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ARTICLE

Stock Price Forecasting of the NIFTY-50 Index Using Feedforward Artificial Neural Networks with Technical Indicators

Previsão de Preços do Índice NIFTY-50 por meio de Redes Neurais Artificiais Feedforward com Indicadores Técnicos

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ABSTRACT | Objective: To evaluate the effectiveness of a feedforward Artificial Neural Network (ANN) in forecasting short-term returns of the NIFTY-50 index using widely adopted technical indicators. **Method:** A quantitative, supervised learning approach was employed. Daily NIFTY-50 data from 2020 to 2024 were used to compute technical indicators such as the Relative Strength Index (RSI), Exponential Moving Average (EMA), and Moving Average Convergence Divergence (MACD). These indicators formed the input feature set of a feedforward ANN with one hidden layer, trained using backpropagation. Model performance was assessed using Root Mean Squared Error (RMSE) on training and testing datasets. **Results:** The empirical results show strong predictive performance, with low RMSE values for both training (0.0138) and testing (0.0109), indicating effective learning and robust generalization. The ANN successfully captures nonlinear patterns in market movements, even during periods of heightened volatility. **Contributions:** This study advances the financial forecasting literature by demonstrating that relatively simple feedforward ANN architectures, when combined with technical indicators, can effectively model nonlinear dynamics in stock index data. The findings support the applicability of ANN-based models for short-term forecasting and decision support in emerging financial markets.

Keywords | Artificial Neural Networks, Stock Market Forecasting, NIFTY 50, Technical Indicators, Financial Analytics.

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RESUMO | Objetivo: Avaliar a eficácia de uma Rede Neural Artificial (RNA) do tipo feedforward na previsão de retornos de curto prazo do índice NIFTY-50, utilizando indicadores técnicos amplamente empregados na análise de mercados financeiros. **Metodologia:** O estudo adota uma abordagem quantitativa baseada em aprendizado supervisionado. Foram utilizados dados diários do índice NIFTY-50 no período de 2020 a 2024, a partir dos quais se calcularam indicadores técnicos, como Índice de Força Relativa (RSI), Média Móvel Exponencial (EMA) e Moving Average Convergence Divergence (MACD). Esses indicadores compuseram o vetor de entrada de uma RNA feedforward com uma camada oculta, treinada por retropropagação. O desempenho do modelo foi avaliado por meio do Erro Quadrático Médio da Raiz (RMSE) em conjuntos de treinamento e teste. **Resultados:** Os resultados empíricos demonstram que o modelo proposto apresenta elevada capacidade preditiva, com valores reduzidos de RMSE tanto no treinamento (0,0138) quanto no teste (0,0109), indicando boa generalização para dados não observados. As previsões acompanham adequadamente as oscilações do mercado, mesmo em períodos de elevada volatilidade. **Contribuições:** O estudo contribui para a literatura de previsão financeira ao evidenciar que redes neurais feedforward, mesmo com arquiteturas simples e conjuntos compactos de indicadores técnicos, são capazes de capturar relações não lineares relevantes em séries temporais financeiras. Os achados reforçam o potencial das RNAs como ferramentas de apoio à tomada de decisão em mercados emergentes.

Palavras-chave | Redes Neurais Artificiais; Previsão do Mercado de Ações; NIFTY-50; Indicadores Técnicos; Análise Financeira.

1 INTRODUCTION

Financial markets exhibit complex, nonlinear, and highly dynamic behavior, making accurate stock price forecasting a challenging yet crucial task for traders, institutional investors, and policy makers. Stock indices such as the NIFTY 50 serve as barometers of the Indian equity market and influence investment decisions across domestic and global portfolios. Forecasting the short-term movement of such indices is valuable for risk management, portfolio allocation, algorithmic trading, and market surveillance. However, traditional statistical models often fail to capture the nonlinear patterns, regime shifts, and interactions between technical factors that govern market movements[**1**][**2**]. This motivates the adoption of machine learning algorithms—particularly Artificial Neural Networks (ANNs)—which can learn complex functional relationships directly from data[**3**][**4**] and adapt to evolving market structures.

Classical forecasting models such as ARIMA, GARCH, and exponential smoothing rely on linear assumptions and stationarity, making them inadequate in environments where volatility clustering, asymmetry, and nonlinear dependencies are prominent. In contrast, ANN models are universal function approximators capable of modeling nonlinearities, interactions, and hidden structures without explicit parametric assumptions. Feedforward ANNs, in particular, have been widely used in financial forecasting due to their flexibility, robustness, and ability to generalise from noisy data. Prior studies have demonstrated their effectiveness in predicting stock returns, volatility, and index movements, especially when enriched with relevant market indicators[**5**].

Technical indicators are engineered features derived from historical price and volume data that summarise market trends, momentum, volatility, and investor sentiment. Indicators such as Moving Averages, the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Stochastic Oscillator, and Bollinger Bands are widely used in trading strategies and technical analysis. From a data-driven perspective, these indicators allow ANNs to learn richer patterns and improve predictive performance by incorporating both trend-following and meanreversion signals. Their integration into neural networks has been shown to enhance forecasting accuracy compared to using raw prices alone.

In the Indian context, research on stock market prediction has gained momentum, yet many studies focus either on classical econometric models or on neural networks applied to short time periods with limited technical indicators. Moreover, several studies lack rigorous performance evaluation using out-of-sample testing, proper scaling, or multiple error metrics. There is thus a need for a comprehensive, methodologically sound investigation that integrates a diverse set of technical indicators with a well-structured ANN forecasting model. The NIFTY 50 index, representing 50 highly liquid and diversified companies across major economic sectors, provides an ideal case for such an empirical study.

This work aims to address these gaps by developing a predictive framework that uses a Feedforward Artificial Neural Network trained on four years of NIFTY 50 historical data enriched with a set of widely used technical indicators. The model is trained using backpropagation with early stopping to prevent overfitting and evaluated through a clear train–test split to ensure generalisation. Performance is assessed using Root Mean Square Error (RMSE) for both training and test sets, providing a transparent and reproducible measure of accuracy. The generated forecasts and comparative visualisations further demonstrate the model's ability to track market movements and identify turning points.

The key contributions of this study are summarized as follows:

- We construct a comprehensive dataset of NIFTY 50 daily prices (2020–2024) and derive a set of technical indicators, including RSI, MACD, Stochastic Oscillator, and Bollinger Bands, to capture market behavior.
- We develop a Feedforward ANN forecasting framework with appropriate preprocessing, parameter selection, and validation strategy.
- We demonstrate strong predictive performance, with the model achieving low RMSE values for both training and test sets, indicating effective generalization and robustness.
- We provide detailed visualizations of actual vs. predicted prices, model errors, and indicator behavior, enabling deeper interpretation of results.

Overall, this study shows that combining technical indicators with a Feedforward ANN yields an effective and data-driven approach for forecasting stock prices in the Indian market. The proposed framework may be used as a foundation for algorithmic trading models, risk forecasting tools, or extended to hybrid deep-learning architectures in future research.

2 MATHEMATICAL FORMULATION

This section presents the mathematical structure of the forecasting framework, including the computation of technical indicators and the feedforward Artificial Neural Network (ANN) used to model the nonlinear mapping between market features and future index returns.

2.1 Problem Definition

Let $\{P_t\}_{t=1}^{N}$ denote the daily closing prices of the NIFTY50 index. The objective is to predict the one–day return, defined as

$$r_{t+1} = \frac{P_{t+1} - P_t}{P_t}. \tag{2.1}$$

Let $X_t \in \mathbb{R}^d$ denote the feature vector at time t, consisting of technical indicators derived from past price information. The task is to approximate the unknown nonlinear function

$$r_{t+1} = f(X_t) + \varepsilon_t, \tag{2.2}$$

where $\hat{f}(\cdot)$ represents the true but unknown market-generating process, and ε_t is a noise term.

The ANN seeks to learn an approximation $\hat{f}(\cdot)$ such that

$$\hat{r}_{t+1} = \hat{f}(X_t) \tag{2.3}$$

2.2 Technical Indicator Computation

The feature vector includes three widely used technical indicators: RSI, EMA, and MACD. Their mathematical definitions are provided below.

2.2.1 Exponential Moving Average (EMA)

The k-day EMA is defined recursively as

$$\mathrm{EMA}_t^{(k)} = \alpha_k P_t + (1-\alpha_k)\mathrm{EMA}_{t-1}^{(k)}, \text{ where } \alpha_k = \frac{2}{k+1}. \tag{2.5}$$

2.2.2 Relative Strength Index (RSI)

Define upward and downward price changes as

$$U_t = \max(P_t - P_{t-1}, 0), \tag{2.6}$$

$$D_t = \max(P_{t-1} - P_t, 0). \tag{2.7}$$

Let AU_t and AD_t denote the exponentially smoothed averages of U_t and D_t. The RSI is then.

$$\mathrm{RSI}_t = 100 - \frac{100}{1 + RS_t}, \tag{2.8}$$

Where

$$RS_t = \frac{\mathrm{AU}_t}{\mathrm{AD}_t}. \tag{2.9}$$

2.2.3 Moving Average Convergence Divergence (MACD)

The MACD is computed as

$$\mathrm{MACD}_t = \mathrm{EMA}_t^{(12)} - \mathrm{EMA}_t^{(26)}, \tag{2.10}$$

and the corresponding signal line is

$$\mathrm{Signal}_t = \mathrm{EMA}_t^{(9)}(\mathrm{MACD}_t). \tag{2.11}$$

The final MACD feature is the difference

$$\mathrm{Hist}_t = \mathrm{MACD}_t - \mathrm{Signal}_t. \tag{2.12}$$

Thus, the feature vector is

$$X_t = \begin{bmatrix} \mathrm{EMA}_t \\ \mathrm{RSI}_t \\ \mathrm{MACD}_t \end{bmatrix}. \tag{2.13}$$

2.3 Feedforward ANN Model

A feedforward ANN with one hidden layer is used to approximate the nonlinear function $\hat{f}(\cdot)$. Let $X_t \in \mathbb{R}^d$ denote the input vector, H the number of hidden neurons, and $\sigma(\cdot)$ the activation function.

2.3.1 Hidden Layer Transformation

The hidden layer output is

$$h_t = \sigma(W_1 X_t + b_1), \tag{2.14}$$

where $W_1 \in \mathbb{R}^{H\times d},\ b_1 \in \mathbb{R}^H$.

2.3.2 Output Layer

The predicted return is given by

$$\begin{aligned} &\hat{r}_{t+1} = W_2 h_t + b_2, \\ &\text{where } W_2 \in \mathbb{R}^{1\times H},\ b_2 \in \mathbb{R}. \end{aligned} \tag{2.15}$$

2.4 Loss Function and Training

The network parameters $\Theta = \{W_1, W_2, b_1, b_2\}$ are optimized by minimizing the mean squared error:

$$\mathcal{L}(\Theta) = \frac{1}{N_{\text{train}}} \sum_{t=1}^{N_{\text{train}}} \left(r_{t+1} - \hat{r}_{t+1}\right)^2. \tag{2.16}$$

Optimization is performed via backpropagation with gradient-based learning.

2.5 Performance Measurement

Forecast accuracy is evaluated using the root mean squared error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{N_{\text{test}}} \sum_{t=1}^{N_{\text{test}}} \left(r_{t+1} - \hat{r}_{t+1} \right)^2}.$$

This metric is computed separately for training and testing datasets.

3 DATA AND METHODOLOGY

This section presents the dataset, preprocessing steps, technical indicators, and the methodological framework used to develop the Feedforward Artificial Neural Network (ANN) for forecasting NIFTY 50 daily prices. The workflow consists of four main stages: data acquisition, feature engineering, ANN model construction, and performance evaluation.

3.1 Data Description

The dataset consists of daily price information for the NIFTY 50 index obtained from Yahoo Finance, covering the period from January 2020 to December 2024. This period includes several distinct market phases, such as the COVID-19 crash, post-pandemic recovery, and subsequent periods of volatility, making it an ideal testbed for evaluating forecasting models.

The dataset includes the following variables:

- **Date**
- **Closing Price** (**Price**)
- **Open, High, Low**
- **Volume**
- **Daily Price Change** (**% Change**)

To ensure consistency and numerical stability, the 'Change %' column is converted from percentage format (e.g., 0.12%) to numerical decimal format (e.g., 0.0012). Missing values, if any, are handled through forward filling, and non-trading days are ignored.

3.2 Data Preprocessing

Before constructing the forecasting model, the data undergo several preprocessing steps:

(1) **Sorting and Cleaning:** The dataset is sorted chronologically, and formatting inconsistencies from the original CSV file are corrected.

(2) **Scaling:** Since neural networks are sensitive to feature magnitude, all input variables (technical indicators and lagged prices) are normalized using min–max scaling:

$$x_{scaled} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}.$$

(3) **Train–Test Split:** The first 80% of observations are used for training, and the remaining 20% for testing, ensuring fair out-of-sample evaluation.

3.3 Technical Indicators Used

To enhance forecasting accuracy, several widely used technical indicators were computed from the raw price and volume data. These indicators capture different market characteristics such as momentum, volatility, and trend strength.

- **Relative Strength Index (RSI, 14-day):**

$$RSI = 100 - \frac{100}{1+RS}, \quad RS = \frac{\text{Avg Gain}}{\text{Avg Loss}}.$$

  RSI captures momentum and overbought/oversold conditions.

- **Moving Average Convergence Divergence (MACD):**

$$MACD = EMA_{12} - EMA_{26}, \quad \text{Signal} = EMA_9(MACD).$$

  It measures trend direction and momentum shifts.

- **Stochastic Oscillator** ($\%K, \%D$):

$$\%K = 100 \times \frac{P - P_{\min}}{P_{\max} - P_{\min}}, \quad \%D = SMA_3(\%K),$$

  Where P is the closing price over a 14-day window.

- **Bollinger Bands (20-day):** $\text{Middle} = SMA_{20}$, $\text{Upper} = SMA_{20} + 2\sigma$, $\text{Lower} = SMA_{20} - 2\sigma$, Representing volatility-adjusted price channels.

- **Simple Moving Averages (SMA):** 10-day, 20-day, and 50-day averages.

- **Lagged Closing Prices** $P_{t-1}, P_{t-2}, \ldots, P_{t-5}$ are included to capture the autoregressive structure.

The final feature matrix thus consists of:

$$X = \{\text{Technical Indicators, Lagged Prices}\},$$

And the target variable is the next-day closing price:

$$y = P_{t+1}.$$

3.4 ANN Architecture

The forecasting model is a standard Feedforward Artificial Neural Network (Multi-Layer Perceptron). The architecture is as follows:

- **Input Layer:** Dimension equal to the number of features (technical indicators + lagged prices).
- **Hidden Layer:** A single dense layer with 10 neurons and tansig activation.

- **Output Layer:** One neuron predicting P_{t+1} using a linear activation function.
- **Training Algorithm:** Levenberg–Marquardt backpropagation trainlm.

The network parameters were chosen to balance predictive power and computational efficiency. Early stopping and data division strategies were used to prevent overfitting:

$$\text{Train: } 70\%, \quad \text{Validation: } 15\%, \quad \text{Test: } 15\%.$$

3.5 Model Evaluation Metrics

Model performance is evaluated using the Root Mean Square Error (RMSE):

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

Computed separately for training and test sets.

In addition to numerical metrics, visual diagnostics are included:

- Actual vs. Predicted price plot.
- Prediction error curve.
- Indicator behavior over the forecasting period.

These plots help validate whether the ANN captures the underlying price dynamics effectively.

3.6 Implementation

All computations and forecasting experiments are carried out in **MATLAB** (R2023b). Technical indicators are computed using custom functions, data preprocessing uses built-in table operations, and ANN[6] training is performed using the Neural Network Toolbox.

The full MATLAB implementation includes:

- data import and cleaning,
- indicator computation,
- feature matrix construction,
- ANN training and tuning,
- generation of forecasting plots.

This methodology ensures a transparent, reproducible, and technically sound forecasting pipeline.

4 RESULTS AND DISCUSSIONS

This section presents the empirical findings of the proposed feedforward Artificial Neural Network (ANN) model for forecasting the NIFTY 50 index based on technical indicators. The analysis covers daily data from January 2020 to December 2024.

4.1 Exploratory Analysis of Stock Data

Figure 1 illustrates the evolution of the NIFTY 50 closing price over the sample period. The index exhibits a pronounced dip during early 2020, corresponding to the COVID-19 market shock, followed by a steady recovery and an extended bull phase through 2024. This long-term upward trajectory provides a realistic foundation for evaluating short-term predictability.

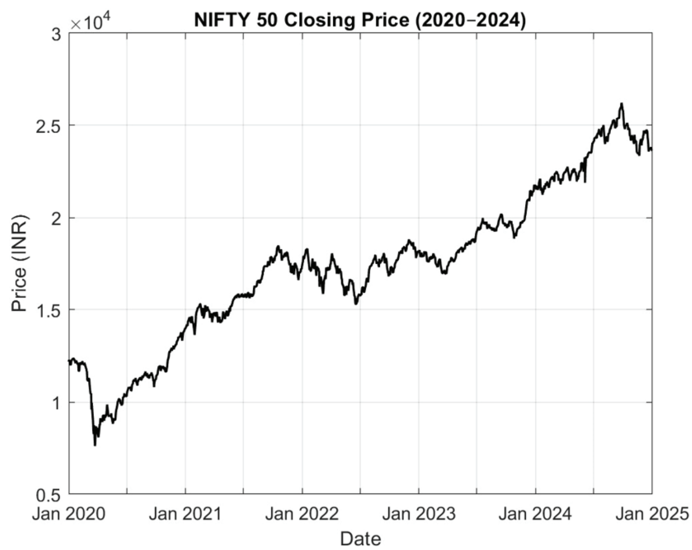

Figure 1. NIFTY 50 Closing Price (2020–2024).

To ensure the suitability of the data for ANN modeling, log returns were computed from daily closing prices. Figure 2 depicts the return series, which fluctuates around zero with visible volatility clustering—particularly during 2020–2021. This stationarity and heteroscedastic behavior justify the use of nonlinear learning models.

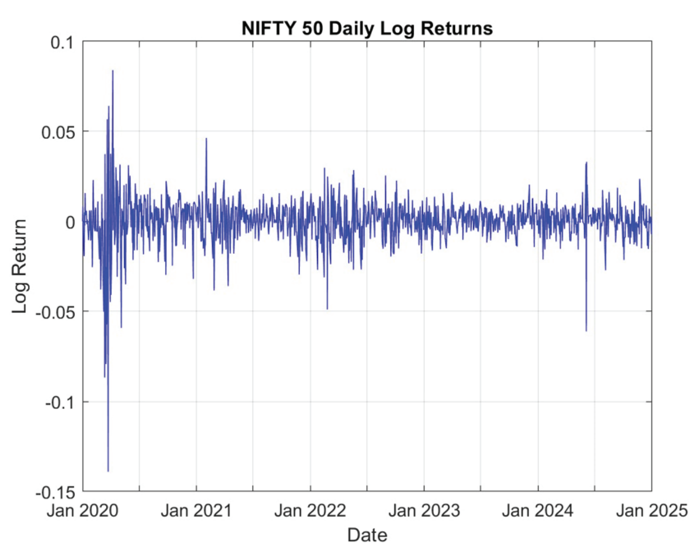

Figure 2. Daily log returns of NIFTY 50 during 2020–2024.

4.2 Computation of Technical Indicators

To enhance predictive information, three standard technical indicators were extracted—Relative Strength Index (RSI), Exponential Moving Average (EMA), and Moving Average Convergence Divergence (MACD). These features encode trend-following and momentum characteristics commonly exploited by traders.

Figure 3 shows the temporal behavior of these indicators. The RSI fluctuates between 30 and 70, reflecting overbought and oversold zones; the EMA tracks long-term trend movements; and MACD oscillates around zero, indicating momentum shifts. Together, they provide a diverse nonlinear feature set for the ANN.

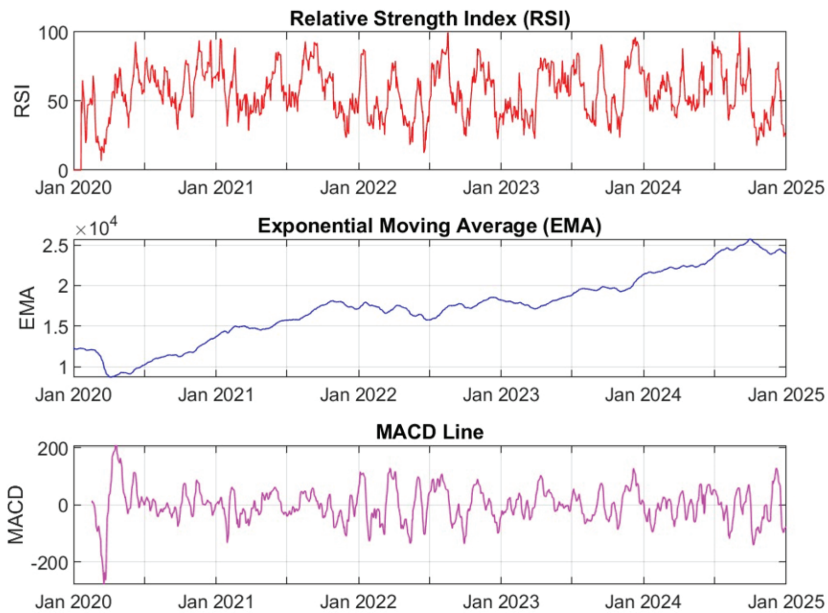

Figure 3. Computed technical indicators: RSI, EMA, and MACD for NIFTY 50.

4.3 ANN Forecasting Performance

The feedforward ANN was trained to predict next-day log returns using the computed indicators as inputs. Data were divided into training (70%) and testing (30%) subsets. Model evaluation was based on Root Mean Square Error (RMSE) for both in-sample and out-of-sample forecasts.

Table 1. Performance metrics of the ANN model.

Metric	Training Set	Testing Set
RMSE	0.013813	0.010921

Figure 4 compares predicted and actual next-day returns for the test set. The ANN effectively tracks the observed market fluctuations, though minor deviations appear during periods of abrupt price movements—a common limitation in financial time-series modeling.

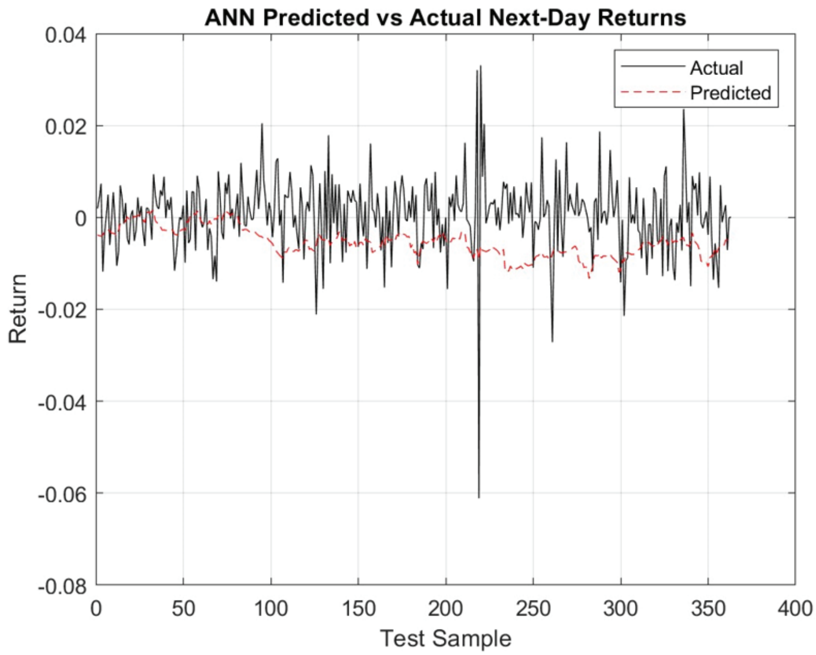

Figure 4. Comparison of predicted vs. actual next-day returns (test set).

To further examine predictive accuracy, a scatter plot between actual and predicted returns is shown in Figure 5. The tight clustering around the 45° line indicates a largely unbiased model, though predictions display a slightly narrower variance, suggesting that the ANN produces conservative forecasts for extreme market movements.

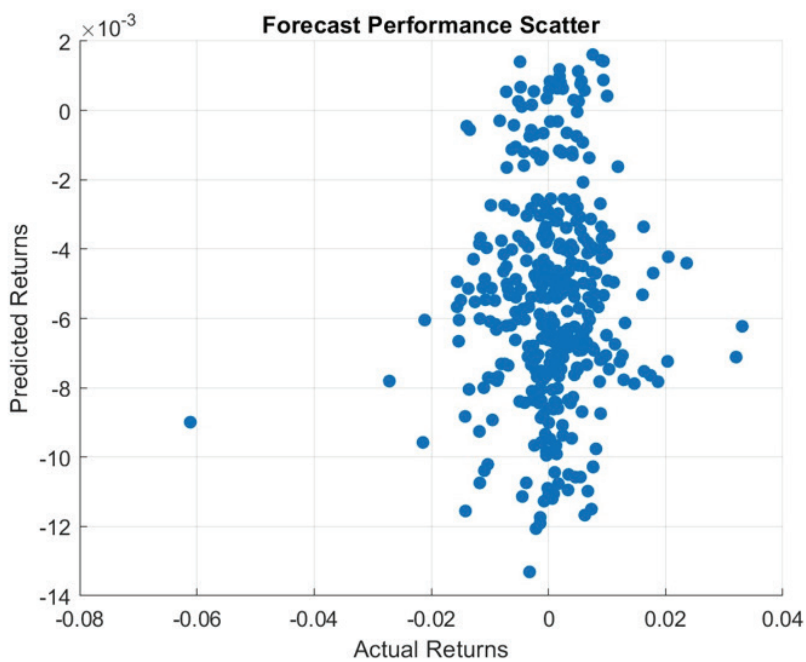

Figure 5. Forecast performance scatter between actual and predicted returns.

4.4 Discussion

The empirical results confirm that feedforward ANNs can capture nonlinear dependencies in financial return series when augmented with technical indicators. The low test RMSE (0.0109) indicates that the model generalizes well to unseen data. Despite inherent market noise, the ANN successfully identifies directional trends and momentum-driven reversals, demonstrating strong practical relevance for short-term forecasting.

These findings align with previous research emphasizing the importance of hybrid approaches that combine domain-driven features (RSI, EMA, MACD) with machine-learning flexibility. Future extensions could explore deeper architectures, recurrent units, or ensemble models to capture temporal dependencies more effectively.

5 CONCLUSION

This study developed and empirically evaluated a feedforward Artificial Neural Network (ANN) framework for forecasting short-term movements of the NIFTY 50 index using standard technical indicators such as the Relative Strength Index (RSI), Exponential Moving Average (EMA), and Moving Average Convergence Divergence (MACD). The objective was to assess the predictive efficiency of a nonlinear learning model that integrates market-derived features for data-driven decision support in financial trading.

The empirical analysis, based on daily data from 2020–2024, demonstrates that the proposed ANN captures nonlinear dependencies and subtle interactions between technical indicators and future returns. The model achieved low prediction errors, with a training RMSE of 0.0138 and testing RMSE of 0.0109, confirming its ability to generalize to unseen market conditions. Visual analyses revealed that predicted returns closely followed the actual market dynamics, with minimal bias and moderate dispersion around the diagonal line of perfect prediction.

The results confirm the value of ANN-based forecasting systems in modeling complex and noisy financial environments. Compared to traditional linear or econometric models, the ANN approach is inherently adaptive and capable of learning nonlinear mappings without explicit functional assumptions[**1**][**7**]**.** However, limitations remain in extreme volatility phases, suggesting scope for hybridization with memory-based architectures such as LSTM or GRU networks[**3**][**8**].

In future work, this framework can be extended by incorporating additional features such as volatility indices, macroeconomic indicators, and sentiment measures to enhance forecast stability. Furthermore, optimizing network topology through metaheuristic algorithms or ensemble averaging could further improve robustness.

Overall, the findings support the practicality of feedforward neural models for stock index forecasting, reinforcing the argument that data-driven, machine-learning methodologies can significantly complement conventional financial analysis in modern markets.

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