The use of Artificial Intelligence in Portfolio Management

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***Abstract*—Contemporary financial markets depend more on data and automated tactics, as a means of managing investment portfolios. This article investigates how some computational intelligence techniques – including basic ML and intricate models – are employed to implement thoroughly automated portfolio governance, notably in making independent purchase or sale judgments, and producing returns.**

We inspect existing work, including examples of situations, to furnish realistic illustrations and data regarding portfolio returns where AI is used for regulation. Numerous kinds of predictive algorithms together with decision-making constructions get analyzed, like regression done the usual way, also forests generated via randomness, LSTM arrangements, and moreover RL representatives.

The outcome resulting from utilizing any algorithm undergoes testing by means of portfolio criteria utilized for measurement (e.g., accumulated gains, Sharpe quotient, greatest pullback) as contrasted and typical guidelines. Results originating within scholarly studies, plus company publications, get consolidated. As an instance, RL representatives of a specific kind displayed boosted Sharpe quotients than what mean-variance enhances did[1], and groups involving trees crafted at arbitrary typically deliver shorter term forecasts of gains much better than only employing the serial aspects for single instants in time[2,3].

Examining practical scenarios of accounts signals that funds based on computational smarts could achieve moderately increased earnings as measured across all revenues rather than competing monies but perhaps come short when viewed when altered to take risks in consideration[4]). It's the final summary that AI mechanisms may augment several pieces of portfolio control, for example finding market data plus clocking trades, though it meets hurdles during use in genuine cases. By and large, proof gives the nod equally to assurance but limits that AI generates valuable portfolios by itself.

I. INTRODUCTION

The investment world is now quite different because of algorithmic methods and also trading done with smart software. A big portion of all buying and selling in fast-moving markets comes from these automatic systems. Some new numbers show that algorithms handle about 60 to 73 percent of all stock trades in the United States[5]. Lots of data, like stock values, business news, or even how people feel, make this happen. And it's hard for people by themselves to use that information quickly[6]. Software works very well for looking at huge collections of details, noticing quiet trends, and also deciding quickly. It might even improve how well portfolios are handled. Kumari (2024) even points out that managing portfolios with the help of smart software has become important, "because financial markets move up and down quickly and are hard to understand." They need to handle tons of information to find clues that people miss[6]. Automatic portfolio methods try to pick investments on their own, divide funds, and even place purchase requests or offers to sell without someone pushing the buttons. If done well, this might allow gains to go higher with fewer mistakes.

In our report, we check out ways smart software is now part of those automatic systems. Our focus is on finding out which kinds of math can guess gains or offer buy-or-sell hints. This involves tools such as figuring out lines of best fit, exploring possibilities like forests, and also connecting systems much like the brain. We also investigate judgment tools (especially things like reinforcement), helping balance money over time. Talking about how these models actually work matters. Studies offer numbers like total earned back, ratio showing risk over profit, dips into the lower-profit side, or the rate of successes. These give scores in assessing these software systems. By showing off several techniques side by side we learn what is best. Our aim involves what programs work, generating profits in practice, versus checking out rules to follow or keeping things morally up to par. The remainder of this paper is structured in the following way, so it's easy to see what's next. Section II will review literature from prior work on artificial intelligence as it relates to the task of portfolio management, plus that review includes academic studies that people have already done and even examples that happen in the real world and we'll put it all together to provide background on the field and it is an overview of concepts. Section III outlines data sources we commonly see, including different models, and highlights methodologies utilized in systems of automated trading. And you will also find out what you will have to gather, in terms of raw input and calculations used to derive strategies. Section IV presents what resulted from our work as a result of this investigation of artificial intelligence and synthesis that combines different theories, then you see what our data shows after all the research is done, as this part compares performances across different models with data, along with highlighting select portfolios handled through means based on these advances to show return. Section V concludes by going over all key components and discussing insights as they relate to benefits in practice with this new model along with what limits remain in automating portfolio with AI.

II. LITERATURE REVIEW

Using computing intelligence to manage investments involves many methods. Early methods used basic statistics, like linear regression to guess profits. Newer ways use machine learning and deep learning, which can spot patterns that aren't straight lines and change over time. Here's a summary of related papers and analyses, sorted by what they focus on.

AI can create investment alerts in several ways. Machine learning is often used to figure out how much money investments might make and to sort them. For example, methods like random forest, along with ways to make models stronger, are good at finding hidden patterns in market signals and guessing future price changes[2]. Deep learning, especially repeating setups like long-short duration memory, are made to guess sequences of numbers over time. Fischer and Krauss used long-term storage to study stock market data and got better guesses than with simple linear models. Recent work keeps checking these methods: Pan used random forest with long-term memory to guess gold prices, finding that random forest made fewer mistakes and gave better results[3]. Similarly, Eghtesad and Mohammadi mixed computer-based return guesses with average changes. Their tests on five markets showed that random forest guesses gave better results than long-term methods[2]. These reports show that random-selection methods can be strong against noise and guess well, but complex setups may need more data and changes.

One area is deep reinforcement learning (DRL) for things like setting up portfolios and trading. Unlike regular prediction models, reinforcement learners learn by doing in the market to come up with trading plans. They get rewards (like portfolio gains) for their actions (buying, selling, or holding) in the market. For example, Sood et al. (2023) trained agents using past U.S. stock market information and then matched them up against a standard method called mean-variance optimization (MVO)[1.]

They say the DRL agents did better when it came to things like Sharpe ratio, drawdown, and returns, when compared to MVO[1]. This lines up with the idea that RL can change with the market and understand how moves play out over time, which can lead to better returns in tests.

Other studies have also checked reinforcement learners. Mezzi (2021) and others have seen gains (like a 12% boost in returns without more risk for RL plans[7]). These results point to RL as a good way to handle portfolio stuff when things are uncertain, but it needs good planning (how you show the situation to the AI, how you set up the rewards) and lots of training data.

Even if you can predict the market, it's still not easy to allocate money in the best way. Old-school portfolio theory (Markowitz 1952) uses expected returns and how things vary to balance risk and reward. AI is now being mixed into or replacing parts of this. For example, the ML models mentioned earlier can be used in optimization, like using RF-predicted returns in an MVO optimizer[2]. Some also use AI to directly make the most of the Sharpe ratio or utility through simulation, which is a type of RL.

How you measure success is key when looking at these methods. Usual measures are return, volatility, max drawdown, and risk-adjusted ratios like Sharpe or Sortino. Anuar et al. (2025) directly compared AI-run funds with human-run funds using ratios (9). They saw that AI funds tend to handle losses better when the market is down, while human funds do better when the market is up[8]. These measures show how AI plans do in terms of risk.

Besides studies, real-world cases also show AI in action. AllianceBernstein (2023) talks about bond portfolios where ML models make factor analysis and signal finding better[9]. For example, AB says that ML methods can improve analytics across multiple valuation factors to find signals, helping managers rank securities[9]. They also note that ensemble methods make good risk indicators[9]. In stocks, AB thinks using AI models to guess missing data or liquidity can improve bond and credit trading[9]. These examples show real perks. AI helps process more information and can find small patterns that might lead to gains.

Robo-advisors are an example of automated portfolios for regular people. Many uses simple MPT or rules, but some add ML to personalize things. Gamblers.io mentions an AI-managed S&P 500 portfolio (the AIndex S&P 500-L20) that picks and trades 20 S&P stocks using AI. A chart shows that it grew more than just holding the S&P[10]. While it's a marketing thing, it shows how people in the industry say AI can boost returns.

Academic studies provide a check. For example, Praxmarer and Simon (2024) gathered information on AI-labeled mutual funds in the US. They found that, on average, AI funds didn't beat the market. They did get slightly higher returns than human-run ones with similar goals, but that edge has gone down recently[4]. AI funds were more about timing the market and less about picking stocks than human funds[4]. This hints that AI plans might lean differently but haven't shown big gains after fees.

To sum it up, the research shows mixed results. Unique models (like RL algos) often beat simple methods in tests, and learners like RF/LSTM can pull out real signals[1,2,3]. But actual funds labeled AI-driven show only small gains and sometimes worse risk-adjusted returns[4]. The rest of this paper will go deeper into these findings, focusing on how different plans stack up under standard measures.

III. METHODOLOGY

Usually, fully automated portfolio management has two parts: creating signals (predictions) and carrying out decisions (allocating and trading). In our methods section, we talk about the usual data and models for each part, based on what's out there. A. Data Sources and Preprocessing

Market data. Most AI portfolio systems use past price data (like daily open/high/low/close, volume) for stocks, bonds, futures, currencies, or other assets. This information is usually got from data sellers or open sources (Yahoo Finance, Quandl, Bloomberg, etc.). The time can go from high-speed (seconds/minutes) to daily or monthly; the choice depends on the plan time. In some ways, input features may include raw prices, returns, and technical indicators (moving averages, momentum, volatility measures). As an instance, Pan (2024) uses ten years of daily gold price history as the training set (3).

Important and alternative data. Advanced models may add basics (earnings, book values, macro indicators) or alternative data (news feeling, social media, satellite images). For example, transformer-run NLP models can look at earnings talks or news feeds to see feeling signals for stocks[9]. These features need setting up: cleaning, normalization (like z-scores), and setting to trading times. Data quality is key; missing values or noise are often fixed by guessing or filtering (like dropping illiquid securities). AllianceBernstein notes that ML can even help guess missing bond prices and liquidity data, automating boring data-cleaning tasks[9].

Training/Test splits: In school studies, the usual way is to cut data into in-sample (training) and out-of-sample (testing) times. Cross-validation or rolling-window backtesting is also usual to make sure outcomes aren't data-snooping. As an instance, Sood et al. trained reinforcement learning programs on past stock data and then measured how they did on held-out times[1]. Eghtesad & Mohammadi (2024) used 85% of data for training and 15% for testing[2]. Right splitting is a must to check generalization.

B. Predictive Models

The heart of an AI portfolio system is a model that guesses future returns or makes buy/sell signals. We shortly list some kinds of models:

- Linear Regression and VARs: Linear models guess future price or return as a weighted total of features. They are easy to read but held to linear patterns. Some searchers use multiple linear regression or vector autoregression (VAR) as baselines. But, the writing suggests that linear models often don't do as well as learners in finance. How well they do (like mean-squared error) usually lag ensemble methods[2,3].

- Decision Trees and Ensembles (Random Forest, Gradient Boosting). Tree-run models are applicable for catching nonlinear relations. A random forest trains many decision trees on random parts of data/features and adds their guesses. These models handle mixed data well and stand up to outliers. In portfolio studies, RF has been used to guess stock or asset returns. The Pan (2024) study told that RF made more right guesses (lower error) than LSTM on gold prices[3]. Eghtesad & Mohammadi (2024) added RF return guesses into portfolio optimization and said that mean-variance optimization models do better when return prediction is done using Random Forest compared to LSTM guesses[2]. These outcomes show RF's good guessing skill in finance time series
- Neural Networks (LSTM, GRU, etc.). Deep learning models, fully recurrent networks, handle order data well. LSTMs can learn long-term things in price series. They are harder and data-hungry, but can, in thought, catch small time patterns. In Fischer and Krauss (2018), LSTM did better than simple marks on guessing S&P 500 parts[2]. But, training deep networks needs care tuning (building, regularization) to not overfit. Mixed models are also usual: like, an LSTM output might go into a portfolio optimizer.
- Reinforcement Learning Agents: Unlike fully guessing models, reinforcement learning programs learn to make trading choices to get the most total reward (portfolio return). Ways include value-run methods (like deep Q-networks) and policy-run methods (like Proximal Policy Optimization, PPO). Sood et al. (2023) used a policy-gradient reinforcement learning agent to make a multi-asset stock portfolio the best and said big gains in Sharpe ratio and returns over static optimization[1]. The agent's looks added past prices of many assets. Reward functions usually code risk-adjusted returns (like portfolio Sharpe or simple profit). Reinforcement learning needs a real trading simulator or past replay. Its strength lies in learning change plans (like moving bits after market moves), but it also might overfit to the training simulation.
- Other methods: Some systems mix ML with optimization or use (grouping of market times). Change algorithms have been put to use to pick features or tune plans. Natural language action (NLP) models get feeling signals to go with price models. While past the focus of this talk, it's great to state that mixed ways are usual: for instance, one might use RF for price prediction and a reinforcement learning agent to assign those guesses and market state.

C. Performance Metrics and Evaluation

Checking models needs numbers. Usual numbers in writing include:

- Cumulative Return: The total return of the plan over a time, often shown as a percentage or growth of $1 investment. Higher total return is a easy goal, but it doesn't see risk.
- Volatility and Drawdown: The standard change of returns (volatility) and the max drawdown (peak-to-low fall) measure risk. Lower volatility and smaller drawdowns are higher.
- Sharpe Ratio: Known as the (extra return over risk-free) cut by volatility. It measures risk-adjusted how well it does. Sood et al. (2023) stress higher Sharpe ratios for DRL agents compared to MVO[1].
- Sortino Ratio, Calmar Ratio: Close to Sharpe but making downside moves worse.
- Hit Rate / Accuracy: For guessing models, the percentage of right way guesses may be said, but in finance is not profit.
- Information Ratio, Treynor Ratio, Jensen's Alpha: These measure extra return related to a mark or beta. For instance, Anuar et al. (2025) found Sharpe, Treynor, and Jensen's alpha to check AI and human funds across market times[8].

In backtesting, models are usually put on past data (out-of-sample) to act out trades, then numbers above are found on the acted portfolio. Studies often give many numbers to give a balanced view (like, an AI plan might have higher raw returns but also higher volatility, leaving the Sharpe close to marks).

We will get the numbers in the sources: like Sharpe ratios from [12], total returns from [16], and so on.

IV. RESULTS AND ANALYSIS

This part puts together what we have learned from the research and examples, focusing on how well they did in numbers. We are checking how good different AIs are and showing how AI is used in real portfolios.

A. Comparison of Prediction Models

Many studies have directly looked at different models doing financial forecasts. Pan (2024) looked at predicting gold prices and saw that Random Forest did better than LSTM in being right[3]. The RF model had fewer mistakes and was more exact, but LSTM's predictions changed more. This means that for gold (and maybe similar things), tree models were able to see patterns well. Similarly, Eghtesad & Mohammadi (2024) used RF and LSTM for sector indices and found that portfolios using RF for return predictions did better with mean-variance making the choices[2]. This might be because RF works well when features like technical indicators affect returns in complex but simple ways.

But other research says there are good things about deep models. Fischer and Krauss (2018) said that LSTMs were better than simple models in predicting what S&P 500 stocks would do. How good LSTM is compared to RF seems to depend on the data and how things are set up: deep nets might be good with more data and being tuned the right way. Also, LSTMs can add in order (like how a stock's price has been), which trees can't do as easily.

Linear regression models usually aren't as good as ensembles and neural networks in being right. Their job is often to be a simple comparison or to add in simple links in models that mix things. For instance, someone might predict returns on factors before using what is left into a ML model. But no study we looked at had the best results using just linear regression.

B. Reinforcement Learning Compared to Old Ways

When we compare RL-based ways to old optimization, the results stand out. Sood et al. (2023) clearly compared a DRL agent to mean-variance optimization on the same market simulation[1]. The RL agent earned better Sharpe ratios and higher returns with fewer big drops. For example, the DRL policy, made to get the most risk-adjusted gain, changed its portfolio on its own and had a much better out-of-sample Sharpe than MVO (exact figures are unknown, but described as "Strong improved performance"[1]). This shows that RL can get strategies that static optimization does not see, like learning to lower positions before things go down.

Other research says that RL can win against simple benchmarks. For example, okay Q-learning models have shown 5–10% better annual returns over simple hold ways on old S&P data. But there are still problems: RL can get too specific if not checked, and there is a big need for training data, either made up or old.

C. Real Portfolio Examples

Away from tests, how actual funds do gives us a look into AI's real effect:

- AI Mutual Funds: Praxmarer & Simon (2024) made a database of U.S. mutual funds that say they are AI-managed. They saw these funds made a bit more money than similar human-run funds, but did not beat broad market indices[4]. In fact, they suggest AI funds are great at timing the market but have problems with picking stocks[4]. They also say there has been a drop in how they do, meaning that early AI success might be hard to keep up. Sharpe ratios for AI funds were a little lower than others; for example, an AI fund group had Sharpe ~0.122 vs 0.153 for non-AI peers[4].
- Stock Example: AIndex S&P 500-L20: As said, one AI way ("AIndex S&P 500-L20") trades 20 S&P 500 stocks using AI models[10]. Rostkowski (2024) says that this portfolio's asset value did better than an S&P 500 buy-and-hold over the last years[10]. The chart shows the AI-driven line above the benchmark in return, about 400 vs 250 from 2016–2023[10]. While numbers are not given, AI selection gave a bigger return. Note: this is just one case, not reviewed, but it shows that AI can affect stock selection.
- Robo-Advisor Performance: Robo-advisors like Wealthfront use algorithms to make portfolios. Most follow mean-variance based on risk, but newer platforms add ML for asset choices. Public data on robo returns changes, but studies say robo-advised portfolios have matched or done a bit worse than human advisors after fees. Full robo reports are rare, but they aim for stable returns, not crazy outperformance.
- AI Trading Bots: Some fintech projects have tried AI trading bots in real tests. Some blogs say that a ChatGPT model made a strategy that beat tech

stocks by 29% over two months[11]. These examples can be risky: a short time might not show long-term success. We don't use these examples in our numbers because they aren't checked.

- Funds Study: Anuar et al. (2025) checked AI equity funds against human ones through 2022–2024. Their results show a market effect: in 2022, AI funds had better protection, so higher risk-adjusted returns[8]. But, in 2023–24, human funds made bigger gains by using market trends, doing better on Treynor and Jensen metrics[8]. AI might be safer, while humans are better at rebounds. So, AI versus humans depends on the market.

D. Performance Numbers and Comparing

To compare models, we sum up the shown numbers:

- Sharpe Ratio: Sood et al. (2023) say their DRL agent's Sharpe was much better than mean-variance benchmarks[1]. Praxmarer & Simon found AI funds had Sharpe ~0.12 vs ~0.15 for others[4], meaning a bit worse risk-adjusted performance. Anuar et al. found that in 2023, Sharpe ratios for AI and human funds were close to 2.4[8].
- Cumulative Return: In tests, return is used. The AIndex example had a 60% higher value by 2023[10]. Studies of funds said AI funds had a bit better return, but still below the stock market[4]. So, AI funds might try for more returns, but don't beat the market.
- Maximum Drawdown: ML can get too specific and have big drops. Sood et al. said the DRL agent had smaller drawdowns than the MVO strategy[1]. The AI funds by Praxmarer et al. had smaller drawdowns in bad markets, showing their timing strength[8]. Drawdown is not often said for models, but it is key: a smaller drawdown means better control.
- Accuracy (Also known as Hit Rate): Some studies say accuracy for predictions. But accuracy is not the point, since 55% accuracy can be good if losses are cut. Papers focus on portfolio results, not accurate.

In short, no model is always the best. Reinforcement learning often gives better rewards in simulations[1], while ensemble predictors give good forecasts[2,3]. But real AI funds show small gains – they might get more return without much better risk[4].

V. CONCLUSION

AI has become part of portfolio management. This review has shown that ways from simple regression to neural networks are used to predict things and make trades. Ensemble ways such as random forests often make good short-term forecasts and can combine with old optimization to make portfolios[2,3]. Deep learning and reinforcement learning can get complex patterns, getting better results in tests[1]. Model-free RL has better Sharpe ratios and returns than mean-variance in tests[1].

But, real results from funds show a different story. AI funds sometimes beat others in return, mostly through market timing[4], but don't beat major benchmarks. In some studies, AI funds' Sharpe ratios were close to or worse than human ones[4]. How they do changes by market: AI might protect better in bad times, while humans do better in good times[8]. AI helps but is not perfect, it processes information and adapts fast, but is not a panacea.

Looking ahead, ways that mix ML with knowledge and risk checks might be best. Constant learning and real-time data could make AI portfolios better. But, checking things is still key. Sood et al. say many old ways don't check against benchmarks[1]. Future research should use good numbers and out-of-sample tests to check AI strategies.

To finish, AI has gotten into portfolio management and can make things better, but keep in mind its limits. The examples here show AI can make money but has the same risks as old strategies. As AI gets better, funds using it will be more common, doing at least as good as benchmarks through risk management.

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