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Optimizing Returns and Mitigating Risks: AI-Driven Dynamic Portfolio Rebalancing in India

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KEYWORDS

AI, Macroeconomic Factors, India Stock Market, Dynamic Rebalancing, Portfolio Optimization, Investor Sentiment, Risk Management.

ABSTRACT

AI is the one contributing factor that has turned everything topsy-turvy for property or portfolio management for emerging markets like India. Portfolio rebalancing has been done using AI for enhanced returns on investment, as well as risk mitigation, thus identifying the core financial management objective among others for dynamic portfolio rebalancing in the volatile market setting of India. AI-enabled advanced machine learning models, predictive analytics, and real-time data processing can thus lead to effective and timely portfolio adjustment by accurately identifying market shifts and risk factors. The paper identifies sectoral trends, regulatory considerations, and unique challenges towards the application of AI in the Indian context. AI-enabled portfolio rebalancing strategies that have been presented provide significantly enhanced risk-adjusted returns vis-a-vis more traditional approaches, thereby boosting investor confidence and trust. This chapter will provide useful insights for both institutional and individual investors about the all-important role of AI toward building resilient, secure and efficient investment strategies in a rapidly changing financial infrastructure.

1. INTRODUCTION

An analysis of the rebalanced stock from the Indian stock market with India VIX, Gold, Dow Jones, and Nasdaq indices is attempted. A detailed analysis of the dynamic rebalanced portfolio and the static portfolio is made to draw conclusions regarding effectiveness. The study aims to provide insights to investors and portfolio managers concerning the effectiveness of periodic portfolio adjustments in enhancing return and minimizing risk. Using the dataset of 30 stocks (mainly cold stocks) listed in the National Stock Exchange (NSE) of India from 2016 to 2024, quantitative data is used in this study. It examines the macroeconomic factors contributing to the situation and investor sentiment toward the dynamic market fluctuations. The empirical analysis is done using a range of statistical approaches, in addition to a host of other techniques for determining the performance drivers of the portfolio. The results of this study provide evidence of the success of dynamic rebalancing strategies within the Indian stock market. Periodic portfolio adjustments enhance returns and reduce risk, especially amid market disturbances. Macroeconomic factors, sentiment predictors, and dynamic market conditions are included in the portfolio selection process as informative. To sum it up, this study provides insights on the dynamic portfolio with reference to the estimated rejiggered cold stocks from the Indian stock market. These insights are advocacy for dynamic positions to enhance returns and diminish risks. These findings are important because they provide useful insight to the investor, portfolio manager, and policy-makers, contributing to the more well-rounded understanding of the driving dynamics of portfolio performances across the Indian stock market.

Rejiggered cold stock portfolio reallocation: A technique of rebalancing continuously, or at specified times, investment portfolios, according to prefixed criteria - asset performance, market volatility, and indicators of the economy, with a view toward achieving returns and risk minimization superior to those provided by static portfolios that typically have a set composition, whatever the market. Adapting in such a way is done to avoid the disadvantages of having the market changed allowing for opportunities taken up or any unfavourable condition offset. It is meant to take advantages of inefficiencies in the market and temporal variations, resulting in the better performance of the investment portfolio.

Rejigging a cold stock portfolio in India involves an evaluation of investments in stocks and restructuring to improve performance and lower risks. A cold portfolio is usually made up of stocks that have remained unmanaged or unaltered for too many months or years, resulting in performance that is well below average. Portfolio re-evaluating in the Indian market gives investors the opportunity to take advantage of emerging trends, even changes in sectors, and recent developments in India. This analysis of the current holdings, current market conditions, and new opportunities is aimed at creating a more dynamic and flexible investment strategy to optimize returns and financial security.

The Indian stock market has been going through its own share of the growth and volatile experiences over the past several decades; it is viewed as a fast-paced developing economy. This volatility represents challenges as well as opportunities for an investor's portfolio optimization event. Most of the typical and conventional investment techniques rely on static portfolio allocations. These normal allocations do not, in fact, react completely to the changes in the market.

2. REVIEW OF LITERATURE

According to a value-investing study by Fama and French (1992), an undervaluation, otherwise called "cold stocks," has usually shown price appreciation much higher than an average price increase in the long run, hence providing an important undercurrent for the AI approach towards selection and rebalancing. Such evidence is supported by studies done by Gu et al. (2020), wherein even their work has proved that machine learning can be required to study processes happening in historical data to identify undervalued or cold stocks with the potential for triggering growth.

Research by Nassirtoussi et al. (2014) on using AI in sentiment analysis in finding hidden value stocks through the AI analysis of market news and sentiments explains this support. Bekaert and Harvey (1995) argue that unlike cold stocks like in India where opportunities may have developed due to various market inefficiencies, emerging markets are characterized by different risk-return conditions.

In particular, their 1993 research in momentum and contrarian strategies, unlike earlier studies, reveals how AI can amplify effectiveness in identifying cold-stock portfolios and "rebalancing" them. The studies show that including cold stocks in a portfolio can increase diversity (Statman 1987), a principle not estranged from AI finding optimum maximization in its application.

The studies of Gupta et al. (2020) examine the performance based on sectors; thus, this opens the door for AI to understand how to identify negative performing sectors or stocks in India set to take off. In predictive analytics through AI, Tsai and Hsiao (2010) showed that cold stocks are likely to turn around. Such findings can help make balanced decisions in portfolios.

Such papers as Dedi and Yavas (2016) show that AI can assist in managing the increased risks associated with venturing into cold or undervalued stocks. The papers by Zetzsche et al. (2020) focus on the very relating issues of such ethical deposition of AIs in financial markets so as to ensure that any use will not be devoid of transparency and fairness as far as cold stocks in emerging markets like India are concerned.

From the literature survey the research gap which has been detected can be summarized as follows:
2.1 Global studies indicated that the power of artificial intelligence was for detecting undervalued stocks; research on its own Indonesia seems sparse due to the nation's own economic, regulatory, and sectoral possibilities.
2.2 The literature pertinent currently gives general approaches toward the identification of undervalued stocks without a relevant sectoral representation for Indian industries, where cold stocks might find refuge in structural inefficiencies.
2.3 Scant literature researches how specific applications of contrarian strategies, with AI enhancement, would be directed

toward the cold stock and dynamically rebalancing portfolio.
2.4 There is no much research involving behavioural finance and sentiment analysis through AI to make predictions for the turnaround potential of cold stocks depressed for inadequate asset classes researched in India.
2.5 Very limited research is on the ethics and real-world applications of AI in investment decisions for undervalued stocks in emerging markets.

OBJECTIVES

Choosing of 30 Cold Stocks based on performance based on Price-to-Earnings (P/E) Ratio, Price-to-Book (P/B) Ratio, Debt-to-Equity Ratio, Earnings Growth Potential, Technical Analysis, Relative Strength Index (RSI), Moving Averages, Volume Trends.

Random Portfolio optimization with Machine Learning and Blended Model with dynamic adjustments of weights as per market conditions for optimized portfolio.

3. METHODOLOGY

Listed cold stocks from NSE are taken into consideration based on performance are as Ujjivan Small Finance Bank, TCL Express Limited, Tanla Platforms Limited, Som Distillers and Breweries Ltd, Sharda Cropchem Ltd, Rajesh Export Ltd, Polyplex Corporation Limited 8. Piramal Enterprise, Optiemus Infracom Ltd, Navin Fluorine International Ltd, LTI Mindtree, Hindustan Unilever, HDFC Bank, Happiest Minds, Gravita India Ltd, Globus Spirits, Gabriel India Ltd, Fertilizers and Chemicals Travancore Ltd, Dr Lal Pathlabs Ltd, Dhunseri Ventures Ltd, Delta Corp, Cosmo First Ltd, Cantabil Retails India Ltd, Bata, Balkrishna Industries, Asian Paints, Ashapurna Minechem Ltd, Aptech Ltd, Alkylamines

Optimal weights of stocks reflect the proportions constituting an investor's total portfolio allotted to each stock calculated for bringing about certain objectives like maximization of returns, minimization of risks, or obtaining the desired results in a risk-return interaction. Metrics is based on Expected Annualized Return, Expected Annualized Volatility, Sharpe Ratio

Efficient frontier is a graph that displays the collection of optimal portfolios giving the highest expected return for each level of risk or the lowest risk for every level of return. It has served as the very basis of Modern Portfolio Theory by Harry Markowitz.

Blended models based on LSTM, ARIMA-LSTM, FUZZY-LSTM

Fuzzy Logic Decision Making for top ten stocks, Optimal weights for portfolio optimization.

Effect of Macroeconomic Indicators NIFTY 50, SENSEX, CRUDE OIL, GOLD, USD Price, DOW JONES with the correlation matrix

Z Scores, RSI and VaR for the cold stocks.

Python programming is used as a tool.

4. RESULTS AND ANALYSIS

From the stocks taken into consideration optimal weights are calculated and optimized portfolio is created with the metrics which includes Annualized Return, Expected Annualized Volatility, Sharpe Ratio. The code and result is given below:

Code 1

```python
# Combine data into a single DataFrame, handling uneven lengths
price_data = pd.concat(data, axis=1, join='inner') # Concatenate along columns with inner join
price_data.columns = price_data.columns.get_level_values(0) # Set columns to stock names
price_data.index = pd.to_datetime(price_data.index) # Convert index to datetime if needed

# Calculate daily returns
returns = price_data.pct_change().dropna()

# Annualized return and covariance
annualized_return = returns.mean() * 252
cov_matrix = returns.cov() * 252

# Portfolio optimization
def portfolio_performance(weights, returns, cov_matrix):
    portfolio_return = np.dot(weights, returns)
    portfolio_volatility = np.sqrt(np.dot(weights.T, np.dot(cov_matrix, weights)))
    return portfolio_return, portfolio_volatility

def negative_sharpe_ratio(weights, returns, cov_matrix, risk_free_rate=0.05):
    p_return, p_volatility = portfolio_performance(weights, returns, cov_matrix)
    sharpe_ratio = (p_return - risk_free_rate) / p_volatility
    return -sharpe_ratio
```

```
# Constraints and bounds
num_assets = len(annualized_return)
constraints = {'type': 'eq', 'fun': lambda weights: np.sum(weights) - 1}  # Weights sum to 1
bounds = tuple((0, 1) for _ in range(num_assets))  # No short selling
```

```
# Initial guess (equal weights)
initial_weights = np.array([1 / num_assets] * num_assets)
```

```
# Optimization
optimized = minimize(
    fun=negative_sharpe_ratio,
    x0=initial_weights,
    args=(annualized_return.values, cov_matrix.values),
    method='SLSQP',
    bounds=bounds,
    constraints=constraints
)
```

```
# Extract optimal weights
optimal_weights = optimized.x
optimal_return, optimal_volatility = portfolio_performance(optimal_weights, annualized_return.values, cov_matrix.values)
sharpe_ratio = (optimal_return - 0.05) / optimal_volatility
```

```
# Display results
print("Optimal Weights:")
portfolio_weights = pd.DataFrame({'Stock': annualized_return.index, 'Weight': optimal_weights})
print(portfolio_weights)

print("\nPortfolio Performance:")
print(f"Expected Annualized Return: {optimal_return:.2%}")
print(f"Expected Annualized Volatility: {optimal_volatility:.2%}")
print(f"Sharpe Ratio: {sharpe_ratio:.2f}")
```

Table1: Portfolio Performance

```
Optimal Weights:
                                    Stock        Weight
0                                     UPL  3.040239e-16
1                   Ujjivan Small Finance Bank  1.916852e-16
2                        TCL Express Limited  5.546819e-16
3                     Tanla Platforms Limited  2.042397e-16
4              Som Distillers and Breweries Ltd  1.281893e-01
5                        Sharda Cropchem Ltd  5.462347e-17
6                          Rajesh Export Ltd  3.063814e-16
7                 Polyplex Corporation Limited  1.702845e-16
8                         Piramal Enterprise  5.059893e-16
9                       Optiemus Infracom Ltd  1.171124e-01
10             Navin Fluorine International Ltd  1.309297e-16
11                              LTI Mindtree  7.651782e-02
12                         Hindustan Unilever  5.746085e-17
13                                 HDFC Bank  6.602405e-17
14                             Happiest Minds  1.522315e-16
15                          Gravita India Ltd  3.027839e-01
16                             Globus Spirits  9.542304e-17
17                          Gabriel India Ltd  3.395927e-02
18    Fertilizers and Chemicals Travancore Ltd  1.174277e-01
19                        Dr Lal Pathlabs Ltd  9.953588e-18
20                      Dhunseri Ventures Ltd  1.443175e-01
21                                Delta Corp  5.557694e-16
22                           Cosmo First Ltd  8.164322e-17
23                  Cantabil Retails India Ltd  4.797461e-02
24                                      Bata  1.034443e-16
25                      Balkrishna Industries  8.486663e-17
26                               Asian Paints  4.714357e-17
27                      Ashapurna Minechem Ltd  3.171751e-02
28                                Aptech Ltd  1.444041e-16
29                                Alkylamines  2.198312e-16

Portfolio Performance:
Expected Annualized Return: 78.97%
Expected Annualized Volatility: 29.70%
Sharpe Ratio: 2.49
```

These metrics describe the performance and risk characteristics of an investment or portfolio:

Expected Annualized Return (78.97%) is the average annual percentage return that an investor can expect to earn on their investments, with the assumption that performance will remain consistent. The high expectation is that the investment will yield a return of 78.97% a year.

Expected Annualized Volatility (29.70%) is a measure of how volatile the returns from the portfolio are, expressed in terms of the standard deviation of the portfolio's returns and represents risk or uncertainty in the target investment. A volatility of 29.70% shows that the returns could vary a lot from the expected return and indicates that the degree of risk is quite high.

Sharpe Ratio (2.49) is great, in the sense that the portfolio is providing the highest return in relation to the degree of risk being taken. In other words, in the risk-neutral expectation, with a min or negligible risk-free fixed interest rate, excess return per unit risk is around 2.49.

This portfolio is highly profitable (high return) and efficient (high Sharpe ratio), but it comes with significant risk (moderate volatility). Such metrics are typically associated with well-diversified portfolios, innovative strategies, or investments in high-growth assets.

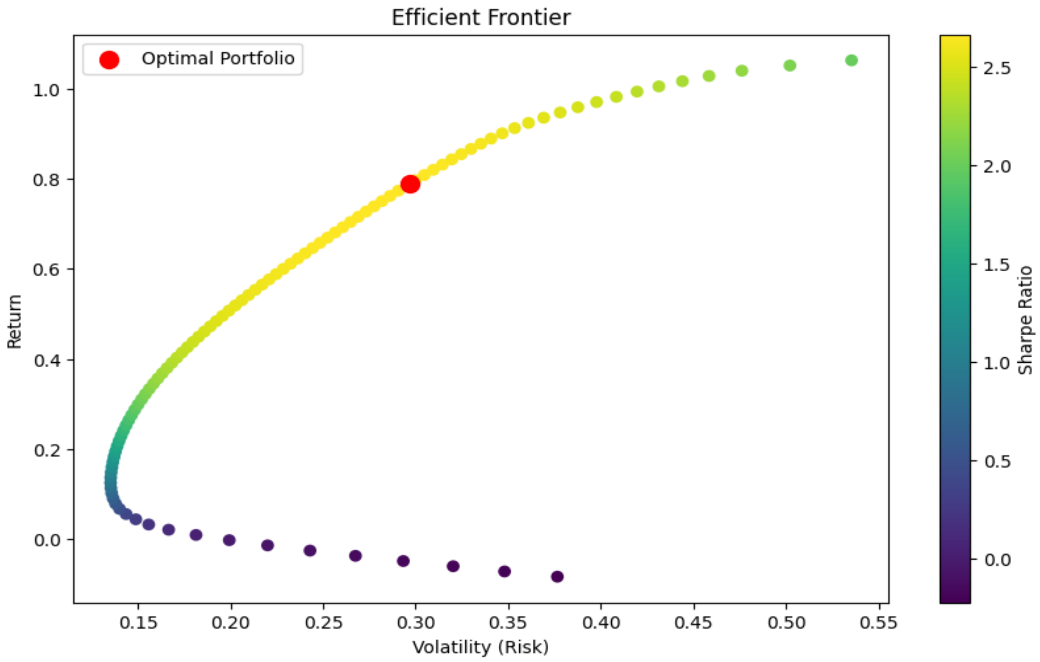

Figure 1: Efficient Frontier

The Efficient Frontier graph can be described as a graphical representation of the nucleation of optimal portfolios that provides maximum possible returns from an illustration at any risk, or minimum risk from a particular level of returns. It is one of the bases in Modern Portfolio

The x-axis represents risk (most often standard deviation or volatility of portfolio returns). The y-axis symbolizes return (usually the expected or annualized return).

Every portfolio lying on the efficient frontier is optimal because it gives maximum possible return at minimum risk. Any portfolio that falls below the efficient frontier line is suboptimal, as it offers lower returns for the same risk level. It, however, changes into Capital Market Line (CML) representing risk-return trade-off while borrowing or lending at a risk-free rate when you introduce risk-free asset into this efficient frontier. The sharpest CML can be identified using the tangency portfolio developed on the assumption that the optimal point between CML and efficient frontier identifies the tangency portfolio, which gives the highest Sharpe ratio and generally regarded as the optimum portfolio. The curvature of the efficient frontier thus reflects the benefits of diversification. More assets result in a lower risk than that of the portfolio without risk reduction up to a particular limit.

With the number of stocks taken into consideration ten best portfolio is generated with the help artificial intelligence by using random simulations with 10000 portfolios and the python code and result is as hereunder:

Code 2: Simulation

```
# Random portfolio simulation
num_portfolios = 10000
results = np.zeros((3, num_portfolios))
weights_record = []

for i in range(num_portfolios):
    # Random weights
    weights = np.random.random(len(annualized_return))
    weights /= np.sum(weights)  # Normalize to sum to 1
    weights_record.append(weights)

    # Portfolio performance
    portfolio_return = np.dot(weights, annualized_return)
    portfolio_volatility = np.sqrt(np.dot(weights.T, np.dot(cov_matrix, weights)))
    sharpe_ratio = (portfolio_return - 0.05) / portfolio_volatility  # Risk-free rate = 5%

    # Store results
    results[0, i] = portfolio_return
    results[1, i] = portfolio_volatility
    results[2, i] = sharpe_ratio
```

```
# Transpose results for easier indexing
results_df = pd.DataFrame(results.T, columns=["Return", "Volatility", "Sharpe Ratio"])

# Find the 10 portfolios with maximum return
top_10_portfolios = results_df.nlargest(10, "Return")

# Extract weights for top 10 portfolios
top_10_weights = [weights_record[i] for i in top_10_portfolios.index]

# Display top 10 portfolios
print("Top 10 Portfolios with Maximum Returns:")
for i, (idx, row) in enumerate(top_10_portfolios.iterrows()):
    print(f"\nPortfolio {i+1}:")
    print(f"Return: {row['Return']:.2%}")
    print(f"Volatility: {row['Volatility']:.2%}")
    print(f"Sharpe Ratio: {row['Sharpe Ratio']:.2f}")
    weights = pd.DataFrame({"Stock": annualized_return.index, "Weight": top_10_weights[i]})
    print(weights)
```

Portfolio 1:
Return: 46.67%
Volatility: 22.12%
Sharpe Ratio: 1.88

	Stock	Weight
0	UPL	0.003837
1	Ujjivan Small Finance Bank	0.034463
2	TCL Express Limited	0.004891
3	Tanla Platforms Limited	0.031166
4	Som Distillers and Breweries Ltd	0.043790
5	Sharda Cropchem Ltd	0.025107
6	Rajesh Export Ltd	0.004183
7	Polyplex Corporation Limited	0.050892
8	Piramal Enterprise	0.032021
9	Optiemus Infracom Ltd	0.072629
10	Navin Fluorine International Ltd	0.014215
11	LTI Mindtree	0.028755
12	Hindustan Unilever	0.049896
13	HDFC Bank	0.001269
14	Happiest Minds	0.062427
15	Gravita India Ltd	0.073574
16	Globus Spirits	0.006698
17	Gabriel India Ltd	0.023233
18	Fertilizers and Chemicals Travancore Ltd	0.072051
19	Dr Lal Pathlabs Ltd	0.001613
20	Dhunseri Ventures Ltd	0.068794
21	Delta Corp	0.007762
22	Cosmo First Ltd	0.061378
23	Cantabil Retails India Ltd	0.009079
24	Bata	0.035810
25	Balkrishna Industries	0.011114
26	Asian Paints	0.030725
27	Ashapurna Minechem Ltd	0.067482
28	Aptech Ltd	0.051439
29	Alkylamines	0.019706

Table 2: Top 10 Portfolios

Portfolio 2:
Return: 43.92%
Volatility: 21.27%
Sharpe Ratio: 1.83

	Stock	Weight
0	UPL	0.014189
1	Ujjivan Small Finance Bank	0.023966
2	TCL Express Limited	0.001433
3	Tanla Platforms Limited	0.061846
4	Som Distillers and Breweries Ltd	0.072122
5	Sharda Cropchem Ltd	0.028864
6	Rajesh Export Ltd	0.029441
7	Polyplex Corporation Limited	0.013036
8	Piramal Enterprise	0.003584
9	Optiemus Infracom Ltd	0.078528
10	Navin Fluorine International Ltd	0.051762
11	LTI Mindtree	0.046773
12	Hindustan Unilever	0.000040
13	HDFC Bank	0.039324
14	Happiest Minds	0.029892
15	Gravita India Ltd	0.058692
16	Globus Spirits	0.036256
17	Gabriel India Ltd	0.050451
18	Fertilizers and Chemicals Travancore Ltd	0.063792
19	Dr Lal Pathlabs Ltd	0.000807
20	Dhunseri Ventures Ltd	0.042182
21	Delta Corp	0.013303
22	Cosmo First Ltd	0.074138
23	Cantabil Retails India Ltd	0.001720
24	Bata	0.018615
25	Balkrishna Industries	0.056732
26	Asian Paints	0.035886
27	Ashapurna Minechem Ltd	0.000267
28	Aptech Ltd	0.013364
29	Alkylamines	0.038995

Portfolio 3:
Return: 43.84%
Volatility: 21.88%
Sharpe Ratio: 1.77

	Stock	Weight
0	UPL	0.011902
1	Ujjivan Small Finance Bank	0.061119
2	TCL Express Limited	0.017611
3	Tanla Platforms Limited	0.032811
4	Som Distillers and Breweries Ltd	0.064537
5	Sharda Cropchem Ltd	0.054812
6	Rajesh Export Ltd	0.008430
7	Polyplex Corporation Limited	0.053402
8	Piramal Enterprise	0.059438
9	Optiemus Infracom Ltd	0.053741
10	Navin Fluorine International Ltd	0.010818
11	LTI Mindtree	0.026633
12	Hindustan Unilever	0.001434
13	HDFC Bank	0.001321
14	Happiest Minds	0.007018
15	Gravita India Ltd	0.062400
16	Globus Spirits	0.018140
17	Gabriel India Ltd	0.051178
18	Fertilizers and Chemicals Travancore Ltd	0.049010
19	Dr Lal Pathlabs Ltd	0.031110
20	Dhunseri Ventures Ltd	0.067334
21	Delta Corp	0.026063
22	Cosmo First Ltd	0.007642
23	Cantabil Retails India Ltd	0.032437
24	Bata	0.013761
25	Balkrishna Industries	0.032041
26	Asian Paints	0.012562
27	Ashapurna Minechem Ltd	0.041043
28	Aptech Ltd	0.042596
29	Alkylamines	0.047658

Portfolio 4:
Return: 43.73%
Volatility: 22.58%
Sharpe Ratio: 1.72

	Stock	Weight
0	UPL	0.016400
1	Ujjivan Small Finance Bank	0.003762
2	TCL Express Limited	0.030845
3	Tanla Platforms Limited	0.028623
4	Som Distillers and Breweries Ltd	0.071601
5	Sharda Cropchem Ltd	0.027860
6	Rajesh Export Ltd	0.009115
7	Polyplex Corporation Limited	0.009790
8	Piramal Enterprise	0.008214
9	Optiemus Infracom Ltd	0.070327
10	Navin Fluorine International Ltd	0.005066
11	LTI Mindtree	0.022655
12	Hindustan Unilever	0.030156
13	HDFC Bank	0.007740
14	Happiest Minds	0.046405
15	Gravita India Ltd	0.005018
16	Globus Spirits	0.070549
17	Gabriel India Ltd	0.043448
18	Fertilizers and Chemicals Travancore Ltd	0.068157
19	Dr Lal Pathlabs Ltd	0.010732
20	Dhunseri Ventures Ltd	0.059392
21	Delta Corp	0.061806
22	Cosmo First Ltd	0.041357
23	Cantabil Retails India Ltd	0.061162
24	Bata	0.011904
25	Balkrishna Industries	0.016823
26	Asian Paints	0.004827
27	Ashapurna Minechem Ltd	0.066426
28	Aptech Ltd	0.064684
29	Alkylamines	0.025154

Portfolio 5:
Return: 43.25%
Volatility: 20.69%
Sharpe Ratio: 1.85

	Stock	Weight
0	UPL	0.016337
1	Ujjivan Small Finance Bank	0.004565
2	TCL Express Limited	0.002714
3	Tanla Platforms Limited	0.029469
4	Som Distillers and Breweries Ltd	0.064907
5	Sharda Cropchem Ltd	0.036737
6	Rajesh Export Ltd	0.005504
7	Polyplex Corporation Limited	0.022724
8	Piramal Enterprise	0.042084
9	Optiemus Infracom Ltd	0.044332
10	Navin Fluorine International Ltd	0.060063
11	LTI Mindtree	0.060845
12	Hindustan Unilever	0.033043
13	HDFC Bank	0.003955
14	Happiest Minds	0.014568
15	Gravita India Ltd	0.064732
16	Globus Spirits	0.016374
17	Gabriel India Ltd	0.018300
18	Fertilizers and Chemicals Travancore Ltd	0.063004
19	Dr Lal Pathlabs Ltd	0.021419
20	Dhunseri Ventures Ltd	0.059916
21	Delta Corp	0.035155
22	Cosmo First Ltd	0.016961
23	Cantabil Retails India Ltd	0.044119
24	Bata	0.020101
25	Balkrishna Industries	0.015866
26	Asian Paints	0.062715
27	Ashapurna Minechem Ltd	0.051224
28	Aptech Ltd	0.043277
29	Alkylamines	0.024988

Portfolio 6:
Return: 43.20%
Volatility: 21.57%
Sharpe Ratio: 1.77

	Stock	Weight
0	UPL	0.010172
1	Ujjivan Small Finance Bank	0.004873
2	TCL Express Limited	0.001915
3	Tanla Platforms Limited	0.067175
4	Som Distillers and Breweries Ltd	0.071836
5	Sharda Cropchem Ltd	0.060641
6	Rajesh Export Ltd	0.030753
7	Polyplex Corporation Limited	0.061008
8	Piramal Enterprise	0.020626
9	Optiemus Infracom Ltd	0.058332
10	Navin Fluorine International Ltd	0.040807
11	LTI Mindtree	0.021326
12	Hindustan Unilever	0.007324
13	HDFC Bank	0.016826
14	Happiest Minds	0.004634
15	Gravita India Ltd	0.045963
16	Globus Spirits	0.004887
17	Gabriel India Ltd	0.001097
18	Fertilizers and Chemicals Travancore Ltd	0.064695
19	Dr Lal Pathlabs Ltd	0.005009
20	Dhunseri Ventures Ltd	0.036843
21	Delta Corp	0.018697
22	Cosmo First Ltd	0.071372
23	Cantabil Retails India Ltd	0.040191
24	Bata	0.035823
25	Balkrishna Industries	0.037535
26	Asian Paints	0.046404
27	Ashapurna Minechem Ltd	0.066852
28	Aptech Ltd	0.006319
29	Alkylamines	0.040064

Portfolio 7:
Return: 43.20%
Volatility: 21.43%
Sharpe Ratio: 1.78

	Stock	Weight
0	UPL	0.006563
1	Ujjivan Small Finance Bank	0.058190
2	TCL Express Limited	0.049413
3	Tanla Platforms Limited	0.059152
4	Som Distillers and Breweries Ltd	0.037149
5	Sharda Cropchem Ltd	0.049752
6	Rajesh Export Ltd	0.006680
7	Polyplex Corporation Limited	0.030767
8	Piramal Enterprise	0.004202
9	Optiemus Infracom Ltd	0.071332
10	Navin Fluorine International Ltd	0.046268
11	LTI Mindtree	0.015913
12	Hindustan Unilever	0.027271
13	HDFC Bank	0.034735
14	Happiest Minds	0.024628
15	Gravita India Ltd	0.069295
16	Globus Spirits	0.072103
17	Gabriel India Ltd	0.022877
18	Fertilizers and Chemicals Travancore Ltd	0.061492
19	Dr Lal Pathlabs Ltd	0.000970
20	Dhunseri Ventures Ltd	0.027512
21	Delta Corp	0.005467
22	Cosmo First Ltd	0.044307
23	Cantabil Retails India Ltd	0.030086
24	Bata	0.021807
25	Balkrishna Industries	0.033730
26	Asian Paints	0.021443
27	Ashapurna Minechem Ltd	0.030977
28	Aptech Ltd	0.031898
29	Alkylamines	0.004020

Portfolio 8:
Return: 42.88%
Volatility: 20.60%
Sharpe Ratio: 1.84

	Stock	Weight
0	UPL	0.015061
1	Ujjivan Small Finance Bank	0.006571
2	TCL Express Limited	0.057738
3	Tanla Platforms Limited	0.010375
4	Som Distillers and Breweries Ltd	0.062588
5	Sharda Cropchem Ltd	0.038040
6	Rajesh Export Ltd	0.000158
7	Polyplex Corporation Limited	0.059119
8	Piramal Enterprise	0.017361
9	Optiemus Infracom Ltd	0.065008
10	Navin Fluorine International Ltd	0.010114
11	LTI Mindtree	0.001268
12	Hindustan Unilever	0.051446
13	HDFC Bank	0.004861
14	Happiest Minds	0.059164
15	Gravita India Ltd	0.072271
16	Globus Spirits	0.072227
17	Gabriel India Ltd	0.005818
18	Fertilizers and Chemicals Travancore Ltd	0.040979
19	Dr Lal Pathlabs Ltd	0.029755
20	Dhunseri Ventures Ltd	0.072389
21	Delta Corp	0.006211
22	Cosmo First Ltd	0.004930
23	Cantabil Retails India Ltd	0.029644
24	Bata	0.045624
25	Balkrishna Industries	0.044566
26	Asian Paints	0.019184
27	Ashapurna Minechem Ltd	0.034305
28	Aptech Ltd	0.027874
29	Alkylamines	0.035351

```
Portfolio 9:
Return: 42.52%
Volatility: 20.96%
Sharpe Ratio: 1.79
                                       Stock    Weight
0                                        UPL  0.005480
1                 Ujjivan Small Finance Bank  0.059084
2                        TCL Express Limited  0.016516
3                    Tanla Platforms Limited  0.039953
4          Som Distillers and Breweries Ltd  0.062577
5                       Sharda Cropchem Ltd  0.019291
6                        Rajesh Export Ltd  0.000466
7             Polyplex Corporation Limited  0.000242
8                      Piramal Enterprise  0.041430
9                   Optiemus Infracom Ltd  0.071626
10          Navin Fluorine International Ltd  0.012901
11                            LTI Mindtree  0.013604
12                       Hindustan Unilever  0.054164
13                               HDFC Bank  0.056560
14                          Happiest Minds  0.011729
15                       Gravita India Ltd  0.030872
16                          Globus Spirits  0.025271
17                       Gabriel India Ltd  0.063196
18  Fertilizers and Chemicals Travancore Ltd  0.072640
19                      Dr Lal Pathlabs Ltd  0.000277
20                   Dhunseri Ventures Ltd  0.065766
21                              Delta Corp  0.000961
22                        Cosmo First Ltd  0.019592
23              Cantabil Retails India Ltd  0.037503
24                                    Bata  0.056889
25                   Balkrishna Industries  0.061985
26                            Asian Paints  0.016962
27                 Ashapurna Minechem Ltd  0.039328
28                              Aptech Ltd  0.037963
29                             Alkylamines  0.005174
```

```
Portfolio 10:
Return: 42.51%
Volatility: 20.86%
Sharpe Ratio: 1.80
                                       Stock    Weight
0                                        UPL  0.023376
1                 Ujjivan Small Finance Bank  0.030094
2                        TCL Express Limited  0.007919
3                    Tanla Platforms Limited  0.009905
4          Som Distillers and Breweries Ltd  0.060906
5                       Sharda Cropchem Ltd  0.055600
6                        Rajesh Export Ltd  0.007362
7             Polyplex Corporation Limited  0.039655
8                      Piramal Enterprise  0.041551
9                   Optiemus Infracom Ltd  0.005607
10          Navin Fluorine International Ltd  0.069006
11                            LTI Mindtree  0.010363
12                       Hindustan Unilever  0.028288
13                               HDFC Bank  0.041665
14                          Happiest Minds  0.006929
15                       Gravita India Ltd  0.073207
16                          Globus Spirits  0.043647
17                       Gabriel India Ltd  0.020834
18  Fertilizers and Chemicals Travancore Ltd  0.069726
19                      Dr Lal Pathlabs Ltd  0.071995
20                   Dhunseri Ventures Ltd  0.062591
21                              Delta Corp  0.002771
22                        Cosmo First Ltd  0.039297
23              Cantabil Retails India Ltd  0.011580
24                                    Bata  0.009027
25                   Balkrishna Industries  0.005842
26                            Asian Paints  0.018034
27                 Ashapurna Minechem Ltd  0.064535
28                              Aptech Ltd  0.017867
29                             Alkylamines  0.050819
```

From the above portfolios we can see that the return is more than 40% over a year and Sharpe Ratio ~2 which is very good. As the volatility is in between (20 – 22) %, the portfolio has a reasonable level of risk, making it relatively stable compared to portfolios with very high volatility. The best portfolio among the ten portfolios are Portfolio 1 and 2.

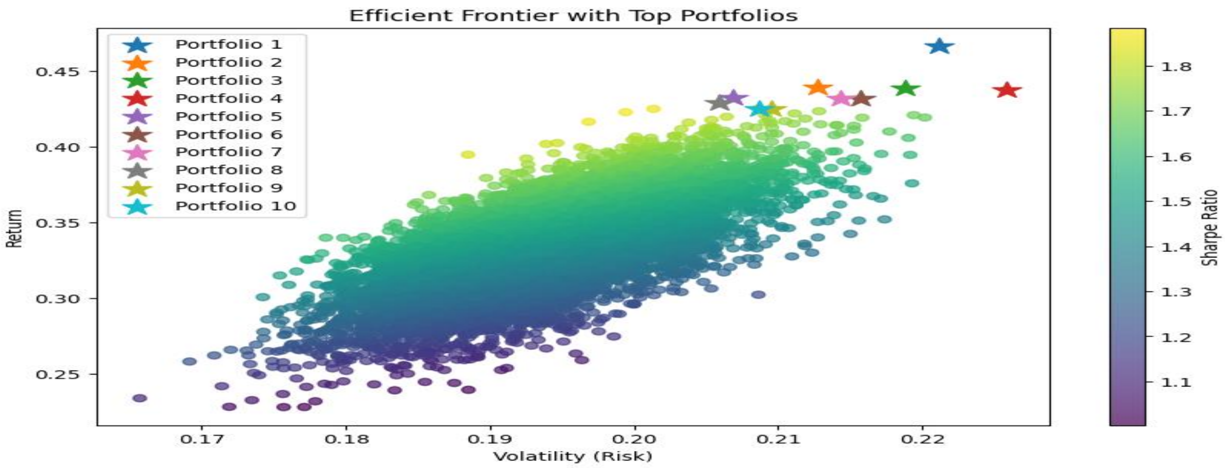

Figure 2: Efficient Frontier of top 10 portfolios

As per the objectives the blended models will be used to forecast returns. ARIMA model blended with LSTM code is given below:

Code 3: Blended Model (ARIMA and LSTM)

```
# Forecasting with a blended model (ARIMA + LSTM)
def forecast_stock(series, forecast_horizon=252):
    # ARIMA Forecasting
    model_arima = ARIMA(series, order=(5, 1, 0))
    arima_fit = model_arima.fit()
    arima_forecast = arima_fit.forecast(steps=forecast_horizon)
```

```
# Forecasting with a blended model (ARIMA + LSTM)
def forecast_stock(series, forecast_horizon=252):
    # ARIMA Forecasting
    model_arima = ARIMA(series, order=(5, 1, 0))
    arima_fit = model_arima.fit()
    arima_forecast = arima_fit.forecast(steps=forecast_horizon)

    # LSTM Forecasting  # This comment was moved to align with LSTM block.
    scaler = MinMaxScaler()  # Indentation corrected to align with function definition
    series_scaled = scaler.fit_transform(series.values.reshape(-1, 1))

    X, y = [], []
    for i in range(60, len(series_scaled)):
        X.append(series_scaled[i-60:i])
        y.append(series_scaled[i])
```

```
X, y = np.array(X), np.array(y)
model_lstm = Sequential([
    LSTM(50, return_sequences=True, input_shape=(X.shape[1], 1)),
    LSTM(50),
    Dense(1)
])
model_lstm.compile(optimizer="adam", loss="mean_squared_error")
model_lstm.fit(X, y, epochs=10, batch_size=32, verbose=0)

last_60 = series_scaled[-60:]
lstm_forecast = []
for _ in range(forecast_horizon):
    prediction = model_lstm.predict(last_60.reshape(1, -1, 1), verbose=0)
    lstm_forecast.append(prediction[0, 0])
    last_60 = np.append(last_60[1:], prediction)

lstm_forecast = scaler.inverse_transform(np.array(lstm_forecast).reshape(-1, 1)).flatten()
```

Code 4: Blended Model Forecasting

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from statsmodels.tsa.arima.model import ARIMA
from keras.models import Sequential
from keras.layers import Dense, LSTM
import matplotlib.pyplot as plt

# Forecasting with a blended model (ARIMA + LSTM)
def forecast_stock(series, forecast_horizon=252):
    # ARIMA Forecasting
    model_arima = ARIMA(series, order=(5, 1, 0))
    arima_fit = model_arima.fit()
    arima_forecast = arima_fit.forecast(steps=forecast_horizon)

    # LSTM Forecasting
    scaler = MinMaxScaler()
    series_scaled = scaler.fit_transform(series.values.reshape(-1, 1))

    X, y = [], []
    for i in range(60, len(series_scaled)):
        X.append(series_scaled[i-60:i])
        y.append(series_scaled[i])

    X, y = np.array(X), np.array(y)
    model_lstm = Sequential([
        LSTM(50, return_sequences=True, input_shape=(X.shape[1], 1)),
        LSTM(50),
```

```
    Dense(1)
])
model_lstm.compile(optimizer="adam", loss="mean_squared_error")
model_lstm.fit(X, y, epochs=10, batch_size=32, verbose=0)

last_60 = series_scaled[-60:]
lstm_forecast = []
for _ in range(forecast_horizon):
    prediction = model_lstm.predict(last_60.reshape(1, -1, 1), verbose=0)
    lstm_forecast.append(prediction[0, 0])
    last_60 = np.append(last_60[1:], prediction)

lstm_forecast = scaler.inverse_transform(np.array(lstm_forecast).reshape(-1, 1)).flatten()

# Combine forecasts
blended_forecast = 0.5 * arima_forecast + 0.5 * lstm_forecast
return blended_forecast
```

```
# Forecast returns for each stock in the top portfolio
forecast_horizon = 252  # 1 year
top_portfolio = top_10_portfolios.iloc[0]
top_weights = top_portfolio["Weights"]
forecasted_returns = []
for i, stock in enumerate(tickers):
    stock_series = data[stock].dropna()
    forecast = forecast_stock(stock_series)
    forecasted_returns.append(np.mean(forecast) * top_weights[i])
```

```
# Portfolio forecast
portfolio_forecast_return = np.sum(forecasted_returns)
print(f"Forecasted Portfolio Return for 1 Year: {portfolio_forecast_return}")
```

Forecasted Portfolio Return for 1 Year: 1303.5653528181067

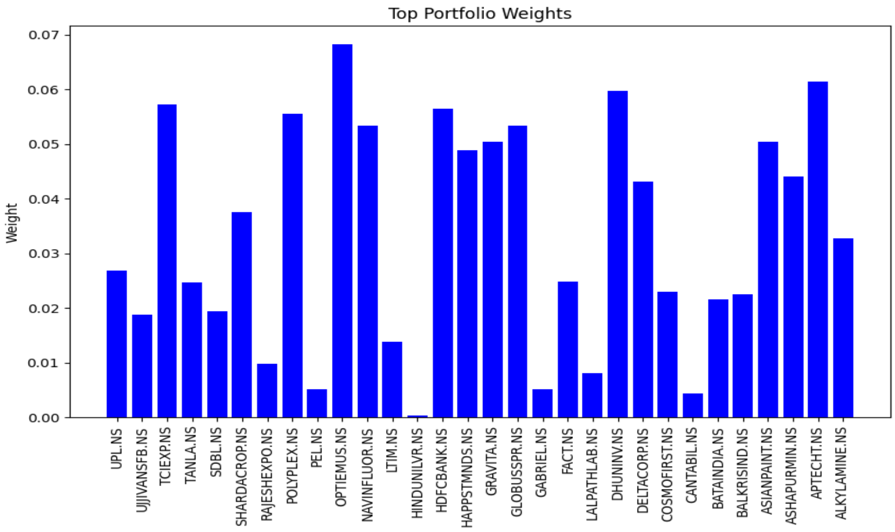

Figure 3: Weights of Top Portfolio

As it is known that "Higher the Standard Deviation Higher is the Volatility, Lower the Standard Deviation Lower is the Volatility", so based on the rule portfolio is made with ten best stocks and not with random simulation.

Table 3: Portfolio with top ten stocks

	Stock	Optimal Weight
0	HINDUNILVR.NS	0.271698
1	HDFCBANK.NS	0.204724
2	ASIANPAINT.NS	0.124034
3	BATAINDIA.NS	0.101120
4	BALKRISIND.NS	0.043764
5	UPL.NS	0.051644
6	NAVINFLUOR.NS	0.035075
7	LTIM.NS	0.023026
8	LALPATHLAB.NS	0.069655
9	RAJESHEXPO.NS	0.075261

The Expected Portfolio Return is 0.06% and the Portfolio Volatility (Standard Deviation) is 0.89%, which means a return of 0.06% is low and will most probably be the result of some very conservative asset allocations or by simply pointing at short-term views. The portfolio is fairly steady; it shows little fluctuations in return and would, therefore, be suitable for a risk-averse investor or one concentrating on capital preservation. This portfolio is more intended towards low volatility - which can usually go along with the lower-return safer investments. Best suited for the investor who is looking for steady returns with less exposure to market fluctuations, like retirees or those averse to risk. If the return and volatility are monthly figures, annualized figures, simple or compounded, would more clearly pattern the overall performance.

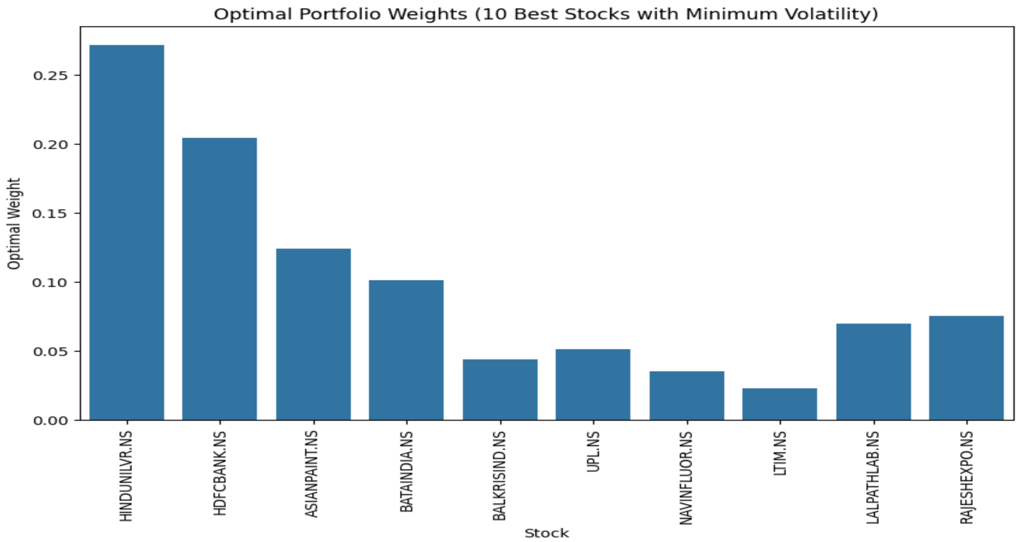

Figure 4: Optimal Portfolio Weights with 10 best stocks

As per Fuzzy Logic Decision Making for top ten stocks, Optimal weights for portfolio optimization are determined as below:

Code 5: Fuzzy Logic Decision making (Low, Medium, High) for Volatility.

```python
# Define fuzzy variables: low, medium, high for return and volatility
returns_low = fuzz.trimf(avg_returns.values, [-0.1, 0, 0.1])
returns_medium = fuzz.trimf(avg_returns.values, [0, 0.1, 0.2])
returns_high = fuzz.trimf(avg_returns.values, [0.1, 0.2, 0.3])

volatility_low = fuzz.trimf(volatility.values, [0, 0.1, 0.2])
volatility_medium = fuzz.trimf(volatility.values, [0.1, 0.2, 0.3])
volatility_high = fuzz.trimf(volatility.values, [0.2, 0.3, 0.4])

# Visualize the fuzzy sets
plt.figure(figsize=(10, 6))
plt.subplot(1, 2, 1)
plt.plot(avg_returns.values, returns_low, label="Low")
plt.plot(avg_returns.values, returns_medium, label="Medium")
plt.plot(avg_returns.values, returns_high, label="High")
plt.title("Return Fuzzy Sets")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(volatility.values, volatility_low, label="Low")
plt.plot(volatility.values, volatility_medium, label="Medium")
plt.plot(volatility.values, volatility_high, label="High")
plt.title("Volatility Fuzzy Sets")
plt.legend()

plt.tight_layout()
plt.show()
```

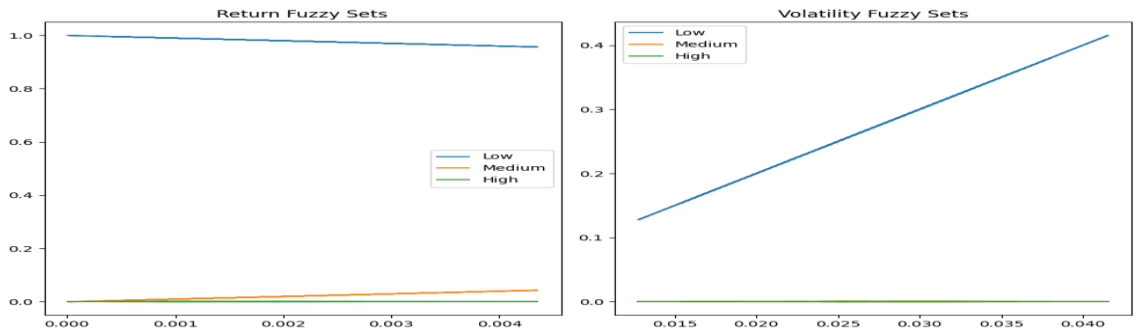

Figure 5: Fuzzy Sets based on Volatility

Using the linguistic terms “Good or Bad” fuzzy rules are created for each stock based on high returns and low volatility top ten stocks are as “ 'UPL.NS', 'UJJIVANSFB.NS', 'TCIEXP.NS', 'TANLA.NS', 'SDBL.NS', 'SHARDACROP.NS', 'RAJESHEXPO.NS', 'POLYPLEX.NS', 'PEL.NS', 'OPTIEMUS.NS'”. Based on these ten stocks the optimum combination is made and ten portfolios are made with five stocks at a time which are as follows:

Portfolio 1: Stocks = ('UPL.NS', 'TCIEXP.NS', 'TANLA.NS', 'POLYPLEX.NS', 'OPTIEMUS.NS'), Expected Return = 0.14%, Volatility = 2.26%

Portfolio 2: Stocks = ('TCIEXP.NS', 'TANLA.NS', 'POLYPLEX.NS', 'PEL.NS', 'OPTIEMUS.NS'), Expected Return = 0.14%, Volatility = 2.34%

Portfolio 3: Stocks = ('TCIEXP.NS', 'TANLA.NS', 'SHARDACROP.NS', 'POLYPLEX.NS', 'OPTIEMUS.NS'), Expected Return = 0.14%, Volatility = 2.36%

Portfolio 4: Stocks = ('UJJIVANSFB.NS', 'TCIEXP.NS', 'TANLA.NS', 'POLYPLEX.NS', 'OPTIEMUS.NS'), Expected Return = 0.14%, Volatility = 2.34%

Portfolio 5: Stocks = ('UPL.NS', 'UJJIVANSFB.NS', 'TCIEXP.NS', 'TANLA.NS', 'POLYPLEX.NS'), Expected Return = 0.12%, Volatility = 2.02%

Portfolio 6: Stocks = ('UPL.NS', 'TCIEXP.NS', 'TANLA.NS', 'POLYPLEX.NS', 'PEL.NS'), Expected Return = 0.12%, Volatility = 2.03%

Portfolio 7: Stocks = ('UPL.NS', 'TCIEXP.NS', 'TANLA.NS', 'SHARDACROP.NS', 'POLYPLEX.NS'), Expected Return = 0.12%, Volatility = 2.06%

Portfolio 8: Stocks = ('UJJIVANSFB.NS', 'TCIEXP.NS', 'TANLA.NS', 'POLYPLEX.NS', 'PEL.NS'), Expected Return = 0.12%, Volatility = 2.11%

Portfolio 9: Stocks = ('TCIEXP.NS', 'TANLA.NS', 'SDBL.NS', 'POLYPLEX.NS', 'OPTIEMUS.NS'), Expected Return =

0.14%, Volatility = 2.47%

Portfolio 10: Stocks = ('UPL.NS', 'TANLA.NS', 'POLYPLEX.NS', 'PEL.NS', 'OPTIEMUS.NS'), Expected Return = 0.13%, Volatility = 2.25%

Using Fuzzy-LSTM blended model will help us for undervalued stock value filtering through fuzzy logic in combination with future price trend predictions via LSTM, Dynamically optimize portfolio weights by combining fuzzy classification of the asset performances with LSTM forecasts, Fuzzy rules will assess the market sentiment, and LSTM will predict the market short-term volatility, Periods of high risk are discovered by fuzzy indicators and are confirmed according to the trends of LSTM predictions.

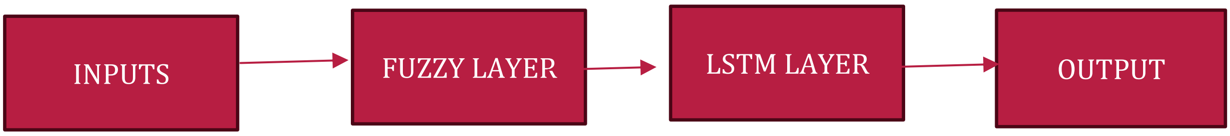

Figure 6: Workflow

Code 6: Top 5 stocks based on LSTM predictions and fuzzy scores

```
from scipy.optimize import minimize

# Use fuzzy logic and predicted return as input for portfolio construction
def portfolio_volatility(weights, returns, covariance_matrix):
    return np.sqrt(np.dot(weights.T, np.dot(covariance_matrix, weights)))

# Define the portfolio optimization function
def optimize_portfolio(selected_stocks, returns, covariance_matrix):
    # Initial guess: equal distribution
    initial_weights = np.array([1. / len(selected_stocks)] * len(selected_stocks))

    # Constraints: weights sum to 1
    constraints = ({'type': 'eq', 'fun': lambda weights: np.sum(weights) - 1})

    # Bounds: weights between 0 and 1
    bounds = [(0, 1) for _ in selected_stocks]

    # Optimize portfolio
    result = minimize(portfolio_volatility, initial_weights, args=(returns, covariance_matrix), method='SLSQP', bounds=bounds, constraints=constraint

    return result.x
```

```
# Select top 5 stocks based on LSTM predictions and fuzzy scores
top_5_stocks = top_10_stocks[:5]  # Example: selecting top 5 stocks
selected_data = data[top_5_stocks]
returns_selected = selected_data.pct_change().mean()
cov_matrix_selected = selected_data.pct_change().cov()

# Optimize portfolio for these 5 stocks
optimal_weights = optimize_portfolio(top_5_stocks, returns_selected, cov_matrix_selected)
print(f"Optimal Weights for the Portfolio: {optimal_weights}")
```

Optimal Weights for the Portfolio: 0.37290511 0.10659506 0.28011987 0.11451666 0.12586331.

The values indicate the percentage of overall investment given to each asset or stock in the portfolio. These weights make up the proportion of the investment needed to achieve an ideal ratio between expected return to risk (volatility). It is generally calculated using a few methods such as the Mean-Variance Optimization or Modern Portfolio Theory (MPT).

Let us now analyse the effect of Macroeconomic Indicators NIFTY 50, SENSEX, CRUDE OIL, GOLD, USD Price, DOW JONES with the correlation matrix with the Z Scores, RSI and VaR for the cold stocks.

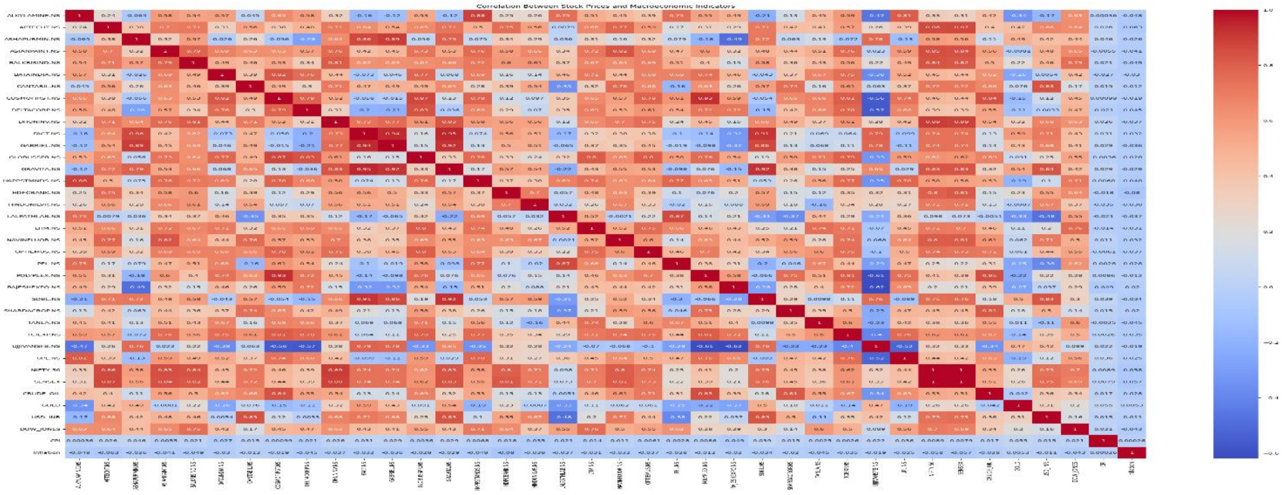

Figure 7: Correlation Matrix of Stocks with the Macroeconomic Indicators

Table 4: Regression Analysis of Stocks with Macroeconomic Indicators

Indicators / Stocks	Constant	Nifty 50	Sensex	Crude Oil	Gold	USD INR	Dow Jones	R^2	Adj R^2	AIC	BIC
UPL	-213.2	-0.02	0.0002	3.062*	-0.29*	5.26*	0.03*	0.62	0.61	8755	8788
UJJIVA NSFB	-28.015*	0.04*	-0.01*	-0.5*	0.04	0.43*	-0.002*	0.65*	0.647*	5236	5269
TCIEXP	753.9661*	-0.24*	0.09*	9.59*	-0.98*	-5.11	0.031*	0.614	0.611	10810	10814
TANLA	2122.051*	-0.024	0.032	9.699*	0.323*	-62.77*	0.028*	0.644	0.641	10600	10630
SDBL	-477.73*	0.063*	-0.015*	-0.64*	0.108*	4.09*	-0.005*	0.841	0.840	6612	6645
SHARDA CROP	-756.80*	-0.06*	0.01*	5.90*	0.24*	7.91*	-0.005*	0.78	0.77	8579	8612
RAJESH EXPO	-53.33	-0.52*	0.15*	3.48*	-0.42*	3.53*	0.03*	0.40	0.39	9348	9380
POLY PLEX	1666.43*	-0.16*	0.05*	24.75*	-1.001*	-9.24*	0.004	0.76	0.76	1.092e+04	1.096e+04
PEL	4200.91*	0.21*	-0.03*	2.05*	-0.44*	-60.40*	0.01*	0.80	0.80	9556	9589
OPTIE MUS	181.55*	0.082*	-0.01*	1.95*	-0.01	-5.56*	-0.005*	0.71	0.71	8266	8299
NAVIN FLUOR	-5628.11*	-1.0024*	0.31*	12.16*	-1.42*	82.94*	0.10	0.77	0.77	1.139e+04	1.142e+04

LTIM	6713.69*	-0.91*	0.43*	9.94*	0.29*	-179.13*	0.05*	0.74	0.74	1.203e+04	1.206e+04
HINDU NILIVR	1107.95*	0.01	0.01*	-4.45*	-0.72*	21.54*	0.005*	0.72	0.71	9584	9617
HDFC BANK	279.38*	-0.44*	0.14*	-1.49*	-0.09*	-1.55*	0.02*	0.84	0.84	8399	8432
HAPPST MNDS	966.06*	0.16*	-0.03*	3.95*	-0.86*	-20.79*	0.05*	0.71	0.70	1.020e+04	1.023e+04
GRAVITA	-3552.10*	0.62*	-0.16*	-2.58*	0.89*	24.93*	-0.02*	0.90	0.90	9215	9248
GLOBUS SPR	1683.04*	-0.55*	0.21*	11.81*	0.36*	-58.05*	-0.01*	0.68	0.68	1.059e+04	1.062e+04
GABRIEL	-355.75*	0.33*	-0.09*	-2.02*	0.17*	3.34*	-0.01*	0.81	0.80	7728	7760
FACT	-2407.94*	0.60*	-0.16*	-4.16*	0.71*	15.24*	-0.01*	0.85	0.85	8935	8967
LALPATH LAB	9858.70*	1.29*	-0.33*	-8.31*	-1.85*	-109.75*	0.08*	0.79	0.79	1.097e+04	1.100e+04
DHUN INV	-1406.49*	0.70*	-0.18*	-0.03	0.27*	7.73*	-0.01*	0.87	0.87	9023	9055
DELTA CORP	432.47*	-0.15*	0.05*	1.67*	-0.04*	-8.48*	0.003*	0.57	0.56	7732	7765
COSMO FIRST	1612.38*	-0.02	0.02*	12.25*	-0.23*	-29.09*	0.001	0.80	0.79	9786	9819
CANTA BIL	-320.72*	0.06*	-0.01*	1.37*	-0.07*	8.51*	-0.01*	0.88	0.88	7240	7272
BATA INDIA	5117.69*	0.05*	0.02*	4.93*	-0.36*	-49.98*	-0.04*	0.72	0.72	9513	9546
BALKR ISIND	-156.50	0.59*	-0.14*	0.62*	0.16*	-10.30*	0.02*	0.77	0.77	1.019e+04	1.022e+04
ASIAN PAINT	3545*	0.45*	-0.08*	1.45*	-0.67*	-26.35*	-0.02*	0.808	0.806	1.020e+04	1.024e+04
ASHA PURMIN	-307.98*	0.42*	-0.11*	-1.79*	0.29*	-0.36	-0.01*	0.68	0.67	8128	8161
APTECH	-805.73*	-0.14*	0.04*	0.30*	0.13*	1.19*	0.01*	0.82	0.82	7605	7638
ALKILA MINE	4449.76*	0.89*	-0.25*	8.47*	-2.78*	-48.24*	0.18*	0.71	0.71	1.158e+04	1.161e+04

N.B: * Significant values at 95 % level of significance.

As per above table the R^2 and Adjusted R^2 for all the stocks are more than 0.6 except Rajesh Expo. So there is a significant effect of macroeconomic indicator on the stock price.

Code 7: Z Scores, RSI, Value at Risk (VaR)

```
z_scores = (stock_data - stock_data.mean()) / stock_data.std()
print(z_scores.head())
```

```
def calculate_rsi(data, window=14):
    delta = data.diff()
    gain = delta.where(delta > 0, 0)
    loss = -delta.where(delta < 0, 0)

    avg_gain = gain.rolling(window=window, min_periods=1).mean()
    avg_loss = loss.rolling(window=window, min_periods=1).mean()

    rs = avg_gain / avg_loss
    rsi = 100 - (100 / (1 + rs))
    return rsi

rsi_data = pd.DataFrame()
for company in stock_data.columns:
    rsi_data[company] = calculate_rsi(stock_data[company])
    print(rsi_data.head())
```

```
def calculate_var(data, confidence_level=0.95):
    daily_returns = data.pct_change().dropna()
    var = daily_returns.quantile(1 - confidence_level)
    return var

var_data = calculate_var(stock_data)
```

Code 8: Visualisation of Z Scores, RSI, VaR

```
# Plot Z-Scores
plt.figure(figsize=(24, 12))
for company in companies[:5]:  # Plot for first 5 companies as an example
    plt.plot(z_scores.index, z_scores[company], label=company)
plt.axhline(y=0, color="black", linestyle="--")
plt.title("Z-Scores of Selected Stocks")
plt.legend()
plt.show()

# Plot RSI
plt.figure(figsize=(24, 12))
for company in companies[:5]:  # Plot for first 5 companies as an example
    plt.plot(rsi_data.index, rsi_data[company], label=company)
plt.axhline(y=70, color="red", linestyle="--", label="Overbought (70)")
plt.axhline(y=30, color="green", linestyle="--", label="Oversold (30)")
plt.title("RSI of Selected Stocks")
plt.legend()
plt.show()

# Plot VaR
plt.figure(figsize=(24, 12))
sns.barplot(x=var_data.index, y=var_data.values, palette="coolwarm")
plt.title("Value at Risk (VaR) at 95% Confidence Level")
plt.xticks(rotation=90)
plt.ylabel("VaR (%)")
plt.show()
```

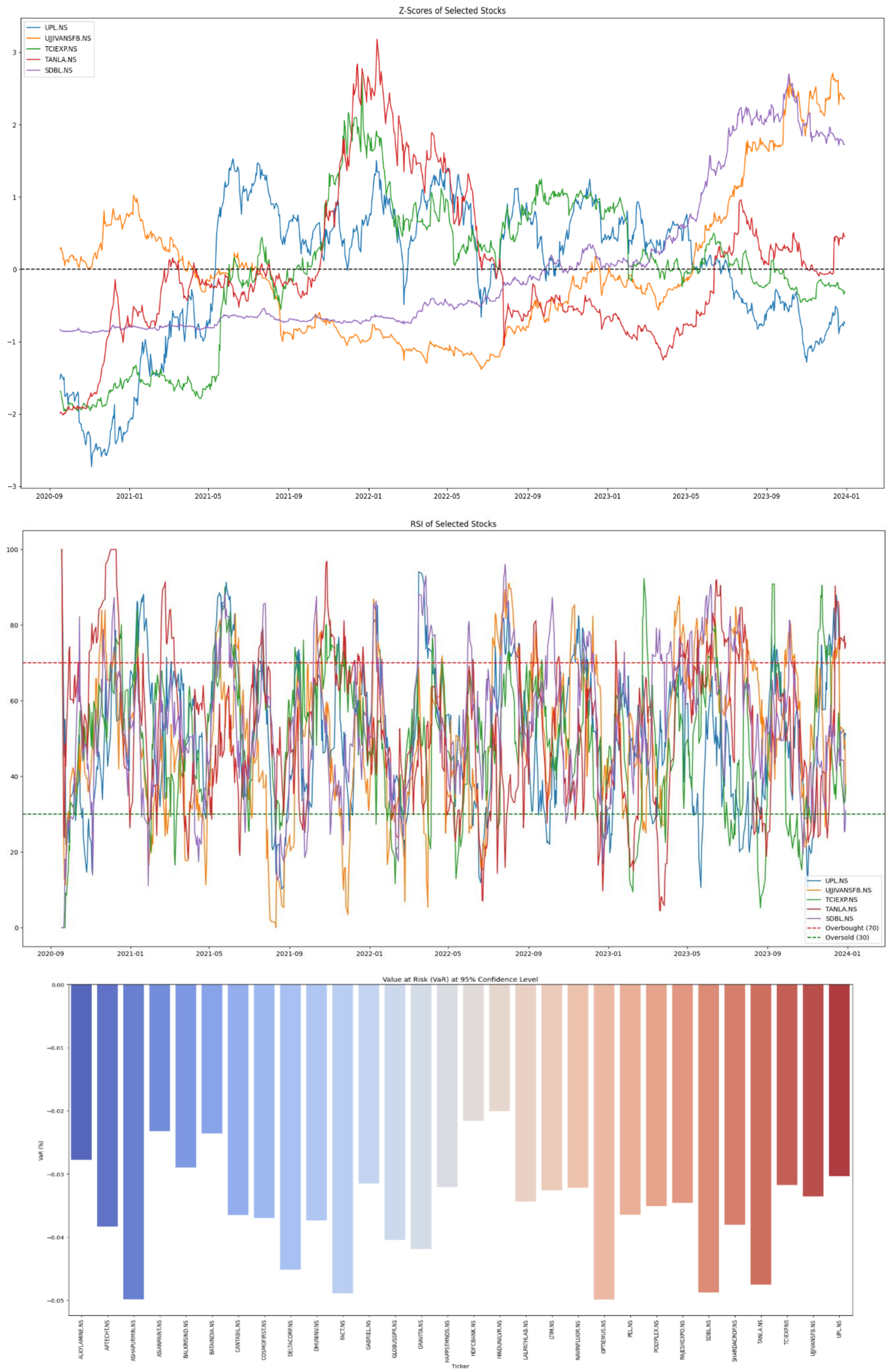

Figure 8: Visualisation of Z Scores, RSI, VaR

SUMMARY AND CONCLUSION

This study covers a wide-ranging slew of dynamic portfolio rebalancing strategies in India, using a data set sourced from the NSE; 30 cold stocks of 2016-2024. This research evaluated the influence of macroeconomic indicators, investor sentiment, and the market on effective periodic rebalancing of investment portfolios. Comparison of dynamic and static portfolio strategies evaluates their enhancement of returns and risk reduction. A dynamic rebalancing technique capitalizes on market inefficiencies, temporal variations, and changing economic scenarios. India VIX, alongside gold prices and global indices, Dow Jones, and Nasdaq provide a solid insight into their performance alongside dynamic portfolios. The empirical outcomes posit that dynamic portfolio adjustments provide significant amplification of returns with a commensurate reduction of risk when the market gets agitated.

RECOMMENDATIONS

The professional (investor) should develop and maintain periodic portfolio reviews in line with preset conditions, asset performance, market volatility, etc. The considerations for inclusion include but are not limited to inflation, interest rates, and global measures of market health that an investor ought to have her on throughout the decision-making process. AI- and machine learning-powered sentiment analysis modeled to pinpoint investment targets or sell-offs approaching oversold territory with rapid growth potential. Scour for sectoral shifts and emerging opportunities in the Indian economy for maximum gain from the portfolio until bitter changes happen. Portfolio re-examination and restructuring will have to be done time and again, in tune with contemporary realities. New strategies in rebalancing should curb risk in the presence of excessive market volatility coupled with worsening economic currents. Encourage financial literacy which will enable players to appreciate active portfolio strategies supported by this dynamic rebalancing methodology.

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