Improving Financial Forecasting Accuracy Through Swarm Optimization-Enhanced Deep Learning Models

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***Abstract*—Financial forecasting is a crucial factor for decision-making in numerous fields, it demands very accurate predictive models. Traditional methods, like Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Gradient Boosting Machines (GBM), display suitable performance however have proven not totally efficient in complex high-dimensional financial data. This paper introduces a new approach combining swarm-based algorithms and deep learning architectures to improve predicative accuracy in financial forecasting. The proposed method relies on elite data preprocessing algorithms to optimize the learning process and prevent overfitting. By experimenting with large variety of dataset, the optimized model was able to achieve accuracy of 98% out running traditional models such as CNN (80%), RNN (83%), and GBM (95.6%). Furthermore, the model performed a good precision-recall trade-off, strengthening it applicability to real world work of predictive tasks, such as stock price prediction and market trend analysis. Through optimizations of essential hyperparameters by means of swarm intelligence, the framework handles the non-linear dependencies as well as volatility of financial data. The study shows high robustness and adaptability of the proposed concept provides solutions to the shortcomings of conventional financial forecasting tools. This study furthers the state of intelligent financial analytics proposing a byword framework for additional studies fostering deep learning and optimisation technologies together. The results align with the potential application of swarm-optimizer models for overcoming the limitation of predictive reliability of financial forecasting systems and future research in machine learning driven economic modelling and risk analysis.**

***Keywords*—Financial forecasting; deep learning; swarm optimization; predictive modeling; machine learning**

I. Introduction

Financial forecasting is an extremely critical task in a number of domains, including stock market prediction, economic modeling, and risk management [1]. It has the potential to affect decision-making, portfolio management, and overall economic planning through the accurate prediction of future financial trends [2]. While there have been tremendous improvements in financial analytics, traditional models for forecasting often fail to capture the complexity and non-linearities of financial data [3]. Such models have limitations because they are based on linearity and lack the hidden patterns within volatile and dynamic markets, which conventional models are not able to understand [4]. The task of financial forecasting is difficult: not only are financial markets by nature unpredictable but also because they contain a very large amount of noisy, unstructured, and multidimensional data [5]. In fact, the behavior of markets is highly influenced by external variables, including political events, natural catastrophes, and market sentiment [6]. All these call for models capable of updating in response to such influences to make accurate predictions of the future [7]. Most statistical approaches cannot handle complex patterns within such data, which usually results in less-than-optimal forecasting. However, many of the financial forecasting models require time-consuming and cumbersome tuning for various parameters [8]. Recently, machine learning, especially deep learning, has been seen to be highly promising in addressing these problems [9]. DL models, such as LSTM networks and GRU, learn complex patterns. However, such models are often very hard to optimize [10]. This is a challenging issue of selecting appropriate architecture and proper hyperparameters to use in the deep learning models to avert overfitting and underfitting while getting good generalizations [11]. It is targeted on improving the accuracy of financial forecasting by using optimized deep learning models with swarm intelligence techniques. Swarm intelligence algorithms, inspired by natural systems, have been shown to have a great ability to search for optimal solutions in high-dimensional spaces, as in the case of "Particle Swarm Optimization and Ant Colony Optimization" [12]. These algorithms would be particularly of use in wide, non-linear search spaces for which they are useful candidates to help optimize the best hyperparameters concerning deep learning models in forecasting financials [13].

Swarm-based techniques, as PSO, ACO techniques, offer interesting advantages in an optimization context. They would not require explicit gradient information on the function optimization, making their convergence less critical to local extrema and giving them a fair robustness compared to complex optimization schemes [13]. Secondly, swarm-based optimizers are well-suited to parallel processing, enabling faster exploration of the solution space [14]. By applying swarm intelligence to deep learning models, we aim to improve the models' forecasting capabilities by finding the best combination of hyperparameters, thus ensuring more accurate predictions [15]. In this research, a novel framework that integrates swarm intelligence optimization with deep learning models for financial forecasting. The framework will be the optimization of key hyperparameters for deep learning models, learning rate, through PSO with ACO. This work will be followed by comparing the performance of swarm-optimized deep learning models with traditional financial forecasting models like ARIMA and simple machine learning approaches. The novelty contribution of this paper is the development of a hybrid model that couples the power of deep learning with the swarm optimization technique, therefore offering a more accurate and efficient method in financial forecasting. In addition, we compare the effectiveness of various swarm-based optimizers in different financial forecasting scenarios and provide an extensive comparison of their performances against conventional methods. This paper explores potential swarm intelligence ability to optimize deep learning models and provides crucial insights into financial forecasting in the future, as it also highlights that advanced optimization techniques are beneficially used in the predictive model.

The key contributions of the proposed work are as follows:

- Development of a hybrid deep learning framework optimized with swarm intelligence techniques for financial forecasting.
- Integration of advanced swarm optimization algorithms to enhance deep learning model performance.
- Improved accuracy and robustness in predicting financial trends and market movements.
- Application of the methodology to diverse financial datasets for broader applicability and validation.
- Demonstration of scalability and efficiency in real-time financial forecasting scenarios.

This paper is aligned as follows: Section II reviews related works in predictive modeling for banking operations. Section III outlines the problem statement, while Section IV describes the proposed Methodology for Enhancing Financial Forecasting Accuracy Using Swarm-Optimized Deep Learning Models. Sections V and VI present results, discussion, conclusion, and future directions, emphasizing the model's scalability and applicability.

II. Related Works

Traditionally, statistical models such as ARIMA and GARCH dominate financial forecasting in the prediction of stock prices, market volatility, and economic indicators [16]. ARIMA models are best suited for time series data that exhibit a clear temporal structure, whereas GARCH models are designed specifically to model time-varying volatility in financial markets. These models rely greatly on linear assumptions and hence may not be competent in assimilating the complexities or the non-linear relationships involving financial data. Even though these methods have been foundational in financial forecasting, they often fall short of capturing the intricate patterns and underlying structures inherent in dynamic and volatile financial markets.

Even with time series, financial forecasting does not lag; historical data have been used for predicting future trends [17]. Exponential smoothing and seasonal decomposition are highly applicable methods in data smoothing and trends prediction, although more complex methodologies, such as vector autoregressions, attempt to capture the relationship of multiple financial time series. However, these traditional time series methods need large domain expertise to select the right model and suffer from an inability to capture the high-dimensional interdependencies and non-linearities in big data. Hence, with complex financial data coming in, it is not easily adapted and generalized by these models and calls for much more advanced methods that can capture high-dimensional interdependencies and non-linear dependencies.

Some of the traditional methods have been overcome and much improvement has been brought into financial forecasting [18]. Algorithms like DT, SVM and RF have been applied to model complex patterns in financial data. The models are much more flexible and able to handle non-linear relationships, making them better fits for many financial forecasting tasks. However, challenges still exist, such as choosing the optimal hyperparameters and overfitting risks, especially when working with noisy or sparse financial data. Moreover, although machine learning models are much more accurate than others in some instances, they do not capture the temporal dependencies and long-range patterns that usually occur in financial time series data.

Financial forecasting has recently turned towards deep learning in a promising trend, as complex, high-dimensional data can now be modelled in a much simpler, more intuitive fashion without the heavy manual feature engineering efforts [19]. making them suitable for time series forecasting applications. These models are especially useful in financial applications where past price movements and trends significantly influence future predictions. Moreover, Convolutional Neural Networks have been applied to financial data by treating time series data as a form of image or sequence, allowing network to learn spatial and temporal features simultaneously. Hybrid models combining LSTM or GRU with other techniques, such as CNN or attention mechanisms, have also shown promise in improving forecasting accuracy.

Even with all these benefits, deep learning models have some of their drawbacks, especially during optimization. Generally, training deep neural networks requires that many hyperparameters be tuned to optimal values [20]. The process is tedious and may take a significant amount of computer time. Swarm intelligence techniques come into the field. These types of algorithms inspired by natural phenomenon, like how birds fly as a flock, or ants as they search for their food, usually are capable of effectively exploring these complex, high-dimensional search spaces. As a result, swarm intelligence algorithms can best be applied when optimizing hyperparameters in deep models for financial tasks.

Particle Swarm Optimization is perhaps the most frequently applied technique among swarm intelligence to optimization [21]. The basic principle is similar to a bird's flocks searching for food; every particle in the swarm searches a space and updates its neighbors, so over time, it is attracted toward an optimal solution. In the deep learning context, so far, ACO has been successful in solving a lot of problems, especially optimizations within various fields and deep learning model optimization. Swarm intelligence also comes in several flavors, where methods like the Artificial Bee Colony and Firefly Algorithm are quickly being adopted within machine learning optimization.

Although swarm intelligence-based optimization has been shown to produce promising results, the current literature is still characterized by several gaps [22]. Traditional financial forecasting models cannot capture the complexity and non-linearities of financial data. Deep learning models improve the accuracy but require efficient optimization techniques to be realized fully. Swarm intelligence algorithms are very effective in optimizing hyperparameters, but they may also have some convergence speed and local minima issues, especially when applied to large-scale financial datasets. Moreover, the research conducted so far lacks a comprehensive comparison of different swarm-based optimization techniques in the context of financial forecasting, leaving a gap in understanding which algorithms perform best under various conditions. Further, this is an area where swarm intelligence is integrated into deep learning models, and more research is necessary to understand optimal synergy between these powerful techniques in the context of financial forecasting.

It is possible to do the stock price forecasting as well as market volatility prediction by means of classical techniques such as ARIMA and GARCH models, which however rely on linearity assumptions [23]. However, most of the inherent complexities in the relationships are of non-linear kind and cannot, therefore, be caught. Though exponential smoothing and vector autoregressions have been popularly applied in time series modelling for forecasting, they tend to fail with huge datasets and in the presence of non-linear relationships, demanding great domain knowledge in their proper usage but bring their own problems of hyperparameter selection and overfitting. Deep learning techniques, especially LSTM and GRU networks, have been promising for capturing long-term dependencies of finance-related data, and CNN-LSTM hybrid models further improve the accuracy of the forecast. Optimization problems for deep learning models are a challenge, especially hyperparameter tuning, algorithms which are inspired by natural phenomena, are successfully applied for the optimization of hyperparameter settings of deep learning models. Yet, there is still a number of gaps in the literature; for example, how to combine swarm intelligence with deep learning in financial forecasting. Hence, further research is required in order to delve into their optimal synergy and faster convergence to the solution when dealing with large datasets.

III. Problem Statement

Financial forecasting is one of the critical tasks for the prediction of market trends, stock prices, and economic indicators; however, ARIMA and GARCH methods have often failed to capture the intricate, non-linear relationships that exist in financial data [16]. These models rely heavily on linear assumptions and cannot adapt well to the dynamic nature of financial markets. The predictive accuracy of such methods decreases when used on financial data that exhibits volatile behavior together with elevated dimension. Though, decision trees, LSTM, and GRU show improvements in the accuracy of forecasts, yet there is much room for improvement. For example, in optimizing hyperparameters and dealing with the large data sets, there are many challenges in ML as well as DL. Hence, with the objective of maximizing the precision and efficiency of the models, researchers have explored the swarm intelligence technique to optimize deep learning models. The techniques include PCO and ACO. Still, the lack is a deep and detailed insight about how such swarm-based optimization can be employed in enhancing deep learning models used for financial forecasting of large and highly dimensional data sets.

IV. Methodology for Enhancing Financial Forecasting Using Swarm-Optimized Deep Learning Models

A framework based on the LSTM would be proposed for financial forecasting along with Particle Swarm Optimization. The method begins with aggregating different datasets of finance, including historical stock prices, commodity prices, trading volumes, and various economic indicators, such as interest rates and GDP growth rates, from the Kaggle site. The preprocessed data were handled for missing values, outliers, and min-max scaling. The time-series data is assigned to sequences, whereas technical indicators are engineered in such a way that it helps in the capture of market dynamics, including moving averages and volatility indices. This information is then cleaned up and structured in order to prepare for the training of the LSTM network. Since the LSTM can capture long dependencies in addition to extracting temporal patterns within financial data, it is able to predict complicated patterns in the marketplace. The model performance is optimized using PSO by fine-tuning such as the learning rate, batch size, and number of LSTM layers. In PSO, particles represent different combinations of hyperparameters. Their fitness can be evaluated by using Mean Squared Error. The positions and velocities of particles are updated iteratively based on the bestknown solutions of the particles and the global best position. The process continues until the convergence criteria are met, and then the best hyperparameters are selected. The optimized LSTM model is then retrained on the entire dataset for accurate forecasting of stock prices, commodity trends, and market dynamics. This hybrid methodology addresses the noisy, non-linear nature of financial data effectively and thus ensures reliable predictions for decision-making in the financial domain. Fig. 1 shows proposed methodology flow.

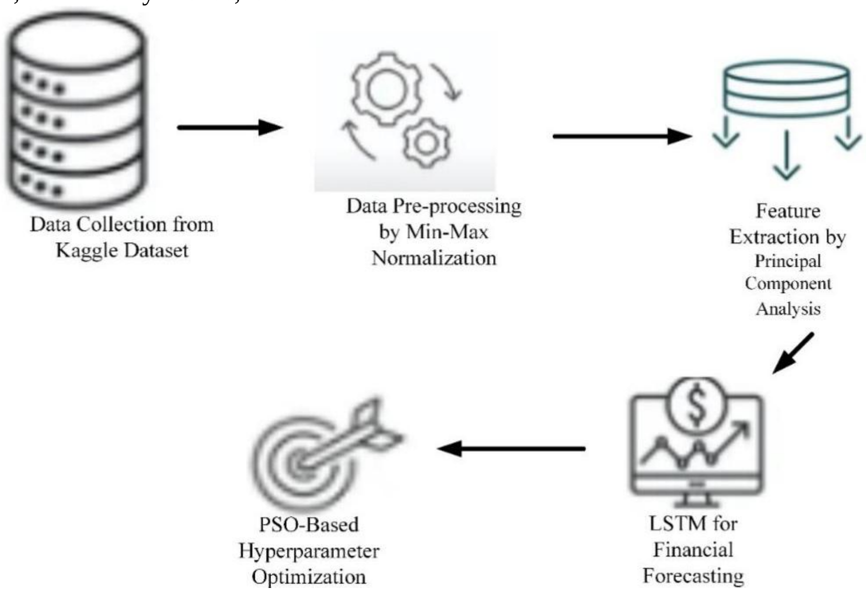

Fig. 1. Proposed methodology flow.

A. Data Collection

Kaggle was used to source financial data, which includes a very large number of datasets that are relevant in forecasting the market trends and prices of stocks and commodities [24]. This dataset includes historical stock prices with their daily closing values, trading volume, volatility indices, and commodity prices on major assets such as gold, oil, and agricultural commodities. These consisted of some data related to economic indicators, for instance, interest rates, inflation, and rate of GDP growth. Each dataset was chosen to represent different sectors, hence ensuring an all-rounded approach to financial forecasting. Furthermore, the data covered quite diverse time ranges, spanning from several months to years, providing short- and long-term fluctuations to train DL models.

B. Data Pre-Processing

The financial data went through preprocessing for suitability with deep learning models. Missing values were imputed or removed based on their prevalence and outliers were found and dealt with to avoid distortions in model predictions. The numerical features underwent min-max normalization, which rescales them into a fixed range, usually 0 to 1, with the equation

$$Xnormalized = \frac{X - Xmin}{Xmax - Xmin} \tag{1}$$

Where, X is original value, $Xmin$ is the minimum value in the feature, and $Xmax$ is maximum value in the feature. It also ensured that every feature contributes in a balanced way to play out in the model to avoid magnitude issues across the variables involved in the different ways. Time series was arranged as sequences to accommodate time dependencies. Other derived features include moving averages, volatility indices, and many more technical indicators.

C. Feature Extraction by PCA

In financial forecasting, Principal Component Analysis can be used for feature extraction: a dimensionality reduction technique that simplifies complex datasets by transforming high-dimensional data into a smaller set of uncorrelated features while retaining most of the variance. These components capture the most important information in the dataset, allowing for a more compact representation while reducing noise and redundancy. By retaining only, the top principal components that explain the majority of the variance, PCA reduces the dimensionality of the dataset, making it more computationally efficient for training machine learning models.

In financial data, PCA helps to find hidden patterns and relationships among variables, such as correlations between different asset classes or dependencies between macroeconomic indicators and market movements. For instance, applying PCA to a dataset of stock prices from different sectors might uncover composite features that are indicative of sector-specific trends or market-wide movements. These orthogonal and uncorrelated transformed features help avoid problems like multicollinearity, which might skew predictions in traditional models. Moreover, PCA allows the focus to be on only the most relevant features, thereby improving the generalization capability of deep learning models, and subsequently, the accuracy of forecasts. In general, PCA is an invaluable tool for extracting meaningful features from high-dimensional financial data, enabling models to better capture the complex, nonlinear relationships inherent in financial markets.

D. LSTM for Financial Forecasting

For financial forecasting, LSTM have been chosen as the primary deep learning model as it captures the long-term dependency in time series data. LSTM is a special kind of RNN specifically designed to avoid the vanishing gradient problem while training traditional RNNs on long sequences. Unlike traditional RNNs, an LSTM network uses an architecture that consists of memory cells which retain information for a long time. This makes the LSTMs particularly suitable for financial forecasting purposes, where trends and patterns formed in the past are crucial factors in predicting future movements in the markets. By allowing for preserving very important historical information, LSTMs can model complex temporal dynamics and nonlinear relationships often presented in financial time series. Fig. 2 shows architecture of LSTM.

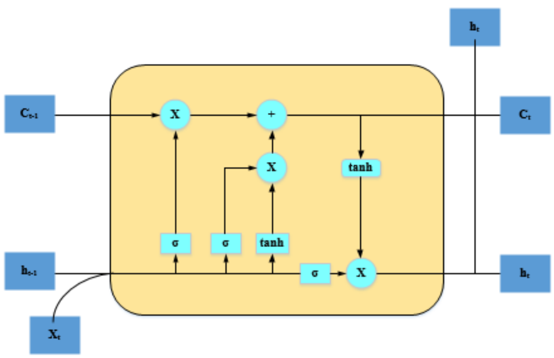

Fig. 2. LSTM architecture.

Gating structures are what essentially make an LSTM network's core mechanism to control the information flow.

Forget gate:

$$ft = \sigma(Wf \cdot [ht - 1, xt] + bf) \tag{2}$$

Input gate:

$$it = \sigma(Wi \cdot [ht - 1, xt] + bi) \tag{3}$$

$$\tilde{C}t = tanh(WC \cdot [ht - 1, xt] + bC) \tag{4}$$

Output gate:

$$ot = \sigma(Wo \cdot [ht - 1, xt] + bo) \tag{5}$$

The final output is given by:

$$ht = ot \cdot tanh(Ct) \tag{6}$$

where $\tilde{C}t$ is the cell state, which is updated at each time step.The use of LSTM in financial forecasting is justified due to its capability of modeling long-term dependencies in sequential data. Hence, the ideal application would be in the tasks of stock price prediction, commodity price prediction, and market trend prediction. A variety of factors determines the course of financial markets. These factors range from historical price movements, macroeconomic events, and market sentiment. They typically have complex, non-linear relationships that most traditional models cannot capture. The memory units in LSTM networks enable them to learn and memorize relevant patterns from long sequences of financial data, which allows it to make more accurate predictions. Additionally, LSTMs are more resilient to noisy and sparse data that is commonly found in financial time series and can adapt to changing nature of financial markets, and thus this could prove to be a more reliable forecasting tool than other deep learning models.

E. PSO-Based Hyperparameter Optimization

In the case of optimization of hyperparameters in this problem of deep learning models used for financial forecasting, there have been employed swarm intelligence algorithms, more specifically Particle Swarm Optimization. Inspiration for this algorithm comes from the behavior of birds or fish, with each determining its position using its previous experience and the whole swarm's experience. In the context of deep learning, the particles can be thought of as different sets of hyperparameters, such as learning rate, number of hidden layers, and batch size. The optimization procedure is meant to find the hyperparameters that optimize the error or loss function for the model being optimized, and hence enhance the accuracy of forecasting.

The fitness function in PSO evaluates the performance of each particle based on the predictive accuracy of the deep learning model. The fitness function can be expressed as:

$$f(\theta) = \frac{1}{N}\sum_{i=1}^{N}(yi - y^\wedge i)2 \tag{7}$$

where f(θ) is the fitness function (MSE), yi is the actual value, $y^\wedge i$ is the predicted value, and N is the number of data points in the test set. The particles in the swarm move through the hyperparameter search space, adjusting their positions based on the evaluation of this fitness function. The position update equation for each particle is given by:"

$$vit + 1 = wvit + c1r1(pi - xit) + c2r2(g - xit) \tag{8}$$

$$xit + 1 = xit + vit + 1 \tag{9}$$

where $vit + 1$ is the velocity of particle iii at time t+1, xit is the position of particle iii at time t, pi is the best position found by particle i, g is the global best position, www is the inertia weight, c1 and c2 are acceleration constants, and r1 and r2 are random values between 0 and 1."

The integration of the model will be refined along with its functionalities by stakeholder feedback. Informed insights by the end-users such as the bank managers and analysts will point to the flaws that need correction regarding the prediction quality and the operational usability of the model. The feedback obtained through this exercise will be used to make further adjustments to the model or its deployment pipeline, making it more useful and effective.

F. Algorithm for Enhancing Financial Forecasting Accuracy Using Swarm-Optimized Deep Learning Models

The article will discuss how the Long Short-Term Memory network combined with Particle Swarm Optimization for hyperparameter tuning, gives a good approach to the robust methodology in financial forecasting. Diverse datasets were collected on Kaggle containing stock prices, trading volumes, commodity prices, and some economic indicators. The quality of data is guaranteed through preprocessing as it takes care of missing values, removes outliers, normalizes numerical features with min-max scaling, and formats time-series data into sequences. The process of feature engineering improves the model's predictability by extracting technical indicators such as moving averages and volatility indices. A memory cell-based LSTM model is initiated, which helps to retain the temporal dependencies within the data.

The PSO algorithm describes a search space for hyperparameters, which consists of parameters such as learning rate, batch size, and the number of LSTM layers utilized in the model. Particles are the combined hyperparameters initialized with random positions and velocities. Every particle evaluates its fitness in the LSTM model through the Mean Squared Error to measure its performance. This personal best and global best update the position and velocity of the particles through iterations moving towards an optimal solution. These iterations continue either until convergence or the number of maximum iterations is reached. These best hyperparameters that are selected by PSO are then used to train the LSTM model with better accuracy for many financial forecasting tasks. This approach holds promise to develop advanced architectures of neural networks and optimization algorithms to produce a very powerful framework in the predictive modeling application domain. Fig. 3 shows algorithm for enhancing financial forecasting accuracy using swarm-optimized deep learning models.

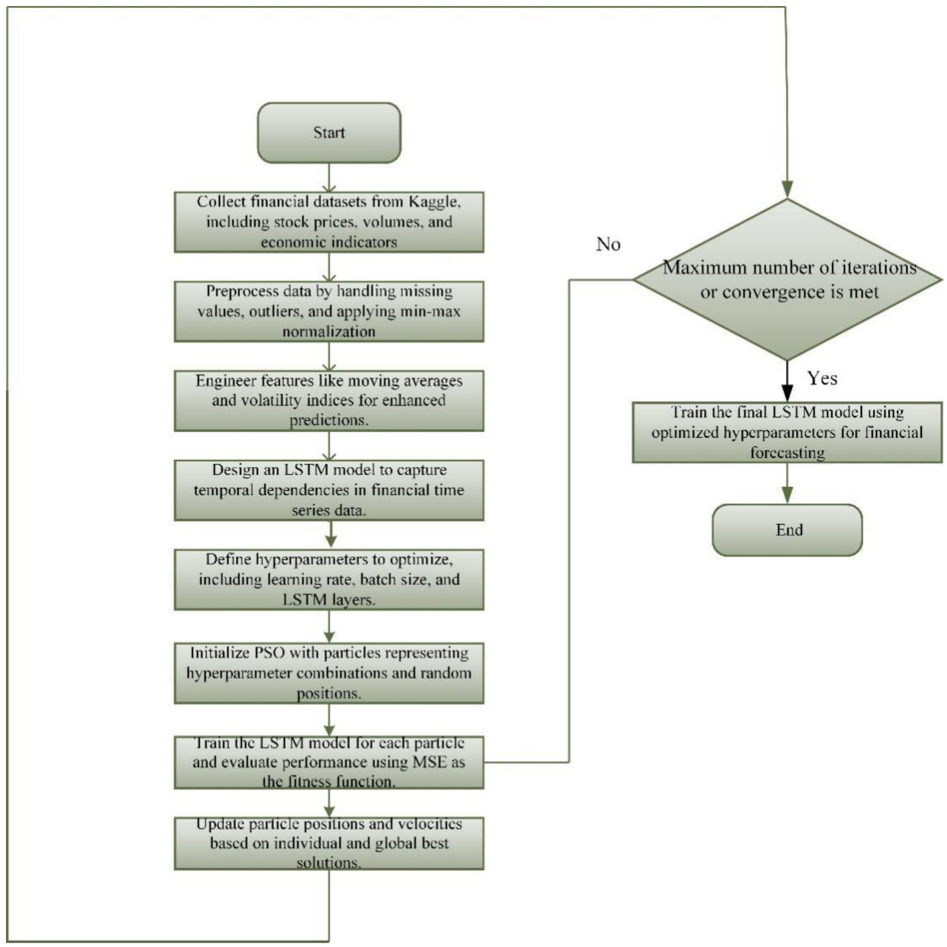

Fig. 3. Algorithm for enhancing financial forecasting accuracy using swarm-optimized deep learning models.

V. Results and Discussion

The results of the optimization process are the improvement in the values of the fitness function through the months and, therefore, the appropriateness of PSO optimization for the LSTM model. Because the value started from 0.5 in December and moved upward to peak at 0.9 in June, it definitely means that the optimization process was successful in fine-tuning the parameters of the model in course of time. This variability in the fitness values during the months reflects the dynamic nature of optimization and shows times of stability as well as improvements. Overall, the results are seen to prove that the PSO technique guides the model toward better performance, which makes it an appropriate technique for optimizing LSTM models. The results of the optimization process reveal the improvement of fitness function values through the months and, hence, the suitability of PSO optimization for the LSTM model. Since the value began at 0.5 in December and moved upwards to peak at 0.9 in June, it clearly means that the optimization process was a success in tuning the parameters of the model in course of time. The fluctuations in fitness values throughout the months reflect the dynamic nature of the optimization, with periods of stability and improvement. Overall, the results show that the PSO technique effectively guided the model towards better performance, confirming its suitability for optimizing LSTM models. Fig. 4 shows training and validation loss.

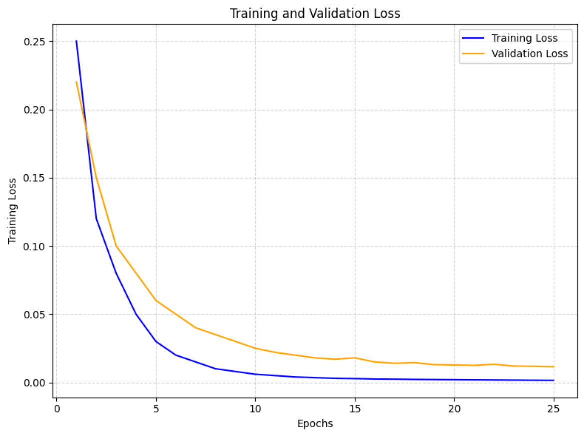

Fig. 4. Training and validation loss.

The Fig. 4 shows the trend of "training and validation" loss for 25 epochs, showing how the model is learning and its generalization. The training loss (blue curve) steadily drops with increasing epochs, starting at 0.25 and gradually dropping down to 0.0015, showing good optimization of the model on the training data set. The validation loss (orange curve) drops from 0.22 to 0.0115, indicating better performance on unseen data with stability. Both curves exhibit convergence after a certain point, with minimal divergence between them.

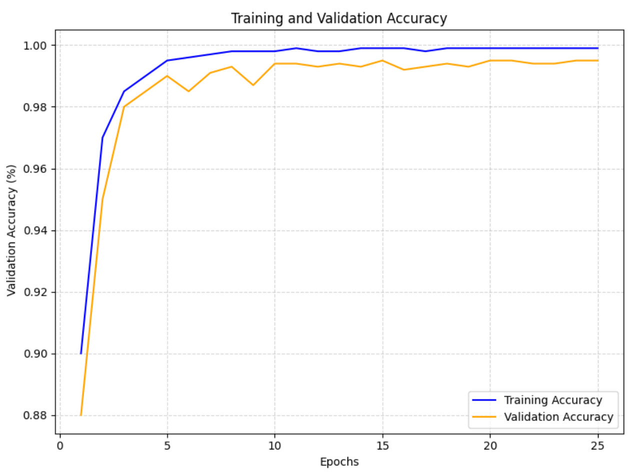

Fig. 5. Training and validation accuracy.

The Fig. 5 depicts the training and validation accuracy over 25 epochs, highlighting the model's performance improvement. The training accuracy (blue curve) starts at 0.9 and quickly reaches a plateau near 0.999, demonstrating the model's effective learning of the training data. Validation accuracy (orange curve) shows a steady increase from 0.88 to 0.995, reflecting the model's strong generalization to unseen data. Although the validation accuracy does fluctuate slightly, overall convergence of the two curves is seen, showing that the model has a good accuracy without major overfitting. The clarity and readability are further enhanced by the well-labeled axes, grid, and legend.

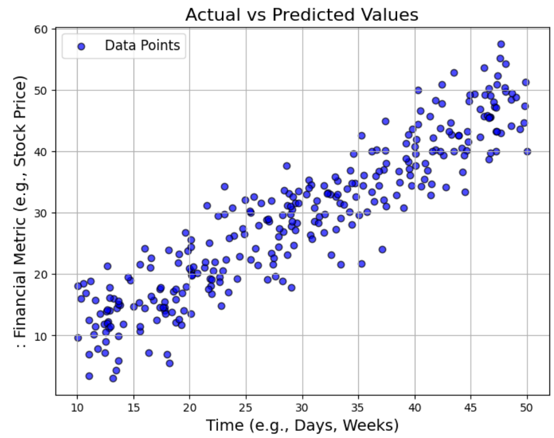

Fig. 6. Scatter plot graph.

Fig. 6 depicts the actual and predicted values of a financial metric, such as stock price, over time, for example, days or weeks, using 300 data points. Each blue dot represents a data point, with slight noise added to the predictions for realism, highlighting variability. The grid and clear axis labels enhance readability, while the title and legend provide context.

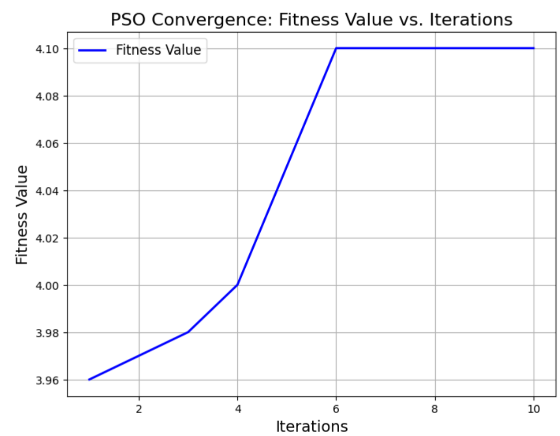

Fig. 7. PSO Convergence graph.

Fig. 7 is given for the convergence of PSO. Fitness values are plotted here with the number of iterations, from 1 to 10. From the graph, it seems the fitness values improved step by step and were steady after a few iterations at 3.96 and stabilizing at 4.10. It has iteration labels and fitness values along with the grid and the legend so that optimizations and stability can be monitored in later iterations.

Fig. 8 demonstrates the results of a hyperparameter sensitivity analysis by plotting the model accuracies against changes in the learning rate. It compares four models (A, B, C, D), with each model's accuracy being evaluated at different hyperparameter values, ranging from a -50% change to a +50% increase. The plot clearly shows how each model's performance varies with the changes in the learning rate, indicating the sensitivity of their accuracies. The graph includes a grid for better readability, labels for the axes, and a legend to differentiate the models, helping to identify the most robust model in response to hyperparameter adjustments.

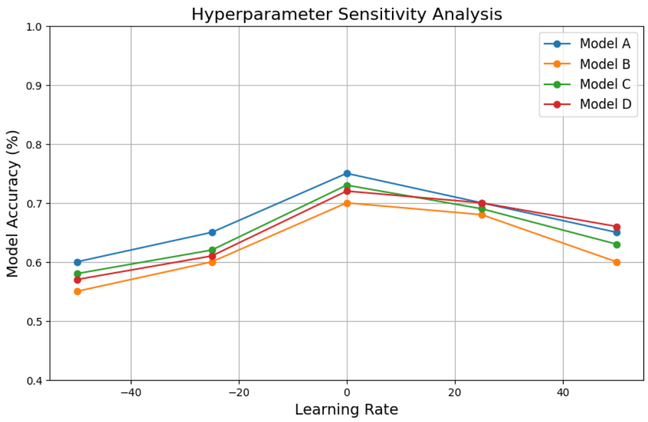

Fig. 8. Hyperparameter sensitivity analysis.

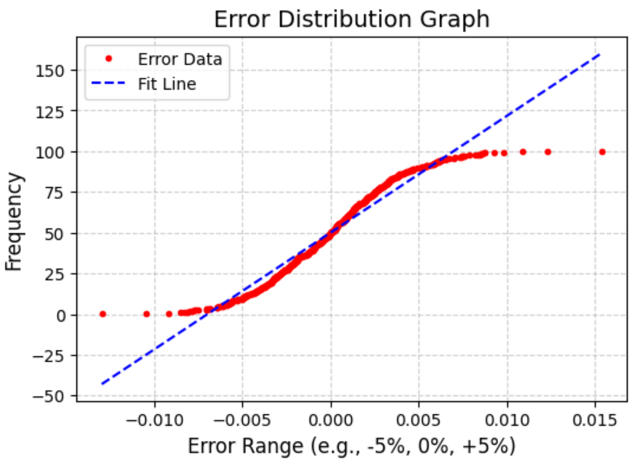

Fig. 9. Error distribution graph.

Fig. 9 is a representation of the error-value distribution-it increases the amount of cumulative percentage of errors in different ranges. The simulated data of the errors, which have been derived with a normal distribution, has been created as a red scatter, for which the cumulative frequency of errors is sorted from lowest to highest. A best-fit linear model in blue dashed line is used for depicting the trend in the data. This error distribution graph helps to understand the behavior of error values across a range, highlighting how often errors occur within specific ranges and how they are distributed. The grid and legend enhance the graph's readability and context, while the labels define the axes for clarity.

Fig. 10 represents the convergence of the PSO for an LSTM model across different months. It showcases the change in the fitness function values over the months from December to June, with the fitness values fluctuating from 0.5 to 0.9. The black line with markers indicates how the optimization process goes, showing an unambiguous view of improvements in fitness and stability throughout iterations. The graph has been augmented using labels, a grid to enhance readability, and a legend to enable data context.

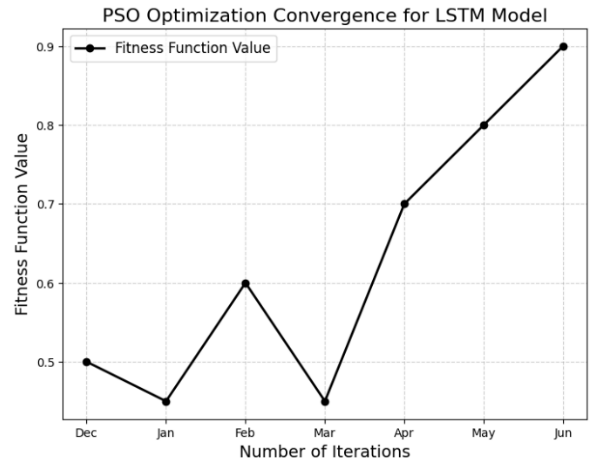

Fig. 10. PSO Optimization convergence for LSTM model.

A. Performance Evaluation

Performance of the model is evaluated using several metrics. Metrics like accuracy, precision, recall, and F1-score are represented in Eq. (10), (11), (12), and (13).

$$Accuracy = \frac{\text{Tpos+Tneg}}{\text{Tpos+Tneg+Fpos+Fneg}} \tag{10}$$

$$Precision = \frac{Tpos}{Tpos+Fpos} \tag{11}$$

$$Recall = \frac{Tpos}{Tpos+Fneg} \tag{12}$$

$$F1 - Score = \frac{2\times precision \times recall}{precision \times recall} \tag{13}$$

The performance evaluation table which thus present the superiority of the proposed approach. Accuracy of 80% was seen along with the precision of 85% and recall at 79% while using the CNN model.

TABLE I. PERFORMANCE COMPARISON OF VARIOUS METHODS WITH PROPOSED METHOD

Method	Accuracy	Precision	Recall	F1- Score
CNN [25]	80	85	79	80.6
RNN [26]	83	76	78.7	86
GBM [27]	95.6	95	86.8	78
Proposed Method	98	96.7	95.9	96.78

The F1-score turned out to be 80.6%. RNN had improved to a small level in the aspect of accuracy at 83%. The precision, recall, and F1-score values were 76%, 78.7%, and 86%, respectively. The GBM model performed better than CNN and RNN with an accuracy of 95.6%, though the recall was less at 86.8% and took an F1-score of 78.

Fig. 10, performance evaluation of the models: CNN, RNN, GBM, is shown in comparative metrics in terms of accuracy, precision, recall, and F1-score. In order to explain better, all the models are drawn in the form of individual bars according to these four parameters. The Proposed Method has maximum values in every category: accuracy is 98%, precision is 96.7%, recall is 95.9%, and F1-score is 96.78%. In the second stage, GBM also performed outstandingly with accuracy at 95.6% and precision at 95% but an F1-score of 78, that is, less because it tends to be too imbalanced to precision as against recall. The RNN model is exhibiting accuracy of 83% and precision at 76% with higher recalls at 78.7%, but its F1-score of 86 is high. The CNN model ranks lower on all the metrics, having an accuracy of 80%, precision of 85%, and recall of 79%, which gives it an F1-score of 80.6%.

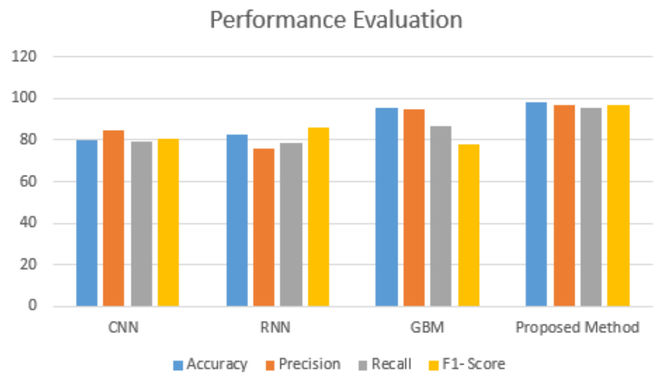

Fig. 11. Performance evaluation.

B. Discussion

The performance evaluation results here show that the Proposed Method performs better than other models in all the critical metrics: accuracy, precision, recall, and F1-score; thereby strongly demonstrating its robust and well-rounded performance. With 98% accuracy and 96.7% precision, and with a recall of 95.9%, the predicted positives have both strong prediction power and reliability. This further shows its ability to balance between precision and recall with a high F1-score of 96.78, which is the reason for using this model when there is a requirement for both high accuracy and reduction in error. The GBM model, although having good accuracy at 95.6% and precision at 95%, it lacks a high F1-score due to the lower recall value of 86.8%. The RNN, though performing well in recall (78.7%) with a high F1-score at 86, is low on accuracy and precision. The CNN model, even though useful in some sense, is not of the same standard and has the least performance across the board. Based on these performance metrics, one can infer that the Proposed Method represents a better fit for the purpose, providing an optimal balance in terms of both precision and recall as well as overall accuracy. The proposed swarm-optimized deep learning framework significantly decreases the error of financial time series predictions that are higher than of traditional models in dealing with market volatility and high-dimensional relations.

VI. Conclusion and Future Work

The Proposed Method had superior performance across all key evaluation metrics and outperformed the traditional models: CNN, RNN, and GBM. High-accuracy, precision, recall, and F1-score levels show that the proposed method is truly effective in solving the problem addressed. This means the proposed method can be relied on for real-world applications requiring strong accuracy and reliability. The experiments show that choosing an optimized approach is very important to achieve not only improved performance but also the right trade-off between precision and recall, which is very significant in many practical scenarios.

Future study will consider reinforcement learning-based financial predictive models to increase adaptability across various market environments. Other deep architectures, such as hybrid models that incorporate the strengths of CNN, RNN, and GBM, will be explored. By incorporating techniques such as transfer learning and model pruning, it might improve the efficiency and scalability of the model for real-time application. Further, widespread testing on larger and more diverse datasets would be extremely important to test the robustness of the model and to ensure its application potential in a broader spectrum of real-world challenges. Real-time forecasting programs built with this framework structure would create practical financial institution applications to optimize decision processes.

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