Hybrid Forecasting and Optimization: ANN-GA Approach for Portfolio Optimization with Sentiment Analysis

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***Abstract*—In recent years, individual participation in financial markets has gathered pace, encouraged by increased accessibility and a speeding focus on wealth management. With investors reacting to better asset allocation strategies for maximizing return while reducing risk, complex computational techniques have taken center stage. This research proposes a hybrid portfolio optimization model incorporating Artificial Neural Networks (ANN) for predicting stock return and risk, the Non-dominated Sorting Genetic Algorithm III (NSGA-III) for multi-objective optimization, and a FinBERT-based news sentiment analysis module for news-based risk adjustment. The model integrates dynamic market sentiment in a real-time manner using scraping company-specific news articles and examining sentiment scores for enhanced stock selection choices. Furthermore, true financial parameters are applied using real-world financial information obtained from the Yahoo Finance API (yfinance), and its perfor- mance is evaluated using comprehensive financial measures like Annualized Return, Annualized Volatility, Sharpe Ratio, Sortino Ratio, and Maximum Drawdown. NSGA-II and MOEA/D are compared apples to apples in order to provide optimization efficacy. Findings indicate that the method proves to be effective in constructing robust portfolios for different holding horizons, offering an extendable AI-driven sentiment-aware methodology to portfolio optimization.**

***Index Terms*—Multi-objective optimization, Portfolio manage- ment, NSGA-II, NSGA-III, ANN, FinBERT, Sentiment Analysis, Financial Metrics.**

I. INTRODUCTION

EFFECTIVE portfolio management is essential for achiev- ing sustainable financial growth, particularly in today's dynamic and complex investment landscape. In the last ten years, there has been a tremendous increase in participation in financial markets by individuals, courtesy of their improve- ment in technology and wealth creation focus. Legacy port- folio optimization methods, like Markowitz's Mean-Variance Optimization, though seminal, tend to be insufficient in dealing with the non-linear and multi-objective nature of contemporary financial markets. Today's investors look for advanced models capable of reconciling competing objectives — maximizing returns and minimizing risk — under the uncertain and information-driven environment.

Multi-objective optimization methods such as the Non- Dominated Sorting Genetic Algorithm (NSGA) series, specif- ically NSGA-III, have proved to be powerful instruments to help meet these challenges. NSGA-III refines the capacity for solving many-objective problems through enhanced di- versity and convergence, thereby being appropriately applied to portfolio optimization problems involving various conflict- ing investment objectives. However, conventional optimization models tend to only use historical numerical data without integrating qualitative variables like market sentiment, which play a growing role in determining stock performance.

To bridge this gap, this research proposes an enhanced hybrid framework that integrates Artificial Neural Networks (ANN) for predicting stock returns and risks, NSGA-III for multi-objective portfolio optimization, and a FinBERT-based sentiment analysis module to incorporate qualitative news sentiment into investment decision-making. By leveraging a company-specific news scraping mechanism, the system dy- namically feeds real-time market sentiment into the prediction layer, offering a more context-aware asset selection process.

Furthermore, the proposed model assesses portfolio perfor- mance using a wide range of financial metrics such as An- nualized Return, Annualized Volatility, Sharpe Ratio, Sortino Ratio, and Maximum Drawdown to guarantee a solid and risk-adjusted investment plan. Comparative analysis is im- plemented by NSGA-II, NSGA-III, and MOEA/D to mea- sure optimization quality. With actual financial data obtained through the Yahoo Finance API (yfinance), and a simulation environment that covers short-term and long-term investment time frames, the architecture seeks to deliver a scalable, AI-powered, and sentiment-driven solution for contemporary portfolio management.

This study not only improves predictive modeling by incor- porating financial sentiment but also overcomes some of the major shortcomings of current models, making a substantial contribution to the area of AI-based financial decision-making.

II. MOTIVATION

With the ever-evolving nature of today's financial markets, investors are presented with an increasingly challenge of building optimal portfolios reflective of their investment hori- zon and risk tolerance. Classical approaches like Markowitz's Mean-Variance Model, while fundamental, tend to fail to deliver when challenged by the nonlinear dynamics, volatility,

and conflicting objectives of contemporary financial products. Increased market volatility and the spread of real-time infor- mation have increased the demand for sophisticated compu- tational strategies that can respond to return and risk more dynamically.

Multi-criteria optimization methods such as the Non-Dominated Sorting Genetic Algorithm (NSGA) family are increasingly being utilized in financial choice-making to help achieve efficient compromise between conflicting investment goals. Though previous methods like NSGA-II suffer from dif- ficulty in convergence and diversity, typical predictive models mostly overlook the central role of timely market sentiment toward asset performance.

To overcome these challenges, the current study proposes a hybrid framework combining Artificial Neural Networks (ANN) for predictive modeling, NSGA-III for portfolio op- timization, and FinBERT for sentiment analysis of company- specific news. By scraping real-time news articles and incor- porating sentiment scores into stock return forecasting, the model adapts better to evolving market conditions and investor psychology.

Besides that, the paper proposes a more stringent portfolio quality assessment by calculating some of the most important finance metrics like Annualized Return, Annualized Volatility, Sharpe Ratio, Sortino Ratio, and Maximum Drawdown so that the analysis is holistic from the risk-adjusted perspective.

The motivation in this work is to bridge current gaps by creating a hybrid ANN–FinBERT–NSGA-III that improves forecast accuracy, considers current market sentiment, and enhances portfolio evaluation — giving investors a robust, flexible, and context-aware optimization framework for various investment horizons.

III. LITERATURE REVIEW

Portfolio optimization and stock market prediction have been the subject of intense research, with various compu- tational approaches having developed over the years. Tradi- tional models like Markowitz's Mean-Variance Optimization (MVO) have been at the forefront of portfolio management but tend to be incapable of handling real-world complexities like nonlinear market behavior and multiple goals in conflict. To counter these deficiencies, researchers have explored hybrid methods that integrate Artificial Neural Networks (ANN), Genetic Algorithms (GA), and the Non-Dominated Sorting Genetic Algorithm (NSGA-II/III) for better financial decision- making. Recent studies have emphasized the point that deep learning models, when integrated with evolutionary optimiza- tion methods, can enhance investment models more effectively by dynamically adapting to changing market conditions.

Artificial Neural Networks (ANN) are increasingly used in financial forecasting since they can learn and model complex stock market patterns. Guresen et al. in [5] demonstrated how ANN models better perform than traditional statistical models in forecasting stock markets. The study highlighted that Multi-Layer Perceptron (MLP) and Dynamic Artificial Neural Networks (DAN2) are better at learning complex relationships in stock price dynamics compared to regression

models. Similarly, in [4], Martnez-Barbero et al. used

LSTM networks to predict market trends and optimize portfolio composition and demonstrated that deep learning significantly improves risk adjusted returns. Subsequent work, such as [18], has further reinforced these findings by examining stock market value prediction with neural network-based models to establish the effectiveness of AI-aided market analysis.

Besides machine learning approaches, Genetic Algorithms (GA) and NSGA-II/III have also been widely utilized in portfolio optimization. Maholi Solin et al. in [3] demon- strated how ANN can be combined with GA to improve investment decision making through optimized stock selection from predicted future values. The study found that ANN- GA models provide better diversification and risk management compared to conventional optimization methods. In addition,

[2] by Cui et al. introduced a Deep Reinforcement Learning (DRL) approach to portfolio optimization and demonstrated that reinforcement learning algorithms can learn dynamically from evolving market conditions to achieve maximum long- term financial returns. Based on these principles, [21] em- ployed a hybrid financial model of analysis for the prediction of business failure to demonstrate the capacity of AI-based approaches to detect market risks at an early stage.

Advances in multi-objective portfolio optimization have yielded improved versions of the NSGA algorithms. Deb et al. in [8] proposed the most widely used NSGA-II algorithm that has been used extensively in financial optimization. However, NSGA-II is poor in handling high-dimensional data, and therefore more research on better algorithms. Ishibuchi et al. introduced NSGA-III in [9] and [10], which is better than NSGA-II in terms of increasing Pareto front diversity and handling many-objective problems more effectively. Fur- ther improvement to NSGA-III has been presented in [11], demonstrating that it can be applied to large-scale finance optimization problems.

The importance of hybrid AI-optimization models that in- tegrate ANN with NSGA-III for financial decision-making has been emphasized in various studies. In [6], Wang et al. examined the contribution of genetic algorithms towards en- hancing portfolio diversification and proved that optimization models based on GA increase the efficiency of asset allocation. Additionally, in [4], Mart´ınez-Barbero et al. integrated LSTM networks with Markowitz's MVO and showed the domi- nance of deep learning-based optimization over traditional investment policies. The subsequent important breakthrough originates in [15], where it used ARIMA for predicting the price of stock with a further statistical outlook being a possible substitute.

Following work has guided the effort to enrich financial modeling. It is with an experiment in comparison completed in forecasting the LQ45 index of Indonesian Stock Exchange via some machine learning approach in [22]. Based on these findings, [23] formulated a weighted ensemble learning model to predict stock prices of construction companies, highlighting the role of ensemble approaches in reducing error in predic- tion. In addition, [14] set out to formulate a novel neural network approach to forecasting stock markets with feature selection routines as proposed in [16] to increase the efficiency of models.

In [26], Colasanto et al. introduced a sentiment-based strategy using a fine-tuned FinBERT model to extract sen- timent scores from financial news headlines, which were integrated into the Black–Litterman portfolio optimization model. Through their study, they showed that incorporating sentiment scores as views into optimization models yielded better portfolio performance than standard procedures without sentiment inclusion.

Correspondingly, Banholzer et al. in [27] proposed a sentiment-based portfolio optimization method with the help of Copula Opinion Pooling (COP) for incorporating investor sentiment directly into optimization. Their experiments in- dicated that sentiment-adjusted medium-term reversal-based portfolios generated appreciably better risk-adjusted returns compared to traditional portfolios.

Additionally, new hybrid optimization models are being formulated, integrating machine learning and metaheuristic techniques. In [24], a GA-LSTM hybrid model was proposed for forecasting stock prices in time series, pointing to the contribution of deep learning towards enhancing predictive analysis. This is alongside research like [17], which explored a GA-based approach to portfolio construction based on asset prices and market movements. Further, [12] contrasted the performance of NSGA-II and NSGA-III on a variety of many- objective test problems and provided insights into their relative efficiency in financial modeling.

One of the essential aspects of financial forecasting is having access to good datasets. In [25], Mandal et al. offered a computerized Python-based platform that utilized the Yahoo Finance API in efficiently extracting large-scale stock market data. The paper provides a fundamental contribution to the study of stock markets because it facilitates easy extraction of historical stock details from top indexes such as the S&P 500 and Nasdaq, guaranteeing improved performance in ma- chine learning models. Support to the increasing use of such automated data gathering systems is also presented by [13], who researched reference-point-based NSGA-III for financial solution optimization.

Some recent studies have begun to incorporate sentiment scores into portfolio optimization models. Colasanto et al.

[26] used FinBERT to create sentiment scores from financial news headlines and included the sentiment scores in the Black–Litterman portfolio optimization model. Their results showed that sentiment-driven portfolios performed better than the traditional models. Likewise, Banholzer et al. [27] put for- ward a sentiment-based portfolio optimization strategy through the use of Copula Opinion Pooling (COP) that incorporated investor sentiment into portfolio design directly, and showed that medium-term sentiment reversals could be exploited sys- tematically in order to achieve better risk-adjusted returns.

In [28], Malineni Lakshmi Narayana et al. presented a hybrid ensemble-based model integrating LSTM, GRU, BiL- STM, and RNN models with financial news sentiment analysis for enhanced stock price prediction and portfolio optimization. Their model showed a mean prediction accuracy of 91.89 and performed better than the Nifty 50 benchmark in every risk tolerance scenario. The paper emphasized that incorporating

technical indicators and sentiment scores increase forecasting accuracy and portfolio returns drastically.

In the midst of AI-based portfolio optimization progress, there are still some problems. Scalability, computational tractability, and responsiveness to real-time financial data are still ongoing issues. Additional research can concentrate on the integration of Graph Neural Networks (GNN) and Transformer architecture for improved forecasting, as [7] stated. Further- more, the expansion of datasets to encompass macroeconomic indicators, sentiment indicators, and other financial metrics could improve stock selection models, improving decision- making accuracy under various market conditions. Studies like [2] suggest that incorporating expert domain knowledge into reinforcement learning models would enhance model generalization under various economic conditions.

IV. PROBLEM STATEMENT

Portfolio decisions in capital markets tend to be difficult owing to time variability of stock prices, market volatility, and the existence of diverse contradicting goals like maximizing returns and minimizing risk. Classic optimization methods to portfolio selection like Mean Variance Optimization (MVO) and Markowitz's Modern Portfolio Theory (MPT) are not strong enough in general to react in a timely manner to shifting trends in the marketplace and fail to make compromises on a variety of disparate objectives. Moreover, such traditional methods make assumptions of linear relationships between securities and usually normally distributed returns, both of which might not exist in the real-world finance.

As investment locations become easier to use, private in- vestors demand more sophisticated tools to optimize portfo- lios. The catch is that such models are not yet good enough to balance short-term and long-term investment goals with multiple risk factors. Existing optimization models are poor at addressing such needs because they are poorly equipped to filter through large numbers of potential portfolio solutions. Traditional approaches also lack predictive modeling and thus are unable to make dynamic modifications for evolving market trends.

In addition, traditional frameworks mostly disregard the qualitative element of financial markets — news impact and real-time investor sentiment — which tends to cause sudden price movements. The omission of sentiment-based forecasting can lead to less adaptive and more exposed portfolio strategies. Likewise, portfolio evaluation in previous methods tended to exclude including full risk-adjusted performance metrics, resulting in partial performance measures.

To overcome these issues, the present research suggests a coupled Artificial Neural Network (ANN), FinBERT-based Sentiment Analysis, and Non-Dominated Sorting Genetic Al- gorithm III (NSGA-III) solution for portfolio optimization. The ANN sub-model is used for predictive modeling to predict stock return and risk factor using historical and sentiment- enriched data, whereas NSGA-III is used to design efficient portfolios that balance return and risk with diversity. Extensive financial measures such as Sharpe Ratio, Sortino Ratio, An- nualized Return, Annualized Volatility, and Maximum Draw- down are utilized to analyze portfolio quality in more detail.

Applying this framework on actual financial data, this study seeks to improve portfolio optimization solutions for various investment horizons speculators' short-term and wealth creation long-term investments for speculators who want quick returns and investors who want wealth creation. The new approach is compared with existing optimization methods to measure improvement in solution quality and investment decision making.

V. OBJECTIVE

The primary objective of the current study is to develop a coupled Artificial Neural Network (ANN) and Non-Dominated Sorting Genetic Algorithm III (NSGA-III) model for portfolio optimization, which optimizes risk and return in a proper way and serves the requirements of both long-term and short-term investment strategies. The research is directed towards this intention by accomplishing some key goals where the first step is the development of an AI-driven portfolio optimization model. This involves developing and utilizing a hybrid model that integrates ANN as a predictive modeling and NSGA-

III for multi-objective optimization. The ANN will be uti- lized to forecast stock returns and estimate associated risks from historical financial information, thus improving decision- making quality in portfolio construction. NSGA-III will be used to optimize portfolios with a well-spread Pareto front, with improved risk versus return trade-offs.

Another significant focus is to maximize multi-objective trade-offs involved in investment models. Portfolio investment optimization will be achieved by considering maximization of returns and risk minimization at the same time, for various types of investors. The study assures diversified and highly balanced solutions for portfolios with the incorporation of decomposition techniques within the NSGA-III framework. Second, the study will compare short- and long-horizon in- vestment strategies separately, analyzing their individual risk-return profiles and producing a comprehensive description of how each strategy performs in different market states.

Improving convergence and diversity in NSGA-III solutions is also a major objective. This will be achieved by imposing improvements to the search process in NSGA-III with a focus on achieving faster convergence with a diverse set of solutions. Through the integration of predictive modeling for enhanced decision-making, this research seeks to utilize the predictive power of ANN with the optimization role of NSGA-

III to construct portfolios based on predicted asset returns and risk. This will ensure enhanced decision-making through the exploitation of ANN's ability to detect subtle patterns in financial data that other techniques cannot.

For this project, financial datasets are fetched using the yfinance library, which provides effective access to Yahoo Finance's historical stock data. Stock prices, volumes, and other financial metrics of interest, which are necessary for the training of the Artificial Neural Networks (ANN) to predict stock returns and quantify risk factors, are included in the information fetched. Employing real financial data, the model can more effectively analyze market trends and dynamics, enabling more accurate forecasting. The data-based approach

enhances the process of portfolio optimization, making it reactive to market investment plans in both short-run and long- run periods.

The study will evaluate the performance of the proposed framework through application of the hybrid ANN-NSGA-

III model to real financial data. The performance of the framework will be compared against traditional portfolio opti- mization models like Mean-Variance Optimization (MVO) and classical NSGA-II in terms of comparison of enhancement in portfolio quality like risk-return trade-off and diversification. Artificial Neural Networks (ANN) are a crucial part of this research in predicting stock returns and risk assessment. With their ability to detect complex, nonlinear relationships in finan- cial data, they are more accurate than traditional techniques. ANN are able to learn from historical data, identifying patterns and trends utilized in decision-making portfolio construction. This dynamic model is particularly relevant in adjusting to market changes and maximizing portfolios in short-run as well as long-run investment strategies. With the inclusion of ANN, the model enhances the level of correctness in its predictions, thereby becoming an effective tool for risk- return balancing. Neural networks belong to more data-based, informed management of portfolios, increasing the overall usefulness of the optimization model proposed. The study will compare performance of the framework under short- and long-term investment horizons and assess the adaptability of the framework to various market environments.

Finally, this research aims to contribute to the field of AI-based financial decision-making by enlightening us about the capabilities of AI-based optimization in the financial markets. The proposed methodology is expected to yield a stronger methodology for portfolio management, giving better outcomes with regard to constructing the optimal portfolio and striking a balance between risk and return across different investment horizons.

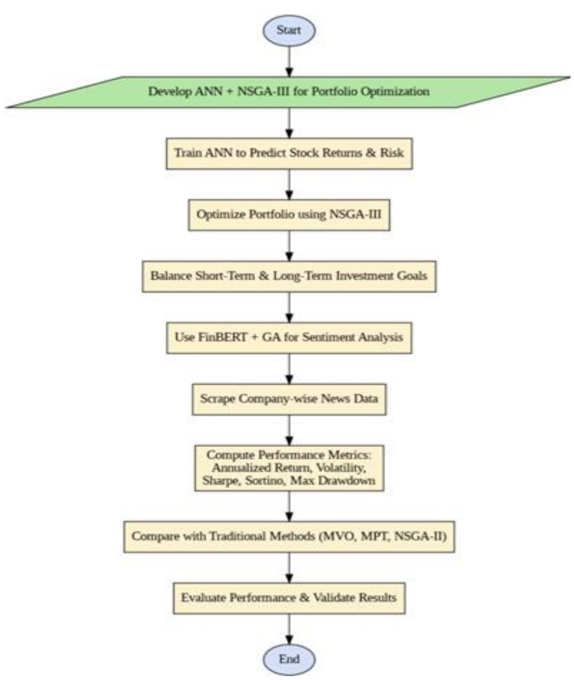

Fig. 1: Objective Flowchart.

VI. PROPOSED ALGORITHM

The algorithm employs Genetic Algorithms (GA), Artificial Neural Networks (ANNs), and Multi-Objective Optimization (MOO) to develop an intelligent stock selection and portfolio optimization system. It is designed to assist investors in making informed investment decisions by determining the optimal risk-return trade-off. Investors can either manually select stocks based on their preference or allow the system to suggest stocks based on market trends and performance indicators.

The algorithm takes and analyzes historical stock exchange data, isolating significant market forces such as volatility trends, trading volumes, and macroeconomics. On the prepro- cessing step of the data, dirty data is cleaned off from the histories of stock prices and normalized ready for prediction modeling. Complex ANNs are then used in the system to find stock action on the basis of multiple finance indicators such as marketplace sentiment, economic sentiment, and business- specific performance metrics.

Subsequent to predictive analysis, the Multi-Objective Op- timization (MOO) phase utilizes NSGA-II (Non-dominated Sorting Genetic Algorithm II) and NSGA-III (highly advanced Pareto Front Optimization) to scan across a heterogeneous pool of portfolio forms. Such frontier-level optimization algo- rithms reduce returns optimization vs. risk minimization trade- off, calculating top-in-class investment plans at various risk- return trade-offs. The Pareto Front strategy allows selected investment plans to meet more than one objective, which includes diversified as well as properly optimized suggestions.

Investors can also have the facility of customizing port- folio selection by entering risk tolerance, industry choices, and overall investment goals. Sectoral distribution analysis is carried out by the system to achieve diversification and hedge any potential market shocks. The system avoids making the portfolio exposed to one industry in particular and therefore keeps overall risk low.

The capital allocation process is further optimized using Genetic Algorithms (GA), which compute the optimal invest- ment capital allocation to the selected stocks. GA contin- ually uses evolutionary strategies—selection, crossover, and mutation—to minimize investment strategies and converge to an optimal allocation model. The resultant is a diversified portfolio with simulated returns, risk measures, and sectoral allocation numbers. Investors can analyze and modify these recommendations prior to initiating their trades, in order to yield an adaptive and data-based investment strategy.

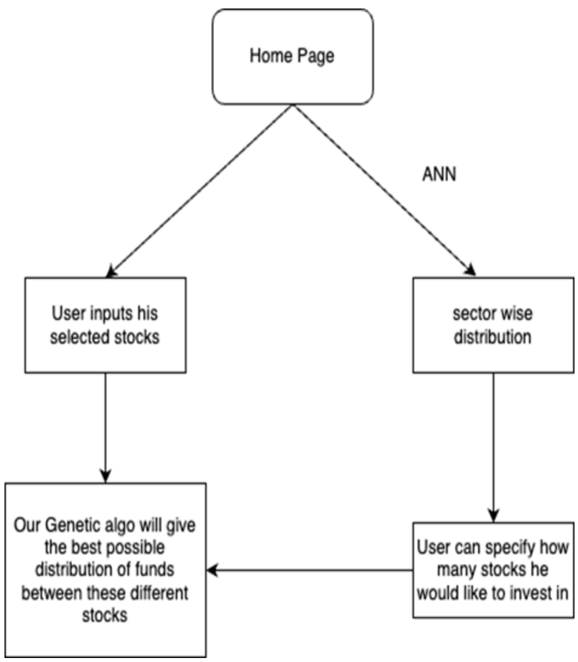

Fig. 2: Flowchart.

- Sta – Starting the model of stock selection and portfolio optimisation is how the process begins.
- Stock Selection – Investors can either choose stocks manually or apply system-suggested stocks according to market trends.
- Retrieve Historical Data – The system fetches historical stock data, comparing short-term (3 years) and long-term (15 years) trends.
- Data Preprocessing – The raw stock data is cleaned, normalized, and formatted before further analysis.
- Stock Price Prediction (ANN + LSTM) – An Artificial Neural Network (ANN) model, namely LSTM, is used to predict future stock prices based on a set of financial indicators.
- Multi-Objective Optimization (NSGA-II/NSGA-III) – Advanced optimization methods are used to optimize return and risk, selecting the best portfolio parameters.
- User Preferences (Risk Sector Selection) – Investors provide risk tolerance and sector preferences to person- alize the portfolio strategy.
- Portfolio Diversification Check – The system verifies that the investments are diversified across sectors to minimize risk.
- Fund Allocation using Genetic Algorithm (GA) – GA is applied for allocating capital on selected stocks in a manner that optimizes returns with controlled risk.
- Generate Optimized Investment Portfolio – The sys- tem produces the final investment plan, including return estimates, risk estimates, and diversification by sectors.
- End – The process terminates, allowing investors to scru- tinize and exercise their maximized investment decision.

VII. SIMULATION PLATFORM AND REQUIREMENT

A. Introduction To Simulation Framework

The simulation process is the systematic workflow of exe- cution for testing and applying the proposed Artificial Neural Network (ANN) and Genetic Algorithm (GA)-driven portfolio optimization model. It describes the step-by-step procedures of data collection, data preparation, predictive modeling, opti- mization, fund allocation, performance measurement, and final recommendation of the portfolio. According to a set workflow, the simulation ensures that all parts of the system operate at their optimal levels, leading to valid and accurate investment decisions.

The process begins with data collection, where Yahoo Finance API (yfinance) gathers historical stock history and the key financial parameters such as trading volume, moving averages, volatility measures, and macroeconomic variables. The data are preprocessed for handling missing values, fea- ture scaling, and computing meaningful technical indicators for efficient predictive modeling. Long Short-Term Memory (LSTM) networks and Artificial Neural Networks (ANNs) are employed to forecast stock price movements based on past trends. The predicted stock returns are utilized in the portfolio optimization phase, where Non-Dominated Sorting Genetic Algorithm III (NSGA-III) is employed to effectively optimize return and risk.

Once optimization is completed, the fund allocation follows Genetic Algorithms (GA) to determine the best ratio of investment in selected stocks. The final investment plan is then subjected to verification by backtesting where portfolio performance is compared with benchmark indices such as S&P 500 and NASDAQ. The system compares the most important financial metrics such as Sharpe ratio, Sortino ratio, and maximum drawdown to verify an optimized and risk-adjusted investment plan.

Apart from the multi-objective optimization method, the Single Index Model (SIM) also offers another method of portfolio optimization in the guise of reducing stock return versus market movement relationships to simpler terms. SIM views a stock return as being influenced most by a single market factor. The workflow of SIM involves data collection of historical stock returns and market index data, followed by linear regression analysis to estimate alpha and beta for each stock. Once beta values are calculated, stocks with optimal risk-return characteristics are selected for portfolio inclusion. Simulation process is important to ensure the validation of the proposed model's efficiency and robustness. The process ensures that data-driven investment decisions have the support of scientific approaches and AI-based optimization algorithms. The simulation process step-by-step and flowchart of the over-

all process will be discussed elaborately in the next section.

B. Simulation Workflow

Simulation workflow outlines the step-by-step execution of the proposed portfolio optimization model. It is a process- oriented approach, beginning with data retrieval and moving on to preprocessing, predictive modeling, optimization, fund

allocation, performance evaluation, and ultimate portfolio sug- gestion while adding to it the FinBert sentiment solution. Each phase is responsible for thorough testing and validation of the model prior to its generation of investment recommendations.

C. Data Collection

- The process begins with gathering financial data using the Yahoo Finance API and other market data sources.
- This includes stock prices, volume, moving averages, technical indicators, and macroeconomic variables such as GDP growth rate, inflation, and interest rates.
- A key addition is scraping company-specific news from financial sites and APIs, which will subsequently be fed into the sentiment analysis pipeline.

D. Data Preprocessing

- Raw financial data often contains noise and outliers that must be cleaned.
- Feature engineering is performed to develop signifi- cant indicators such as Relative Strength, Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands, which help predict stock movements.
- Normalization techniques are applied to normalize the data, making them uniform for the prediction models.

E. Stock Price and Sentiment Prediction

- This stage combines both price prediction and sentiment analysis. Predictive modelling is used via Artificial Neu- ral Networks (ANNs) for forecasting future stock prices.
- Both stock price pattern over time are learned by a deep learning model (ANN), and simultaneously, FinBERT (a transformer-based model fine-tuned for financial senti- ment) classifies every news article as negative, positive, or neutral.
- A Genetic Algorithm is utilized for optimal weights distribution to sentiment scores to enhance the effect of news on final ranking of stocks. Hyperparameters are tuned to attain strong predictive performance.

F. Portfolio Optimization

- Multi-objective optimization techniques such as Non- Dominated Sorting Genetic Algorithm II (NSGA-II) and NSGA-III are used to construct optimal portfolios.
- The optimization algorithm balances the trade-off be- tween maximizing returns and minimizing risks while ensuring portfolio diversity.
- FinBERT-based sentiment scores, which are weighted using GA, are included as a decision

variable within the optimization procedure. This is to ensure portfolios not only have a statistical optimum but also consider sentiment.

G. Fund Allocation

- After identifying the optimal portfolio, the Genetic Algo- rithm (GA) is used to allocate capital efficiently among selected stocks.
- GA simulates evolutionary processes, including selection, crossover, and mutation, to find the best asset allocation strategy.
- This algorithm simulates biological evolu- tion—performing operations such as selection, crossover, and mutation—to decide the optimal method of allocating capital. Stocks with high forecasted performance and positive sentiment (based on FinBERT + GA scores) are given higher weights.

H. Performance Evaluation

- The performance of the optimized portfolio is measured in terms of leading financial measures including Sharpe Ratio, Sortino Ratio, Maximum Drawdown, and Volatil- ity. These helps quantify returns adjusted for risk.
- The performance of the sentiment-integrated portfolio is benchmarked against traditional strategies, such as historical backtesting, ensuring that sentiment actually improves decision making.
- A detailed comparison is also made between standard portfolios and those given with sentiment intelligence in order to justify performance gains.

I. Portfolio Recommendation

- The final investment plan is generated, providing in- vestors with a detailed report, including anticipated re- turns, risk assessments, and sector-based allocation.
- Dynamic portfolio rebalancing is facilitated, allowing the system to adjust investments according to market fluctuations.
- With changes in market conditions and news sentiment, the system dynamically modifies the portfolio to provide optimal performance and maintain real-time responsive- ness to financial developments.

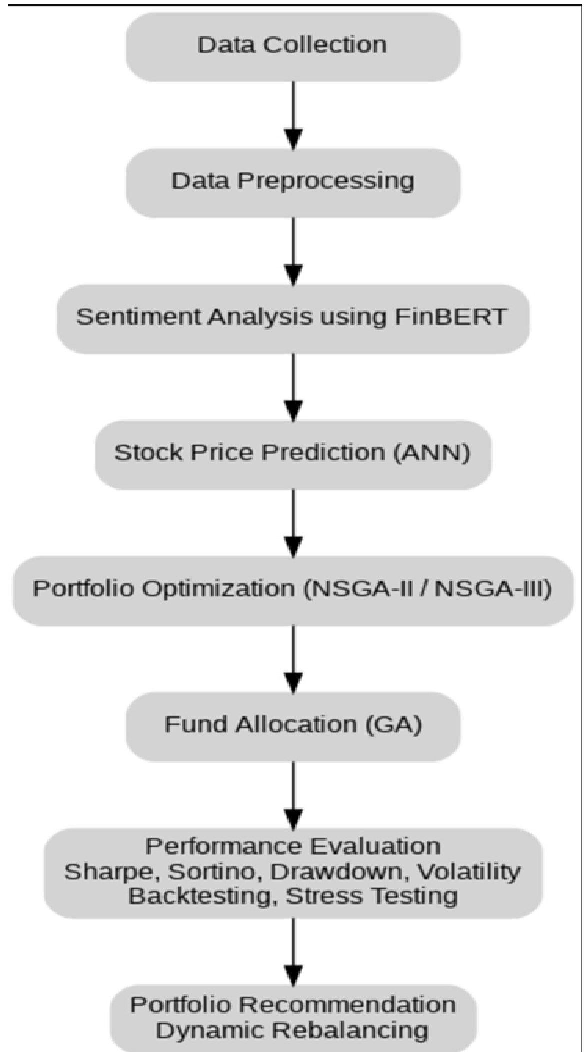

Fig. 3: Simulation Workflow.

VIII. RESULTS

A. Results

Fig. 4: Detailed analytics view.

1). Results using the Sentiment Analysis: Our hybrid ANN–GA investment optimization model results as shown in Figure 4 illustrate the effectiveness of combining data-driven forecasting with sentiment-driven decision-making. FinBERT was used to examine company-specific news sentiment and found that MSFT had the highest positive sentiment score

(0.369) followed by T (0.106) and AAPL (0.086), while TSLA demonstrated a negative sentiment (-0.207). Such scores were utilized to influence stock prioritization when optimizing the portfolio. Concurrently, the Black–Litterman model predicted expected returns with TSLA leading at 31.94%, followed by MSFT (19.81%), AAPL (18.56%), and T (5.70%). The final portfolio performance reflected strong risk-adjusted returns of 31.79% annualized and a Sharpe Ratio of 104.61%. The Sortino Ratio reached an impressive 160.28%, demonstrating outstanding downside protection. The maximum drawdown of -40.08%, however, points to vulnerability to market fluc- tuations. One of the most significant realizations was the heavy portfolio weighting given to T, not driven by senti- ment or return but by the lowest predicted variance that had been found using ANN simulation—demonstrating the value added by incorporating AI-based risk prediction in portfolio construction. Overall, application of FinBERT, ANN, and Genetic Algorithms enabled a dynamic, adaptive investment strategy that balances quantitative performance with qualitative sentiment analysis well

Metric	Value
Annualized Return	0.1934
Volatility	0.2014
Sharpe Ratio	0.9599
Sortino Ratio	1.3779
Max Drawdown	-0.2724

TABLE I: Metrics for sentiment analyzed model

As depicted in Table I, the sentiment-aware portfolio re- turned 19.34% annually with comparatively minimal volatility of 20.14%, meaning an analyzed returns. Sharpe Ratio of 0.96 and Sortino Ratio of 1.38 indicate excellent risk-adjusted performance, with the latter focusing on downside protection. The highest drawdown of -27.24% reveals the worst peak-to- trough loss, yet is within acceptable bounds for an equity- oriented portfolio. Overall, these figures affirm that incorpo- rating sentiment data enhanced portfolio quality by improving return efficiency while controlling risk.

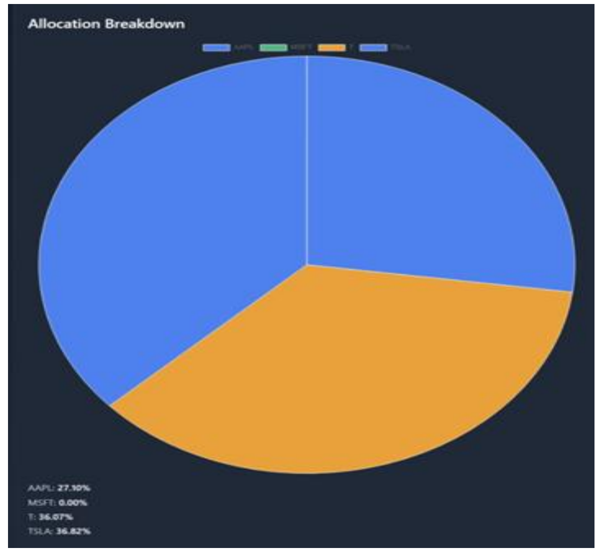

Fig. 5: Allocation Breakdown using Sentiment Analysis.

The end-optimized portfolio, as shown in Figure 5, illus- trates the efficiency of our hybrid ANN–GA model in striking a balance between returns predicted, sentiment, and risk.

TSLA was assigned the highest portion (36.82%) even with adverse sentiment, courtesy of its high return forecast under Black–Litterman model. T also had a high portion (36.07%), preferred for its low predicted variance from the ANN model. AAPL was moderately weighted (27.10%), and MSFT was omitted even with positive sentiment, due to inferior risk- return tradeoffs. The portfolio as a whole registered a 31.79% annualized return with high Sharpe and Sortino ratios, prov- ing the model's capability to produce sentiment-aware, risk-optimized investment strategies.

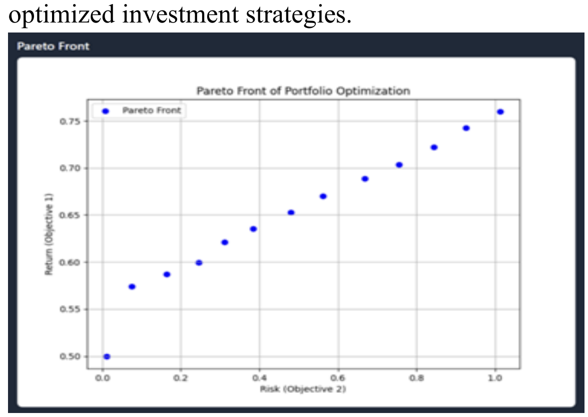

Fig. 6: Pareto Front of Portfolio Optimization using Sentiment Analysis.

Figure 6 highlights the Pareto Front generated from our sentiment-aware portfolio optimization which clearly demon- strates the effectiveness of multi-objective modeling. Each point on the curve represents a trade-off between maxi- mizing return (Objective 1) and minimizing risk (Objective 2). As expected, portfolios on the front exhibit a smooth gradient—moving rightward increases risk but also enhances return. The addition of sentiment scores (through FinBERT) enabled the optimization algorithm to adjust portfolio al- locations wisely based not just on forecasted metrics but also on market sentiment, resulting in more context-specific trade-offs. This enriched Pareto frontier demonstrates that the inclusion of sentiment analysis in the portfolio optimization process provides improved decision points for investors across different risk appetites.

Stock	Count	Mean	St.Dev	Skewness	Kurtosis	Min	Max
AAPL	1257	162.86	39.23	0.24	-0.42	74.86	258.74
MSFT	1257	305.66	78.48	0.30	-1.17	172.05	464.85
TSLA	1257	232.35	74.15	0.22	0.44	52.73	479.86
T	1257	16.91	3.11	1.82	3.24	12.14	28.30

TABLE II: Descriptive Statistics for Selected Stocks

Table II shows the time series statistics which revealed important information on the past behavior of each stock, which was used to train the ANN in our sentiment-sensitive model. T had the lowest mean price and volatility, hence presenting itself as risk-stable to the ANN, while MSFT and TSLA had greater volatility, raising their risk profiles. Significantly, T's high kurtosis and skewness also highlighted its asymmetrical but stable pattern of returns. These quanti- tative characteristics aided the ANN in estimating variance of stock level that, when coupled with sentiment scores from FinBERT, allowed the model to make better and more balanced portfolio choices.When combined with sentiment analysis from FinBERT, this dual-input framework allowed for more nuanced portfolio construction, capturing both statistical and psychological dimensions of the market.

1) Results without using the Sentiment Analaysis: The op- timization performance of NSGA-II, NSGA-III, and MOEA/D was compared using Pareto front approximations. The gener- ated Pareto fronts for each algorithm are shown in Figures 7, 8, and 9, respectively.

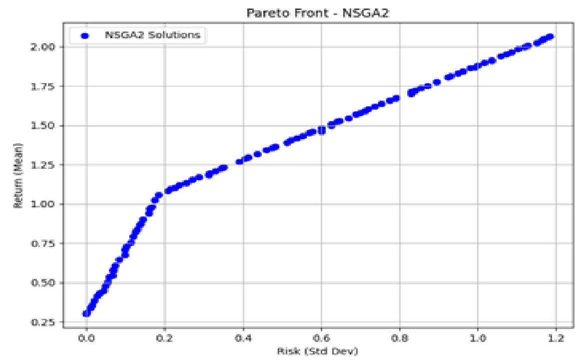

Fig. 7: NSGA-II Pareto Front

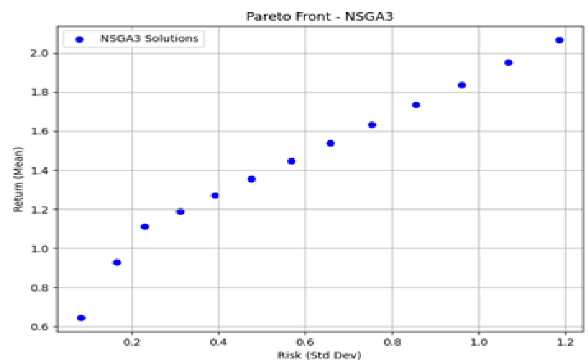

Fig. 8: NSGA-III Pareto Front

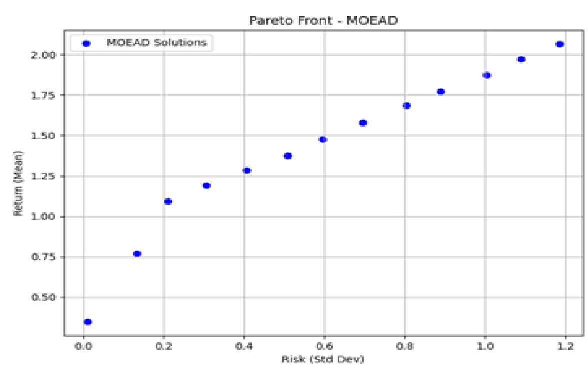

Fig. 9: MOEA/D Pareto Front

- NSGA-II Pareto Front: The Pareto front obtained through NSGA-II demonstrates a well-converged solution set with a reasonable distribution of points. However, certain regions exhibit crowding or sparsity, which may affect solution diversity.
- NSGA-III Pareto Front: The NSGA-III approach pro- duces a Pareto front with a more evenly spread set of solutions. This suggests that NSGA-III maintains diver- sity more effectively, especially in higher-dimensional objective spaces.
- MOEA/D Pareto Front: The Pareto front generated

by MOEA/D follows a structured decomposition-based ap- proach. The solutions are well-spaced, indicating that the algorithm efficiently handles convergence and diversity through weight vector decomposition.

Comparing these results, NSGA-III exhibits better diversity, while MOEA/D provides a structured distribution. NSGA-II performs well but may have limitations in maintaining diver- sity across the entire front. These observations indicate the effectiveness of decomposition-based approaches in achieving well-distributed solutions in multi-objective optimization.

The optimal fund distribution of NSGA2, MOEA/D, and NSGA3 as shown in figure 10 illustrates different asset allocation techniques for portfolio optimization. NSGA2 in- vests heavily in MSFT (89.31%) with minimal contribution to TSLA (10.61%) and minimal investment in other stocks. MOEA/D, having the highest confidence (39.43%), distributes funds more evenly to MSFT (49.17%), TSLA (48.39%), and AAPL (2.36%). NSGA3 concentrates on MSFT (63.03%) and TSLA (36.87%) with minimal diversification. Figure 3 highlights the two algorithms' distinct optimization strategies, with MOEA/D yielding the most diversified investment, while NSGA2 and NSGA3 favor compact investments.

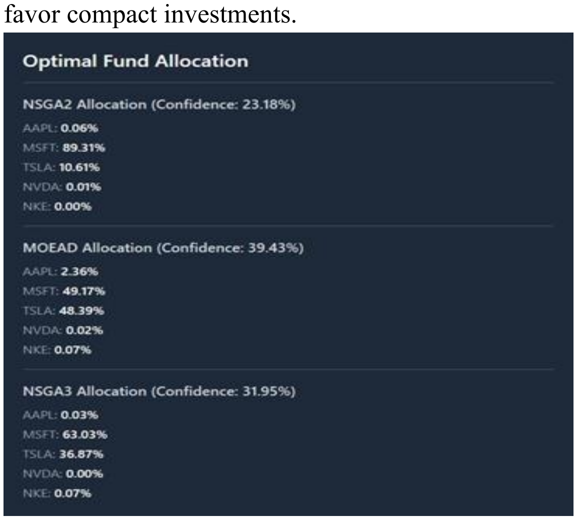

Fig. 10: Optimal Fund Allocation

These variations in Figure 10 indicate the difference in each algorithm's optimization approach in obtaining risk and return balance, which mirrors their effectiveness in multi-objective portfolio optimization. It is evident that MOEA/D provides the best diversified allocation with significant diversification, while NSGA2 and NSGA3 favor concentrated investment. The

values of confidence represent varying levels of reliability of the allocation and, with MOEA/D having the highest confidence in the solutions.

Fig. 11: Stock Price Prediction for Nike

The historical price action is graphed in blue on the chart presented in Figure 11, followed by an estimated increase through a green dashed line. The current price is approxi- mately $76.96, and the future price is estimated at $155.49 around early 2026. This estimate suggests huge growth po- tential, almost doubling the stock value in the estimated time- frame. The research can use machine learning or optimization algorithms to predict future price action from historical action and market data.

Fig. 12: Stock Price Prediction for Apple Inc.

The homepage, as shown in Figure 13 gives an overview of the trading solutions offered by the platform, including access to advanced trading software, real-time market analysis, and expert insight. Our Portfolio Optimization platform offers two essential services: Optimum Allocation of Funds and Sector-Wise Allocation. The optimal allocation service helps maximize returns by efficiently distributing funds between various investment options based on risk, return, and liq- uidity. Meanwhile, the Sector-Wise Allocation tool ensures that your portfolio is balanced across different industries to protect against market volatility. To extend the benefits of this framework to everyone, we have created a user-friendly website. It can be accessed at Website link.

Fig. 13: Homepage Interface

Fig. 14: Sector-Wise Companies Visualization.

The Figure 14 depicts a treemap chart of the top companies by sectors, illustrating their distribution in the market. Com- pany symbols, names, ratings, and market weights are given in a table below to enable users to analyze sector-wise investment prospects.

Fig. 15: Portfolio Optimizer Section.

Figure 15, presents the ability of the portfolio optimizer to search for specific stocks and retrieve real-time current market data. It displays selected stocks with an interactive chart of historical price movements, helping users monitor and compare stock performances for making better investment decisions.

The Figure 16, 17 and 18 illustrate portfolio allocation breakdown across selected stocks for NSGA-II, NSGA-III and MOEA/D algorithms respectively.

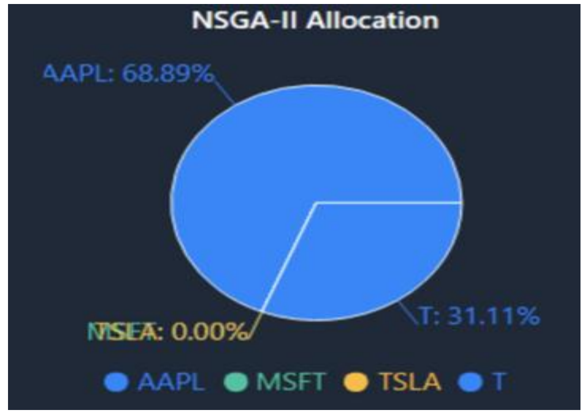

Fig. 16: Allocation Breakdown using NSGA-II.

This NSGA-II allocation outcome, as depicted in Figure 16 is the result of our previous model that used only historical return and risk predictions of the ANN, without using any sentiment analysis or scoring based on FinBERT. Optimization resulted in a very concentrated portfolio with 68.89% weight to AAPL and 31.11% to T, while MSFT and TSLA were allocated 0%. This implies that NSGA-II preferred stocks with relatively lower forecasted variance and stable returns, but without any regard for real-time market mood or qualitative investor opinion. Consequently, although the model is math- ematically efficient in a static environment, it fails to capture the adaptive nature or diversified decision-making inherent in our improved, sentiment-aware model.

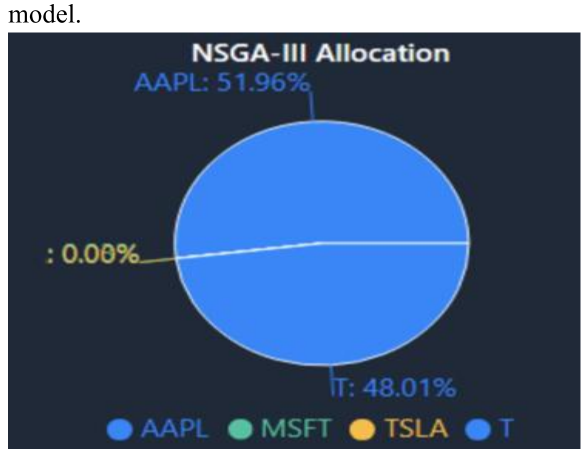

Fig. 17: Allocation Breakdown using NSGA-III.

This NSGA-III allocation outcome, as depicted in Figure 17 mirrors the performance of our previous model based solely on numerical return and risk

predictions, and not including senti- ment data. The portfolio was divided predominantly between AAPL (51.96%) and T (48.01%), with MSFT and TSLA
excluded once more with 0% allocation. In comparison to NSGA-II, NSGA-III provided a slightly more even distribu- tion, but still indicated signs of over-concentration. The choice was presumably driven by low predicted variance from the ANN and historically consistent return behavior, especially for
T. But with no sentiment analysis, the model was oblivious to current market perception and its capacity to learn from qualitative changes in investor mood was curtailed.

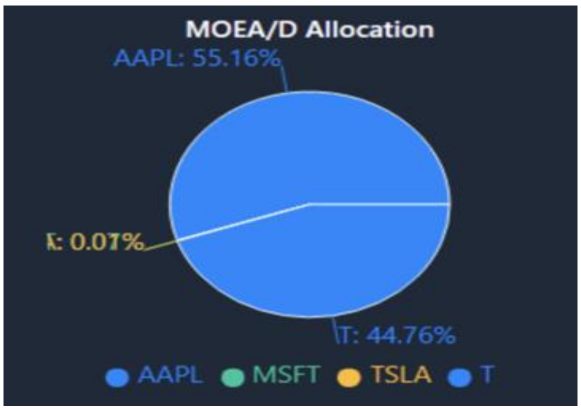

Fig. 18: Allocation Breakdown using MOEA/D.

The MOEA/D allocation result, as depicted in Figure 18 indicates a portfolio highly biased towards two assets: AAPL (55.16%) and T (44.76%), with TSLA being included very minimally at 0.07% and MSFT being excluded altogether. Like NSGA-III, this result indicates the optimizer's incli- nation towards stocks with consistent return-risk profiles as forecast by the ANN. TSLA's minimal allocation shows that its increased volatility or ANN-estimated variance exceeded its potential return. The omission of MSFT also implies that without sentiment information, the model was unable to reflect positive investor sentiment that could warrant its inclusion. In general, although MOEA/D provides a more evenly distributed solution than NSGA-II, the absence of sentiment awareness still restricts the model's flexibility and market responsiveness.

2) Comparison Between Both Models:

- Optimization Criteria : The previous model used just two primary goals, maximizing returns and reducing risk—under the NSGA-II and NSGA-III. The new model, however, comes with a third goal: sentiment-guided weighting, incorporated through a Genetic Algorithm. This n-dimensional set of objectives allows the system to create portfolios that are quantitatively sound and sentiment-informed.
- Inclusion of Sentiment Analysis: In the previous model, portfolio optimization was based on the price and risk factor using historical data. The new model intro- duces FinBERT-based sentiment analysis, which analyzes company-specific news articles and assigns a sentiment score. These scores provide a behavioral aspect to the model, enabling it to take into account not only how stocks have performed, but how they are now perceived by the market.
- Decision-Making Perspective: Although the model is currently configured to trade stocks, adding bonds, com- modities, forex, ETFs, and cryptocurrencies will con- tinue to achieve risk-adjusted returns and diversify. An investment strategy that covers several asset classes has the potential to behave more ideally in differing market environments

IX. LIMITATIONS

Although the proposed Artificial Neural Network (ANN) and Genetic Algorithm (GA)-based portfolio optimization model has a significant edge over traditional investment schemes, there are certain constraints which might influence its suitability in practice. These constraints are.

- One of the major disadvantages of the proposed model is its dependency on historical data for predicting. Even if deep learning-based models like LSTM networks can master complex patterns of financial time series, they remain oblivious to sudden market shocks like policy updates, financial crises, or global geopolitical events. The model also assumes that trends witnessed in the past will continue, which is not true in case of very highly volatile markets.
- The processing and computational time required to train deep learning models and run genetic algorithms. Both NSGA-II and NSGA-III when applied for multi-objective optimization require substantial computing power, es- pecially when the optimization is to be done across numerous stocks. In

actual application, the very high computational load may limit scalability and responsive- ness in a way that it may not be straightforwardly feasible to utilize the model for high-frequency trading.

- Data quality and availability: The model relies on stock market data accessed through platforms such as Yahoo Finance API (yfinance). Financial information tends to suffer from gaps, inconsistency, or even inaccuracies in it, thus affecting the quality of made predictions. Also, other external sources such as social sentiment, financial news, and macroeconomic data are yet to be incorporated, thus limiting the model's ability to explain externalities.
- Lastly, the proposed model is not aware of transaction costs, liquidity risk, or market impact when carrying out trades. In real-life instances, buying and selling large quantities of shares may yield slippage, where trade execution prices are not similar to projected prices due to market movement. The effect of taxes and brokerage commissions is also not reflected in portfolio optimiza- tion, which may lead to overestimation of true returns.

X. SCOPE FOR FUTURE WORK

- Integration of Multimodal Data: Real-time extensions in the future can also add real-time sentiment from social media (Twitter/X, e.g.), macroeconomic news feed data, and geopolitics event tracker data. That would improve responsiveness and awareness for the context-sensitive sentiment model and enhance short-term invest- ment decision-making reliability.
- Computational Cost and Scalability: The current model is computationally costly with regard to big data, par- ticularly NSGA-II and NSGA-III. The algorithm for the future can be improved upon with parallel computation, cloud computing, or reinforcement learning to further improve speed and scalability to align it with big financial applications.
- Expansion to Other Instruments: Although the model is currently configured to trade stocks, adding bonds, commodities, forex, ETFs, and cryptocurrencies will con- tinue to achieve risk-adjusted returns and diversify. An investment strategy that covers several asset classes has the potential to behave more ideally in differing market environments
- Inclusion of Real-World Trading Limitations: To en- hance the model's applicability, future studies can include transaction costs, liquidity limits, brokerage charges, and tax considerations while optimizing portfolios. Including these limitations will render the investment strategy more relevant for real-world trading scenarios.
- Reinforcement Learning for Real-Time Portfolio Rebal- ancing : Integration with Reinforcement Learning (RL) agents that learn optimal rebalancing policies as a func- tion of market movements and sentiment drift can make

the portfolio dynamically adaptable, particularly benefi- cial in periods of high volatility.

XI. CONCLUSION

This paper presents a robust hybrid portfolio optimiza- tion framework sentiment-sensitive that integrates Artificial Neural Networks (ANN), Genetic Algorithms (GA), and senti- ment analysis with FinBERT. Unlike other models based only on historical return-risk estimates, our frame- work dynamically integrates qualitative sentiment indicators from company-specific financial news with FinBERT, thereby making the stock picks more context-aware. The sentiment- guided ANN facilitates improved return and risk forecast- ing, while the GA optimizes the sentiment-weighted options in a multi-objective environ- ment. Comparative assessments with NSGA-II, NSGA-III, and MOEA/D with actual finan- cial data have established that the FinBERT-based model consis- tently performs better in portfolio generation with superior Sharpe and Sortino Ratios, along with less extreme maximum drawdown. The evidence of this confirms its efficacy in different periods of investment. The capacity of the model to add market sentiment alongside quantitative measures ensures greater short-run fluctuation response and long-run growth strategy enforcement. The potential of sentiment-driven AI- based financial models has been iden- tified and addressed in this work, laying a foundation for further improvement through added data incorporation, real-world boundary enforcement, and scalability.

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