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 any 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 between maximizing shareholder value and obligations to development aims worldwide [5, 6]. Financial resilience and predictive financial analysis are essential factors in this regard /citeIN7. 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 significant 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. Those firms that continually incorporate financial projections and economic realities are in a better position

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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

The current developments in the fields of artificial intelligence (AI), machine learning (ML), and deep learning (DL) have unveiled a revised picture in the spheres of economic forecasting, financial modeling, and digital

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innovation. Specifically, models that combine the learning strategies of neural architectures and ensemble learning are currently emerging as the leading paradigm, offering advantages in both accuracy and adaptability over more conventional methods [15]. Such a hybrid design is recently being extended to various economic sectors, including corporate banking, e-commerce, stock markets, and cryptocurrency, reflecting the broad applicability of these designs in addressing highly nonlinear and complex environments. These advances also indicate a consistent trend towards more advanced deep learning frameworks that utilize cross-computational framework synergies. Another important line of research focuses on forecasting economic variables related to resources. For example, hybrid AI methods, particularly those incorporating recurrent neural networks and discrete wavelet transforms, have been highly effective in forecasting mineral resource rents [16]. These methods can not only increase the accuracy of predictions but also shed more light on how renewable energy, environmental policy, and macroeconomic determinants affect the resource dynamics. Notably, the results indicate that renewable energy and environmental activities may have beneficial influences, but conventional measures, like economic growth and producer price indexes, may have adverse effects, which makes policy-making in this field more complicated. In the financial markets, the most challenging and impactful application of AI is the prediction of stock movements. Financial time series do not follow any predictable patterns. They are also worsened by external shocks and fluctuating trading conditions, which demand the use of event-based and macroeconomic information to enhance predictions more effectively [17]. Hybrid frameworks, including autoencoders (AEs) and kernel extreme learning machines (KELMs), have shown an impressive boost in predictive accuracy on various stock indices, providing powerful results even in the high-frequency regime [18]. The increased importance of sustainability-related indicators is also emphasized in other works regarding the 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, and gated recurrent units (GRU) are often more effective than long short-term memory (LSTM) networks, especially when it comes to prediction speed and training efficiency of technology sector forecasting [20]. Beyond technical innovations, a wide array of survey studies emphasizes 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]. At the same time, comparative assessments of reinforcement learning, sentiment analysis, and hybrid models 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 strike a balance between statistical rigor and interpretability. At a macroeconomic level, AI technologies are increasingly recognized as transformative forces that reshape productivity, innovation, and global competitiveness [23]. Cognitive computing, in particular, has been shown to enhance operational efficiency across various 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 socio-economic structures. The literature also extends into the domain of small and medium-sized enterprises (SMEs), where the combination of ensemble ML techniques and explainable AI (XAI) frameworks, such as SHAP and LIME, has enabled more reliable and transparent growth predictions [24]. These tools are particularly valuable in addressing challenges associated with 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 various sectors, including healthcare, agriculture, and transportation, while also identifying hybridization and generative AI as the most promising future research directions [27]. However, the adoption of AI in financial markets also highlights pressing concerns: regulatory frameworks, ethical considerations, workforce adaptation, and the protection of consumer data remain significant barriers [28]. Consequently, while 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 a mixed picture of 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, issues of transparency, interpretability, and ethical deployment remain central to future progress. The convergence of economic forecasting, sustainable finance, and AI-driven innovation thus represents a fertile ground for continued exploration, with implications that extend far beyond technical performance into the realms of policy, regulation, and societal impact.

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3 Materials and Methods

The methodological design of this research paper is based on combining deep learning architectures with feature selection through the use of optimization-based methods and hyperparameter optimization to maximize financial forecasting accuracy. This section describes the datasets used, the preprocessing plan employed to ensure data quality, and the experimental design to be used in model development. Specific attention is paid to using Long Short-Term Memory (LSTM) networks as the central forecasting model and the Football Optimization Algorithm (FbOA) as the feature selection and hyperparameter optimization account. The proposed framework aims to address the challenges of high-dimensional, noisy, and nonlinear financial data by combining the latest neural networks with metaheuristic optimization. In the succeeding subsections, the data source, feature engineering process, model configurations, optimization strategy, and evaluation metrics used to validate the effectiveness of the proposed approach are detailed.

3.1 Dataset Description

This research is based on a broad sample of the world's most successful enterprises, comprising a total of 9,912 companies across various industries and geographic locations. The dataset records extensive financial indicators that are crucial in measuring corporate performance and the global economic position. Through these dimensions, we gain a comprehensive understanding of scale, profitability, market value, and growth potential. The main characteristics of the dataset are:

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, which allows for cross-country comparability.
Country	The 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.

The publication of financial values shows that the dataset is highly heterogeneous. To illustrate, profits range from negative values (indicating losses) to exceeding **£228 billion**, highlighting the vast disparities among firms. The share prices span a broad range from below **£2,000** to over **£16,500**, reflecting variations in investor perception, liquidity, and equity structure. Market capitalisation similarly varies widely, with some firms classified as mid-sized and others as mega-cap, reaching valuations exceeding hundreds of billions of dollars. Geographically, the dataset reflects the concentration of financial power, with the United States hosting approximately 37% of the firms, exhibiting dominance in international markets. India accounts for nearly 6%, while the remaining 57% of firms are distributed across diverse countries, offering a basis for regional comparison. For analytical purposes, companies are grouped into ranges based on metrics such as rank, earnings, and price. This stratification allows visualization of firm concentration within specific financial bands and facilitates the statistical exploration of correlations between earnings, valuation, and market performance. Such structuring supports the identification of overarching trends related to investor confidence, regional leadership, and sectoral strengths. By integrating this multi-dimensional data, the dataset provides a robust foundation for comprehensive financial analysis. It enables benchmarking individual firms, evaluating country-level performance, identifying economic dominance within sectors, and exploring the interconnectedness of financial indicators reflecting global competitiveness and sustainability. To gain preliminary insights into the dataset, it

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is essential to examine the statistical properties of the numerical variables. Figure 1 illustrates the distribution of key attributes: company rank, market capitalisation, and share price in GBP. The figure highlights significant heterogeneity and skewness, demonstrating concentrated distributions in market capitalisation and price, while the rank variable presents a more uniform spread. These exploratory observations inform the choice of preprocessing and modeling strategies suitable to handle the dataset's complexity.

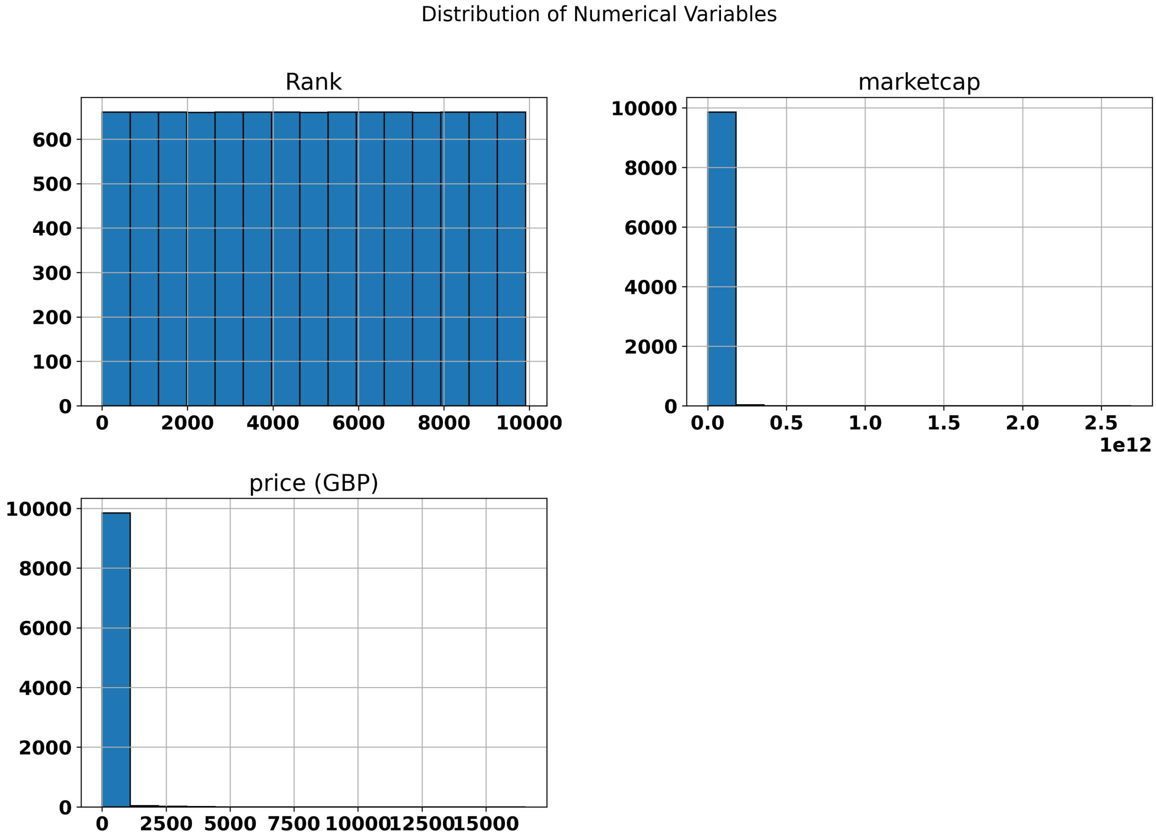

Figure 1: Distribution of numerical variables in the dataset

3.2 Data Preprocessing

The dataset underwent a series of preprocessing procedures to ensure precision, stability, and predictive financial analysis before model development. These steps will be necessary to address the issue of data quality and enhance the interpretability of findings. The key procedures include: The data were initially checked for missing values on features such as earnings, price, and market capitalization. Where the gaps in values were identified, relevant imputation policies were used. With numerical variables, the imputation consists of mean imputation or median imputation based on the skewness of the distribution, and categorical attributes (e.g., country) were imputed with mode values. In this manner, no companies were excluded without a purpose, and the data set was too rich. Some of the attributes, including company identifiers and categorical descriptors, were converted into machine-readable forms. For example, time-dependent variables were coded in a numerical order to preserve temporal explainability, enabling models to capture trends over periods. On the same note, categorical variables, e.g., country, were one-hot encoded to avoid bias in comparing regions. To remove distortion due to differences in measurement units, numerical features were rescaled. Specifically, share price and exchange rate sensitive variables were normalized or standardized. Where proportionality was required (e.g., dividend yields), normalization was used, whereas standardization was favored where the range of the variable was extensive (e.g., earnings and market capitalisation). This guaranteed the consistency of all characteristics when optimizing and increased the stability of gradient-based training procedures.

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3.3 Deep Learning Models

We utilized a set of deep learning models to extract the intricate patterns in financial data. All models offer unique advantages in processing sequential, structural, and nonlinear dependencies, making them suitable for analyzing various financial indicators, including revenue, earnings, market capitalization, and stock prices. Among the models, the **Long Short-Term Memory (LSTM)** network is recommended to serve as the central forecasting system for the present study, and the remaining architectures are included as control models for comparison. **Artificial Neural Network (ANN):** The ANN forms the core architecture of deep learning, a network of interacting layers of neurons. ANNs have been helpful in the field of finance in modelling nonlinear relationships between inputs (e.g., earnings, prices and ratios) and outputs (e.g., future valuation or growth projections). Although simple, they provide a convenient reference point for comparing the performance of more complex architectures, due to their simplicity. **Recurrent Neural Network (RNN):** RNNs generalize the ANN architecture by adding feedback links to enable information to be sustained over time steps. This makes them suitable for sequential financial data, such as stock price histories or quarterly earnings. However, traditional RNNs often face issues with vanishing or exploding gradients, which limit their performance on long sequences. They serve as an intermediate benchmark in our comparative framework.

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

Proposed Model: Long Short-Term Memory (LSTM): LSTMs were introduced to overcome the limitations of standard RNNs by incorporating memory cells and gating mechanisms (input, output, and forget gates). These features 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**, owing to its ability to effectively handle high-dimensional financial data, model nonlinear temporal dependencies, and provide robust predictive performance. Furthermore, the integration of LSTM with the proposed FbOA optimization framework enhances its efficiency by simultaneously optimizing feature selection and hyperparameters. In summary, ANN, RNN, and CNN are employed as benchmark models, while the LSTM serves as the **proposed architecture** for financial forecasting. This setup allows us to rigorously compare baseline deep learning models with the optimized LSTM, thereby highlighting the contribution of our methodology.

3.4 Metaheuristic Algorithms

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

FbOA (Proposed): The **Football Optimization Algorithm (FbOA)** is introduced as 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:** Expanding the global search 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:

$$V_n = F_{\max}\Big(b_x \cdot a_i(F_{\text{ext}} - F_{\min}) + r \cdot b_y \cdot a_j(F_{\text{best}} - F_{\min}) \cdot \cos\left(\frac{\pi}{\text{Iteration}}\right)\Big)$$

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

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- **Exploitation:** Once promising regions are identified, FbOA intensifies the search locally by refining solutions, analogous to coordinated team play in a focused attack. The exploitation process is modeled as:
$$Fb(S_{t+1}) = F_i + z_3 \cdot Fb(S_t) + K \cdot \sin\left(\frac{\pi}{\text{Iteration}}\right)$$
where $Fb(S_{t+1})$ is the updated solution at iteration $t+1$, F_i represents the current position, z_3 is a control parameter, K is an exponential factor shifting focus from exploration to exploitation, and $\sin(\cdot)$ modulates convergence speed.

A mutation strategy further enhances robustness by injecting variability:

$$S(t) = K \cdot aq\left(\frac{2n+1}{x}\right) + K \cdot \cos\left(\frac{\pi}{\text{Iteration}}\right)$$

where $S(t)$ denotes the mutated solution, aq is a scaling factor, and the cosine function introduces stochastic diversity.

By integrating these mechanisms, FbOA provides superior optimization in both feature selection and hyperparameter tuning, making it particularly suitable for high-dimensional, nonlinear financial forecasting problems [29].

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

GWO (Grey Wolf Optimizer): The Grey Wolf Optimizer models leadership hierarchies and hunting mechanisms of grey wolves. It is widely applied for 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 behaviors of birds and the schooling of fish. Every particle modifies its path according to individual and collective experience, and thus PSO is especially effective in tuning the parameters of predictive financial models.

BA (Bat Algorithm): The Bat Algorithm is a model that mimics the echolocation behavior, allowing local and global searches to be dynamically adjusted. Financial applications of BA have been utilized in risk optimization and multi-objective investment problems.

WOA (Whale Optimization Algorithm): The WOA is a humpback hunting strategy based on a bubble net. It performs well on complex optimization topographies and excels in optimizing deep learning models for financial forecasting problems.

BBO (Biogeography-Based Optimizer): BBO takes its inspiration from the migration and distribution of species in different environments, which are optimized in high-dimensional spaces. It can smoothly exchange features in its migration operator, which is well-suited for exploring financial data.

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

SBO (Satin Bowerbird Optimizer): SBO mimics the mating and nest-building behaviors of bowerbirds. It includes probabilistic methods of learning, making it suitable for feature selection and noise minimization in financial data. This study also assesses the relative predictive gains by comparing these algorithms with the proposed FbOA. It demonstrates the value of an exploration-exploitation balance in the development of optimization-enabled financial analytics.

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3.5 Evaluation Metrics

Two sets of metrics were used to measure the performance of the models: (i) regression metrics to measure predictive accuracy and predictive reliability, and (ii) feature selection metrics to measure the efficiency of the optimization process. The metrics present a holistic appraisal system since they measure the quality of forecasting and optimization. Regression metrics determine the predictive efficiency of the suggested models based on the observed financial values of the financial variables and the estimates. They quantify errors, bias, the strength of correlation, and the efficiency of the models; hence, the developed forecasting models are accurate and reliable in terms of financial applications. The regression measures developed are summarized in Table 2.

Table 2: Regression Performance Metrics

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

The quality of optimization for the suggested FbOA and benchmark algorithms is evaluated using feature selection measures. The measures of error reduction, subset size, and fitness stability quantify the trade-off between accuracy and complexity. This is also necessary in financial forecasting, where selecting the most informative variables can enhance interpretability, reduce overfitting, and improve computational efficiency. The measures of feature selection applied in this research are summarized in Table 3.

Table 3: Feature Selection Metrics

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

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In these equations, y_i and $\hat{y}_i$ denote observed and predicted values, $\bar{y}$ is the mean of observed values, F_i represents the fitness value of the i-th run, S_i is the subset size selected, E_i is the error for the i-th run, and N denotes 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. By systematically evaluating the models across multiple metrics, the analysis provides insights into both predictive accuracy and computational efficiency. Furthermore, the results are 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. The following subsections detail the outcomes of baseline model evaluation, feature selection experiments, optimization procedures, and comparative analyses against competing methods.

4.1 Baseline Model Comparison

To establish a performance benchmark, we first evaluated the baseline deep learning models without applying 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 2.7. Table 4 summarizes the raw performance outcomes across all models.

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 results show that the LSTM model outperforms the other baselines across most evaluation metrics, achieving the lowest error values (MSE, RMSE, MAE, MBE) and the highest correlation measures (r, R^2, NSE, 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 behind significantly in both accuracy and reliability. Overall, these findings justify the choice of LSTM as the proposed baseline architecture, to be further enhanced through feature selection and optimization. To gain a deeper understanding of the interdependence among the various evaluation criteria, it may be helpful to examine the correlation between the performance metrics. Figure 2 shows the correlation table of the metrics under consideration, such as mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean bias error (MBE), correlation coefficient (r) and coefficient of determination (R^2) as well as relative root mean squared error (RRMSE) and Nash-Sutcliffe efficiency (NSE). The high positive and negative correlations depicted in the matrix indicate redundancy within some of the measures, providing insight into the most informative measures for evaluating the model.

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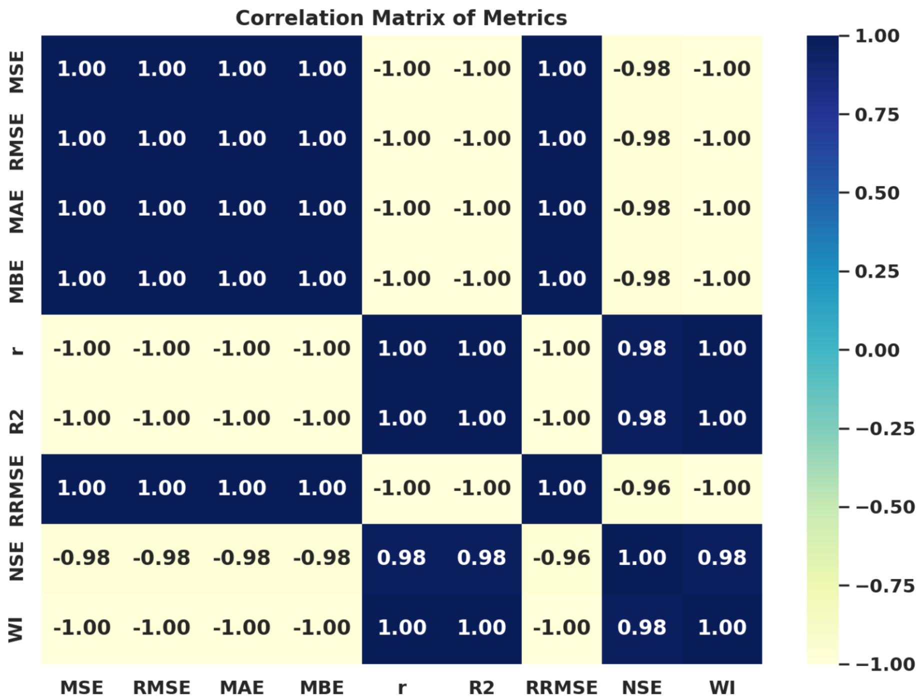

Figure 2: Correlation matrix of performance metrics

To complement the correlation analysis, it is also important to examine the empirical distribution of each performance metric. Figure 3 displays the histograms with kernel density estimation (KDE) curves for the considered evaluation measures, including mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean bias error (MBE), correlation coefficient (r), coefficient of determination (R^2), relative root mean squared error (RRMSE), Nash–Sutcliffe efficiency (NSE), and Willmott's index (WI). These plots provide insights into the spread and central tendency of the metrics, allowing a clearer understanding of their variability and stability across different experiments or model configurations.

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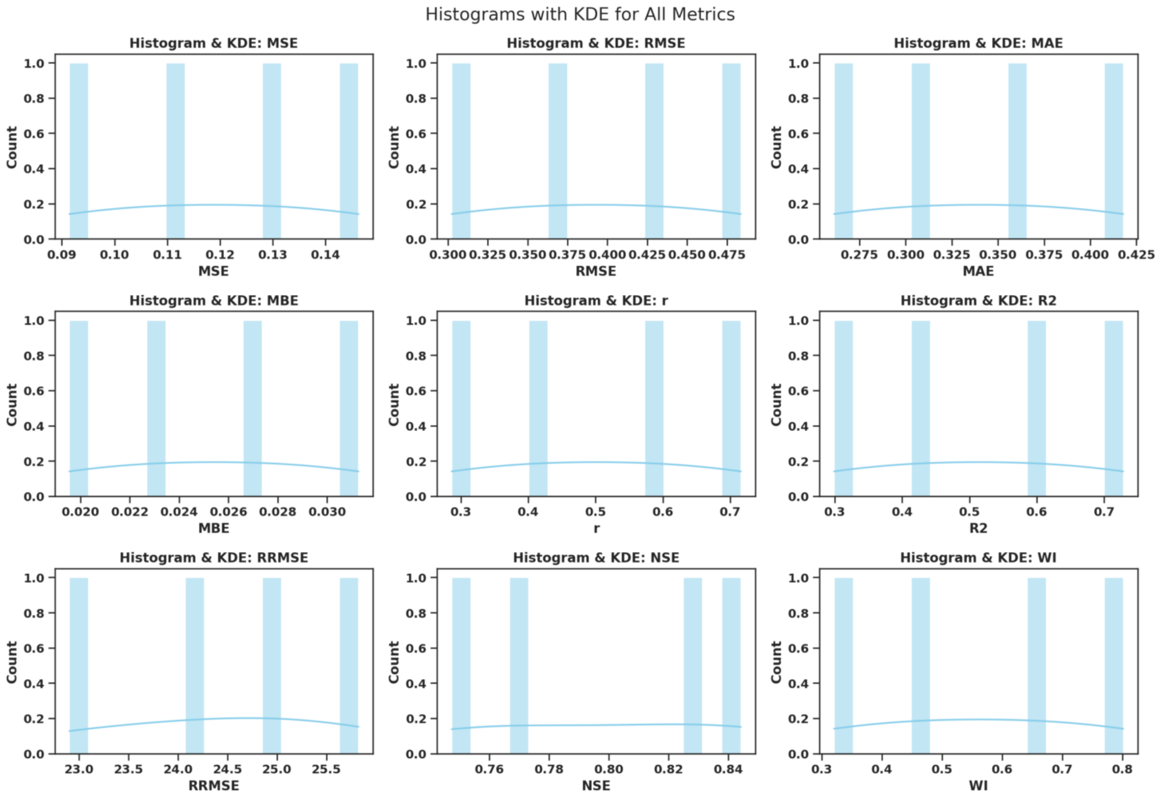

Figure 3: Histograms with kernel density estimation (KDE) for all evaluation metrics

4.2 Before Feature Selection

To evaluate the effectiveness of different optimization strategies, we compared the proposed **FbOA** with other state-of-the-art metaheuristic algorithms prior to applying feature selection. The assessment was conducted using the feature selection metrics introduced in Section 2.7. Table 5 presents the results across all algorithms.

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

The results demonstrate that **FbOA consistently outperforms** the 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 (0.218). In contrast, other optimizers such as bPSO, bBA, bWOA, and bSBO yield higher error values and larger selected feature sizes, indicating less efficient exploration–exploitation balance. This indicates that FbOA is particularly effective at identifying **compact and informative feature subsets**, crucial for financial forecasting where redundancy and noise impair model performance.

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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 the post-feature-selection performance across LSTM, CNN, RNN, and ANN, measured using the regression metrics defined in Section 2.7.

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

The results confirm that **feature selection significantly enhances** model performance, with LSTM consistently achieving the best outcomes across all metrics. Compared to baseline results, LSTM shows dramatic reductions in error (MSE, RMSE, MAE), and improvements in correlation (r), determination (R^2), and efficiency indicators (NSE, WI). CNN, RNN, and ANN also improve but remain less reliable. These findings highlight two key insights: (1) **FbOA-driven feature selection reduces redundancy and noise**, focusing models on informative variables; and (2) **LSTM remains the superior forecasting architecture**, especially when optimized with FbOA. To compare all models comprehensively, Figure 4 shows a parallel coordinates plot of multiple evaluation metrics, illustrating trade-offs and stability across models.

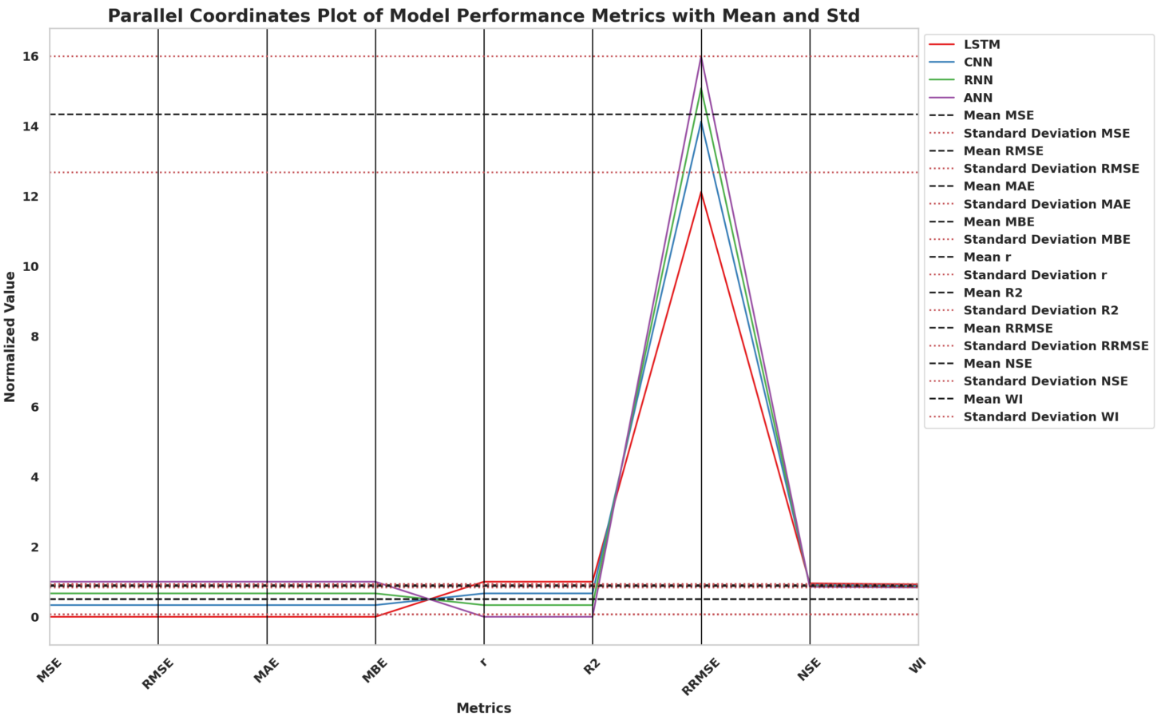

Figure 4: Parallel coordinates plot of model performance metrics with mean and standard deviation

Figure 5 presents boxplots with swarm plots for key metrics, highlighting distribution, variability, and potential outliers among the models.

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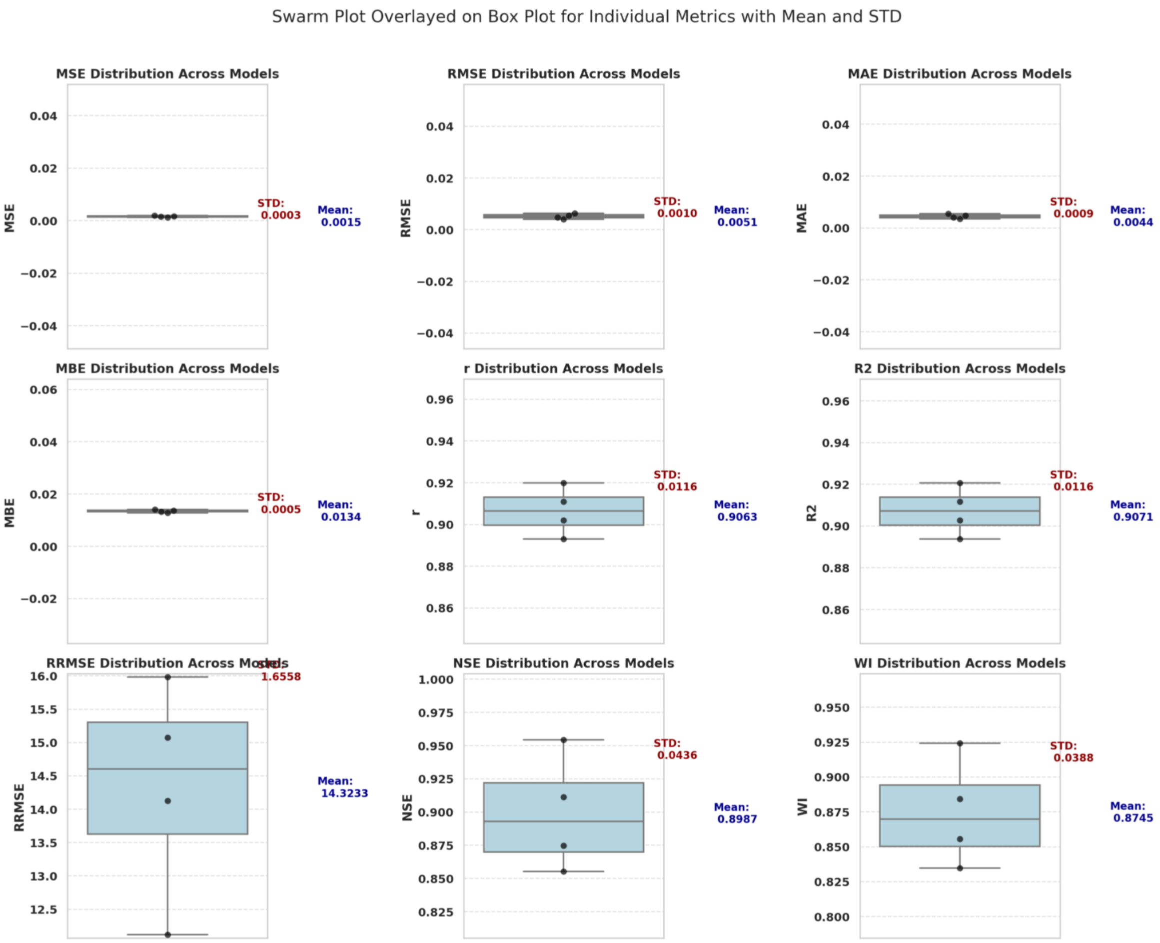

Figure 5: Swarm plots overlaid on box plots for performance metrics with mean and standard deviation

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 the performance metrics across all optimized variants.

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

The results clearly demonstrate that **FbOA + LSTM achieves the strongest performance** across all evaluation metrics. Specifically, FbOA optimization yields the lowest error values (MSE, RMSE, MAE, MBE), the highest correlation (r), and the strongest efficiency indicators (R^2, NSE, WI). Compared to other optimizers, 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 less effective balance between exploration and exploitation. Taken together, these findings confirm that the integration of **FbOA with LSTM not only enhances predictive accuracy but also improves 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 enables the algorithm to efficiently

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navigate complex solution spaces while avoiding premature convergence. Thus, the results provide strong empirical evidence that **FbOA-optimized LSTM models are best positioned to deliver accurate, reliable, and efficient forecasts in the financial domain**. To gain deeper insights into the distributional characteristics of the evaluation metrics, it is useful to consider both their spread and density. Figure 6 illustrates violin plots with kernel estimation (KDE) for mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean bias error (MBE), correlation coefficient (r), coefficient of determination (R^2), relative root mean squared error (RRMSE), Nash–Sutcliffe efficiency (NSE), and Willmott index (WI). This representation combines advantages of box plots with density estimation to show distribution shape, variability, and concentration regions. Such analysis supports identification of asymmetries and potential outliers, enriching model robustness evaluation.

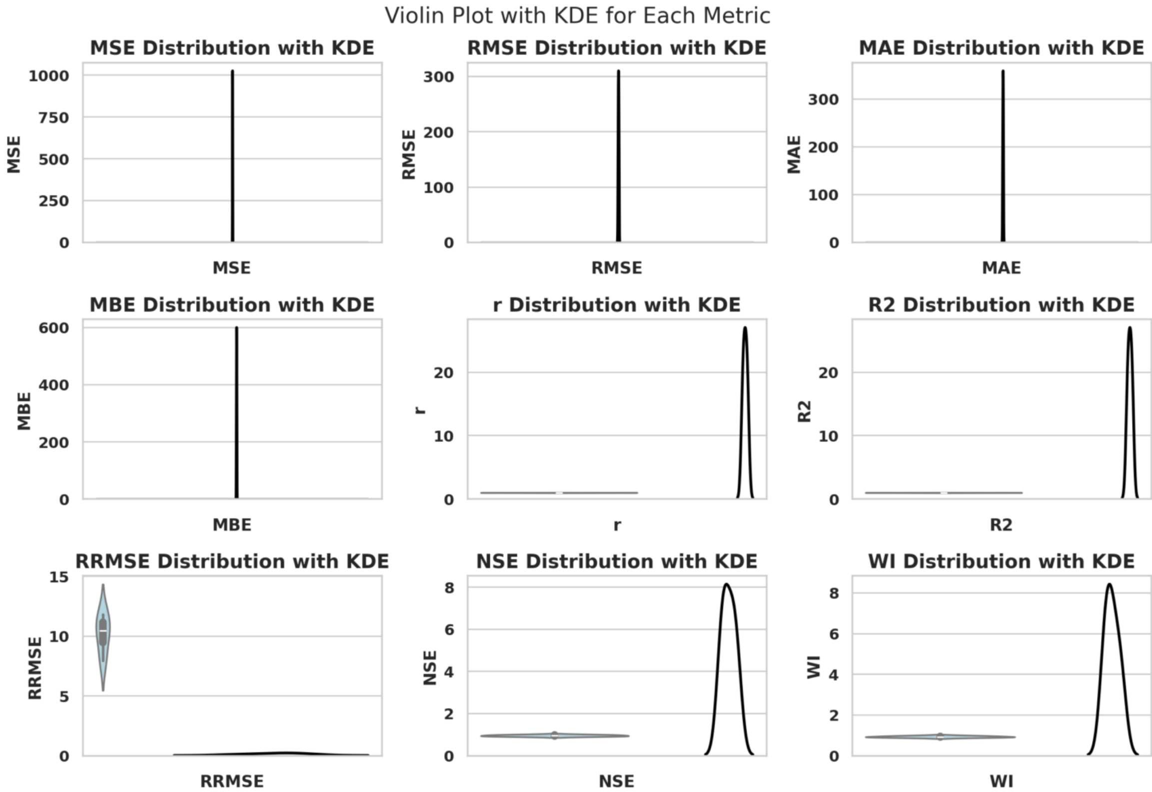

Figure 6: Violin plots with KDE showing distribution of evaluation metrics

Besides descriptive statistics and correlation analysis, the visual representation of probability distributions provides a clearer perspective on metric behavior. Figure 7 shows density plots with kernel density estimation (KDE) of key performance metrics, including MSE, RMSE, MAE, MBE, r, R^2, RRMSE, NSE, and WI. The smooth distributions enable identification of concentration regions and consistency across trials, crucial for assessing model credibility and predictive strength.

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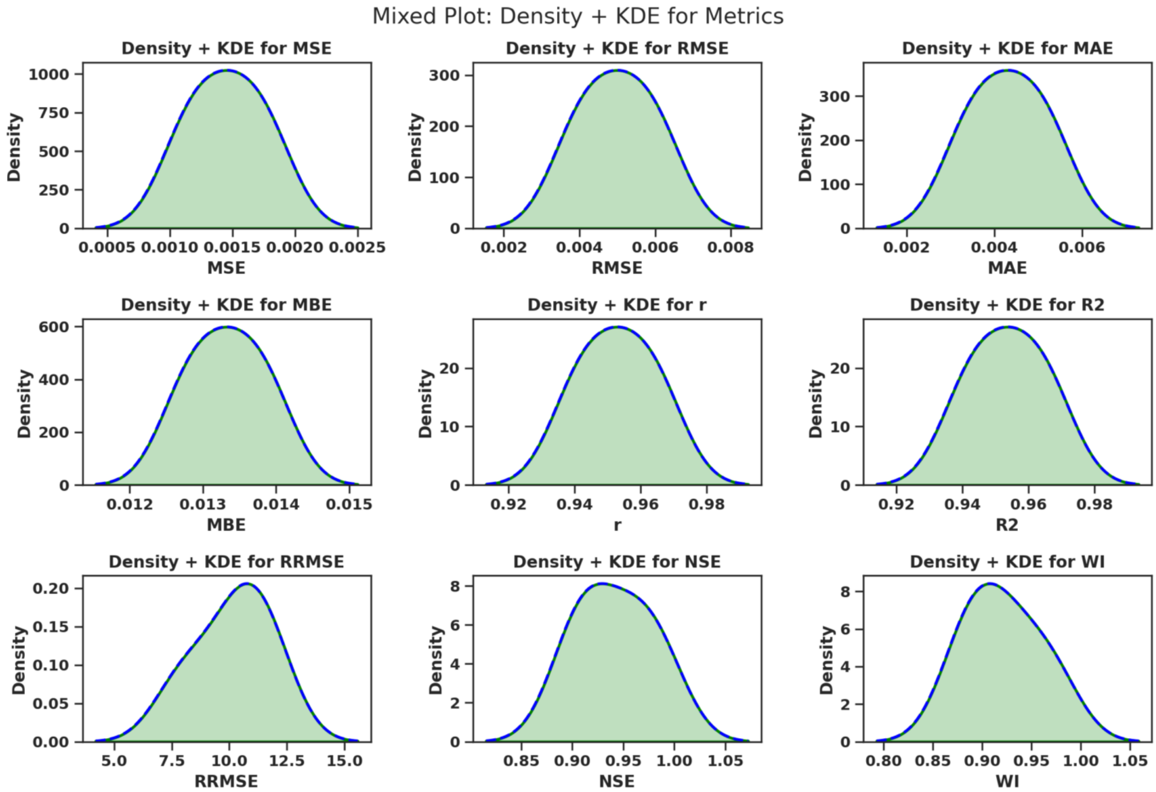

Figure 7: Density plots with KDE of evaluation metrics showing distribution and variability

5 Discussion

The results of this study demonstrate the promising potential of combining advanced deep learning architectures with metaheuristic optimization techniques to enhance the accuracy and stability of financial forecasting models. Our proposed hybrid framework, integrating Long Short-Term Memory (LSTM) networks with the Football Optimization Algorithm (FbOA), consistently outperformed benchmark deep learning models and alternative optimization strategies across a comprehensive set of evaluation metrics. This performance advantage highlights the practical importance of adopting 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 stakeholders including corporate managers, investors, and financial regulators. Improved predictive accuracy directly translates to more effective risk management, enabling firms to better anticipate downturns and capitalize on growth opportunities. The reduction in forecasting errors achieved by the FbOA-optimized LSTM model supports more reliable valuation, portfolio allocation, and capital budgeting decisions, which are critical components in fostering long-term value creation and sustaining competitive advantage. Moreover, 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 not only improves interpretability but also enhances computational efficiency, thus enabling scalable deployment in real-world corporate finance applications. This aspect is particularly relevant for large multinational corporations and asset managers who 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 our approach. As environmental, social, and governance (ESG) factors become increasingly integral to investment and strategic planning, forecasting frameworks that incorporate such metrics alongside traditional financial variables will be better equipped to reflect the multifaceted risks and opportunities companies face today. Our 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, the strong performance of FbOA in balancing exploration and

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exploitation in complex solution spaces underscores the value of domain-inspired optimization strategies in financial analytics. The analogy to team dynamics in football captures the iterative, cooperative adjustment processes inherent in financial markets and corporate ecosystems, offering a novel avenue for model refinement and robustness. This connection not only enriches methodological innovation but also provides a conceptual framework that resonates with practitioners focused on strategy, teamwork, and dynamic adaptation. Overall, this study contributes to bridging the gap between 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 into real-time forecasting, cross-country financial resilience assessment, and incorporation of 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 based on sophisticated deep learning and novel metaheuristic optimization methods. The Long Short-Term Memory (LSTM) network has proven to be more competent at grasping intricate, nonlinear, and sequential trends in financial time-series data. It can thus be considered a strong option when faced with an economic forecasting problem. In line with this, the Football Optimization Algorithm (FbOA) was successful in the combination of exploration and exploitation in both the feature selection and hyperparameter optimization phases, as well as producing streamlined models with a higher predictive quality and stability. Financially, the increased accuracy of forecasting results obtained with the FbOA-optimized LSTM model makes it easier to make informed corporate decisions based on this information, as well as to more accurately estimate risks and design strategies that respond to changing market situations. The ability to isolate the most informative financial measures from the extensive, heterogeneous data set can enable firms to optimize capital allocation, enhance valuation methods, and foster investor confidence. It is especially valuable in the current dynamic economy, where market volatility and regulatory complexities necessitate complex analytical tools. In the future, by applying this framework to larger, multisource datasets that include a wider range of economies, the framework will become more generalizable and help analyze global financial resilience. Transformer architecture adoption can also enhance predictive power, as it will capture long-distance dependencies as well as multifaceted interactions in financial data. FbOA optimization-driven real-time forecasting applications promise a lot in dynamic portfolio adjustment and tactical investment decisions. Additionally, the integration of Environmental, Social, and Governance (ESG) metrics into the forecasting pipeline may serve as a key indicator of a corporation's long-term sustainability and risk profile, which is becoming increasingly common in the investment community. Implications regarding economic policy can also emerge, as the accuracy of forecasts increases, making them more likely to be utilized in macroprudential regulation and systemic risk management, which highlights the broader social value of such analytical improvements. To sum up, the FbOA-optimized LSTM model is a highly scalable and powerful financial analytics tool with the potential to become a comprehensive approach that combines technical complexity with business relevance. It has the potential to significantly improve economic forecasting, which is associated with the new requirements of the global financial system to be more resilient, sustainable, and strategic in its approach; hence, it represents a paradigm shift in corporate finance and investment management.

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