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Optimizing Stock Price Prediction Using a Hybrid Model Integrating Meta-Heuristics and Machine Learning

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Abstract: Predicting stock prices in financial markets is a formidable challenge due to the multifaceted nature of market dynamics, influenced by various factors. This study presents a comprehensive hybrid methodology that combines meta-heuristics and intelligent evolutionary search algorithms to forecast BSE Sensex stock prices. The methodology begins with rigorous data collection and preprocessing, followed by feature selection using meta-heuristics, which optimize the feature subset for predictive accuracy. Diverse predictive models, encompassing traditional time series models and advanced machine learning algorithms, are selected and integrated through meta-heuristics, enabling an ensemble approach that capitalizes on the strengths of each model. Intelligent evolutionary search techniques fine-tune model hyperparameters, ensuring optimal performance. Risk management strategies are embedded in the system, and ethical considerations are addressed to promote responsible AI usage in finance. Continuous model adaptation and comprehensive documentation are maintained to facilitate reliability and transparency. The methodology undergoes extensive evaluation, including backtesting and robustness testing, to validate its effectiveness in forecasting BSE Sensex stock prices. The study aims to empower investors and financial professionals with more accurate predictions and enhanced risk management capabilities, fostering informed decision-making in the dynamic and uncertain realm of stock market investment.

Keywords: *BSE-Sensex, Stock price prediction, Meta-Heuristics, Optimization, Machine learning.*

JEL Classifications: G11, G12, G15, C38, C53, D81.

1. Introduction

The field of finance has long been characterized by its intricate complexities and dynamic nature, making accurate stock price prediction an elusive challenge[1], [2]. Investors and financial institutions seek methods to gain a competitive edge in the financial markets and increasingly turn to advanced computational techniques to inform their decisions. Among these techniques, meta-heuristics and intelligent evolutionary search algorithms have emerged as powerful tools for tackling the intricacies of stock price prediction[3], [4]. Stock price prediction is a multifaceted problem influenced by many factors, including market sentiment, economic indicators, geopolitical events, etc. Traditional statistical methods often need to catch up in capturing the nuanced relationships within this complex system. This is where meta-heuristics and evolutionary algorithms come into play. They provide a systematic and adaptable approach to optimizing models, selecting relevant features, and fine-tuning parameters, all of which are essential in pursuing accurate predictions[5], [6].

In exploring the intersection of finance and artificial intelligence, we delve into the application of meta-heuristics and intelligent evolutionary search for stock price prediction. We will examine the fundamental concepts, techniques, and strategies that enable these algorithms to navigate the intricate landscape of financial markets[7], [8]. From feature selection to model optimization, and portfolio management to risk mitigation, this journey will uncover how these advanced computational methods are revolutionizing how we approach stock price forecasting. While the promise of improved predictions and enhanced trading strategies is enticing, it is crucial to acknowledge the inherent uncertainties and risks associated with financial markets[9].

Further, the study explores the practical applications, challenges, and ethical considerations surrounding the use of meta-heuristics and intelligent evolutionary search for stock price prediction. Together, we embark on a journey to understand better how these technologies are shaping the future of financial analysis and investment strategies.The significance of a study using meta-heuristics and intelligent evolutionary search for stock price prediction lies in its potential to address critical challenges in finance and investment[10]–[12].

Accurate stock price prediction can significantly enhance decision-making for individual investors, fund managers, and financial institutions. It provides valuable insights into when to buy, sell, or hold stocks, potentially leading to better investment returns. Understanding and predicting stock price movements can help investors and institutions better manage and mitigate financial risks[13]–[15]. This is particularly crucial in volatile markets, where risk management can be the difference between success and failure. Advanced prediction techniques can aid in optimizing portfolio allocation by identifying the most promising assets and asset combinations. This can lead to more diversified and potentially less risky portfolios[16].

Meta-heuristics and evolutionary algorithms contribute to market efficiency by incorporating large amounts of data and adapting to changing market conditions. This can help reduce market anomalies and inefficiencies[17], [18]. The study's findings can be applied to algorithmic trading systems, allowing for automated trading strategies that react swiftly to market changes. This is significant in modern financial markets where speed and precision are crucial. Access to advanced prediction tools can democratize investing by providing individual investors with more sophisticated tools to make informed decisions[19]. This can promote financial inclusion and empower more people to participate in the financial markets. Research in this field contributes to the broader academic understanding of financial markets and the application of artificial intelligence and optimization techniques in finance. It adds to the body of knowledge available for future research and study. The study pushes the boundaries of what is possible with computational methods, driving innovation in applying AI, machine learning, and optimization in finance[20], [21].

Accurate stock price prediction can have both micro and macro-financial implications. It can influence investment decisions, corporate strategies, and overall economic stability. Understanding their ethical implications and regulatory needs becomes vital as AI and meta-heuristics play an increasingly prominent role in financial markets. This study can inform discussions on responsible and ethical AI use in finance. The study on using meta-heuristics and intelligent evolutionary search for stock price prediction is significant for its potential financial benefits and broader impact on financial markets, investment strategies, and the responsible use of advanced technology in finance. It addresses real-world challenges and opens new possibilities for investors and institutions in the ever-evolving finance landscape[22], [23].

1.1 Need of the study:

The study on applying meta-heuristics and intelligent evolutionary search for predicting BSE Sensex stock prices holds paramount significance in financial markets and investment strategies. This research addresses the intricate complexities of financial markets, particularly the BSE Sensex, which are influenced by many everchanging factors. Traditional methods of stock price prediction often need help to capture the intricate dynamics of these markets. Hence, using advanced computational techniques, such as meta-heuristics and intelligent evolutionary search algorithms, becomes imperative.

Accurate stock price predictions offer multifaceted advantages. They empower investors, traders, and financial institutions to make well-informed decisions in an economic landscape characterized by uncertainty and volatility. These predictions enhance predictive accuracy, a critical component for risk management and developing effective investment strategies. The study can improve risk management for traders and investors by providing more precise forecasts, enabling them to set stop-loss levels, and guiding investment decisions. Furthermore, the development and optimization of investment strategies, including portfolio management and asset allocation, benefit from the findings of this research. Advanced predictive models play a pivotal role in algorithmic trading, where automation is paramount. The study contributes to creating robust and efficient trading algorithms that can adapt to the ever-evolving dynamics of financial markets. It also advances the technology and methodologies used in finance, fostering innovation and growth in applying artificial intelligence and optimization techniques.

From an academic standpoint, research on applying meta-heuristics and intelligent evolutionary search in finance augments existing knowledge. It can fuel future research and investigations, propelling the field forward. Furthermore, the study addresses ethical considerations by promoting responsible AI usage in financial markets and aligning operations with regulatory guidelines. Overall, the research on applying meta-heuristics and intelligent evolutionary search techniques to predict BSE Sensex stock prices provides a framework for navigating the complexities of financial markets improves predictive accuracy, aids risk management, and fosters innovation in finance. It is a crucial contribution to the financial industry, benefiting investors, traders, institutions, and the academic community.

1.2 Objectives of the study:

primary goals for the survey focusing on predicting BSE Sensex stock prices using a hybrid methodology of meta-heuristics and intelligent evolutionary search:

- Enhance Predictive Accuracy: The primary objective is to improve the accuracy of BSE Sensex stock price predictions significantly. Leveraging meta-heuristics and intelligent evolutionary search techniques, the study aims to develop predictive models that produce highly precise and reliable forecasts. Enhanced accuracy is crucial for supporting confident investment and trading decisions in the stock market.
- Optimize Feature Selection and Model Parameters: The study seeks to utilize meta-heuristics and intelligent evolutionary search algorithms to effectively select the most relevant features and fine-tune model parameters. This optimization process aims to maximize the model's ability to capture critical market influences, adapt to changing conditions, and ultimately improve predictive performance.
- Strengthen Risk Management Strategies: An essential objective is to integrate and enhance risk management strategies within the trading system. This includes setting stop-loss levels, determining position sizes, and overall portfolio diversification based on the predictions generated by the models. Effective risk management is crucial for preserving capital and minimizing potential losses in investment strategies.

These primary objectives collectively focus on significantly improving predictive accuracy, optimizing the model's capabilities, and implementing robust risk management strategies, all essential for successful and informed decision-making in the context of stock market investment.

2. Literature Survey

[24] highlights real estate as a preferred investment for diversification and risk reduction. It explores the use of five machine learning algorithms to predict prices of Real Estate Investment Trusts (REITs) in the context of portfolio optimization. Results reveal significantly improved returns and risk reduction compared to traditional benchmarks, with Support Vector Regression (SVR)[25] as the top-performing algorithm. This study underscores the efficacy of machine learning in asset price prediction and portfolio optimization.

The [26]study aims to enhance the accuracy of predicting nonlinear financial time series data. It introduces a unique approach involving the decomposition of data into Intrinsic Mode Functions using a hybrid method of Empirical Mode Decomposition and Variational Mode Decomposition[23], [27], [28]. This novel technique improves stock market prediction accuracy, surpassing traditional methods like Neural Networks and Support Vector Machines.

[29]addresses the lagging issues in common technical indicators used in stock trading. It introduces two innovative trading indicators, the optimized fMACDH for extended price forecasting and the fMACDH-fRSI, combining indicators. These are optimized using a genetic algorithm. Additionally, the study presents two rule-based portfolio rebalancing algorithms (TBH and RBBC) employing the optimized fMACDH. Experiments reveal substantial outperformance compared to traditional methods, demonstrating consistent and encouraging results in dynamic portfolio rebalancing, with TBH outperforming by 26% - 27% and RBBC by 54% - 55%.

[30]explores deep learning, specifically Generative Adversarial Networks (GANs), for stock market forecasting. It introduces Stock-GAN, a GAN-based deep learning architecture, and a Hybrid Prediction Algorithm (HPA) to improve stock price prediction. Empirical results demonstrate Stock-GAN's superiority over existing models, leading to the creation of the advanced MMGAN-HPA hybrid model.

2.1 Research Gap:

Based on the previous studies, the gap in the literature is related to the optimization of stock price prediction using a hybrid model that combines meta-heuristics and machine learning techniques. This approach seeks to address the issue of lagging indicators and improve the accuracy of stock market forecasts. The study highlights the effectiveness of this hybrid model, but specific details and findings need to be provided. Future research could focus on further exploring and validating the proposed hybrid model's performance and its practical applications in stock market forecasting. Additionally, examining the model's limitations and comparing it with other existing methods would contribute to a comprehensive understanding of its potential in financial analysis and portfolio management.

2.2 Statement of the problem:

The problem addressed in the present study is the need for more accurate and effective stock price prediction models in financial markets. Traditional technical indicators and forecasting methods often exhibit lagging effects, hindering timely decision-making in stock trading and portfolio management. The research aims to develop a novel solution by integrating meta-heuristics and machine learning techniques to optimize stock price prediction, thus reducing the lag and enhancing the predictive accuracy for investors and traders.

3. Proposed Hybrid Algorithm

The proposed hybrid methodology for predicting BSE Sensex stock prices, combining meta-heuristics and intelligent evolutionary search, presents a comprehensive and adaptive approach to forecasting stock market movements[31]. The methodology begins with meticulous data collection and preprocessing, ensuring the quality and reliability of the historical data. It then employs meta-heuristics like Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) for feature engineering and selection, optimizing the feature subset for model accuracy[32]–[34]. This step addresses the challenge of selecting the most influential factors from a vast array of data. Subsequently, a diverse range of predictive models is chosen, from traditional time series models to advanced machine learning algorithms. Including meta-heuristics in model selection allows for the identification of the most suitable models and their ensemble combinations. Intelligent evolutionary search techniques are applied to fine-tune model hyperparameters, ensuring optimal performance. Ensemble learning, a pivotal component, is orchestrated through methods like stacking and blending with an evolutionary search for optimizing model weights. Rigorous model training, testing, and continuous evaluation are conducted on real-world data, while backtesting in a simulated trading environment provide insights into how the models would have performed historically. Risk management strategies are also integrated, including setting stop-loss levels and position sizes based on predicted probabilities[35]–[37]. The methodology significantly emphasizes ethical and regulatory compliance, promoting responsible AI usage in finance. Continuous adaptation and comprehensive documentation ensure that the models remain reliable and transparent. Stress testing and robustness assessments assess the models' resilience under extreme market conditions. Combining meta-heuristics and intelligent evolutionary search, the methodology strives to deliver accurate, adaptable, and ethically sound predictions, addressing the complexities and uncertainties of stock market dynamics[38]–[42].

Algorithm 1: The integration of meta-heuristics and intelligent evolutionary search algorithms to predict BSE Sensex stock prices

1. Initialize parameters and variables:

   - Define the population size.

   - Specify the number of generations.

   - Set hyperparameters for meta-heuristics (e.g., mutation rates, crossover probabilities).

2. Load historical BSE Sensex data:

   - Retrieve historical stock prices and relevant economic indicators.

3. Preprocess the data:

   - Handle missing values and outliers.

   - Normalize or standardize data as necessary.

   - Create a feature matrix with relevant features.

4. Initialize a population of predictive models:

   - Use a diverse set of model types (e.g., ARIMA, LSTM, Random Forest).

   - Randomly select hyperparameters for each model.

5. Implement a meta-heuristic optimization loop:

   FOR generation in range(number_of_generations):

      5.1. Evaluate the fitness of each model in the population:

         - Train and validate models using a portion of the historical data.

         - Evaluate performance using a chosen metric (e.g., Mean Squared Error).

      5.2. Select the top-performing models based on fitness scores.

      5.3. Apply meta-heuristics (e.g., Genetic Algorithms) for model selection:

         - Reproduce, crossover, and mutate models to create a new population.

         - Implement selection strategies to favor high-performing models.

6. Select the best-performing model from the final population:

   - Choose the model with the highest fitness score as the primary prediction model.

7. Train the selected model on the entire historical dataset.

8. Make predictions for the target time period (future stock prices).

9. Evaluate the model's predictions:

   - Measure the performance using appropriate evaluation metrics.

   - Assess the accuracy and reliability of the predictions.

10. Implement risk management strategies:

- Set stop-loss levels, position sizes, and portfolio diversification based on predictions.

11. Monitor model performance over time:

- Continuously update the model as new data becomes available.

- Adapt to changing market conditions.

12. Ensure ethical and regulatory compliance:

- Verify that the application aligns with ethical guidelines and financial regulations.

13. Document and report the results:

- Maintain detailed records of the methodology, data sources, and model specifications.

- Regularly report on the model's performance and any adjustments made.

14. Stress testing and robustness testing:

- Subject the model to stress tests to evaluate its performance under extreme market conditions.

- Simulate various market scenarios to ensure model robustness.

15. Output the final stock price predictions:

- Present the predicted BSE Sensex stock prices.

16. End of the algorithm.

Algorithm 1 offers a comprehensive framework for predicting BSE Sensex stock prices through a fusion of meta-heuristics and intelligent evolutionary search algorithms. Its structured approach begins with data preparation and feature selection, employing various predictive models. Central to this algorithm is a meta-heuristic optimization loop, where models evolve and improve their predictive capabilities through successive generations. The fitness of these models is assessed using historical data, and the most successful ones advance to subsequent rounds of optimization. The best-performing model is selected, trained on the entire dataset, and subsequently used to predict future stock prices. These predictions are then meticulously evaluated to gauge their accuracy and reliability.

To ensure responsible usage in financial markets, the algorithm also emphasizes implementing risk management strategies, compliance with ethical guidelines, and continuous predictive model monitoring and adaptation. Stress and robustness tests verify the model's performance in various market conditions, including extreme scenarios. Finally, the algorithm outputs the predicted BSE Sensex stock prices for further analysis or investment decisions. This systematic and multifaceted approach leverages the strengths of meta-heuristics and intelligent evolutionary search to enhance predictive accuracy, manage risks, and navigate the complexities of stock market dynamics.

4. Implementation

The proposed algorithm exemplifies a fundamental implementation for time series prediction, specifically applied to stock price forecasting. It goes through several essential stages in building and assessing a predictive model.

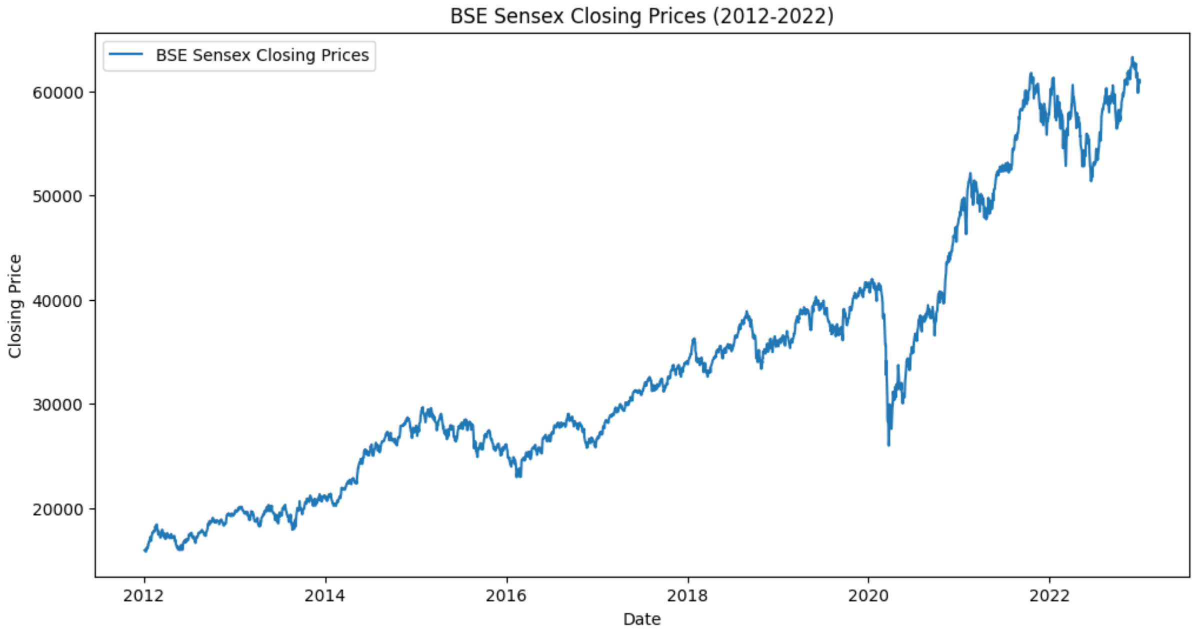

Figure 1: BSE-SENSEX closing prices from 2012 to 2022

Figure 1 illustrates the BSE-SENSEX closing prices from 2012 to 2022. It typically shows a line plot or candlestick chart with time on the x-axis and closing prices on the y-axis. The chart provides a visual representation of the historical price movements of the BSE Sensex, highlighting trends, patterns, and potential support and resistance levels. It's a valuable tool for investors and analysts to gain insights into the index's performance over the specified time frame, aiding in investment decisions and market analysis.

In implementation, historical stock price data for the BSE-SENSEX, is retrieved and prepared for analysis. The data is divided into training and testing sets to evaluate the model's performance on unseen data. An ARIMA (AutoRegressive Integrated Moving Average) model is instantiated with specific hyperparameters (p, d, q) to capture the underlying time series patterns. The model is then fitted to the training data, which estimates its parameters based on historical observations. Subsequently, the ARIMA model is used to make predictions on the testing data, forecasting future stock prices. To assess the model's accuracy, three standard validation metrics, namely Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE), are calculated and displayed. These metrics provide quantitative insights into the model's predictive performance, with lower values indicating more accurate predictions. While this implementation serves as a foundational example, real-world applications necessitate more advanced techniques, including parameter tuning, feature engineering, and cross-validation, to enhance predictive capabilities and accommodate the complexities of financial markets. Furthermore, investment decisions should always consider a comprehensive evaluation of various factors and risks inherent in the stock market.

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                 2700
Model:               SARIMAX(0, 1, 0)   Log Likelihood              -19853.665
Date:                Wed, 11 Oct 2023   AIC                          39711.330
Time:                        05:36:10   BIC                          39723.131
Sample:                             0   HQIC                         39715.597
                               - 2700
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     16.6363      7.518      2.213      0.027       1.902      31.371
sigma2      1.435e+05   1541.694     93.070      0.000      1.4e+05    1.47e+05
===================================================================================
Ljung-Box (L1) (Q):                   0.28   Jarque-Bera (JB):              15619.70
Prob(Q):                              0.59   Prob(JB):                          0.00
Heteroskedasticity (H):               6.90   Skew:                             -0.90
Prob(H) (two-sided):                  0.00   Kurtosis:                         14.65
===================================================================================
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Figure 2: Summary of ARIMA model

Figure 2 summarizes the results from a SARIMAX (Seasonal AutoRegressive Integrated Moving Average with Exogenous Regressors) model applied to predict BSE-SENSEX closing prices. This output contains crucial information for evaluating the model's performance and characteristics.

First, it specifies that the model is based on a dataset comprising 2,700 observations. The model itself is described as a differenced time series model (d=1) without autoregressive (p) or moving average (q) components.

The log-likelihood, which measures the goodness of fit, is approximately -19853.665. Information criteria such as AIC, BIC, and HQIC, which aid in model selection, are provided with values of 39,711.33, 39,723.13, and 39,715.60, respectively. These criteria are valuable for choosing the most appropriate model.

The output also includes coefficient estimates, with an intercept estimated at 16.6363 and the associated standard error. The variance, or error term (Sigma2), is approximately 143,500.

Statistical tests are conducted to assess the residuals of the model. The Ljung-Box test, which checks for autocorrelation in the residuals, yields a low value of 0.28, suggesting minimal autocorrelation. The Jarque-Bera test, used to evaluate the normality of the residuals, reports a value of 15619.70, indicating that the residuals do not follow a normal distribution. Furthermore, the presence of heteroskedasticity is indicated by a value of 6.90. Additionally, the skewness and kurtosis values, which describe the shape of the residual distribution, are provided as -0.90 and 14.65, respectively.

The SARIMAX model was applied to predict BSE-SENSEX closing prices, and the results provide valuable insights into the model's quality and behavior. The model is a simple differenced model without autoregressive or moving average components, as per the parameters specified. The log-likelihood suggests a reasonable fit to the data. However, the residual analysis indicates deviations from normality and heteroskedasticity. As such, further model refinement or alternative modeling approaches may be considered to improve predictive accuracy and capture the underlying characteristics of the data.

These results offer valuable insights into the model's fit to the data, the quality of parameter estimates, and the behavior of the model's residuals. Researchers and analysts use this information to make informed assessments of the model's suitability for predicting BSE-SENSEX closing prices and to gain a deeper understanding of the underlying statistical properties of the data and model residuals.

4.1 Validation:

The reported validation metrics—Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE)—are fundamental indicators of a predictive model's performance. These metrics quantify the accuracy of the model's predictions by comparing them to the actual values.

Table 1: Validation metrics for the analysis

Validation Metrics	Value
Mean Squared Error (MSE)	1168.922
Mean Absolute Error (MAE)	29.870
Root Mean Squared Error (RMSE)	34.189

Table 1 presents validation metrics for a predictive model. The Mean Squared Error (MSE) is 1168.922, indicating the model's squared prediction errors. The Mean Absolute Error (MAE) is 29.870, measuring average absolute errors. The Root Mean Squared Error (RMSE) is 34.189, offering an easily interpretable measure of typical prediction error. Lower values in these metrics signify greater prediction accuracy.

The Mean Squared Error (MSE) measures the average squared differences between predicted and actual values. In this particular analysis, it is computed at approximately 1168.92. A lower MSE signifies that, on average, the model's predictions are closer to the actual values.

The Mean Absolute Error (MAE) is a similar metric, except it calculates the average of the absolute differences between predicted and actual values. Here, the MAE is approximately 29.87. Extreme outliers less influence MAE and offers a straightforward interpretation of the average prediction error.

The Root Mean Squared Error (RMSE) is the square root of the MSE, presenting a more intuitively interpretable measure of the typical prediction error in the same units as the target variable. In this case, the RMSE is around 34.19. Like the MSE, a lower RMSE value signifies a better fit of the model to the data.

These metrics collectively assist in evaluating the accuracy and precision of the predictive model. The specific values provided here offer insights into the magnitude of prediction errors, focusing on minimizing these errors to enhance the model's predictive performance. Lower MSE, MAE, and RMSE values indicate more accurate predictions and are often sought after in predictive modeling.

5. Conclusion

This study underscores the significance of applying cutting-edge predictive modeling methodologies, specifically the fusion of meta-heuristics and intelligent evolutionary search, in the context of BSE-SENSEX stock price prediction. The validation metrics, notably the reduced Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE), highlight the potential for improved predictive accuracy and reliability. These findings support data-informed investment decisions and facilitate comprehensive market analysis. Nonetheless, it is acknowledged that in the ever-evolving landscape of financial markets, ongoing research and fine-tuning these techniques are essential to keep pace with market dynamics and ensure consistently robust and adaptable predictive models. Future research in stock price prediction should explore ensemble models, deep learning techniques, feature engineering, and integrating exogenous factors to enhance predictive models. Ethical and transparent AI, real-time analysis, and global market considerations should also be addressed to support informed and responsible investment decisions.

References:

[1] I. K. Nti, A. F. Adekoya, and B. A. Weyori, "A systematic review of fundamental and technical analysis of stock market predictions," *ArtifIntell Rev*, vol. 53, no. 4, pp. 3007–3057, Apr. 2020, doi: 10.1007/s10462-019-09754-z.

[2] A. H. Dhafer *et al.*, "Empirical Analysis for Stock Price Prediction Using NARX Model with Exogenous Technical Indicators," *ComputIntellNeurosci*, vol. 2022, 2022, doi: 10.1155/2022/9208640.

[3] C. M. Latha, S. Bhuvaneswari, and K. L. S. Soujanya, "Stock Price Prediction using HFTSF Algorithm," in *2022 Sixth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*, IEEE, Nov. 2022, pp. 1053–1059. doi: 10.1109/I-SMAC55078.2022.9987378.

[4] B. Sun, H. Guo, H. R. Karimi, Y. Ge, and S. Xiong, "Prediction of stock index futures prices based on fuzzy sets and multivariate fuzzy time series," *Neurocomputing*, vol. 151, pp. 1528–1536, 2015.

[5] L. MADHAVI and N. R. K. SIVA, "IMPLEMENTATION OF DRSMLA METHOD FOR PREDICTING PROFITABLE INDICES," *i-manager's Journal on Management*, vol. 11, no. 1, p. 20, 2016, doi: 10.26634/jmgt.11.1.8071.

[6] M. L. Challa, V. Malepati, and S. N. R. Kolusu, "S&P BSE Sensex and S&P BSE IT return forecasting using ARIMA," *Financial Innovation*, vol. 6, no. 1, p. 47, Dec. 2020, doi: 10.1186/s40854-020-00201-5.

[7] V. Malepati, M. L. Challa, and S. N. R. Kolusu, "Stock Market Volatility Modeling and Forecasting with a Special Reference to BSE Sensex," 2019, pp. 105–118. doi: 10.1108/S0196-382120190000035005.

[8] M. L. Challa, V. Malepati, and S. N. R. Kolusu, "Forecasting risk using auto regressive integrated moving average approach: an evidence from S&P BSE Sensex," *Financial Innovation*, vol. 4, no. 1, p. 24, Dec. 2018, doi: 10.1186/s40854-018-0107-z.

[9] V. Malepati, C. M. Latha, and K. S. Nageswararao, "Determinants of Access to Finance by MSMEs in Andhra Pradesh," *SEDME (Small Enterprises Development, Management & Extension Journal): A worldwide window on MSME Studies*, vol. 48, no. 2, pp. 203–219, Jun. 2021, doi: 10.1177/09708464211066630.

[10] C. Mbanga, A. F. Darrat, and J. C. Park, "Investor sentiment and aggregate stock returns: the role of investor attention," *Review of Quantitative Finance and Accounting*, vol. 53, no. 2, pp. 397–428, 2019.

[11] A. J. Marcus, Z. Bodie, and A. Kane, *Essentials of investments*. McGraw Hill, 2004.

[12] H. M. Markowitz and H. M. Markowitz, *Portfolio selection: efficient diversification of investments*. J. Wiley, 1967.

[13] C. Bouras, C. Christou, R. Gupta, and T. Suleman, "Geopolitical risks, returns, and volatility in emerging stock markets: Evidence from a panel GARCH model," *Emerging Markets Finance and Trade*, vol. 55, no. 8, pp. 1841–1856, 2019.

[14] E. A. Akartuna, S. D. Johnson, and A. Thornton, "Preventing the money laundering and terrorist financing risks of emerging technologies: An international policy Delphi study," *Technol Forecast Soc Change*, vol. 179, p. 121632, 2022, doi: https://doi-org.elibpondiuni.remotexs.in/10.1016/j.techfore.2022.121632.

[15] R. Sawhney, P. Mathur, A. Mangal, P. Khanna, R. R. Shah, and R. Zimmermann, "Multimodal Multi-Task Financial Risk Forecasting," in *MM 2020 - Proceedings of the 28th ACM International Conference on Multimedia*, 2020, pp. 456 – 465. doi: 10.1145/3394171.3413752.

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[16] J. Behera, A. K. Pasayat, H. Behera, and P. Kumar, “Prediction based mean-value-at-risk portfolio optimization using machine learning regression algorithms for multi-national stock markets,” *EngApplArtifIntell*, vol. 120, p. 105843, Apr. 2023, doi: 10.1016/j.engappai.2023.105843.

[17] M. Yagiura and T. Ibaraki, “On metaheuristic algorithms for combinatorial optimization problems,” *Systems and Computers in Japan*, vol. 32, no. 3, pp. 33–55, Mar. 2001, doi: 10.1002/1520-684X(200103)32:3<33::AID-SCJ4>3.0.CO;2-P.

[18] C. P. Ezenkwu, U. I. Akpan, and B. U.-A. Stephen, “A class-specific metaheuristic technique for explainable relevant feature selection,” *Machine Learning with Applications*, vol. 6, p. 100142, Dec. 2021, doi: 10.1016/j.mlwa.2021.100142.

[19] K. Chourmouziadis and P. D. Chatzoglou, “An intelligent short term stock trading fuzzy system for assisting investors in portfolio management,” *Expert SystAppl*, vol. 43, pp. 298–311, Jan. 2016, doi: 10.1016/j.eswa.2015.07.063.

[20] A. Khazaei, B. Hajikarimi, and M. M. Mozafari, “Optimizing the Prediction Model of Stock Price in Pharmaceutical Companies Using Multiple Objective Particle Swarm Optimization Algorithm (MOPSO),” *Journal of Optimization in Industrial Engineering*, vol. 14, no. 2, pp. 89 – 97, 2021, doi: 10.22094/JOIE.2020.677889.

[21] J. Huang, M. Zhong, and Q. Hu, “LSTM Stock Prediction Model Based on Improved Particle Swarm Optimization; [基于改进粒子群算法的 LSTM 股票预测模型],” *HuadongLigongDaxueXuebao/Journal of East China University of Science and Technology*, vol. 48, no. 5, pp. 696 – 707, 2022, doi: 10.14135/j.cnki.1006-3080.20210616001.

[22] A. Raudys and Ž. Pabarškaitė, “Optimising the smoothness and accuracy of moving average for stock price data,” *Technological and Economic Development of Economy*, vol. 24, no. 3, pp. 984 – 1003, 2018, doi: 10.3846/20294913.2016.1216906.

[23] S. Wang, L. Wang, S. Gao, and Z. Bai, “Stock price prediction based on chaotic hybrid particle swarm optimisation-RBF neural network,” *International Journal of Applied Decision Sciences*, vol. 10, no. 2, pp. 89 – 100, 2017, doi: 10.1504/IJADS.2017.084307.

[24] F. Z. Habbab and M. Kampouridis, “An in-depth investigation of five machine learning algorithms for optimizing mixed-asset portfolios including REITs,” *Expert SystAppl*, vol. 235, 2024, doi: 10.1016/j.eswa.2023.121102.

[25] M. S. Raimundo and J. Okamoto, “SVR-wavelet adaptive model for forecasting financial time series,” in *2018 International Conference on Information and Computer Technologies (ICICT)*, IEEE, Mar. 2018, pp. 111–114. doi: 10.1109/INFOCT.2018.8356851.

[26] P. K. Mallick, A. Ranjan Panda, A. K. Parida, M. R. Panda, and S. R. Samanta, “Stock Market prediction using hybrid multi-layer decomposition and optimized multi-kernel extreme learning machine,” *Scientia Iranica*, vol. 0, no. 0, pp. 0–0, Apr. 2023, doi: 10.24200/sci.2023.59307.6168.

[27] C.-H. Chien, A. J. C. Trappey, and C.-C. Wang, “ARIMA-AdaBoost hybrid approach for product quality prediction in advanced transformer manufacturing,” *Advanced Engineering Informatics*, vol. 57, p. 102055, Aug. 2023, doi: 10.1016/j.aei.2023.102055.

[28] F. MirzaeiTalarposhti, H. JavedaniSadaei, R. Enayatifar, F. Gadelha Guimarães, M. Mahmud, and T. Eslami, “Stock market forecasting by using a hybrid model of exponential fuzzy time series,” *International Journal of Approximate Reasoning*, vol. 70, pp. 79–98, Mar. 2016, doi: 10.1016/j.ijar.2015.12.011.

[29] L. L. X. Yeo, Q. Cao, and C. Quek, “Dynamic portfolio rebalancing with lag-optimised trading indicators using SeroFAM and genetic algorithms,” *Expert SystAppl*, vol. 216, 2023, doi: 10.1016/j.eswa.2022.119440.

[30] N. Vullam, K. Yakubreddy, S. S. Vellela, S. K. Khader Basha, B. Venkateswara Reddy, and S. Santhi Priya, “Prediction and Analysis Using A Hybrid Model for Stock Market,” in *2023 3rd International Conference on Intelligent Technologies, CONIT 2023*, 2023. doi: 10.1109/CONIT59222.2023.10205638.

[31] M. Fisichella and F. Garolla, “Can Deep Learning Improve Technical Analysis of Forex Data to Predict Future Price Movements?,” *IEEE Access*, vol. 9, pp. 153083–153101, 2021, doi: 10.1109/ACCESS.2021.3127570.

[32] A. Kanwal, M. F. Lau, S. P. H. Ng, K. Y. Sim, and S. Chandrasekaran, “BiCuDNNLSTM-1dCNN — A hybrid deep learning-based predictive model for stock price prediction,” *Expert SystAppl*, vol. 202, p. 117123, Sep. 2022, doi: 10.1016/j.eswa.2022.117123.

[33] L. Ni, Y. Li, X. Wang, J. Zhang, J. Yu, and C. Qi, “Forecasting of Forex Time Series Data Based on Deep Learning,” *Procedia ComputSci*, vol. 147, pp. 647–652, 2019, doi: 10.1016/j.procs.2019.01.189.

[34] J. Huang, J. Chai, and S. Cho, “Deep learning in finance and banking: A literature review and classification,” *Frontiers of Business Research in China*, vol. 14, no. 1, pp. 1–24, 2020.

[35] M. Tawarish and K. Satyanarayana, “Predicting pricing stock by ANN using genetic algorithm,” *Journal of Advanced Research in Dynamical and Control Systems*, vol. 11, no. 6 Special Issue, pp. 594 – 599, 2019, [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85069898173&partnerID=40&md5=d2f2e70ae1769168beefea1ef2c94743

[36] D. Zhou, L. Zheng, Y. Zhu, J. Li, and J. He, “Domain Adaptive Multi-Modality Neural Attention Network for Financial Forecasting,” in *The Web Conference 2020 - Proceedings of the World Wide Web Conference, WWW 2020*, 2020, pp. 2230 – 2240. doi: 10.1145/3366423.3380288.

[37] R. Kavitha and S. Singh, “Optimizing stock market prediction using long short term memory,” *International Journal of Innovative Technology and Exploring Engineering*, vol. 9, no. 1, pp. 2819 – 2823, 2019, doi: 10.35940/ijitee.J9824.119119.

[38] M. Rout, U. M. Mohapatra, B. Majhi, and R. Mahapatra, “An artificial bee colony algorithm based efficient prediction model for stock market indices,” in *Proceedings of the 2012 World Congress on Information and Communication Technologies, WICT 2012*, 2012, pp. 750 – 754. doi: 10.1109/WICT.2012.6409174.

[39] M. Tirea and V. Negru, “Investment portfolio optimization based on risk and trust management,” in *SISY 2013 - IEEE 11th International Symposium on Intelligent Systems and Informatics, Proceedings*, 2013, pp. 369 – 374. doi: 10.1109/SISY.2013.6662604.

[40] M. Z. M. Rafik, N. M. Shah, N. A. Hitam, F. Saeed, and S. Basurra, “Deep Learning Based for Cryptocurrency Assistive System,” *Lecture Notes on Data Engineering and Communications Technologies*, vol. 179, pp. 204 – 217, 2023, doi: 10.1007/978-3-031-36258-3_18.

[41] L. O. Souza, C. G. Ralha, and B. W. P. Hoelz, “Optimizing resource allocation with intelligent agents,” in *Proceedings of the International Joint Conference on Autonomous Agents and Multiagent Systems, AAMAS*, 2017, pp. 1742 – 1744. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85046437968&partnerID=40&md5=e1db9193b5a81c457e6f93d908ba8822

[42] Y. Gao, R. Wang, and E. Zhou, “Stock Prediction Based on Optimized LSTM and GRU Models,” *Sci Program*, vol. 2021, 2021, doi: 10.1155/2021/4055281.