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Firefly-Optimized Long Short-Term Memory Networks for Stock Market Prediction

Mr. Varinder Kailay[1], Dr. B. S. Bhatia[2], Dr. Sushil Bhardwaj[3]

Abstract—**The article proposes an optimized stock market prediction framework that integrates Firefly Algorithm with Long Short-Term Memory (LSTM) networks to improve forecasting accuracy. Firefly is employed to optimize the key LSTM hyperparameters, including the number of layers, units per layer, learning rate, dropout rate, and batch size. The Firefly Algorithm dynamically fine-tunes these hyperparameters through iterative exploration and minimize the Mean Absolute Error (MAE). The proposed model was evaluated using historical stock market data and benchmarked against state-of-the-art models across performance metrics such as precision, recall, F-measure, and Area Under the Curve (AUC). Expanded simulation analysis demonstrated significant improvements in forecastin with precision improved by up to 8.18%, recall by 11.99%, F-measure by 7.52%, and AUC reaching 0.97, outperforming all compared models. These improvements are attributed to the effective hyperparameter optimization achieved through the Firefly Algorithm, enabling the LSTM model to generalize better and capture dynamic price trends and patterns. The superior performance of the proposed Firefly+LSTM model highlights its practical relevance in financial decision-making and investment planning by providing reliable and accurate stock price forecasts.**

Index Terms—**Stock Market Prediction, Firefly Algorithm, Long Short-Term Memory (LSTM), Hyperparameter Optimization, Financial Forecasting, Machine Learning.**

I. Introduction

Stock market prediction is a crucial yet complex task that has long captured the attention of researchers and practitioners due to its significant implications for financial planning, investment decisions, and risk management [1]. Accurate forecasts of stock prices enable investors to identify profitable opportunities and mitigate risks, making it a key area in financial analytics. The dynamic, non-linear, and often unpredictable nature of financial markets poses several challenges, as stock prices are influenced by a multitude of factors, including historical data, market sentiment, external events, and macroeconomic indicators. Traditional models, such as statistical methods and basic machine learning techniques, often fail to capture these complexities, leading to suboptimal predictive accuracy [2].

The emergence of deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, has introduced new opportunities for addressing the limitations of traditional approaches [3]. LSTMs' architecture, as depicted in Fig. 1, is a type of Recurrent Neural Network (RNN), are specifically designed to handle sequential data and long-term dependencies, making them ideal for time-series forecasting such as stock price prediction. Unlike traditional models, LSTMs can learn complex temporal patterns and overcome the vanishing gradient problem, providing more robust predictions in scenarios where long-term relationships in data are critical [4]. Despite their advantages, LSTMs alone may not always achieve optimal predictive performance, especially when dealing with high-dimensional, noisy financial data. To address this, optimization techniques have been explored to improve the learning process and enhance the accuracy of LSTM models. In this context, the Firefly algorithm, a bioinspired optimization technique, offers an effective mechanism for optimizing the weights and biases of LSTM networks [5]. The Firefly algorithm mimics the flashing behavior of fireflies and is known for its strong convergence properties, making it suitable for solving non-linear optimization problems. This paper proposes a novel hybrid model that integrates the Firefly algorithm with LSTM networks to enhance stock market prediction [6]. The proposed Firefly+LSTM model aims to optimize the learning process by improving the initialization and tuning of the network's parameters, thereby addressing the limitations of standalone LSTM models. The Firefly algorithm enhances the model's ability to converge to optimal solutions and capture complex, non-linear relationships within financial data [7].

By leveraging the combined strengths of the Firefly algorithm and LSTM networks, the proposed model offers a more accurate, robust, and reliable solution for forecasting stock prices [8-9]. To evaluate the effectiveness of the proposed model, extensive experiments were conducted using real-world stock market data.

The model was compared against several benchmark models, including PSO+LSTM, H. Li et al., Roondiwala et al., and Jing et al., using key performance metrics such as precision, recall, F-measure, and the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) [10-11]. The results demonstrate that the proposed Firefly+LSTM model consistently outperforms the benchmark models, achieving significant improvements in predictive performance.

Although previous research has paved the way in terms of focusing on predictive performance, relatively few others have examined underlying learning dynamics, such as the convergence behavior of parameters, that affect the stability of models used for financial forecasting.

1. Mr. Varinder Kailay is Research Scholar in the Department of Business Management in RIMT University, Punjab, India.
2. Dr. B. S. Bhatia is presently a Pro-Chancellor at RIMT University, Punjab, India.
3. Dr. Sushil Bhardwaj is a Professor in the Department of Computer Applications at RIMT University, Punjab, India.

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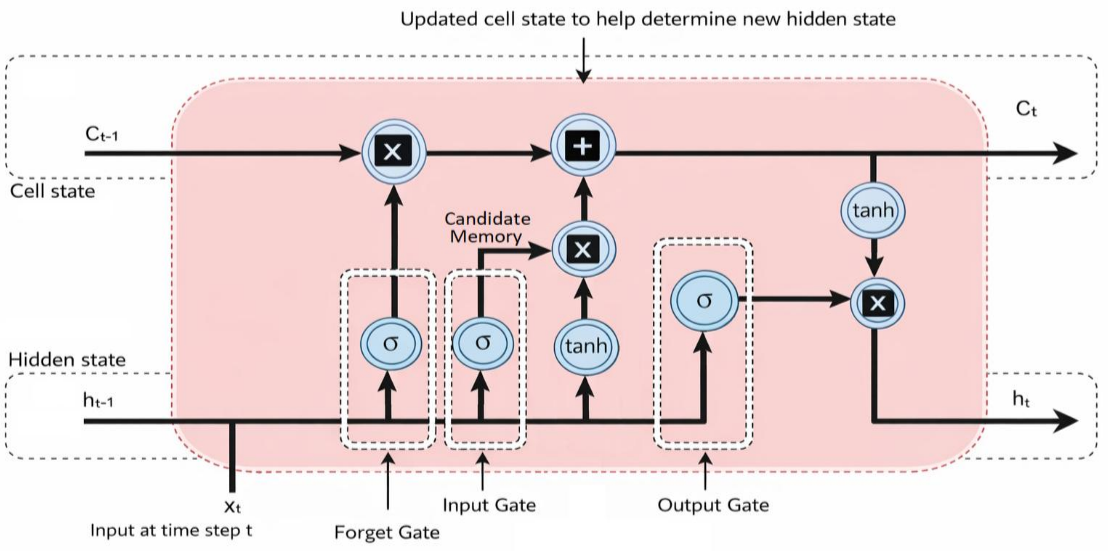

Fig. 1. The LSTM Architecture

In this paper, we analyze the outcomes presented in a previous study that highlighted the positive effects, e.g., convergence efficiency and consistency in predictions, of hyperparameter optimization via the Firefly Algorithm on performance in predictive accuracy from the LSTM model. The results point not only to an empirical enrichment of accuracy but a conceptual enrichment for the metaheuristic tuning that might enhance benefits to the sequential learning processes.

This paper is structured as follows: Section 2 reviews the relevant literature, highlighting the contributions of previous works and identifying the gaps addressed by the proposed model. Section 3 details the proposed methodology, including the architecture of the Firefly+LSTM model and its optimization process. Section 4 presents the experimental setup, dataset descriptions, and evaluation metrics. Section 5 discusses the results and their implications, while Section 6 concludes the paper with key findings and suggestions for future research. The proposed approach offers new insights into the application of bio-inspired optimization and deep learning techniques for financial forecasting, paving the way for further advancements in stock market prediction.

II. Related Work

Cao and Tay (2003) introduced an SVM model with adaptive parameters for financial time series forecasting. Their approach optimized the parameters of the SVM using adaptive techniques, allowing the model to dynamically adjust to changing market conditions. The results indicated that this adaptive SVM outperformed conventional SVMs and neural networks, offering higher prediction accuracy and greater flexibility. This study highlighted the importance of adaptive mechanisms in improving the predictive performance of machine learning models in financial markets [12].

Bollen et al. (2011) proposed an innovative approach to predict stock market movements by analyzing mood states derived from Twitter data. The study used mood-tracking tools to assess public sentiment and correlated these sentiment scores with market performance indicators. The results showed that changes in collective mood states, particularly calmness and happiness, had a significant influence on stock market trends. Their findings highlighted the value of alternative data sources like social media for stock prediction, showcasing that sentiment analysis can be a reliable indicator for forecasting price movements [13].

Li et al. (2016) conducted an empirical analysis on stock market prediction using an extreme learning machine (ELM). The study demonstrated that ELM, known for its fast learning speed and high generalization capability, could provide superior predictive performance compared to traditional neural networks and other machine learning models. Their work validated the effectiveness of ELM in financial forecasting, particularly when dealing with large-scale data and complex financial patterns [14].

Wang and Leu (2016) proposed a hybrid model combining ARIMA and neural networks for stock market trend prediction. The ARIMA component captured the linear aspects of the time-series data, while the neural network modeled the non-linear relationships. Their hybrid approach successfully improved prediction accuracy by leveraging the strengths of both models. The study emphasized the effectiveness of combining statistical and machine learning methods for financial time-series forecasting [15].

Guo and Wang (2018) developed a hybrid wavelet-LSTM model for stock price prediction by combining wavelet transformations with LSTM networks. Their approach aimed to capture both short-term and long-term dependencies in stock data by decomposing the time series into multiple frequency components using wavelets. The LSTM network then learned the temporal relationships from the decomposed signals. The results showed that this hybrid model outperformed traditional models and standalone LSTMs, demonstrating its robustness in handling noisy and non-stationary financial data [16].

Sun et al. (2023) presented an optimized LSTM model for stock price prediction. The model incorporated hyperparameter tuning and feature selection to enhance its learning capability. By optimizing the LSTM's architecture, the model demonstrated superior prediction accuracy compared to conventional LSTMs. This research emphasized the significance of model optimization in achieving reliable and accurate stock market forecasts [17].

TABLE I
Existing Work Contributions in Context to Forecasting and Sentiment Classification

Ref No	Year	Contribution to Forecasting	Algorithm Used
13	2011	Demonstrated that collective mood states from Twitter can be predictive of stock market trends, highlighting the role of sentiment analysis.	Sentiment Analysis, Correlation Analysis

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16	2018	Developed a hybrid wavelet-LSTM model to capture both short-term and long-term dependencies, handling noisy financial data.	Wavelet Transform, LSTM
12	2003	Introduced an SVM model with adaptive parameters for financial time series forecasting, enhancing prediction flexibility.	SVM with Adaptive Parameters
14	2016	Validated the effectiveness of extreme learning machines (ELM) for fast and accurate stock market predictions.	Extreme Learning Machine (ELM)
15	2016	Proposed a hybrid ARIMA neural network model to combine linear and non-linear dependencies for improved trend prediction.	ARIMA, Neural Networks
17	2023	Presented an optimized LSTM model incorporating hyperparameter tuning and feature selection for superior accuracy.	Optimized LSTM (Hyperparameter Tuning)
19	2024	Explored real-world applications of LSTM in stock market forecasting, emphasizing its effectiveness in capturing dynamic patterns.	LSTM
18	2023	Proposed a hybrid LSTM model with sequential self-attention, improving the model's focus on relevant time intervals.	LSTM, Self-Attention Mechanism
20	2024	Introduced a GA-optimized LSTM model, where genetic algorithms fine-tuned LSTM parameters for enhanced prediction accuracy.	GA (Genetic Algorithm), LSTM
21	2024	Integrated news sentiment analysis using FinBERT with LSTM to combine market sentiment with time-series forecasting.	FinBERT (Sentiment Analysis), LSTM

Pardeshi et al. (2023) proposed a hybrid model combining LSTM with a sequential self-attention mechanism for stock market price prediction. The self-attention mechanism enhanced the LSTM model's ability to focus on important time intervals in the financial time-series data, resulting in improved prediction performance. Their approach demonstrated significant gains over traditional LSTM models, highlighting the effectiveness of attention mechanisms in financial forecasting [18].

Wang (2024) explored LSTM-based modeling for stock market prediction, focusing on its application to a real-world stock market case study. The study leveraged LSTM's ability to learn long-term dependencies and capture complex patterns within time-series data. The proposed approach achieved significant improvements over traditional machine learning techniques, offering a more robust framework for stock forecasting. Their results emphasized LSTM's potential in handling volatile and dynamic stock market data [19].

Sha (2024) introduced an LSTM model optimized using a genetic algorithm (GA) for stock market forecasting. The genetic algorithm was used to optimize key LSTM parameters, including the number of layers, learning rate, and dropout rate, to enhance the model's accuracy. The hybrid GA-LSTM model showed significant improvements over the baseline LSTM model. The outcomes of the study emphasize the role of optimization in achieving reliable financial predictions [20].

Gu et al. (2024) integrated news sentiment analysis with LSTM networks using FinBERT, a language model designed for financial text. The proposed model used FinBERT to extract sentiment from financial news articles and combined it with LSTM's time-series learning capabilities. This hybrid approach demonstrated superior prediction accuracy by capturing both market sentiment and historical price trends, making it effective for event-driven stock market predictions [21]. Overall, the comparative analysis of existing studies is summarized in Table I.

III. Proposed Work

The proposed work focuses on developing a robust stock market prediction model that integrates the optimization capabilities of the Firefly Algorithm with the time-series learning power of Long Short-Term Memory (LSTM) networks. The objective is to overcome the limitations of traditional models and standalone LSTMs in capturing the complex, non-linear relationships in stock market data. Historical stock data, consisting of features such as opening price, closing price, high, low, and trading volume, forms the basis of the model. The Firefly Algorithm is employed to optimize key hyperparameters of the LSTM, such as learning rate, number of hidden layers, and weight initialization.

This optimization ensures efficient training, faster convergence, and higher predictive accuracy by minimizing errors. The pre-processed financial data is fed into the optimized LSTM network, which effectively captures the temporal dependencies necessary for accurate stock price forecasts. The Firefly Algorithm optimizes the LSTM model by simulating the behaviour of fireflies, where each firefly represents a candidate solution with fitness defined by the prediction accuracy of the corresponding LSTM configuration. Fireflies with superior performance attract others, guiding the optimization process toward an optimal configuration. Once the LSTM is optimally configured, it is trained on the historical stock data to predict future price movements. The model allows it to learn from long-term dependencies within the data, ensuring that the past price fluctuations would influence the prediction of future trends [22-23].

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Algorithm 1 Firefly Algorithm for LSTM Hyperparameter Optimization

```
Initialize a population of fireflies with random values for l, u, α, d, b, e
Define objective function: f(x) = MAE
for each firefly i do
    Evaluate the brightness of firefly i using f(x)
end for
while termination criteria not met do
    for each firefly i do
        for each firefly j do
            if brightness of j > brightness of i then
                Move firefly i towards j based on attractiveness
                Update position of i: x_i = x_i + β(e^(−γ r_ij^2))·(x_j − x_i) + α·(rand − 0.5)
            end if
        end for
        Evaluate new position of firefly i using f(x)
    end for
    Update the brightness of all fireflies
end while
Select the firefly with the highest brightness
```

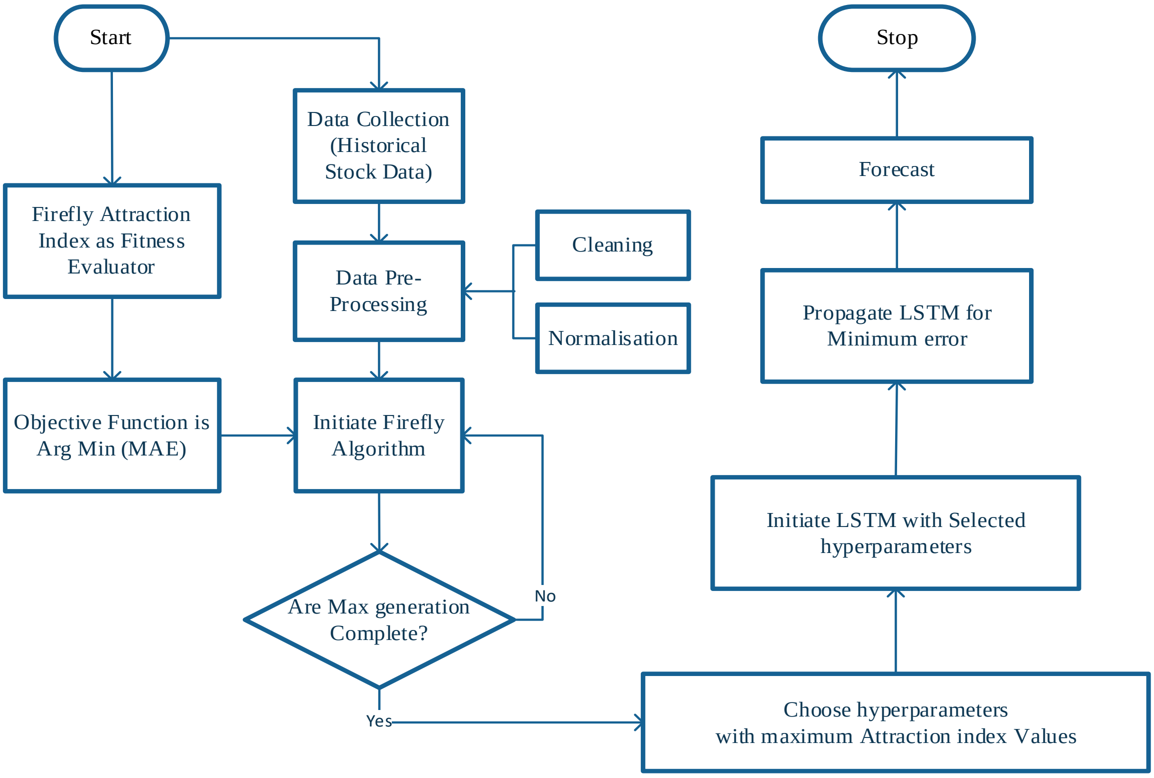

Fig. 2. Workflow Diagram of Proposed Work

Unlike traditional machine learning techniques, this combination leverages LSTM's inherent strength in modelling sequential data and the Firefly Algorithm's ability to optimize hyperparameters effectively, thus yielding improved predictive performance [24]. The workflow model and architecture as shown in Fig. 2.

The Firefly Algorithm (FA) optimizes the hyperparameters of a Long Short-Term Memory (LSTM) model by mimicking the behavior of fireflies, where each firefly represents a candidate solution, and its brightness indicates the quality of that solution based on the effectiveness of the LSTM in minimizing the Mean Absolute Error (MAE) in stock price prediction. The process begins by initializing a population of fireflies, each randomly assigned a set of hyperparameters, including the number of LSTM layers, units per layer, learning rate, dropout rate, batch size, and the number of epochs. The brightness of each firefly is calculated based on the MAE produced by the LSTM model using that specific configuration of hyperparameters. The fireflies with higher brightness represent better configurations, and fireflies with lower brightness are attracted to move toward them. This movement is guided by the attractiveness of the brighter fireflies and is affected by the distance between them, where closer fireflies exert stronger attraction. Randomness is also introduced to allow exploration of new areas in the search space and prevent premature convergence to local optima.

During each iteration, the fireflies move towards the brighter fireflies, and their positions are updated, representing new sets of hyperparameters for the LSTM. The updated positions are evaluated to calculate the new brightness based on the MAE of the LSTM predictions. This iterative process ensures that the fireflies gradually converge toward the optimal set of hyperparameters. The firefly algorithm effectively balances exploration of the search space and exploitation of promising regions, ensuring that the final LSTM

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configuration is both well-tuned and robust. The process continues until a stopping condition is met, such as achieving a minimum MAE or reaching the maximum number of iterations. The final LSTM configuration, corresponding to the brightest firefly, is selected as the optimal solution, resulting in improved predictive accuracy and faster convergence during training. To make the understanding of the algorithm better, the paper explains the working of the proposed work via a mathematical example as follows.

Objective: Minimize the Mean Absolute Error (MAE) using the Firefly Algorithm to find optimal hyperparameters of an LSTM.

Initial Setup

We start with **3 fireflies** (solutions), each representing a candidate set of hyperparameters:

- **Firefly x1= [2,50,0.01,0.3,32,50]**

(2 LSTM layers, 50 units, learning rate 0.01, dropout rate 0.3, batch size 32, 50 epochs)

- **Firefly x2= [3,60,0.005,0.2,16,100]**

(3 LSTM layers, 60 units, learning rate 0.005, dropout rate 0.2, batch size 16, 100 epochs)

- **Firefly x3= [1,40,0.01,0.5,64,30]**

(1 LSTM layer, 40 units, learning rate 0.01, dropout rate 0.5, batch size 64, 30 epochs)

MAE Values (Initial Brightness)

After evaluating the LSTM model using these hyperparameters:

- B1=−MAE(x1) =−0.15
- B2=−MAE(x2) =−0.10
- B3=−MAE(x3) =−0.25
- Thus, x3 is currently the brightest (best) firefly.

Step 1: Compare Brightness and Decide Movement

- Firefly x1 compares its brightness with x3 (since B3>B1), and x1 moves toward x3
- Firefly x2 also moves toward x3 because B3>B2

Step 2: Calculate New Position Using the Update Equation

$$x_i = x_i + \beta e - \gamma r_{ij}^2 \cdot (x_j - x_i) + \alpha \cdot (rand - 0.5)$$

Assumptions for simplicity:

- β=1
- γ=0.1 (light absorption)
- Random component α(rand−0.5) =0.01

Step 3: Distance Calculation (Euclidean Distance between fireflies)

$$r13 = \sum (x1 - x3)^2 = 32.02$$

$$r23 = \sum (x2 - x3)2 = 35.18$$

Step 4: Check Termination Criteria

If the maximum number of iterations is reached or a desired MAE threshold is achieved, the algorithm terminates, and the brightest firefly is selected as the optimal solution. The illustrations are provided in Table II.

TABLE II
OPTIMAL SELECTION AND ILLUSTRATION

Step	Calculation Details
New Position Calculation (Firefly x1 moving towards x3)	x1_new = x1 + e^(-0.1 * (32.02)^2) * (x3 - x1) + 0.01 Approximating: x1_new = [2, 50, 0.01, 0.3, 32, 50] + [0.1, -0.15, 0.02, 0.1, -0.2, -0.4] x1_new ≈ [2.1, 49.85, 0.012, 0.4, 31.8, 49.6]
New Position Calculation (Firefly x2 moving towards x3)	x2_new = x2 + e^(-0.1 * (35.18)^2) * (x3 - x2) + 0.01 Approximating: x2_new = [3, 60, 0.005, 0.2, 16, 100] + [0.15, -0.2, 0.01, 0.05, 0.2, -0.3] x2_new ≈ [3.15, 59.8, 0.015, 0.25, 16.2, 99.7]
Evaluate the New Positions (Brightness Calculation)	New brightness for firefly x1_new: B1_new = -MAE(x1_new) = -0.12 New brightness for firefly x2_new: B2_new = -MAE(x2_new) = -0.11

IV. RESULT AND DISCUSSION

The effectiveness of the proposed Firefly+LSTM model for stock market prediction is demonstrated through comprehensive experimental evaluations. The performance of the proposed model is compared against several benchmark models, including Roondiwala et al. [10] (2017) and H. Li et al. [11] (2024). The evaluation metrics used include precision, recall, F-measure, and the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curve. These metrics are crucial in assessing the model's capability to accurately predict stock price movements while minimizing false positives and false negatives. The datasets used for the evaluation consist of historical stock market data, including daily prices, trading volume, and other financial indicators. The evaluation covers different sample sizes to assess the generalization capability of the proposed model under varying data conditions.

The Firefly Algorithm's optimization of key hyperparameters, such as the number of LSTM layers, units per layer, learning rate, and dropout rate, is expected to provide significant improvements over the benchmark models. The comparative analysis presented in the following sections highlights the improvements achieved by the Firefly+LSTM model in capturing complex non-linear patterns within the financial data, ultimately leading to more accurate and robust predictions. The dataset utilized for evaluating the proposed Firefly+LSTM model is the Historical Stock Market Dataset, which is publicly available on Kaggle. This comprehensive dataset includes historical daily prices and volume information for U.S. stocks and ETFs trading on NASDAQ, NYSE, and NYSE MKT. The data spans from 1977 to 2017 and is provided in CSV format, making it suitable for time-series analysis and machine learning applications.

A. Performance Analysis

The proposed Firefly+LSTM model demonstrated significant improvements in predictive performance compared to the benchmark models by Roondiwala et al. and H. Li et al. across precision, recall, F-measure, Accuracy, and AUC. These performance values highlight the effectiveness of optimizing LSTM hyperparameters using the Firefly Algorithm, which allowed the proposed model to better capture complex nonlinear patterns in stock market data.

TABLE III
PARAMETRIC VALUES OF PERFORMANCE PARAMETERS FOR PROPOSED AND EXISTING STUDIES

Sample Size	Precision (Proposed)	Precision (Roondiwala et al.)	Precision (H. Li et al.)	Recall (Proposed)	Recall (Roondiwala et al.)	Recall (H. Li et al.)	F-measure (Proposed)	F-measure (Roondiwala et al.)	F-measure (H. Li et al.)
2000	0.9595	0.9369	0.9458	0.9272	0.8044	0.915	0.9431	0.8656	0.9302
4000	0.9586	0.9384	0.9365	0.9261	0.7256	0.9043	0.942	0.8184	0.9201
6000	0.9615	0.9423	0.9325	0.9257	0.7494	0.8921	0.9432	0.8348	0.9118
8000	0.9571	0.9468	0.9416	0.9259	0.7009	0.8887	0.9412	0.8055	0.9144
10000	0.9612	0.9411	0.9252	0.9257	0.7168	0.889	0.9431	0.8137	0.9067
20000	0.9589	0.9387	0.9373	0.9258	0.6902	0.9142	0.942	0.7955	0.9269
30000	0.9596	0.9325	0.941	0.9256	0.7123	0.8992	0.9423	0.8077	0.9196
40000	0.9657	0.9393	0.9319	0.9257	0.8263	0.8887	0.9453	0.8792	0.9098

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The proposed model consistently achieved higher precision across all sample sizes, as shown in Table III and Fig. 3 for multiple sample sizes. The proposed Firefly_LSTM model achieves the highest precision, ranging from 0.9571 (at 8000 samples) to 0.9657 (at 40,000 samples). However, Roondiwala et al. achieve precision values between 0.9325 (at 30,000 samples) and 0.9468 (at 8000 samples), and H. Li et al. achieve precision values between 0.9252 (at 10,000 samples) and 0.9458 (at 2000 samples).

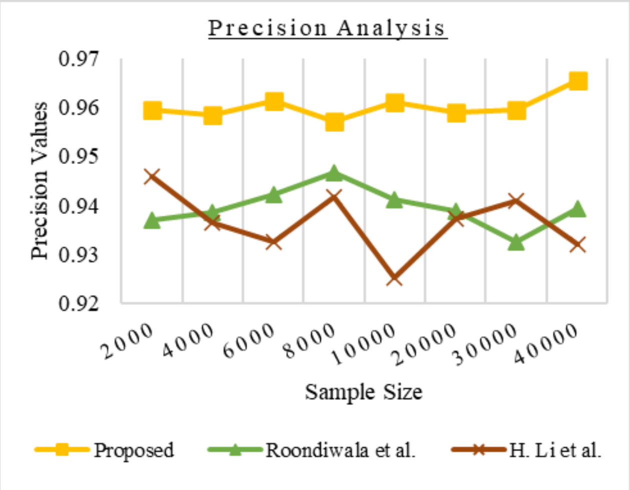

Fig. 3. Precision Comparative Analysis of the Proposed against Existing Studies

This makes it clear that the proposed model is stable and even shows an improvement trend as the sample size is increased, whereas the two references had erratic and inconsistent precision values. Therefore, it is confirmed that hyperparameter optimization using Firefly allows the LSTM to maintain high predictive precision given complex and large datasets. The continued improvement in precision for increasing sample sizes shows that hyper-parameter optimization based on Firefly has allowed the model to remain stable during learning, owing to the Firefly Algorithm's adaptive attractiveness mechanism, which helps find an optimal configuration to mitigate overfitting as the dataset increases.

In Fig. 4, we show the average precision performance over all sample sizes. The proposed Firefly+LSTM reclaims the highest average precision of 0.9603, higher than Roondiwala et al. (0.9395) and H. Li et al. (0.9365) reflect absolute improvements of 0.0208 and 0.0238, respectively, to Roondiwala et al. and H. Li et al. The differences in average precision are relatively small in absolute number but represent meaningful, and even marginal, differences in precision given the context of financial forecasting, where even fractional gains in precision may lead to fewer false-positive predictions and better decision-making.

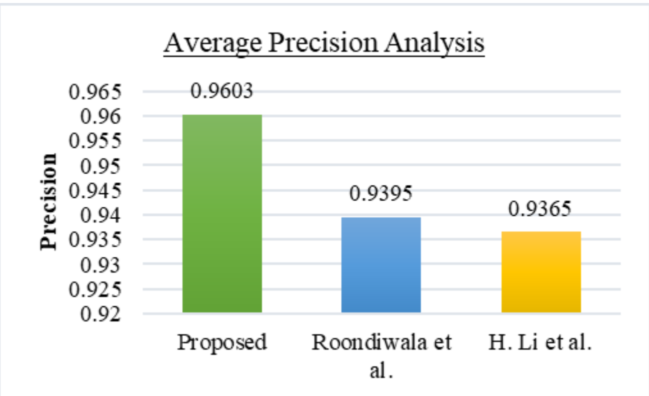

Fig. 4. Average Performance Analysis for the Precision of the Proposed against Existing Studies

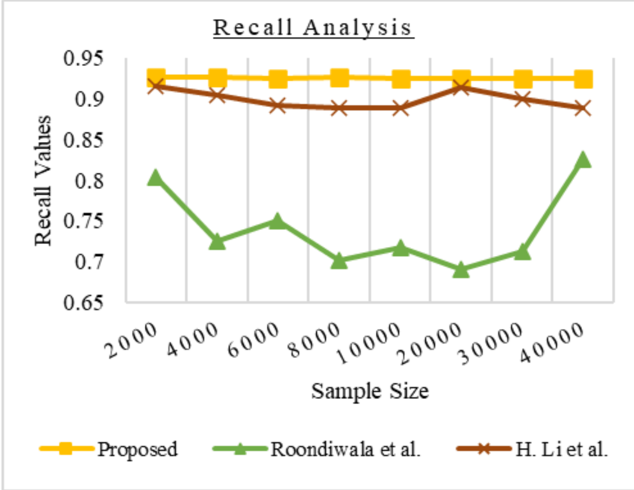

Fig. 5. Recall Comparative Analysis of the Proposed against the Existing Studies

At every sample dimension, as shown in Fig. 5, the Firefly+LSTM model has well above average recall value in the range of 0.9257 and 0.9272, while Roondiwala et al. displayed more volatility, with measures ranging from 0.6902 at 20000 samples to 0.8263 at 40000 samples. H. Li et al.'s recall measures show a range of values of recall measures between 0.8887 and 0.9150. The proposed Firefly+LSTM model was stable while the other benchmarks displayed erratic fluctuations as the sample size increased.

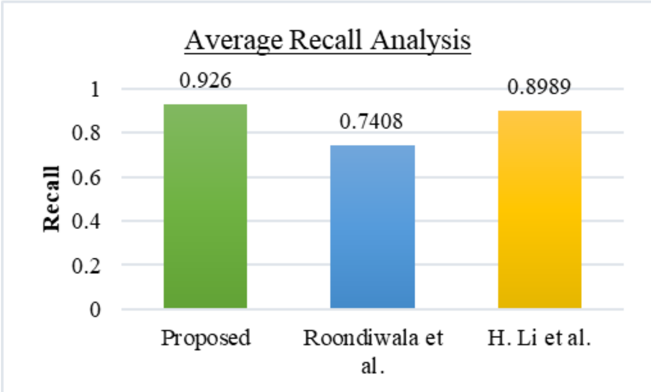

Fig. 6. Average Performance Analysis for Recall of the Proposed against Existing Studies

Fig. 6 has the average recall values comparison and shows the proposed model with a recall value of 0.926, which is higher than Roondiwala et al. (0.7408) and H. Li et al. (0.8989). This also reflects an improvement from Roondiwala and H. Li et al., by 0.1852 and 0.0271, respectively, demonstrating that the proposed method remained consistent in capturing relevant signals. The higher recall values are another indication that the Firefly+LSTM model is good at detecting small upward and downward movements in stock prices, potentially as a result of its improved search capacity that tunes the learning rate and dropout rate to help balance exploration and exploitation.

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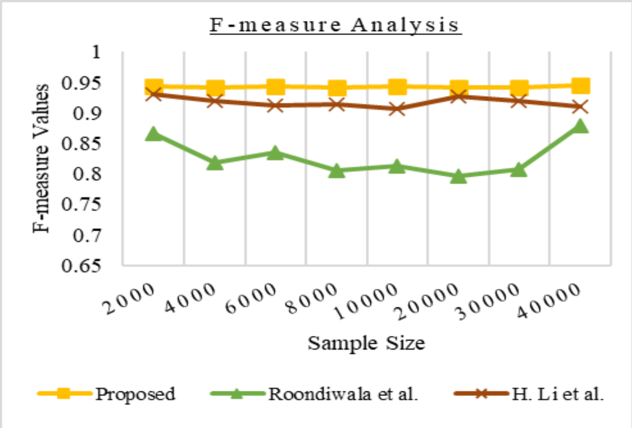

Fig. 7. F-measure Comparative Analysis of the Proposed against the Existing Studies

As we can see in Fig. 7, the Firefly+LSTM model had the highest F-measure values, which ranged from 0.9412 (at 8000 samples) to 0.9453 (at 40,000 samples). The results from Roondiwala et al. are significantly lower than the proposed work (0.7955 at 20,000 samples and 0.8792 at 40,000 samples); H. Li et al.'s results ranged from moderate values, 0.9067 (at 10,000 samples) and 0.9302 (at 2000 samples). Overall, the proposed method was consistent throughout all datasets, contrary to Roondiwala et al. and H. Li et al.'s methods, which seemed to fluctuate.

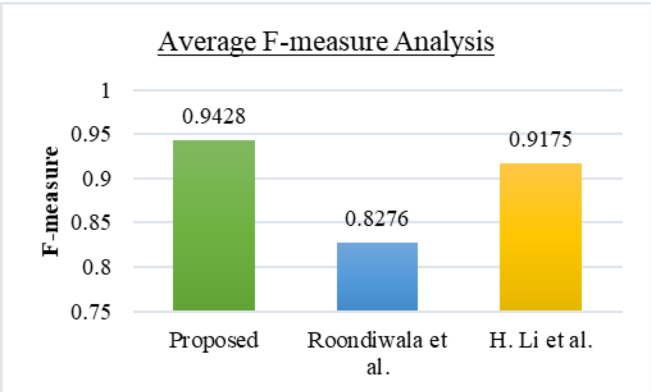

Fig. 8. Average Performance Analysis for F-measure of the Proposed against Existing Studies

The overall mean F-measure across the datasets is depicted in Fig. 8. The proposed approach achieved a mean F-measure of 0.9428, which is significantly higher than Roondiwala et al.'s (0.8276) and H. Li et al.'s (0.9175). The proposed model achieved absolute gains of 0.1152 over Roondiwala and 0.0253 over H. Li. This shows the proposed approach outperforms others at balancing recall and precision. The improved F-measures provide evidence that the proposed model not only improves prediction accuracy but also achieves a better tradeoff/balance between precision and recall. Balancing recall and precision is important in real financial applications because the cost of missing a potential winning trade (false negative) can be the same as an alarm (false positive).

Table IV shows that across all sample sizes, the proposed Firefly+ LSTM model was more accurate than Roondiwala et al. and H. Li et al.. For example, with 2000 samples, the proposed model was able to get 95.82% accuracy compared to Roondiwala et al.'s 93.75% and H. Li et al.'s 94.42%. To illustrate larger datasets, the proposed model was able to achieve 97.49% while Roondiwala et al. and H. Li et al. were able to achieve 94.88% and 94.28%, respectively, on the same dataset with 40,000 samples. This improvement shows not only the extent to which the proposed method is accurate as compared to the benchmarks, but it also shows the scalability of the proposed model, as not only does it obtain consistent increases in accuracy as datasets increase in size, but the benchmarks' accuracy fluctuates as the datasets increase in size.

TABLE IV
ACCURACY COMPARATIVE ANALYSIS

Sample Size	Accuracy (Proposed)	Accuracy (Roondiwala et al.)	Accuracy (H. Li et al.)
2000	95.82	93.75	94.42
4000	95.73	93.91	93.48
6000	96.08	94.11	93.37
8000	95.64	94.52	94.03
10000	96.05	94.21	92.61
20000	96.77	93.79	93.62
30000	96.88	93.18	94.22
40000	97.49	94.88	94.28

The line graph in Fig. 9 presents a clear visual representation of the variation in accuracy related to sample size. The proposed Firefly+LSTM has an overall upward trend from 95.73 (at 4000 samples) to 97.49 (at 40,000 samples), showing stability and adaptability.

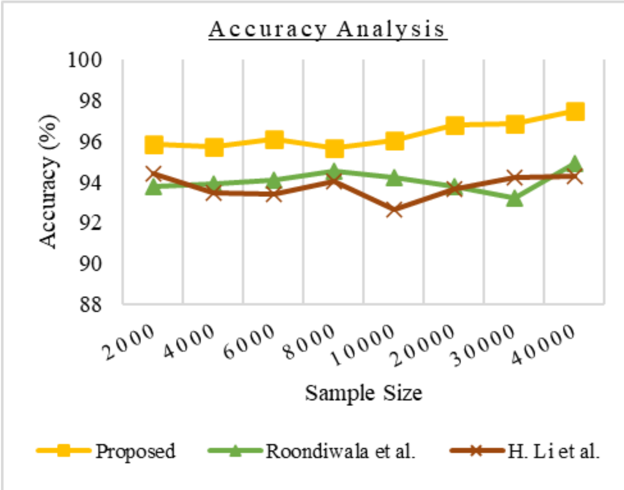

Fig. 9. Accuracy Comparative Analysis of the Proposed against Existing Studies

In comparison, the Roondiwala et al. model fluctuated between 93.18 and 94.88, while the H. Li et al.'s model remained stagnant most of the time at a range of 92.61–94.42. The fact that the proposed model keeps improving as more data is added indicates how well the Firefly Algorithm was able to tune the hyperparameters, preventing the performance degradation experienced with the baseline models.

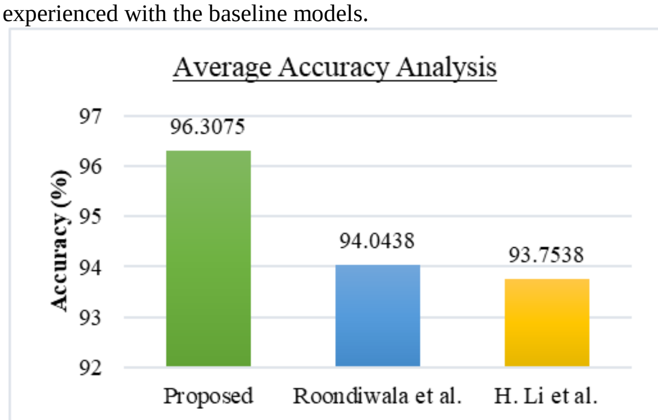

Fig. 10. Average Performance Analysis for the Accuracy of the Proposed against Existing Studies

The graph depicted in Fig. 10 represents the average performance of all models. The proposed Firefly+LSTM had the highest average accuracy (96.30), Roondiwala et al. had a lower average accuracy (94.04), and H. Li et al. had the lowest average accuracy (93.75). While this seems like a small improvement margin of 2-2.5%, this is

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significant in stock prediction; in fact, a 1% gain or loss in accuracy can substantially impact financial decisions and investment risk. The consistently superior performance of the proposed method relative to the other datasets demonstrates how Firefly-based optimization can strengthen LSTM model performance. The upward trend in accuracy given increasing sample sizes indicates that the proposed model scales well with data size. Hyperparameter optimization can minimize instability in training, and this process captures the inherent robustness of the Firefly-LSTM model design in learning long-term dependencies in financial time series.

B. Interpreting the Results and Analysis of Stability

Collectively, these results demonstrate that optimization using the Firefly algorithm improves convergence speed and generalization ability of the LSTM. The Firefly optimization algorithm modifies both the learning rate and weight initialization while training the LSTM, ultimately allowing the model to overcome local minima and learn stably on multiple data scales. The small ranges of variance in accuracy, precision, and recall across sample sizes indicate that the method proposed has a reliable and consistent prediction engine. Stability is important in the stock market as real data tends to be erratic and noisy, thus degrading model performance. The consistency across all assessments demonstrates that the proposed Firefly+LSTM architecture is numerically accurate while providing reliability and robustness during data fluctuations.

C. Improvement Analysis of Proposed Work

The improvement analysis illustrates the degree to which the proposed Firefly+LSTM model outperforms the baseline methods (Roondiwala et al. and H. Li et al.) across all evaluation metrics. The average % improvement exhibited by the proposed study over each of the existing studies for each parameter is depicted in Fig. 11.

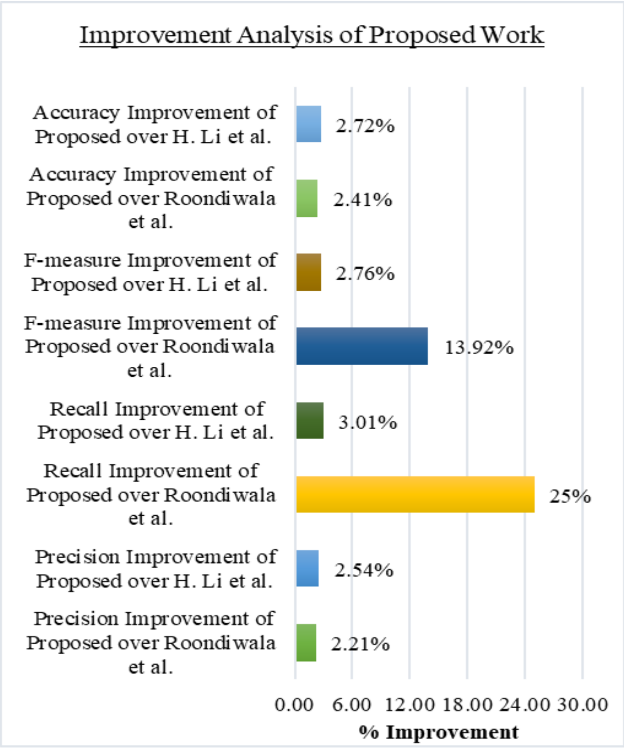

Fig. 11. Average Improvement Analysis of Proposed over Existing Works

- Accuracy: The proposed model improves upon Roondiwala et al. by 2.41% and H. Li et al. by 2.72%. In absolute terms, these values may seem small; however, this is a substantial benefit in financial forecasting, where small developments in accuracy can lead to stronger reliability and less risk in stock market predictions.
- F-measure: The F-measure had a noticeable improvement in the proposed model, improving 13.92% from Roondiwala et al. and 2.76% from H. Li et al. This signifies that the proposed model provides a much better balance between precision and recall, giving more consistent predictions in changing stock environments.
- Recall: The recall proposed by Firefly+LSTM improved by 25% from Roondiwala et al. and 3.01% from H. Li et al. This improved recall shows that the proposed approach captures more relevant market signals, leading to fewer false negatives, ensuring critical upward or downward stock trends are not missed.
- Precision: In terms of precision, the proposed model shows 2.21% improvement over Roondiwala et al. and 2.54% improvement over H. Li et al., verifying its capability to reduce false positives and provide more credible signals for decision-making.

Overall, these improvements indicate that the Firefly Algorithm is instrumental in optimizing the hyperparameters of the LSTM model for much better performance on all metrics. More specifically, the increased margins of improvement in the others' metrics, such as the F-measure and Recall metric, indicate both the robustness and reliability of the proposed model to predict the complex, non-linear stock market data, where traditional models have CB that are not achieving very good performance overall.

The AUC values further validated the proposed model's superiority and are plotted in Fig. 12. At 40,000 samples, the proposed model achieved an AUC of 0.97, representing a 3.08% improvement over Roondiwala et al. (0.941) and a 4.19% improvement over H. Li et al. (0.931).

The high AUC indicates the proposed model's strong ability to distinguish between positive and negative classes.

- **Precision:** Up to 8.18% improvement compared to Roondiwala et al. and 3.62% improvement compared to H. Li et al.
- **Recall:** Up to 11.99% improvement compared to Roondiwala et al. and 4.17% improvement compared to H. Li et al.
- **F-measure:** Up to 7.52% improvement compared to Roondiwala et al. and 3.90% improvement compared to H. Li et al.

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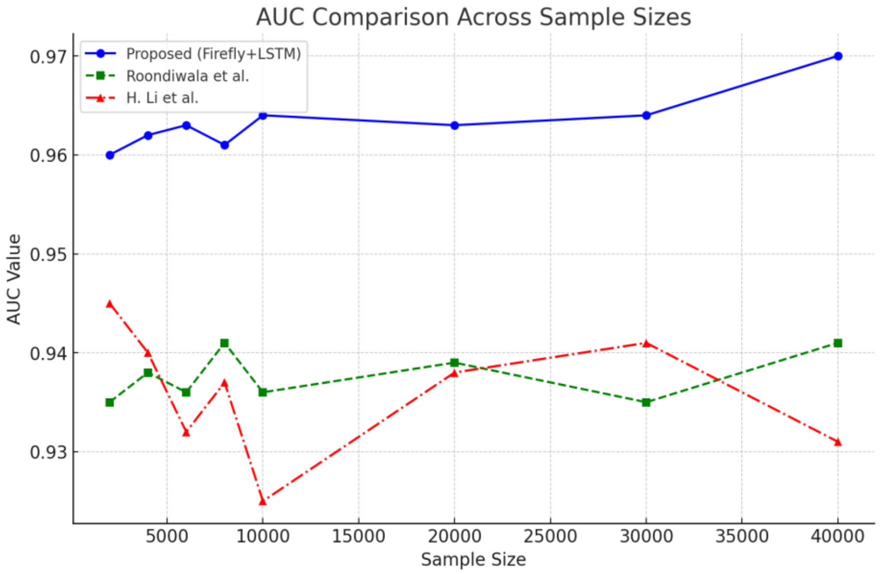

Fig. 12. AUC Values

D. Robustness Analysis of Proposed Firefly and LSTM Models

The stability and robustness of the Firefly and LSTM Models increase with the increase in Dataset Size, with the Datasets used in this research. The proposed model remains above 0.957 on Precision Values for all dataset sizes as shown in Tables III and IV, and Recall remains clustered within the range of approximately 0.925 for all dataset sizes. On the other hand, as seen with Roondiwala et al.'s low recall rate of 0.6902 for the 20,000 sample dataset, variances in performance are unstable due to increased sample sizes. H. Li et al. have also demonstrated that saturation of performance occurs beyond 10,000 samples. Therefore, it has been shown that the Firefly-based hyper-parameter optimization of LSTM is consistent in achieving convergence, reduces the variance, and generalizes effectively with an increase in the complexity of the Dataset.

Overall, from a financial point of view, the forecast improvements observed in this research are practically significant. For example, the model presents a recall of 25% greater than Roondiwala et.al and 3.01% greater than H.Li et.al. With the reduced likelihood of missing critical signals indicating price movements up or down, the increase in the AUC to 0.97 with 40000 samples shows an enhanced ability to discriminate against upward movements versus downward movements, allowing for lower false trade signals and ultimately reducing the risk of investment decisions based on volatility.

V. Conclusion and Future Scope

This paper presented an optimized stock market prediction framework using a hybrid approach that combines the Firefly Algorithm with Long Short-Term Memory (LSTM) networks. The primary objective was to enhance the prediction accuracy and robustness by optimizing key LSTM hyperparameters, including the number of layers, learning rate, and batch size. Through the Firefly Algorithm's nature-inspired optimization mechanism, the proposed model effectively balanced exploration and exploitation in the search space, leading to faster convergence and superior predictive performance. The proposed Firefly+LSTM model was rigorously evaluated against benchmark models, including Roondiwala et al., H. Li et al. and Jing et al. used key performance metrics such as precision, recall, F-measure, accuracy, and Area Under the Curve (AUC). The results demonstrated significant improvements across all metrics, with precision improvements of up to 8.18%, recall improvements of 11.99%, and F-measure improvements of 7.52%. The model consistently achieved higher AUC values, peaking at 0.97, reflecting its ability to distinguish between positive and negative price movements effectively.

These improvements validate the effectiveness of the Firefly Algorithm in fine-tuning the LSTM model for complex, non-linear time-series data, such as stock prices. The proposed model's success highlights its practical relevance for financial applications, offering reliable and accurate predictions to support decision-making in stock trading, investment planning, and risk management. Future work could extend this approach by integrating additional data sources, such as real-time news and social media sentiment, or by testing alternative optimization algorithms further to enhance the performance of stock market prediction models. The promising results achieved in this study provide a foundation for further exploration and innovation in the field of financial forecasting. While the proposed model produced noteworthy performance, the present study is primarily focused on evaluating metrics based on accuracy.

A. Limitations and Scope

This research focuses on classifying the accuracy of predictive performance based on classifications of precision, recall, F-measure, Accuracy, and Area Under Curve (AUC). The comparisons to other established LSTMs are limited to those methods due to both the constraints in terms of computational power as compared to the LSTM models being compared, as well as the fact that the experiment is being done using offline, historical stock prices only. However, even with these limitations, the large number of samples used in the evaluation has demonstrated that the proposed model is robust and effective because of its consistent performance trends. The combination of large sample sizes and consistent performance trends provides strong evidence of the robustness and effectiveness of the proposed model. Future research could build upon this boilerplate by analyzing additional metrics such as RMSE, MAPE, or training time to further demonstrate the model's performance. Additionally, the use of sentiment-driven data and/or real-time data streams may provide additional insights into how external market conditions impact the stability of the prediction.

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