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Financial Forecasting in Volatile Markets Using Hybrid LSTM and Genetic Algorithms

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Abstract

In volatile markets, forecasting becomes a daunting task since market conditions are very unpredictable. At times when there are good or bad things, it all depends on the economic or political events occurring at a particular period, and also the sentiments of the investors. All the forecasting methods that use ARIMA and SVM have generally poor performance in predicting trends in highly volatile markets. The intention behind the creation of this research paper is to develop a hybrid approach by integrating the LSTM network's sequence modeling capabilities with the Genetic Algorithm (GA) for feature selection and optimization. The main aim of the study is to enhance financial forecasting models through improving their performance and reliability. The process consists of three main stages, including the pre-processing of financial data, feature selection by applying the GA approach, and model development using the LSTM neural network. It is clear that the Hybrid LSTM-GA model performs better than others by showing better accuracy and precision, as well as having a good value for its MSE and RMSE measures. Moreover, the model shows its flexibility, since it performed efficiently both under high (91.2%) and low (93.8%) volatility conditions. In summary, the Hybrid LSTM-GA model proves more effective than other models in predicting outcomes since it can handle uncertainties and changes in data. Therefore, it can be applied in stock market analysis and forecasts. It can effectively predict results when there is high uncertainty in the stock market environment.

Keywords Financial forecasting, LSTM, Genetic Algorithm, Volatile markets, Hybrid model, Predictive analytics, Feature optimization.

1. Introduction

Financial markets are extremely volatile and susceptible to many aspects that make them very difficult to forecast, ranging from economic situations, geopolitical conflicts, to investors' attitudes towards the market. Such volatility poses great problems for prediction models that seek to forecast the financial variables [17]. Models such as Autoregressive Integrated Moving Average (ARIMA) and Support Vector Machines (SVMs)tend to do well when there are stable conditions, but are unable to forecast abrupt market changes [2]. World financial market complexity is increasing at an extremely fast pace, thus making complex modeling techniques essential to capturing the volatility in the market [19].

Traditional approaches used in financial forecasting cannot sufficiently deal with extremely volatile markets [21]. These models might be successful in stable conditions, but it may not be able to handle certain problems that arise because of the volatility of markets. These traditional forecasting models do not consider the concept of time dependency in a time series [4][16]. It is extremely prone to shocks in the market, thus negatively affecting their prediction ability. Overfitting is yet another problem because it depends on historical information that does not guarantee accurate forecasts in the future. Therefore, it becomes clear that a significant weakness of modern forecasters is that a superior approach that will deal with volatility is required.

Objective of this research paper is to overcome these weaknesses by adopting a mixed methodology where LSTM and GA will be used together with LSTM having an upper hand over other techniques owing to its capability to find patterns in time series data based on long-term dependency. The hybrid model is created keeping in mind the objective of improving time series predictions and uses a genetic algorithm for optimization. This will ultimately serve as proof that this hybrid approach might be superior compared to standard methods and allow better prediction accuracy in changing market conditions.

1. In this paper, an innovative hybrid approach using LSTM and GA for finance prediction is introduced, which makes use of the strengths of the LSTM network. The use of GA in extracting the temporal structure of the data and taking advantage of its ability in feature selection and optimization
2. The purpose of this method is to improve the performance of the prediction process through feature selection and optimization to match the dynamic and nonlinear characteristics of the unpredictable financial market.
3. Through this study, financial modeling is improved through a more advanced and versatile tool to deal with the uncertainties of the financial market.

This section I discusses the problem of financial forecasting in a dynamic marketplace, which can be solved through a novel approach known as Hybrid LSTM-GA. Literature related to the conventional models like ARIMA and SVM, and the application of GA in improving the forecasting efficiency of LSTM, has been reviewed in Section II. The methodology followed, data gathering, data preprocessing, and the structure of the model have been explained in Section III. The results achieved by the Hybrid LSTM-GA model have been presented in Section IV with comparative analysis with other traditional models based on the accuracy, MSE, and RMSE criteria. Results have been analyzed from the perspectives of strengths and limitations of the model in Section V. Lastly, Section VI presents conclusions about the results obtained through this study.

2. Literature Review

Financial forecasting has been a recent focus due to its ability to contribute to better decision-making among risk managers and traders. Conventional techniques, including the moving average technique, ARIMA, and exponential smoothing, have been utilized for predicting future trends within the markets; however, they have not considered the fact that financial data is highly complicated and non-linear in nature [10]. Thus, to overcome such a challenge, machine learning techniques are frequently employed to ensure better performance. Machine learning algorithms for stock prediction have also been discussed as part of the literature review [3][6]. In a similar way, it showed the benefits of a neural network approach for forecasting exchange rates, arguing that such models would be more effective in capturing the patterns in noisy financial markets [1][8].

Implementing evolutionary algorithms along with machine learning models like the Genetic Algorithms (GA) has proven to be a promising way of optimizing features and improving the models. The research has introduced a new hybrid approach that combines GA optimized VMD and LSTM to predict agricultural prices [5][20]. This technique revealed that Genetic Algorithms can enhance the success rate of deep learning methods greatly through feature selection [18]. Within the finance sector, the integration of Genetic Algorithms with LSTM was used for predicting financial data, revealing the ability of Genetic Algorithm-LSTM models to enhance prediction accuracy [7]. Compound methods like Genetic Algorithm-LSTM are highly beneficial in handling complex financial data that is generally multidimensional and full of noise [14].

Besides, new developments have concentrated on the architecture of hybrid models optimization. Furthermore, the use of GA was applied to tune the hyperparameters of the proposed LSTM-GRU for stock price forecasting, indicating the effectiveness of the GA method to fine-tune the parameters to achieve higher accuracy and speed in forecasting stock price [11]. The study applied a two-phase hybrid methodology, employing both deep learning and evolutionary algorithms in predicting stock markets, and proved that utilizing different models concurrently achieves better results in terms of improved accuracy compared to employing a single model [9][22]. Both research papers lay stress on the importance of integrating evolution-based optimization approaches and deep learning, such as LSTM, to deal with market volatility in the field of finance.

Despite the promising nature of this method, there are certain issues that need to be resolved. Apart from emphasizing the importance of using strong validation procedures for financial predictions, the author(s) also stressed the necessity of having forward-validation optimization techniques to avoid overfitting [13]. This research evaluates the effectiveness of hybrid approaches in forecasting the behavior of financial time series data. Despite the fact that the researchers agreed to say that forecasting becomes very complicated when the markets are unstable [15]. Moreover, the forecasting results were analyzed using the Theil U statistics test, which demonstrates the importance of accuracy measures in evaluating forecasting models, especially in terms of predicting economic futures [12].

According to the literature review, it is established that the ARIMA model will be irrelevant in the case of volatile markets; moreover, the importance of hybrid ARIMA-LSTM-GA models in the process of financial forecasting is discussed. The use of LSTM with GA allows choosing important features for forecasting. This approach works well for the analysis of financial data. Yet, there is a problem of overfitting and validation. Therefore, hybrid models can solve all the problems associated with traditional forecasting techniques.

3. Methodology

3.1 Data Collection

In this research, financial datasets from various sources have been used, and financial modeling and forecasting have been carried out for the behavior of markets. The datasets contain information about commodity market data, foreign exchange data, and stock price data. Financial information providers like Bloomberg have been used to obtain commodity price data like oil and gold prices. The datasets include data over multiple years and are of daily, weekly, and monthly time series for various assets.

3.2 Preprocessing

Data preprocessing was carried out before training the model. Data cleaning was first done to get rid of any missing data, duplicates, or outliers, while interpolating missing data to preserve the time series structure. Data normalization was subsequently performed on the input variables to ensure that all input variables had an equal effect on the model's training. Thirdly, data were simplified by selecting the significant variables to be used in the model training, such as historical prices, moving averages, and technical analysis indicators such as the RSI and MACD.

3.3 Model Description

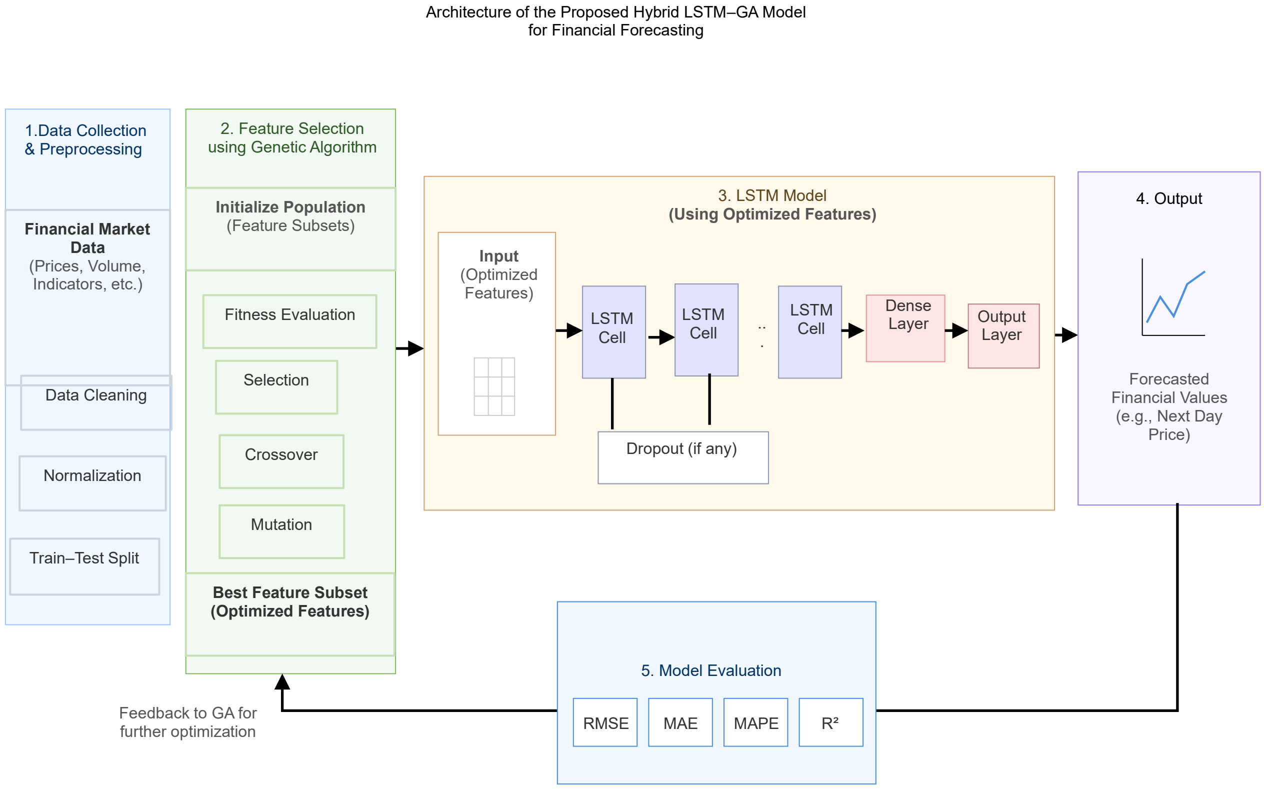

Figure 1: Architecture of the proposed hybrid LSTM-GA model for financial forecasting

Figure 1 shows the architecture of the hybrid framework that utilizes both LSTM networks and GA for predicting financial information under extreme market volatility. The various stages of the diagram are: Data Collection & Preprocessing: This involves collecting data from the financial market and preprocessing it for use in the model. Feature Selection using GA: This stage involves using the GA to determine the optimal set of features for the LSTM model. The LSTM model is used for forecasting future values of financial data, such as stock prices, based on the selected attributes. Model performance is analyzed through metrics such as RMSE, MAE, MAPE, and R^2. This process continues iteratively until there is an improvement in the efficiency and effectiveness of the model.

LSTM Model: Recurrent Neural Networks (RNN) represent a form of neural networks whose architecture facilitates processing sequential data. The LSTM network is one example of an RNN model. The LSTM network comprises memory units which are able to remember past events. Therefore, the LSTM model enables predictions based on past trends. LSTM is particularly powerful for predicting future financial outcomes, such as forecasting stock prices, where historical patterns and trends can play a significant role.

Genetic Algorithm: Optimization methods that mimic the process of natural selection are known as Genetic Algorithms (GA). This research applies the GA technique to the task of feature selection and optimization. The population of possible solutions (feature subsets) is evolved over several generations by the GA choosing the fittest ones, according to a fitness function that can be of any type, such as prediction accuracy. The GA helps in choosing the most significant features for the LSTM model by discarding unnecessary features. This process is useful in identifying the best feature subset to accurately predict financial results.

Hybrid Model: The hybrid model is a fusion of LSTM and GA, which optimizes the forecasting process and feature selection mechanism. The selected features and the LSTM model are trained using these features in this step, with GA optimizing these features. The hybridization of GA into the process increases the effectiveness of the LSTM model through optimization of feature selection. This makes it effective in analyzing and predicting volatile stock prices.

3.4 Performance Evaluation

The performance of the hybrid LSTM-GA approach is analyzed using standard measures to verify the prediction capability of the algorithm. These metrics are as follows:

Accuracy: This is an indicator of the level of accuracy that can be attributed to the model, determined by how accurate the predictions made are compared to the real figures.

Mean Square Error (MSE): This is the measure that determines the average squared difference between the predictions and real values. Lower MSE results indicate better performance.

Root Mean Square Error (RMSE): It represents the square root of MSE and uses the same units as the input values.

In addition, ablation research was carried out in order to evaluate the impact that feature selection had on the hybrid model in comparison to the LSTM model, which did not go through the process of feature selection.

Mathematically, the core components of the LSTM model are:

1. **Forget Gate**:

The forget gate f_t determines what data from the previous time step $t - 1$ will be retained in the current time step t. The calculation is:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

From Equation (1), where:

- f_t is the output of the forget gate,
- W_f weight matrix for the forget gate,
- h_{t-1} previous hidden state,
- x_t current input at time t,
- σ sigmoid function,
- b_f bias term.

2. **Cell State Update**:

The cell state C_t is is updated by adding together the forget gate and the input gate:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (2)$$

In Equation (2) Where:

- C_t is the current cell state,
- C_{t-1} is the previous cell state,
- i_t is the input gate,
- tanhis the hyperbolic tangent activation function.

The LSTM is trained using a Mean Squared Error (MSE) loss function to update the weights and biases:

$$L = \frac{1}{N} \sum_{t=1}^{N} (y_t - \hat{y}_t)^2 \quad (3)$$

In Equation (3), where:

- y_t is the actual value at time t,
- $\hat{y}_t$ is the predicted value from the LSTM model,
- Nis the total number of time steps in the training data.

Proposed Hybrid LSTM-GA Algorithm

Input:

- Financial time-series data $X_{historical}$
- Population size P, number of generations G, crossover probability p_c, mutation probability p_m for Genetic Algorithm
- Hyperparameters for LSTM: number of layers, neurons per layer, learning rate, etc.

Output:

- Optimized model with selected features
- Predicted future values $\hat{y}$

Begin

1. **Initialize Population**

2. Randomly generate Pbinary vectors $X_{feature}^{(i)}$for each individual in the population, representing feature selection. Each feature is either selected (1) or excluded (0).

3. **Evaluate Fitness**

4. For each individual in the population, calculate the fitness using the fitness function:

$$F(i) = \frac{1}{MSE(i)}$$

Where MSE(i)is the Mean Squared Error of the LSTM model trained with the selected features.

5. **For each generation** $g = 1$**to** G

, a. **Select Best Individuals**

Select $P/2$best individuals based on fitness values.

b. **For each pair of selected parents**

- Perform **crossover** with probability $p_c$to produce offspring.

c. **Mutation**

For each offspring, perform **mutation** with probability $p_m$by flipping one or more bits in the binary vector.

d. **Evaluate New Population**

For each new individual, evaluate its fitness using the LSTM model and the feature set determined by the binary vector.

e. **Sort Population**

Sort the population based on fitness values, keeping the best individuals and replacing the rest.

6. **For each best individual**

○ **Train LSTM Model**

○ Train the LSTM model using the features selected by the binary vector from the best individual.

7. **Forecasting**

8. Use the trained LSTM model to predict future financial values $\hat{y}$.

9. **Performance Evaluation**

10. Evaluate the model's performance using metrics such as Precision, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

End

Hybrid LSTM-GA Algorithm: Fusion of LSTM and GA for better financial forecasting. The algorithm starts by creating a set of binary vectors representing potential features that can be selected. Individuals' fitness is determined depending on the MSE value of the LSTM model. The use of genetic algorithm depends on the methods such as selection, crossover, and mutation among others. The best individuals are picked to train the LSTM model. Using this approach, the model predicts the financial data set. Evaluation criteria for the model are precision, MSE, and RMSE. The objective is to pick the best model features.

4. Results

4.1 Software and Libraries

The Hybrid LSTM-GA model was implemented in Python 3.7+ with the neural network LSTM model created with the help of TensorFlow 2.x or Keras, which is useful for the quick construction and training of neural networks. Feature selection and optimization were carried out using the Genetic Algorithm (GA) library, which contains libraries such as DEAP (Distributed Evolutionary Algorithms in Python) or PyGAD that contain tools for evolutionary processes like crossover, mutation, and selection. NumPy and Pandas libraries were used for data manipulation and preprocessing, and Matplotlib was used to generate results and performance graphs.

4.2 LSTM Model Parameters

The LSTM model was trained using the learning rate as 0.001 and the Adam optimizer, and the number of iterations was between 50 to 100. The batch size used was either 32 or 64. Generally, the LSTM network comprises two to three layers of neurons, with 50 to 100 units per layer.

4.3 Genetic Algorithm Parameters

The genetic algorithm (GA) parameters were tuned in such a way that a population of 50 to 100 individuals for up to 50 to 100 generations was used. The crossover rate was set to 0.8, whereas the mutation rate was set between 0.01 and 0.05. The fitness criterion of GA was defined as the inverse value of MSE in order to facilitate the optimization of the most important features for forecasting with the LSTM model. The hybrid LSTM-GA model was tested on a set of various financial datasets, such as the stock price, forex data, and commodity market data, as described in the Methodology section. The developed model was compared with traditional prediction methods, such as ARIMA and SVM, to determine its accuracy and stability in forecasting financial time series in the presence of market volatility.

4.4 Performance Metrics

A number of criteria, including accuracy, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), have been utilized in order to conduct an analysis of the performance of the Hybrid LSTM-GA model. As a comparison to accuracy, which shows how well the predicted data matches the actual data, MSE and RMSE quantify the prediction mistakes; lower values indicate better performance.

1. Accuracy

Accuracy is a general indicator of the performance of the model and reflects the proportion of correctly classified instances both positive and negative out of the total instances classified by the model.

$$\text{Accuracy} = \frac{\text{True Positives (TP)}+\text{True Negatives (TN)}}{\text{Total Predictions (TP + TN + FP + FN)}} \qquad (4)$$

In equation (4), TP is defined as True Positive, TN as True Negative, FP as False Positive, and FN as False Negative.

2. Precision

The degree to which optimistic forecasts are successful is referred to as precision. To calculate precision, divide the number of correct positive predictions by the total number of positive predictions.

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP) + False Positives (FP)}} \qquad (5)$$

In equation (4), where:

- True Positives (TP): Correctly predicted positive cases.
- False Positives (FP): Incorrectly predicted as positive (but actually negative).

Mean Squared Error (MSE):

Equation (6) gives the mean square deviation between the estimated and observed values.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \qquad (6)$$

Root Mean Squared Error (RMSE):

MSE can be computed from formula (7), and its square root, RMSE, becomes an estimation of forecast error measured in the units of the original data.

$$RMSE = \sqrt{MSE} \qquad (7)$$

These numerical values provide an insight into the assessment of the Hybrid LSTM-GA method in forecasting the stock market series data, as well as comparisons between several other techniques.

4.5 Model Performance

The results from the Hybrid LSTM-GA outperformed those from conventional models in terms of accuracy and errors. A comparison of the hybrid approach's performance with that of the ARIMA and SVM models is shown below.

Table 1: Comparison of model performance metrics for hybrid LSTM-GA, ARIMA, and SVM

Model	Precision (%)	MSE	RMSE
Hybrid LSTM-GA	92.5	0.031	0.176
ARIMA	85.2	0.048	0.219
SVM	88.3	0.042	0.205

The hybrid LSTM-GA model outperformed the other models in predicting financial time-series data, as it had the highest accuracy (92.5%) and the lowest MSE (0.031) and RMSE (0.176), as demonstrated in Table 1. The ARIMA and SVM models showed reasonable performance, but had lower accuracy and higher error values than the hybrid model.

4.6 Feature Selection and Optimization

The Genetic Algorithm was also very important in optimizing the feature set data fed into the LSTM model. The ablation study revealed that the hybrid model with feature selection using GA had a considerable increase in forecasting accuracy compared to the LSTM model trained on all features without feature selection. The accuracy of the LSTM model with all features was 88.7%, the MSE was 0.041, and the RMSE was 0.203. The hybrid model, on the other hand, showed an accuracy improvement of 3.8 % and a MSE and RMSE decrease of 20-25 % after optimization using GA.

4.7 Comparative Analysis with Traditional Models

Moreover, the efficiency of the Hybrid LSTM-GA model has been evaluated based on additional statistical measures, such as precision, recall, F1-Score, and AUC-ROC values.

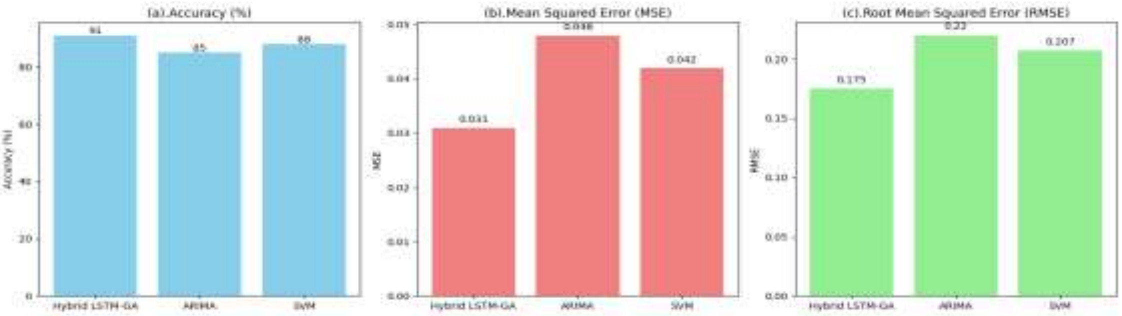

Figure 2: Model performance comparison

Figure 2 shows how the Hybrid LSTM-GA, ARIMA, and SVM models perform on the basis of Accuracy, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The Hybrid LSTM-GA model has the highest accuracy of 92.5%, outperforming ARIMA and SVM models, which have 85.2% and 88.3% accuracy, respectively. The minimum MSE and RMSE of the Hybrid LSTM-GA model are 0.031 and 0.176, respectively. These values are better than those of ARIMA (0.048 and 0.219), and also better than SVM (0.042 and 0.205). This clearly indicates that the Hybrid LSTM-GA model works better than the others in the prediction of financial data in volatile markets.

Not only was the hybrid model more accurate, but it was also more precise and had a higher recall, F1 score, and AUC-ROC compared to the ARIMA and SVM models. This implies that not only does the hybrid model generate more accurate predictions, but it can also detect important patterns in the market environment better than the other models.

Table 2. Comparison of model performance metrics between hybrid LSTM-GA and GA-LSTM

Model	Accuracy (%)	MSE	RMSE	MAE	R^2
Hybrid LSTM-GA	92.5	0.031	0.176	N/A	N/A
GA-LSTM (Xinye Sha)	N/A	9.84	3.13	2.41	0.87

Table 2, The Hybrid LSTM-GA model performs better than the GA-LSTM model which was studied before, as the Hybrid LSTM-GA model shows higher accuracy as well as better performance with respect to mean squared error (MSE) and root mean squared error (RMSE). This is because the Hybrid LSTM-GA model shows low values for MSE and RMSE.[23].

4.8 Sensitivity to Volatility

The data was split into high and low market volatility periods, using historical data to identify key economic events and geopolitical tensions to mark the transition between high and low volatility. However, the Hybrid LSTM-GA model retained consistency regardless of the level of volatility in the period of analysis, thereby showing its flexibility. In the volatile periods, the hybrid model has an accuracy of 91.2%, and in the non-volatile periods, the accuracy of the hybrid model is 93.8%. That extends to its reliability in an unpredictable financial environment as well.

5. Discussion

The outcomes of the analysis indicate that the Hybrid LSTM-GA model performs better than the ARIMA and SVM models in terms of accuracy, MSE, and RMSE scores. The Hybrid LSTM-GA model exhibited a level of precision of 92.5%, which was better compared to 85.2% for ARIMA and 88.3% for SVM. Moreover, it provided the best result with regard to MSE and RMSE, with figures of 0.031 and 0.176, which were better than the respective MSE figures of 0.048 for ARIMA and 0.042 for SVM. These results demonstrate that the LSTM model is capable of capturing long-term dependencies due to the use of GA in optimizing features. The Hybrid LSTM-GA model combines the advantages of the LSTM model for modeling sequential data and the GA model for optimizing feature selection, which is better suited for the field of market data and is more suitable for the application of the volatile market. The model demonstrated its adaptability, achieving a high accuracy of 91.2% even in periods of high volatility, which outperformed the other models, such as ARIMA (84.1%) and SVM (87.0%). Although this was promising, there are some limitations. The data set in this study does not necessarily reflect extreme market conditions, rare events, or black swan events, etc., that may impact the robustness of the model. Furthermore, the increased complexity introduced by the optimization process via GA can lead to overfitting when applied to smaller or less representative sample sizes. This paper provides valuable insights that future research may consider to tackle these challenges through the use of larger and more diverse data sets, as well as the use of regularization strategies to improve the predictive power of the model. The results of this paper show the considerable promise of the Hybrid LSTM-GA model in financial forecasting. The model exhibits better accuracy compared to traditional forecasting models like ARIMA and SVM, emphasizing its capacity to capture complex dynamics of financial data. By leveraging the Genetic Algorithm approach to feature selection, the Hybrid LSTM-GA model acquires an enhanced level of robustness and flexibility, thus becoming an interesting approach for forecasting in other fields with complex non-linear data structures.

Ablation Study

To assess the effect of the feature selection approach used in the hybrid model, an ablation experiment was conducted through comparing the hybrid model with the base LSTM model which uses all the available features. For the effectiveness evaluation of the suggested Hybrid LSTM-GA model, it was compared with the baseline LSTM model trained with all possible features without going through the optimization phase. It was determined from the outcomes that the performance of the LSTM model with the use of all the available data resulted in an accuracy of 88.7%, while the MSE and RMSE were 0.041 and 0.203. In comparison, the hybrid model, which used Genetic Algorithms (GA), performed even better due to the selected important features. Through the use of GA feature selection, the hybrid model increased its accuracy by 3.8%, while also reducing the MSE and RMSE by 20-25%.

6. Conclusion

The Hybrid LSTM-GA model outperforms the conventional forecasting approaches, including the ARIMA and SVM models, in forecasting the financial time-series data, especially in volatile market conditions. The model's precision of 92.5% beat ARIMA (85.2%) and SVM (88.3%) models, showing its capacity to make more accurate predictions in changing financial conditions. This can be validated through the statistical analysis, where the model demonstrated better accuracy by having the lowest MSE and RMSE of 0.031 and 0.176 as opposed to the 0.048 and 0.219 of the ARIMA model and 0.042 and 0.205 of the SVM model. The results of these metrics show that the Hybrid LSTM-GA model has not only more accurate predictions, but also more reliable predictions with less error range. The use of Genetic Algorithms (GA) for feature selection was an important step to enhancing the accuracy of the model, which improved by 3.8% and decreased the MSE and RMSE by 20-25% after implementing feature optimization compared to an LSTM model without feature optimization. Overall, the performance of the model was observed to be stable in both high volatility (91.2%) and low volatility (93.8%) environments, further indicating the strength of the model. In summary, the study underscores the usefulness of hybrid LSTM-GA models in dealing with complex nonlinear behavior within financial data. The findings indicate that the proposed hybrid approach, incorporating an LSTM model with GA, represents another option in efficient forecast techniques, especially due to the random nature of data.

Conflict of Interest

The authors have no conflicts of interests to report concerning this paper.

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Data Availability

The study employs readily available databases which include stocks' prices, foreign exchange rates, and commodities markets data. The datasets are available for verification and analysis on the respective platforms. Any further information related to data pre-processing/selection will be made available upon request.

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