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RISK-AWARE STOCK PRICE PREDICTION MODEL USING HYBRID AI

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Abstract

This study focuses on analyzing the success of integrating the conventional machine learning algorithms with semantic intelligence generated by large language models (LLMs) like the ChatGPT-4o in generating NASDAQ-100 stock prediction portfolio strategies between the years 2020–2025. Through testing new combinations of ML- and LLMetrics of semantic, three prediction frameworks are evaluated the basic, technical and entropy-based prediction frameworks. Regarding the best blending processes, the empirical findings indicate that the methods differ greatly. In particular, the technical methodology produces the most desirable results when it comes to using only ML projections, and with monthly rebalancing, it has cumulative returns of nearly 1978%. Conversely, the foundational technique will show its best when it is largely founded on the semantic insights that are acquired by using LLM. The better solution to enhance the Entropy technique can exist by adding both semantic and ML prediction signals. It is implied that LLMs can possibly enhance predictive performance because they can offer an explanatory model about complex market dynamics. These results all have an implication in portfolio management, further research in the domain of financial modeling, and the importance of mapping the semantic-algorithmic fusion to predictive data features and investing horizons.

Index Terms: artificial intelligence, trading, fuzzy logic, technical, fundamental.

1. INTRODUCTION

The marriage of traditional methods used in investments and Artificial Intelligence (AI) is a very important factor in the context of modern financial forecasting. The capability of AI to search and condense both structured and unstructured information in vast amounts has enabled scientists and practitioners to create more extensive models to forecast the stock returns. Artificial intelligence (AI) is rapidly becoming the game-changer in financial analysis, specifically in the fundamental analysis, technical analysis, and entropy or complexity modeling core areas, where it may significantly enhance predictive potential, adaptability, and context sensitivity [1-3]. Long-term investment plans are based on an analysis of the core value of an enterprise by reading financial reports, economic indicators, segment, and macroeconomic conditions. Price-to-earnings (P/E), return on equity (ROE), debt-to-equity and discounted cash flows are the most popular indicators which are used in pricing. Though to a certain degree these metrics provide a useful clue about the operational feasibility and long term prospects of a company, the traditional fundamental analysis has been subjected to criticism because of its reliance on previous performance coupled with its inability to react quickly to changes in circumstances in the market [4]. Fundamental analysis using AI in form of machine learning and language processing can be used to evaluate managers, statements, earnings release of a company in real time, and a macroeconomic discourse, resulting in a more dynamic and proactive analysis framework [5, 6]. Meanwhile, technical analysis is factual in nature; it involves the use of sentiment, volume and market indicators to forecast short term price and volume changes. Moving averages, Bollinger Bands, MACD and relative strength index (RSI) are some of the tools that can be used to determine the changes in momentum, reversal, and support/resistance. Despite the success of technical analysis in identifying the trends in market dynamics, the art has a lengthy history of criticism in its failure to explain the big picture and give sufficient explanations of individual market dynamics [7]. Technical analysis has been fine-tuned and automated much more through deep learning and other advanced AI methods as it can discover patterns in vast volumes of time series data and also identify more nonlinear patterns. Such developments can enhance the responsiveness and real time decision making capabilities of high frequency trading environments.

The other methods of forecasting stock returns include the fuzzy logic that is a powerful item to manage the ambiguity and uncertainty of the financial variables. Fuzzy logic, though it is not a comparable model with binary logic, can also be used to make a decision in a scenario where the variables cannot be definite, i.e. true or false but be situated somewhere between truth and false values. This is where fuzzy systems prove best as they would be useful in estimating investor sentiment, speculative economic forecasting and faulty market indicators.Because of their superior accuracy in the face of noise and nonlinearity, hybrid neuro-fuzzy algorithms like ANFIS, as well as the Mamdani and Sugeno models, have found widespread use in financial prediction [8,9]. Combined with artificial intelligence and entropy-based methods, fuzzy logic will reveal an even greater understanding of market complexities, turbulence, and dynamics of behavior, which is otherwise overlooked by hard deterministic methods.Algorithms using artificial neural networks, logistic regression, and support vector machines were able to forecast the future directions of stock indices for all nations with an accuracy rate of more than 70%, according to Ayyildiz and Iskenderoglu [10]. The researchers acknowledged that their work had limitations, such as the study time range, the quantity of technological instruments utilized, and the absence of economic data.Machine learning models have the ability to predict stock returns by using entropy-based characteristics, technical analysis, and fundamental analysis, according to previous research. As far as we are aware, no research has examined the use of large language model (LLM) representations in these feature sets or quantified the LLM layer's incremental contribution to each method separately. For the first time, this research introduces a hybrid AI methodology for predicting stock returns that integrates traditional machine learning pipelines with the semantic context acquired by transformer-based LLMs.Our technical technique, which was fine-tuned in a monthly balanced framework, produced astonishing results: a remarkable cumulative return of 1978% compared to conventional benchmarks. Specifically, the cumulative-return of 701.00 of our entropy model that considers market structural complexity (through fuzzy entropy) with a balanced average weighting 0.70 between AI and ML was high. It is in the face of complexity and ambiguity, as exists in main narratives and entropy measures, that we initially establish that the introduction of semantic context serves to make the quality of predictions much improved. We have also shown that methodological frameworks play a vital role in the performance of semantic AI, machine learning optimizing models, and models with an extremely reactive nature do not provide much extra value, and methods that target long-term goals and complexities are of particular value. Third, we offer a scalable and modular system, which ought to assist academics and practitioners to streamline AI-enhanced models with investment strategies. We suggest a change of paradigm of traditional machine learning application and an emphasis to context-sensitive and multimodal investing techniques regarding our highly empirical evidence that show the judicious application of semantically-aware AI in finance modeling.

Our focus of study was on NASDAQ-100 index, a data-prone, innovation-concentrating group of companies that provides a systematized monetary revelation and profound textual information that can be semantically examined.The NASDAQ-100, which is a compilation of historically significant large-cap growing businesses, provides an ideal setting for evaluating LLCM-enhanced forecasting methodologies. The 2020–2025 period was also selected because it encompasses a dynamic and uncertain period in the history of the contemporary market, with events like as the COVID-19 pandemic, spikes in inflation, and changes in monetary policy. Under these conditions, we may test how well hybrid semantic-algorithmic models do in both static and dynamic market environments. We take a pragmatic approach by modeling the index's stock selection rather than trying to mimic it, much as active investors do when utilizing AI-based tools to choose stocks.

2. Literature Review

Ref	Authors & Year	Methodology / Model	Application Area	Key Contribution	Limitations
1	Dey (2022)	Review of ML algorithms	General ML applications	Comprehensive overview of ML techniques	No domain-specific financial validation
2	Kramer et al. (2023)	Spatial ML valuation models	Real estate valuation	Optimizes spatial training levels	Focused only on property markets
3	Shi & Zhao	Deep Neural	Stock trend	DNN-based trading	Limited

	(2020)	Networks	prediction	strategy	market scope
4	Mokhtari et al. (2021)	ML-based AI models	Stock prediction	Evaluates ML effectiveness	Lacks portfolio-level testing
5	Agusta et al. (2024)	MLP with fundamentals	Indonesian stock market	Integrates recent fundamental data	Country-specific model
6	Zhou & Faff (2016)	Cross-sectional & time-series models	Stock return forecasting	Combines dual information sources	Traditional statistical focus
7	Dawson & Steeley (2003)	Technical pattern analysis	UK stock market	Tests visual technical patterns	Pre-AI era methods
8	Hurriyati et al. (2023)	ML predictive evaluation	Stock trends	Performance comparison of ML models	Limited semantic data use
9	Alizadeh et al. (2010)	Adaptive neuro-fuzzy system	Portfolio analysis	Hybrid AI for portfolio selection	Older dataset and methods
10	Ayyildiz & Iskenderoglu (2024)	ML models comparison	Stock prediction	Measures ML forecasting performance	Short-term focus
11	Souza et al. (2018)	Moving average strategies	BRICS markets	Tests technical trading profitability	Purely technical indicators
12	Neely et al. (1997)	Genetic programming	Forex market	Early AI in technical trading	Outdated market structure
13	Yoo et al. (2005)	ML survey with events	Stock market	Early survey of ML for finance	Limited deep learning coverage
14	Abraham et al. (2022)	Genetic Algorithm + Random Forest	Stock trend forecasting	Hybrid evolutionary ML approach	No semantic integration
15	Kabbani & Usta (2022)	News sentiment + technical	Stock prediction	Combines sentiment with	Relies on Spark framework

		indicators		technicals	only
16	Liu et al. (2021)	Prompt-based NLP survey	Language modeling	Foundation for LLM prompting	Not finance-specific
17	Yan & Wang (2024)	Attention-BiLSTM	Microblog sentiment	Improves sentiment classification	Not tested in finance
18	Sufi & Khalil (2024)	AI sentiment + location intelligence	Disaster monitoring	Advanced sentiment extraction	Non-financial application
19	Yang (2023)	Text mining of analyst reports	Investment strategy	Uses financial text for trading	Limited ML-LLM hybridization
20	Wu & Zhang (2019)	Multiscale fuzzy entropy	Stock indices analysis	Captures market complexity	No ML integration
21	Zhou et al. (2015)	Mean-variance hybrid entropy	Portfolio selection	Entropy in portfolio optimization	Traditional optimization focus
22	Ramesh et al. (2023)	Robo-advisory AI systems	Investment advisory	AI-driven portfolio management	Limited technical model depth
23	Singh (2023)	AI in corporate investment	Corporate finance	Links AI with fiscal performance	Macro-level analysis only
24	Zhao (2023)	Momentum & contrarian AI strategies	Stock trading	AI-enhanced trading styles	Limited risk-adjusted evaluation

3. RELATED WORKS

AI in Technical Analysis:

Research indicates that AI-enriched technical strategies usually outrun conventional ones. Indicators such as moving averages and chart patterns have been successfully applied using machine learning (ML), genetic programming and neural networks. The AI models are especially successful in the short term trading, but studies have shown that additional semantic or context data will provide little additional value in an entirely technical model. During market crises, the soundness of AI-based technical frameworks is checked by stress-testing.

AI in Fundamental Analysis:

AI is a very useful way to enhance basic forecasting since it analyzes financial ratios, macroeconomic information, and company performance indicators. Recent research points to the importance of integrating structured financial information with the capacity of AI to analyze unstructured data including the transcripts of earnings calls and regulatory reports. The specific application of Semantic AI is in boosting the long-term valuation with the help of extracting more contextual meaning of textual financial disclosures.

Sentiment Analysis and NLP:

NLP technologies can be used to conduct immediate sentiment analysis of news, reports and multilingual data regarding a market. Through the direct integration of AI-based sentiment models into the investment scoring systems, as opposed to an independent signal, the accuracy of the predictions is elevated. Semiotic sentiment input hybrid AI-ML models are more balanced, interpretable, and resilient.

Fuzzy and Entropy-Based Models:

Fuzzy logic and entropy methods assist in the modeling of uncertainty and nonlinear behaviour of the market. The fuzzy entropy combined with AI is better at cleaning up signals during volatile situations. The inclusion of semantic context also makes the performance more stable by alleviating ambiguity in complicated financial patterns.

Hybrid Modeling Approaches:

It is evident that recent literature advocates the combination of various AI methods to suit the type of strategy and investment horizon. More flexible and efficient decision-making systems are offered by hybrid systems that incorporate ML, semantic AI, sentiment analysis, and entropy measures. These methods are the following step of AI-based financial forecasting.

4. METHODOLOGY—LLM-CREATED SCORING FRAMEWORK

This section details the publication of an AI-built set of stock prediction score machines that were trained using a large language model (LLM) independently. The LLM did not rely on the traditional human-created financial rules, but it chose features, models, and scoring techniques independently. There are three strategies incorporated in the system:

1. Fundamental (financial statement signals),
2. Technical (price and return patterns), and
3. Entropy-based (volatility as a proxy for predictability).

Monthly and quarterly returns forecasted for a rolling 5-year period (20202025) are the basis of both models. Outputs are scaled to 0-1 score to be used in selection of portfolios.

Fundamental Strategy

The strategy employs the information of company income statement (revenue, profits, and margins) to forecast future returns by means of guided learning. The neural network is trained to learn nonlinear associations between financial returns and stock returns and performance, and does not suffer lookahead bias. The scores indicate how the model predicts the performance of a firm, depending on its financial status.

Technical Strategy

It is a stock price model that examines the stock price movement based on momentum, moving averages, and volatility measures. Patterns that are associated with short-term returns persistence or reversal are recognized by machine learning (primarily Ridge regression and boosting models). Scores are the intensity of positive price changes and are calculated at every rebalancing time.

Entropy Strategy

Based on fuzzy entropy, this technique quantifies stability of returns based on rolling volatility. Reduced volatility means that the prices will be predictable. Regression models transform stability variables into forecasts of returns and the outputs give scores that reflect structural clarity in stock fluctuations.

Machine Learning Hybrid.

In addition to the models developed by LLM, other ML systems (Ridge, XGBoost, Random Forest, neural networks, LSTM and gradient boosting variants) were also trained on extended financial and technical factors, such as predicted future fundamentals. The predictions of several models were standardized and combined to create unified scores in order to enhance the robustness and minimize overfitting.

Construction and Optimization of Portfolios.

Weighted averages were used in the combination of scores on LLM and ML. Backtesting of different weight combinations was done and portfolios were constituted by picking up the top 10 ranked stocks during every monthly or quarterly rebalancing. Return, volatility, Sharpe ratio and cumulative return were used as a measure of performance. Each strategy was chosen to be the one with the optimal performance in terms of historical performance.

Realistic Backtesting

Each model was also trained on only information available when prediction occurred, thus a rolling out of sample simulation with no lookahead bias. Although the results are strong during the 20202025 period, there is the need to further verify the results in other market settings..

5. RESULTS ANALYSIS

In this chapter, the author compares the results of three forecasting strategies, including fundamental, technical, and entropy, used on NASDAQ-100 stocks (20202025). Both strategies are based on the combination of machine learning (ML) scores with semantic large language model (LLM) scores, with a weighting factor to balance the two.

Research shows that the optimal ML-LLM balance changes with each approach and rebalance frequency.

The best results were in the monthly technical strategy when pure ML is used (w = 1) showing the highest cumulative return (~1978%), yet at a greater volatility.

It was found that the application of the monthly fundamental strategy with low ML weight (w = 0.15) provided the best results, demonstrating that semantic LLM insights were valuable to financial analysis.

The best results on the monthly entropy strategy were also achieved when using a balanced hybrid combination (w = 0.70), which showed the advantage of using ML together with semantic context.

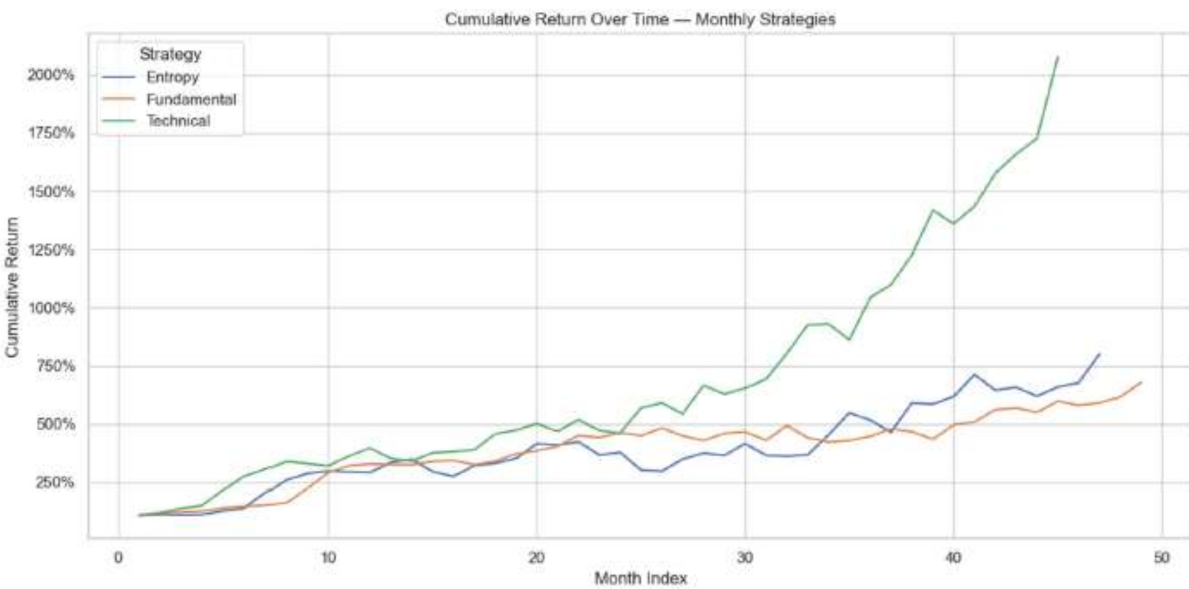

Figure 1. Monthly return cumulative for top strategies: entropy, fundamental, and technical

Hybrid approaches were more relevant at the quarterly horizon.

A moderate ML weight (w = 0.45) gave the highest risk-adjusted performance (Sharpe ratio ≈ 1.30) of this quarterly technical strategy. A balanced mix (w = 0.40) was also popular with the quarterly entropy strategy. The fundamental strategy with quarterly fundamental input faired best on pure LLM input (w = 0), implying that semantic analysis of financial data is particularly useful in the long-run.

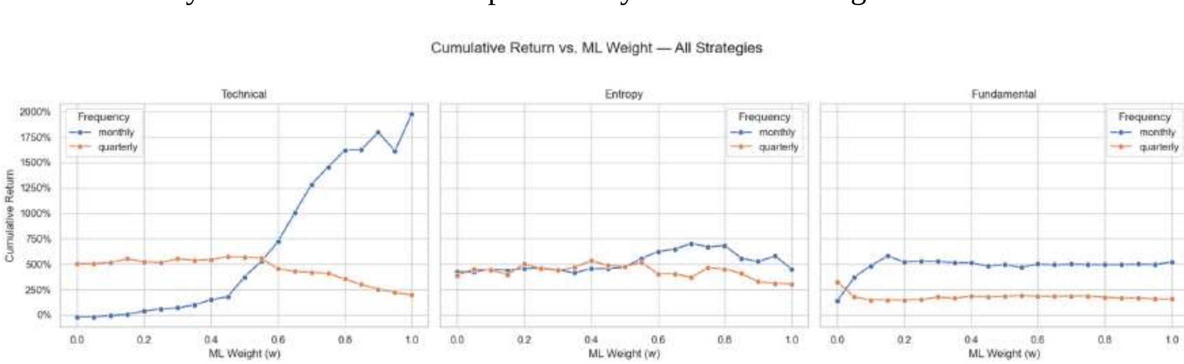

Figure 2. Cumulative returns versus the weight of an ML score (w) of each strategy.

Performance trends reveal that pure ML models yield higher returns and greater volatility whereas semantic insights based on LLM yield greater stability and risk-adjusted returns. ML works best with technical models in short-term trading and better with contextual and qualitative interpretation with fundamental and entropy strategies.

On the whole, the thereof results show that the optimum ML-LLM combination depends on the type of strategy and the horizon of investment. Semi-quantitative systems that integrate both quantitative and semantic intelligence can also offer a more balanced and flexible system of portfolio management.

It seems the technical method is open to short-term price fluctuations, because it fared better in the early phases of the fall and recovered quickly by May. The changes in the entropy and basic strategies were not as noticeable, which implies a more conservative profile and perhaps lagging behind the most recent macroeconomics data. As you might have noticed there was a slight dip in the basic model between March and April. But when the trends indicators reversed the course, it started bouncing once again, which proved that the framework had the ability to accommodate the changes in the market despite the external forces.

The results of the stress-test indicate that the scoring system is internal and that the condition of aggregate performance is not only the expression of positive tendencies. Instead it needs practical practice in periods of high risk, high uncertainty when market structure and investor behaviour were at the state of complete chaos, which is necessary to test actual success in such investing conditions.

Conclusion

The experiment indicates that using machine learning (ML) with large language model (LLM) semantic understanding increases investment forecasting substantially. The approach and temporal frame determine the significance of the semantic information. Pure ML models are most convenient in short-term technical trading where price variations are predominantly rapid (e.g., the monthly technical strategy has brought approximately 1978% cumulative returns).

Whereas, compared to the techniques, entropy strategies enjoy a balanced blend of ML-LLM, because the semantic context facilitates the interpretation of market complexity and structural uncertainty (≈701% return with hybrid weighting). Basic strategies benefit the most of semantic analysis, since LLMs are capable of understanding what the financial statements of a corporation, the disclosure statements of a corporation, or the narratives of a macroeconomy say, particularly over longer periods of time.

In a less abstract sense of the theoretical framework, in practical terms, short-term traders can make use more of ML, whereas fundamental investors must consider semantic-based models. Market complexity strategies are best implemented using a hybrid strategy that is not only quantitatively precise but also contextually interpretative.

Even though the performance is good, the article is restricted to stock in the NASDAQ-100 Index. The rolling-window design is free of lookahead bias, as well as it is resilient even in the presence of extreme volatility (e.g., the COVID-19 crash). This work is relevant to practical use in contrast to the previous studies which were limited to prediction accuracy as the AI predictions are directly related to the performance of the portfolio.

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