RMSE. This result confirms that the TCN-GAN model is substantially more capable of capturing the nonlinear and volatile dynamics of SSMS.JK stock price movements compared to the linear ARIMA model, which is consistent with the limitations of statistical approaches in financial time series forecasting.

3.5. 5 Period Prediction

After identifying the best-performing model, the next step is to predict stock prices using the TCN-GAN model for the five periods following the test data to provide an overview of short-term stock price movements.

Table 13. 5 Period Prediction

Date	SSMS.JK
2025-10-01	1,695.41
2025-10-02	1,656.47
2025-10-03	1,634.35
2025-10-06	1,623.01
2025-10-07	1,629.88

Based on Table 13, the 5-period prediction indicates that the stock price of PT Sawit Sumbermas Sarana Tbk. (SSMS.JK) decreases at the beginning of the period and then stabilizes. This result demonstrates that the model can effectively capture the price movement of data not used during training.

3.6. Investment Risk Analysis Using VaR-HS

Investment risk analysis was conducted using the predicted returns from the test data covering the period from August 29, 2024, to September 30, 2025, as well as the predicted returns for the next five periods from October 1 to October 7, 2025. The analysis was performed using the Value-at-Risk (VaR) method with the Historical Simulation approach at a 95% confidence level, an initial investment of IDR 1,000,000, and a five-day investment horizon.

Table 14. VaR Analysis Results

VaR Return	VaR in IDR
−14.62%	IDR 146,204

Based on Table 14, the Value-at-Risk analysis indicates that the maximum potential investment loss for PT Sawit Sumbermas Sarana Tbk (SSMS.JK) is −14.62%, which is equivalent to IDR 146,204. This result reflects a relatively high level of investment risk for SSMS.JK stock during the observation period.

Previous studies applied the TCN-GAN model to ITMG stock and reported an MAPE of 2.16% and an RMSE of 814.25. In this study, the TCN-GAN model was applied to SSMS.JK stock, yielding a MAPE of 3.22% and an RMSE of 84.23. The difference in MAPE values is influenced by the more volatile price movements of SSMS.JK. The key distinction between this study and previous research lies in the utilization of prediction results for investment risk analysis using the VaR-Historical Simulation method. Assuming an investment of IDR 1,000,000, a 95% confidence level, and a five-day investment horizon, the analysis produces a maximum potential loss of IDR 146,204.

4. Conclusion

In conclusion, the experimental findings indicate that the proposed TCN-GAN model significantly outperforms the ARIMA baseline, which yielded a MAPE of 18.12% and RMSE of 368.68, by achieving a MAPE of 3.22% and RMSE of 84.23 in predicting the stock price of PT Sawit Sumbermas Sarana Tbk (SSMS.JK). A sliding window sensitivity analysis confirmed that a window of 20 days provides the optimal input configuration, validating the robustness of the model. The TCN-GAN model was subsequently employed to forecast stock prices for the next five periods as the basis for investment risk analysis using the Value-at-Risk (VaR) method with the Historical Simulation approach. The VaR analysis at a 95% confidence level with a five-day holding period indicates a maximum potential loss of IDR 146,204, reflecting a relatively high investment risk for SSMS.JK stock. These findings suggest that integrating the TCN-GAN model with VaR-based risk analysis provides a more comprehensive assessment of investment risk and can serve as a reference for investors in making informed investment decisions.

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