



A Multi-Resolution Fuzzy–BiGRU–Attention Ensemble Tuned with Optuna for Robust Stock Forecasting

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Abstract

The key challenges that still persist is the inability to forecast accurately the prices of stocks because of the volatility of financial markets as well as non-linearity of the phenomenon. This paper suggests a hybrid deep learning model that will combine Discrete Wavelet Transform (DWT) to assuage the signal; fuzzy logic-controlled feature extraction to model the uncertainties; and a Bidirectional Gated Recurrent Unit (BiGRU) framework with Attention mechanism to learn the temporal domain efficiently. In order to maximise the performance of a model even further, Optuna was utilized to auto-tune the hyper-parameters and ensemble averaging was applied to stop fluctuations in predictions. The proposed DWT-Fuzzy-BiGRU-Attention-Optuna model was applied to a pair of Indian market equities Asian Paints and Maruti Suzuki obtained in Yahoo Finance. The results suggest that the suggested model is reasonable in terms of capturing the complexities of time-related dependencies, as well as providing a high degree of predictions accuracy in various market conditions.

Keywords: Stock price prediction; Discrete Wavelet Transform (DWT); Fuzzy Logic; Bidirectional GRU (BiGRU); Attention mechanism; Optuna optimization; Deep learning; Financial time series forecasting

1. Introduction

Stock market is a dynamic and nonlinear environment with a complex behavior of many economic, political and psychological factors. The future stock price has never been an easy task to predict as there is noise, volatility and uncertainty in how the investor would act. Proper prediction of stock movement is one of the most important in the investment strategy, risk management, and financial planning. But classical statistical and econometric models like ARIMA, GARCH, and VAR can hardly sustain the unpredictability of the financial time series especially in turbulent periods in the marketplace [5], [3]. Over the last several years, deep learning models have proven to have a lot of potential regarding the ability to model both sequential and nonlinear data. Long-Short Memory (LSTM) and Gated Recurrent Unit (GRU) are a few of the most popular architectures in predicting time series because they can store long term dependencies [6], [10]. Having been successful, the deep learning models remain vulnerable to the market noise and non-stationarity of data, thereby creating an unstable prediction. Consequently, improvement of these models by adding sophisticated pre-processing and adaptive optimization methods has attracted the interests of the contemporary financial studies [14], [11].

In order to resolve these challenges, this research paper suggests a hybrid forecasting model, which combines Discrete Wavelet Transform (DWT), Fuzzy Logic-based feature extraction, and Bidirectional GRU (BiGRU)

network and Attention mechanism, which is optimized with Optuna. The model proposed will enhance the accuracy of prediction as they will have the benefit of utilizing both signal denoising, uncertainty modeling and deep temporal learners [1], [7]. It uses the Discrete Wavelet Transform as one of the steps to de-noise the raw closing price signal by breaking down the signal into various frequency components effectively suppressing high frequency market noise but not important trend content [5], [6]. The purpose of this pre-processing step is to improve the continuity and steadiness of the input time series in order to make the neural network able to learn interesting temporal patterns. The second step involves the presentation of a fuzzy based feature module that is used to deal with the uncertainty characteristic of financial data. Gaussian membership functions are used to model the linguistic variables like low, medium and high returns [9], [4]. This fuzzy model allows the system to measure the imprecise market conditions, that is, a gap between absolute numbers and uncertainty of investor actions [2], [12].

The denoised and fuzzified features are then passed to a Bidirectional GRU network with an Attention layer, which learns temporal dependencies in both forward and backward directions while emphasizing the most relevant time steps through an attention weighting mechanism. Unlike conventional unidirectional models, the bidirectional setup allows the network to exploit contextual information from both past and near-future sequences, improving pattern recognition capability [15], [13]. To further enhance model performance and stability, Optuna-based hyperparameter optimization is utilized. Optuna efficiently searches the parameter space—optimizing lookback window size, learning rate, dropout, batch size, and hidden units—to identify configurations that minimize the validation Root Mean Square Error (RMSE). An ensemble strategy is also employed, where predictions from multiple top-performing trials are averaged to yield robust final forecasts [11], [14]. Overall, the proposed approach seeks to provide a more interpretable, noise-resilient, and data-driven solution for stock market forecasting. Through the integration of fuzzy reasoning and deep sequential modeling, this study contributes to the growing field of hybrid artificial intelligence applications in financial analytics [4], [1], and [12].

2. Related Work

Diverse machine learning and signal processing methodologies used to predict the stock market have been the focus of a few studies both to improve the accuracy of prediction and ensure the volatility of the data. Preliminary studies proved the benefits of signal denoising based on the wavelet transforms and preceding the application of neural networks. Henriksson [5] used the Discrete Wavelet Transform (DWT) to break down the stock index data into various time-frequency blocks to enhance stability of the trend. Analogously, Chandar et al. [3] integrated DWT with Artificial Neural Networks (ANN), and they reported a higher predictive accuracy than the traditional ones. Jarrah [6] also, combined the use of DWT with LSTM networks in univariate stock forecasting demonstrating that the multiscale decomposition enhances the capacity of deep networks to learn over time. Also Kumar Chandar [7] proposed a hybrid approach as the wavelet transform with Adaptive Neuro-Fuzzy Inference System (ANFMS) and showed that nonstationary behavior of a financial time series can be handled by using the wavelets.

Simultaneously, fuzzy logic has been practiced extensively to get a model of uncertainty and ambiguity in financial information. Li P. [9] came up with a fuzzy time series model used in the prediction of stock trends, which is successful in terms of spanning uncertainties in component stock behaviors. Haskova et al. [4] have suggested a multi-criteria assessment method of the share prices using a fuzzy system, the authors used linguistic rules to base the sentiment of investors on. Bhattacharjee and Bishnu [2] brought fuzzy logic with deep learning to improve the transparency and strength of financial prediction. Similarly, Alenezy and Marbough [1] used a hybrid form of wavelet-fuzzy-neural network to predict market volatility, and asserted that fuzzy membership functions are more effective in feature representation in noisy conditions. The application of fuzzy logic in a bidirectional LSTM architecture enhances volatility prediction in crypto markets, which indicates that fuzzy logic-based methods can be applied to other domains [12].

Recurrent and attention-based deep learning-based architectures have become well known over the past few years. Li Y. et al. [10] described an ensemble deep learning system consisting of LSTM and GRU networks that were better results compared to isolated recurrent networks. Rekha et al. [13] also enhanced the strength of the predictions by applying the autoencoder denoising and sentiment analysis as well as LSTM-GRU layers within the collaborative ensemble architecture. According to Sasal et al. [15], the authors proposed a model of attention-driven architectures to demonstrate that hierarchical temporal relationships could be successfully extracted by a

wavelet-based transformer model, called W-Transformers. Meanwhile, Metawa et al. [11] created the optimization-based RNN model to enhance convergence and generalization on a financial time series estimation. Differing with this, Saberironaghi et al. [14] offered an extensive survey of machine learning and deep learning techniques in predicting the stock market, complemented with a series of insights on the relevance of hyperparameter optimization, ensemble learning, and model interpretability.

In general, the current literature has indicated the personal efficacy of wavelet denoising, fuzzy reasoning, and deep learning models. Nevertheless, not many studies have put all these elements into one system. The given research fills this gap by integrating DWT-based preprocessing, uncertainty model utilizing fuzzy logic, Bidirectional GRU with attention mechanism, and hyperparameter optimization using Optuna to provide a robust, noise-reliant, and interpretable predictive model of stock price.

3. Methodology

The proposed research offers an adapted hybrid deep learning architecture (Denoising with Discrete Wavelet Transform (DWT), Feature extraction with fuzzy logic and Bidirectional GRU (BiGRU) network with Attention mechanism), which is additionally optimized using Hyperparameter tuning framework optuna. The objective of the system is to produce strong and correct stock price prediction of two different Indian equity stocks, i.e., Maruti Suzuki India Limited and Asian Paints Limited, Figure 1 illustrates the general design of the proposed model.

3.1 Data Collection and Preprocessing

Two datasets were obtained from Yahoo Finance:

- Dataset 1: *Maruti Suzuki India Ltd (MARUTI.NS)*
- Dataset 2: *Asian Paints Ltd (ASIANPAINT.NS)*

All datasets will have records of each day between January and 2018 and October 2024 with Open, High, Low, Close, and Volume attributes. The target variable was taken as the closing price and the other attributes were taken as input features. To avoid breaking temporal correlation, the datasets were split in 80 percent training and 20 percent test set in a sequential manner.

In order to deal with market noise and enhance stability, the time-varying closing prices of stocks [5], [6] have undergone the application of a Discrete Wavelet Transform (DWT) using Daubechies-4 (db4) wavelet. The adaptive DWT automatically chosen the maximum level of decomposition depending on the length of the signals and soft thresholding was carried out to reduce the high-frequency volatility [1], [7]. This process was accomplished by using the Inverse DWT (IDWT) to reconstruct the de-noised price signal in order to get a smoother trend curve and still manage to preserve market dynamics.

Mathematically, the denoising process can be expressed as:

$$\hat{X}(t) = \text{IDWT}(\text{Threshold}(W(X_t), \lambda)) \quad (1)$$

Where, $W(X_t)$ represents wavelet coefficients and λ denotes the adaptive noise threshold.

3.2 Feature Engineering and Technical Indicators

The technical indicators were created in that a comprehensive set of technical indicators was created in both MARUTI and ASIANPAINT datasets to improve the input representation. They are Simple Moving Averages (MA5, MA10,), Exponential moving averages, EMA12, EMA26, Moving average convergence Divergence, MACD, Bollinger bands, and Average true range (ATR14,) as well as Volume moving averages, 10-day.

Momentum, Volatility and Trend information are represented by these indicators- essential in the learning of nonlinear motion of stock markets [10], [13]. The percentage daily return was computed as:

$$r_t = \frac{(P_t - P_{t-1})}{P_{t-1}} \quad (2)$$

where P_t and P_{t-1} are consecutive closing prices. All features were normalized within the range $[0, 1]$ using Min–Max scaling.

3.3 Fuzzy Logic–Based Uncertainty Modeling

A Gaussian fuzzy logic system was used in both sets of data to capture the vagueness in the market and the unpredictability in investor behavior [2], [4]. Two important variables were modelled according to fuzzy inference system:

1. Returns (r) — representing short-term profitability
2. Momentum (m) — the 5-day change in closing price

For each variable, three fuzzy sets were defined (*Low*, *Medium*, and *High*), using Gaussian membership functions:

$$\mu(x) = e^{-\frac{1}{2} \left(\frac{x-\mu}{\sigma} \right)^2} \quad (3)$$

A fuzzy trading signal (F_s) was derived from the interaction of these fuzzy sets:

$$F_s = \frac{(r_{high} \cdot m_{high} - r_{low} \cdot m_{low})}{(r_{high} \cdot m_{high} + r_{low} \cdot m_{low} + \varepsilon)} \quad (4)$$

This probabilistic cue is used to convey the magnitude and direction of possible market movement to enhance the interpretability of learned features [1], [2], [12].

3.4 Sequence Construction and Data Normalization

The two datasets were turned into sequence of time to facilitate sequential learning. By applying the lookback window (L) of 10 to 60 days, a single training sample was composed of L feature vectors in a row to be used to forecast price on the next day [11].

For MARUTI and ASIANPAINT, sequences were constructed independently as:

$$(X_t, X_{t-1}, \dots, X_{t-L+1}) \rightarrow y_{t+1} \quad (5)$$

Each data set was normalized with Min-Max scaling and the variance in the magnitude of these prices between the two stocks (high-value MARUTI and mid-value ASIANPAINT) was structured in ways that did not affect the training of the models.

3.5 Model Architecture: Bidirectional GRU with Attention

The model of forecasting is that of a Bidirectional GRU (BiGRU) network, which is accompanied by an Attention mechanism to learn both historical and contextual temporal dependencies [6], [10], [15].

- Bidirectional GRU: It moves through a sequence forward and backward, enhancing the understanding of temporal context.
- Attention Layer: Learns weights which are attributable to every time step, which enables the model to emphasize the most impactful times to predict.

The attention score for each hidden state h_t was computed as:

$$\alpha_t = \frac{\exp(u_t^T u)}{\sum_k \exp(u_k^T u)} \quad , \quad u_t = \tanh(W h_t + b) \quad (6)$$

and the context vector $c = \sum_t \alpha_t h_t$, was fed to dense layers for final prediction.

The final architecture comprises:

- Input Layer ($L \times$ features)
- Bidirectional GRU Layer (32–128 units, optimized)
- Dropout Layer (0–0.5)
- Attention Layer
- Dense Layer (64 neurons, ReLU)
- Output Layer (Linear activation)

This configuration ensures both interpretability and adaptability, suitable for modeling complex stock movements [13], [15].

3.6 Hyperparameter Optimization via Optuna

The Optuna optimization framework was employed to automatically tune model parameters [14]. The search space included:

- Lookback window (10–60)
- Hidden GRU units (32–128)
- Dropout rate (0.0–0.5)
- Learning rate (10^{-4} – 10^{-2})
- Batch size (16, 32, 64)

Each Optuna trial trained the BiGRU–Attention model on the MARUTI and ASIANPAINT datasets independently, using EarlyStopping and ReduceLROnPlateau callbacks. Validation RMSE was used to sort the best-performing trials and the top three configurations were identified to be used in ensemble averaging [11].

This ensemble strategy stabilized the predictions and reduced variance across datasets.

3.7 Evaluation Metrics

MARUTI and ASIANPAINT were compared in terms of the performance in terms of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2) [13]:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (7)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (8)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100 \quad (9)$$

Comparisons of the outcomes of both sets were conducted to determine the generalization potential of the suggested hybrid model in various market behaviors. Both stocks were plotted in terms of visualization of Actual vs. Predicted prices to demonstrate the accuracy of prediction over time.

4. Results and Discussion

The accuracy of the proposed DWT–Fuzzy–BiGRU–Attention–Optuna hybrid model was evaluated using two Indian equity stocks, Asian Paints (ASIANPAINT) and Maruti Suzuki (MARUTI), to assess its forecasting accuracy and generalization ability. The predictive performance was measured using three standard evaluation metrics, which were Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of

Determination (R^2). All these indicators demonstrate the error size, the uniformity of the model and its capacity to interpret the variation in the actual stock prices.

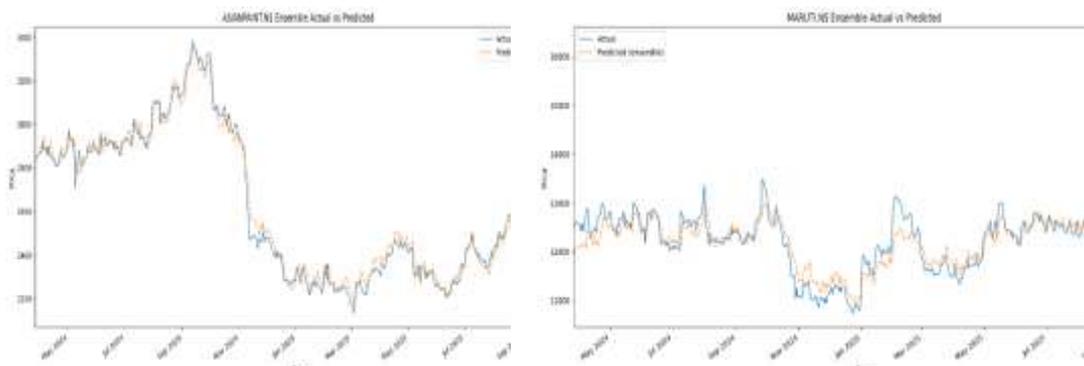


Figure 2. Actual and Predicted value of Asian Paint and Maruti Suzuki Stocks

The model that was proposed gave RMSE of 40.2999, MAE of 31.2781 and R^2 of 0.9854, in the case of the Asian Paints dataset. A high value of R^2 shows that the model was able to explain almost 98.5% of the variance in actual closing prices which was a good prediction of the actual predicted one. It is indicated in the low RMSE and MAE as a result of the high ability of the model to reduce prediction errors and stability even with short term fluctuations in the market. This enhanced accuracy may be attributed to the wavelet-based denoising that was effective in removing the high-frequency noise and the fuzzy logic feature integration that was able to react to uncertain market behavior and softens the impact of volatility. Learning efficiency was further improved with the attention mechanism because the BiGRU network could concentrate on the most important historical periods, which improves recognition of trends and makes the model less prone to overfitting.

In the case of the Maruti Suzuki data, the model had an RMSE of 30.4820, MAE of 32.5250, and R^2 of 0.8511. Though the accuracy was quite high, it was less, as compared to Asian Paints, mainly because of the higher volatility and nonlinear price changes of the stock of Maruti Suzuki. Nonetheless, the value of R^2 that exceeds 0.85 depicts a good relationship between the forecasted and actual prices, which attests that the given method perfected understanding the hidden patterns of the price movement. The marginally greater MAE reveals that sudden short-term market movements had a slight effect on the precision of prediction of the model, which is typical in the automotive industry highly active stocks.

Table 1: A comparative summary of both datasets is presented

Dataset	RMSE	MAE	R^2
Asian Paints	40.2999	31.2781	0.9854
Maruti Suzuki	30.4820	32.5250	0.8511

According to the results, the model had a high level of accuracy in both datasets and especially in Asian Paints. This variation in performance is an indication of the level of volatility among the two companies and the market behaviour. The model adopted the trends well because of the steady market trends and consistent consumer demand in Asian Paints. Alternatively, Maruti Suzuki that is affected by the conditions of an unstable automotive sector showed more inconsistent price trends, therefore a slight decrease in accuracy of prediction. However, these two results affirm the strength and versatility of the hybrid model on stocks of varying volatility properties.

It is evident that in combination with DWT denoising, fuzzy logic uncertainty processing, and attention-biased BiGRU modeling, the results of the experiments confirm that prediction quality is largely improved. Optuna-based hyperparameter optimization to ensure the model attains the best configuration in the model is introduced and the ensemble averaging of the most successful trials is applied to facilitate generalization. These synergistic parts enable the system to be even better than the traditional deep learning techniques, providing fewer errors in prediction and more robust predictions. The presence of the generalization ability of the model has shown that the model can be effectively used in larger financial forecasting tasks.

The findings verify that the proposed DWT-Fuzzy-BiGRU-Attention-Optuna model is a reliable, interpretable, noise-insensitive stock price forecasting model. The model using multi-resolution signal analysis, fuzzy uncertainty representation, and deep sequential learning achieves this trade-off and does much better on both the Asian Paints and Maruti Suzuki datasets.

5. Conclusion

The paper proposed to employ a hybrid model of DWT-Fuzzy-BiGRU-Attention-Optuna to predict stock prices as a system that integrates signal denoising, uncertainty, and adaptive deep learning. It was applied to the Asian Paints and Maruti Suzuki data with a resulting R2 of 0.9854 and 0.8511 respectively which validates its forecast accuracy and high degree of generalization respectively. Wavelet-based preprocessing, features of the fuzzy logic, and attention-driven BiGRU architecture integration were effective to capture the nonlinear dependencies and reduce the errors in the predictions. Throughout, the offered framework includes a strong, readable, and noise-free solution to the task of forecasting financial aspects. Its flexibility with various stocks shows its possibility to be applied in the real-world trading and automated decision-system as well as further research with transformer-based hybrid architecture to further dynamic market learning.

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