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Decision Tree-Based Hedging: Risk and Return Analysis

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Abstract— Effectiveness of a decision tree-based hedging strategy in the stock market, compared to a traditional hedging approach, is explored in this research paper. Historical stock data is used to employ a decision tree model for predicting price movements and devising a corresponding hedging strategy. The performance of both strategies is evaluated based on several financial metrics, including cumulative returns, Sharpe Ratio, Maximum Drawdown, and Calmar Ratio. It is indicated by our results that, while higher returns and superior risk-adjusted performance are yielded by the decision tree-based strategy, significantly higher risk is also entailed, as evidenced by a substantial maximum drawdown. Insights into the trade-offs between risk and reward in advanced hedging strategies are provided by this study, offering valuable considerations for investors with varying risk appetites.

Keywords—Decision Tree, Hedging, Stock market, Machine Learning, Time Series

I. INTRODUCTION

Hedging is one of the simplest and most important strategies used by investors to minimize the exposure of negative consequences of price changes in the financial market. Conventional methods of hedging include diversification of assets, portfolio insurance and derivatives – options and futures – which are used to manage the level of exposure to risk in order to achieve return. These methods have found a lot of application because of their ease and efficiency in managing portfolio risk and limiting downside risk.

However, the financial industry is gradually changing and the effectiveness of the conventional hedging may be questionable in the conditions of the non-linear and intricate markets. More possibilities for improving hedging strategies are opened by the use of machine learning. Of them, decision trees stand out because they can capture complex dependencies in the data while making few assumptions about the generating process. A kind of supervised learning algorithm, known as the decision tree, partitions data into subsets based on features and then makes predictions or decisions. They have been found to be most advantageous where the connections between variables are not easy to predict and can be best described as tangled. Decision trees create a tree like structure of decisions, with one single characteristic defining a node, branches being the decision made based on the characteristic and leaves being the predicted outcome.

In business analysis, decision trees may be used for forecasting and analyzing trends with regards to prices, and for making sound investment decisions. It includes the following advantages, which are; ease of interpretation, and the ease of handling

numerical and categorical data. Nonetheless, there are some disadvantages of decision trees which must not be forgotten: They can be overfitting thus, some precaution must be taken to ensure that they perform at their best.
The use of decision tree algorithms in the formulation of a hedging strategy for stock market investments is assessed in this research and a contrast made with a conventional hedging model. Whether the decision tree based strategy can offer better risk adjusted returns than the traditional methods is checked and how well it controls the downside risk is also analyzed.
The growing focus on applying state of the art machine learning algorithms to enhance investment decisions is the reason for this research. Thus, while credibility has been achieved through conventional hedging techniques, the flexibility needed for operating in today's environment characterized by increased risk may be wanting. New opportunities for improving the existing hedging techniques are planned to be opened with the help of the decision tree algorithms, which can provide investors with a more detailed approach to risk management and profit maximum.

II. LITERATURE REVIEW

These conventional strategies include Delta hedging, Portfolio diversification and Derivatives including options and futures. Even though these methods have been around for a while, they may not be very dynamic in changing market conditions. The application of machine learning with the use of decision tree algorithms in the financial market has been common in the recent past and some of the tasks include; stock price prediction, market regime classification and trading strategy enhancement. Since they are relatively easy to understand and implement in addition to their ability to work with linear and nonlinear data. Nonetheless, the use of decision trees in hedging strategies as a tool of riskmanagement has received little attention. Fama and French [1] provided the analysis of the common risk factors in stock and bond returns to establish the foundation for the understanding of the market factors that affect return. Their research on the three factor model of market risk, size and value has been greatly helpful in the formulation of conventional hedging strategies. Jegadeesh and Titman [2] have developed the concept of momentum strategies which entails purchasing assets with good recent returns and selling those with poor returns. Momentum investing is not a conventional hedge, but it is used in tandem with hedging to structurally control the risk of a portfolio. Syriopoulos, Theodore [3] focused on Stock market volatility spillovers and an efficient portfolio hedge. Batten, Jonathan [4] describe the possibility of hedging stock exposure with oil. Gennotte, Gerard [5] analysed market liquidity, hedging and associated crashes. They came up with rational expectation model. In the work of Ma, Rufei, Bianxia Sun [6], the impacts of stock market volatility on the correlations between the stocks and bonds, and between the stocks and gold are examined and the ability of the bonds and gold in Managing the stock market risk is also investigated. To the best of our knowledge, decision trees have been used to make predictions on stock prices and market directions in the financial market with certain level of accuracy. Karim, Rezaul, Md Khorshed [7] used the current algorithms and open source libraries to forecast the future stock price and shuffling of stocks. They employed Linear Regression and Decision Tree. Hindrayani, Kartika Maulida [8] conducted the Indonesian stock price prediction in the Covid19 era using decision tree regression. In [9], a hybrid model of GBDT and DE is put forward to detect insider trading based on the data of some related indicators. In [10], Basak, Suryoday, Saibal Kar used tree based classifiers to predict the direction of the stock market price. Ampomah, Ernest Kwame, Zhiguang Qin [11] examined Tree-Based Ensemble Machine Learning Models for Predicting Direction of Stock Price Movement. Awan Aizaz Imtiaz [12] used Decision Trees to predict Stock Exchange Behaviour. Chen, Rongjuan and Ruoxi Dong [13] have used the decision trees to determine the Twitter Sentiment and Stock Performance. Polamuri, Subba Rao [14] have used decision trees in order to predict stock prices. Dadej, Mateusz [15] used ensemble gradient boosting decision trees to predict share price on WSE. Hutapea, Joan Yuliana, Yusran Timur Samuel [16] compared precision between two techniques: Naïve Bayes Algorithm and Decision Tree-J48 for the Stock Price Forecast of Pt Astra International tbk of Having Data from Indonesia Stock Exchange. Jiang, Minqi, Jiapeng Liu, Lu Zhang [17] proposed a more effective stacking architecture with deep learning methods and tree-based ensembles for stock index forecasting.

III. METHODOLOGY

Proposed method entails a comparison between conventional and decision tree based strategies in hedging stock market investment. First, we gather and clean historical stock data, which is further split into two as training set and testing set. The conventional hedging approach [18-20] is integrated with the decision tree model to forecast stock price shifts for on-going hedging adjustments. Both strategies are assessed based on cumulative return, Sharpe ratio, maximum drawdown, and Calmar ratio. Last of all, the current metrics are compared to determine the level of effectiveness of the decision tree based approach in enhancing the risk-adjusted returns as well as improving the overall performance of the portfolio.

A. Data Collection and Preprocessing

For the purpose of comparison of the traditional and decision tree based hedging approaches, historical stock price data has been used. The data was pulled from the finance module and the data set includes the following. Data for this study includes a five-year period of data of Apple Inc. starting from 1st January 2017. Adjusted Closing Prices: Dividends and stock splits are given to bring more clarity to the changes in the stock price over a given period. It includes Trading Volume Data which can be included in the model as an extra feature to consider market activities.
Other features like moving averages [21], volatility measures [22] or macroeconomic variables [23] are introduced into decision tree based strategies. The data covers a five year period in order to be useful and reflective of a range of conditions

in the market. This data was then divided into training and testing sets in order to analyse how well the model is capable of working on data which it has not seen before.
For the pre-processing of data the given steps are taken as follows. Data that was incomplete was completed by using interpolation techniques [24] and imputation techniques [25] to allow for proper data analysis. To make the features comparable, which is important for most of the machine learning techniques, features were normalized or standardized. Other useful inputs for the decision tree model were created and included lagged returns and other features.

B. Traditional Hedging Strategy

The traditional hedging strategy used a basic method that involved making assumptions using the historical stock pricing information. The key elements of this strategy included:

- **Lagged Returns:** The traditional strategy relied on lagged returns [26] (e.g., returns from the previous day or two days prior) to predict future price movements. Lagged returns serve as proxies for identifying trends and potential price reversals.
- **Hedging Position:** A hedging position [27], either long or short, was determined based on the observed relationship between the lagged returns and future price changes. For example, if the historical data suggested that positive lagged returns often led to continued price increases, a long position in the stock or derivatives (such as put or call options) would be taken. Conversely, if a drop in price was expected, a short position or the purchase of put options would be used to mitigate risk.
- **Execution of Hedge:** The hedging strategy was executed by adjusting positions based on the historical data's predicted direction of stock price movements. This method is static and depends solely on historical price patterns without incorporating machine learning predictions.

Here is the pseudo code of this strategy.
Input:

- Historical stock price data (Prices[])
- Length of lag (n), Threshold for significant price movement (threshold)
- Financial instruments for hedging (e.g., long, short positions, or options)

Output:

- Hedging position (Long or Short)
- Profit/Loss from the hedging strategy

Step 1: Data Collection

1. Fetch historical stock price data:
   Prices[] = get_historical_prices(stock_symbol, start_date, end_date)

Step 2: Data Preprocessing

1. For each day t, calculate daily returns:
   Return[t] = (Prices[t] - Prices[t-1]) / Prices[t-1]
2. Compute lagged returns for a specified lag nnn:
   Lagged_Return[t] = (Prices[t-n] - Prices[t-n-1]) / Prices[t-n-1]

Step 3: Define Hedging Parameters

1. Set threshold for significant price movement:
   threshold = 1%
2. Define financial instruments for hedging:
   instruments = {"long_position", "short_position", "put_options"}

Step 4: Generate Hedging Signal Based on Lagged Returns

1. For each day t, compare the lagged return to the threshold:
   If Lagged_Return[t] > threshold **Then** Set signal to "Long Position"
   Else If Lagged_Return[t] < -threshold **Then**Set signal to "Short Position"
   ElseNo hedge action required

Step 5: Execute Hedge

1. **If** signal is "Long Position":Buy stock or call options execute_long_position(stock, quantity)
2. **If** signal is "Short Position":Short the stock or buy put options: execute_short_position(stock, quantity)

Step 6: Evaluate Hedging Position

1. Track the price movement after the hedge is placed:
   Profit/Loss = Position_Size * (Price_exit - Price_entry)

Step 7: Monitor and Adjust Position

1. On each subsequent day t, recalculate lagged returns:
   Lagged_Return[t] = (Prices[t-n] - Prices[t-n-1]) / Prices[t-n-1]
2. Adjust the hedging position based on new signals:
   If signal changes, close existing position and open a new one.
   close_position()
   open_new_position(signal, stock, quantity)

Step 8: Performance Evaluation

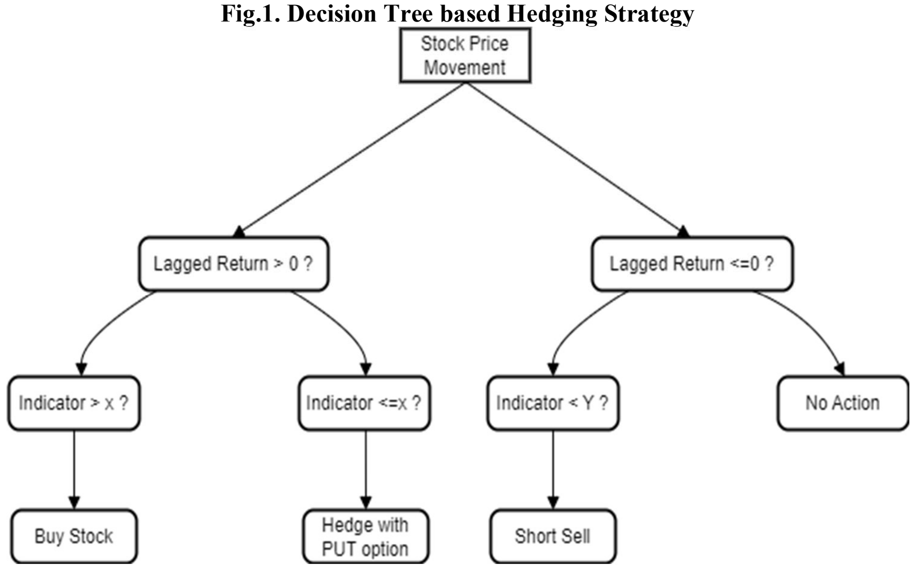
1. At the end of the period, compute cumulative return:
   Cumulative_Return = sum(Profit/Loss)
2. Calculate performance metrics such as Sharpe ratio, maximum drawdown, and Calmar ratio to evaluate risk-adjusted returns:
   Sharpe_Ratio, Max_Drawdown, Calmar_Ratio = compute_performance_metrics()

C. Decision Tree-Based Hedging Strategy

The decision tree-based hedging strategy leverages machine learning to enhance predictive accuracy and dynamic hedging. One well-liked and easily understandable machine learning method is the decision tree model. was trained on the historical data to predict stock price movements. The key steps in this strategy are as follows:

- **Model Training:** The historical data, which included parameters like lagged returns, trade volume, and technical indicators, was employed in the decision tree model's training. The direction (e.g., up or down) of future stock price movement was the target variable. By recursively dividing the data according to feature values, the decision tree method creates a model that, by following decision paths inside the tree, predicts future events.
- **Prediction:** Once trained, the model was used to predict the future direction of the stock price. The decision tree model examines the input features (e.g., lagged returns and technical indicators) and follows the trained decision paths to output a prediction—either an upward or downward price movement.
- **Hedging Position:** The predicted price movement determined the hedging position. If the model predicted a price increase, a long position was taken in the stock or derivatives. Conversely, if a decrease was predicted, a short position or the purchase of put options was implemented. The dynamic nature of this approach allows for continuous adjustments to the hedge, adapting to new data and changing market conditions.
- **Execution of Hedge:** According to the model's output, hedging positions were updated with high frequency to ensure that the decision making was more timely and effective as opposed to the conventional approach. The basis for these hedging decisions was derived from the decision tree model in an effort to minimize risk exposure while still trying to earn some profit

Fig.1. Decision Tree based Hedging Strategy



IV. PERFORMANCE METRICS

In order to assess and compare the performance of the traditional and decision tree-based hedging strategies we use several financial measures. These metrics also provide information on the returns on each strategy and the risk, risk management, and stability of the strategies. Below is an elaboration on each of the performance metrics used in this study:

A. Cumulative Return

Compound return [28] means the net percentage profit or loss achieved in investment throughout a given period. It is determined by finding the difference between the last value of the investment and the first value of the investment then divided by the first value.

Cumulative Return= $(V_{final}-V_{initial}) / V_{initial} \times 100\%$

Which V_{final} is the final value of a portfolio and $V_{initial}$ is the first value of a portfolio. This metric gives a direct indication of the extent to which the size of the portfolio had expanded or contracted in the course of testing. Its usefulness is very important for understanding the absolute performance of the hedging strategies. Cumulative return serves as relative performance index, and the larger sum of cumulative return is, the higher overall performance is. Nevertheless, this measure fails to consider how high-risk or volatile the returns are which may be obtained.

B. Sharpe Ratio

The Sharpe Ratio [29] is a ratio of excess return with the standard error of the excess return. In it the extent to which extra return (above the risk free rate) is available for each unit of risk taking as measured by the standard deviation of portfolio returns.

Sharpe Ratio = $(R_A - R_f) / \sigma_R$

Where RA is the average portfolio return, Rf is the risk-free rate that can be from the returns of government securities, σR is the standard error of portfolio returns. The Sharpe Ratio aids in learning the performance of the process in utilizing risk to generate returns. It is especially necessary when one wants to make a comparison between the strategies with dissimilar level of risk. Sharpe Ratio increases when there is better risk-adjusted returns in the selected stocks for investment. It is common that a value of the ratio greater than 1 is desirable and where the ratio is less than 1 may mean that possibly the returns may not adequately compensate for the risk.

C. Maximum Drawdown

Maximum Drawdown (MDD) [30] represent the biggest single falling from the lip to the bottom in the course of the analysis period in value of the portfolio. It quantifies the maximum possible loss which the investor is likely to experience in the investment.

Maximum Drawdown=Trough Value−Peak Value×100%

The major importance of this measure can be described with the help of the following statement: This metric is a key in measuring the probability of the large potential losses within the portfolio. It aids investors in determining the risk of adverse turns and in evaluating whether a particular strategy will protect capital should the market go south. A smaller Maximum Drawdown shows that the strategy is capable of helping to avoid more substantial losses. A large drawdown can be quite problematic because of the big amount to be made to restore the lost value.

D. Calmar Ratio

The Calmar Ratio [31] is a measure of the amount of return against the drawdown risk. It hold the portfolio's average annual return against the Maximum drawdown occur within the period.

Calmar Ratio=Average Annual Return / Maximum Drawdown

The major advantage of the Calmar Ratio is that it takes into account money making as well as drawdown risk involved in the strategy. Although useful generally, it is especially effective in critiquing plans which might yield high value-added at the expense of risk. A Calmar Ratio greater than the value signifies a better risk-return ratio for drawdown. That would imply that the strategy can make good returns, while also not taking all that much risk in the process.

V. RESULTS AND DISCUSSION

Appointment of a Tree Deployment Strategy for the decision tree was achieved and the results yielded a final Portfolio return of 147.64% in contrast to the traditional hedging approach return of 19.37%. This stark difference underscores the advantage of machine learning models to identify opportunities in the market that ordinary approaches miss.

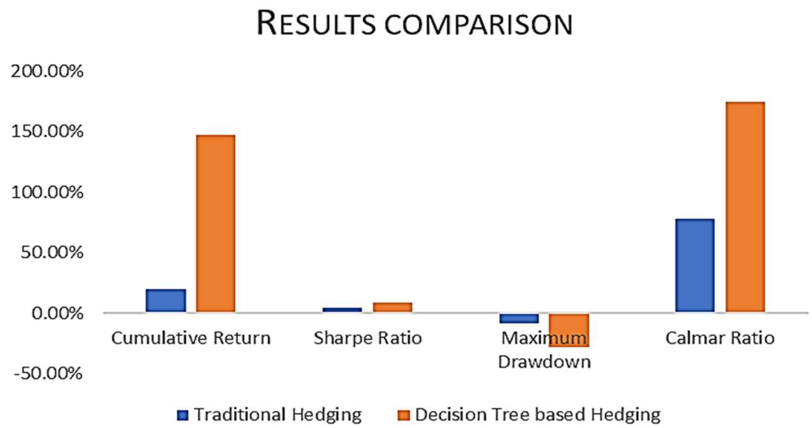
From table 1, the Sharpe Ratio for the decision tree-based strategy was 0.09 while that of the traditional strategy was 0.04. Although both ratios are low meaning that there are moderate risk adjusted returns the tree-based method performed better. This means that the decision tree model was capable of giving higher returns for the incurred risk as compared to normal risk adjust returns, nonetheless the effectiveness of both strategies in converting risk into return is still mediocre.

Table 1. Results comparison

Metric	Traditional Hedging	Decision Tree based Hedging
Cumulative Return	19.37%	147.64%
Sharpe Ratio	0.04	0.09
Maximum Drawdown	-8.28%	-28.28%
Calmar Ratio	0.78	1.75

maximum drawdown comes out as one of the most important identification from the two strategies. The maximum drawdown of the traditional strategy was at -8.28% which inferring that the involved risk was low. On the other hand, the strategy that used the decision tree approach suffered a much greater draw down of 28.28% thus opening up the model to more downside risk. Such a divergence also epitomises the standard deviation and probable losses inherent in the decision tree based strategy constant even with increased returns.
We can result comparison in following graph in fig.2

Fig.2. Results Comparison of Traditional Hedging Strategy vs Decision Tree based Hedging Strategy



The Calmar Ratio for the decision tree based strategy was 1.75 while for the traditional strategy the Calmar ratio was 0.78. This means that given the higher drawdown of the decision tree-based strategy the returns were even bigger than the drawdown risk it had taken. The downside, also, is that the drawdown percent is higher, indicating investors using this strategy may suffer significant fluctuations in their totals.

VI. CONCLUSION

As the findings of this study show, decision tree-based hedging approach's configuration could be more profitable, as well as providing superior risk-adjusted returns to a traditional hedging strategy, but the risk that the new hedging technique incurs is higher and is manifested in the way of a larger maximum drawdown. Accomplished these objectives may come with some extra risk and thus such strategies should benefit of doubt when used by investors. Traditional hedging strategy on the other hand may appeal to the decision makers of the conservative investors as it has relatively low level of risks. On the other hand, those investors with a relatively higher risk tolerance target higher returns and will therefore prefer the decision tree based method as they have high variability with the potential for steep declines. Further studies may be directed toward combining these algorithms with more advanced and sophisticated versions of the ML models, which could support enhanced performance of the models and, therefore, lower risk. Moreover, a study assessing how changing market conditions affect the effectiveness of these strategies would also offer some understanding of their flexibility.

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