**Enhancing REITs Portfolios through Advanced Machine Learning Analysis (using fundamental data)**

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Abstract:

This paper's main contributions are the successful combination of Genetic Algorithms to search for outperforming Alphas, thereby creating a portfolio optimisation model that is more profitable and less risky than the market index. The paper also extends past research by incorporating fundamental analysis into ML models and implements a trade execution logic for portfolio allocation for ML models.

Keywords: Portfolio optimization, stock price prediction, fundamental analysis, trade execution

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# Introduction

The saying goes that once a profitable trading formula has been discovered and traded on by enough people, its profits will be eroded away and it will cease to be profitable. Traders and investors appear to be playing a never-ending game of "Hide-and-Seek" in search of profitable trading strategies. Due to the evolving nature of the financial markets, traditional financial time-series forecasting models which are static in nature are becoming less effective than Machine Learning models and dynamic algorithms in identifying the best investments (Sheth & Manan, 2023). The success of Machine Learning has led to numerous research papers applying a myriad of Machine Learning techniques to predict stock prices (Obthong et.al., 2020). However, fewer papers apply these approaches in the Real Estate sector and these papers largely focus on future stock price prediction rather than portfolio allocation as a whole (Habab & Kampouridis, 2024). Many of these papers also use price-volume data without fundamental financial data as inputs. In 2022, the global real estate sector was worth more than $380 trillion and worth more than the global equity and bond markets combined (Tostevin & Rushton, 2023), with approximately 893 listed Real Estate Investment Trusts (REITs) (Nareit, 2024). Hence, addressing the research gaps in this sector is particularly valuable.

## Problem Definition

The aim of this report is to develop an effective real estate portfolio optimisation model that maximises profits, minimises risks and outperforms the market indexes with a sharpe ratio of more than 2. Three Machine Learning models, namely, Multiple Linear Regression (MLR), Neural Networks (NN) and Long-Short Term Memory (LSTM) are used to construct models. A trading agent is also constructed to allocate funds to the portfolio based on the results from the models. The input data to the Machine Learning models will be extended beyond price-volume data to include fundamental stock data. The models will be trained on 10 years worth of real market data. Then, the performances of these approaches will be compared with traditional financial models and the market indexes.

## Motivations

Interviews of traders and financial journalists have revealed that both technical and fundamental analysis are used for forecasting investments, for shorter and medium to long term investment horizons respectively (Oberlechner, 2001). Given that most investments in real estate are meant for the medium to long term, the lack of fundamental data inputs for REITs stock price predictions reveals a pressing need for fundamental data to be incorporated.

## Contribution and Creativity

This project analyses REITs stock datasets with more than 150 features of technical and fundamental indicators. It expands the dimensionality of the input training data significantly beyond price-volume features to incorporate REIT company data from financial statements. The comprehensive dataset covers 150 out of the total worldwide population of 893 REITs and includes up to 20 years of historical data.

The next contribution is the implementation of a trading agent or trade execution logic that acts on individual REIT price predictions to allocate funds to selected REITS in a portfolio.

Overall, this research paper has expanded the body of knowledge on the application of Machine Learning models in Optimising Real Estate Portfolios.

# Background

In order to better communicate ideas, the key financial terminologies and formulas are synthesised from Stephen Ross' Corporate Finance textbook (2021) and applied to the context of this paper. Particularly the difference between a stock, REIT and a portfolio and the difference between technical and fundamental analysis. This builds the foundation for further discussions on the measures of portfolio performance, namely, profits/losses and the sharpe ratio. Other methods of analysis such as sentiment and macro-economic analysis is also briefly discussed.

## Key Terms

The relationship between stocks, REITs and Portfolios can be illustrated in the figure below.

A diagram of a company's portfolio

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Figure 2.1: Stock vs REIT vs Portfolio

### Stock

A stock also called a share, represents ownership over a company's assets. Each stock is represented in the market by a unique identifier called a ticker. For instance, Apple's ticker is "AAPL". The proportion ownership depends on how many shares are owned out of the total number of shares in the market and stocks of publicily listed companies can be purchased on the stock exchange. Over time, share prices can rise and fall, and owners can receive a share of the company's profits through dividends. The daily movement of the share prices over time will be represented in this paper by the formula:

* Prices: P is the price of a specific stock at a particular time
* Date: T in this paper is the daily date
* Ticker: i is the stock ticker for a specific stock

A math equation with numbers and symbols

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### REITs

A REIT company invests in properties. Typically these companies invest or own a mix of housing, commercial or industrial properties. Buying shares of REITs allow investors to own a share of the real estate that these REITS are managing and indirectly invest their monies in the real estate sector. Of course, each of the 893 REITs are different companies which own a wide range of different properties across the world. In this paper, a REIT is used to refer to the stock of a REIT company. A REIT is a type of stock.

### Portfolio

A portfolio is a collection of stocks i.e a portfolio is a combination of more than one stock. For example, the portfolio in Figure 2.1 consists of 10% of stock A, 11% of stock B and 9% of stock C. The relative proportions of each stock in a portfolio can be represented by weights. This paper will represent a portfolio of stocks with the vector and matrix below:

* Weight: W is the percentage value of a ticker in the portfolio.



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This paper aims to develop an effective Real Estate Portfolio Optimisation Model that maximises profits and minimises risks, outperforming the market indexes with a sharpe ratio of more than 2.

### Shorting

Conventionally, we need to own a certain stock before we can sell it. However, market makers also allow investors to borrow stocks to sell them first, with the contractual obligation for the investor to repurchase the stocks from the market at a later date to return to the market maker. This mechanism of selling first and buying back later is called shorting and is represented by a negative weight. This paper's analysis allows shorting.

## Evaluating Investments with Data

In this subsection, various measures of investment performance and how they are applied in the paper are discussed. It covers the two main schools of thought in investment analysis, technical and fundamental analysis before discussing Alpha formulas.

### Technical Analysis with Price Volume Data

Technical analysis is one method of evaluating investments in stocks and identifying prospective stocks to invest in. It focusses primarily on identifying short term trends in price and volume data. Table 2.1 provides the key features required for technical analysis.

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* Open: The price of the stock at the start of a trading day
* High: The highest price of the stock in a trading day
* Low: The lowest price of the stock in a trading day
* Close: The price of the stock when the market closes for the day
* Volume: The total number of shares traded throughout the day

The features Open, High, Low and Close are derived from the Price of a stock at different points in the day and trends of these features can indicate future movements, while volume signals the strength of a price trend.

### Profit and Loss (PnL)

Profits from the purchase of a single stock arises when the selling price of the stock is greater than the original purchase price. However, if the share price falls below the original purchase price then a loss is incurred. Profit or Loss is given by the formula:



It's important to note that profits or losses are only realised when the closing transaction is made i.e. when the stock is sold. When a stock is shorted, a rise in price will result in a loss because it becomes more expensive for the investor to repurchase the share. Hence, for shorting the Profit or Loss formula is negated.

### Risk and Volatility

Volatility is a statistical measure of how varied share price and returns on an investment are over a period of time. It is a proxy of the risk of an investment, the likelihood of an investment performing worse than expected.

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Figure 2.3a shows the distribution of prices of Stocks A and B over a period of time. Stock A has a lower standard deviation σA than Stock B σB, lower volatility and lower price risk. The returns on both stocks can also be plotted on a similiar distribution as shown in Figure 2.3. Because this paper seeks to minimise risk, the variance of prices and returns need to be considered.

### Sharpe Ratio

Deciding between stocks or portfolios with different expected returns and risk like in Figure \ref{graph: risk\_returns} where Stock B has higher returns but also higher risk than Stock A, requires a formula that evaluates these two measures together. The sharpe ratio combines both measures of profit/loss and risk into a single formula as follows:

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* Rp: The annualised return of portfolio
* Rf : The risk free rate
* σp: The standard deviation of portfolio return

The risk free rate Rf is the return from a zero risk investment such as government bonds.

Hence Rp − Rf gives us the excess returns of the portfolio investment compared to a zero

risk investment. σp measures volatility as covered in section 2.2.1.2.

In this paper, the sharpe ratio is used as the overall measure of performance of the portfolio

optimisation models and is incorporated in the various objective functions.

### Fundamental Analysis with Financial Statements

Fundamental analysis is a second method of investment analysis that is widely used by finance practitioners but less often applied by Machine Learning researchers. It involves examining the assets and incomes of the companies behind the different stock tickers by looking at their financial statements to evaluate the intrinsic value of a stock.

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The predictive value of each statement is as follows:

* Income Statement: Profitability of the company’s business and the rate of growth of its value
* Balance Sheet: The asset value and financial stability of the company
* Cash Flow Statement: How cash is generated by the company

Incorporating both technical and fundamental data into machine learning models can provide a more holistic picture to the analysis and better inform these models with an extended set of short, medium and long term features.

### Other Methods of Analyses

Sentiment Analysis: Given that share prices in the short run are largely driven by investor sentiment, some researchers have employed Natural Language Processing (NLP) techniques to process trade forum discussions and financial news for trade decision making resulting in good sharpe ratios (Alexandria, 2023).

Macro-economic Analysis: Considering various measures of the wider economic environment such as GDP growth rates, unemployment rates, inflation and interest rates are important as well because these are strong factors that can influence the overall market performance. It suggests the broader market direction.

# Literature Review

## Comparison of Traditional and Machine Learning Techniques

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Methods | Data Inputs | Scope for REITs | Strengths | Weaknesses | References |
| Autoregressive  Integrated  Moving  Average  (ARIMA) | Daily Price Volume Data | Stock Price Prediction | +Suitable for short-term time-series analysis  + Widely used in the field  of finance for prediction  + More explanable than  complex ML models | -Unsatisfactory for long term prediction  -Higher RMSE than ML models | (Ariyo et.al., 2014), (Habbab & Kampouridis, 2022), (Obthong et. al., 2020) |
| Generalised  AutoRegressive Conditional Heteroskedasticity (GARCH) | Daily Commodities  Price-Volume  data | Stock Volatility Prediction | +Outperforms ARIMA for price prediction and  volatility forcasting | - Model assumes volatility  can be predicted based on  past returns, but volatility  in reality is very unpredictable | (Fiszeder & Chung,  2020), (Lama et. al.,  2015), (Yuan et. al,  2017 |
| Multiple Linear Regression (MLR) | Daily Price- Volume Data | Stock Price Predic- tion | +Relatively low RMSE error for stock price predic- tion  + Relatively easy to implement | - Only considers input features and not historical  price data | (Obthong et. al.,  2020), (Shakhla et.  al., 2023) |
| Recurrent  Neural Networks (RNN) | Daily Price Volume Data |  | +Relatively low RMSE error for stock price prediction  + Remembers historical  stock prices | - Susceptible to vanishing and exploding gradient  problem | (Dey et. al., 2021) |
| Long-Short  Term Memory  (LSTM) | Daily Price Volume Data | Stock Price Predic- tion | + One of the lowest RMSE error for financial time series prediction  + Remembers historical  stock prices which are good  indicators of future prices  + Solves the vanishing and  exploding gradient problem | - Mixed results when predicting REIT stock prices | (Axelsson & Song, 2023), (Habbab & Kampouridis, 2022), (Obthong et. al., 2020) |
| Random Forest (RF) | Daily Price- Volume Data,  Fundamental  Data |  | + One of the few papers  to incorporate fundamental  data into machines learning models | - Relatively low sharpe ratio compared to market indexes | (Cao, 2021), (Huang et. al., 2021) |

## Predictive Accuracy

A recent paper aimed at predicting REIT share prices through 5 machine learning algorithms and 3 traditional benchmarks, which includes many of the methods in Section 3.2

above, found that machine learning models (MLR, LSTM) appear more accurate than

traditional benchmarks (ARIMA). The algorithms were trained solely on daily price data,

and Figure 3.1 shows the RMSE results for out-of sample predictions over different time

periods (30, 60, 90, 120 and 150 days).

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**Figure 3.1: RMSE results for REITs using various ML Models (Source: Habbab &**

**Kampouridis, 2024)**

## Gaps in Past Research to be Addressed

From the literature review in Section 3.3, it appears that there are the following gaps that

can be further explored in this paper:

1. From the ”Data Inputs” column, it appears most papers use price-volume (technical) data without fundamental data to make predictions.
2. From the ”Objectives” column, most papers are focussed on predicting stock prices and rarely address portfolio allocation or optimisation (i.e. to use these predictions to inform buy/sell decision of each stock in a portfolio or to find the optimal weights of each stock in a portfolio to maximise the sharpe ratio).

# Datasets

## Extended Fundamental Data Features

While many papers have obtained price-volume data from Yahoo Finance’s API (yfinance), this data only contains 10 or so price-volume indicators listed in Appendix A. This paper goes further by obtaining a comprehensive list of 161 fundamental features from FinancialModelingPrep’s (FMP) API.

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A script was written to combine the data from various api endpoints and backfill any missing values. Because price-volume data is available daily while fundamental data is generally available quarterly, a function is written to backfill the fundamental data such that daily numbers are available.

## Feature Exploration with Decision Trees

Running a 25 layer Decision Tree on all 171 features reveals the strongest predictors for the next day’s closing price. The top 4 layers are in Figure 4.2:

A diagram of a tree

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Figure 4.3 also shows the weights of the top 10 features in the Decision Tree. From both figures, it appears many of the balance sheet, income and cash flow statement features are indeed strong predictors of share price, coupled with technical features like Volume and Percentage Change in Share Price.

A graph of a tree

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## Feature Selection

From the decision tree, it also appears that many of the top features can be encapsulated by other features. For example, Other Current Liabilities is a component of Total Current Liabilities, Expenses are part of Net Income and Cash Items are a part of Cash From Activities. Given that the tree was generated from only one stock ticker, to make the feature selection generalisable to all 150 tickers, the results are contextualised with financial knowledge to derive the final 22 Selected Features presented in Figure 4.4. The financial significance of each feature is explained in the column ”Domain Importance”.

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In the preprocessing step, up to 20 years of historical data with these 22 features are retrieved for 150 stock tickers, and appended to a dictionary which stores all the required data for each ticker.

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Figure 5.1: Overall Workflow For This Paper

## Machine Learning for REITs Portfolio Optimisation

**With reference to Figure 5.1, the first approach of machine learning for optimisation**

**consists of two parts, A) Price Prediction and B) Trade Execution.**

### MLR / NN / LSTM Predictions with Extended Features

At the pre-processing stage of all three models, data for each ticker is split into the training and test sets with a 80:20 ratio. The close price for each row is also shifted one day forward so that all 21 features can work on predicting the next day’s close. By and large, the implementation for all the models are relatively similiar except the lines of code where the model is actually used.

Each ticker will have an output prediction dataframe saved as a csv as follows:

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* Predicted: Predicted T+1 Day Closing Price
* Actual: Actual T+1 Day Closing Price
* Actual(t-1): Today’s Closing Price
* % Change Predicted: Forecasted % Change from Today to T+1 Day’s Close

The inputs to the LSTM model are slightly different. A lookback window of 7 days is

created by shifting the closing price one day backwards at a time for 7 days to form the

additional 7 features as in the Table 5.2.

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These prior days closing prices are appended to the 22 features input into the LSTM model.

### Trade Execution Logic

The second part of the machine learning approach requires implementing the logic to decide how to trade on these predictions. This extends past research by implementing the trading logic that decides how to act on predicted prices in order to optimise portfolios. All the predicted prices for all the dataframes are appended into a single large data frame, the parameters as follows are set and the green columns in Figure 5.2 are computed.

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A table with numbers and a green line

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* Predicted (t-1): Yesterday’s Predicted (T-1 of Predicted)
* Abs % Change Predicted: abs(%Change Predicted)
* error (t-1): Difference Between Yesterday’s Predicted and Actual
* rank: Rank of all 150 Ticker’s Abs % Change Predicted
* trade: If Abs % Change Predicted exceeds the action threshold parameter, trade an amount equal to % Change Predicted / trade factor denominator in millions. If shorting is disabled, does not take action on negative % Change Predicted.

Next, a transaction class is defined to store the historical price of the original transaction until the position is closed

A screenshot of a computer screen

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For every non-zero Trade amount in Figure 5.3, the transaction class is called with the required inputs and a transaction object is created in yellow.

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The closing transaction details are then added to each transaction object by iterating through the ticker’s price movement over time and calling the Action method of the transaction class, which will close the position when the conditions in Listings 5.5 are met.

### Performance Evaluation

In the evaluation phase the various dataframes will be consolidated to calculate the following time series from the start to the end of the test data:

1. The total daily value of each ticker over the entire period
2. The daily cash balance which started at 10 million
3. The daily total portfolio value = Sum of all the daily ticker values in point 1. and daily cash balances in point 2.

Expected Return: Following which the total expected return from the investment is calculated as follows:





Annualised Rate of Return:



Standard Deviation:



Sharpe Ratio:

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# Post-Processed Financial Dataset

Figure 6.1 presents a sample of the post-processed data for a single Ticker of its 23 fundamental and technical features. This extends the analysis beyond the usual price-volume data used in ML. Data for 150 tickers and up to 20 years are used to train the models.

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# Machine Learning Results

This section presents the results of porfolio allocation using MLR, NN and LSTM models.

## Evaluating Stock Price Predictions

In terms of the first part of the ML approach of stock price prediction, it appears all 3

models have predicted prices that closely mirror the actual prices in Figure 7.1.A graph of a graph showing the price of a stock market

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However, comparing their Mean Square Errors (MSE) reveals that LSTM provides the

most accurate price prediction, followed by NN and then LR, with a MSE of 212, 252 and

323 respectively in Figure 7.2.

A graph with different colored bars

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It appears that even while including fundamental data features, LSTM’s memory of historical price information does aid its ability to identify trends and make more accurate predictions (Obthong et. al.,2020). And NN’s multiple layers help to further reduce the error in predictions.

## Trade Execution Results with Different Parameters

In the second phase of the ML approach, the buy/sell decisions are made based on the

predicted prices. Using MLR as an example, where shorting is not allowed, the total value

of each ticker after trade execution over the test period from 2019 to 2024 is shown in

Figure 7.3.

A graph of different colored lines

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Each line in Figure 7.3 represents the total value of one out of the 150 investible tickers

throughout the portfolio allocation period. Correspondingly, the cash balances after various stock tickers are bought or sold is given in Figure 7.4. The sum of the total daily

value of stocks and the cash balance for the day will result in Figure 7.5, which is the

total portfolio value throughout the investment horizon.

The Figures show an inverse relationship between cash balances and value of shares held

because cash is traded for shares. The total portfolio value was maintained consistently

above the starting investment of 10 Million, although it spiked in early 2020 and fell

sharply thereafter. It is worthy to note that the COVID-19 pandemic started to seriously

impact the financial markets in mid-2020 which coincided with the total fall in portfolio

value.

The same trade execution logic is implemented for NN and LSTM as well, generating the

total portfolio value graph in Figure 7.5, upon which porfolio performance is evaluated.

A graph of a graph showing a number of cash balances

Description automatically generated with medium confidence A graph of a graph showing a number of stocks

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## Overall Evaluation of Performances

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After the total portfolio value graph of each approach is generated, the Risk and Profitability measures are calculated with the formulas in Section 5.1.3.

From the results, it appears that trading without shorting is superior in terms of profitability and sharpe ratio. This is possibly because short selling creates the potential for unlimited losses (Bryant, 2023), because regardless of how high share prices rise, the investor will have to buy back the share to return to the market maker.

Surprisingly, the NN approach has the highest Sharpe Ratio of 3.5 followed by LR with 2.53 and LSTM with 1.52. This could be because of how the trade execution logic is devised, which requires the change predicted to be above the action threshold percentage. The changes predicted by the LSTM model are relatively small and hence much fewer trades are made resulting in less profits. Nevertheless, NN and MLR have resulted in a profitable trading strategy that minimises risk and maximises profits with a sharpe ratio greater than 2.

## Benchmarking Against Indexes, ARIMA, GARCH

A graph with green and blue bars

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From Figure 9.1, it appears that ML models significantly outperform traditional approaches to portfolio optimisation with more than double the sharpe ratio. T Algorithm especially outperforms with its high sharpe ratio of 9.72 compared to the market index of 0.14 or the average REIT stock of 0.6. In terms of risk and volatility, the

ML models also have significantly lower volatity than the market index and ARIMA as

represented by the blue line.

## Key Findings

The key findings for this paper are as follows:

1. The extension of input data for ML models to include fundamental data results in acceptable predictions and portfolio returns that have a sharpe ratio of more than 2 for NN and LR approaches.
2. As whole the ML approaches adopted by this paper outperforms the traditional and market approaches.
3. It is surprising that despite LSTM’s highest accuracy in predicting the next day’s closing price, the portfolio allocation based on LSTM’s predictions perform the poorest. This emphasises that for the ML models, the trade execution logic that implements the actual portfolio allocation based on predictions has a large effect on the overall portfolio performance beyond price prediction.

## Future Work

As observed in this paper, the trade execution logic has a large impact on the overall profitability of the portfolio allocation for ML price prediction approaches. Hence, more experiments can be done with regards to the various parameters input into the trade execution code, and possibly refine the logic to improve performance. It is also conceivable that trade execution can be done with a Reinforcement Learning agent.

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