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Comparison of Adaptive Neural-Based Fuzzy Inference System and Support Vector Machine Methods for the Jakarta Composite Index Forecasting

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Abstract

The Jakarta Composite Index (JCI) is a pivotal benchmark for evaluating the performance of all stocks listed on the Indonesia Stock Exchange (IDX). Given the inherent complexity, nonlinearity, and non-stationarity of stock market data, selecting robust forecasting methods is essential. This study compares the performance of the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Support Vector Machine (SVM) in forecasting JCI movements. The researcher assessed prediction accuracy using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The training phase revealed that the optimal ANFIS model employed the generalized bell membership function, outperforming trapezoidal and Gaussian alternatives. Concurrently, the best SVM configuration utilized a linear kernel (cost = 10), demonstrating superior performance compared to radial basis function (RBF) and sigmoid kernels. In the testing phase, ANFIS achieved an RMSE of 39.894 and MAPE of 0.4647, while SVM recorded an RMSE of 38.728 and MAPE of 0.4516. These results underscore the superior predictive capabilities of SVM, positioning it as a reliable tool for stock market forecasting. The study's findings provide valuable insights for investors and policymakers in navigating market uncertainties and optimizing investment strategies.

Keywords: Forecasting; Support Vector Machine; Jakarta Composite Index; Adaptive Neural-based Fuzzy Inference System.

Introduction

The Jakarta Composite Index (JCI) serves as a crucial benchmark, reflecting the overall performance of all stocks listed on the Main Board and Development Board of the Indonesia Stock Exchange (IDX) (1). Stock price movements within the JCI exhibit diverse patterns throughout the trading day, with some stocks experiencing gains, others losses, and a subset remaining unchanged (2). Figure 1 illustrates the general structure of a fuzzy inference system, while Figure 3 depicts the specific ANFIS architecture used in this study. A rising JCI trend signals an overall increase in stock prices, whereas a declining trend indicates a general downturn. For participants in the capital market, are closely monitoring stock price movements is essential to inform strategic investment decisions. However, forecasting stock market behavior poses significant challenges due to

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its inherently complex, nonlinear, and non-stationary nature.

In addressing these complexities, there have been various advanced forecasting approaches leveraging artificial intelligence developed, including the Adaptive Neuro-Fuzzy Inference System (ANFIS), Support Vector Machine (SVM), Genetic Programming (GP), and Artificial Neural Networks (ANN). In a study by When-Chuan Wang (3), the forecasting performance of these methods was compared to daily river flow data. The results demonstrated that ANFIS and SVM surpassed traditional statistical approaches such as ARMA, as well as other AI-based methods like GP and ANN, in terms of Coefficient of Determination (R^2), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). Notably, the predicted values of ANFIS and SVM closely aligned with observed data trends, highlighting their efficacy in handling nonlinear datasets.

The ANFIS model excels at identifying intricate nonlinear patterns in data, combining the strengths of fuzzy inference systems and neural network architectures. While fuzzy inference systems can translate expert knowledge into rule-based models, determining optimal membership functions can be computationally intensive. ANFIS addresses this limitation by integrating neural network learning mechanisms, automating the search for optimal membership functions, and thus expediting the modeling process. This dual capability makes ANFIS a versatile tool for applications across various domains. For example, ANFIS has been successfully utilized to forecast and analyze air quality in Wuhan City, particularly in studying the effects of COVID-19 on environmental parameters (4).

Similarly, the Support Vector Machine (SVM) method offers a robust alternative for time series forecasting, including stock price prediction. SVM is particularly well-suited for complex, nonlinear datasets and has demonstrated high predictive accuracy when its hyperparameters are optimally tuned. A comparative study of SVM and Backpropagation-based ANN for forecasting foreign tourist arrivals in Bali Province revealed that SVM, using a radial basis function kernel, outperformed ANN by achieving the lowest forecasting errors (5).

The high potential returns offered by the Indonesian stock market have attracted significant interest from domestic and international investors, particularly in comparison to other regional markets. The potential underscores the importance of accurate stock price forecasting to maximize investment returns. Previous studies have consistently shown that ANFIS and SVM outperform other forecasting methods in terms of predictive accuracy. Therefore, this study seeks to apply ANFIS and SVM methodologies to forecast the Jakarta Composite Index (JCI) to contribute to more informed investment strategies.

Materials and Methods

Forecasting

Forecasting involves estimating future values based on historical data, typically employing statistical and computational methods. It is an essential tool in decision-making processes, allowing for predicting future trends using past observations. Time series analysis is widely used among the various approaches, relying on historical values and error patterns to predict future outcomes over time (6).

Adaptive Neural-Based Fuzzy Inference System (ANFIS)

ANFIS integrates fuzzy inference systems with neural network architecture, leveraging the strengths of both approaches. While fuzzy inference systems excel in translating expert knowledge into rule-based models, they often require significant effort to determine optimal membership functions. Neural networks streamline this process by automating the search for membership functions, enhancing the applicability of ANFIS across diverse fields (7). Assuming a Fuzzy inference system with two inputs, x_1 , x_2, and single output Y., the first-order Sugeno fuzzy model can be represented as follows:

if $x_1 = A_1$ and $x_2 = B_1$, than $f_1 = p_{1x} + q_{1y} + r_1$

if $x_1 = A_2$ and $x_2 = B_2$, than $f_1 = p_{2x} + q_{2y} + r_2$

Here $\boldsymbol{A_i}$ and $\boldsymbol{B_i}$ are linguistic labels (e.g., low, medium, high) represented by membership functions, and pi, qi, and ri are consequent parameters.

Member Functions of ANFIS

Fuzzy set theory extends classical set theory by allowing degrees of membership for elements. The degree of membership, denoted by μA(x), quantifies how much an element x belongs to a fuzzy set A (8). Membership values are defined using functions such as:

1. Trapezoidal Membership Function:

$$f(x,a,b,c,d) = \begin{cases} 0; & x < a \\ \dfrac{x-a}{b-a}; & a \le x \le b \\ 1; & b \le x \le c \\ \dfrac{d-x}{d-c}; & c \le x \le d \\ 0; & x > d \end{cases}$$

2. Generalized Bell Membership Function:

$$B(x,a,b,c,d) = \frac{1}{1+\left[\left(\frac{x-c}{a}\right)^2\right]^b}$$

3. Gaussian Membership Function:

$$G(x,\mu,\sigma) = exp\left(\frac{-(x-\mu)^2}{2\sigma^2}\right)$$

A Fuzzy Inference System (FIS) is a computational framework grounded in Fuzzy set theory, utilizing Fuzzy rules (in the form of IF-THEN statements) and Fuzzy reasoning. The system receives a crisp input, which is then processed by a knowledge base containing Fuzzy rules in the IF-THEN format. The system evaluates the "fire strength" for each rule. When multiple rules are present, the system aggregates the outcomes of all the rules. Finally, the aggregated results are defuzzified to produce a crisp output value (9).

Architecture of ANFIS

The network architecture of the ANFIS method consists of five layers, as illustrated in Figure 2 (10). The ANFIS network comprises five layers, each with distinct roles:

1. Fuzzification Layer: Calculates the degree of membership for each input using membership functions. The premise parameters are adapted in this layer. Suppose $x_1 = X_1$ and $x_2 = X_2$, the node function is described by the following equation:

$$O_{1,1} = \mu_{A_1}(X_1)$$
$$O_{1,2} = \mu_{A_2}(X_1)$$
$$O_{1,3} = \mu_{B_1}(X_2)$$
$$O_{1,4} = \mu_{B_2}(X_2)$$

2. Fuzzy Logic Operation Layer: Computes the firing strength of rules using the product of input memberships. The node function for this layer can be described by the following equation:

$$O_{2,1} = w_i = \mu_{A_i}(X_1)\mu_{B_i}(X_2)$$

3. Normalization Layer: Normalizes the firing strengths to ensure proportionality.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{\sum_i w_i}$$

4. Defuzzification Layer: Calculates the weighted output of each rule using consequent parameters.

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(c_{i1}x_1 + c_{i2}x_2 + c_{i0})$$

5. Output Layer: Aggregates the results from all rules to produce the final model output.

$$O_5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

Parameter estimation is performed using hybrid learning, combining the Recursive Least Squares Estimation (RLSE) for linear parameters and Backpropagation for nonlinear parameters (17).

Support Vector Machine (SVM)

SVM is a machine learning algorithm grounded in statistical learning theory, suitable for classification and regression tasks (11, 12). SVM maps input data into a

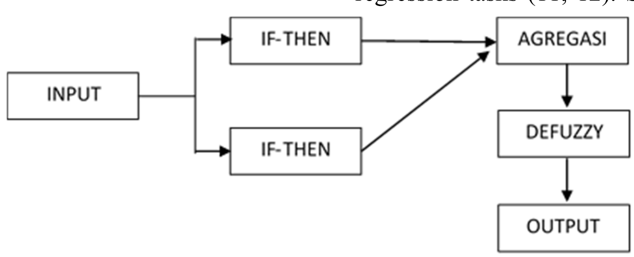

Figure 1. Fuzzy Inference System

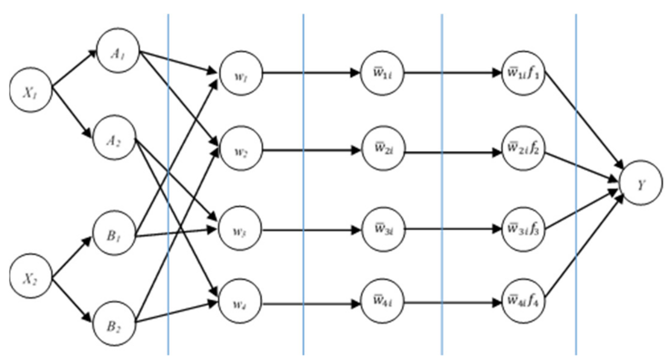

Figure 2. Architecture of ANFIS

high-dimensional feature space using kernel functions, enabling the separation of non-linearly separable data. The kernel trick transforms data into a higher-dimensional space, facilitating linear separation (13).

Commonly used kernels include:

1. Linear Kernel:
$$\mathrm{K}(\mathrm{x},\mathrm{z}) = x^T z$$
2. Sigmoid Kernel:
$$\mathrm{K}(\mathrm{x},\mathrm{z}) = \tanh\,(\gamma\,.\,x^T z + r)$$
3. Radial Basis Function (RBF) Kernel:
$$\mathrm{K}(\mathrm{x},\mathrm{z}) = exp\left\{-\frac{\|x-z\|^2}{2\sigma^2}\right\}$$

The optimal SVM parameters are typically identified using a grid search algorithm, which systematically evaluates combinations of parameters.

Performance Metrics for Model Evaluation

The accuracy of forecasting models is assessed using the following metrics:

Root Mean Square Error (RMSE)

$$RMSE = \left(\frac{\sum(y_i - \hat{y}_i)}{n}\right)^{\frac{1}{2}}$$

Lower RMSE values indicate better predictive accuracy (14).

Mean Absolute Percentage error (MAPE)

$$MAPE = \frac{\sum_{t=1}^{n} |(\frac{y_i - \hat{y}_i}{y_i})|\ 100\%}{n}$$

Lower MAPE values denote higher forecasting precision (15).

Results

This study utilizes a dataset comprising daily closing prices of Jakarta Composite Index (JCI) shares over two years, specifically from January 2, 2020 to December 29, 2023. The movement pattern of stock prices is highly volatile and exhibits non-linear characteristics. To address this, the research applies artificial intelligence methods, including the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Support Vector Machine (SVM). Before modeling, the dataset is divided into training and testing subsets, as detailed in Tables 1 and 2.

Table 3 shows that the dataset consists of 974 observations of JCI stock prices collected during the study period. The data is split so that 80% is allocated for training, and 20% is reserved for testing. The training data is utilized to build prediction models, which are subsequently validated using the testing data to evaluate their predictive performance.

ANFIS Training Process

The ANFIS model is implemented using MATLAB software, with an error tolerance of zero and a maximum of 20 epochs. Before the training process, the data is normalized to 0 to 1 to enhance computational efficiency and meet system requirements. The ANFIS model uses the JCI stock closing price as the target variable and includes six input variables derived from the prior six days. Mathematically, the ANFIS model is expressed as:

Table 1. Training Data and Target Data

Data	Training Data	Target Data
1	Data from the 1st day to the 6th day	Data from the 7th day
2	Data from the 2nd day to the 7th day	Data from the 8th day
3	Data from the 3rd day to the 8th day	Data from the 9th day
…	…	…
774	Data from the 768th day to the 773th day	Data from the 774th day

Table 2. Dataset division

No	Dataset division	Period	Number of Data
1.	Training Data	January 2, 2014 – March 6, 2023	780
2.	Testing Data	March 7, 2023 – December 29, 2023	194

Table 3. Nonlinear Parameters of Trapezoidal Function

Input	a	b	c	d
Input 1 mf1 (A1)	-0.7000	-0.3000	0.3032	0.6919
Input 1 mf2 (A2)	0.2536	0.6983	1.3000	1.7000
Input 2 mf1 (B1)	-0.7000	-0.3000	0.2986	0.6892
…	…	…	…	…
Input 6 mf2 (F2)	0.2879	0.6988	1.3000	1.7000

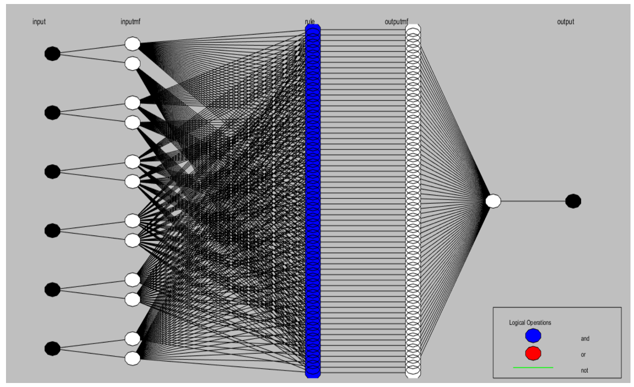

Figure 3. Anfis Structure Of Jci Stock Price Data

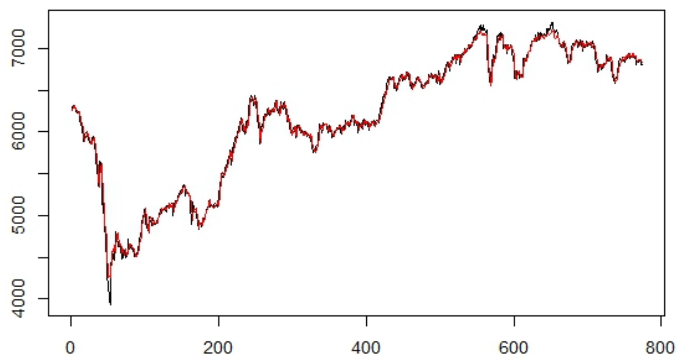

Figure 4. Svm Prediction Before Optimization

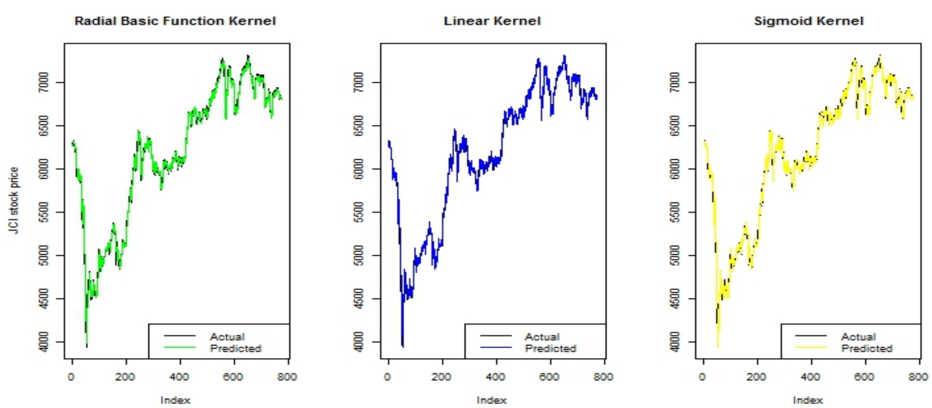

Figure 5. Svm Prediction Using Kernels

$$\begin{aligned}\overline{w}_{1t.}f_1 = \overline{w}_{1t}\big(&C_{1,1}X_1 + C_{1,2}X_2 + C_{1,3}X_3 + C_{1,4}X_4 \\ &+ C_{1,5}X_5 + C_{1,6}X_6 + C_{1,0}\big) + \cdots \\ &+ \overline{w}_{64t}\big(C_{64,1}X_1 + C_{64,2}X_2 + C_{64,3}X_3 \\ &+ C_{64,4}X_4 + C_{64,5}X_5 + C_{64,6}X_6 \\ &+ C_{64,0}\big)\end{aligned}$$

Here $X_1, X_2, X_3, X_4, X_5$and X_6 represent the six input variables.wwithh denotes the normalized. firing strength for rule,Cij,and i represent the linear parameters for rule i.

In the ANFIS architecture, the first layer performs fuzzification, transforming crisp values into Fuzzy numbers based on membership functions, such as Trapezoidal, Generalized Bell, and Gaussian. The nonlinear parameters in the membership functions are optimized using a backpropagation error method, as

Table 4. Nonlinear Parameters of Generalized Bell Function

Input	a	b	c
Input 1 mf1 (A1)	0.4823	2.0050	-0.0036
Input 1 mf2 (A2)	0.4414	2.0005	1.0465
Input 2 mf1 (B1)	0.4246	2.0113	-0.0250
…	...	...	...
Input 6 mf2 (F2)	0.4260	2.0132	1.0192

Table 5. Nonlinear Parameters of Gaussian Function

Input	μ	σ
Input 1 mf1 (A1)	0.3614	-0.0213
Input 1 mf2 (A2)	0.3477	1.0324
Input 2 mf1 (B1)	0.3641	-0.0187
…	...	...
Input 6 mf2 (F2)	0.3493	1.0255

illustrated in Tables 3–5. The mathematical representations of the membership functions are as follows:

a. Trapezoidal Membership Function:

$$\mu_{A1}(X_1) = \begin{cases} 0, & X_1 < -0.7 \\ \dfrac{X_1 - (-0.7)}{-0.3 - (-0.7)}, & 0.7 \le X_1 \le -0.3 \\ 1, & -0.3 \le X_1 \le 0.3032 \\ \dfrac{(0.5505 - X_1)}{0.6919 - 0.3032}, & 0.3032 \le X_1 \le 0.6919 \\ 0, & X_1 > 0.6919 \end{cases}$$

b. Generalized Bell Membership Function:

$$\mu_{A1}(X_1, 0.4823, 2.0050, -0.0036) = \frac{1}{1 + \left[\left(\frac{x - 0.0036}{0.4823}\right)^2\right]^{2.0050}}$$

c. Gaussian Membership Function:

$$\mu_{A1}(X_1, 0.3614, -0.0213) = exp\left(\frac{-(x - 0.3614)^2}{2(0.0213)^2}\right)$$

The second layer computes the firing strength (αα-predicate) using Zadeh's AND operator, combining the membership degrees generated in the first layer. The step produces 64 rules derived from 2^6, representing all possible combinations of inputs and membership functions.

In the third layer, the firing strengths are normalized by dividing each by the total sum of all firing strengths. The normalized values are then defuzzified in the fourth layer, where fuzzy outputs are converted to crisp values using linear parameters optimized through the Least Squares Estimation (LSE) method, Tables 6–8 present detailed model parameters. The fifth and final layer aggregates the outputs to generate the final predictions in Table 9.

A comparison of membership functions is carried out to find the best model with the following ANFIS best model criteria comparison. Based on the goodness of output model criteria in Table 10, the Generalized Bell function in ANFIS performs best with the lowest MAPE value of 0.4284. This function shows the highest relative accuracy in forecasting stock prices compared to the Gaussian and Trapezoidal functions. Therefore, the ANFIS model with the Generalized Bell membership function will be used for testing the Test Data.

SVM Training Process

SVM models are implemented using the e1071 package in R Studio. This method transforms input data into a high-dimensional feature space using kernel functions, constructing an optimal hyperplane for classification or regression. Initially, the SVM model uses default parameters, resulting in predictions that deviate significantly from the actual data, as shown in Figure 4.

Parameter optimization is conducted using a grid search method, testing combinations of parameters: $\varepsilon = \{0,0.1,0.2,\ldots,1\}$, $cost = \{2^{-2}, 2^{-1}, \ldots, 2^9\}$ and $gamma = \{2^9, 2^8, \ldots, 2^2\}$. Cross-validation is employed to evaluate model performance for each parameter combination. The tested kernel functions are the Radial Basis Function (RBF), linear, and sigmoid. The linear kernel produces predictions closest to actual data, as illustrated in Figure 5.

The linear kernel achieves the lowest Root Mean Square Error (RMSE) compared to other kernels, with optimal parameter values of cost=10cost=10. This kernel is selected to forecast test data and predict future JCI stock prices.

Discussion

Following the training data analysis using both

Table 6. Linear Parameters of Trapezoidal Function

Input	C_1	C_2	C_3	...	C_6	C_0
Output mf1	-0.1262	0.1866	-0.2717	...	0.8620	0.0656
Output mf2	-3.0476	-4.4460	1.1517	...	-0.7315	1.6118
Output mf3	0.5082	-10.7592	0.5622	...	-10.9661	2.7333
...	...	...	...	...	...	...
Output mf64	0.0305	-0.0868	-0.0596	...	0.9014	0.0273

Table 7. Linear Parameters of Generalized Bell Function

Input	C_1	C_2	C_3	...	C_6	C_0
Output mf1	0.4425	-0.0151	-0.9043	...	-0.4460	0.4707
Output mf2	-0.5735	-12.2232	3.5131	...	3.0817	1.8571
Output mf3	-7.0566	4.5672	6.7993	...	0.9636	-5.0750
...	...	...	...	...	...	...
Output mf64	-1.8858	0.7730	0.4699	...	0.6007	0.3415

Table 8. Linear Parameters of Gaussian Function

Input	C_1	C_2	C_3	...	C_6	C_0
Output mf1	0.1104	-0.2049	-0.5585	...	-0.4439	0.4432
Output mf2	-2.7432	-12.6954	5.3103	...	-3.1770	4.4031
Output mf3	-2.5234	4.1647	2.6423	...	0.3907	-2.8141
...	...	...	...	...	...	...
Output mf64	-1.9919	1.2109	0.6571	...	0.5844	-0.0962

Table 9. Forecasting Result of ANFIS

Date	Actual Data	Gaussian Training Output	Trapezoidal Training Output	Generalized Bell Training Output
1/10/2020	6274.941	6285.760	6282.905	6295.116
1/13/2020	6296.567	6253.760	6280.237	6251.545
1/14/2020	6325.406	6291.051	6299.900	6286.146
1/15/2020	6283.365	6310.446	6292.180	6304.323
…	…	…	…	…
12/29/2023	6807.001	6822.114	6819.001	6816.086

Table 10. Comparison of ANFIS Model Goodness Criteria

Member Functions	MAPE	RMSE
Trapezodial Function	0.6206	50.438
Generalized Bell Function	0.4284	37.637
Gaussian Funcstion	0.6520	52.153

Adaptive Neuro-Fuzzy Inference System (ANFIS) and Support Vector Machine (SVM) models, forecasting was performed on the testing data to identify the most effective approach for predicting JCI stock prices. In the case of ANFIS, the model employed a Generalized Bell membership function, which demonstrated strong performance in the training phase. Conversely, the SVM model utilized a linear kernel with a cost parameter set to 10, which was optimized during the grid search process.

To evaluate and compare the forecasting performance of both models on the testing data, accuracy metrics, including Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE), were calculated and are presented in Table 11. ANFIS achieved a MAPE of 0.4647 and an RMSE of 39.894, whereas SVM outperformed ANFIS with a MAPE of 0.4516 and an RMSE of 36.728. These results clearly indicate that SVM offers superior accuracy and predictive power for forecasting JCI stock prices compared to ANFIS.

As shown in Figure 6 and Table 12, the SVM model's predictions are noticeably closer to the actual stock prices than the ANFIS model's. The graphical representation further underscores the conclusion that the SVM method provides more accurate and reliable predictions for the Jakarta Composite Index (JCI) stock prices than the ANFIS model.

Table 11. Comparison of SVM model goodness criteria

Kernel	MAPE	RMSE
Radial Basic Function	0.7851	64.483
Sigmoid	0.7789	63.893
Linear	0.7787	63.564

Table 12. Comparison of ANFIS and SVM Forecasting Results

Time	Actual Data	ANFIS	SVM
27-Mar-2023	6628.137	6657.343	6667.709
28-Mar-2023	6565.728	6628.467	6658.872
29-Mar-2023	6678.237	6564.476	6574.031
30-Mar-2023	6612.490	6663.021	6675.338
31-Mar-2023	6691.611	6628.246	6607.709
3-Apr-2023	6762.254	6698.378	6696.484
4-Apr-2023	6708.933	6766.400	6727.627
5-Apr-2023	6760.328	6724.016	6719.136
6-Apr-2023	6839.436	6772.216	6759.006
15-Mar-2023	6808.951	6833.755	6811.873
16-Mar-2023	6805.277	6818.610	6812.346
17-Mar-2023	6827.175	6819.812	6814.796
20-Mar-2023	6833.178	6826.516	6820.83
…	…	…	…
29-Dec-2023	7272.797	7288.872	7302.981

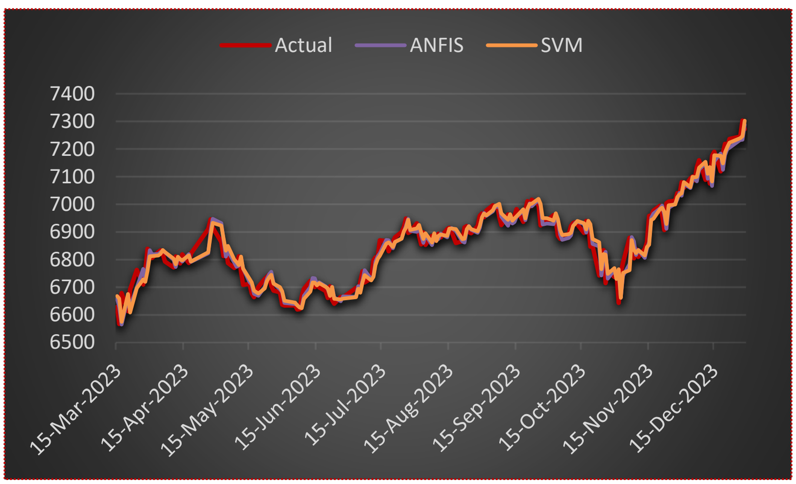

Figure 6. Anfis And Svm Forecasting Result Graphs

This outcome suggests that SVM can effectively optimize hyperparameters using kernel methods and is better suited for capturing the non-linear patterns inherent in stock price data. Meanwhile, although ANFIS showed reasonable performance, SVM outperformed it in terms of both MAPE and RMSE, highlighting the advantage of SVM in this particular forecasting context.

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