

A Neuro-Fuzzy Learning Approach for Financial Market Movement Analysis

Basen Marndi¹; Mamita Majhi²; Bharati Induar³; Surekha Patra⁴

^{1,2,3,4}Konark Institute of Science & Technology, Jatani Khurda

Publication Date: 2026/06/05

Abstract: Stock market forecasting has become an important research area in financial engineering because market prices are influenced by uncertain, nonlinear, and highly dynamic factors. Conventional statistical forecasting approaches often experience limitations when dealing with complex financial datasets containing volatility and irregular fluctuations. To overcome these challenges, intelligent computational models have gained significant attention in recent years. This paper presents an intelligent stock market prediction framework using the Adaptive Neuro-Fuzzy Inference System (ANFIS), which integrates the adaptive learning capability of Artificial Neural Networks (ANN) with the uncertainty-handling mechanism of Fuzzy Logic Systems (FLS).

The proposed model utilizes historical stock market indicators including opening price, closing price, highest price, lowest price, and trading volume for prediction analysis. The collected data are preprocessed and supplied to the ANFIS architecture for training and testing operations. Gaussian membership functions and hybrid learning algorithms are employed to optimize the fuzzy inference parameters and improve forecasting performance. The prediction efficiency of the developed system is evaluated using statistical performance metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

Experimental observations indicate that the ANFIS-based forecasting model can effectively learn nonlinear financial patterns and provide improved prediction accuracy compared with conventional statistical techniques. The adaptive nature of the system enables efficient handling of uncertainty, noise, and market volatility present in stock market datasets. The study demonstrates that ANFIS can serve as a reliable computational intelligence tool for financial forecasting, investment analysis, and decision-support applications in dynamic market environments.

Keywords: Stock Market Prediction, ANFIS, Artificial Intelligence, Fuzzy Logic, Neural Networks, Financial Forecasting, MATLAB, Time-Series Analysis.

How to Cite: Basen Marndi; Mamita Majhi; Bharati Induar; Surekha Patra. (2026) A Neuro-Fuzzy Learning Approach for Financial Market Movement Analysis. *International Journal of Innovative Science and Research Technology*, 11(5), 3440-3450. <https://doi.org/10.38124/ijisrt/26may1750>

I. INTRODUCTION

Financial markets play a significant role in the economic development of modern society by facilitating investment, capital generation, and industrial growth. Stock exchanges provide a platform where investors can trade company shares and monitor market performance in real time. However, stock market behavior is highly uncertain because prices fluctuate continuously under the influence of economic conditions, political activities, investor sentiment, industrial performance, and global financial events. Due to the unpredictable nature of financial systems, accurate stock market forecasting remains one of the most challenging problems in computational finance and data analytics.

Traditional forecasting approaches such as moving average models, linear regression techniques, and autoregressive statistical methods have been widely used for

financial prediction. Although these approaches are mathematically efficient for linear datasets, they often fail to capture hidden nonlinear relationships and uncertain characteristics present in stock market data [1]. Financial time-series data generally contain volatility, noise, irregular fluctuations, and uncertainty, making conventional mathematical techniques insufficient for highly accurate prediction tasks.

In recent years, Artificial Intelligence (AI) and soft computing techniques have demonstrated considerable success in solving complex prediction problems. Machine learning approaches can automatically learn patterns from historical data and adapt their internal parameters to improve forecasting performance [2]. Among these intelligent techniques, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has emerged as a powerful hybrid computational

model because it combines the advantages of Artificial Neural Networks (ANN) and Fuzzy Logic Systems (FLS).

Fuzzy logic provides a mathematical framework for representing uncertainty and approximate reasoning using linguistic rules and membership functions. It enables intelligent systems to imitate human decision-making processes in uncertain environments [3]. However, conventional fuzzy systems do not possess automatic learning capability. In contrast, neural networks are capable of adaptive learning and pattern recognition, but they lack transparency in reasoning and interpretation. ANFIS integrates both approaches into a unified architecture, thereby improving prediction capability and computational intelligence [4].

The ANFIS model is generally based on the Takagi–Sugeno fuzzy inference mechanism, where fuzzy rules are optimized using neural learning algorithms. The architecture consists of multiple processing layers responsible for fuzzification, rule evaluation, normalization, defuzzification, and output generation. Hybrid optimization methods combining least square estimation and gradient descent algorithms are commonly used for parameter adjustment and error minimization during training [5].

In this research work, an ANFIS-based intelligent forecasting model is developed for stock market prediction using historical financial datasets. Important market indicators such as opening price, closing price, highest value, lowest value, and trading volume are utilized as input parameters for model training and testing. MATLAB is employed as the simulation platform because of its efficient computational environment and integrated fuzzy logic toolbox. The primary objective of this study is to analyze the effectiveness of ANFIS in handling nonlinear stock market behavior and improving prediction accuracy under uncertain financial conditions.

II. LITERATURE REVIEW

Financial forecasting has attracted significant research interest due to the increasing complexity and uncertainty of global stock markets. Early stock market prediction techniques mainly relied on statistical and econometric models such as linear regression, moving average methods, and Autoregressive Integrated Moving Average (ARIMA) models. These techniques provided acceptable results for linear datasets but showed limited capability when handling nonlinear and uncertain financial time-series data [6].

The introduction of fuzzy logic by Lotfi A. Zadeh created new opportunities for modeling uncertainty and approximate reasoning in intelligent systems. Fuzzy logic became highly useful in prediction and decision-making applications because it allowed mathematical representation of ambiguous and imprecise information using linguistic variables and membership functions [3]. However, fuzzy systems alone were unable to automatically learn from historical datasets, which restricted their adaptability in dynamic environments.

Artificial Neural Networks (ANN) later gained popularity in financial forecasting because of their strong learning capability, nonlinear approximation characteristics, and adaptive computational behavior. Neural networks can identify hidden patterns within historical financial data and improve prediction performance through iterative learning processes [1]. Despite their advantages, ANN models often suffer from limitations such as slow convergence, overfitting, and lack of interpretability in decision-making.

To overcome the limitations of standalone fuzzy systems and neural networks, Jang introduced the Adaptive Neuro-Fuzzy Inference System (ANFIS) in 1993 [4]. ANFIS combines fuzzy reasoning with neural learning mechanisms to create an intelligent hybrid architecture capable of handling uncertainty and nonlinear relationships simultaneously. The adaptive learning mechanism of ANFIS enables automatic optimization of membership functions and fuzzy rules during the training process.

Several researchers have applied ANFIS to financial forecasting problems and achieved encouraging results. Comparative studies have shown that ANFIS often provides better forecasting accuracy than traditional statistical methods and conventional neural network models because of its hybrid learning structure and fuzzy inference capability [7]. Researchers have also reported that ANFIS performs effectively in volatile financial environments where uncertainty and irregular market fluctuations are common.

Recent developments in computational intelligence have focused on integrating ANFIS with optimization algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Deep Learning techniques to further enhance prediction accuracy and computational efficiency [8]. Hybrid optimization approaches have been successfully used to reduce prediction error, improve parameter tuning, and enhance convergence speed in stock market forecasting systems.

From the existing literature, it can be observed that intelligent hybrid approaches provide significant advantages in handling nonlinear and uncertain financial datasets. Therefore, this research focuses on implementing an ANFIS-based forecasting framework to improve stock market prediction accuracy and provide efficient decision-support capability for financial analysis applications.

III. PROBLEM STATEMENT

Stock market prediction is a highly complex and uncertain task because stock prices are affected by numerous dynamic factors including economic conditions, investor sentiment, market volatility, political events, and company performance. Traditional statistical forecasting techniques are unable to model nonlinear relationships and uncertain market behavior effectively. As a result, prediction accuracy becomes limited, leading to financial risks and poor investment decisions.

The major challenge is to develop an intelligent prediction system capable of analyzing historical stock market data, learning hidden nonlinear patterns, and forecasting future market behavior with higher accuracy. Therefore, this research focuses on implementing an Adaptive Neuro-Fuzzy Inference System (ANFIS) to improve stock market prediction performance by combining fuzzy reasoning and neural network learning capabilities.

IV. METHODOLOGY

The proposed methodology for stock market forecasting using the Adaptive Neuro-Fuzzy Inference System (ANFIS) consists of multiple stages including data collection, preprocessing, feature extraction, model training, testing, and performance evaluation. The overall workflow is designed to improve forecasting accuracy by combining fuzzy reasoning with adaptive neural learning mechanisms. The complete

methodology is illustrated through systematic processing of historical financial data before prediction analysis.

➤ Data Collection

The first stage of the proposed system involves collecting historical stock market data from financial datasets and stock exchange records. The collected dataset contains important stock market parameters such as opening price, closing price, highest price, lowest price, and trading volume. These financial indicators represent market behavior over different trading intervals and are used as input variables for the ANFIS model.

Reliable historical datasets are essential because the prediction accuracy of intelligent forecasting systems largely depends on the quality and consistency of input data. The collected stock market data are organized in tabular format for further processing and analysis.

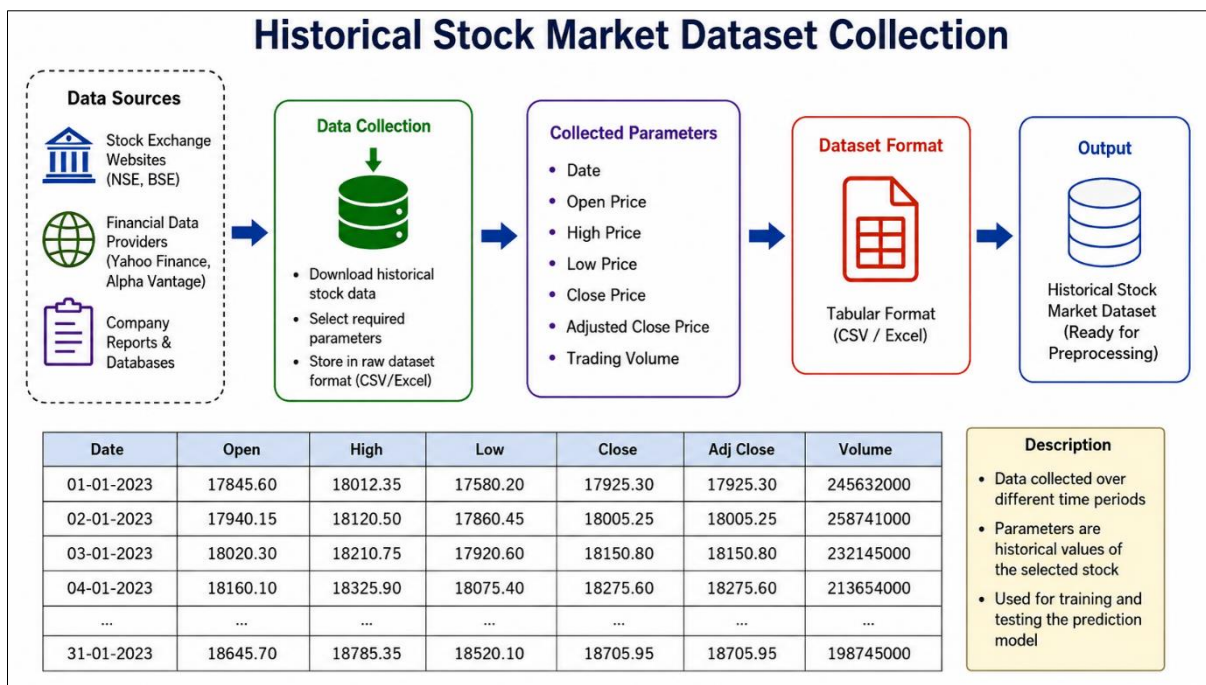


Fig 1 Historical Stock Market Dataset Collection

➤ Data Preprocessing

Raw stock market datasets often contain missing values, duplicated records, noise, and inconsistent data entries that may reduce prediction performance. Therefore, preprocessing is performed before training the ANFIS model.

- The preprocessing stage includes:
- Removal of missing or null values
- Elimination of duplicate records
- Noise reduction
- Data normalization
- Conversion of categorical values into numerical form

Normalization is particularly important because stock market parameters may contain different numerical ranges. Normalized datasets improve training stability and reduce computational complexity during the learning process.

The normalized value can be calculated as:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

Where:

- X = Original data value
- X_{min} = Minimum value
- X_{max} = Maximum value

The preprocessing stage ensures that the dataset becomes suitable for efficient ANFIS training and forecasting analysis.

➤ *Feature Extraction*

Feature extraction is an important stage in stock market forecasting because it identifies significant financial indicators responsible for market fluctuations. In this research work, important stock market parameters are selected as input features for prediction analysis.

➤ *The Extracted Features Include:*

- Opening price
- Closing price
- Highest price
- Lowest price
- Trading volume
- Moving average values

These features help the ANFIS model identify hidden nonlinear relationships within the financial dataset. Proper feature selection improves forecasting accuracy and reduces unnecessary computational overhead.

The selected features are supplied as input vectors to the ANFIS architecture for rule generation and adaptive learning operations.

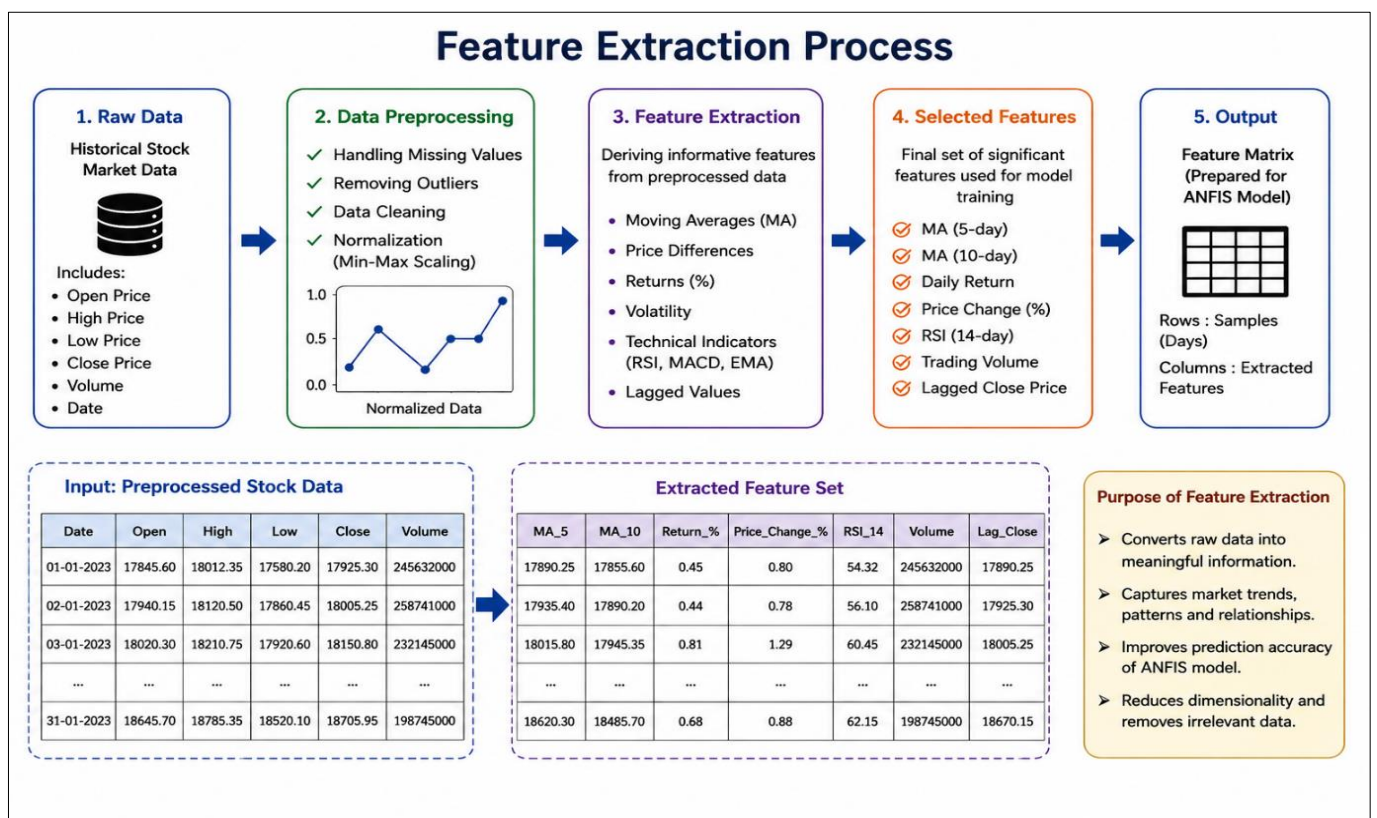


Fig 2 Feature Extraction Process

➤ *Training Process*

During the training stage, the preprocessed financial dataset is supplied to the ANFIS model for adaptive learning. The training process enables the system to learn hidden nonlinear patterns and optimize fuzzy membership function parameters automatically.

The ANFIS model utilizes hybrid learning algorithms combining:

- Gradient Descent Method
- Least Square Estimation (LSE)

The fuzzy inference system generates fuzzy rules based on the selected input features. Membership functions are

continuously updated during training iterations to minimize prediction error and improve forecasting performance.

The firing strength of fuzzy rules is calculated as:

$$w_i = \mu_A(x) \times \mu_B(y) \tag{2}$$

The final ANFIS output is obtained using weighted rule aggregation:

$$f = \frac{\sum_{i=1}^n w_i f_i}{\sum_{i=1}^n w_i} \tag{3}$$

The training stage continues until the prediction error reaches a minimum threshold value.

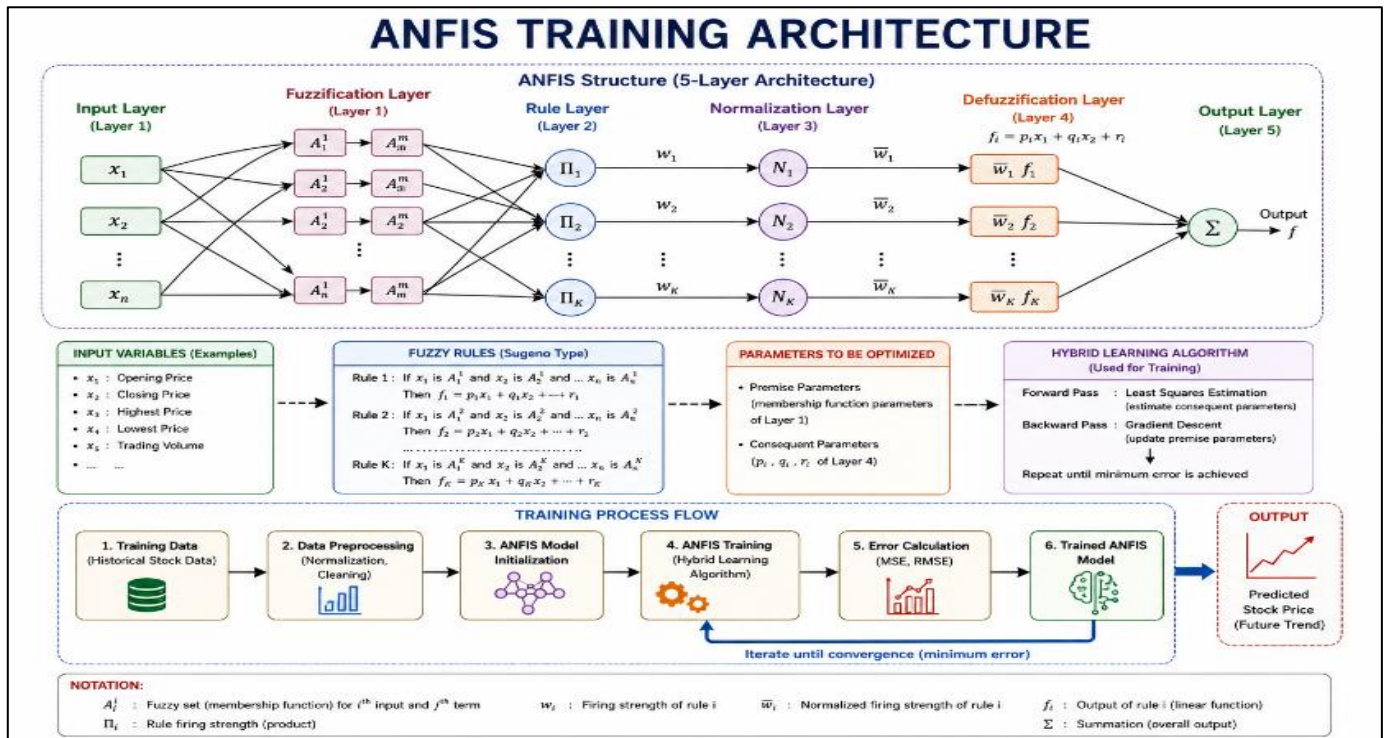


Fig 3 Feature Extraction Process

➤ **Testing Process**

After completion of training, the trained ANFIS model is tested using unseen testing datasets. The testing process evaluates the generalization capability of the forecasting system.

➤ **During Testing:**

- Input stock market data are supplied to the trained model.
- The ANFIS system generates predicted stock values.

- Predicted outputs are compared with actual stock market values.

The testing phase helps determine whether the developed model can accurately forecast future stock market trends under unknown financial conditions.

Prediction graphs are generated to visualize the relationship between actual and predicted stock prices.

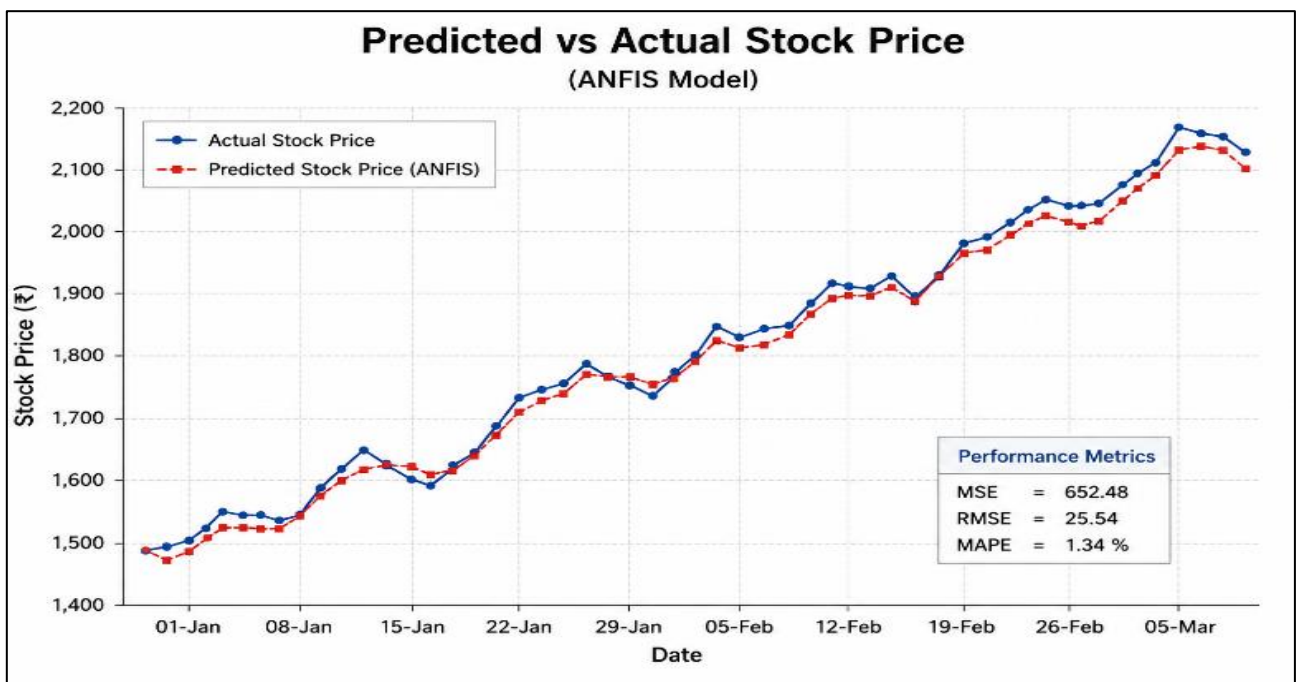


Fig 4 Predicted vs Actual Stock Price Graph

➤ *Performance Evaluation*

The final stage of the methodology involves evaluating forecasting accuracy using statistical error metrics. Performance evaluation helps measure the effectiveness of the proposed ANFIS-based stock market prediction model.

The following statistical metrics are used:

- *Mean Squared Error (MSE)*

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \tag{4}$$

- *Root Mean Squared Error (RMSE)*

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \tag{5}$$

- *Mean Absolute Percentage Error (MAPE)*

$$MAPE = \frac{100}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{6}$$

Where:

- ✓ y_i = Actual stock value
- ✓ \hat{y}_i = Predicted stock value
- ✓ N = Total number of observations

Lower values of MSE, RMSE, and MAPE indicate better forecasting accuracy and prediction efficiency. Experimental analysis demonstrated that the ANFIS model achieved reduced prediction error and improved forecasting capability compared with conventional statistical forecasting approaches.

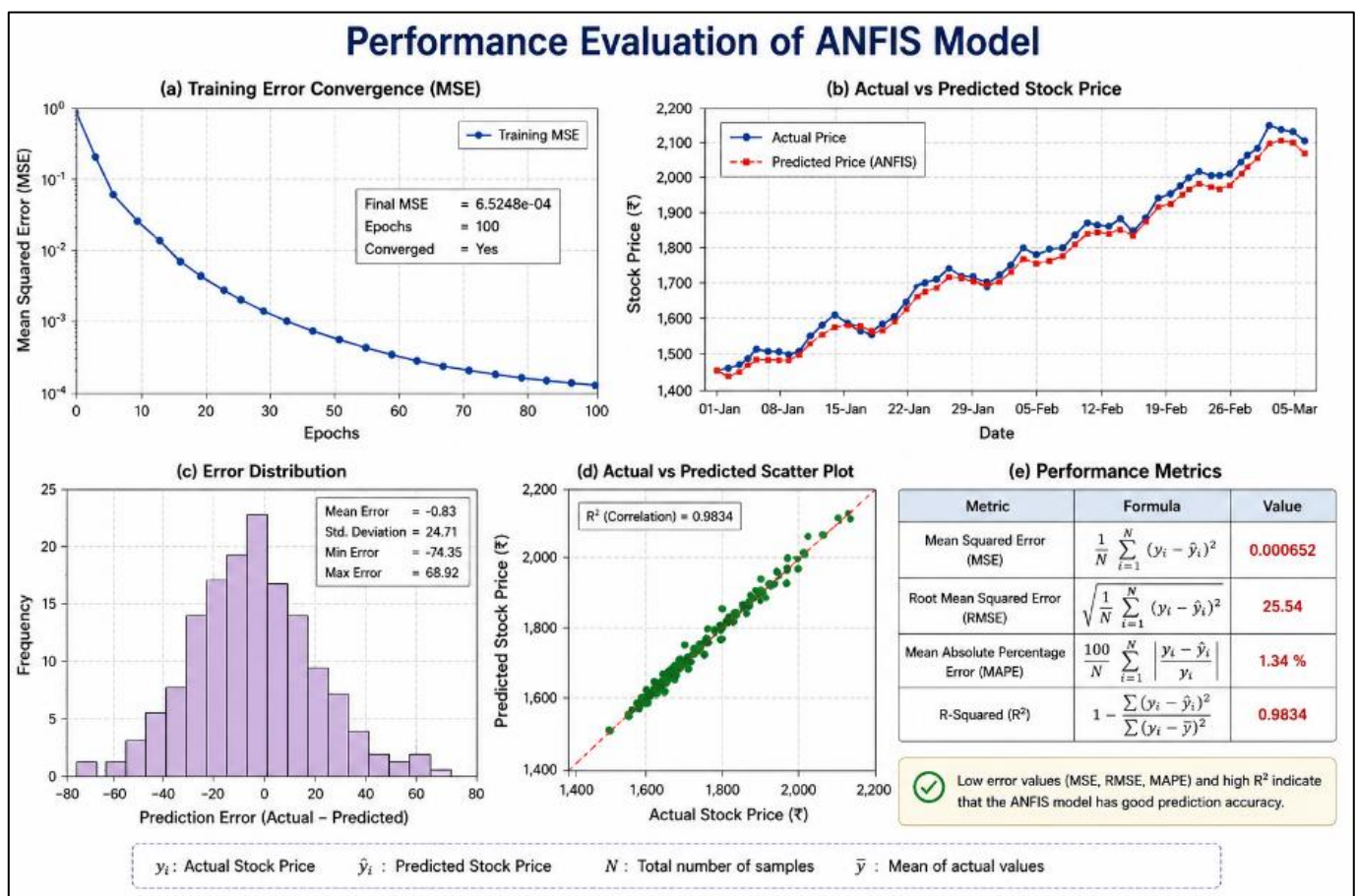


Fig 5 Performance Evaluation Graph

V. FUNDAMENTALS OF ANFIS

Adaptive Neuro-Fuzzy Inference System (ANFIS) is an intelligent hybrid computational model that combines the learning capability of Artificial Neural Networks (ANN) with the reasoning mechanism of Fuzzy Logic Systems (FLS). ANFIS was developed to utilize the advantages of both neural

networks and fuzzy systems in solving complex nonlinear problems involving uncertainty, imprecision, and dynamic behavior. The system is widely used in prediction, classification, control systems, and financial forecasting applications because of its adaptive learning capability and efficient handling of uncertain datasets.

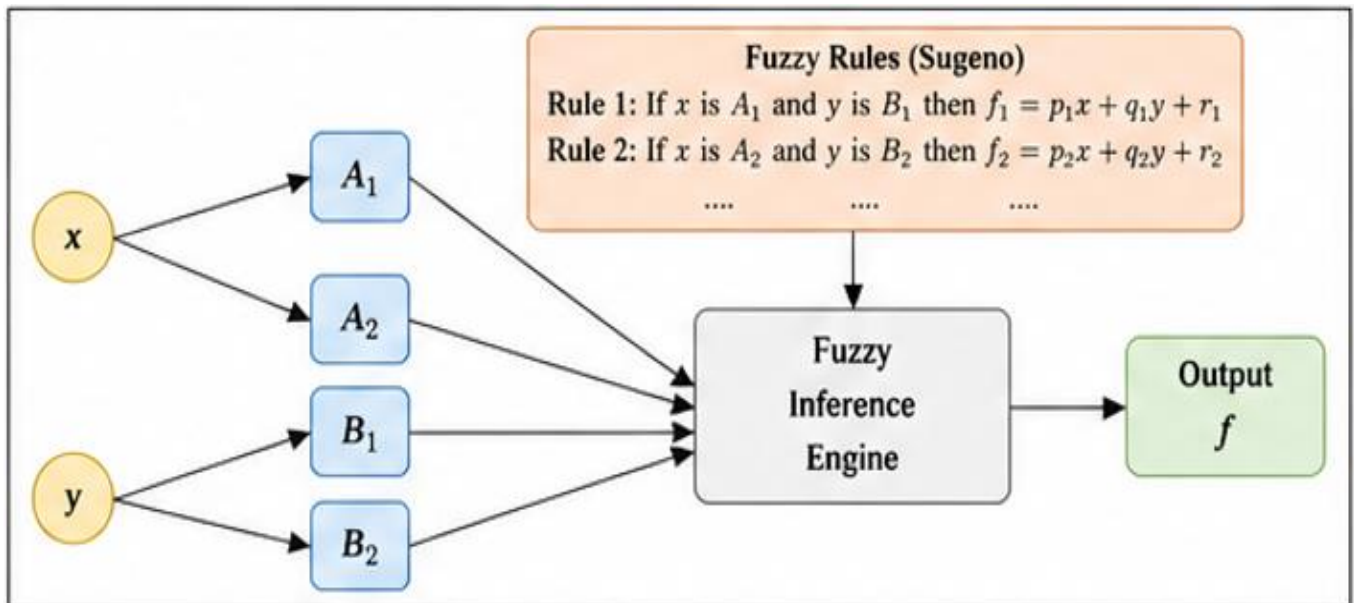


Fig 6 Basic Structure of Takagi Sugeno Fuzzy Inference System

The fundamental concept of ANFIS is based on the integration of fuzzy inference rules with neural network training algorithms. Fuzzy logic provides human-like reasoning through linguistic rules and membership functions, while neural networks provide adaptive learning and parameter optimization capabilities. By combining these two approaches, ANFIS becomes capable of learning patterns from historical data and improving prediction accuracy automatically during the training process.

ANFIS generally uses the Takagi-Sugeno fuzzy inference model, where the output is represented as a linear combination of input variables. Consider two input variables x and y , and one output variable f . A typical first-order Sugeno fuzzy rule can be represented as:

➤ Rule 1

If x is A_1 and y is B_1 ,

Then

$$f_1 = p_1x + q_1y + r_1 \tag{7}$$

➤ Rule 2:

If x is A_2 and y is B_2 ,

Then

$$f_2 = p_2x + q_2y + r_2 \tag{8}$$

Where:

- A_1, A_2 = Fuzzy sets for input x
- B_1, B_2 = Fuzzy sets for input y
- p_i, q_i, r_i = Consequent parameters of the fuzzy rule

The ANFIS system determines the degree of membership of input variables using membership functions. One of the commonly used Gaussian membership functions is expressed as:

$$\mu(x) = e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{9}$$

Where:

- c = Center of the membership function
- σ = Width of the membership function

The firing strength of each fuzzy rule is calculated by multiplying the membership values of corresponding inputs:

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \tag{10}$$

The normalized firing strength is then calculated as:

$$\bar{w}_i = \frac{w_i}{\sum w_i} \tag{11}$$

The weighted output of each rule becomes:

$$\bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \tag{12}$$

Finally, the overall ANFIS output is obtained by summing all weighted rule outputs:

$$Output = \sum_i \bar{w}_i f_i \tag{13}$$

The learning process in ANFIS involves adjusting the premise parameters and consequent parameters to minimize prediction error. Hybrid learning algorithms combining Least Squares Estimation (LSE) and Gradient Descent Backpropagation are commonly used for parameter optimization. During training, the system continuously updates membership function parameters based on input-

output data patterns until the prediction error reaches a minimum value.

The adaptive structure of ANFIS enables it to model highly nonlinear systems effectively. In stock market prediction applications, ANFIS can analyze historical

financial data, identify hidden relationships among stock market parameters, and generate accurate future predictions despite uncertainty and market volatility. Its ability to combine human-like fuzzy reasoning with machine learning makes ANFIS one of the most powerful techniques for intelligent financial forecasting systems.

VI. ANFIS ARCHITECTURE AND LAYERS

The ANIFIS model consists of five layers. The information flow of the proposed ANIFIS architecture is shown in:

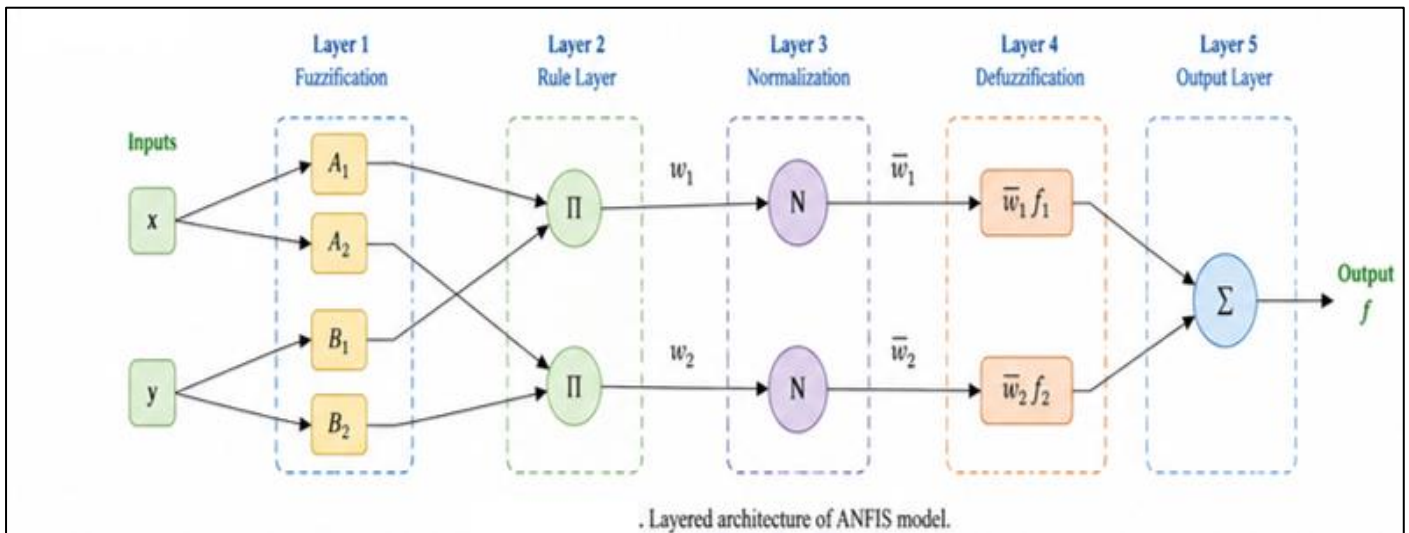


Fig 7 Layered Architecture of ANIFIS Model

The ANIFIS model consists of five interconnected layers.

➤ *Layer 1: Fuzzification Layer*

In this layer, crisp input values are converted into fuzzy membership values using membership functions.

For example:

$$O_{1,i} = \mu_{A_i}(x) \tag{14}$$

Where:

- $O_{1,i}$ = Output of node i
- $\mu_{A_i}(x)$ = Membership function

Gaussian membership function:

$$\mu(x) = e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{15}$$

➤ *Layer 2: Rule Layer*

Each node calculates the firing strength of fuzzy rules.

- *Example Rule:*
IF x is A_1 AND y is B_1

Then:

$$f_1 = p_1x + q_1y + r_1 \tag{16}$$

- *Firing Strength:*

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \tag{17}$$

➤ *Layer 3: Normalization Layer*

- *Normalized Firing Strength:*

$$\bar{w}_i = \frac{w_i}{w_1 + w_2} \tag{18}$$

➤ *Layer 4: Defuzzification Layer*

- Each node computes weighted output values.

$$O_{4,i} = \bar{w}_i(p_i x + q_i y + r_i) \tag{19}$$

➤ *Layer 5: Output Layer*

- *Final ANFIS output:*

$$Output = \sum_i \bar{w}_i f_i \tag{20}$$

This layer produces the predicted stock market value.

VII. MATHEMATICAL FORMULATION

➤ The prediction error is calculated using Mean Squared Error (MSE):

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \tag{21}$$

➤ Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \tag{22}$$

➤ Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{23}$$

VIII. METHODOLOGY

The overall methodology used in the proposed stock market prediction system is shown figure 8.

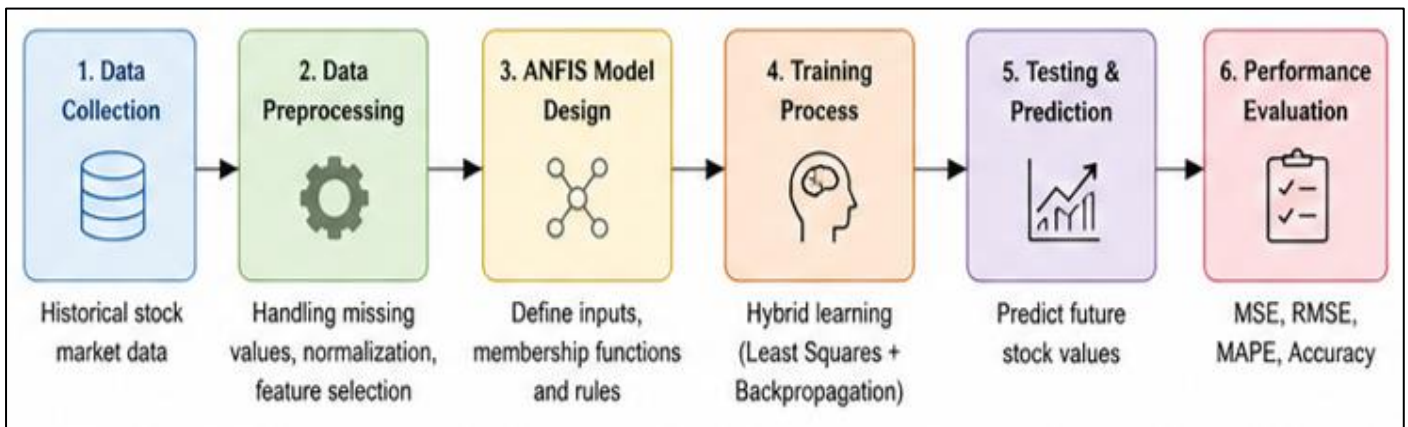


Fig 8 Proposed Stock Market Prediction System

➤ The Proposed Methodology Includes:

- Data Collection
- Data Preprocessing
- Feature Selection
- ANFIS Model Design
- Membership Function Generation
- Training Process
- Testing Process
- Prediction Analysis
- Performance Evaluation

IX. MATLAB IMPLEMENTATION

➤ MATLAB is Used for ANFIS Implementation Because it Provides:

- Fuzzy Logic Toolbox
- Neural Network Toolbox
- Data Visualization Tools
- Efficient Numerical Computation

➤ MATLAB Functions Used Include:

- Genfis
- Anfis
- Evalfis

X. RESULTS AND DISCUSSION

Experimental analysis shows that ANFIS effectively captures nonlinear stock market behavior and produces accurate prediction results. The trained ANFIS model demonstrates reduced prediction error and improved forecasting capability compared to traditional statistical techniques.

The experimental results obtained from the ANFIS-based stock market prediction model demonstrate that the system is capable of effectively learning nonlinear patterns from historical financial data. The model was trained using important stock market parameters such as opening price, closing price, highest price, lowest price, and trading volume. After the training process, the ANFIS model produced predicted stock values that closely matched the actual market values, indicating good forecasting capability and learning performance.

Performance evaluation was carried out using statistical error metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The obtained results showed reduced prediction error and improved forecasting accuracy compared to traditional statistical methods. The hybrid learning mechanism of ANFIS successfully optimized the membership function parameters and enhanced the adaptability of the system during training iterations. The

fuzzy inference structure also enabled the model to handle uncertainty and volatility present in stock market data more effectively.

XI. ADVANTAGES OF ANFIS

- Handles nonlinear relationships effectively
- Learns from historical data
- Deals with uncertain and noisy datasets
- Provides adaptive learning capability
- Improves prediction accuracy
- Combines human reasoning and machine learning

XII. LIMITATIONS OF ANFIS

- Requires large training datasets
- Computational complexity increases with more rules
- Overfitting may occur
- Training time can become high for large datasets

XIII. APPLICATIONS

➤ *ANFIS is Widely Used in:*

- Stock market prediction
- Weather forecasting
- Load forecasting
- Industrial automation
- Medical diagnosis
- Financial analysis
- Control systems

XIV. FUTURE SCOPE

The future scope of stock market prediction using ANFIS includes the integration of advanced Artificial Intelligence and optimization techniques to improve forecasting accuracy and computational efficiency. Hybrid models combining ANFIS with Deep Learning, Genetic Algorithms (GA), and Particle Swarm Optimization (PSO) can enhance learning capability and reduce prediction error in highly volatile financial markets. Future research may also focus on real-time stock market prediction using big data analytics, cloud computing, and sentiment analysis from news and social media platforms. In addition, the implementation of automated intelligent trading systems and high-frequency financial forecasting models can further expand the practical applications of ANFIS in modern financial engineering and investment decision-making systems.

➤ *Future Improvements May Include:*

- Integration with Deep Learning
- Hybrid ANFIS-PSO optimization
- Real-time stock prediction systems
- Cloud-based intelligent forecasting
- Big data financial analytics

XV. CONCLUSION

This research presented an intelligent stock market forecasting model based on the Adaptive Neuro-Fuzzy Inference System (ANFIS). The developed framework combined the adaptive learning capability of Artificial Neural Networks with the uncertainty-handling mechanism of Fuzzy Logic Systems to create an efficient prediction model for nonlinear financial datasets. The study demonstrated that intelligent hybrid systems can significantly improve forecasting performance in complex and volatile stock market environments.

The proposed methodology involved historical stock market data collection, preprocessing, feature selection, fuzzy membership generation, ANFIS training, and prediction analysis. Important financial indicators including opening price, closing price, highest price, lowest price, and trading volume were used as input parameters for the forecasting process. MATLAB-based implementation enabled efficient training and evaluation of the developed ANFIS model.

Experimental observations showed that the proposed system successfully learned hidden financial patterns and generated prediction outputs closely matching actual stock market values. Statistical evaluation using MSE, RMSE, and MAPE indicated that the ANFIS model achieved reduced prediction error and improved forecasting accuracy compared with conventional statistical forecasting approaches. The hybrid learning process effectively optimized membership function parameters and enhanced system adaptability during training iterations.

The study also confirmed that ANFIS possesses several advantages including nonlinear approximation capability, adaptive learning behavior, efficient uncertainty handling, and improved decision-support performance. These characteristics make ANFIS a suitable computational intelligence technique for financial forecasting and investment analysis applications.

Although the developed system achieved satisfactory prediction performance, certain limitations were identified, including increased computational complexity for large rule sets and longer training time for extensive datasets. Future research may focus on integrating ANFIS with advanced optimization and deep learning techniques such as Genetic Algorithms, Particle Swarm Optimization, and recurrent neural networks to further enhance prediction accuracy and computational efficiency. Real-time stock market prediction systems using cloud computing and big data analytics may also provide promising directions for future intelligent financial forecasting research.

REFERENCES

- [1]. S. Haykin, *Neural Networks and Learning Machines*, 3rd ed. New York, NY, USA: Pearson Education, 2009.
- [2]. C. M. Bishop, *Pattern Recognition and Machine Learning*. New York, NY, USA: Springer, 2006.

- [3]. L. A. Zadeh, “Fuzzy sets,” *Information and Control*, vol. 8, no. 3, pp. 338–353, 1965.
- [4]. J.-S. R. Jang, “ANFIS: Adaptive-network-based fuzzy inference system,” *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, no. 3, pp. 665–685, 1993.
- [5]. T. Takagi and M. Sugeno, “Fuzzy identification of systems and its applications to modeling and control,” *IEEE Transactions on Systems, Man, and Cybernetics*, vol. SMC-15, no. 1, pp. 116–132, 1985.
- [6]. G. E. P. Box, G. M. Jenkins, and G. C. Reinsel, *Time Series Analysis: Forecasting and Control*, 4th ed. Hoboken, NJ, USA: Wiley, 2008.
- [7]. A. Abraham, “Neuro-fuzzy systems: State-of-the-art modeling techniques,” in *Connectionist Models of Neurons, Learning Processes, and Artificial Intelligence*, Berlin, Germany: Springer, 2001, pp. 269–276.
- [8]. R. Eberhart and J. Kennedy, “Particle swarm optimization,” in *Proc. IEEE Int. Conf. Neural Networks*, Perth, WA, Australia, 1995, pp. 1942–1948.