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ORIGINAL RESEARCH

Portfolio optimization in stocks using mean–variance optimization and the efficient frontier

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Abstract Portfolio optimization is always the priority of market researchers, large financial institutional investors, Mutual Fund, and Pension funds managers. Due to high volatility in the stock market, people are less interested in the Stock market. Therefore, we designed a fusion model to predict the future stock prices which gives us maximum returns on the selected group of companies. Previously it requires a wealth manager to study how to get maximum returns on our capital. But now, in this new era, we can do it with the help of techniques like Machine Learning, Dynamic Programing, Artificial Intelligence, and Linear Programming. If we invest in one Stock, the risk is more; however, we reduce the risk by diversifying the portfolio. To diversify the risk, we need a strong portfolio of fundamentally strong stocks. Various deep learning and machine learning models have been implemented previously, but none of them has implemented Efficient Frontier combined with the approach of Mean–Variance optimization. This paper makes a novel attempt to predict realistic and correct ratios of stocks and minimum/maximum returns. This paper proposed two new algorithms: one for the Selection of fundamentally solid stocks and the next for Diversification. In-Depth research is done on the Indian Stock Market, i.e., Nifty 50. Our model will provide you with ratios in which you have to diversify capital based on fundamentals, log returns, and a dynamic approach to take maximum returns.

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1 Introduction

Large financial institutional inverters, Mutual Fund managers, Pension funds, and market researchers are always interested in portfolio management and Diversification of risk [1]. Stock Market growth plays a significant role in the development of the country. Predicting the stock market price in finance, mathematics, economy, and engineering [2, 3] is challenging. Firstly, let us start with the basics of a portfolio and why we need it. A stock market Portfolio in Simple words, is a diversification of risk. If we invest in one company, it might grow or fall to zero, but this is not a good way of investing in the Stock market. Therefore, we have to invest in multiple companies of different sectors to diversify risk and get maximum returns. Our Dataset is Nifty 50 companies; being a part of Nifty 50, the company is considered a fundamentally strong company. Choose a market leader company in a particular sector and balanced portfolio based on various sectors like paint, footwear, chemicals, banking, insurance, food, and petroleum. Try to balance your portfolio based on which sector company you like. Let's get introduced to various formulas.

1.1 Harry Markowits optimal portfolio solution

Selecting an optimal portfolio is a challenging task, and Harry Markowits [4, 5] gave one solution to this problem in 1952. To make this optimal Selection of the portfolios

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having n securities, we have to evaluate the two factors. As shown in Eqs. 1 and 2.

1. **Expected Returns** are given by Eq. 1, shown below.

$$R_t = \sum_{x=1}^{n} R_x f_X \tag{1}$$

2. **Risk (Volatility)** is given by Eq. 2, shown below.

$$V_t = \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_{ij} X_i X_j \tag{2}$$

R_t is expected to return on 't' security; X_i, X_j implies the proportion of funds; α_{ij} implies covariance of returns.

1.2 Research on P/E ratio

To minimize the risk, we use the portfolio management technique, which the above idea shows the old method used by professionals to manage the portfolio couple of years ago. As the world is advancing, various machine learning methods have come forward. This paper proposes using a fusion of predicted stock price combined with Mean–variance optimization and the efficient frontier [6] to forecast the expected portfolio return. Knowledge of basic terminologies of terms like P/E ratio is necessary; in Eq. (3), the Formula is shown below to find the companies' P/E.

$$\mathrm{P/E} = \frac{\text{Price of share}}{\textit{Earnings made on per share}} \tag{3}$$

Observation made by seeing the P/E of the companies is that if P/E is high then the company is Overvalued, companies stock price may fall [7]. The next essential thing we have to understand is Return on Equity (ROE) which means Returns made on a particular investment or Equity. ROE plays a vital role while investing in a company. It also shows how effectively the company uses the shareholder's invested Amount.

1.3 Research on ROE

Let's look at the Formula for Return on Equity (ROE) [8]; see Eq. (4) and analyze the basics.

$$ROE\,(Return\ of\ Equity) = \frac{Net\ income\ of\ comapny}{Equity\ of\ share\ holders} \tag{4}$$

As shown in Eq. 4, it plays an essential role in the analysis of the company, but ROE is not so significant for specific sectors like Banking and financial services. ROE can be high also if the company [9] is taking much debt.

1.4 Returns of stocks

This paper will focus on returns, so let's look at the future values of the stocks by the basic Formula. These points will guide you on which stocks should be in your portfolio or not. See Eq. (5) shown below, which shows the stock price calculation.

$$Fp = A * (1 + R)T \tag{5}$$

Fp implies the future price of the investment; A means the Amount invested or present worth of the investment; T means the duration of time on which compounding is performed; R implies the Rate of returns or periodic Rate of interest.

Various conclusions from the study of the company's fundamentals can be made by seeing Eq. 5 above. Factors responsible for the stock price need to be studied, as these factors guide the company selection in the portfolio. We will also discuss the volatility and how combining these two factors will help you choose the perfect Stock for your portfolio [10].

"No risk, no reward" was said by Dorothy E Leidner in 2019. The same applies to the stock market also; with more risk you will get more returns; with less risk, you will get fewer returns [11, 12]. Your overall portfolio can also be negative if you invest in a high-risk company [13]. Follow the rule, never lose the capital. This paper will provide you with in-depth knowledge of how portfolio optimization will generate maximum returns in the worst situation and how another sector's rise can cover one sector's fall.

1.5 Effect of market on stock price

Let's look at how the stock prices are decided and how market variance plays a major role in deciding the stock price [12, 14]. The Formula shown in Eq. 6 below shows how each of the factors is responsible for the prediction of stock prices.

$$Stock\,price\ =\ V\ +\ F * L \tag{6}$$

V implies Variance of Stock; F means Fluctuation in the Stock; L implies the level of the market.

The formulas show that various factors like Variance, Fluctuation, and market-level play a critical role in deciding the stock price in the stock market. Take reference from Eq. 1–6 in research paper to understand the company's fundamentals. This paper provided the uses of the equation for calculation and understanding of the Stock's fundamentals.

1.6 Key contributions in the proposed work are as follows

- Algorithm 1 is offered for the Selection of fundamentally strong Stock.

- Algorithm 2 proposed the modification in modern portfolio theory.
- Use of new feature in the dataset Log Returns.
- Proposed the method that uses Forecasted price for portfolio optimization based on a new technique using 0–1 Knapsack to avoid short-selling.

2 Literature survey

Tsao [12] researched portfolio selection using the traditional approach of the mean–variance framework. He evaluated of mean–variance framework approach with NSGA-2. He concluded that investors might ineffectively allocate their wealth by using this approach.

Sun [13] used mean–variance, linear programming to calculate expected returns. The efficient frontier and sharp ratio measurement concept to evaluate the portfolio G created by the random allotment. The proposed method does not deal with the forecast of returns on the Stock; no proper diversification is involved, and fundamental analysis of companies is not done. The overallotment is done, the risk is very high more than 90% is invested in only four companies.

Calvo et al. [14] researched the interpolation procedure for the kernel. The proposed method can be applied only for general purposes, not specific to stock optimization.

Boyle [15] used the capital asset pricing model referred to as CAPM in the market using the efficient frontier model. It uses an efficient frontier with a positive weight to calculate the returns. Through the covariance matrix, expected returns in the vector are obtained.

Grasse et al. [16] studied and examined the revenue structure of non-profitable organizations; by using modern portfolio theory, they have concluded with the ideal theoretical revenue portfolio examine the return, risk, and covariance of revenue stream.

Abu Bakar and Rosbi [17] used efficient frontier analysis for their investment portfolio in the Malaysian stock market. He uses modern portfolio theory through which he attempted to maximize the returns.

Yang et al. [18] published a research article that proposed the alpha Tail distance method with portfolio optimization, tested under various market conditions. This method was introduced with the criteria measurement methods for traditional Distance and assumed no change in the stock returns. They devise out new plan of alpha tail distance, which provides the process for evaluating market conditions. They introduced the α-tail Distance into the techniques for traditional distance clustering for the Stock's selection problem in portfolio selection with the cardinality constraints.

The petrochemical industry is a high volatility market. Also, various world factor plays a significant role in deciding on price. Market researcher Baghmolaei et al. [19] takes the data from Tehran Stock Exchange from 2013 to 2019 of Fifteen petrochemical companies. Solve the problem on the Markowitz portfolio optimization model by using particle swarm optimization. The median value of the return of stock function is less than the median value of the function of stock return in the Markowitz model. In contrast, the median value of the portfolio's risk function is much lower than the average value of the risk function of the portfolio in the Markowitz portfolio optimization model.

Gondkar et al. [20], with his fellow researcher at MIT university, does deep research to like portfolio optimization and stock market price prediction. With his fellow researcher, he worked on optimizing the stacked LSTM model with the network of stock market price prediction. He designed a model and used six different techniques, focusing on the best portfolio. He created LSTM layers and a hybrid neural network containing 1D-Convolutional layers. He focused on one sector and limited his research to optimize one industry, which was a drawback. One market sector can be down, while other sectors can cope with that loss. But with shear research, it can be helpful only for one sector problem, not all.

Thakkar and Chaudhari [21] did excellent research on trend prediction using particle swarm optimization. Various machine learning algorithms are developed to study the market characteristics and improve prediction accuracy. The article aims to balance the economics and aspects of computational intelligence and also analyze the superiority of PSO for stock portfolio optimization, stock price and trend prediction, and other related stock market aspects along with implications of PSO.

Ma et al. [22] used machine learning and deep learning technique to select the stocks. They make a fusion of return prediction done by machine learning and portfolio optimization done by deep learning. They have made the advancement with the help of the mean–variance model combined with random forest (RF) and support vector (SV). They see the optimization and improvement in their results using this technique.

Faia et al. [23] researched the forecasting error in risk formulation on electricity market participation. The use of particle swarm optimization does this research. They have used the Formula of return to do the optimization. Furthermore, they measure the risk.

Now, let's get to the mean–variance optimization. This field's research work uses a machine learning-based model for stock price prediction. The research was carried out by Chen et al. [24]. They say that the success of a portfolio depends on the future performance of the stock market. They developed a hybrid model based on machine learning for predicting the Stock and using the mean–variance model for portfolio selection.

Below Table 1 is the comparative studies performed till now. Since it is a relatively new topic, all recent research papers are attached to the report.

Now let's look at the research done on the Nifty 50.

Table 1 Comparative analysis of different algorithm

Author	Technique used	Sector targeted
Tsao [12]	Mean–variance	Asset management
Sun [13]	Mean–variance and linear programming	Indonesia Stock Market (LQ 45)
Calvo et al. [14]	KTEF interpolation method	General purpose
Boyle [15]	Capital asset pricing model (CAPM)	Stocks
Abu Bakar and Rosbi [17]	Efficient frontier analysis for portfolio investment	Astro Malaysia Holdings Berhad and Nestle Malaysia
Yang et al. [18]	Alpha Tail distance method	Chinese Market
Baghmolaei et al. [19]	Particle swarm optimization	Petrochemical
Gondkar et al. [20]	LSTM layers and hybrid neural network contains 1D-Convolutional layers	Indian Banking sector
Thakkar and Chaudhari [21]	Particle swarm optimization with market characteristics	Indian stock market
Ma et al. [22]	Random forest + Support vector	Chinese Market
Faia et al. [23]	Particle swarm optimization	Electricity market
Chen et al. [24]	Mean–variance (MV) model	Shanghai Stock Exchange SSE 50

Table 2 Comparative analysis of different algorithm on the Indian dataset

Author	Technique used	Sector targeted
Batra and Taneja [25]	Generalized information theoretical measures	Liquid Stocks of NIFTY 50
Sen et al. [26]	LSTM	Eight portfolios Different sector NSE
Srivastava et al. [27]	Mean–variance and CPT	Nifty 50

Batra and Taneja [25] proposed the mathematical method to solve the portfolio optimization problem using the mathematical way, which is based on generalized information theoretical measures. They have researched the Indian dataset and selected the ten most liquid Nifty 50. Measure the ratio of Award and risk ratio. They proposed a model for higher Diversification. Their model responds to the changes in market characteristics by efficient reallocation. They show how their model is better than all traditional benchmark existing models.

Sen et al. researched portfolio optimization using the LSTM method and predicted stock price from Jan 2016 to Dec 2020. They form Eight portfolios of different sectors [26] of the National stock exchange in India. They compared the seven months of analysis with their model of research. They attain high-level accuracy of predicted and actual returns using the LSTM model.

Srivastava et al. [27] used the Markowitz model of Mean–variance. They studied the CPT-based efficient frontier technique and selected the Nifty 50. Their approach is compared with the performance of the behavioral investor and that which are rational investors (Table 2).

3 Methodology

Firstly, we have to collect the data of 50 different Indian companies. In this paper, the author's dataset is uploaded on the IEEE data port. The Data Source is https://finance.yahoo.com/. The API for Yahoo finance is yfinance, is used to collect the data.

3.1 Data collection

The collection of data from yahoo finance is an important part. Yahoo finance library provides the company's data by using the company's symbol and the time duration from 13–04–2015 to 13–04–2022. After downloading the data of all 50 companies' part of NIFTY 50 from yahoo finance, we merged these 50 companies' data by creating an extra column with a label name that indicates their name. After updating these details, the csv file is now forwarded for data processing.

The dataset has the following attributes.

- Name: Shows the name of the company.
- Date: Shows what is the date on that day.
- Open: Shows at what price stock is open on that particular day.
- Close: Shows at what price Stock closed on that day.
- Adj Close: Stands for adjusted close and shows the close price—dividend given on the Stock.
- High: This shows the highest price stock touched on that particular day.

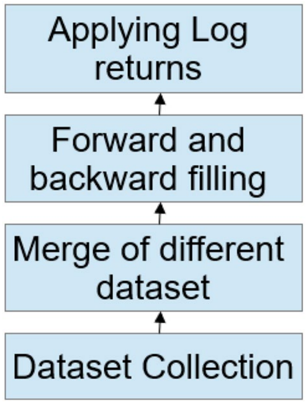

Fig. 1 Shows the data processing and merge operation performed

- Volume: This shows how much stock quantity is traded on that particular day.

3.2 Data processing

In the dataset processing, the forward and backward filling is used for filling the stock price for holidays (Market off days) and old data (Historical data which is not present) of the company. The dataset created by merge and Data processing of 50 company of NIFTY-50 is uploaded on IEEE Data port [28], https://doi.org/10.21227/b2k0-pb76.

The given below Fig. 1. Shows the steps of data processing and flow chart of operation.

The dataset used in this paper is uploaded to IEEE Data port. The Dataset collection is explained in Sect. 3.1. As shown in Fig. 1. we have to done forward and backward filling. On non-trading dates forward filling is used. Backward filling in the case when we don't have the company's previous data. The last step is to calculate the log returns as per the Formula shown in Eq. 15.

3.3 Analysis of fundamentals and Selection of stocks

3.3.1 Alpha

This paper studies the different measures to analyze the company's fundamentals. Based on this analysis, let us discuss in-depth and select some fundamentally strong companies. See Eq. 7. which shows the alpha perimeter of a particular stock. Professional portfolio managers [29, 30] always check the Alpha of their portfolio [31], It shows how much your portfolio performs better than the benchmark set by the market. For this model, we have to use Nifty-50 as a benchmark.

$$Alpha = \frac{(End\ price + Distribution\ per\ share - Start\ price)}{Start\ price} \tag{7}$$

3.3.2 Beta

Let us now understand the Beta and its importance for market analysis; Beta indicates the volatility of a stock. If Beta is very high, the risk is very high as it is highly volatile. Beta compares stock volatility with the market [28–31]. See Eq. 8, which shows the Formula for the calculation of Beta.

$$Beta = \frac{Covariance\ of\ assets's\ returns\ with\ returns\ of\ market}{Variance\ of\ Rerturns\ of\ market} \tag{8}$$

3.3.3 CAGR (compound annual growth rate)

Let's now see CAGR and why it is so essential for analysis. CAGR stands for Compound Annual Growth Rate [32]. If the company is consistent CAGR of more than 20. Let's see the Formula used for CAGR see Eq. 9. A consistent compounder company is found by using this Formula. Some companies are consistent compounders [33], part of Nifty 50 like Titan, Asian Paints, Infosys, Hdfc Bank Bajaj Finance, etc.

$$CAGR = \left(\frac{Vf}{Vs}\right)^{\frac{1}{T}} - 1 \tag{9}$$

Here is the Algorithm which will guide you to select a fundamentally strong stock. We have to look for a consistent compounder company and High Long term CAGR company for our portfolio. The proposed Algorithm 1 is for shortlisting the fundamentally strong company.

Algorithm 1. Fundamentally strong and consistent compounder stock selection algorithm

Input: *List of companies and their 5-year close price*
Output: *List of fundamentally strong companies*

Let us take 50 Indian company's name and their Yearly profit report
STEP 1. *Select the Profitable company from the list of Indian stock market.*
STEP 2. *Verify the following condition, Repeat steps 3 to 6 for 5 years*
STEP 3. *Calculate the PE of company as shown in Eq 1. Validate PE should be less than 200.*
STEP 4. *Calculate the ROE as Shown in Eq 2 and verify that ROE>10.*
STEP 5. *Calculate the value of Alpha and Beta as shown in Eq 7 and 8 and verify that β<0.8 and α>=1*
STEP 6. *Calculate the CAGR of company as shown in Eq 9 and Verify that CAGR>20.*
STEP 7. *Store the List of selected company in the array*

Algorithm 1 proposed will help shortlist fundamentally strong stocks with high CAGR and low risk.

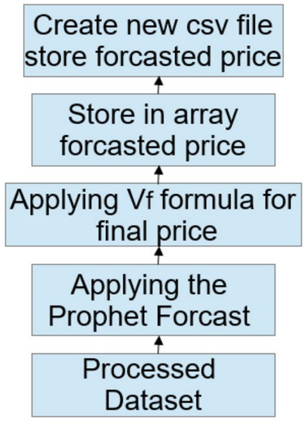

Fig. 2 The flow chart operation to find the forecasted stock price using Prophet

3.4 Machine learning algorithm used for price prediction

Upon analysis of different machine learning algorithms, it is found that Facebook Prophet is more suitable for long-duration prediction as it includes trends, error, holidays, and seasonality [34].

The flowchart operation for the forecast is shown in Fig. 2. The steps to get forecast price the novelty in this approach we have use log returns to Prophet for making long-duration prediction [35]. The following Eq is given below Eq. 10 as shown below the model formula used for prediction. Each component of the given model is calculated by curve fitting.

We have to develop the model based on it [36]. It has four things.

1. Growth represented by g(t).
2. Seasonality is represented by s(t).
3. Holidays represented by h(t).
4. The error which is represented by e_t.

Finally, we discuss an output function represented by y(t), as shown in Eq. 10 below [37].

$$Y(t) = g(t) + s(t) + h(t) + e_t \tag{10}$$

The output achieved is stored in the new csv file. This csv file is then used for future processing. We have presented the novel approach, i.e., firstly shortlisting the fundamentally solid and consistent compounder stocks, forecasting price by using the new feature, and then using the forecasted price for portfolio optimization.

3.5 Portfolio optimization

The following rules are used in portfolio optimization. These rules are formed by market analysis and research. The Algorithm 2 used in portfolio optimization is shown below.

Algorithm 2. Portfolio optimization

Input: *List of companies from Algorithm 1 array*
Output: *Expected returns of the portfolio*

Step 1*. Arrange the companies as per the returns in the decreasing order*
Step 2. *Assign a weightage of 10% for high CAGR companies and 5% for the low CAGR companies*
Step 3. *Apply 0-1 Knapsack for Stock Ratio in a portfolio. Avoid over-diversification.*
Step 4. *Predict the returns using Mean-Variance optimization as per Eq.12 and short selling avoidance.*
Step 5*. Validating the results by applying Efficient Frontier as per Eq 14 and sharp ratio.*

The above Algorithm 2 provides a modification to modern portfolio theory. We limit the user to invest only 5% of the portfolio on risky stocks and fundamentally sound and renowned stocks. We restrict the user to 10%, beyond which we will not allow the user to add the Stock. So that Diversification of risk is always maintained. Let's introduce mean Variance portfolio optimization. It is a process of weighing risk expected as Variance against the expected returns. The analysis of the mean–variance model helps the investor calculate the rewards at the given level of risk. We can also say it like less risk at the given returns. We in this model follow the rule, never lose money. We eliminate the probability of earning more rewards by doing short selling by taking less risk. Figure 3 shows the steps used for portfolio optimization used.

The mean–variance approach provides modification to modern portfolio theory. This approach has two components, i.e., the Variance and expected retunes [36]. Let's analyze each. Variance tells about spread out returns of different security monthly or yearly. Expected returns provide us the probability expressing the forecasted or expected return of the investment in the particular security. Portfolio construction is a challenging task [37]. Equation 11 shows the Formula for the expected return of the portfolio.

$$E\left(R_{Portfolio}\right) = \sum_{i=1}^{i=n} W_i E\left(R_i\right) \tag{11}$$

$R_{Portfolio}$ means the return of the portfolio; R_i is return of security or assets; I = 1 to n is for n different companies in the portfolio; W_i represents the weight of the different companies.

Let's look at portfolio returns variance and volatility calculation and how to solve the optimization problem. As shown in the Eq. 12 given below, we calculate the return variance of the portfolio [38].

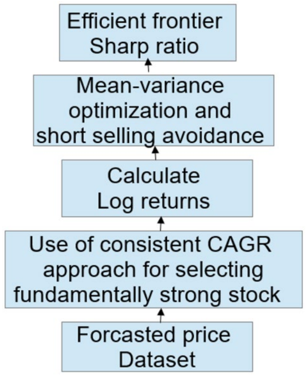

Fig. 3 Flowchart for the procedure used for portfolio optimization

$$\Sigma^2_{portfolio} = \sum_{i=0}^{n} w_i^2 \sigma_i^2 + \sum_i \sum_{i \neq j} w_i w_j \sigma_i \sigma_j \rho_{ij} \tag{12}$$

σ_i represent the standard deviation of the periodic forecasted returns achieved on the security or assets; ρ_{ij} represents the correlation coefficient of the forecasted returns achieved on returns on security or assets I and j.

Let's look at how to calculate the volatility of the portfolio. Equation 13 below shows the Formula for calculating the standard deviation of expected portfolio returns Variance [39].

$$\Sigma_{portfolio} = \sqrt{\sigma^2_{portfolio}} \tag{13}$$

Now we will look at the efficient frontier for Diversification. The modification we proposed to the modern portfolio theory. It is to go with the model with 5% rule of not buying the Stock with high risk and high returns and 10% maximum allocation with less risk and high returns. We should construct a 20–30 stocks portfolio maximum for good returns from the market, over-diversification limits the portfolio's returns. We prefer the matrix calculation for the efficient frontier [40].

Shown the given below the Eq. 14 in the form of the matrix for the given' risk tolerance' q϶ [0, ∞), the efficient frontier minimizes the given below expression.

$$w^T \sum w - q * R_e^t w \tag{14}$$

The above equation shown below provides the details of the Diversification of assets.

w represents the vectors of the weights of the portfolio; q ≥ 0 shows the risk tolerance factor, where the value of q = 0 represents zero risk; R represents the vector of the forecasted returns; $w^T \sum w$ IndicatesVariance of return made for selected portfolio; $R_e{}^t w$ shows the expected or forecasted returns of the portfolio.

The Formula for log returns calculation is shown in Eq. 15.

$$R_{log} = \frac{ln\left(\frac{Vf}{Vi}\right)}{t} \tag{15}$$

Here, R_{log} shows log returns; V_f shows final close price After 't' time; V_i shows the initial close price at staring; t indicates the time duration.

We can solve this problem by using Lagrange multiples; the technique behind solving the problem stated above is finding local maxima and minima [41, 42] of the function used, which is subjected to the equality constrained used in the problem shown above. The proposed method of the matrix is shown below. The above issue was solved by Harry Markowitz, who developed the critical line algorithm procedure.

4 Results and discussion

We are showing the results of the selected Stock as per Algorithm 1 proposed by this paper.

The Algorithm results are given the Table 3. shown below.

After calculation, the total error is the sum of the error divided by the total Amount of the company after calculation error percentage is 7.18%.

The given above Fig. 4. is the Plot of the portfolio comprised of Asian Paint, Astral, Dmart, Hero moto cop, ICICI Bank, Infosys, ITC, Pidilite, SBI Bank, Tata Motors, TCS, and Titan. The Plot is made by running 1000 times on the random ratio. The red dot signifies the total investment made to the company, and all other points show the different proportions and combinations. Upon running the Algorithm, the minimum and Maximum returns achieved are 28% and 64% of returns. We have shortlisted different companies from different sectors. The accuracy achieved by the model is 92.82% in the prediction of price.

Comparison of the sharp ratio will analyze the risk to reward ratio. Sharp ratio is defined as average excess returns earned more than the risk-free rate per unit of total risk. Equation 16 shows the Formula to calculate the sharp ratio.

$$Sharp\ Ratio = \frac{R_p - R_F}{\sigma_p} \tag{16}$$

R_p Shows the return of portfolio; R_f Shows the Rate of Returns on risk-free rate; σ_p Shows the standard deviation of the excess returns of the portfolio.

Comparison of our proposed model with the Yen Sun paper's most optimal portfolio G. Table 4 shows the

Table 3 Portfolio formed and expected returns

Stock name	Weight (W) (%)	Forecasted returns in 1 year (%)	Achieved returns (%)	Error (%)
Titan	9.97	45	67.09	22.09
Asian Paints	12.03	27	20	− 7.00
Astral	6	28.5	29.76	1.26
SBI Bank	4.16	29.5	43	13.50
ITC	5.53	15	21.61	6.61
Pidilite	12.07	30.7	34.13	3.43
Relaxo	7.79	19.3	22.4	3.10
TCS	14.93	20	14.69	− 5.31
Infosys	4.84	20.6	27.95	7.35
DMart	4	30.6	41.97	11.37
ICICI Bank	4.89	30.7	25.69	− 5.01
Tata Motors	4	25.6	48.31	22.71
Nifty Bees	5.79	17	20.17	3.17
Tata motors DVR	4	25	48.31	23.31
Total Returns	100	36.5	46.505	7.74

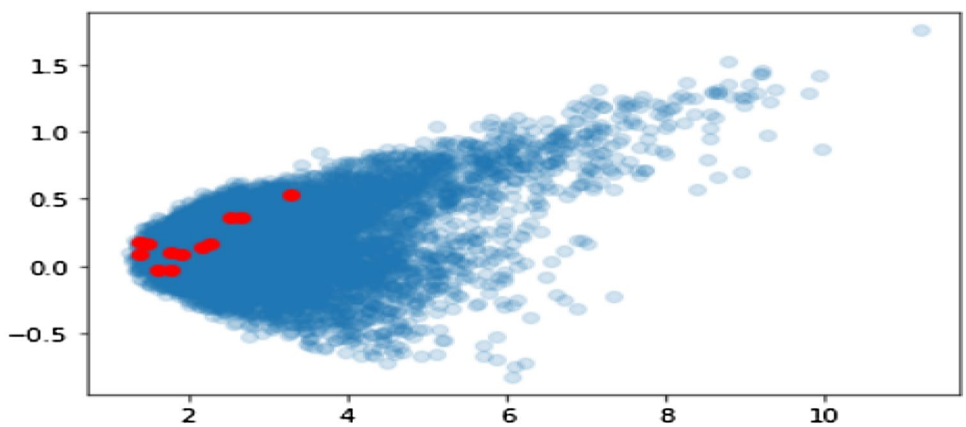

Fig. 4 The Plot of single stocks' expected returns compared to portfolio expected portfolio returns

comparison report with Yen Sun's Portfolio G created using Mean–Variance and Linear programming with our portfolio designed using Fundamental analysis, Mean–Variance, and Efficient frontier.

Table 4 shows the comparison report. Our proposed model performed better than yen sun's optimal portfolio G. Our proposed model performed better in Diversification as we made proper Diversification based on Algorithm 2 in 13 companies' Stock. Yen Sun's paper does no such fundamental and profound analysis of the Stocks. Stocks in Yen sun paper are randomly chosen based on companies of different sectors, whereas in our proposed model, the Stocks selected by our Algorithm 1 makes a fundamental analysis of different Stocks involved in various sectors and selects the market leader. Our model has avoided short selling, ensuring that no company has negative returns. Therefore, our proposed model follows a novel approach and gives better results. Compared to predicted and achieved output, our error is 7.74%, which is very low.

5 Conclusion

The main objective of this study is to develop the Algorithm to shortlist the fundamentally strong companies that are consistent compounders and the ratio calculation for the Diversification. Detail analysis is given in this paper for improvement of the Returns on assets. This paper proposed a relatively new technique to calculate the portfolio's expected return by using the predicted price. This proposed new method is to avoid short selling using 0–1 knapsack techniques which performs better in the Diversification of risk, Returns, sharp ratio, and Alpha.

Table 4 Comparative analysis of Our model with mean Variance and linear programming

Performance measure	Yen Sun et al. mean–variance and linear programming (Portfolio G)	Proposed model (Our Portfolio)	Analysis
Diversification	Portfolio has Six companies with more than 90% invested in only four companies	Portfolio has Thirteen companies with proper Diversification	Our portfolio provides better Diversification with less Risk
Negative returns companies	Two companies	Zero companies	Our proposed method reported no company with negative returns which is best for long-term holding
Alpha	+0.004554015	+0.01045786	Our portfolio performs better in market growth
Returns	46.102%	46.505%	Our returns on the portfolio are higher with low risk
Sharp ratio	0.128749	0.245678	Higher is better
error between expected and achieved returns	19.000%	7.74%	Our model gives less error

Our portfolio optimization technique provides a better risk-free return by benchmarking and testing the proposed portfolio based on mean–variance optimization, efficient frontier, and sharp ratio. Investment is made in the ratio as proposed by the model in the Indian stock market, which achieved 46.505% returns. Compared with the techniques involving short-selling giving more return at more risk, our proposed method will provide a consistent return with less risk. Our proposed approach provides better risk management and a low difference between expected and achieved returns.

6 Future scope

This paper proposes algorithm 1, used to check fundamentally strong Stock, which can be used in the future to calculate expected future growth of returns in the company to predict prospective blue-chip companies from the potential midcap companies. Furthermore, research can be done by integrating Tweets and market news analysis for the company, which can expect the company's volatility, indicating this volatility can be used in algorithm 2 to make a more accurate and realistic prediction of the returns.

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