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Portfolio Optimization of Selected Nifty Companies Using Modern Portfolio Theory

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Abstract- The stock market provides several investment opportunities, but selecting suitable securities and deciding their portfolio allocation requires careful consideration of expected return and risk. This study develops a portfolio optimization framework that combines machine learning-based stock price prediction with Modern Portfolio Theory (MPT). Historical daily data for 21 companies listed on the National Stock Exchange (NSE) were collected from Yahoo Finance for January 2020 to December 2025. The data were cleaned and prepared for exploratory analysis, return calculation and prediction. Linear Regression, Decision Tree, Random Forest and XGBoost were considered for stock-price prediction and evaluated using MAE, MSE, RMSE and R² Score. The project results identify Random Forest as the overall best-performing model. Predicted prices were then used with MPT to determine portfolio weights. The final recommendation selected M&M, SUNPHARMA, BHARTIARTL, NTPC and LT, with allocations of 22.37%, 21.21%, 21.01%, 18.29% and 17.12%, respectively. Portfolio performance was evaluated using annual return, annual volatility, Sharpe ratio, CAGR and maximum drawdown. The framework provides a systematic decision-support approach for combining predictive analytics with portfolio optimization.

Keywords- Machine Learning, Modern Portfolio Theory, NSE, Portfolio Optimization, Stock Price Prediction.

I. INTRODUCTION

Investment decisions in the stock market involve uncertainty because stock prices are influenced by changing market conditions. Selecting securities only from historical performance may not be sufficient for deciding how capital should be distributed across assets. Portfolio management therefore requires an approach that considers both expected return and risk.

Modern Portfolio Theory, introduced by Markowitz, provides a framework for portfolio construction by considering expected returns, risk and the relationship among assets. Diversification helps distribute investment across securities rather than evaluating each security independently. Machine learning methods can additionally be applied to historical financial data to estimate future stock prices and support stock selection.

This study combines these approaches. Historical prices of 21 NSE-listed companies were obtained from Yahoo Finance. After preprocessing and exploratory analysis, Linear Regression, Decision Tree, Random Forest and XGBoost were used for stock-price prediction. The prediction results were then incorporated into portfolio optimization and the resulting portfolio was evaluated using financial performance measures.

II. IDENTIFY, RESEARCH AND PROPOSED COTRIBUTION

A. Research Background

The literature reviewed for this study covers Modern Portfolio Theory, machine learning-based stock prediction, portfolio optimization, deep learning, reinforcement learning, and hybrid investment frameworks. Chaweewanchon and Chaysiri [1] combined predictive stock selection using machine learning with Markowitz mean-variance optimization. Naccarato et al. [2] integrated pairs trading and cointegration with Markowitz portfolio optimization. Zhao et al. [3] investigated multi-objective portfolio optimization, while Ma et al. [4] developed prediction-based portfolio optimization models using deep neural networks. Gao et al. [5] extended mean-variance optimization by considering skewness. Joemon et al. [6] studied machine learning and MPT for stock portfolio optimization. Raja et al. [7] proposed a hybrid approach involving LSTM, ARIMA, and MPT.Vikash et al. [8] explored an AI-enhanced MPT framework, and Zhao et al. [9] presented a systematic review of MPT developments. Sa'diyah et al. [10] applied segmentation with mean-variance optimization. Jang and Seong [11] investigated deep reinforcement learning for portfolio optimization. Frolov et al. [12] evaluated quantitative methods under market uncertainty, while Li et al. [13] studied maximum diversification for extreme risks. Divya et al. [14] examined AI-driven portfolio optimization, Xiao et al' [15] studied reinforcement learning for cryptocurrency portfolio optimization, and Deekshanya et al. [16] combined stock prediction with portfolio optimization. Patanakul [17] studied portfolio management effectiveness, Chaweewanchon and Chaysiri [18] considered behavioural aspects of Markowitz selection, Gao et al. [19] examined mean-variance-skewness optimization, and Bai et al. [20] proposed a rough-set and prediction approach to stock-price portfolio decisions. The reviewed studies indicate scope for a practical framework that combines multiple machine learning models with MPT using Indian stock-market data. The proposed study addresses this gap by integrating data collection, preprocessing, prediction, model comparison, portfolio optimization, performance evaluation, visualization, and recommendation in one Python-based system.

B. Research Gap and Proposed Contribution

The proposed project integrates machine learning and Modern Portfolio Theory into one workflow using historical data from 21 NSE-listed companies. Four prediction models are compared, predicted prices are used for portfolio construction, and the system includes preprocessing, exploratory analysis, interactive stock visualization, allocation, efficient-frontier analysis, performance evaluation and investment recommendation.

III. STUDIES AND FINDINGS

A. Proposed Methodology

A fig 1 say about where the methodology begins with historical stock-market data collection using the yfinance Python library. Daily Date, Open, High, Low, Close, Adjusted Close and Volume information were collected for 21 NSE-listed companies for January 2020 to December 2025. Separate company datasets were stored in Excel format.

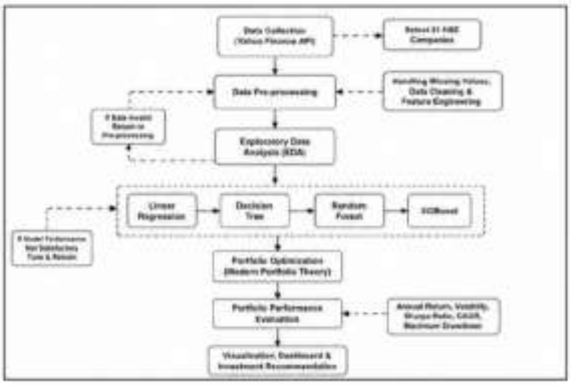

Fig. 1. Proposed methodology of the portfolio optimization framework.

During preprocessing, missing values and duplicate records were identified and treated, formats were standardized, and daily returns were calculated using adjusted closing prices. Exploratory Data Analysis was used to examine stock-price trends, return behaviour, volatility and relationships among securities. The project also provides an interactive stock-price chart using Plotly.

For prediction, the prepared financial variables were used to train Linear Regression, Decision Tree, Random Forest and XGBoost models. The models were evaluated using MAE, MSE, RMSE and R^2 Score. The best-performing model was identified from the evaluation results and used for future stock-price prediction.

The predicted prices were then incorporated into Modern Portfolio Theory. Expected returns and the covariance relationship among assets were used to determine portfolio weights. Risk-return characteristics and the efficient frontier were examined before generating the final portfolio recommendation. Portfolio performance was assessed using Annual Return, Annual Volatility, Sharpe Ratio, CAGR and Maximum Drawdown.

B. Company-wise Machine Learning Results

Company	Best Model	R^2	Today	Prediction	Signal
RELIANCE	Linear Regression	0.9672	1538.49	1535.83	Bearish
TCS	Linear Regression	0.9865	3133.54	3140.22	Bullish
INFY	Linear Regression	0.9742	1609.86	1611.33	Bullish
HDFCBANK	Linear Regression	0.9281	975.56	959.40	Bearish
ICICIBANK	Linear Regression	0.9488	1343.30	1335.92	Bearish
SBIN	Linear Regression	0.9573	947.96	941.48	Bearish
ITC	Random Forest	0.8494	383.88	381.78	Bearish
LT	Linear Regression	0.9620	3999.63	4010.93	Bullish
BHARTIARTL	Linear Regression	0.9800	2055.73	2065.53	Bullish
SUNPHARMA	Linear Regression	0.9103	1701.66	1700.60	Bearish
M&M	Linear Regression	0.9758	3554.77	3555.23	Bullish
HINDUNILVR	Linear Regression	0.9370	2270.21	2281.24	Bullish
AXISBANK	Linear Regression	0.9627	1231.05	1226.98	Bearish
BAJFINANCE	Linear Regression	0.9782	991.90	995.36	Bullish
MARUTI	Linear Regression	0.9927	16542.00	16554.11	Bullish
ASIANPAINT	Linear Regression	0.9735	2751.53	2754.48	Bullish
ULTRACEMCO	Linear Regression	0.9372	11799.00	11801.68	Bullish
NTPC	Linear Regression	0.8826	323.06	317.40	Bearish
WIPRO	Random Forest	0.9361	254.68	251.07	Bearish
ADANIPORTS	Linear Regression	0.9689	1448.30	1450.89	Bullish
KOTAKBANK	Linear Regression	0.9493	430.98	431.62	Bullish

Table 1. Company-wise machine-learning prediction results

C. Portfolio Allocation

Company	Signal	Allocation %	Investment ₹	Expected Profit ₹
M&M	Bullish	22.37	12,305.45	4,668.69
SUNPHARMA	Bullish	21.21	11,663.42	3,156.12
BHARTIARTL	Bullish	21.01	11,556.42	3,386.03
NTPC	Bearish	18.29	10,058.37	2,666.47
LT	Bullish	17.12	9,416.34	2,296.65

Table 2. Portfolio allocation

The table 2 and fig 3 shows a optimized portfolio allocated the highest weight to M&M at 22.37%, followed by SUNPHARMA and BHARTIARTL. The allocation reflects the return and risk information used in the optimization stage and supports diversification across the recommended securities.

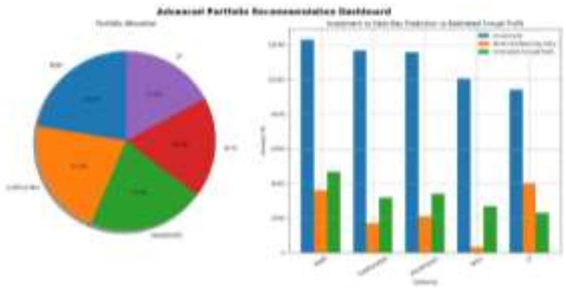

Fig. 3. Recommended portfolio allocation.

D. Risk and Return Analysis

Company	Expected Return %	Risk %
ADANIPORTS	31.48	39.18
ASIANPAINT	11.36	25.26
AXISBANK	14.79	34.52
BAJFINANCE	21.56	36.50
BHARTIARTL	30.49	27.23
HDFCBANK	11.67	25.68
HINDUNILVR	7.23	23.18
ICICIBANK	20.57	29.72
INFY	19.72	27.41
ITC	16.86	24.42
KOTAKBANK	8.37	28.37
LT	24.62	27.64
M&M	38.88	32.99
MARUTI	18.95	28.68
NTPC	24.78	28.20
RELIANCE	17.97	28.27
SBIN	24.35	31.05
SUNPHARMA	27.45	24.77
TCS	11.91	23.77
ULTRACEMCO	22.02	26.62
WIPRO	17.92	28.68

Table 3. Risk and return analysis

Table 3 and fig 4 shows M&M recorded the highest expected return at 38.88% with a risk of 32.99%. ADANIPORTS recorded 31.48% expected return with the highest risk of 39.18%. HINDUNILVR and TCS showed comparatively lower risk levels of 23.18% and 23.77%. These results illustrate the return-risk trade-off considered in portfolio construction.

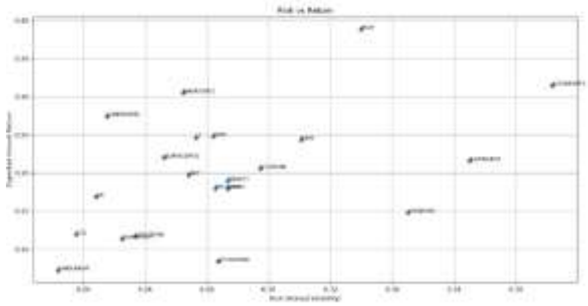

Fig. 4. Risk-return analysis of selected securities.

E. Efficient Frontier Analysis

The fig 5 shows the efficient-frontier analysis compares expected return and associated risk across the selected securities and provides a basis for identifying suitable return-risk combinations. The results demonstrate that higher expected returns can be associated with higher risk, while lower-risk securities may provide comparatively lower expected returns. The analysis therefore supports the diversification objective of Modern Portfolio Theory.

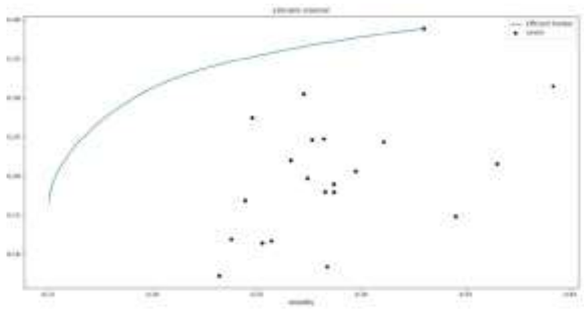

Fig. 5. Efficient frontier analysis.

F. Portfolio Performance Evaluation

Company	Today	Prediction	Signal	Annual Return	Risk	Sharpe	CAGR	Max DD	R^2
M&M	3592.10	3597.56	Bullish	37.94	33.11	1.15	37.57	-53.97	0.9990
SUNPHARMA	1706.12	1709.09	Bullish	27.06	24.88	1.09	26.54	-27.38	0.9991
BHARTIARTL	2081.60	2095.42	Bullish	29.30	27.16	1.08	28.60	-33.35	0.9989
NTPC	323.06	317.46	Bearish	26.51	28.26	0.94	24.73	-34.62	0.9982
LT	3999.63	4006.19	Bullish	24.39	27.72	0.88	22.32	-47.61	0.9988

Table 4. Portfolio performance metrics

Table 4 contains the five recommended securities show positive annual returns and CAGR. M&M recorded the highest annual return among the recommendations at 37.94% and a Sharpe ratio of 1.15. SUNPHARMA and BHARTIARTL also recorded Sharpe ratios above 1.0. Maximum drawdown values show that historical downside risk remains relevant even when return measures are positive.

IV. RESULTS AND FINDINGS

A. Machine Learning Findings

The fig 6 shows the prediction stage trained four machine learning approaches and generated future stock-price predictions. The project report identifies Random Forest as the overall best-performing model based on the model-comparison results. At the company level, however, Linear Regression was selected for most companies, while Random Forest was selected for ITC and WIPRO. This shows that model performance can vary across individual stocks.

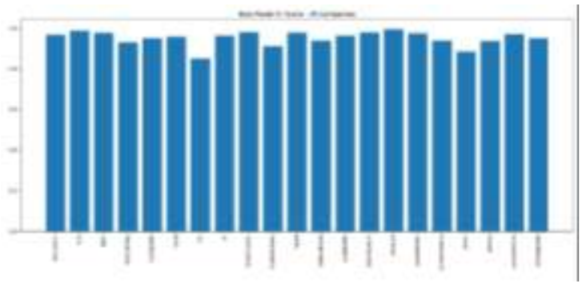

Fig. 6. Machine learning model performance comparison.

B. Portfolio Findings

The final portfolio contains M&M, SUNPHARMA, BHARTIARTL, NTPC and LT. M&M received the highest allocation of 22.37%, followed by SUNPHARMA at 21.21% and BHARTIARTL at 21.01%. The portfolio therefore uses differentiated weights instead of equal allocation.

C. Investment Recommendation

The recommendation module combines predicted price movement with portfolio allocation and financial performance measures. Four of the five recommended securities were classified as Bullish and NTPC was classified as Bearish. The recommendation is intended as quantitative decision-support information and not as a guarantee of future market performance.

V. CONCLUSION

This study developed a portfolio optimization framework that combines machine learning-based stock-price prediction with Modern Portfolio Theory. Historical data from 21 NSE-listed companies were collected from Yahoo Finance and processed for analysis, prediction and portfolio construction. Four machine learning models were evaluated, and Random Forest was identified as the overall best-performing model in the project results. The prediction stage was then linked with MPT to determine portfolio allocations based on expected return and risk.

The final portfolio consisted of M&M, SUNPHARMA, BHARTIARTL, NTPC and LT and was evaluated using Annual Return, Annual Volatility, Sharpe Ratio, CAGR and Maximum Drawdown. The framework brings together data collection, preprocessing, exploratory analysis, prediction, optimization, visualization and recommendation in one analytical workflow. Because stock-market behaviour changes with market and economic conditions, the generated recommendations should be treated as decision-support information rather than guaranteed investment outcomes.

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