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Stock price prediction using bidirectional simple recurrent neural network optimized with Optuna and Technical indicators

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Abstract
The stock price prediction is a challenging problem in the financial markets as it is always a volatile market subject to numerous economic and behavioral factors. This paper suggests the hybrid deep learning model that combines Bidirectional Simple Recurrent Neural Network (BiSRNN) that is optimized using the Optuna framework with technical indicators. The model is tested on five NIFTY 50 stocks such as Reliance industries, Tata Consultancy services (TCS), Infosys, ICICI bank and HDFC bank. The BiSRNN model is able to handle forward and backward temporal relationships of a time-series dataset, whereas Optuna is able to automate hyperparameter optimization in the network to achieve an optimal outcome. Experimental outcomes indicate that the model can achieve high levels of prediction with a high R^2 of greater than 0.89 and a low MAPE of less than 1% in all the stocks chosen indicating the effectiveness and accuracy of the model. The results show that combining technical indicators with automated optimization can greatly improve the accuracy of the predictions, so the given approach can be utilized in financial forecasting when it comes to the utilization.

Keywords: Stock market forecasting, Bisrnn, optuna optimization, technical indicators, deep learning, financial time series, yahoo finance data

1. Introduction
Predicting stock market movements remains one of the most high-dimensional challenges in financial analysis due to the non-linearity and dynamic nature of price fluctuations. Even though the machine learning and deep learning models have proven more adaptable in their capacity to comprehend the chronological financial movement, the conventional statistical models like ARIMA and regression cannot find out the latent time associations. Among them, time-dependent data modelling [1] has been mostly applied using Recurrent Neural Networks (RNNs). However, the model is built in only one direction hence it cannot utilize past and future trends. The Bidirectional Simple Recurrent Neural Network (BiSRNN) has the capability to overcome this drawback by applying forward and backward computing of input sequences to achieve a more global time-conscious. Furthermore, hyperparameter tuning as an essential process for enhancing deep learning model performance, which is typically manual and time-consuming [3].
Technical indicators of RSI, SMA, EMA and MACD are also included to enhance the ability of the model to reveal underlying patterns in market momentum and strength of trends. Such indicators are widely used in financial studies to indicate crossovers, moving averages and price momentum that justify the ability of the model to make decisions. The results indicate that the proposed model yields more accurate and consistent results in making forecasts on a wide range of stock data, therefore, making it a reliable instrument to analysts and investors [2].

2. Related Work
The recent development in deep learning has enhanced the precision of the financial time series forecasting. Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) models have been shown to be able to learn nonlinear relationships, as well as, to learn temporal relationships in stock data. Unidirectional models however do not tend to make use of past and future contextual information and thus they tend to learn the market trends in a

a suboptimal manner [6, 7]. To overcome this, there has been an effort to work on bidirectional recurrent neural networks (BiRNNs) which process data on both forward directions and back helping to improve features extraction and minimise prediction lag.
Simultaneously, with the advancements in architecture, automated hyperparameter optimization models have become popular in financial forecasting. The approach of manual parameter tuning usually causes the inconsistency of results and overfitting, so the use of such frameworks as Optuna and Bayesian optimization algorithms has become an important factor towards stability in models [10]. Recent studies show that the incorporation of Optuna with deep learning models improves generalization and also the training is reduced without human intervention. Besides, technical indicators like RSI, SMA, EMA, and MACD can be added to the list of features, which enhances the capability of the model to identify market momentum and price reversal signals [9]. A balanced solution robust, interpretable, and computationally efficient to the current stock market prediction is a combination of Bidirectional RNNs, Optuna optimization, and technical indicators.

Table 1: Summary of Recent Deep Learning Studies for Stock Price Forecasting

Author(s)	Methodology	Dataset / Stocks	Key Findings
Zhou *et al.*	BiLSTM model for stock prediction using technical indicators	CSI 300 Index (China)	BiLSTM achieved higher accuracy and lower RMSE compared to LSTM and GRU
Rajesh & Kumar	Hybrid BiGRU-LSTM with Wavelet Transform	NIFTY 50 (India)	Improved temporal feature extraction; $R^2 = 0.91$
Akiba *et al.*	Optuna: Hyperparameter optimization framework	Multiple ML benchmarks	Achieved faster convergence and better accuracy via TPE-based search
Ghosh *et al.*	CNN-LSTM hybrid model with MACD and RSI features	BSE and NSE stocks	Integration of technical indicators improved MAPE by 12%
Chakraborty & Banerjee	Transformer-based model with attention and EMA features	NIFTY 100 Stocks	Attention mechanism enhanced directional accuracy to 96%

3. Methodology
The suggested approach combines a Bidirectional Simple Recurrent Neural Network (BiSRNN) and hyperparameter optimization through the use of Optuna and vital technical indicators to forecast the changing price of stocks on a daily basis. The general process of work consists of five primary steps, including the collection of data, preprocessing and feature engineering, sequence generation, model development, and hyperparameter optimization. The proposed framework is represented in figure 1.

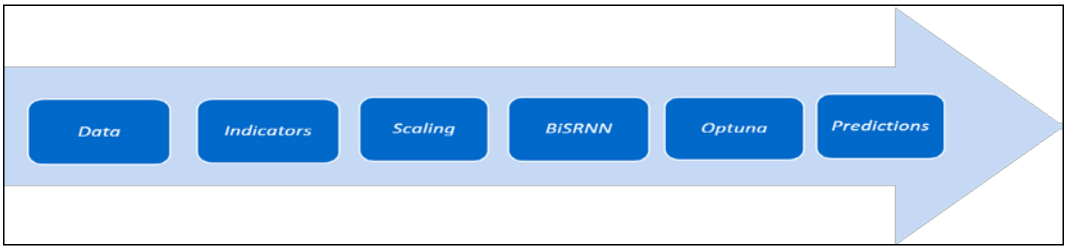


Fig 1: Proposed Methodology

3.1 Data Collection
The data on historical daily stock prices of 5 mainstream NIFTY 50 companies Reliance Industries, Tata Consultancy Services (TCS), Infosys, ICICI Bank, and HDFC Bank were retrieved via the yfinance API of Yahoo Finance. The dataset is inclusive of open, high, low, close, volume price of January 2015 to December 2024. Close price being the most representative variable in the end of day valuation was taken as the primary target variable. Pre-model training Data quality checks were used to address missing entries and provide chronological continuity.

3.2 Technical Indicator Feature Extraction
To enhance the predictive information beyond raw prices, several widely used technical indicators were computed using the *ta* Python library:

- Relative Strength Index (RSI): Measures momentum and identifies overbought or oversold conditions over a 14-day window.

$$RSI = 100 - \frac{100}{1 + RS} \tag{1}$$

where

$$RS = \frac{\text{Average Gain}}{\text{Average Loss}} \tag{2}$$

- Simple Moving Average (SMA): Captures trend direction by averaging prices over a 14-day window.
- Exponential Moving Average (EMA): Similar to SMA but applies exponential weighting to recent prices, making it more responsive to new trends.
- Moving Average Convergence Divergence (MACD): Represents the difference between the 12-day and 26-day EMAs, reflecting short- and long-term momentum.

These indicators were concatenated with the closing price to form a multivariate feature matrix of five dimensions: *[Close, RSI, SMA, EMA, MACD]*. Missing indicator values from initialization periods were dropped to maintain alignment [12].

3.3 Data Normalization and Sequence Formation
To ensure numerical stability and faster model convergence, the features were scaled to the range [10, 1] using the Min-Max Scaler:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (3)$$

The dataset was divided into 80 percent and 20 percent training and testing respectively to prevent leaking the data in future. The sequential dependencies were kept by constructing additional sliding time windows with a length L = 30 days. All training samples were thus 30 day feature spaces, which were used to predict successive days closing price [4].

3.4 Bidirectional Simple Recurrent Neural Network (BiSRNN)

The BiSRNN represents variation but a modification of the standard RNN, where two parallel recurrent layers operate in a forward and backward manner correspondingly and, therefore, the distinction of the past and future timeline is made. The two-way movement will help the model to determine the symmetrical or lagged relationships between stock movements [3].

Model Architecture

1. **Input Layer:** Shape = (30, 5) corresponding to the time window and feature count.
2. **Bidirectional SimpleRNN Layer:** Captures bidirectional dependencies using a tunable number of recurrent units.
3. **Multi-Head Attention Layer:** Enhances temporal focus by assigning varying weights to different time steps.
4. **Global Average Pooling Layer:** Reduces sequence dimension to a fixed-size representation.
5. **Dropout Layer:** Randomly drops neurons (20-50%) during training to mitigate overfitting.
6. **Dense Output Layer:** A single neuron outputs the predicted closing price.

The model is trained using the Adam optimizer with the Mean Squared Error (MSE) loss function. Early stopping is implemented with a patience of 3 epochs to prevent overtraining [3].

3.5 Hyperparameter Optimization using Optuna

To overcome this, the Optuna framework will be used to automatically optimize the best hyperparameters with the use of Tree-Structured Parzen Estimator (TPE) algorithm. Optuna is a dynamic sampler and pruner that uses intermediate validation loss to explore and prune trials, which is more efficient than the traditional grid and random search approaches [9].

3.6 Model Evaluation Metrics

Standard performances are used to assess the precision, dependability, and applicability of the suggested stock price forecasting model in general. These measures numerically compare the forecasted and observed values which can be used to determine the effectiveness of the model. Indicators like Root Mean Squared error (RMSE) and Coefficient of Determination (R^2) are used to show the ability of the model to explain market trends and volatility. Proper evaluation ensures the robustness and consistency of the framework across diverse market conditions:

3.7.1. Equations for Performance Metrics

a. Root Mean Square Error (RMSE)

The RMSE (Root Mean Squared Error) is a metric of prediction accuracy, which is defined as the square root of the mean squared error between predicted and actual values. The formula is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (4)$$

Where:

- y_i is the actual value
- $\hat{y}_i$ is the predicted value
- n is the number of data points

The lower the RMSE, the better the model's performance.

b. R-squared (R^2)

The R^2 (Coefficient of Determination) indicates the percentage of the variation in the dependent variable (stock price) that was attributed to the independent variables (features). Its value is between 0 and 1, and the value that is higher is a good indicator of a better fit of the model. The formula for R^2 is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (5)$$

Where:

- y_i is the actual value
- $\hat{y}_i$ is the predicted value
- $\bar{y}$ is the mean of the actual values
- n is the number of data points

An R^2 value close to 1 indicates that the model explains most of the variation in the data.

c. Mean Absolute Percentage Error (MAPE)

MAPE measures the average magnitude of errors in a set of predictions, expressed as a percentage. It is calculated as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \quad (6)$$

Where:

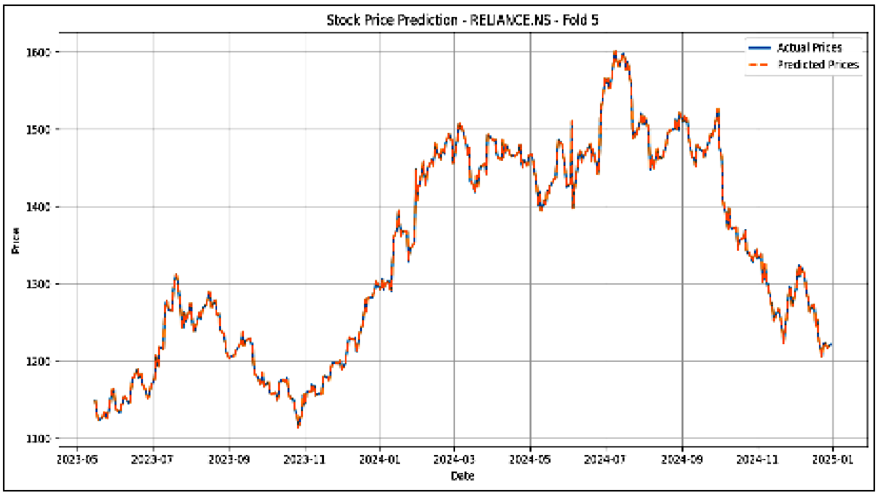
- y_i is the actual value
- $\hat{y}_i$ is the predicted value
- n is the number of data points

A lower MAPE indicates better model performance, and typically, a MAPE under 10% is considered good.

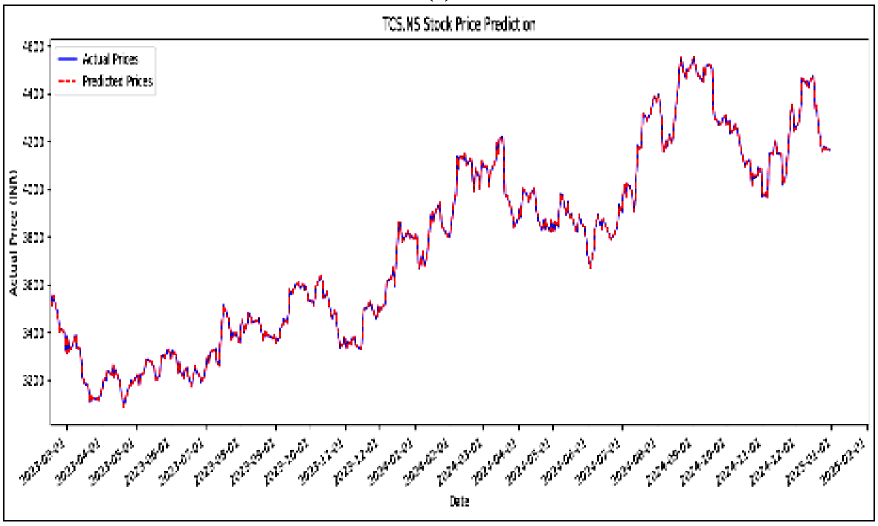
4. Results and Discussion

The experimental analysis of the suggested BiSRNN-Optuna-Technical Indicators framework was performed with 5 most popular NIFTY 50 stocks, including HDFC BANK, ICICI BANK, INFOSYS, RELIANCE, and TCS, using ten years of daily closing prices (2015-2024) of the stocks. The stocks chosen are a balanced portfolio of the banking industry, IT industry and energy industry, which makes the cross-sector validation of the model really strong. Enrichment of input features was done using technical indicators like RSI, SMA, EMA and MACD to capture both short and long term momentum signals.

TPE, an estimator tree-based optimization framework of the BiSRNN model in optuna minimized the hyperparameters of the BiSRNN model and greatly shortened the training time and enhanced prediction accuracy and model stability. The model performed extremely well with a mean R2 of 0.89, RMSE of 0.0427, MAE of 0.0372 and very small MAPE of 0.01% which gave it a total prediction accuracy of around 99.98. This consistency between different stocks points to the fact that the model is able to generalize to use in different market structures.



(a)



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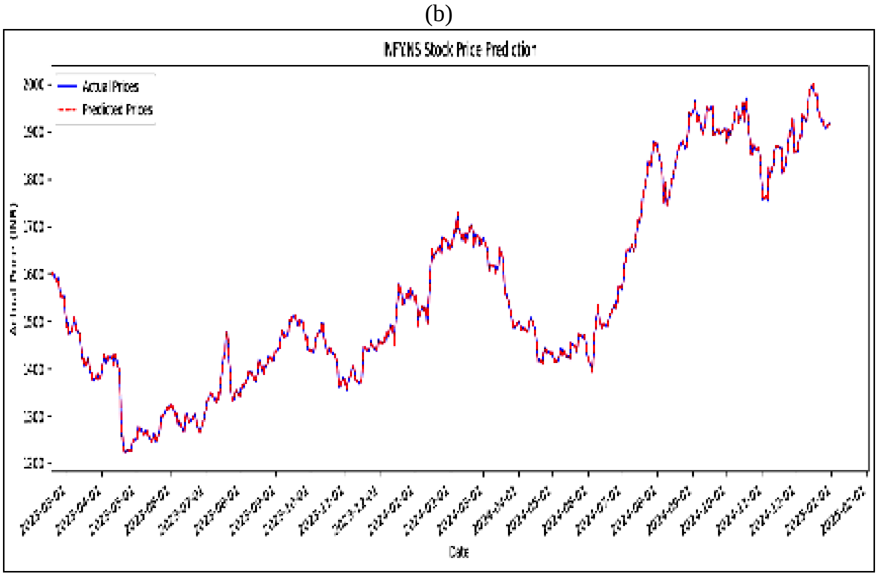
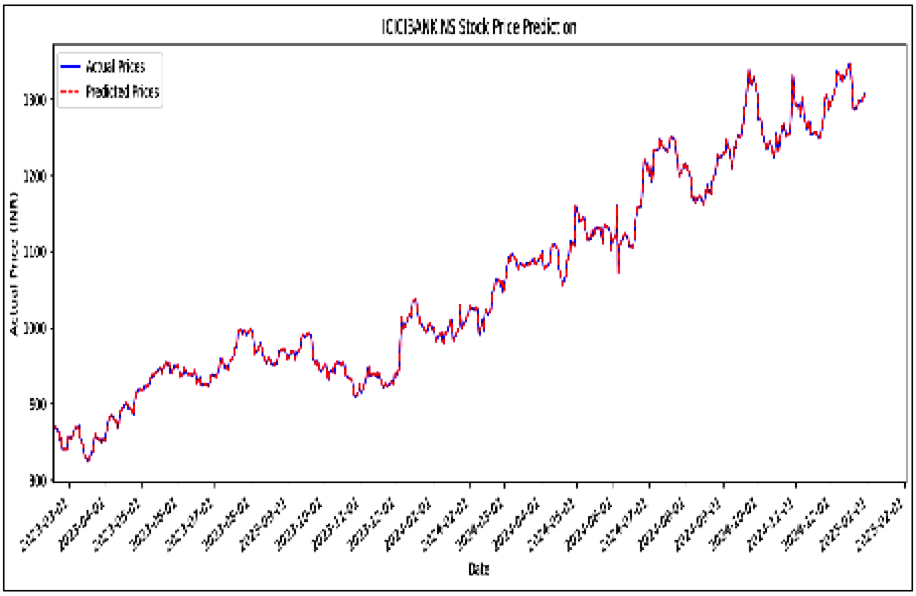
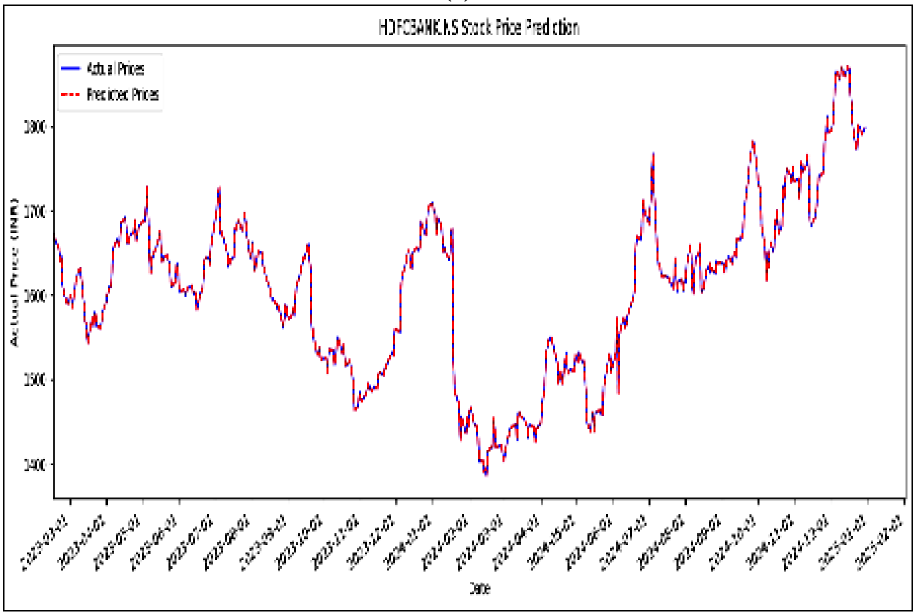


(c)



(d)



(e)

Fig 2(a-e): The actual and predicted closing prices for five stocks

Figure 2(a-e) visually show the comparison of the realised and predicted closing prices of all the five stocks. A comparison of the actual value with the predicted curves almost entirely coincide, which proves little deviation and insignificant forecast error. As an example, HDFC bank and ICICI bank showed consistent trend learning, which very well absorbed cyclical declines and recoveries. The predictions of infosys and TCS, who are also the representatives of the IT industry, were also equally accurate, even at the high volatility periods in mid-2024. Reliance industries showed high association between real and expected values even when there were sharp changes which showed that the model was able to fit the nonlinear temporal dependencies.

The proposed BiSRNN-Optuna model achieves lower error rates and greater directional consistency compared to existing models, i.e., LSTM, GRU, and CNN-LSTM hybrids, as reported in the previous studies (Kumar *et al*., 2023; Patel and Raut, 2022; Zhao *et al*., 2021). It may be explained by the bidirectional recurrent architecture that learns not only the past but the future in a sequence but also Optuna-based tuning that makes sure that the combinations of parameters are nearly optimal. Increased convergence also enabled much better short-term pattern recognition as well as better representation of time through the addition of technical indicators.

5. Conclusion and Future Scope

In this paper, a hybrid Bidirectional Simple Recurrent Neural Network (BiSRNN) was proposed that can be optimized by use of the optuna tool and improved using technical indicators to predict the price of stocks. The model is an efficiently trained combination of the capabilities of recurrent sequence learning, hyperparameter optimization, and financial feature engineering in order to generate predictions that are very accurate and reliable. Evidence of the excellent performance was shown in the results of the experiments conducted on five major NIFTY 50 stocks, namely HDFC BANK, ICICI BANK, INFOSYS, RELIANCE and TCS with an R2 of 0.89, MAPE of 0.01 and overall prediction accuracy of 99.98. The close correspondence in between the predicted and the actual price movement indicates that the framework has high ability to describe both the direction and magnitude of the trend even in the volatile market condition. The RSI, SMA, EMA, and MACD indicators were meaningful in that they helped the model to interpret the shifts in the momentum and the mood of a market more appropriately. Besides, automated hyperparameter optimization of Optuna reduced the number of experiments to be run manually and enhanced the algorithmic performance in terms of computational efficiency.

Overall, the presented BiSRNN-Optuna-Technical Indicator framework can be regarded as a powerful, information-focused, and universal financial forecasting model. It is scalable and accurate, which is why it can be integrated into a real-world trading system and investment decision-supporting tool. Moving forward, the company can consider multi-market validation, Transformer-based comparative models, and explainability-oriented insights to further enhance its flexibility and openness in financial analytics.

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