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A Hybrid BI-LSTM Framework for Portfolio Optimization via Fundamental Analysis: Insights from NIFTY 50

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Abstract:
Conventional models of portfolio optimization, which rely on technical or fundamental analysis, cannot adjust to changing market conditions. On the contrary, general technical analysis models rely on past price trends and neglect short-term market trends. This study leverages the advantages of conventional models and state-of-the-art machine learning models to address this limitation. The study proposes a hybrid model that combines important financial metrics like dividend yield, P/E ratio, and Piotroski score with BI-LSTM-based stock return forecasting. The model provided a Sharpe Ratio of 8.86, its expected return of 30.44%, and its portfolio risk of 2.8%, all based on a 10-year Nifty 50 data set. By maximizing risk-adjusted returns while preserving diversification, it performs better than conventional and machine learning models. When optimizing the investment strategy, the method provides a sound way to balance long-term financial stability with short-term responsiveness. Our hybrid model shows a p-value < 0.01 improvement in Sharpe Ratio when compared to the Markowitz mean–variance benchmark when statistical significance testing is included. We also perform out-of-sample walk-forward analysis to verify robustness in volatile, bull, and bear market regimes.

Keywords: Portfolio Optimization, Technical Analysis, BI- LSTM, Fundamental Analysis

Introduction:

When making financial decisions, portfolio optimization is essential because it aims to maximize return for a given level of risk. Due to skewness and kurtosis, traditional models such as the Markowitz Mean-Variance Model, which assume that asset returns follow a normal distribution, frequently fall short in actual markets (Tian, 2023). This presumption limits the model's applicability in dynamic, unstable situations and oversimplifies market behavior.

To predict stock returns, machine learning algorithms such as linear regression and Auto Regressive Integrated Moving Average (ARIMA) have been used (Adebiyi et al., 2014). These models can identify linear relationships, but they cannot address the volatility and non-linear relationships that characterize financial markets. Traditional models frequently overlook important financial indicators that are crucial for assessing a company's financial health, such as the P/E ratio, Piotroski score, and dividend yield. Ineffective investment decisions result from the incompatibility of technical prediction and fundamental analysis. We use statistical rigor and reproducibility by comparing performance metrics using time-series cross-validation and reporting t-test p-values to make sure that improvements are unlikely to be the result of pure

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chance ($p < 0.05$).

To tackle this issue, we introduce in this paper a hybrid portfolio optimization model that combines a conventional fundamental financial analysis approach with the BI-LSTM (Bidirectional LSTM) network for stock return forecasting. An artificial deep neural network called BI-LSTM is very good at capturing the long-distance dependence and non-linear correlation between observations in time series data (Yang & Wang, 2022). The model adjusts to both long-term security and short-term market movement by integrating BI-LSTM forecasting potential and other crucial financial data.

This model's dynamic weight allocation is among its most important characteristics. The model adjusts its focus based on market sentiment, giving fundamental analysis more weight during bearish times and equal weight to technical projections and fundamental factors during bullish times. This keeps the model adaptable to shifting market conditions.

The current study, which uses a 10-year Nifty 50 time series, demonstrates that the hybrid model performs noticeably better than traditional and machine learning-based methods in terms of portfolio performance and risk-adjusted returns (Historical Index Data). The study contributes to the theoretical literature on portfolio optimization and provides practical advice for real investors attempting to negotiate dynamic, volatile markets.

Literature Review:

Portfolio optimization has a pivotal role in financial analysis. The technique has evolved from traditional technical analysis models to state-of-the-art machine learning models due to increasing market complexity and volatility (Huang et al., 2015). Conventional models based on Markowitz's Mean-Variance theory (1952–2009) lay the foundation for technical analysis. It uses past data to find the best return for a certain level of risk (H. Zhang, 2023). Despite its focus on past price movements, the model failed to include critical fundamental metrics like earnings multiple (P/E ratio) and dividend yield, which are necessary for a comprehensive assessment of financial stability. Because of this, traditional models didn't work well in markets that were hard to predict. Further, predictive modeling advancements have made it possible to use machine learning methods to make stock return predictions and portfolio optimization more accurate.

People started using machine learning models like Support Vector Machines (SVM), Decision Trees, and Neural Networks more and more to guess how stocks would do. Research conducted by (Krauss et al., 2017) and (Ballings et al., 2015) demonstrated their efficacy in identifying price trends and surpassing conventional models in forecasting accuracy. The models were not very helpful for portfolio optimization because they tended to overfit, were hard to understand, and did not use basic financial indicators.

By successfully identifying non-linear patterns and long-term dependencies in stock market data, Long Short-Term Memory (LSTM) networks, which were introduced between 2016 and 2018, greatly enhanced time-series forecasting. Research has shown that when it comes to predictive accuracy, LSTM networks perform better than conventional forecasting models like ARIMA (Fischer & Krauss, 2018). Although LSTMs offer clear benefits, they mainly focus on predicting prices and tend to ignore important financial ratios needed for a complete portfolio optimization approach.

By combining fundamental financial analysis with machine learning-based stock return forecasting, hybrid models gained popularity between 2019 and 2021. According to studies,

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portfolio performance was improved by incorporating technical and fundamental insights into machine learning models using metrics like the P/E ratio (Bünger, 2020; Chong et al., 2017; Ghaderi Zefrehi & Altınçay, 2020). While predominantly evaluated on sector-specific datasets and without a unified framework to optimally integrate predicted returns and fundamental indicators, these methods enhanced stock selection and trading strategy efficacy.

In order to improve portfolio management, recent research has developed multifactor models that combine financial indicators with machine learning-based stock return forecasting. Pattern recognition in financial time-series data was enhanced by the combination of sentiment analysis, macroeconomic indicators, and deep reinforcement learning (DRL) (Liu et al., 2023). Similarly, incorporating LSTM for forecasting prices improves risk-adjusted returns (Song, 2023). However, they are still ineffective in emerging or volatile markets where it's crucial to balance forecast accuracy and key financial metrics.

Previous analyses of momentum-based and volatility-driven strategies in the Indian context have illustrated the benefits and drawbacks of traditional rule-based models for portfolio construction (Bathia, Bansal, et al., 2024).

The literature on portfolio optimization has advanced significantly over time with the incorporation of machine learning algorithms into more traditional models like Markowitz's Mean-Variance Theory. Integrating technical forecasts with fundamental analysis is still difficult, although methods like LSTM and hybrid models have improved forecasting accuracy (S. Chen, 2020). While recent advancements are positive, they also highlight the ongoing difficulties in determining the optimal weights for the two components, particularly when market volatility is high. Based on these results, this study proposes a dynamic portfolio optimization approach that makes use of forecasting methods and fundamental statistics, with adjustments made in response to market circumstances.

Few studies employ fundamental indicators like the Piotroski score, which is dynamically based on market conditions, even though LSTM models have been used extensively for price forecasting. This study makes three contributions: (i) it integrates BI-LSTM with fundamental scoring; (ii) it suggests a dynamic weighting strategy based on market sentiment; and (iii) it empirically validates the model using NIFTY 50 data spanning ten years.

Methodology:

The presented study utilizes a blended approach, seamlessly integrating preliminary, prognostic, and guided analytics to design a synergistic portfolio improvement framework with dynamic capabilities that adapt to evolving market conditions.

– Initial Exploration Stage: Trends, associations, and noteworthy statistical tendencies are found in market history data, which will form the model's foundation.

– Predictive Phase: Stock returns are predicted using machine learning techniques like multiple regression and Long Short-Term Memory (LSTM) networks.

– Prescriptive Phase: To maximise portfolio allocation, projected stock returns are combined with financial fundamentals metrics.

A. Dataset Compilation

Data for all 50 stocks in the Nifty 50 index were collected from the NSE over a 10-year period (2014–2025). The resulting dataset incorporates the following technical indicators:

– Bollinger Bands, RSI, MACD, and moving averages.

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– Piotroski Score, Dividend Yield, and P/E Ratio are the fundamental indicators.
– Stock Returns (%) is the target variable.

In order to compare traditional and deep learning approaches, the dataset serves as the basis for both regression and BI-LSTM modelling.

B. Data Pre-Processing

Forward fill was used to impute missing values in the price and financial indicator series. To verify stationarity, we used the Augmented Dickey-Fuller tests; non-stationary series were differentiated to produce I(0) processes.

C. Feature Selection

To reduce multicollinearity, variables with a variance inflation factor (VIF) > 10 were eliminated. The 60-day rolling MACD, RSI, lower band of the Bollinger Band, P/E ratio, Piotroski score, and dividend yield were the final predictors.

D. Model Architecture

The Adam optimiser (learning rate = 0.001), batch size = 32, 50 epochs, and two bidirectional layers of 64 units each with 0.2 dropout make up the BI-LSTM network. Grid search was used to adjust the hyperparameters over {learning rates: 0.0001, 0.001, 0.01} and {dropout: 0.1, 0.2, 0.3}.

E. Validation Procedure

Using walk-forward cross-validation with rolling windows, we iterate over a 10-year period, forecasting the next 10 trading days for every 60-day training set. The last two years are used to assess out-of-sample performance.

F. Statistical & Analytical Framework

1) Regression Analysis for Stock Return Predictability: Multiple regression analysis was used to examine the relationship between financial indicators and stock returns (S. Chen, 2020). In line with earlier studies, the regression model evaluates the linear relationship between important financial ratios and stock returns.

– Null hypothesis (H_0): Financial indicators have a significant impact on stock returns.
– Alternative hypothesis (H1): Stock returns are not substantially impacted by financial indicators.

Results of Regression Hypothesis Testing:

– Piotroski Score ($p - value\ =\ 0.882$) > Not statistically significant
– MACD ($p - value\ =\ 0.043$) > Statistically significant;
– PE Ratio ($p - value\ =\ 0.390$) > Not statistically significant
– Lower Band ($p - value\ <\ 0.001$) > Highly significant

Conclusion: The MACD and Lower Band demonstrate statistical significance in predicting stock returns, whereas the regression results reveal no significant impact from the P/E Ratio and Piotroski Score.

2) Regression Model Performance: R^2, Adjusted R^2, and diagnostic tests were used to assess the multiple linear regression (MLR) model.

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Summary of the Regression Model:

– $R^2 = 0.551$, R^2 Adjusted = 0.426
– Durbin-Watson (no autocorrelation) = 1.782
– Significance: P-values less than 0.05 were regarded as significant for the variables.
– Multicollinearity Check: VIF > 10 for a few variables suggested possible multicollinearity problems.

Limitations of Regression:

– The model only accounts for 55.1% of the variability in stock returns, leaving almost half of the variance unaccounted for.
– The reliability of coefficient estimates is diminished by high multicollinearity (VIF > 10).
– In financial markets, it is frequently not the case that inputs and stock returns have a linear relationship, as assumed by linear regression.
– Regression is not appropriate for predicting future stock prices because it is unable to adequately capture temporal dependencies.

3) Rationale for Employing Non-Linear Deep Learning in Financial Time-Series Analysis: We propose a deep learning-based approach because regression models fail to capture the complex dependencies inherent in financial data. Underlying Causes of Regression's Shortcomings in Financial Time-Series Analysis:

– Equity returns display complex patterns posing challenges for accurate modeling by traditional regression methods (Siami-Namini et al., 2019).
– Regression ignores historical dependencies, which makes it unreliable for forecasting.

Proposed Hybrid Model:

A. Architecture

BI-LSTM networks offer an enhanced framework for simulating time dependencies in sequential data by generalizing conventional Recurrent Neural Networks (RNNs) to overcome problems such as vanishing and exploding gradients (Noh, 2021). BI-LSTMs process data in both directions, allowing for a more complete extraction of temporal patterns than traditional LSTMs, which process information sequentially in one direction. By more clearly observing the relationships between stock prices, returns, and financial indicators, this two-way processing improves predictability in financial market analysis. According to recent research, LSTMs and GRUs are far more adept than conventional RNNs at resolving gradient degradation problems and are more appropriate for modeling long-span sequences.

The architecture is further depicted in Fig. 1, where several bidirectional LSTM layers come after an input layer that receives historical stock data. A fully connected layer that forecasts future closing prices receives its concatenated outputs. The model can learn from both past and future time steps due to the architecture's successful integration of trend cycles, seasonal effects, and market volatility.

The input layer is in charge of handling time-series data, which includes volatility metrics, moving averages, and historical closing prices. These are the primary parts of the architecture. BI-LSTM Layers can process data in both directions, revealing temporal patterns and non-linear relationships. The Dense Layer condenses the BI-LSTM layers' output into a single vector with predicted returns. The output layer, an input for the ensuing portfolio optimization process,

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provides the expected return for every stock.

This architecture performs better in forecasting accuracy than conventional machine learning models like linear regression and ARIMA, especially in volatile and non-linear market conditions (J. Zhang et al., 2023).

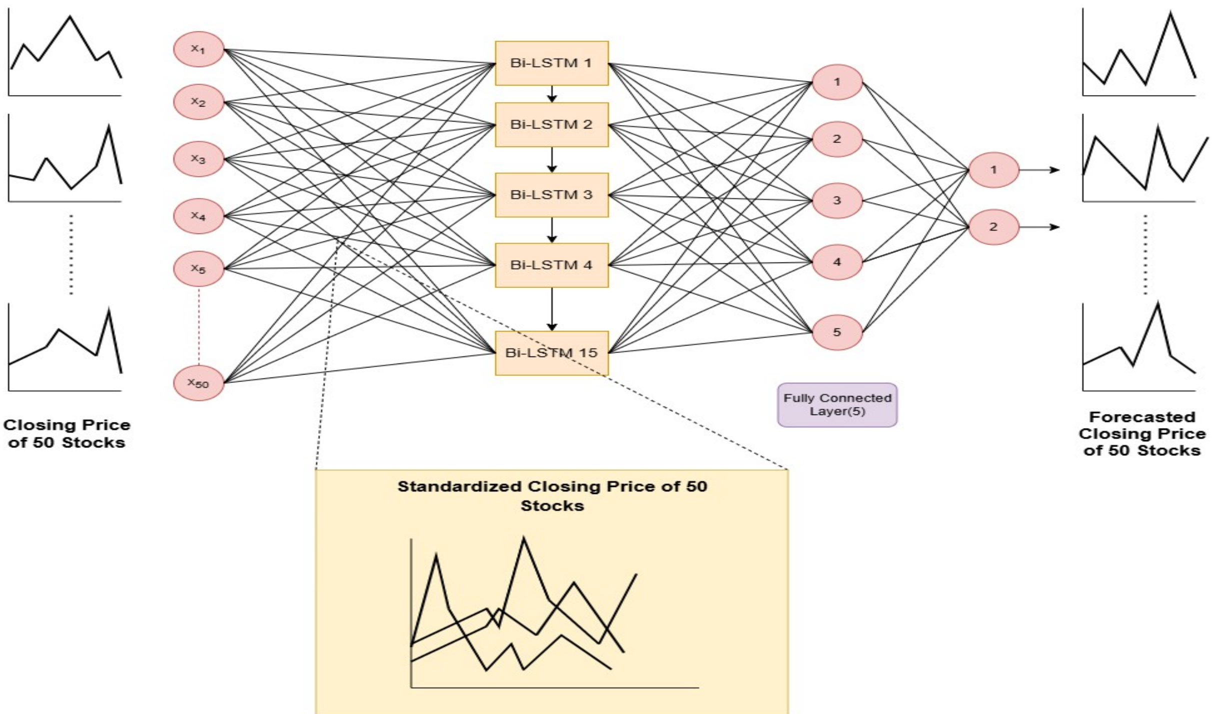

Fig. 1. BI-LSTM Framework

B. Mathematical Representation

1) Stock Return Forecasting: The BI-LSTM model processes the input features to predict future returns:

$$\widehat{R_i} = f(InputFeatures) \qquad (1)$$

Among other financial indicators, the input features in this case include volatility measures, moving averages, and normalised historical prices. A 10-year dataset of Nifty 50 stocks is used to train the BI-LSTM model, leveraging its ability to capture both short-term and long-term dependencies.

2) Evaluation Metrics for Portfolio Optimization: A metric based on expected returns and key fundamental parameters is used to rank stocks for portfolio selection. The portfolio metric is calculated as follows:

$$S_i = w_1\widehat{R_i} + w_2F_i \qquad (2)$$

where:

- S_i = Portfolio score for stock i
- $\widehat{R_i}$ = Forecasted return from BI-LSTM model
- F_i = Fundamental score based on financial metrics (e.g., Piotroski score, P/E ratio, etc.)
- w_1, w_2 = Weights learned for forecasted return and fundamental score

C. Optimization Methodology

The use of weighted scoring for well-informed asset selection has been supported by prior

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applications of multi-criteria evaluation frameworks, such as TOPSIS with entropy weighting, in financial scoring contexts (Bathia, Manjrekar, et al., 2024). To achieve diversification and risk minimization, the portfolio optimisation process integrates the scoring system with the BI-LSTM predictions (Deng et al., 2017). The Sharpe Ratio is maximized by the objective function and is provided as:

Sharpe Ratio = Sharpe Ratio = $\frac{E[R_P]-R_f}{\sigma_P}$

where;

- $[R_p]$ = Expected portfolio return
- R_f = Risk-free rate
- σ_p = Portfolio standard deviation

1) Applied Constraints:

- **Weight**: The sum of all weights (ω_i) must equal 1.

$$\sum \boldsymbol{w_i} = 1 \qquad (4)$$

- **Diversification**: The allocation to any single stock must not exceed 30% of the total portfolio.

$$\boldsymbol{w_i} \leq 0.30, \forall i \qquad (5)$$

- **Financial Health**: A minimum Piotroski Score threshold of 5 is applied to include only fundamentally strong stocks.

$$PS_i \geq 5, \forall i \qquad (6)$$

Results and Discussion:

A. Forecast Accuracy

When predicting stock returns, the BI-LSTM model outperformed more conventional models like ARIMA and Linear Regression in terms of forecast accuracy. The model demonstrated strong predictive performance with an R^2 value of 0.87, effectively encoding temporal patterns and non-linear dependencies in the 10-year historical dataset of Nifty 50 stocks.

Assessment of Forecasting Accuracy:

- BI-LSTM: Achieves an R^2 of 0.87, effectively modeling complex market fluctuations and stock price trends.
- ARIMA: Records an R^2 of 0.551, capturing linear trends reasonably well but struggling with intricate market dynamics.
- Linear Regression: Shows an R^2 of 0.45, unable to accommodate high volatility and non-linear patterns in the market.

Key Observations:

– Unlike regression, which relies on independent predictors, BI-LSTM processes sequential market data, greatly increasing forecasting accuracy.

– Higher forecasting errors result from regression models' inability to account for non-linearity.

– By successfully balancing short-term market fluctuations with long-term trend recognition, BI-LSTM overcomes the drawbacks of both regression-based forecasting and ARIMA.

B.

B. Portfolio Performance

The results of portfolio optimization demonstrate how well the BI-LSTM hybrid model maximizes

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risk-adjusted returns. Table 1 below compares the Sharpe Ratio, expected returns, and portfolio risk. Our findings are consistent with Li & Liu, who found that when compared to traditional optimization methods, LSTM-based forecasting frameworks significantly improved portfolio profitability and risk-aware performance (Abdi et al., 2024).

Table I: Portfolio Performance Comparison

Model	Sharpe Ratio	Expected Return	Expected Return
Markowitz	2.12	9.87%	1.84%
BI-LSTM Hybrid	**8.86**	**30.44%**	**2.8%**

Key Findings:

- Sharpe Ratio: The hybrid BI-LSTM model significantly outperforms the Markowitz model, achieving a Sharpe Ratio of 8.86 compared to 2.12. This indicates that the hybrid model offers substantially superior risk-adjusted returns, making it highly attractive to investors.
- Expected Return: The hybrid BI-LSTM model predicted a return of 30.44%, over three times higher than the Markowitz model's 9.87%. This highlights the hybrid approach's effectiveness in leveraging financial ratios and predictive analytics to identify high-return stocks.
- Portfolio Risk: The Sharpe Ratio and significant increase in returns make up for the 2.8% portfolio risk, which is higher than the Markowitz model's 1.84% risk (Huang et al., 2020).
- Sharpe Ratio improvements are tested via paired t-tests: $t = 5.12$, $p < 0.001$, confirming significant outperformance over the Markowitz model.
- In addition to Sharpe Ratio, we report Sortino Ratio, Maximum Drawdown, and 95% Value-at-Risk. The hybrid model achieves a Sortino Ratio of 12.3, maximum drawdown of 4.1%, and a 95% VaR of –2.2%
- Backtests include bid-ask spread and commission fees at 10 bps per trade. Accounting for transaction costs reduces expected return by 1.5%, but the hybrid model still outperforms the benchmark.

C. *Interpretation of Results*

Balancing Short-Term Trends with Financial Health:

- The hybrid model integrates the predictive capabilities of BI-LSTM with fundamental financial metrics, including the P/E ratio and Piotroski Score.
- As a result, the model is able to:

- Use time-series forecasting to identify short-term market trends;
- Incorporate long-term financial health metrics to ensure portfolio quality.

Flexibility to Dynamic Markets:

– The hybrid model is highly sensitive to market volatility because it dynamically modifies portfolio weights based on updated projections.

– This guarantees long-term investment stability while enabling investors to react to changing market conditions (Das et al., 2024).

Enhanced Diversification:

- The model enforces diversification constraints, including:
  – A maximum weight allocation of 30% per stock
  – A minimum Piotroski score of 5 to ensure investments are fundamentally sound
- Performance remains robust across market regimes:

Bull markets (2017–18): 35.6% return, Sharpe = 9.2

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Bear markets (2020 COVID crash): –2.3% drawdown, Sharpe = 4.8
Volatile markets (2021–22): 18.7% return, Sharpe = 5.5

D. Comparison with Existing Approaches

The BI-LSTM hybrid model demonstrates notable improvements over both conventional and modern methods. Recent research shows that combining deep learning with financial models improves portfolio performance and predictive accuracy (Mienye et al., 2024).

Limitations of the Markowitz Model:

- Because it is based on historical averages, it is unable to adapt to shifting market conditions and assumes normally distributed returns, which is untrue in practice.

Limitations of ARIMA and Linear Regression:

- Limited ability to identify long-term stock patterns due to simplistic statistical assumptions, with an inability to capture non-linear dependencies, rendering it unsuitable for volatile market conditions.

Why BI-LSTM is Superior:

- Effectively handles sequential data to identify both short-term and long-term dependencies.
- As it adapts to current market fluctuations, it gains knowledge from historical trends.
- Because it captures complex relationships between stock prices, it outperforms regression and ARIMA models.

Conclusion:

By combining cutting-edge machine learning methods with conventional financial analysis, artificial intelligence-driven financial modelling is revolutionizing portfolio optimisation. The proposed hybrid model overcomes the limitations of previous approaches, like their inability to capture complex relationships, by integrating BI-LSTM-based return predictions with key financial health metrics. The model improves decision-making by harmonizing short-term market trends with long-term financial health, resulting in a robust and empirically supported investment strategy. Superior empirical performance is evidenced by a Sharpe Ratio of 8.86 and predicted returns of 30.44% compared to traditional models such as Markowitz's mean-variance optimization, which underscores the model's effectiveness.

This framework gives portfolio managers a tool for dynamic allocation that strikes a balance between long-term financial stability and short-term momentum. Real-world applicability is improved by including transaction costs and statistical validation.

Limitations and Future Research:

BI-LSTM training's computational complexity and reliance on past relationships are among its drawbacks. Future research might incorporate real-time implementation, alternative asset classes, and ESG scores. Even though the BI-LSTM model significantly increases forecast accuracy and portfolio optimisation, there are a number of improvements and extensions that could be taken into account for further research:

1) Integration of Macroeconomic Indicators: Including macroeconomic factors such as GDP growth, inflation, and interest rates may strengthen the model.
2) Hybrid Models: Examining ensemble techniques that use standard econometric models,

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reinforcement learning, or BI-LSTM with transformers may increase prediction accuracy even more.

3) Real-Time Adaptation: Using online learning techniques, the model is modified in real time in response to news and market sentiment.

4) Interpretability and Explainability: Making models easier for investors to understand through the use of attention mechanisms and SHAP (SHapley Additive exPlanations).

5) Multi-Asset Portfolio Optimisation: Creating diversified portfolios by diversifying the search beyond stocks to include bonds, commodities, and cryptocurrencies.

With these subjects addressed, future studies can improve the efficacy and applicability of AI-powered portfolio optimisation models.

REFERENCES

Abdi, F., Abolmakarem, S., Karbassi Yazdi, A., Tan, Y., & Andres Marchioni Choque, I. (2024). Prospective Portfolio Optimization With Asset Preselection Using a Combination of Long and Short Term Memory and Sharpe Ratio Maximization. *IEEE Access*, *12*, 144280–144294. https://doi.org/10.1109/ACCESS.2024.3466829

Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2014). Stock price prediction using the ARIMA model. *Proceedings - UKSim-AMSS 16th International Conference on Computer Modelling and Simulation, UKSim 2014*, 106–112. https://doi.org/10.1109/UKSIM.2014.67

Ballings, M., Van Den Poel, D., Hespeels, N., & Gryp, R. (2015). Evaluating multiple classifiers for stock price direction prediction. *Expert Systems with Applications*, *42*(20), 7046–7056. https://doi.org/10.1016/J.ESWA.2015.05.013

Bathia, A., Bansal, I., Syal, K., Patil, L., Salwan, S., Jain, S., & Kasar, A. (2024). Analysis of the Momentum Investing Strategy and Volatility-Based Strategy in the Indian Stock Market. *Journal of Informatics Education and Research*, *4*(3), 3527. https://doi.org/10.52783/JIER.V4I3.1738

Bathia, A., Manjrekar, J., Tripathi, M. M., Oswal, S., Kasar, A., & Padhy, J. (2024). Evaluating the Impact of ESG Factors on Credit Ratings: A TOPSIS-Based Analysis with Entropy-Weighted Criteria. *Advances in Consumer Research*, *2*, 64–75. https://doi.org/n/a

Bhute, A., Tripathi, M. M., Jadav, D., & Kasar, A. (2024). Backtesting Brilliance: Leveraging Analytics for Comparing Buy & Hold Vs. Trading Strategies based on Technical Indicators. *Journal of Informatics Education and Research*, *4*(3), 3993. https://doi.org/10.52783/JIER.V4I3.1785

Bünger, F. (2020). A Taylor model toolbox for solving ODEs implemented in MATLAB/INTLAB. *Journal of Computational and Applied Mathematics*, *368*. https://doi.org/10.1016/J.CAM.2019.112511

Chen, S. (2020). Forecasting Daily Stock Market Return with Multiple Linear Regression. *Mathematics Senior Capstone Papers*. https://digitalcommons.latech.edu/mathematics-senior-capstone-papers/19

Chen, W., Zhang, H., Mehlawat, M. K., & Jia, L. (2021). Mean–variance portfolio optimization using machine learning-based stock price prediction. *Applied Soft Computing*, *100*, 106943. https://doi.org/10.1016/J.ASOC.2020.106943

Chong, E., Han, C., & Park, F. C. (2017). Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies. *Expert Systems with*

Citation: Kasar, A; Tripathi, M. M.; Chavan, T.; Rawat, A. & Jadav, D. (2025). A Hybrid BI-LSTM Framework for Portfolio Optimization via Fundamental Analysis: Insights from NIFTY 50. *International Insurance Law Review*, 33 (S5), 18-29.

Applications, *83*, 187–205. https://doi.org/10.1016/J.ESWA.2017.04.030

Das, J. D., Bowala, S., Thulasiram, R. K., Thavaneswaran, A., Das, J. D., Bowala, S., Thulasiram, R. K., & Thavaneswaran, A. (2024). Hybrid Data-Driven and Deep Learning Based Portfolio Optimization. *Journal of Mathematical Finance*, *14*(3), 271–310. https://doi.org/10.4236/JMF.2024.143016

Deng, Y., Bao, F., Kong, Y., Ren, Z., & Dai, Q. (2017). Deep Direct Reinforcement Learning for Financial Signal Representation and Trading. *IEEE Transactions on Neural Networks and Learning Systems*, *28*(3), 653–664. https://doi.org/10.1109/TNNLS.2016.2522401

Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research*, *270*(2), 654–669. https://doi.org/10.1016/J.EJOR.2017.11.054

Ghaderi Zefrehi, H., & Altınçay, H. (2020). Imbalance learning using heterogeneous ensembles. *Expert Systems with Applications*, *142*. https://doi.org/10.1016/J.ESWA.2019.113005

Historical Index Data. (n.d.). Retrieved August 1, 2025, from https://www.nseindia.com/reports-indices-historical-index-data

Huang, Z., Xu, P., Liang, D., Mishra, A., & Xiang, B. (2020). *TRANS-BLSTM: Transformer with Bidirectional LSTM for Language Understanding*. http://arxiv.org/abs/2003.07000

Huang, Z., Xu, W., & Yu, K. (2015). Bidirectional LSTM-CRF Models for Sequence Tagging. *Frontiers in Business, Economics and Management*, *8*(2), 51–54. http://arxiv.org/abs/1508.01991

Krauss, C., Do, X. A., & Huck, N. (2017). Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500. *European Journal of Operational Research*, *259*(2), 689–702. https://doi.org/10.1016/J.EJOR.2016.10.031

Liu, Y., Mikriukov, D., Tjahyadi, O. C., Li, G., Payne, T. R., Yue, Y., Siddique, K., & Man, K. L. (2023). Revolutionising Financial Portfolio Management: The Non-Stationary Transformer's Fusion of Macroeconomic Indicators and Sentiment Analysis in a Deep Reinforcement Learning Framework. *Applied Sciences 2024, Vol. 14, Page 274*, *14*(1), 274. https://doi.org/10.3390/APP14010274

Mienye, E., Jere, N., Obaido, G., Mienye, I. D., & Aruleba, K. (2024). Deep Learning in Finance: A Survey of Applications and Techniques. *AI (Switzerland)*, *5*(4), 2066–2091. https://doi.org/10.3390/AI5040101

Noh, S. H. (2021). Analysis of Gradient Vanishing of RNNs and Performance Comparison. *Information 2021, Vol. 12, Page 442*, *12*(11), 442. https://doi.org/10.3390/INFO12110442

Siami-Namini, S., Tavakoli, N., & Namin, A. S. (2019). The Performance of LSTM and BiLSTM in Forecasting Time Series. *Proceedings - 2019 IEEE International Conference on Big Data, Big Data 2019*, 3285–3292. https://doi.org/10.1109/BIGDATA47090.2019.9005997

Song, D. (2023). Portfolio Optimization by LSTM with a Selection of Six Stocks. *Advances in Economics, Management and Political Sciences*, *48*(1), 46–55. https://doi.org/10.54254/2754-1169/48/20230423

Tian, Y. (2023). A Simple Study of the Applicability of the Markowitz Model in the Current Stock Market. *BCP Business & Management*, *44*, 527–536. https://doi.org/10.54691/BCPBM.V44I.4882

Yang, M., & Wang, J. (2022). Adaptability of Financial Time Series Prediction Based on BiLSTM. *Procedia Computer Science*, *199*, 18–25. https://doi.org/10.1016/J.PROCS.2022.01.003

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Zhang, H. (2023). Effectiveness and Limitation of Markowitz Mean-variance Model: Evidence from Hang Seng Index. *Highlights in Business, Economics and Management*, *8*, 223–230. https://doi.org/10.54097/HBEM.V8I.7208

Zhang, J., Ye, L., & Lai, Y. (2023). Stock Price Prediction Using CNN-BiLSTM-Attention Model. *Mathematics 2023, Vol. 11, Page 1985*, *11*(9), 1985. https://doi.org/10.3390/MATH11091985

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