Empirical Analysis of Linamar Corporation's Monthly Stock Return Rates using Machine Learning Models

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***Abstract*—Stock market prediction has long been a hot topic that attracts a lot of talented researchers. Needless to say, the ability of making accurate prediction about the stock market will prove huge financial benefit; however, due to the high volatility nature of financial data, despite of the intensive research, efficient algorithms that can make accurate prediction of the stock market still need to be discovered. In this paper, several machine learning algorithms, i.e. linear regression, decision tree, random forest are tested based on the last 20 years' Linamar Corporation's stock's monthly return data. These models are evaluated using standard strategic indicators: RMSE (for regression) and Accuracy (for classification). The Result shows time series sliding window model (RMSE = 10.78%) and multi-variable linear regression model (RMSE = 11.42%) performs slightly better than the last 20years historical average, but more research still needed to improve the performance of the models.**

***Index Terms*—stock market, machine learning algorithms, decision tree, random forest, CAPM, monthly return rate, time-series analysis**

I. Introduction

Eugene Fama, the laureates of the 2013's Nobel Economic Prize, also know as the father of Efficient-Market Hypothesis has demonstrated that the past history of securities prices are indeed rich information content, in an efficient market; however, these information have been fully reflected on the securities current prices already (price change is stochastic, and has no memory) [1]. This is to say, in an equilibrium market, all new information affect prices almost immediately and any successive price changes can only be triggered by new information; therefore, there is no any meaning full way to make prediction on stock price to try to beat the market's average return rate.

However, on the other hand, with the development of modern machine learning technologies, if one can identify certain extra information from the historical data, online data or even social media data [2] that not has been realized by general public yet, these additionally information could form information barriers, and market equilibrium could be broken for a short period of time. As an privilege, this non-equilibrium market position could potentially be used to provide excess return rate higher than what the market average can provide [3].

This research aims to answer the following question: Does there exist any machine learning trading strategy that guarantees a better return rate on a certain stock that is better than the market average?

The structure of this paper will be as the following. In Section II, several commonly used economic terms such as Excess Return Rate, Leverage, Market Equality, Book-to-Market ratio are reviewed (these servers as different features to train any machine learning model), then several commonly used machine learning stock market prediction model are reviewed (these are the potential models that can be used for this research topic); From Section III to Section IV, Time Series Move Average, Linear Regression, Decision Tree and Random Forest are explored and result are presented. In Section V, the different performance between different models has been discussed, which is suggesting the potential further research direction of this topic

II. Literature Review

A. Financial Variables

There are several factors that have been shown that have great effect on the stock market monthly return rate. The Capital Asset Pricing Model (CAPM) developed by Sharper, Linter, and Black in the late 1970s [4], has successfully explained the stock market monthly return between 1941 and 1965 [5]. This model is also referred as the SLB model.

$$R_i = \beta_{market}\left(R_{market} - R_{free}\right) + R_{free} \tag{1}$$

This model demonstrated a simple and beautiful linear relationship between the expected monthly return rate of a security, R_i, and the whole stock market's average monthly return rate R_{market}. The exposure coefficient, $\beta market$, is the so-called market β while the risk free monthly return rate is denoted as R_{free}. Normally, people use the monthly return rate of the three-month U.S. Treasury bill as an estimator for R_{free} [6]

In 1992, by empirical analysis of the 1963 to 1990's NASDAQ, NYSE, AMEX's historical record, Fama and French proofed that there are actually multi-variables that are affecting each stock's monthly returns rate [7], [8]. Fama obtained great reputation from this work, and later on was awarded the 2013 Nobel Economic Prize. Inspired by Fama's theory and utilizing Fama's approach, one of Fama's students and research assistant (1969-1971), David Booth, started an index-trading fund, Dimensional Fund Advisor (D.F.A.) in 1981. It didn't took Booth too long to become a billionaire, D.F.A. quickly developed into a hug mutual fund empire, and Booth donated $300 million to University of Chicago, and named the business school after this name, "The University of Chicago Booth School of Business" [9].

In 2015, Fama and French wrapped their theory in a more complete 5 variables equation [10]:

$$\begin{aligned} R_i = &\beta_{market}\left(R_{market} - R_{free}\right) + \beta_{size} SMB + \\ &\beta_{value} HML + \beta_{earn} RMW + \beta_{behavior} CMA + R_{free} \end{aligned} \tag{2}$$

Where the term SMB is the difference variable between small market capitalization companies minus the large market capitalization companies; the term HML is the difference between high book-to-market equity companies minus the low book-to-market equity companies, the RMW term is difference between the companies with robust earning ability minus weak earning ability, and the CMA term is the difference between companies with conservative investment behavior minus the companies with the aggressive investment behavior. These five Fama-French variables can be downloaded from French's research website [11], and will be used as variables for the following sections to feed into the machine learning models.

For clarity, several frequently used financial variables are explained as below [12]:

- Market Equity (ME), also known as market capitalization, is defined as a stock's price times the number of outstanding shares on the market;
- Book Equity (BE) is defined as the book value of a company's common equity;
- Book-to-Market Ratio (BE/ME) is defined as the book equity over the market equity of a company. A company of low book-to-market ratio is considered as a grown company (like Google, Facebook, and DoorDash) while, a company of high book-to-market ratio is considered as a value company (like Oil, Steel, Railway, Airports companies) .
- Earning/Price Ration (E/P) is defined as the net income of a company after tax dividing by the the companies market equity. This variable stands for how much money per share price the company can make.
- Leverage, also known as Debt-to-Equity ratio (DER) is defined as the company's total book value of assets minus the company's book value of common equity divide by the company's market equity.
- Historical Stock Price (HSP) is the past stock price including opening, closing, high, low price as well as volume.

B. Machine Learning Models

Stock price prediction is a subset of time series forecasting, and in the past decades, there are intensively studies attempting to reveal and capture the patterns of stock market.

- Sliding Window: By setting a constant working window length, sliding windows approaches update the latest data into the stack, and pop out the oldest data. In 2018, Jui-Sheng [13] demonstrated a novel approach to expand a time series data into higher dimensional space by setting a vector of different time delays. This approach has shown high efficiency and accuracy in short period time series prediction, but lack of accuracy in long term prediction [13]–[15].
- K-Nearest Neighbors: K-Nearest Neighbors (KNN) method is easy to understand and implement with relative short training time. This method is particularly a good fit for multi-modal classes [16]. Rudra has shown that the hybrid model of Support Vector Machine (SVM) and K-Nearest Neighbor is effective in making prediction for India Stock Market [17]. Yingjun has shown that SVM combined with a feature weighted KNN model is robust and presented good capability for forecasting Chinese stock market indices [18].
- Random Forest: Some researchers has shown that tree-based classifiers are potentially good approaches for forecasting the direction of stock market [19]–[21]. Perry has shown that Random Forest is outperform SVM and ANN in predicting the direction of stock market in a 20 days prediction horizon [22]. Focusing on clean energy stock returns, he has obtained a more than 85% accuracy rates with random forest, while the conventional logit models can only make about 60% accurate predictions
- Long Short-Term Memory: Long Short-Term Memory (LSTM) is a subset of Recurrent Neural Network (RNN), and is reported to have a better performance than conventional neural networks in stock prediction and speech recognition [23]. Inside of a LSTM block, a computation unit replaced the traditional hidden layer of neural networks. In the computation unit, short term memory are treated as direct neuron activity (inputs), while the long term memory are treated as the connection weight between the input neuron and output neurons, this is the so-called long-term memory trace. Dev has reported that LSTM outperformed the deep neuron network in weekly Indian stock market prediction [24].

C. Evaluation of Models

The evaluation of clustering models, classification models and regression models are different. Due to the nature of stock return rate prediction, regression models are use in this paper. A few of the commonly used evaluation metrics for stock prediction are listed below [13], [25]:

- Correlation (R) is defined as the co-variance between depend variable, x, and independent variable, y, over the square root of the standard deviation of x and standard deviation of y

$$R = \frac{COV\left(x, y\right)}{\sqrt{Var\left(x\right)}\sqrt{Var\left(y\right)}} \tag{3}$$

- Root Mean Squared Error (RMSE) is defined as the average of squared error between predicated value, y, and true value, t. This index is commonly used to measure the discreteness of a series of estimated values (spread).

$$RMSE = \sqrt{\frac{\sum_{i}^{n} (t_i - y_i)^2}{n}} \tag{4}$$

- Mean Absolute Percentage Error (MAPE) is defined as the averaged and scaled absolute percentage error, and this is commonly used for index the performance of a prediction model.

$$MAPE = \sum_{i}^{n} \left| \frac{t_i - y_i}{t_i} \right| \times \frac{100}{n} \tag{5}$$

- Mean Absolute Error (MAE) is defined as the averaged but unscaled summation of magnitude of errors in a series of predictions. This is an index for the accuracy of the prediction model.

$$MAE = \frac{1}{n} \sum_{i}^{n} |t_i - y_i| \tag{6}$$

III. Method

A. Data

Linamar Cooperation, with more than 40 dividends and 27,000 employees worldwide, is the second largest automobile parts supplier in Canada, based in Guelph, Ontario. Linamar's stock are public traded in Toronto Stock Exchange with symbol LNR.TO. In this research, the Linamar Corporation's last 20 years monthly return (dividend included in each individual month) are used as source data. As shown in Fig. 1, the past 241 months' monthly return, from 2001 Oct, to 2021 Oct, is following a normal distribution with slightly positive mean (1.5%) and slightly kurtosis on the positive side. These 241 data points are divided into training dataset (the leading 221 months' data) and testing dataset (the last 20 months' data). Fig. 1 basically illustrating that if one keeps buying LNR.TO at the start of a month, and selling out at the end of the month, for the past 20 years, the expectation of monthly return should be almost zero (1.5%). This makes buying stocks no different than playing a fair coin. Therefore, we indeed in the need of an effective machine learning algorithm to provide us extra guidance in selecting the good time to buy and sell the stocks.

Magna is the first largest automobile parts supplier in Canada, and is the direct competitor with Linamar. Both Linamar and Magna are considered as "value stock" as they all have high book-to-market equity ratio. On the contrast, International Business Machine, IBM, is a world famous IT company, is considered as a "growth stock". According to (1), Magna and Linamar should have similar market β, while, the market β between Linamar and IBM should be different. This can be easily observed from Fig. 2, the red and green linear fit line has very similar intercepts and slope, this is indicating the similarity between Linamar and Magna; while the blue linear

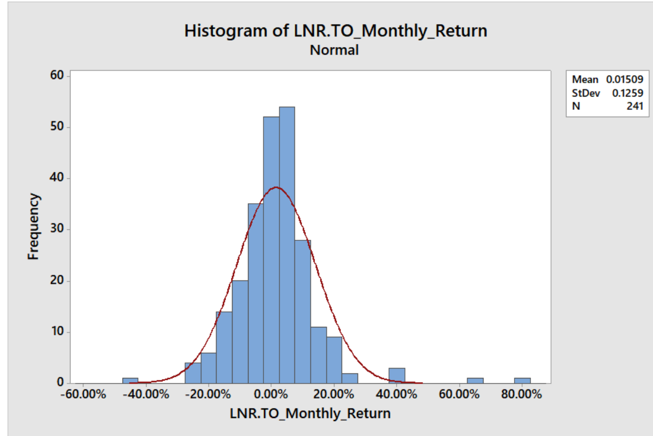

Fig. 1. The histogram of Linamar Cooperation's stock monthly return rate. 241 month's monthly return rate is collected from the past 20 years, this histogram shows that more than 100 months, the monthly return rate for this stock is almost zero. The histogram form a normal distribution with 0.15% average monthly return rate, and 12.6% standard deviation.

fit line for IBM clearly have a different slope, indicating that IBM is actually has less volatility with the market vibration. On the contrast, the Barrick Gold Corporation (ABX.TO) is the world's largest gold mining company, with headquarter based in Toronto. As the black triangle and fitting line shows in Fig. 2, Gold company generally has no risk exposure to the market's volatility, the slightly downward slope of the black fitting line indicates that it is generally believed that gold can be used to hedge the risk from the stock market [26], so it tend to slightly move to the opposite direction as the direction where the stock market moves to. Due to this fact, we can conclude that SPY500 and Gold are two independent variables, so both of them will be considered as features for the following machine learning models when possible.

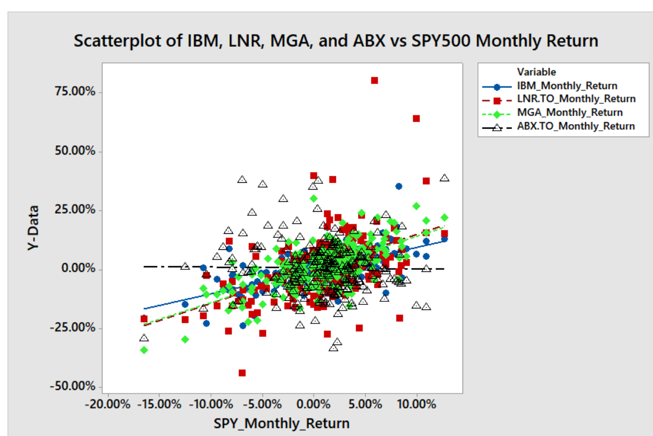

Fig. 2. The scatter plot of SPY500's monthly return rate vs. IBM (blue), Linamar (red), Magna (green) and ABX(black)'s monthly return rate, the latest 241 months' data are collected from Yahoo Finance (from 2001, Oct to 2021, Oct, dividends included). In general, return rate for stocks are positively related to market return rate (SPY500), as explained by (1), while return rate for gold is negatively related to the market.

IV. Result

A. Time Series Prediction

First, the most simple and naive time series prediction method is tested. As shown in (7), in this subsection, the last 12 months data is used to estimate the LNR.TO's return rate, x, at month t. The size of the sliding window, N, therefore is set to be 12, and $\vec{y}$ is the 12 dimensional vector of lagged x values [27].

$$\begin{aligned} x\,(t+d) \equiv & x\,(t+1) = f\,(x\,(t)\,, ..., x\,(t-N+1)) \\ x\,(t+d) = & f\,(\vec{y}\,(t)) \end{aligned} \tag{7}$$

For simplicity, the $\vec{y}$ in (7) is chosen as the numerical average of all the x values inside of the slide window (recall that N is the size of the slide window). The first step is to determine the optimized size of the slide window. As a rule of thumb, the long term pattern of a stock is saved in the time scale of 5 years, and the short term pattern of a stock is saved in daily basis. The totally 241 months' Linamar stock's monthly return data are divided into 80% for training + validation, and 20% for testing (the first 154 months for training, the middle 38 month for validation, and the last 49 months for testing). Sliding window size from 1 month to 60 months (5 years) were tested, and as shown in Fig. 4, the best slide window size is 10 months. This is to say, based on the validation dataset, the best strategy to forecast next month's Linamar stock monthly return is to use the average of the previously 10 month's monthly return rate.

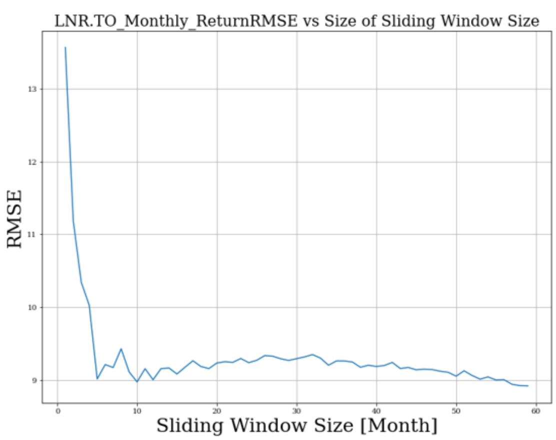

Fig. 3. The Root Mean Squared Error (MAPE) vs. Size of Sliding Window, based on training and validation dataset build upon the 210 months' Linamar stock (LNR.TO)'s monthly return data (from Oct, 2001), the best sliding window size is 10 months with RMSE equals to 8.97

Use 10-month as the sliding window size, the predicted result of the validation data and the testing data can be plotted (green and purple curve in Fig. 4). The sliding window result seems to have a more smooth trend than the real data, this is due to the selection of $\vec{y}$ function in (7). The average function of $\vec{y}$ will tend to smooth the volatility. The RMSE for the testing data is calculated as 10.78%. Comparing this number with the standard deviation value in Fig. 1, 12.59%, we can conclude that at least, this time series prediction model is better than make investment decision based on flip a fair coin. Future research could be done by changing the definition of $\vec{y}$ in (7) to try to capture more texture of the volatility and reduce the RMSE; however, due to the scope of this course project, different $\vec{y}$ will not be tested here in this paper.

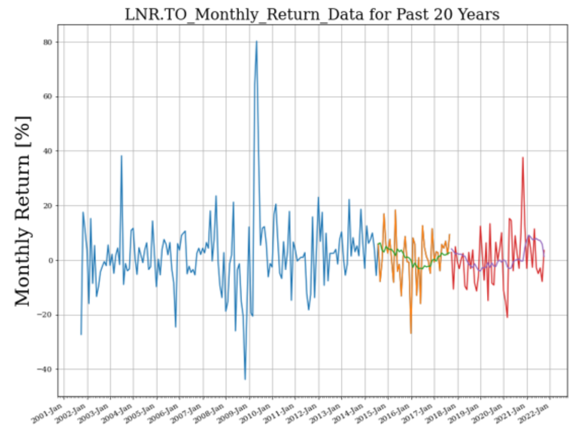

Fig. 4. The sliding window time series model's prediction result: the last 20 years Linamar stock's monthly return rates are displayed, the blue line is the historical data, the orange line is the validation used to calculate the best sliding window size, the red line is the testing data to evaluate the correctness of this model. The green line and the purple line are the predicted value for the validation data and the testing data, the RMSE for the testing set is 10.78%

B. Linear Regression

Fama and French 5 factor model (as shown in (2)) has demonstrated that in an equilibrium market, the expected monthly return rate of a stock should be a linear function of 5 features [10]. However, this is just a model to explain what have happened already, not a model to make prediction for what is going to happen in the future, as this equation is trying to use the current month's market return rate to explain the current month's individual stock return rate. In 1993, Titman has shown that the market index does contains momentum information in short period scale [28], the winners from the previous month tend to outperform the losers in the following month. Therefore, in this subsection, I use the previous month's Fama-French factors to fit next month's Linamar stock return rate, again, the 241 months data are divided into 80% for training, and 20% for testing (the first 192 months for training, and the last 49 months for testing). Training set is used to get the best coefficient parameters, and testing set is used to calculate the error of the model.

The first try is to use all Fama-French factors (SMB, HML, RMW, CMA, Risk-free) together with SP500, Magna stock return rate, IBM stock return rate, and ABX.TO's return rate (justification is given in Fig. 2). Following the same procedure as the ENGG6500 class's second assignment, 12.41% RMSE for training set and 11.42% RMSE for testing set was obtained.

As shown in Fig. 6, the correlation study shown that in the past 20 years, not all the fama-french factors are linear independent from each other, and the stock prices (IBM, Magana, ABX, are also correlated together) are also highly correlated with each other. By looking at the 1st row of heap map in Fig. 6, we can see a higher correlation between Linamar and IBM's monthly return. By finding more of the stocks have high correlation with Linamar should potentially increase the accuracy of our model. It also worth to point out that the reason why Linamar is showing no correlation with Magna in Fig. 6 is that we have shift down the data for all the linear regression variables by one month (we are correlating Linamar's Feb data with Magna's Jan data, and correlating Linamar's Feb data with Magna's March data, etc) so that we are not involve any future information when we make prediction. The accuracy of the model can be improved by finding more variables that have strong correlating with Linamar stock's monthly return, or by applying principle component analysis to make the variables more independent with each other.

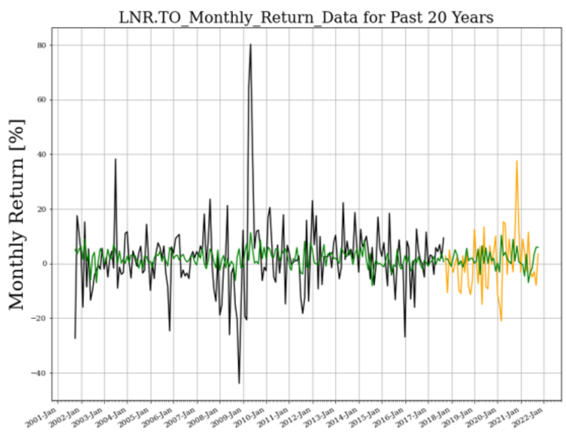

Fig. 5. The linear regression model's prediction result: the last 20 years Linamar stock's monthly return rate are displayed, the black line is the training set, the orange line is the testing set, and the green line is the trained linear regression model (regression details are discussed in Chapter IV section B), the RMSE for the training set is 12.41%, and RMSE for the testing set is 11.42%

C. Decision Tree and Random Forest

Utilizing the same dataset as the linear regression model, we can try to fit a decision tree to make prediction about the direction of Linamar stock's monthly return rate. If we expect the next month's return rate is positive, we report a "Long" position to indicate that we should hold the stock, while, if we expect the next month's return rate is negative, we report a "Short" position to indicate that we should sell the stock at month end. Use the same method as the first assignment of the ENGG6500 course, a decision tree was build based on all the variables same as the previous section. 80% of the data were used to build the tree, and 20% of the data were used for testing, as shown in Fig. 7, the accuracy of the decision tree was fairly low (only 41%). This model is no better than make prediction with a fair coin. The reason for the failiur of decision tree is that the features used to build the tree is not strongly related with the predicted variable, and this problem actually can be seen from the heat map in Fig. 6 in the previous subsection.

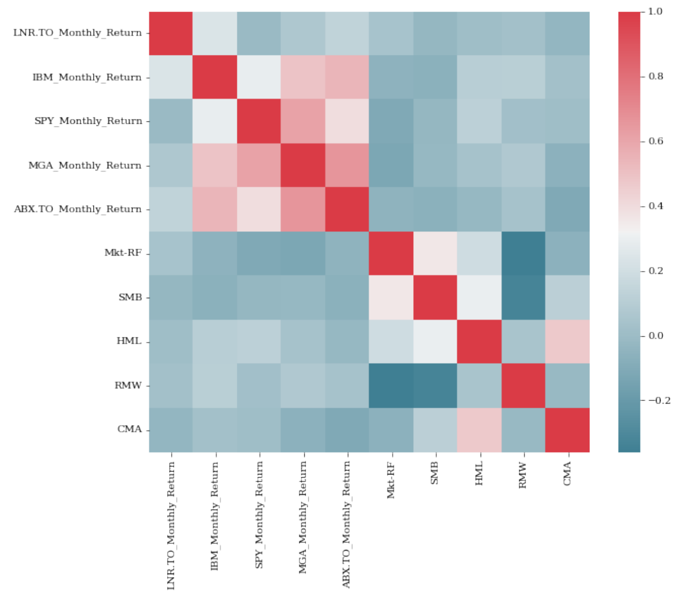

Fig. 6. The correlation matrix for all the linear regression variables, the IBM, SPY500, and Magna and ABX.TO are highly correlated, and the Mkt-RF, SMB, HML CMA Fama-French factors are also correlated, all these parameters are used for linear regression.

The next question would be: Can the poor testing accuracy of decision tree could be saved by expanding the decision tree to a random forest? In order to answer this question, I have conducted an experiment to expand the decision tree model to different size of random forest. As shown in Fig. 8, as we increase the number of estimators in the random forest, the training set accuracy is increasing and reached to 100% with about 30 estimators; while, the testing accuracy is just vibrating around 50% . Fig. 8 is suggesting that random forest can not save the bad performance of the decision tree model.

V. Conclusion

In summary, to predict the next month's Linamar Stock's return rate (regression), 1) time series sliding window prediction model and 2) multi-variable linear regression model are tested; to predict the direction of next month's Linamar Stock's return rate (classification), 3) decision tree and 4) random forest are tested. RMSE is used to estimate the power of the regression models, while accuracy on the test set (generalization accuracy) is used to estimate the power of the classification models.

My result shows that time series sliding window model (RMSE = 10.78%) and multi-variable linear regression model (RMSE = 11.42%) performs slightly better than the last 20 years historical average (StDev = 12.59% in Fig.1). The classification models has less than 50% accuracy (worse than flip a fair coin), and expanding decision tree model to random forest does not have significant improvement. My result shine a light into the problem of numerical prediction of stock market. On the other hand, my result also yield that more factors still need to be investigated/constructed to make more accurate prediction for stock market.

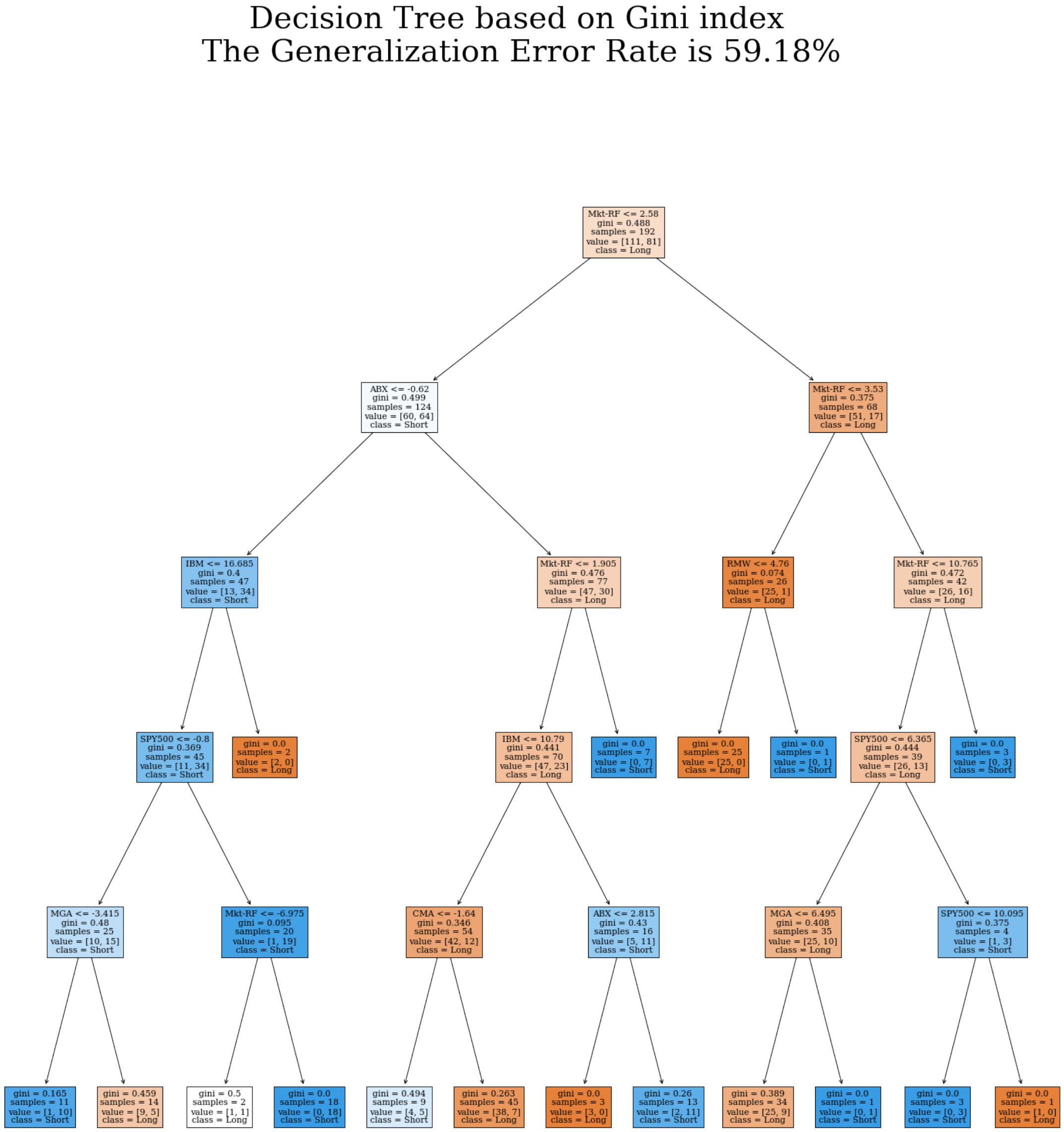

Fig. 7. The Decision Tree Prediction Model: 80% of Linamar's stock monthly return rate were used for building the tree, and 20% data were used for testing the tree. The error rate is high (59%) while the accuracy is low (only about 41% accuracy).

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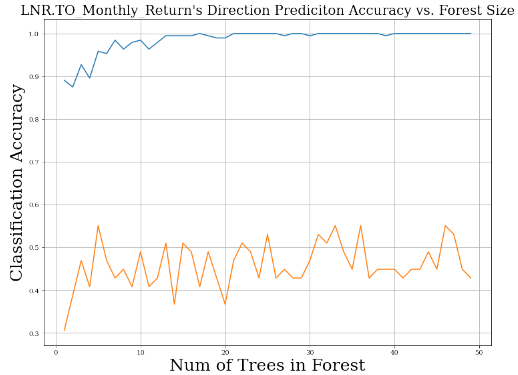

Fig. 8. The accuracy plot for random forest model, the blue line is the training accuracy, and the orange line is the testing accuracy, the number of estimators in the random forest change from 1 to 50. The raw data is Linamar stock's last 20 years monthly return rate, 80% used for training, and 20% used for testing.

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