Indonesian Journal of Electrical Engineering and Computer Science
Vol. 33, No. 3, March 2024, pp. 1903~1914
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v33.i3.pp1903-1914

Monte carlo simulation with bilstm for day-ahead stock portfolio management

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Article Info

Article history:

Received Nov 23, 2023
Revised Dec 18, 2023
Accepted Dec 26, 2023

Keywords:

Bidirectional LSTM
Financial market
Monte carlo simulation
Risk adjustment return
Stock portfolio management

ABSTRACT

Predicting stock price movement and optimizing day-ahead stock portfolios are challenging tasks due to the inherent complexity and volatility of financial markets. This study proposes a novel approach that combines bidirectional long short-term memory (BiLSTM) neural networks with monte carlo simulation (MCS) to enhance day-ahead stock portfolio management. In the proposed methodology, historical data of the top-performing 10 stocks from different sectors of the National Stock Exchange of India (NSEI) is obtained from 1 January 2004 to 30 June 2023 and utilized to train a BiLSTM model. This model effectively extracts intricate patterns and trends from the time series, leading to more accurate and robust stock price predictions. MCS generates different scenarios, considering various market conditions and uncertainties. These scenarios provide a comprehensive view of the portfolio's performance under different conditions, thus mitigating the risk of relying solely on a single prediction. The study evaluates the proposed framework and compares its performance against traditional portfolio management strategies. Results demonstrate that the MCS with the BiLSTM approach outperforms traditional methods in terms of risk-adjusted returns and portfolio stability.

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1. INTRODUCTION

Stock portfolio management is a crucial aspect of finance, aiming to maximize returns and minimize risks for investors and professionals. Traditional approaches rely on statistical models for decision-making, but financial markets' complexity and uncertainties present challenges in accurate predictions and risk assessments. In recent times, advanced deep learning methods like long short-term memory (LSTM) and bidirectional long short-term memory (BiLSTM) neural networks have displayed significant potential in analyzing time series data. Moreover, financial markets are inherently unpredictable, and deterministic models alone cannot fully capture their behavior. To overcome this limitation, monte carlo simulation (MCS), a widely adopted computational technique, introduces random variables and probabilistic distributions to simulate numerous future scenarios. By generating a diverse set of simulated outcomes, this method offers valuable insights into potential portfolio performances under various market conditions, empowering investors to make well-informed and resilient investment choices. This research is motivated by the desire to address the constraints of conventional portfolio management techniques and leverage the capabilities of deep learning and simulation methods to tackle the complexities posed by volatile financial markets.

The novel stochastic fractal search (SFS) method, incorporating risk-budgeting constraints, aims to assess its effectiveness by comparing it with particle swarm optimization, simulated annealing, and differential evaluation. The study confirms the superior performance of the SFS model among its peers [1]. The utilization of support vector machine (SVM) over random forest proves to yield lower correlation errors, making it a suitable choice for stock price prediction. The two algorithms are compared i.e., OGWO and NSGA II. The performance of oppositional grey wolf optimization (OGWO) are much more better than NSGA II [2]. The bio-inspired distributed beetle antennae search (DBAS) is employed to optimize the multi-portfolio selection algorithm. Simulation results demonstrate that DBAS efficiently and robustly selects the optimal portfolio [3]. The study proposes a method using macroeconomic factors to analyze market trends, employing flexible time series to represent key elements like returns and risks.

Through Bayesian theorem and a VN-index case study, it presents a dependable portfolio optimization strategy, consistently effective across diverse stock types [4]. The bayesian optimization (BO) presents an effective and sophisticated strategy to optimize stock portfolios, considering environmental social governance (ESG) criteria as soft constraints within the objective function, thereby enhancing portfolio performance in the presence of complex, costly-to-compute expressions [5]. The study assesses the effectiveness of three portfolio optimization methods-mean variance, hierarchical risk parity, and reinforcement learning-by analyzing their performance metrics across diverse stock datasets. RL outperform among all [6]. The TAKMV method, integrating technical analysis, K-means clustering, and mean-variance portfolio optimization to identify investment portfolios, using Philippine Stock Market data from 2018 and 2020. Evaluating strategies like moving average convergence-divergence MACD and MACD-ALMA, it finds MACD more effective pre-COVID-19 while MACD-ALMA performs better during COVID-19, with the technical analysis, K-means algorithm, and mean-variance model (TAKMV) method validated against subsequent year data for consistency [7]. The classical Markowitz mean-variance optimization algorithms for portfolio selection problems are discussed with computational complexity [8]. The study offers a comprehensive review of current portfolio optimization research, examining 82 scholarly articles to highlight that fuzzy decision theory and goal programming are key mathematical techniques utilized in solving these problems [9]. The study explores cutting-edge multi objective optimization techniques—NSGA-II, PESA, and SPEA2-to solve mixed-integer problems, conducting a comparative analysis of their performance using established community metrics. The results demonstrate that NSGA-II outperform among all [10].

The method explores five risk-return objectives, accommodating individual preferences via utility functions. The results demonstrate that the genetic algorithm can be efficiently used to solve the problem [11]. A BiLSTM model used to predict stock price movement by incorporating public sentiment data resulted in the smallest mean square error (MSE) and root mean square error (RMSE) values [12]. The convolution neural network (CNN)-BiLSTM model, which outperformed other models in predicting stock closing prices [13]. Liu [14] introduced an attention-based BiLSTM model, which demonstrated higher prediction accuracy and lower error rates compared to other models. The prediction accuracy of stock price prediction by introducing an attention mechanism to a CNN-BiLSTM model, which outperformed other models in predicting various stock indices [15]. The BiLSTM model demonstrates strong predictive capabilities and effectively captures trends and patterns in testing data, despite potential challenges with abrupt market changes [16]. Attention-enhanced CNN-BiLSTM model shows superior performance in stock price prediction, outperforming benchmarked machine learning models [17]. By integrating news events, sentiment trends, and quantitative financial data, the author enhance stock trend prediction accuracy. Using this integrated approach, the CNN-BiLSTM model outperforms benchmarked machine learning models by 11.6% in real estate and 25.6% in communications sectors [18]. The proposed BLSTM-based Seq2Seq Model predicts stock closing prices, surpassing K-Nearest neighbor, decision tree, and linear regression models. Comparative analysis demonstrates the proposed model's superior performance with the lowest root mean square error among all tested algorithms [19]. Introducing a novel mixed frequency neural network: it decomposes time series, aligns frequencies, and employs CNN-BiLSTM-attention to forecast. Empirical findings reveal its superiority in predicting high frequency components and yielding smaller errors in ensemble results, promising potential for forecasting mixed time series reversals [20].

Monte carlo simulation handles uncertainty and complex problem by consideration different variables. Research advancements optimize scenario accuracy and efficiency, offering varied computational techniques for pricing, risk management, and precise scenario generation [21]. Employing monte carlo simulation on equity growth models with historical data resampling, the study estimates future equity, earnings, and stock returns' probability distributions for S&P 500 and Coca-Cola. Findings reveal inconsistent risk premiums amid USA government bonds, S&P 500, and DJVC indices, yet significant monthly return correlations between S&P 500 and DJVC [22]. The system integrates financial risk management, data exchange, and background risk services, with modules for risk monitoring, allocation, and decision-making. Evaluation demonstrates predictive capabilities for economic risks, showcasing the system's ability to anticipate inflection points and contribute to market development using the markov chain monte carlo algorithm [23]. The study explores market volatility statistics using Python, employing geometric brownian motion (GBM) to simulate US and Malaysian stock prices. Conducted over 1,000 cycles, the simulations, driven by mean return and historical return standard deviation, offer valuable insights for retail traders through monte carlo analysis in finance, aiding in understanding market dynamics [24]. The antithetic monte carlo method to price up-and-out barrier options, dividing the dataset for machine learning analysis. Comparing support vector regression, random forest, boosting, and neural networks, it concludes that random forest and artificial neural networks exhibit superior fitting and prediction accuracy among the methods assessed [25].

Despite the progress in deep learning and simulation techniques, there exists a research gap concerning the integration of BiLSTM neural networks with MCS specifically for day-ahead stock portfolio management. Investigating the feasibility and effectiveness of the proposed approach in real time implementation in the NSEI is an important research gap. Furthermore, the day-ahead investment decisions remain underexplored, leaving room for a more tailored and dynamic portfolio management strategy.

The research aims to address the limitations of traditional stock portfolio management approaches by integrating BiLSTM neural networks, with the powerful monte carlo simulation method. The primary problem is to develop a novel framework that can accurately predict day-ahead stock prices and comprehensively assess portfolio performance under diverse market conditions, thereby enabling investors and financial professionals to make more informed and robust day-ahead investment decisions.

2. METHOD

2.1. Data collection and pre-processing

Data collection is a crucial step in the day-ahead stock portfolio management framework. It involves gathering historical stock price data (open, high, low, close, adj. close, volume) and relevant financial indicators such as earnings per share (EPS), price-to-earnings ratio (P/E ratio), and dividend yield for the assets of interest. The NSEI India data is sourced from yahoo.finance.com by considering the top performing sector's highest contributing stocks. Further, the data pre-processed by handling missing values, treating of outlier. The pre-processed data is normalized. Additionally, the relevant features from the existing data to enhance the model's predictive power. For instance, once can calculate moving, relative strength index (RSI), or other technical indicators to capture different aspects of market behavior.

Figure 1 illustrated the closing prices of selected companies. It is clearly observed that the performance of Maruti Suzuki India Limited (MARUTI) is good, oil, gas and consumable fuels (ONGC) has Steady performance to all other stocks. HDFC Bank Limited (HDFC Bank) and Reliance Industries have relatively high mean closing prices, while ITC Limited (ITC) and ONGC have lower mean closing prices. Stocks like housing development finance corporation limited (HDFC), HDFC Bank, ICICI Bank Limited (ICICI Bank), and reliance industries have relatively higher price volatility, as indicated by their larger standard deviation values. The minimum closing price for tata consultancy services limited (TCS) is significantly higher than that of ITC, suggesting a wider price range for TCS shares. Stocks with lower volatility may be suitable for conservative investors, while those with higher volatility may offer more significant growth opportunities.

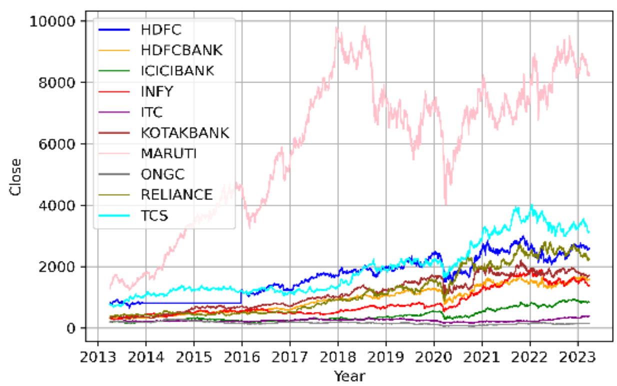

Figure 1. Stock closing prices for selected companies

In Figure 2 illustrated the sales volume of different stocks. The HDFC, ICICIBANK, ITC, ONGC, and RELIEANCE follows under High sales volume. It indicates a high level of interest and activity in that stock. Several factors can contribute to high sales volume, including positive news about the company, increased investor interest, or significant market events. High volume can sometimes indicate strong price movements or trends in the stock. All other stocks follow under medium to low level. Medium sales volume can be a common occurrence for many stocks during routine trading days when there is no significant news or events affecting the market or the specific stock.

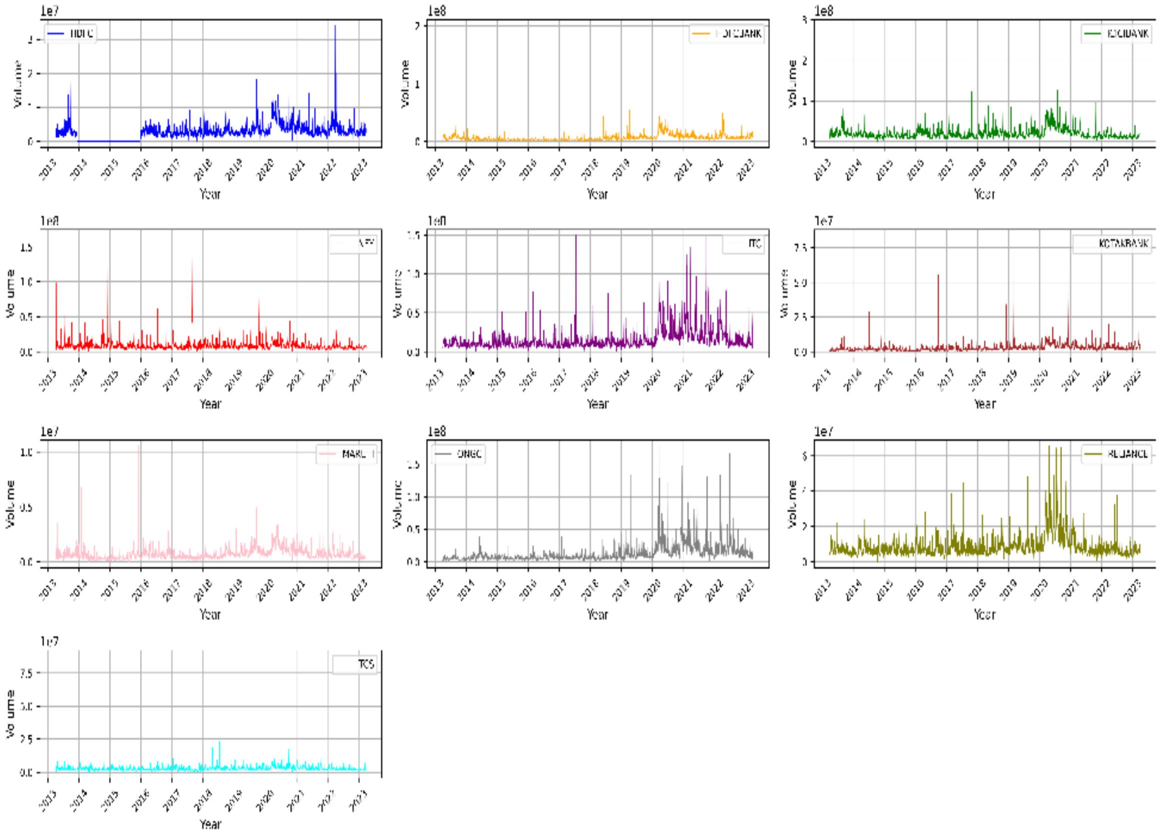

Figure 2. Sales volume analysis of ten stocks

In Figure 3 effectively portrays the daily return characteristics of different stocks. It highlights the wide range of returns, with ICICIBANK displaying frequent high positive returns and technology stocks like INFY experiencing frequent significant negative returns. All other stocks fall under moderate range.

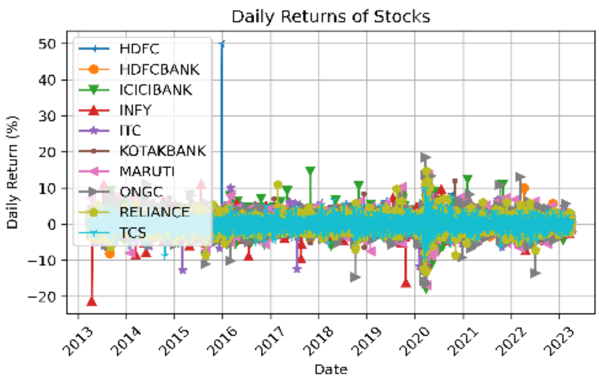

Figure 3. Daily return of stocks

2.2. BiLSTM

BiLSTM is a type of recurrent neural network (RNN) that processes sequential data bidirectionally, incorporating information from both past and future time steps. It consists of two LSTMs, one processing the sequence in the forward direction and the other in the reverse direction. BiLSTM is effective for capturing long-term dependencies in sequential data, making it popular for tasks like time series forecasting and natural language processing [26]. The forward LSTM expressed using in (1)-(8).

$$h_t^f = LSTM_f(x_t, h_{t-1}^f) \tag{1}$$

$$h_t^f = \sigma(W^f \cdot x_t + U^f \cdot h_{t-1}^f + b^f) \tag{2}$$

$$c_t^f = Tanh(W_c^f \cdot x_t + U_c^f \cdot h_{t-1}^f + b_c^f) \tag{3}$$

$$i_t^f = \sigma(W_i^f \cdot x_t + U_f^f \cdot h_{t-1}^f + b_i^f) \tag{4}$$

$$f_t^f = \sigma(W_f^f \cdot x_t + U_f^f \cdot h_{t-1}^f + b_f^f) \tag{5}$$

$$o_t^f = \sigma(W_o^f \cdot x_t + U_f^f \cdot h_{t-1}^f + b_0^f) \tag{6}$$

$$c_t^f = f_i^f \cdot x_{t-1} + i_t^f \cdot c_t^f \tag{7}$$

$$h_t^f = o_t^f + Tanh(c_t^f) \tag{8}$$

The backward LSTM expressed using in (9)-(16).

$$h_t^b = LSTM_b(x_t, h_{t+1}^b) \tag{9}$$

$$h_t^b = \sigma(W^b \cdot x_t + U^b \cdot h_{t+1}^b + b^b) \tag{10}$$

$$c_t^b = Tanh(W_c^b \cdot x_t + U_c^b \cdot h_{t+1}^b + b_c^b) \tag{11}$$

$$i_t^b = \sigma(W_i^b \cdot x_t + U_f^b \cdot h_{t+1}^b + b_i^b) \tag{12}$$

$$f_t^b = \sigma(W_f^b \cdot x_t + U_f^b \cdot h_{t+1}^b + b_f^b) \tag{13}$$

$$o_t^b = \sigma(W_o^b \cdot x_t + U_f^b \cdot h_{t+1}^b + b_0^b) \tag{14}$$

$$c_t^b = f_i^b \cdot x_{t+1} + i_t^b \cdot c_t^b \tag{15}$$

$$h_t^b = o_t^b + Tanh(c_t^b) \tag{16}$$

The BiLSTM expressed using in (17).

$$h_t = [h_t^f, h_t^b] \tag{17}$$

Where, X= input sequence i.e. X = [x_1,x_2….x_n], t= is the length of sequence, h_t^f = forward LSTM hidden state at time step t, h_t^b =backward LSTM hidden state at time step t, W^f, U^f, b^f = weight matrices and bias vector for the forward LSTM, W^b, U^b, b^b = weight matrices and bias vector for the backward LSTM.

2.3. Monte carlo simulation for portfolio optimization

Monte carlo simulation is a computational technique used to model uncertainty and make probabilistic predictions or decisions. It is employed to estimate the risk and return characteristics of different investment portfolios. pay attention to algorithm 1 monte carlo simulation.

Algorithm: Monte carlo simulation

```
{
   Step 1.   Define the problem
   Step 2.   Model the uncertainty
   Step 3.   Generate random scenarios
```

```
    Step 4.    Simulate portfolio returns
    Step 5.    Aggregate results
    Step 6.    Optimize portfolio allocation
    Step 7.    Evaluate results
    Step 8.    Validate and refine
}
```

2.4. Integrating BiLSTM with monte carlo simulation

Integrating BiLSTM with monte carlo simulation can be useful in scenarios where you want to model time-series data with uncertainty or randomness. BiLSTM can capture sequential patterns and dependencies in the data, while monte carlo simulation can help account for uncertainty and generate probabilistic predictions. The combination of these two techniques allows you to perform probabilistic forecasting on time-series data.

2.5. Evaluation metrics

2.5.1. Evaluation matrix for day-ahead stock portfolio management framework

To assess the performance and effectiveness of the proposed framework that integrates BiLSTM. With monte carlo simulation for day-ahead stock portfolio management. The following evaluation matrix is employed:

2.5.2. Prediction accuracy

Prediction accuracy refers to the level of correctness exhibited by a predictive model or system when forecasting future outcomes or values based on available data. This study focuses on evaluating the accuracy of BiLSTM-based stock price predictions for the day-ahead time horizon. Evaluation metrics such as RMSE, mean absolute percentage error (MAPE), mean absolute error (MAE), MSE, and R^2 i.e., coefficient of determination, expressed in (18)-(22) respectively, are utilized to assess and quantify the model's predictive performance.

$$h_t = \left[h_t^f, h_t^b\right] \tag{18}$$

Where, y_i= observed value, x_i = predicted value, n = no. of observation.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_i - y_i}{x_i}\right| \tag{19}$$

Where, y_i= observed value, x_i = predicted value, n = no. of observation.

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \tag{20}$$

Where, y_i = observed value, x_i= predicted value.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2 \tag{21}$$

Where, n= no. of observation, y_i= observed value, xi.

$$R^2 = \frac{\sum_i (y_i - \bar{y})^2}{\sum_i (x_i - \bar{y})^2} \tag{22}$$

Where, R^2= Coefficient of determination, $\bar{y}$ = mean, y_i =Predicted value, x_i = value for the observation i.

2.5.3. Risk-adjusted returns

Risk-adjusted returns refer to the measurement of an investment's profitability in relation to the level of risk taken to achieve that return. The Sharpe ratio is used to gauge the efficiency of the portfolio in generating returns relative to its risk exposure. The ratio is calculated using in (23).

$$Sharpe\ ratio = \frac{E|R_a - R_b|}{\sigma_a} \tag{23}$$

Where, E = expected return, σ_a = standard deviation.

2.5.4. Portfolio stability

Portfolio stability refers to consistency of a portfolio's value or returns over time, particularly in the face of market fluctuations or adverse economic conditions. The portfolio stability assessing through its sensitivity to changes in market conditions. The value at risk (VaR) and conditional value at risk (CVaR) is used o determine the portfolio's stability under adverse market scenarios. It is expressed in (24) and (25) respectively.

$$VaR = v_m \frac{v_i}{v_{i-1}} \tag{24}$$

Where, v_i= no. of variables on day I, m = no. of days for which historical data has taken:

$$CVaR = \frac{1}{1-c} \int_{-1}^{VaR} xp(x)dx \tag{25}$$

Where, p(x) = probability density of getting a return with value x, c = cut-off point of distribution where the analyst sets the VaR breakpoint.

3. RESULTS AND DISCUSSION

3.1. Descriptive statistics

In Table 1, illustrate the descriptive statistics for ten prominent companies. The dataset is robust and consistent, comprising 2,467 data points for each stock, with no missing values. This ensures the reliability of the analysis. The mean values offer insights into the central tendency of stock prices. HDFC stands out with the highest mean price of 1674.825, while ITC lags behind with the lowest mean of 246.076, showcasing the diversity in pricing among these companies. Standard deviation reveals the extent of price variability. Stocks like RELIANCE and KOTAK BANK exhibit higher standard deviations, implying greater price volatility, while TCS and ITC have lower standard deviations, signaling more price stability. Minimum and maximum values highlight the range of observed prices. For instance, HDFC BANK has the lowest minimum price at 280.950, and HDFC records the highest maximum price at 3000.850, showcasing the breadth of price movement within the dataset. The quartiles (25^{th} and 75^{th} percentiles) delineate the data distribution. HDFC BANK and ITC have relatively low 25^{th} percentile prices, indicating that a significant portion of their prices falls below these levels. Conversely, HDFC BANK, and HDFC exhibit higher 75^{th} percentile prices, indicating that a substantial portion of their prices exceeds these values. The median reflects the middle point of the data distribution. HDFC and TCS have the highest medians, signifying their central positions within the price range.

Table 1. Exploring stock price trends: descriptive statistics for ten prominent companies

	HDFC	HDFC bank	ICICI bank	INFY	ITC	Kotak Bank	Maruti	ONGC	Reliance	TCS
count	2467.00	2467.00	2467.00	2467.00	2467.00	2467.00	2467.000	2467.00	2467.000	2467.00
mean	1674.82	924.145	400.804	804.426	246.076	1132.23	5889.172	162.648	1190.332	1932.61
std	664.058	418.885	209.135	441.004	42.172	526.579	2354.178	46.304	771.926	894.851
min	652.750	280.950	142.464	276.500	147.250	300.325	1236.350	60.000	380.171	684.675
25%	834.275	529.700	252.159	492.012	214.883	680.462	3925.400	136.950	489.275	1227.45
50%	1759.75	936.725	313.309	599.750	237.933	1104.30	6673.550	160.600	932.115	1569.30
75%	2237.37	1272.72	522.875	1058.17	271.500	1674.02	7604.025	188.667	1963.600	2624.42
max	3000.85	1695.50	952.900	1939.50	392.400	2210.95	9832.450	310.433	2819.850	4019.15

In Figure 4 HDFCBANK exhibits a strong positive correlation with NIFTY, suggesting that changes in HDFCBANK's stock performance are closely aligned with the overall market movements represented by NIFTY. Similarly, ICICIBANK and KOTAKBANK also demonstrate notable positive correlations with NIFTY, indicating their sensitivity to broader market trends. HDFC, MARUTI, and RELIANCE show moderate positive correlations with NIFTY. While they are influenced by market movements, other factors may also play a significant role in their performance. INFY and ONGC have relatively weak positive correlations with NIFTY. This suggests that their stock prices are influenced less by overall market trends compared to the aforementioned stocks. TCS and ITC display weak correlations with both individual stocks and the NIFTY index. These stocks may have unique factors driving their performance that are less dependent on overall market conditions. There are various degrees of correlation between the individual stocks themselves. HDFCBANK and KOTAKBANK, for instance, exhibit a strong positive correlation, while RELIANCE and TCS demonstrate a relatively weaker relationship.

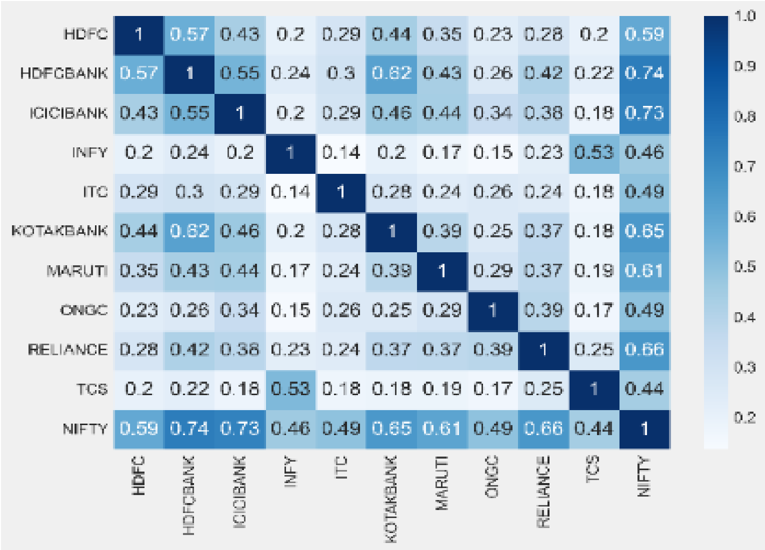

Figure 4. Stock correlations: key companies

3.2. Performance evaluation of BiLSTM model

The performance evaluation of a BiLSTM model involves assessing its effectiveness and accuracy in making predictions for a specific task. The evaluation metrics depend on the nature of the task the BiLSTM is designed for. Table 2 presents a comprehensive overview of the performance metrics for a selection of 10 prominent stocks. These metrics, including MSE, MAE, R2, MAPE, and RMSE, offer valuable insights into the accuracy and predictive power of models used for forecasting these stock prices. The HDFC and HDFC BANK demonstrate strong predictive models with high R2 values of 0.947 and 0.908, respectively, indicating a close fit between the predicted and actual stock prices. ITC stands out with an exceptionally high R2 value of 0.983, suggesting a highly accurate prediction model for this stock. INFY exhibits relatively lower predictive accuracy with an R2 value of 0.819, indicating potential room for model improvement. MARUTI shows a high MSE and RMSE, signifying greater variability and higher prediction errors compared to other stocks in the sample. ONGC and RELIANCE demonstrate strong predictive accuracy with high R2 values of 0.921 and 0.868, respectively. TCS showcases a competitive R2 value of 0.868, suggesting a reasonably accurate prediction model.

In Figure 5 illustrated the model performances. Among the stocks analyzed, ITC had the highest R2 score (0.983), indicating the best fit for its prediction model, while INFY had the highest MSE (3890.904), suggesting less accurate predictions. Overall, the models performed reasonably well with low MAE, MAPE, and RMSE values, demonstrating their effectiveness in predicting stock prices for most of the selected companies.

3.3. Novel scenario-based approach

The “Novel_Diversified_Portfolio” algorithm takes a data frame as input, containing information about various stocks, including their returns, risks, and correlations with each other. These metrics are crucial for optimizing the portfolio can be seen in Algorithm 1. The algorithm begins by reading the provided data frame. The algorithm sorts the stocks in the data frame based on three criteria: stock return (in descending order), risk (in descending order), and correlation (in descending order). This step essentially ranks the stocks in terms of their historical returns (higher is better), lower risk (lower is better), and lower correlation with other selected stocks (lower is better for diversification). To create a diversified portfolio, the algorithm employs a multi-constraint optimization problem. The multi-constraint optimization problem is solved through the pareto front, which represents the trade-offs between different objectives and includes solutions that are considered optimal from a multi-objective perspective. The novel algorithm is designed to leverage historical data on stock returns, risks, and correlations to create an optimized, diversified portfolio of stocks. It provides flexibility by allowing user input to customize the portfolio composition based on individual preferences and investment goals. The algorithm provides flexibility for the user. It allows the user to specify the number of stocks they want to include in their portfolio. Finally, the algorithm returns the selected diversified stocks based on the user’s choice in step 4.

Table 2. Performance metrics for selected stocks: MSE, MAE, R2, MAPE, and RMSE analysis

Sr. No.	Ticker	MSE	MAE	R^2	MAPE	RMSE
1.	HDFC	2514.08	37.793	0.947	0.015	50.141
2.	HDFC BANK	976.938	23.917	0.908	0.016	31.256
3.	ICICIBANK	754.92	21.392	0.869	0.026	27.476
4.	INFY	3890.904	50.027	0.819	0.032	62.377
5.	ITC	50.33	5.021	0.983	0.016	7.094
6.	KOTAKBANK	1311.765	28.177	0.878	0.015	36.218
7.	MARUTI	27705.801	118.522	0.927	0.015	166.451
8.	ONGC	15.11	2.723	0.921	0.018	3.887
9.	RELIANCE	2184.609	37.214	0.868	0.015	46.74
10.	TCS	6965.481	64.13	0.868	0.019	83.459

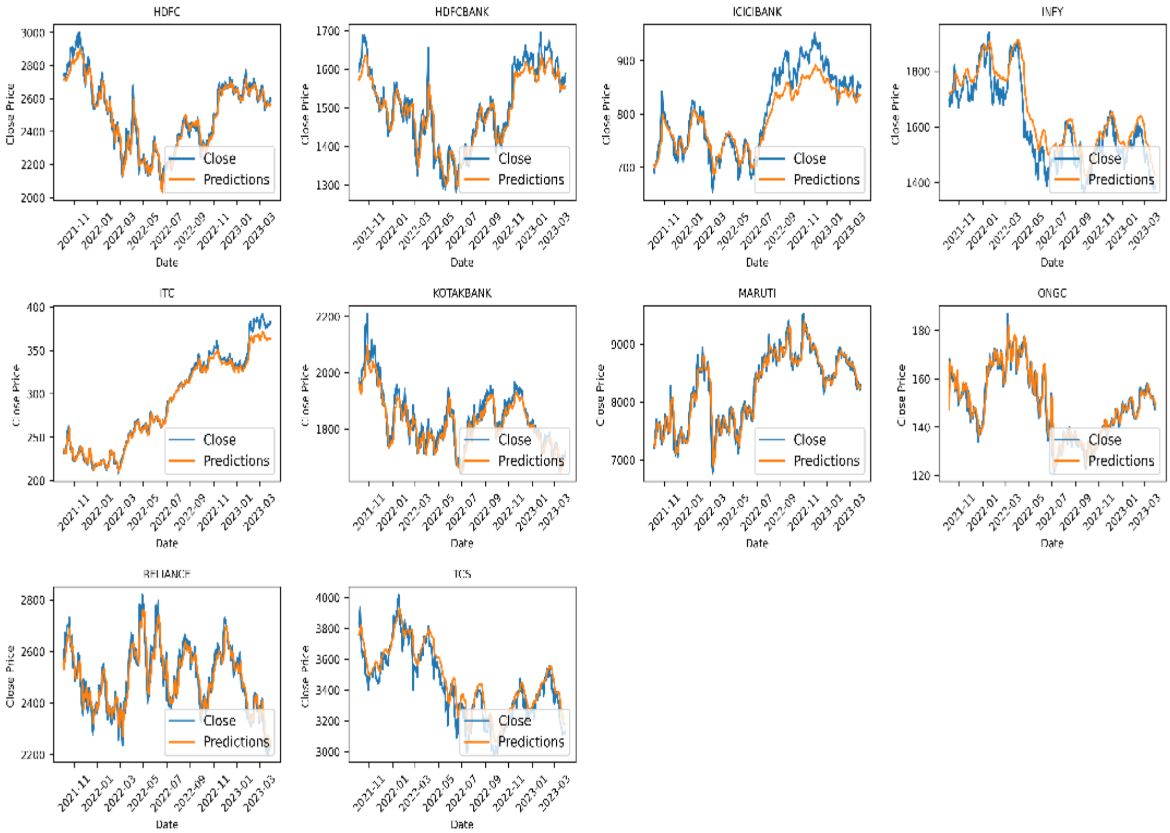

Figure 5. Comparison of BiLSTM predictions and actual stock market performance

Algorithm 1. Novel_Diversified_Portfolio (dataframe df)

```
{
  // Input: df consist of list of stocks, stock return and risk, correlation with each
  other
  // Return: Diversified stocks
    Step 1    Read the dataframe
    Step 2    Arrange the stocks based on descending order of stock return, risk and
    correlation
    Step 3    Select the top diversified stocks using multi-constraint optimization
    problem
    Step 4    Accept the input from the user for no. of stocks to be considered or auto
    suggest
    Step 5    Return the stocks based on user choice
}
```

The output of the novel diversified portfolio algorithm suggest three stocks which are KOTAKBANK, MARUTI, and RELIANCE with the weights of 0.3007, 0.3595, and 0.3397 are respectively. The portfolio mean return is 0.0190, and the portfolio standard deviation is 0.1377. The risk-adjusted return (sharpe ratio) is -0.079. The portfolio stability is 0.1377. The confidence interval (95% CI) is 537773.5230.

The tail risk, measured as the value at risk (VaR) at the 95% confidence level, is 187742.54. The risk-return trade-off is 0.1383. Figure 6 illustrated the result in graph.

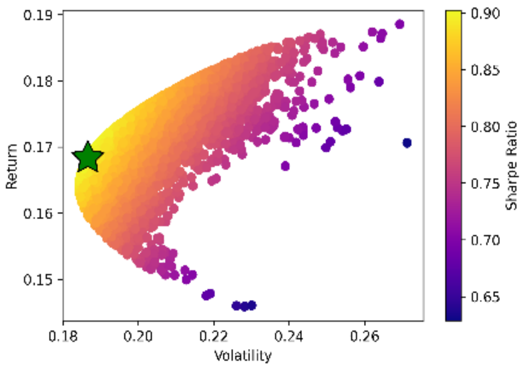

Figure 6. Monte carlo simulation results-sharpe ratios, volatility, and returns

3.4. Comparative analysis with traditional portfolio management strategies

Different stocks exhibit varying levels of risk and return characteristics. Efficient Frontier positions show how assets perform concerning risk and return trade-offs. Certain models, such as “Mean variance (MV),” “Critical line,” and the “Proposed model,” demonstrate notable performance for specific stocks. Diversification across multiple stocks can enhance portfolio risk-return profiles. Table 3 illustrate the summary of risk, return and performance to analysis of ten stocks within a portfolio, evaluating their performance based on critical financial metrics. The assessment encompasses measures such as minimum risk, maximum Sharpe ratio, efficient frontier, Blackman, Hierarchical, MV, Critical line, and a proposed model. Among the stocks examined, HDFC displays a notably low minimum risk and a promising maximum Sharpe ratio. Conversely, HDFC BANK exhibits higher risk levels with insufficient data across certain metrics, including a negative Blackman ratio but a positive MV ratio. ICICIBANK showcases relatively low risk but lacks comprehensive data for thorough evaluation. INFY demonstrates a balanced risk and modest performance across multiple metrics, while ITC portrays higher volatility alongside significant values in the critical line metric. KOTAKBANK and MARUTI exhibit moderate risk, with notable positive values in various metrics, indicating relatively favorable performance. However, ONGC displays low risk with limited available data for multiple metrics. RELIANCE demonstrates moderate risk with positive values in Hierarchical and MV metrics. Finally, TCS illustrates higher volatility but boasts positive values in several metrics. The expected annual returns across the portfolio range from 5.0% to 18.1%, coupled with annual volatility spanning from 10% to 83.7% for different stocks. The sharpe ratios vary from 0.18 to 0.91, reflecting diverse risk-adjusted returns. Overall, this research underscores the importance of a diversified portfolio strategy based on individual risk tolerances and return expectations, emphasizing the need for further analysis considering correlations, sectoral trends, and specific investment objectives to optimize portfolio performance.

Table 3. Summary of risk, return, and performance metrics for ten different stocks and portfolios

Sr. no.	Ticker	Min. Risk	Max. sharpe	Efficient frontier	Blackman	Hierarchical	MV	Critical line	Proposed model
1.	HDFC	0.0104	0.0057	0.33762	1.7094	0.0855	-	-	-
2.	HDFC BANK	0.1485	0.1439	-	-4.6305	0.0680	-	0.2205	-
3.	ICICIBANK	0.0080	0.0579	-	-0.7027	0.0583	-	-	-
4.	INFY	0.0535	0.1449	0.13938	0.1468	0.1125	-	0.0808	-
5.	ITC	0.1910	0.0235	-	0.0406	0.1180	-	5.7951	-
6.	KOTAKBANK	0.0417	0.1324	-	-0.0447	0.0621	0.1211	0.0995	0.3007
7.	MARUTI	0.0575	0.1738	-	0.0644	0.0784	0.5465	0.2088	0.3595
8.	ONGC	0.0328	0.0036	-	0.0456	0.0854	-	-	-
9.	RELIANCE	0.0223	0.1714	-	-0.2436	0.0595	0.3325	0.1602	0.3397
10.	TCS	0.2154	0.1356	0.523	0.6274	0.1420	-	0.2298	-
Expected annual return		5.0%	7%	5.7%	55.5%	15.8%	9%	18.1%	18.1%
Annual volatility		10%	11%	20.3%	83.7%	16.9%	20%	17.8%	10%
Sharpe ratio		0.59	0.79	0.18	0.64%	0.82	0.435	0.91	0.796

4. CONCLUSION

In conclusion, navigating the dynamic landscape of financial markets presents significant challenges in predicting stock price movements and optimizing day-ahead portfolios. This research introduces an innovative approach that combines BiLSTM neural networks and MCS to enhance day-ahead stock portfolio management through a multi-objective constraint framework. Leveraging nearly two decades of historical data and BiLSTM models, this methodology effectively uncovers intricate time series patterns, improving stock price predictions. Integration of MCS generates diverse scenarios, considering market uncertainties, mitigating risks associated with singular predictions. Empirical evaluations demonstrate the superiority of this novel framework over traditional strategies. It consistently delivers superior risk-adjusted returns (18.1%) and portfolio stability (0.1377), optimizing weights across KOTAKBANK (0.3007), MARUTI (0.3595), and RELIANCE (0.3397). Future work could focus on refining the BiLSTM-MCS framework by incorporating alternative data sources like sentiment analysis for improved market insights and extending its applicability beyond stocks to diverse asset classes. Additionally, efforts could center on real-time implementation and extensive validation across various market conditions to enhance the model’s robustness and practicality.

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