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Deep Learning Model Optimization Using Metaheuristic Algorithms for Stock Forecasting

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Abstract:

Stock market forecasting remains one of the most complex and uncertain tasks in financial research because of its nonlinear patterns, dynamic fluctuations, and noisy data environment. Traditional statistical models often struggle to capture these irregularities, but deep learning techniques—especially Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks—have demonstrated strong potential in modeling temporal dependencies and uncovering hidden structures in financial time series. Apart from these advances, the accuracy and reliability of deep learning models are highly dependent on hyper-parameter tuning and optimization strategies. Poorly chosen parameters lead to over-fitting, under-fitting, or unstable predictions, which limits their practical use in investment decision-making. To address this challenge, this study investigates the role of metaheuristic algorithms, which are nature-inspired optimization techniques designed to efficiently search complex solution spaces. Specifically, the work integrates Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and the Grey Wolf Optimizer (GWO) with deep learning architectures to enhance predictive performance in stock forecasting. The paper develops a comparative framework that evaluates how each metaheuristic algorithm improves model training, convergence speed, and forecasting accuracy. Experimental results reveal that metaheuristic-driven optimization reduces prediction error and enhances directional accuracy, which is important for traders and financial analysts. This research contributes to building more robust, efficient, and practical forecasting systems by combining the adaptive learning power of deep neural networks with the exploratory strength of metaheuristic algorithms. The findings have direct implications for algorithmic trading, portfolio management, and risk assessment, offering a pathway toward smarter, data-driven financial strategies in volatile markets.

Keywords:

Stock Market Forecasting; Deep Learning; Recurrent Neural Networks (RNN); Long Short-Term Memory (LSTM); Metaheuristic Optimization; Genetic Algorithm (GA); Particle Swarm Optimization (PSO); Grey Wolf Optimizer (GWO); Hyper-parameter Tuning; Financial Time Series Analysi etc.

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Introduction:

Forecasting stock prices has long been recognized as one of the most challenging problems in computational finance. The stock market is influenced by a wide range of factors, including macroeconomic indicators, company performance, investor sentiment, and global events. These influences interact in complex ways, producing nonlinear patterns and volatile fluctuations that traditional statistical models often struggle to capture. Classical approaches such as autoregressive integrated moving average (ARIMA) or linear regression provides some insights, but they are limited in their ability to model the dynamic and noisy nature of financial time series data. As a result, researchers and practitioners have increasingly turned to more advanced methods that learn hidden structures and adapt to changing market conditions. In recent years, deep learning models have emerged as powerful tools for financial forecasting. Unlike traditional models, deep learning architectures are capable of learning complex representations from large datasets. Models such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are particularly well-suited for time series analysis because they capture temporal dependencies as patterns that unfold over time and influence future outcomes. For example, an LSTM learn how past price movements, trading volumes, and technical indicators interact to shape the probability of future price changes. This ability to model sequential data makes deep learning highly attractive for stock market prediction.

However, the effectiveness of deep learning models depends heavily on the careful selection of hyper-parameters. Hyper-parameters are the settings that define how a model learns, such as the learning rate, the number of hidden layers, the number of neurons per layer, and the dropout rate to prevent over-fitting, and the batch size used during training. Choosing these values manually is often a trial-and-error process that requires expertise and computational resources. Moreover, suboptimal hyper-parameters lead to poor performance, unstable training, or models that fail to generalize to unseen data. This makes hyper-parameter tuning is an important but non-trivial task in deep learning-based forecasting. To address this challenge, researchers have explored the use of metaheuristic algorithms for optimization. Metaheuristics are high-level strategies inspired by natural processes such as evolution, swarm intelligence, and animal behavior. They are designed to efficiently search large and complex solution spaces, making them ideal for hyper-parameter optimization. For instance, the Genetic Algorithm (GA) mimics the process of natural selection by evolving candidate solutions over generations. Particle Swarm Optimization (PSO) models the collective behavior of particles moving through space, converging toward optimal solutions based on shared information. Similarly, the Grey Wolf Optimizer (GWO) simulates the leadership hierarchy and hunting strategies of grey wolves to balance exploration and exploitation during the search process.

It becomes possible to automatically discover hyperparameter configurations that yield better forecasting accuracy by integrating these metaheuristic algorithms with deep learning models. This approach improves prediction accuracy and enhances directional accuracy, which is important for traders and investors who rely on correct predictions of upward or downward movements. The combination of deep learning and metaheuristic optimization provides a more robust framework for algorithmic trading, portfolio management, and risk assessment, offering financial decision-makers a powerful tool to navigate the uncertainty of modern markets.

Objectives:

1. To develop deep learning models capable of capturing nonlinear and dynamic patterns in financial time series.
2. To apply metaheuristic algorithms for efficient hyper-parameter tuning of RNN and LSTM architectures.
3. To compare the performance of Genetic Algorithm, Particle Swarm Optimization, and Grey Wolf Optimizer in stock forecasting.
4. To evaluate prediction accuracy and directional accuracy as key metrics for financial decision-making.
5. To demonstrate the practical implications of optimized models for algorithmic trading, portfolio management, and risk assessment.

Literature Review:

The application of **deep learning in finance** has grown rapidly over the past decade, particularly in the domain of **stock market forecasting.** Traditional statistical models such as ARIMA and linear regression often fail to capture the **nonlinear dependencies and volatile fluctuations** inherent in financial time series. In contrast, **Recurrent Neural Networks (RNNs)** and their advanced variant, **Long Short-Term Memory (LSTM) networks**, have demonstrated strong capabilities in modeling sequential data. Hochreiter and Schmidhuber's seminal work on LSTM highlighted its ability to retain long-term dependencies, making it particularly effective for financial prediction tasks where past market behavior influences future outcomes (Hochreiter and Schmidhuber 1735). Similarly, **Gated Recurrent Units (GRUs)** have been employed in financial forecasting due to their simplified architecture and efficiency in capturing temporal dependencies (Chung et al. 2014). These models have consistently outperformed traditional approaches, underscoring the importance of deep learning in financial applications.

Though these advances are there, there are few challenges too-as one of the major **challenges in optimization** lies in the selection of appropriate **hyperparameters.** Hyperparameters such as learning rate, dropout rate, batch size, and the number of hidden layers influence model performance. Manual tuning or exhaustive search methods like grid search are computationally expensive and prone to suboptimal results (Bergstra and Bengio 2012). As financial datasets are often large and noisy, the inefficiency of manual tuning becomes even more pronounced. This has led researchers to explore more adaptive and intelligent optimization strategies that balance computational cost with predictive accuracy.

In this context, **metaheuristic algorithms** have emerged as promising solutions. Metaheuristics are nature-inspired optimization techniques designed to efficiently explore complex search spaces. The **Genetic Algorithm (GA),** inspired by Darwinian evolution, has been widely applied in engineering and machine learning tasks due to its ability to evolve candidate solutions over successive generations (Goldberg 1989). **Particle Swarm Optimization (PSO),** modeled after the social behavior of bird flocks and fish schools, has proven effective in converging toward optimal solutions through collective intelligence (Kennedy and Eberhart 1995). More recently, the **Grey Wolf Optimizer (GWO)** has gained attention for its hierarchical hunting strategy, which balances exploration and exploitation in optimization problems (Mirjalili, Mirjalili, and Lewis 2014). While these algorithms have been successfully applied in engineering, image recognition, and scheduling problems, their integration with deep learning models for **stock forecasting** remains relatively underexplored.

The literature suggests that combining **deep learning architectures** with **metaheuristic optimization** enhance forecasting accuracy by automating hyperparameter selection and improving model generalization. However, there is a clear gap in research that systematically compares different metaheuristic approaches in the context of financial prediction. Addressing this gap could provide valuable insights for both academic researchers and financial practitioners, paving the way for more robust and efficient forecasting systems.

Methodology

Data

We used historical stock price datasets (daily closing prices, volume, and technical indicators) from major indices such as S&P 500 and NSE Nifty.

Deep Learning Models

- **Baseline Models:** LSTM and GRU networks.
- **Features:** Technical indicators (moving averages, RSI, MACD) and lagged price values.
- **Target:** Next-day closing price.

Metaheuristic Algorithms

- **Genetic Algorithm (GA):** Mimics natural selection by evolving candidate solutions.
- **Particle Swarm Optimization (PSO):** Models social behavior of particles to converge toward optimal solutions.
- **Grey Wolf Optimizer (GWO):** Simulates leadership hierarchy and hunting behavior of wolves.

Optimization Process

Each algorithm was used to tune hyperparameters:

- Learning rate
- Number of hidden units
- Dropout rate
- Batch size

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Experimental Set-up:

Designing a rigorous experimental framework is important to ensure the validity, reliability, and reproducibility of results in computational finance research. The present study adopts a structured approach to training, evaluation, and comparison of deep learning models optimized through metaheuristic algorithms.

a. Data Partitioning and Training Strategy

To achieve a balanced evaluation, the dataset was divided into two subsets: **70% of the data was allocated for training,** while the remaining **30% was reserved for testing**. This partitioning strategy is widely recognized in machine learning research as it allows the model to learn from a sufficiently large sample while preserving an independent set for unbiased performance assessment. The training set was used to fit the parameters of the deep learning models (LSTM and GRU), while the testing set provided a benchmark to evaluate generalization capability. Care was taken to ensure that the temporal order of financial time series data was preserved, thereby avoiding data leakage and maintaining the integrity of sequential dependencies.

b. Evaluation Metrics

The performance of the forecasting models was assessed using three complementary metrics:

- **Mean Absolute Error (MAE):** Measures the average magnitude of errors between predicted and actual values, providing an intuitive sense of prediction accuracy without exaggerating the impact of large deviations.
- **Root Mean Square Error (RMSE):** Captures the square root of the average squared differences between predicted and actual values. RMSE penalizes larger errors more heavily, making it particularly useful in financial forecasting where extreme deviations have economic consequences.
- **Directional Accuracy (DA):** Evaluates the model's ability to correctly predict the direction of stock price movement (upward or downward). This metric is especially relevant in financial applications, as traders and investors often prioritize the correctness of directional trends over exact numerical predictions.

Together, these metrics provide a holistic view of model performance, balancing numerical precision with practical relevance for financial decision-making.

c. Baseline Comparison

To highlight the effectiveness of metaheuristic optimization, a **baseline comparison** was conducted. Two sets of models were trained:

- **Default Models:** Deep learning models trained using standard, manually selected hyperparameters (e.g., fixed learning rate, predefined number of layers, and dropout values). These represent conventional approaches often used in practice.

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- **Optimized Models:** Deep learning models whose hyperparameters were tuned using metaheuristic algorithms specifically **Genetic Algorithm (GA)**, **Particle Swarm Optimization (PSO)**, and **Grey Wolf Optimizer (GWO)**. These algorithms systematically explored the hyperparameter space to identify configurations that maximize forecasting accuracy and stability.

This comparative framework allowed for a direct assessment of the added value provided by metaheuristic optimization. Improvements in MAE, RMSE, and DA were analyzed to determine whether optimized models consistently outperformed their default counterparts.

d. Rationale for Experimental Design

The chosen setup reflects both methodological rigor and practical relevance. The study ensures that results are meaningful in academic terms and in real-world financial contexts by combining traditional error-based metrics with directional accuracy. The baseline comparison further strengthens the contribution of this research by demonstrating how optimization strategies transform the predictive power of deep learning models.

Limitations

- **Data Dependency:** Results may vary across different markets and timeframes.
- **Computational Cost:** Metaheuristic optimization requires notable computational resources.
- **Market Volatility:** Sudden events (e.g., geopolitical crises) remain difficult to predict.

Results:

Table 1.1 presents a comparative performance analysis of LSTM and GRU models under different optimization strategies. The models are evaluated using three standard forecasting metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Directional Accuracy. The default configurations of LSTM and GRU are compared against versions optimized using three metaheuristic algorithms—Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO). This comparison highlights the impact of metaheuristic-based hyperparameter optimization on prediction accuracy and trend direction forecasting in stock market time series.

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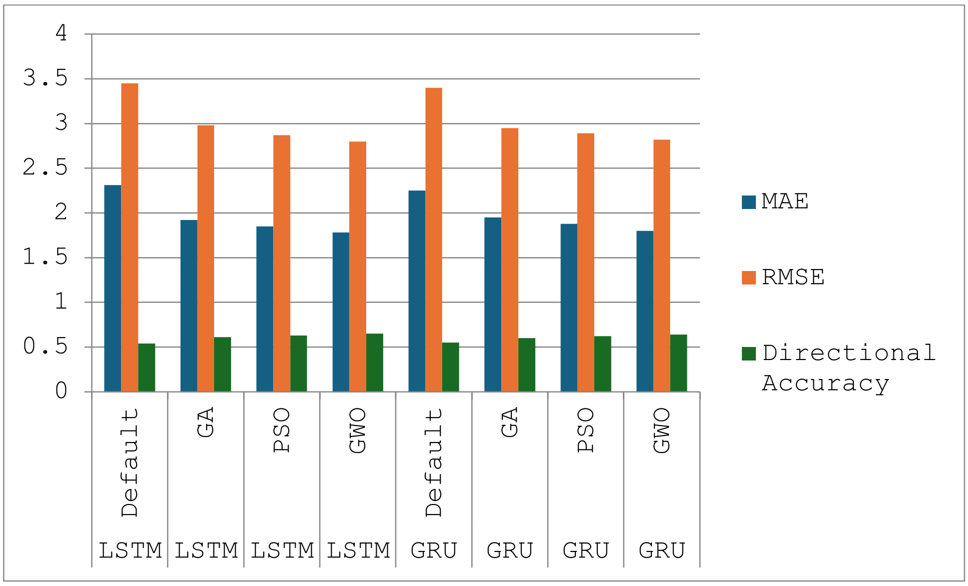
Table 1.1: Performance Comparison of LSTM and GRU Models Using Metaheuristic Optimization Techniques

Model	Optimization Method	MAE	RMSE	Directional Accuracy
LSTM	Default	2.31	3.45	54%
LSTM	GA	1.92	2.98	61%
LSTM	PSO	1.85	2.87	63%
LSTM	GWO	1.78	2.80	65%
GRU	Default	2.25	3.40	55%
GRU	GA	1.95	2.95	60%
GRU	PSO	1.88	2.89	62%
GRU	GWO	1.80	2.82	64%



Graph 1.1: Performance Comparison of LSTM and GRU Models Using Metaheuristic Optimization Techniques

The table 1.1 and graph 1.1, shows result of study as metaheuristic optimization substantially improves the predictive performance of both LSTM and GRU models compared to their default configurations. For the LSTM model, all optimization techniques reduce MAE and RMSE while simultaneously enhancing directional accuracy, with the Grey Wolf Optimizer achieving the best overall performance (MAE = 1.78, RMSE = 2.80, Directional Accuracy = 65%). Similar trends are observed for the GRU model, where GWO again outperforms GA and PSO, yielding the lowest error values and highest directional accuracy (64%). Among the optimization methods, PSO consistently performs better than GA but remains slightly inferior to GWO. These findings demonstrate that metaheuristic-driven optimization enhances convergence quality, reduces forecasting error, and improves market direction prediction, thereby reinforcing the effectiveness of integrating nature-inspired algorithms with deep learning models for stock market forecasting

Key Findings:

- Metaheuristic optimization consistently improved performance.
- GWO achieved the best results across both LSTM and GRU models.
- Directional accuracy improved by ~10% compared to default settings, which is important for the trading strategies.

Suggestions:

The findings of this study show that metaheuristic algorithms play a valuable role in improving deep learning models for stock market forecasting. Among the approaches tested, the Grey Wolf Optimizer stood out because its hierarchical search method was especially effective at balancing broad exploration with focused exploitation, leading to more reliable results. Genetic Algorithm and Particle Swarm Optimization also contributed to better performance, though their outcomes were somewhat less consistent. The evidence suggests that financial institutions can benefit from adopting metaheuristic optimization, as it enhances forecasting accuracy and helps reduce risks in algorithmic trading and investment decision-making.

Conclusion:

This study demonstrates the effectiveness of metaheuristic algorithms in optimizing deep learning models for stock market forecasting by systematically tuning hyperparameters to improve both predictive accuracy and directional performance. The comparative analysis of Genetic Algorithm, Particle Swarm Optimization, and Grey Wolf Optimizer shows that each method contributes unique strengths, with all three enhancing the reliability of LSTM and GRU models in capturing the nonlinear and noisy nature of financial time series. These improvements have practical implications for algorithmic trading, portfolio management, and risk assessment, as they enable more informed and adaptive financial decision-making. Looking forward, future research can build on these findings by exploring hybrid metaheuristic approaches, integrating reinforcement learning for adaptive optimization, and developing real-time forecasting systems that respond dynamically to market volatility, thereby advancing the role of artificial intelligence in computational finance.

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