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FULL LENGTH ARTICLE

Financial Sector-Ready Framework for Corporate Performance Forecasting Using Football Optimization

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ABSTRACT

In today's interconnected global economy, accurate financial forecasting is critical for strengthening corporate decision-making, mitigating investment risks, and maintaining competitive advantage over the long term. Traditional forecasting models often struggle with the complexities of high-dimensional and nonlinear financial data. To address this challenge, we present a hybrid forecasting framework that integrates advanced machine learning techniques with an intelligent optimization algorithm. Specifically, the model combines Long Short-Term Memory (LSTM) networks with the Football Optimization Algorithm (FbOA) to optimize key features and tuning parameters. This approach yields more stable, efficient, and accurate financial predictions using a compact set of influential variables. The proposed framework offers a cost-effective solution for corporate finance applications, enhancing investor confidence and supporting strategic economic development. By bridging cutting-edge AI methodologies and practical financial analytics, this study highlights the transformative potential of hybrid models in reshaping financial forecasting in dynamic markets.

Keywords: Economic and Financial Forecasting ▪ Metaheuristic Optimization in Finance ▪ Football Optimization Algorithm (FbOA) ▪ Deep Learning for Financial Analytics ▪ Corporate Economic Performance

1. INTRODUCTION

The objects of economic and financial development lie in the centre of sustaining growth, enhancing competitiveness, and reducing exposure to external shocks in the new generation of globalization [1, 2, 3]. The global sustainability targets also require companies to streamline their operations in terms of profitability, resource efficiency, and long-term resilience [4]. This twofold goal of financial performance and sustainability has made financial foresight a key instrument among firms that wish to balance maximizing shareholder value with obligations to development aims worldwide [5, 6].

Financial resilience and predictive financial analysis are essential factors in this regard. Like predictive maintenance in engineering, which aids in preventing expensive failures, predictive financial systems enable companies to anticipate risks, prevent losses caused by market changes, and reduce inefficiency in the capital allocation process through sophisticated predictive methods [7, 8]. Early detection of financial weaknesses, such as liquidity constraints, high levels of debt exposure, or falling return on equity, may save sig-

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nificant costs in restructuring or crisis recovery. For major global enterprises, financial analysis extends beyond quarterly reporting, informing strategic investment, shareholder governance, and decision-making that aligns with long-term sustainability goals. Firms that continually incorporate financial projections and economic realities are better positioned to attain operational solvency, minimize uncertainty, and remain competitive in turbulent international markets [9].

Financial markets today are characterized by significant volatility and complexity, influenced by rapid technological advances, geopolitical events, and evolving regulatory frameworks. Accurate forecasting of key financial indicators—including earnings, valuation metrics, and risk exposures—is vital for corporate leaders, investors, and policymakers to make informed decisions. Superior predictive models contribute to optimizing capital allocation, improving risk-adjusted returns, and enhancing firm valuation. Incorporating sustainability dimensions such as environmental, social, and governance (ESG) factors into financial forecasting has become critical, responding to growing demands for responsible investment and transparency. These dynamics highlight the pressing need for robust, interpretable, and scalable forecasting tools to navigate complex financial landscapes and promote long-term economic growth.

Despite its importance, financial analysis in large multinational firms faces significant challenges. The primary hurdle is the high dimensionality of data: firms generate vast, heterogeneous datasets encompassing revenues, expenditures, capital structures, market risks, and sustainability metrics [10]. Processing, managing, and interpreting such big financial data requires sophisticated models capable of capturing nonlinear relationships, complex interdependencies, and evolving market conditions. Moreover, decision-making must integrate both traditional financial indicators and emerging ESG considerations, escalating analytical complexity. These challenges call for rigorous, computationally efficient methodologies [11, 12]. Traditional econometric techniques often fall short under these conditions, motivating the adoption of advanced machine learning and metaheuristic optimization approaches [13].

The present research aims to develop and evaluate predictive models capturing the economic and financial dynamics of top global enterprises [14]. By analyzing and benchmarking various forecasting and optimization methods, the study seeks to enhance prediction accuracy for major financial variables, improve cost-effective risk management, and inform corporate strategy and investment decisions. This work contributes a comparative framework elucidating how advanced modeling techniques can reinforce corporate stability and profitability while aligning with sustainability goals. Importantly, it underscores the role of optimized predictive analytics in building investor trust and supporting sustainable economic development.

The key contributions of this study are summarized as follows:

- We introduce the Football Optimization Algorithm (FbOA), a novel metaheuristic optimizer addressing challenges in feature selection and hyperparameter tuning for high-dimensional financial datasets. FbOA enhances model flexibility in complex corporate finance forecasting.
- We propose an integrated optimization framework where FbOA simultaneously optimizes data representation and model architecture, achieving more precise and efficient predictions. This joint optimization improves model interpretability and stability.
- We benchmark FbOA against state-of-the-art optimization techniques and demonstrate its superiority in achieving enhanced forecasting accuracy and robustness across financial prediction tasks.
- We highlight the practical impact of FbOA-driven optimization in economic contexts, showing its potential for improving corporate decision-making, risk assessment, portfolio management, and long-term value creation.
- We present a comprehensive comparative analysis bridging metaheuristic optimization with advanced deep learning models, offering novel insights into the future of predictive analytics in finance, particularly for forecasting, valuation, and sustainability integration.

The remainder of the paper is organized as follows. Section 2 reviews related literature on corporate financial forecasting, sustainable finance applications, and metaheuristic optimization advances. Section 3 details the datasets, preprocessing, modeling architectures, optimization strategies, and evaluation metrics. Section 4 presents experimental results, including model benchmarking, feature selection, and optimization performance. Section 5 discusses findings in the context of previous work and outlines limitations. Finally, Section 6 concludes and suggests directions for future research.

2. LITERATURE REVIEW

Current developments in artificial intelligence (AI), machine learning (ML), and deep learning (DL) have unveiled a revised picture in economic forecasting, financial modeling, and digital innovation. Specifically, models that combine the learning strategies of neural architectures and ensemble learning are emerging as a leading paradigm, offering advantages in both accuracy and adaptability over more conventional methods [15]. Such hybrid designs are being extended to various economic sectors, including corporate banking, e-commerce, stock markets, and cryptocurrency, reflecting their broad applicability in highly nonlinear and complex environments. These advances also indicate a consistent trend toward more advanced deep learning frameworks that utilize cross-computational framework synergies.

Another important line of research focuses on forecasting economic variables related to resources. Machine-learning methods, including artificial neural networks and the Facebook Prophet model, have been applied effectively to forecast strategic mineral-resource prices [16]. These methods can improve prediction accuracy and support economic planning, investment-risk assessment, and policy analysis in resource-dependent markets.

In financial markets, one of the most challenging and impactful applications of AI is the prediction of stock movements. Financial time series do not follow predictable patterns and are worsened by external shocks and fluctuating trading conditions, which demand event-based and macroeconomic in-

formation to enhance predictions [17]. Hybrid frameworks, including autoencoders (AEs) and kernel extreme learning machines (KELMs), have shown impressive improvements in predictive accuracy across various stock indices, providing powerful results even in the high-frequency regime [18]. The increased importance of sustainability-related indicators is also emphasized in work on RU-LSTM models, which combine ecological data with traditional characteristics to demonstrate the mutual dependency of ecological investment strategies [19]. The effectiveness of recurrent architectures is further validated by comparative studies; gated recurrent units (GRUs) are often more effective than LSTM networks, especially in prediction speed and training efficiency for technology-sector forecasting [20].

Beyond technical innovations, survey studies emphasize the importance of methodological diversity and reproducibility. These reviews highlight the need for broader datasets, standardized evaluation metrics, and replicable neural-network designs to support more transparent and generalizable research outcomes [21]. Comparative assessments of reinforcement learning, sentiment analysis, and hybrid models also illustrate how financial forecasting benefits from capturing behavioral and psychological dimensions of market dynamics [22]. Taken together, these findings highlight both the promise and limitations of current approaches, underscoring the need for more integrated frameworks that balance statistical rigor and interpretability.

At a macroeconomic level, AI technologies are increasingly recognized as transformative forces reshaping productivity, innovation, and global competitiveness [23]. Cognitive computing has been shown to enhance operational efficiency across industries ranging from healthcare to manufacturing, while simultaneously raising questions about labor displacement, regulation, and ethics. This duality reflects AI's paradoxical role as both a driver of economic growth and a disruptor of traditional socioeconomic structures.

The literature also extends to small and medium-sized enterprises (SMEs), where combining ensemble ML techniques with explainable AI (XAI) frameworks such as SHAP and LIME has enabled more reliable and transparent growth predictions [24]. These tools are particularly valuable for addressing data imbalance, feature selection, and regional heterogeneity. In developing economies, the digital revolution has amplified the predictive power of AI, with artificial neural networks outperforming conventional models in forecasting financial markets influenced by variables such as Bitcoin prices, coal, and renewable-energy indices [25]. On a more microeconomic scale, AI has also been applied to assess financial literacy among youth, offering cost-effective and scalable approaches for identifying at-risk populations through advanced ML models such as gradient boosting and random forests [26].

Comprehensive surveys of ML and DL confirm their growing applicability across healthcare, agriculture, transportation, and other sectors, while identifying hybridization and generative AI as promising future research directions [27]. However, the adoption of AI in financial markets also highlights pressing concerns: regulatory frameworks, ethical considerations, workforce adaptation, and consumer-data protection remain significant barriers [28]. Consequently, although AI has proven its potential to enhance predictive accuracy and operational efficiency, its sustainable integration requires careful attention to governance and accountability. Overall, the reviewed literature presents both opportunities and challenges. Hybrid architectures and advanced deep learning methods are pushing the boundaries of predictive modeling, achieving levels of accuracy unthinkable with classical methods [29]. Yet transparency, interpretability, and ethical deployment remain central to future progress. The convergence of economic forecasting, sustainable finance, and AI-driven innovation thus represents fertile ground for continued exploration, with implications extending beyond technical performance into policy, regulation, and societal impact.

3. MATERIALS AND METHODS

The methodological design of this research combines deep learning architectures with optimization-based feature selection and hyperparameter optimization to maximize financial forecasting accuracy. This section describes the datasets, the preprocessing plan used to ensure data quality, and the experimental design for model development. Specific attention is paid to Long Short-Term Memory (LSTM) networks as the central forecasting model and the Football Optimization Algorithm (FbOA) as the feature-selection and hyperparameter-optimization mechanism. The proposed framework addresses high-dimensional, noisy, and nonlinear financial data by combining modern neural networks with metaheuristic optimization. The following subsections detail the data source, feature-engineering process, model configurations, optimization strategy, and evaluation metrics used to validate the approach.

3.1 Dataset Description

This research is based on a broad sample of the world's most successful enterprises, comprising 9,912 companies across industries and geographic locations. The dataset records extensive financial indicators that are crucial for measuring corporate performance and global economic position. These dimensions provide a comprehensive view of scale, profitability, market value, and growth potential. The main characteristics are summarized in Table 1.

The distribution of financial values shows that the dataset is highly heterogeneous. Profits range from negative values, indicating losses, to more than £228 billion, highlighting vast disparities among firms. Share prices range from below £2,000 to more than £16,500, reflecting variations in investor perception, liquidity, and equity structure. Market capitalisation similarly varies widely, with firms ranging from mid-sized companies to mega-cap companies valued at hundreds of billions of dollars.

Geographically, the dataset reflects the concentration of financial power: the United States hosts approximately 37% of the firms and exhibits dominance in international markets. India accounts for nearly 6%, while the remaining 57% are distributed across diverse countries, providing a basis for regional comparison. For analytical purposes, companies are grouped into ranges based on metrics such as rank, earnings, and price. This stratification enables visualization of firm concentration within financial bands and facilitates statistical exploration of relationships among earnings, valuation, and market performance. Such structuring supports the identifi-

Table 1. Core Features of the Dataset

Feature	Description
Rank	A numerical measure reflecting each company's position in terms of financial standing and overall performance.
Name and Symbol	Identifiers for each company, linking financial performance to brand recognition and market presence.
Earnings (TTM)	Earnings over the trailing twelve months, providing a measure of profitability and operational efficiency.
Price (GBP)	Market price per share, reported in British pounds, allowing cross-country comparability.
Country	Nation of incorporation, enabling country-level performance analysis and the study of regional economic dominance.
Market Capitalisation, P/E Ratio, and Dividend Yield	Broader financial metrics, derived and provided within the dataset, that indicate size, valuation, and investor confidence.

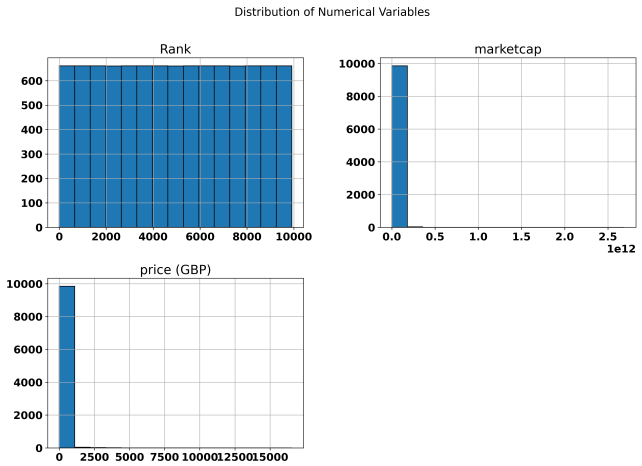


Figure 1. Distribution of numerical variables in the dataset.

cation of overarching trends related to investor confidence, regional leadership, and sectoral strength.

By integrating these multidimensional data, the dataset provides a robust foundation for comprehensive financial analysis. It enables benchmarking of individual firms, evaluation of country-level performance, identification of economic dominance within sectors, and exploration of the interconnected financial indicators that reflect global competitiveness and sustainability. To gain preliminary insights, it is essential to examine the statistical properties of numerical variables. Figure 1 illustrates the distribution of company rank, market capitalisation, and share price in GBP. The figure highlights significant heterogeneity and skewness, with concentrated market-capitalisation and price distributions and a more uniformly spread rank variable. These exploratory observations inform preprocessing and modeling strategies suitable for the dataset's complexity.

3.2 Data Preprocessing

The dataset underwent a series of preprocessing procedures to ensure precise, stable, and predictive financial analysis before model development. These steps address data quality and enhance the interpretability of findings. The data were first checked for missing values in features such as earnings, price, and market capitalization. Where gaps were identified, relevant imputation policies were used. Numerical variables were imputed using the mean or median according to distribution skewness, while categorical attributes such as country were imputed using their mode. This retained the richness of the dataset without excluding companies unnecessarily.

Some attributes, including company identifiers and categorical descriptors, were converted into machine-readable forms. Time-dependent variables were encoded in numerical order to preserve temporal explainability and allow the models to capture trends over time. Categorical variables such as country were one-hot encoded to avoid bias in regional comparisons.

To remove distortion caused by different measurement units, numerical features were rescaled. Share price and exchange-rate-sensitive variables were normalized or standardized. Normalization was used where proportionality was required, such as for dividend yields, whereas standardization was favored for variables with extensive ranges, such as earnings and market capitalisation. This ensured consistency across characteristics during optimization and increased the stability of gradient-based training.

3.3 Deep Learning Models

We utilized a set of deep learning models to extract intricate patterns in financial data. Each model offers advantages in processing sequential, structural, and nonlinear dependencies, making the models suitable for analyzing indicators including revenue, earnings, market capitalization, and stock prices. The Long Short-Term Memory (LSTM) network serves as the central forecasting system, while the remaining architectures are control models for comparison.

Artificial Neural Network (ANN): The ANN forms the core architecture of deep learning as a network of interacting layers of neurons. ANNs are useful in finance for modeling nonlinear relationships between inputs, such as earnings, prices, and ratios, and outputs, such as future valuation or growth projections. Their simplicity provides a convenient reference point for comparing more complex architectures.

Recurrent Neural Network (RNN): RNNs generalize the ANN architecture by adding feedback links that sustain information over time steps. This makes them suitable for sequential financial data such as stock-price histories or quarterly earnings. Traditional RNNs, however, often face vanishing or exploding gradients, limiting their performance on long sequences. They therefore serve as an intermediate benchmark in the comparative framework.

Convolutional Neural Network (CNN): Although traditionally applied to image data, CNNs have shown effectiveness in extracting spatial and local patterns from structured datasets. Applied to financial data, CNNs capture localized correlations among features, including interactions among valuation ratios, growth indicators, and market trends. Convolutional filters enhance feature representation and reduce noise, making CNNs a valuable comparative model for structured financial signals.

Proposed Model—Long Short-Term Memory (LSTM): LSTMs were introduced to overcome limitations of standard RNNs by incorporating memory cells and input, output, and forget gates. These mechanisms allow LSTMs to capture both short-term fluctuations and long-term dependencies in financial time series. In this study, LSTM is adopted as the

proposed forecasting model because it can effectively handle high-dimensional financial data, model nonlinear temporal dependencies, and provide robust predictive performance. Integrating LSTM with the proposed FbOA optimization framework further improves efficiency by simultaneously optimizing feature selection and hyperparameters. ANN, RNN, and CNN are therefore employed as benchmark models, while LSTM serves as the proposed architecture.

3.4 Metaheuristic Algorithms

Metaheuristic optimization techniques play a vital role in addressing the high dimensionality and nonlinear dynamics of financial datasets. They are particularly effective in feature selection, parameter tuning, and predictive-model optimization, where traditional deterministic approaches often fall short. In this study, several well-established algorithms are compared with the proposed FbOA method to evaluate their effectiveness in corporate financial forecasting.

FbOA (Proposed): The Football Optimization Algorithm is a novel metaheuristic technique inspired by the cooperative dynamics of a football team. FbOA models tactical strategies such as short passes, lob passes, and through-ball movements to simulate how agents (players) navigate and adapt in the solution space. This design enables FbOA to maintain a strong balance between exploration and exploitation.

- **Exploration:** The global search is expanded by distributing agents across different regions of the solution space, preventing premature convergence and ensuring diversity in financial-variable selection. The exploration phase is modeled as

$$V_n = F_{\max}\left[b_x a_i (F_{\text{ext}} - F_{\min}) + r b_y a_j (F_{\text{best}} - F_{\min}) \cos\left(\frac{\pi}{\text{Iteration}}\right)\right], \quad (1)$$

  where V_n denotes the velocity of agent n; $F_{\max}$ and $F_{\min}$ are maximum and minimum force; F_{best} is the current best solution; a_i and a_j are acceleration factors; b_x and b_y are directional coefficients; r is a random factor; and Iteration is the current iteration number.

- **Exploitation:** Once promising regions are identified, FbOA intensifies the local search by refining solutions, analogous to coordinated team play in a focused attack. The exploitation process is modeled as

$$F_b(S_{t+1}) = F_i + z_3 F_b(S_t) + K \sin\left(\frac{\pi}{\text{Iteration}}\right), \quad (2)$$

  where $F_b(S_{t+1})$ is the updated solution at iteration $t+1$; F_i is the current position; z_3 is a control parameter; K is an exponential factor that shifts focus from exploration to exploitation; and the sine term modulates convergence speed.

A mutation strategy further enhances robustness by injecting variability:

$$S(t) = K a_q \left(\frac{2n+1}{x}\right) + K \cos\left(\frac{\pi}{\text{Iteration}}\right), \quad (3)$$

where $S(t)$ denotes the mutated solution, a_q is a scaling factor, and the cosine function introduces stochastic diversity. By integrating these mechanisms, FbOA provides optimization mechanisms for both feature selection and hyperparameter tuning, making it suitable for high-dimensional, nonlinear financial forecasting problems [30].

HHO (Harris Hawks Optimization): Inspired by the cooperative hunting strategy of Harris hawks, HHO simulates surprise-pounce and chasing behaviors. In financial contexts, it is effective in capturing abrupt changes and adapting to dynamic market movements.

GWO (Grey Wolf Optimizer): GWO models the leadership hierarchy and hunting mechanisms of grey wolves. It is widely applied to feature selection and portfolio optimization, mimicking the balance between exploration and exploitation required in financial decision-making.

PSO (Particle Swarm Optimization): PSO is motivated by the social flocking behavior of birds and schooling of fish. Each particle modifies its path according to individual and collective experience, making PSO effective for tuning predictive financial-model parameters.

BA (Bat Algorithm): BA models echolocation behavior, allowing local and global searches to be dynamically adjusted. Financial applications include risk optimization and multi-objective investment problems.

WOA (Whale Optimization Algorithm): WOA is based on the humpback whale's bubble-net hunting strategy. It performs well on complex optimization topographies and in optimizing deep learning models for financial forecasting.

BBO (Biogeography-Based Optimizer): BBO is inspired by the migration and distribution of species in different environments. Its migration operator smoothly exchanges features, making it well suited to exploring financial data in high-dimensional spaces.

MVO (Multi-Verse Optimizer): MVO is founded on cosmological theories that simulate white holes, black holes, and wormholes. Its mechanism balances exploration and exploitation in optimization problems such as financial-risk modeling.

SBO (Satin Bowerbird Optimizer): SBO mimics the mating and nest-building behavior of bowerbirds. It includes probabilistic learning methods, making it suitable for feature selection and noise minimization in financial data. Comparing these algorithms with FbOA demonstrates the value of a strong exploration–exploitation balance in optimization-enabled financial analytics.

3.5 Evaluation Metrics

Two sets of metrics measure model performance: regression metrics assess predictive accuracy and reliability, while feature-selection metrics assess optimization efficiency. Together, they provide a holistic appraisal of forecasting quality and optimization. Regression metrics quantify errors, bias, correlation strength, and model efficiency based on observed and estimated financial values. The regression measures are summarized in Table 2.

Table 2. Regression Performance Metrics

Metric	Equation
Mean Squared Error (MSE)	$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
Root Mean Squared Error (RMSE)	$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
Mean Absolute Error (MAE)	$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$
Mean Bias Error (MBE)	$\text{MBE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)$
Correlation Coefficient (r)	$r = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}\sqrt{\sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2}}$
Coefficient of Determination (R^2)	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$
Relative RMSE (RRMSE)	$\text{RRMSE} = \frac{\text{RMSE}}{\bar{y}} \times 100\%$
Nash–Sutcliffe Efficiency (NSE)	$\text{NSE} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$
Willmott Index (WI)	$\text{WI} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(\lvert\hat{y}_i - \bar{y}\rvert + \lvert y_i - \bar{y}\rvert)^2}$

Feature-selection measures evaluate the quality of optimization for FbOA and the benchmark algorithms. Measures of error reduction, subset size, and fitness stability quantify the trade-off between accuracy and complexity. This is important in financial forecasting because selecting the most informative variables can improve interpretability, reduce overfitting, and increase computational efficiency. Table 3 summarizes the measures used.

Table 3. Feature Selection Metrics

Metric	Equation
Average Error (AE)	$\text{AE} = \frac{1}{N}\sum_{i=1}^{N}E_i$
Average Select Size (ASS)	$\text{ASS} = \frac{1}{N}\sum_{i=1}^{N}\lvert S_i\rvert$
Average Fitness (AF)	$\text{AF} = \frac{1}{N}\sum_{i=1}^{N}F_i$
Best Fitness (BF)	$\text{BF} = \min(F_1, F_2, \ldots, F_N)$
Worst Fitness (WF)	$\text{WF} = \max(F_1, F_2, \ldots, F_N)$
Standard Deviation of Fitness (StdF)	$\text{StdF} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(F_i - \text{AF})^2}$

In these equations, y_i and $\hat{y}_i$ denote observed and predicted values, $\bar{y}$ is the mean of observed values, F_i is the fitness value of the ith run, S_i is the selected subset, E_i is the error for the ith run, and N is the total number of independent runs.

4. RESULTS

This section presents the experimental findings obtained from implementing the proposed forecasting framework. The results are organized to highlight the comparative performance of different deep learning architectures, the impact of optimization-based feature selection, and the effectiveness of hyperparameter tuning in improving forecasting accuracy. Systematic evaluation across multiple metrics provides insights into predictive accuracy and computational efficiency. The results are also discussed in relation to their economic and financial implications, underscoring the practical relevance of the proposed approach for decision-making, risk management, and long-term strategic planning.

4.1 Baseline Model Comparison

To establish a performance benchmark, we first evaluated the baseline deep learning models without the proposed optimization strategy. Four widely used architectures—LSTM, CNN, RNN, and ANN—were trained on the financial dataset, and their predictive accuracy was assessed using the regression metrics introduced in Section 3.5. Table 4 summarizes the raw performance outcomes.

Table 4. Baseline Model Performance Metrics

Model	MSE	RMSE	MAE	MBE	r	R^2	RRMSE (%)	NSE	WI
LSTM	0.0914	0.3023	0.2612	0.0195	0.716	0.728	22.90	0.844	0.801
CNN	0.1097	0.3628	0.3134	0.0235	0.573	0.585	24.10	0.829	0.641
RNN	0.1280	0.4233	0.3656	0.0274	0.429	0.442	24.94	0.772	0.481
ANN	0.1463	0.4837	0.4179	0.0313	0.286	0.299	25.82	0.747	0.321

The LSTM model outperforms the other baselines across most evaluation metrics, achieving the lowest error values (MSE, RMSE, MAE, and MBE) and the highest correlation measures (r, R^2, NSE, and WI). This reinforces the suitability of LSTM for modeling nonlinear and sequential dependencies in financial time-series data. CNN provides competitive results but falls short in capturing long-term dependencies, while RNN and ANN lag significantly in accuracy and reliability. These findings justify selecting LSTM as the baseline architecture to be enhanced through feature selection and

optimization.

To understand the interdependence among evaluation criteria, Figure 2 shows the correlation matrix of MSE, RMSE, MAE, MBE, r, R^2, RRMSE, NSE, and WI. The high positive and negative correlations indicate redundancy among some measures and identify the most informative criteria for model evaluation.

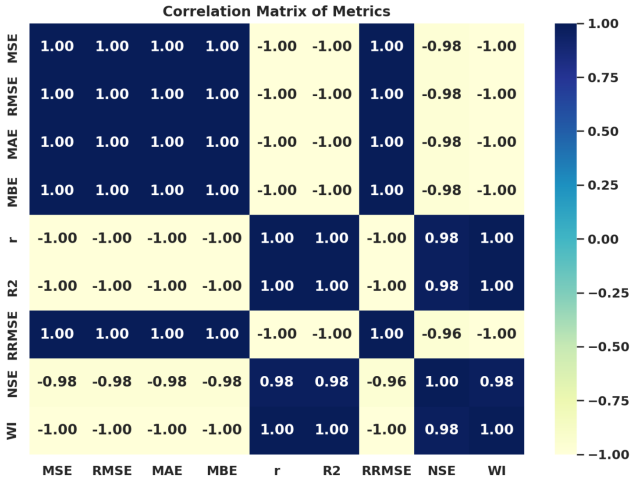


Figure 2. Correlation matrix of performance metrics.

To complement the correlation analysis, Figure 3 displays histograms with kernel density estimation (KDE) curves for all evaluation measures. The plots provide insights into the spread and central tendency of the metrics, clarifying their variability and stability across experiments or model configurations.

4.2 Before Feature Selection

To evaluate different optimization strategies, we compared the proposed FbOA with other state-of-the-art metaheuristic algorithms before applying feature selection. The assessment used the feature-selection metrics introduced in Section 3.5. Table 5 presents the results.

FbOA consistently outperforms competing algorithms across all feature-selection metrics. It achieves the lowest average error (0.3325), smallest subset size (0.2853), and strongest stability, with the lowest standard deviation of fitness (0.2180). In contrast, optimizers such as bPSO, bBA, bWOA, and bSBO yield higher errors and larger selected feature sizes, indicating a less efficient exploration–exploitation balance. FbOA is therefore particularly effective at identifying compact, informative feature subsets, which is crucial in financial forecasting because redundancy and noise impair model performance.

4.3 Deep Learning Performance After Feature Selection

After applying feature selection using the proposed FbOA-based optimization, all deep learning models demonstrated substantial improvements in predictive accuracy and stability. Table 6 summarizes post-feature-selection performance across LSTM, CNN, RNN, and ANN.

Feature selection significantly enhances model performance, with LSTM consistently achieving the best outcomes across all metrics. Compared with the baseline results, LSTM shows dramatic reductions in MSE, RMSE, and MAE, along with improvements in r, R^2, NSE, and WI. CNN, RNN, and ANN also improve but remain less reliable. These findings provide two key insights: FbOA-driven feature selection reduces redundancy and noise by focusing the models on informative variables, and LSTM remains the superior forecasting architecture, especially when optimized with FbOA.

Figure 4 compares all models using a parallel-coordinates plot, illustrating performance trade-offs and stability. Figure 5 presents boxplots with overlaid swarm plots for key metrics, highlighting distribution, variability, and potential outliers.

4.4 Optimized Models

To further evaluate the contribution of optimization, the LSTM model was combined with different metaheuristic algorithms, including the proposed FbOA, Genetic Algorithm (GA), Greylag Goose Optimizer (GGO), and Whale Optimization Algorithm (WOA). Table 7 reports performance across all optimized variants.

FbOA + LSTM achieves the strongest performance across all evaluation metrics. FbOA optimization yields the lowest error values (MSE, RMSE, MAE, and MBE), the highest correlation, and the strongest efficiency indicators (R^2, NSE, and WI). GA + LSTM and GGO + LSTM also improve baseline performance but fall short of FbOA's robustness. WOA + LSTM produces the weakest outcomes among the tested optimizers, indicating a less effective balance between exploration and exploitation. Taken together, these findings confirm that integrating FbOA with LSTM enhances predictive accuracy, stability, and generalization, making it the most effective optimization-driven forecasting framework in this study.

The superiority of FbOA can be attributed to its dynamic exploration–exploitation mechanism, which efficiently navigates complex solution spaces while avoiding premature convergence. Thus, the results provide strong empirical evidence that FbOA-optimized LSTM models are well positioned to deliver accurate, reliable, and efficient forecasts in the financial domain.

To gain deeper insights into the distributional characteristics of the evaluation metrics, Figure 6 illustrates violin plots with kernel density estimation for MSE, RMSE, MAE, MBE, r, R^2, RRMSE, NSE, and WI. This representation combines the advantages of boxplots and density estimation to show distribution shape, variability, and concentration regions. It supports identification of asymmetries and potential outliers, enriching evaluation of model robustness.

Besides descriptive statistics and correlation analysis, visualizing probability distributions provides a clearer perspective on metric behavior. Figure 7 shows density plots with KDE for the key performance metrics. The smooth distributions identify concentration regions and consistency across trials, which are crucial for assessing model credibility and predictive strength.

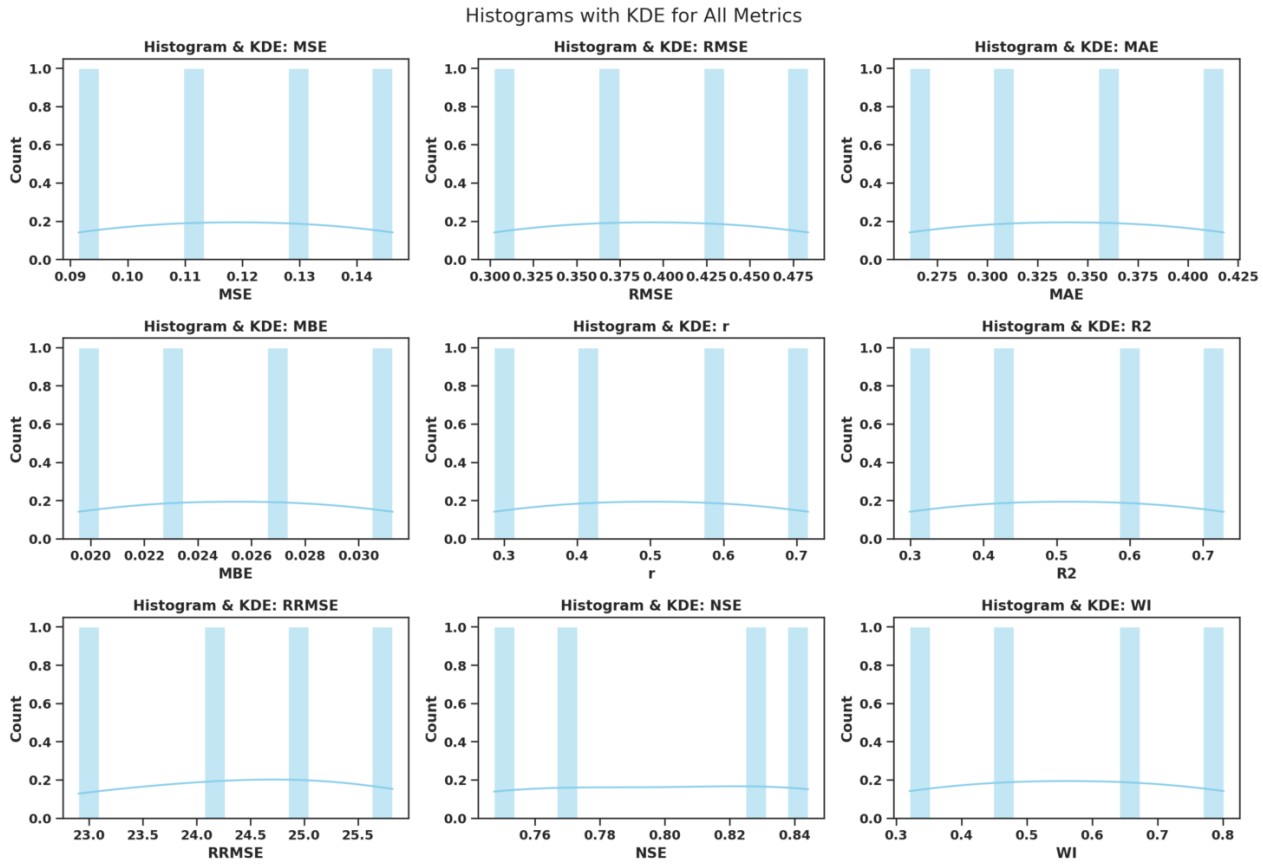


Figure 3. Histograms with kernel density estimation (KDE) for all evaluation metrics.

Table 5. Comparison of Optimizers Before Feature Selection

Algorithm	Average Error	Average Select Size	Average Fitness	Best Fitness	Worst Fitness	Std. Fitness
bFbOA	0.3325	0.2853	0.3957	0.2975	0.3960	0.2180
bHHO	0.3573	0.4929	0.4195	0.3398	0.4067	0.2303
bGWO	0.4414	0.6710	0.4726	0.4261	0.5361	0.2933
bPSO	0.5349	0.6367	0.5617	0.5420	0.6097	0.3735
bBA	0.5445	0.7761	0.5846	0.4743	0.5759	0.3834
bWOA	0.5347	0.8001	0.5695	0.5336	0.6097	0.3757
bBBO	0.5031	0.8005	0.5674	0.5571	0.6436	0.4184
bMVO	0.5116	0.7332	0.5914	0.5166	0.6346	0.4242
bSBO	0.5432	0.8070	0.6014	0.5445	0.6242	0.4344

Table 6. Deep Learning Model Performance After Feature Selection

Model	MSE	RMSE	MAE	MBE	r	R^2	RRMSE (%)	NSE	WI
LSTM	0.00118	0.00390	0.00337	0.01280	0.920	0.921	12.12	0.954	0.924
CNN	0.00142	0.00469	0.00405	0.01320	0.911	0.912	14.12	0.911	0.884
RNN	0.00165	0.00547	0.00472	0.01361	0.902	0.903	15.07	0.875	0.855
ANN	0.00189	0.00625	0.00540	0.01401	0.893	0.894	15.98	0.855	0.835

Table 7. Performance of Optimized LSTM Models

Model	MSE	RMSE	MAE	MBE	r	R^2	RRMSE (%)	NSE	WI
FbOA + LSTM	0.00110	0.00382	0.00329	0.01272	0.966	0.967	7.95	0.986	0.971
GA + LSTM	0.00134	0.00460	0.00397	0.01312	0.957	0.958	9.96	0.958	0.931
GGO + LSTM	0.00157	0.00538	0.00464	0.01353	0.948	0.949	10.91	0.921	0.902
WOA + LSTM	0.00181	0.00617	0.00531	0.01393	0.939	0.940	11.82	0.902	0.881

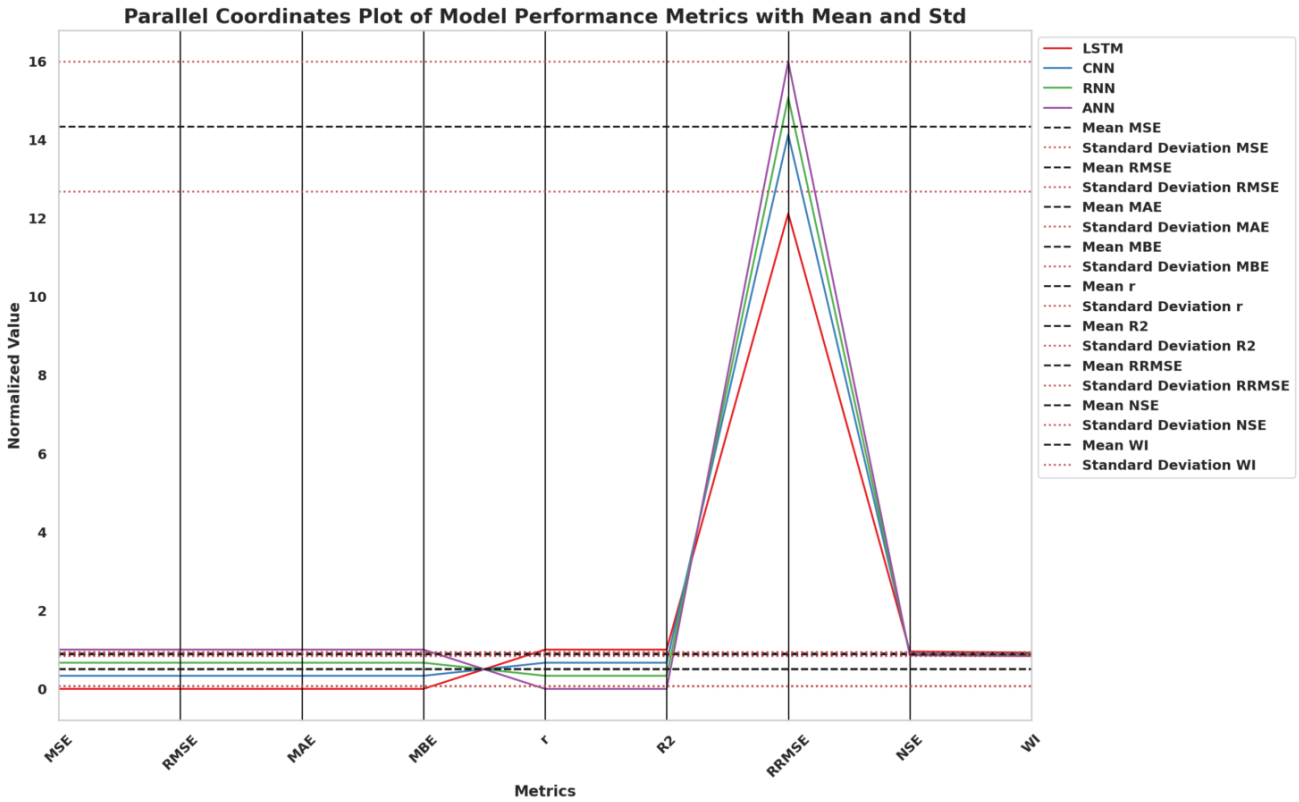


Figure 4. Parallel-coordinates plot of model performance metrics with mean and standard deviation.

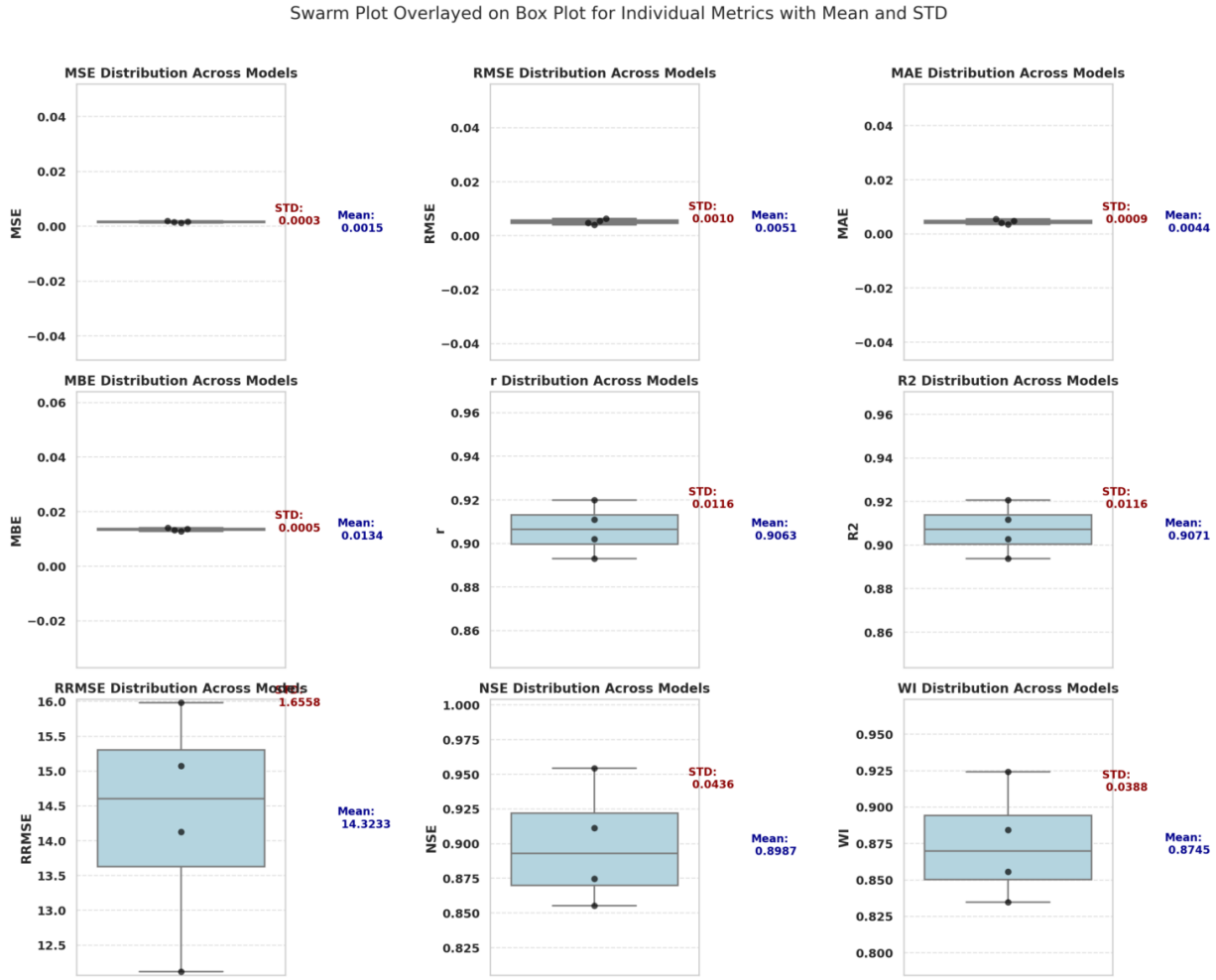


Figure 5. Swarm plots overlaid on boxplots for performance metrics with mean and standard deviation.

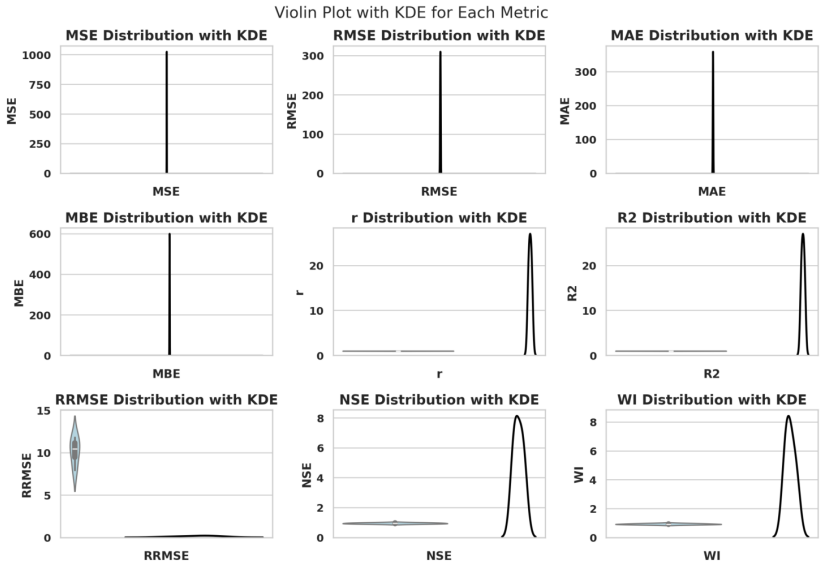


Figure 6. Violin plots with KDE showing the distribution of evaluation metrics.

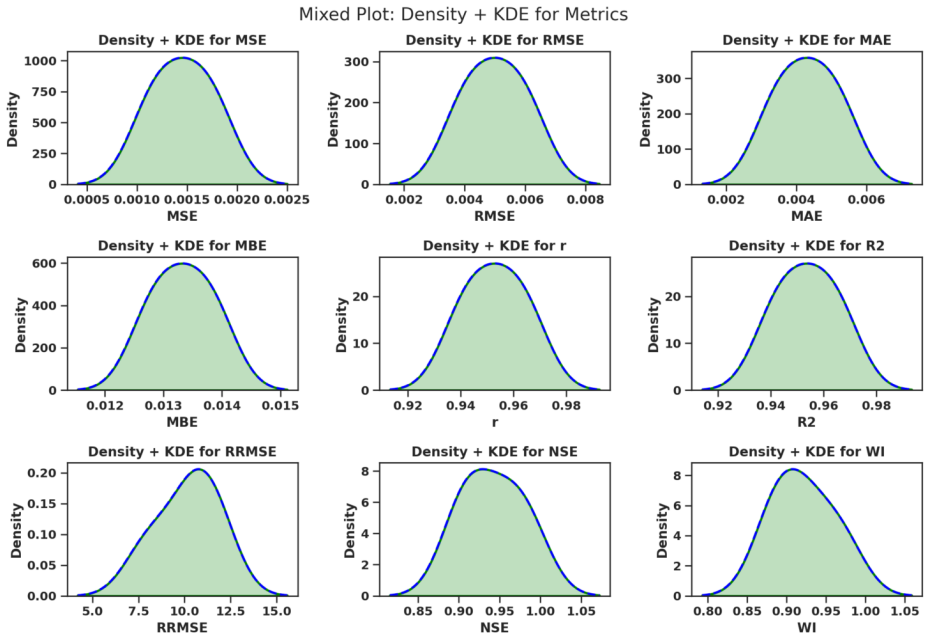


Figure 7. Density plots with KDE of evaluation metrics showing distribution and variability.

5. DISCUSSION

The results demonstrate the promising potential of combining advanced deep learning architectures with metaheuristic optimization techniques to enhance the accuracy and stability of financial forecasting models. The proposed hybrid framework, integrating LSTM networks with FbOA, consistently outperformed benchmark deep learning models and alternative optimization strategies across a comprehensive set of evaluation metrics. This advantage highlights the practical importance of sophisticated optimization methods for feature selection and hyperparameter tuning in complex financial environments.

From a financial perspective, accurate forecasting of corporate performance indicators such as earnings, market capitalization, and price is essential for informed decision-making by corporate managers, investors, and financial regulators. Improved predictive accuracy translates directly to more effective risk management, enabling firms to anticipate downturns and capitalize on growth opportunities. The reduced forecasting errors achieved by the FbOA-optimized LSTM model support more reliable valuation, portfolio allocation, and capital-budgeting decisions, which are critical to long-term value creation and sustained competitive advantage.

The ability of the proposed framework to select compact, informative feature subsets addresses a fundamental challenge in financial modeling: the high dimensionality and noisy nature of corporate financial data. By reducing redundancy and focusing on the most predictive variables, the model improves interpretability and computational efficiency, enabling scalable deployment in real-world corporate-finance applications. This aspect is especially relevant to large multinational corporations and asset managers that must process vast arrays of heterogeneous financial signals in increasingly volatile and interconnected markets.

The integration of financial-sustainability considerations further elevates the relevance of the approach. As ESG factors become increasingly integral to investment and strategic planning, forecasting frameworks that incorporate these metrics

alongside traditional financial variables will better reflect the multifaceted risks and opportunities companies face. The findings suggest that optimization-driven deep learning models can be adapted to incorporate ESG dimensions, thereby supporting the financial industry's transition toward more sustainable and responsible investment practices.

Finally, FbOA's strong performance in balancing exploration and exploitation in complex solution spaces underscores the value of domain-inspired optimization strategies in financial analytics. The analogy to football-team dynamics captures the iterative, cooperative adjustment processes inherent in financial markets and corporate ecosystems, offering a novel avenue for model refinement and robustness. This connection enriches methodological innovation and provides a conceptual framework that resonates with practitioners focused on strategy, teamwork, and dynamic adaptation. Overall, this study bridges cutting-edge artificial intelligence techniques and practical financial analytics, demonstrating how hybrid models can strengthen corporate decision-making and risk evaluation. The results encourage further exploration of real-time forecasting, cross-country financial-resilience assessment, and novel data sources to fully harness the transformative potential of AI-driven financial prediction.

6. CONCLUSION

This paper introduces a unified framework for predicting the financial performance of global enterprises using sophisticated deep learning and novel metaheuristic optimization methods. The LSTM network proved competent at grasping intricate, nonlinear, and sequential trends in financial time-series data, making it a strong option for economic forecasting. In parallel, FbOA successfully combined exploration and exploitation in both feature-selection and hyperparameter-optimization phases, producing streamlined models with higher predictive quality and stability.

From a financial standpoint, the increased accuracy achieved by the FbOA-optimized LSTM model facilitates informed corporate decisions, more accurate risk estimation, and strategies that respond to changing market situations. Isolating the most informative financial measures from an extensive, heterogeneous dataset can help firms optimize capital allocation, enhance valuation methods, and foster investor confidence. This is especially valuable in a dynamic economy where market volatility and regulatory complexity necessitate sophisticated analytical tools.

Future work can apply the framework to larger, multisource datasets spanning a wider range of economies, increasing its generalizability and supporting analysis of global financial resilience. Adopting transformer architectures may further improve predictive power by capturing long-range dependencies and multifaceted interactions in financial data. Real-time forecasting driven by FbOA optimization also shows promise for dynamic portfolio adjustment and tactical investment decisions. Additionally, integrating ESG metrics into the forecasting pipeline may provide key indicators of long-term corporate sustainability and risk profiles. More accurate forecasts may also inform macroprudential regulation and systemic-risk management, highlighting the broader social value of these analytical improvements.

In summary, the FbOA-optimized LSTM model is a scalable and powerful financial-analytics tool that combines technical sophistication with business relevance. It has the potential to improve economic forecasting in line with the global financial system's growing requirements for resilience, sustainability, and strategic decision-making, representing a paradigm shift in corporate finance and investment management.

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