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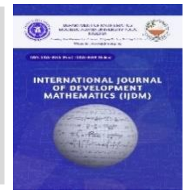

Foreign Exchange Prediction using Decision Tree Algorithm: A Machine Learning Approach

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ABSTRACT

The study used decision tree algorithm of machine learning to design a tool for predicting foreign exchange to help traders make well-informed trading decisions. The processes involve data analysis, preprocessing, model design, validation, and programming integration. The model was created using Python programming language in Jupita-Note to predict the forex market based on the FOREXTIME Meta Trader 4 dataset and applied preprocessing techniques for data normalization. Stochastic oscillator and Linear Weighted Moving average indicators were incorporated. It used historical data obtained from FOREXTIME for the decision tree. A predictive model utilizing a decision tree algorithm was designed to leverage these indicators for accurate forecasting. Evaluation metric techniques were employed to assess and evaluate the model's performance and reliability. The historical data gathered covered the years 2018 through 2023. The accuracy of the model was found to be 98%. This has shown the usefulness of decision trees in forex predictions. At implementation, Meta Quote Language 4 was used. Twenty transactions were executed based on the signal generated by the system over various time frames and currency pairs; 13 (65%) of the transactions were profitable, while 7 (35%) recorded loss. This practical implementation shows the applicability of the research findings in real-world trading scenarios. The achieved results underline the potential of combining machine learning and technical indicators to enhance trading decisions.

1. Introduction

The currency market, commonly known as the foreign exchange market or FOREX (FX), is a decentralized financial marketplace where currencies are exchanged. This covers every facet of purchasing, selling, and converting currencies at established or current rates. It is by far the biggest market in the world in terms of trade volume, with the credit market coming in second (Record, 2014). The bigger international banks are the primary players in this industry. With the exception of weekends, financial hubs all over the world serve as anchors for trade between a variety of different types of buyers and sellers. The foreign exchange market functions on multiple levels and is mediated by financial organizations. Banks use dealers, a smaller group of financial companies that engage in significant foreign exchange trading, behind the scenes. Although a few insurance companies and other financial institutions are active, this backroom sector is commonly referred to as the Interbank market because banks make up the majority of foreign exchange dealers. The foreign currency market, which is the biggest financial market in the world, now has six trillion dollars in daily trading activity, with terminal retail users accounting for 45% of all transactions (Bank for International Settlement, 2022). Exchanges worth hundreds of millions of dollars have been known to occur between foreign exchange brokers. Due to the problem of sovereignty when dealing with two currencies, FOREX has very few, if any, supervisory bodies overseeing its operations. (Investopedia, 2017).

Through currency conversion, the foreign exchange market facilitates global trade and investment. For instance, although its revenue is in US dollars, it allows an American company to import items from members of the European Union, particularly those in the Eurozone, and pay in euros. (Flassbeck and Marca 2007). it also encourages direct speculation and assessment on currency values as well as carry trade speculation based on the difference in interest

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rates between two currencies. Even when done within the bounds of local laws, financial speculating for the sole purpose of making money is immoral in the grand scheme of things. Dealers profit from supplying liquidity to customers, but they also run the risk of pricing risk due to flow uncertainty. They have two options: either they trade with other dealers on the open market to hedge their position and lower their inventory, or they can effectively skew their prices and wait for customers to reduce risk (externalization). Naturally, externalization has a greater degree of control, but it also has an impact on the market and raises transaction costs. The foreign currency (FX) community has been actively debating the internalization vs. externalization conundrum lately. The Fisher Effect barely makes a difference. The favorable but negligible impact of inflation on lending rates reflects this. Conversely, policy rate appears to play a significant role in determining lending rates at commercial banks (Doe and Tuffour, 2019). This article provides an ideal framework for market making that addresses both pricing and hedging, so providing a response to the commonly asked question among dealers: "Should I hedge or not?" (Bergault, Gueant, and Barzykin, 2021).

Rokach, Lior, and Maimon (2008). financial forecasting is still a really difficult task with a lot of ongoing study. To assist aspiring traders in analyzing the state of the market in order to make trading decisions, numerous scholars have put forth a variety of approaches. However, a higher proportion of novice and seasoned traders nevertheless suffer losses from time to time. For accurate forecasting and financial gain, numerous algorithms were created. The objective of this thesis is to effectively predict FOREX market movement through the application of machine learning and the decision tree method. Professionals, academic circles, and the media all frequently use the term "technical analysis." Technical analysis looks for identifiable patterns, or trading rules (or signals), that may be able to forecast future price movements. It is based on historical prices (and, in some circumstances, volumes) of securities. Decision trees, or predictive models, based on machine learning can be used to make inferences about an item's target value (shown in the leaves) based on observations about the object (shown in the branches). It is one of the methods for predictive modelling that data mining and statistics use. Classification trees are tree models in which the target variable is discretely variable; leaves in these tree structures represent class labels, and branches represent conjunctions of features that lead to those class labels. Regression trees are decision trees where the target variable is capable of taking continuous values, usually real numbers (Rokach, Lior; Maimon, 2008). Various markets, including stocks, FX, and commodities, can benefit from the application of machine learning trading strategies (Nelson, Pereira and Oliveira, 2017). Neural networks have demonstrated a high degree of predictive accuracy when applied to short-term exchange rate prediction for EUR/USD, GBP/USD, and USD/JPY. As a result, these networks can be utilized in practical systems to anticipate exchange prices one step ahead of time. (Svitlana, 2016)

Artificial Intelligence methodologies, particularly advanced Machine Learning and deep learning protocols, have become central to exploring non-obvious correlations and phenomena that influence the probability of trading success in the U.S. financial markets. (Cohen, 2022). Decision trees are a type of supervised learning algorithm (with a predefined target variable) that are frequently used in classification problems. It supports both categorical and continuous input and output variables. Tree-based learning algorithms are thought to be one of the best and most often used supervised learning methods. Tree-based approaches improve predictive models' accuracy, stability, and ease of understanding. The foreign exchange market is the world's largest and most accessible financial market, and while there are many FOREX investors, only a small number are actually successful. Many traders fail for the same reasons as investors in other asset classes (Botsvadze, 2018).

Furthermore, the market's tremendous leverage - the use of borrowed capital to maximize the possible return on investment - and the relatively narrow margins required when trading currencies prevent dealers from making repeated low-risk mistakes. Factors unique to currency trading can lead some traders to expect higher investment returns than the market can regularly provide, or to take on more risk than they would in other markets (Investopedia, 2017). Further investigation reveals that the economics of supply and demand have a significant role in exchange rate variations. Calculating the supply and demand curves to determine the exchange rate has proven impracticable (Alamili, 2011). As a result, one must use a variety of predicting techniques. Traditional linear forecasting approaches are limited by their linear nature, as empirical research has shown that exchange rates contain nonlinearities. Furthermore, the effectiveness of parametric and nonparametric nonlinear models has been proven to be limited (Alamili, 2011). With the transition to online buying, it has become vital to tailor clients' demands and provide them with additional options. Buyers investigate the attributes of a product before purchasing it. A recommender system filters information by assessing the similarity between members of a cluster to identify the elements that would result in more accurate recommendations (Shakoor and Maihimi, 2021). For these reasons, the application of computer intelligence in predicting foreign exchange rates was examined, and the constraints described earlier were resolved. This method employs the decision tree machine learning algorithm.

The study developed a Foreign Exchange forecasting tool that will assist traders in making trading decisions by using machine learning approach with a decision tree algorithm. Historical data was evaluated, pre-processed, and then normalized. A decision tree model for an expert advisor tool was built using the Python programming language, and stochastic oscillators and linear weighted moving average indicators were incorporated to improve the expert advisor tool's prediction capacity. The model's performance was validated using the cross-validation technique, and it was implemented on the Meta Trader 4 platform with the MQL4 programming language. The proposed Expert Advisor tool would assist traders in achieving automation and efficiency, increasing trading speed and accuracy, managing risk, and continuous monitoring. The expert advisor tool integrates the stochastic oscillator and linear weighted moving average (LWMA) in the context of technical analysis to improve trading decisions. It generates systematic signals for potential entry and exit points in forex markets and can execute trades to buy or sell. The tool integrates technical analysis, identifies trends, detects overbought and oversold conditions, generates signals, and is customizable. All of the generated signals are consistent with technical analysis principles. Though the program provides a structured framework for trading decisions, it accepts that it can be used as part of a full trading strategy that includes fundamental examination. Developing a comprehensive and complex trading system requires time, a solid understanding of the forex financial market, and programming skills.

2. Literature Review

2.1 Foreign Exchange Market

The foreign exchange market, often referred to as Forex or FX, is a global decentralized market for trading currencies. It is the largest and most liquid financial market in the world, with an average daily trading volume exceeding $6 trillion (Bank for International Settlements, 2022). The Forex market operates 24 hours a day, five days a week, allowing participants from around the world to engage in currency trading. The Forex market has a decentralized structure, meaning there is no central exchange or physical location. Instead, trading occurs electronically through a network of interconnected participants (Bank for International Settlements, 2022). The market comprises three main tiers: *Interbank Market*; this tier involves major banks and financial institutions trading currencies directly with each other. They act as market makers, providing liquidity and setting bid/ask prices (Bank for International Settlements, 2022*). Over-the-Counter (OTC) Market*; the OTC market consists of transactions between participants such as banks, corporations, institutional investors, and retail traders. Trades are conducted via electronic platforms, where buyers and sellers negotiate prices. *Retail Market;* the retail market caters for individual traders, including small investors and speculators. They access the Forex market through online platforms offered by brokerage firms. (Bank for International Settlements, 2022).

2.2 Traditional Forecasting Techniques for the Currency Market

The traditional methods for foreign exchange prediction face significant challenges, including volatility, unpredictability, and overreliance on economic indicators. These methods struggle to account for sudden changes, external factors, and non-linear relationships, leading to inaccurate predictions. Moreover, they rely on limited data, simplifying assumptions, and flawed models, which can further compromise their effectiveness. These limitations are exacerbated by the inability of traditional methods to adapt to changing market conditions in real-time, making them less effective in fast-paced markets. Forecasting currency movements is crucial for financial decision-making, risk management, and international trade. Traditional forecasting techniques have been widely employed in the field of currency market analysis. This section reviews the key traditional forecasting techniques used for predicting currency movements.

Fundamental analysis is a prominent approach used in currency forecasting. Researchers and analysts examine various economic indicators, such as GDP growth, inflation rates, interest rates, trade balances, and government policies, to assess the underlying economic fundamentals that drive currency movements *(Doe et al., 2002).* For instance, a study by Johnson and Brown (2001) utilized fundamental analysis to forecast exchange rate fluctuations by analyzing the impact of monetary policy decisions on currency values. Technical analysis is another widely used method in currency forecasting. Traders and analysts rely on historical price and volume data to identify patterns and trends that can help predict future currency movements. Chart patterns, trend lines, moving averages, and technical indicators such as the Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD) are commonly employed in technical analysis (Doe and Smith, 2002). Several studies have shown the effectiveness of technical analysis in predicting short-term currency movements (Lee and Wang, 2013).

2.3 Factors Influencing Exchange Rate Movements

Exchange rates in the Forex market are influenced by a variety of factors, including: Macroeconomic Indicators: Economic data such as gross domestic product (GDP), inflation rates, interest rates, employment figures, and trade balances impact exchange rates. Stronger economic indicators may lead to currency appreciation, while weaker indicators can result in depreciation (Afzal, Mohammad, Hamid and Bushra, 2013). Decisions made by central banks regarding interest rates, money supply, and intervention in the Forex market significantly affect exchange rates. Central bank actions are closely monitored by Forex traders for potential trading opportunities. Geopolitical events, such as elections, geopolitical tensions, and policy changes, can create volatility in the Forex market. Market participants closely follow geopolitical developments to gauge their impact on currencies. Investor sentiment, risk appetite, and market expectations play a vital role in determining currency demand and supply. Positive sentiment can lead to currency strength, while negative sentiment can weaken a currency. (Afzal, Mohammad, Hamid and Bushra, 2013).

2.4 Fundamental Analysis and Technical Analysis

Fundamental analysis is a prominent approach used in currency forecasting. Researchers and analysts examine various economic indicators, such as GDP growth, inflation rates, interest rates, trade balances, and government policies, to assess the underlying economic fundamentals that drive currency movements *(Doe et al., 2002).* For instance, a study by Johnson and Brown (2001) utilized fundamental analysis to forecast exchange rate fluctuations by analyzing the impact of monetary policy decisions on currency values. Technical analysis is another widely used method in currency forecasting. Traders and analysts rely on historical price and volume data to identify patterns and trends that can help predict future currency movements. Chart patterns, trend lines, moving averages, and technical indicators such as the Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD) are commonly employed in technical analysis (Doe and Smith, 2002). Several studies have shown the effectiveness of technical analysis in predicting short-term currency movements (Lee and Wang, 2013).

2.5 Machine Learning

Machine learning is the concept that a computer program can learn and adapt to new data without human intervention. Machine learning is a field of artificial intelligence (AI) that keeps a computer's built-in algorithms current regardless of changes in the worldwide economy(Charbuty 2021) . predicting stock markets has been an endeavour a lot of people have always tried to do. But it seems artificial intelligence may be better than humans in that regard. Machine learning has revolutionized trading, and hedge funds use machine learning trading strategies to predict market trends and beat the competition. But what are machine learning trading strategies? **A machine learning trading strategy is a method of using algorithms and statistical models to analyse market data and make predictions about future price movements. These predictions are then used to inform buying and selling decisions in the financial markets, but the algos can also be automated to execute trades. Machine learning trading strategies can be applied to various markets such as stocks, forex, and commodities (Nelson, Pereira and Oliveira, 2017).** The use of AIs has been on the rise in many industries, including the financial markets. Machine learning algorithms are used by hedge funds to analyse market data and make predictions, leading to more efficient markets. However, it also poses a risk of increasing volatility and dependence on technology. Machine learning is used in a wide range of applications such as natural language processing, computer vision, speech recognition, and financial forecasting. In financial trading, it is used to learn patterns of price movements and social media trends and then use such information to make trading decisions (Nelson *et al*, 2017).

2.6 Machine Learning as a Decision Tree

Machine learning as a decision tree (as a predictive model) can go from observations about an item (represented in the branches) to conclusions about the item's target value (represented in the leaves). It is one of the predictive modelling approaches used in statistics, data mining and machine learning. Tree models where the target variable can take a discrete set of values are called classification trees; in these tree structures, leaves represent class labels and branches represent conjunctions of features that lead to those class labels. Decision trees where the target variable can take continuous values (typically real numbers) are called regression trees (Rokach, Lior; Maimon, 2008). Decision tree is a type of supervised learning algorithm (having a pre-defined target variable) that is mostly used in classification problems. It works for both categorical and continuous input and output variables. In this technique, we split the population or sample into two or more homogeneous sets (or subpopulations) based on most significant splitter / differentiator in input variables. Tree based learning algorithms are considered to be one of the best and mostly used supervised learning methods. Tree based methods empower predictive models with high accuracy, stability and ease of interpretation.

I. Decision trees are very powerful models which help us classify data and make predictions. Not only that, they also give us a great deal of information about the data.

II. Decision trees are trained with labelled data, where the labels (or targets) that we want to predict are given by a set of classes

Decision trees are a very intuitive way to build classifiers, and one that really resembles human reasoning.

2.7 Decision Tree Algorithms in FOREX Prediction as compared to related algorithms

Despite the proven effectiveness of Support Vector Machines (SVM) and Artificial Neural Networks (ANN) in FOREX prediction, there are notable research gaps and limitations that decision tree algorithms can address. Support Vector Machines and Artificial Neural Networks have shown significant promise in handling complex and non-linear relationships within foreign exchange markets. However, these methods have inherent limitations that impact their overall effectiveness. One primary issue with SVMs is their complexity and lack of interpretability. The application of SVMs often necessitates complex kernel functions and meticulous parameter tuning, making the models computationally intensive and challenging to interpret (Tay and Cao, 2001). This complexity poses a barrier to understanding and trusting the model's predictions, a critical aspect in financial decision-making where transparency is essential. Similarly, ANNs, particularly deep learning models, suffer from a black-box nature. While ANNs can model highly complex patterns, their decision-making processes are not easily interpretable, which limits their transparency and trustworthiness (Zhang and Hu, 1998). This lack of interpretability is a significant drawback in financial applications, where stakeholders need to understand the rationale behind the predictions to make informed decisions.

Overfitting and generalization are other concerns associated with SVMs and ANNs. SVMs can be prone to overfitting, especially when dealing with small datasets or when an inappropriate kernel or hyperparameters are chosen (Tay and Cao, 2001). On the other hand, ANNs, due to their high flexibility, can overfit to the training data if not properly regularized. They require large amounts of data and careful tuning to generalize well to unseen data (Zhang and Hu, 1998). Moreover, computational efficiency is a significant challenge for both SVMs and ANNs. Training SVMs on large datasets, particularly with non-linear kernels, can be computationally expensive (Tay and Cao, 2001). Similarly, training neural networks, especially deep learning models, involves significant computational resources and time, which may not be feasible for all applications (Zhang and Blumeistin, 2017).

3. Materials and Methods

In developing the system, the architectural model was first created followed by the system flowchart, then a trading system decision tree was developed after which the system was analyzed and implemented. Developing a machine learning model is an iterative process. The method guarantees that the model is data-driven and able to make sound predictions and decisions. The relevant data needed for the model was identified through data identification. Preprocessing was performed, the training data was set, the model was developed, trained, and tested, and lastly prediction and evaluation was carried out.

3.1 Decision Tree Algorithm

The decision tree algorithm is a machine learning technique used to perform classification and regression tasks. In this study, all of the components and processes involved in the decision tree algorithm were applied. The procedure begins with a root node that represents the entire dataset, and then recursively splits the data into smaller subsets based on the values of different features. Each split creates a new node in the tree, resulting in branches representing various decision paths.

3.2 Data Collection and Extraction

Historical data for testing and training of the trading tool were downloaded online from the Meta Trader 4 platform through a broker called ForexTime. The historical data collected were for a period of five (5) years from 2018 to 2023. The dataset consists of 2167 rows and 7 columns. A sample of the data collected is in Appendix 1 After collecting the historical dataset, all the necessary libraries were imported into Python. These libraries *are Pandas, matplotlib, NumPy, Seaborn, mean_squared_error*. The dataset was then loaded into *colab*. Colab is an online Python platform for running Python.

3.3 Data Preprocessing

Data preprocessing is required to clean and replace missing values by meaningful values The historical data for testing and training the trading tool was sourced online from the MetaTrader 4 (MT4) platform via a broker called ForexTime (FXTM). This platform was chosen due to its widespread use in the financial industry and its reputation for providing reliable and comprehensive financial data. The dataset encompasses a five-year period from November 2018 to May 2023. The data was exported in a CSV file, which is then prepared by ensuring consistency in formatting, removing unnecessary columns or rows, and converting date and time columns to a uniform format. The prepared data was then cleaned by checking for missing or duplicate values, removing rows with missing values, and handling outliers or anomalies to ensure the data is accurate and reliable for analysis. The cleaned data was then analyzed by calculating technical indicators, performing statistical analysis, identifying trends and patterns, and using data visualization tools to illustrate findings to help uncover insights into market behavior and trends. The analyzed data was stored securely for efficient storage and retrieval. Furthermore, several essential libraries were imported into Python to facilitate data manipulation, visualization, and analysis. The libraries used include *Pandas for data manipulation, Matplotlib and Seaborn for data visualization, NumPy for numerical operations, and metrics such as mean_squared_error from Sklearn for model evaluation.* The dataset was then loaded into Google Colab. The dataset was preprocessed and cleaned. *It was then split into a feature dataset tagged as (X) and a target dataset as (Y) respectively.*

3.4 Feature Selection

The selection of features is a very important task in forex prediction future values. In this study, the feature used for independent variable extraction are OPEN, HIGH, LOW and CLOSE prices columns in the dataset table. The Table 1 shows the attributes or features of the data in the datasets and their descriptions.

Table 1 Dataset Feature Description Table

S/NO	Feature	Description
1.	Date	It shows the date in the format: yy.mm.dd.
2.	Open	It shows the price of the forex at market opening.
3.	High	It shows the highest price reached on that day.
4.	Low	It shows the lowest price reached on that day.
5.	Close	It shows the lowest price reached on that day.
6.	Volume	It shows the number of shares traded on that day.
7.	Time	It shows the time.

(Investopedia, 2023)

Independent and dependent variables were extracted. The independent variables are K, D dependent (target) is tagged "Signal", and encoded 0,1 and 2 values. 0 implies sell, 1 means buy, and 2 means "No trade". A sample of the table with the extracted dataset features with the target values is shown Appendix 2

3.5 Data Splitting

The dataset was split into a feature or independent data set (X) and a target or dependent data set (Y). using

X= df.iloc[:, 0:df.shape[1] -1].values.

(eq1) to obtain all the rows and columns except for the target column and

Y = df. iloc[:, df. shape[1]-1].values

(eq2) to obtain all the rows from the target column. After that, the pre-processed data is then divided into 80% training data and 20% testing data using the *train_test_split* method. Here 16000 data are taken as training data and the rest 4000 is kept for testing. The training data values are taken from 2018.11.23 to 2020.03.04 and the testing data are from 2020.03.05 to 2023.05.22

3.6 Building the model

The model was built and trained to predict either BUY or SELL or NO TRADE base on the signal generated in the forex market using *decisionTreeClassifier () and fit () functions.*

3.7 Training the model

The decision tree model was trained by recursively splitting the training data into subsets based on the most significant feature at each node. This process continued until the model could accurately predict the target variable or until a pre-defined stopping criterion (such as maximum tree depth) was reached. The decision tree's structure allows it to capture complex, nonlinear relationships in the data, making it well-suited for forex prediction. Training is the process that helps ML algorithms to extract useful information to train the models so that they are capable of producing accurate predictions and hence desired outcomes. The technique used in this study is a decision tree. In building the model, independent and dependent features were specified. The independent are *K, D, LWMA* and were used to predict the target (signal).

The performance of the model on the trained data is checked to see how well the model did on the training dataset using a *tree. score () method.*

Similarly, the model was tested on the testing dataset to predict the forex market and was checked to see how well the model did on the testing dataset, *a tree. score () method* was used as well.

The tree rules of the decision tree in prediction are shown below

```
|--- %D <= 19.03
|   |--- LWMA <= 1.20
|   |   |--- class: No trade
|   |--- LWMA > 1.20
|   |   |--- %K <= 20.02
```

```
|  |  |  |--- class: Buy
|  |  |--- %K > 20.02
|  |  |  |--- class: No trade
|--- %D > 19.03
|  |--- %D <= 80.02
|  |  |--- %D <= 19.91
|  |  |  |--- class: No trade
|  |  |--- %D > 19.91
|  |  |  |--- class: No trade
|  |--- %D > 80.02
|  |  |--- LWMA <= 1.29
|  |  |  |--- class: Sell
|  |  |--- LWMA > 1.29
|  |  |  |--- class: No trade
```

Figure 1 Model of the decision rule in prediction

The model decision rule is based on Entropy. Mathematically, the entropy of a node is calculated as:

$$\boldsymbol{E = -\sum_{i=1}^{N} pi\ log_2\, pi} \quad (3.1)$$

where:
pi represents the proportion of samples of class i in the node. Entropy is more sensitive to changes in class distribution, and it can lead to more balanced splits when classes are imbalanced.

3.8 Model performance test

The final stage of model development is the testing. Here the trained model performance was evaluated by the use of performance parameters. The Decision Tree was tested. The performance evaluation parameters used were *Accuracy, Precision and Recall.*

The formulae for the calculation of Accuracy, Precision and Recall are shown as follows:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (3.2)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+TN}} \quad (3.3)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (3.4)$$

where:
True Positives (TP) are the instances that are correctly predicted as positive by the model.
False Positives (FP) are the instances that are incorrectly predicted as positive by the model when they are actually negative.

3.9 Stochastic Oscillator

The stochastic oscillator is used as technical indicator in financial trading that helps traders analyze price movements and identify potential turning points in the market. It provides insights into overbought and oversold conditions. In this system the stochastic oscillator period length of 14 for the % K and 3 for % D was set. In the calculation of the %K and %D values of the stochastic oscillator the following formulas were used:

$$\%K = \frac{Current\ Close - Lowest\ Low}{Highest\ High - Lowest\ Low} * 100 \quad (3.5)$$

%D = Moving Average of %K over a specified number of periods (3.6)

The threshold levels of overbought and oversold conditions were defined.

80 for overbought and 20 for oversold.

If the %K value crosses above the overbought threshold, it indicates an overbought condition.

If the %K value crosses below the oversold threshold, it indicates an oversold condition.

The calculated %K and %D values was further integrated into the decision-making process of the EA.

The logic signal that generates trading signals based on the overbought and oversold conditions were set thus:

Overbought Signal: If the %K value crosses above the overbought threshold, it indicates a potential opportunity to sell or take profits.

Oversold Signal: If the %K value crosses below the oversold threshold, it may suggest a potential opportunity to buy or enter a long position.

3.10 Linear Weighted Moving Average

An Additional technical indicator called Linear weighted Moving Average was integrated into the EA for further confirmation of the trading signal generated by the stochastic oscillator: The Linear Weighted Moving Average (LWMA) is a type of moving average that assigns varying weights to each data point and gives more weight to recent price data points within the specified period. It is used to identify trends and generate trading signals.

The formula used for calculating the LWMA is as follows:

$$\text{LWMA} = \frac{W1*P1+W2*P2+\cdots WN*PN}{W1+W2+\cdots+WN} \quad (3.7)$$

Where:

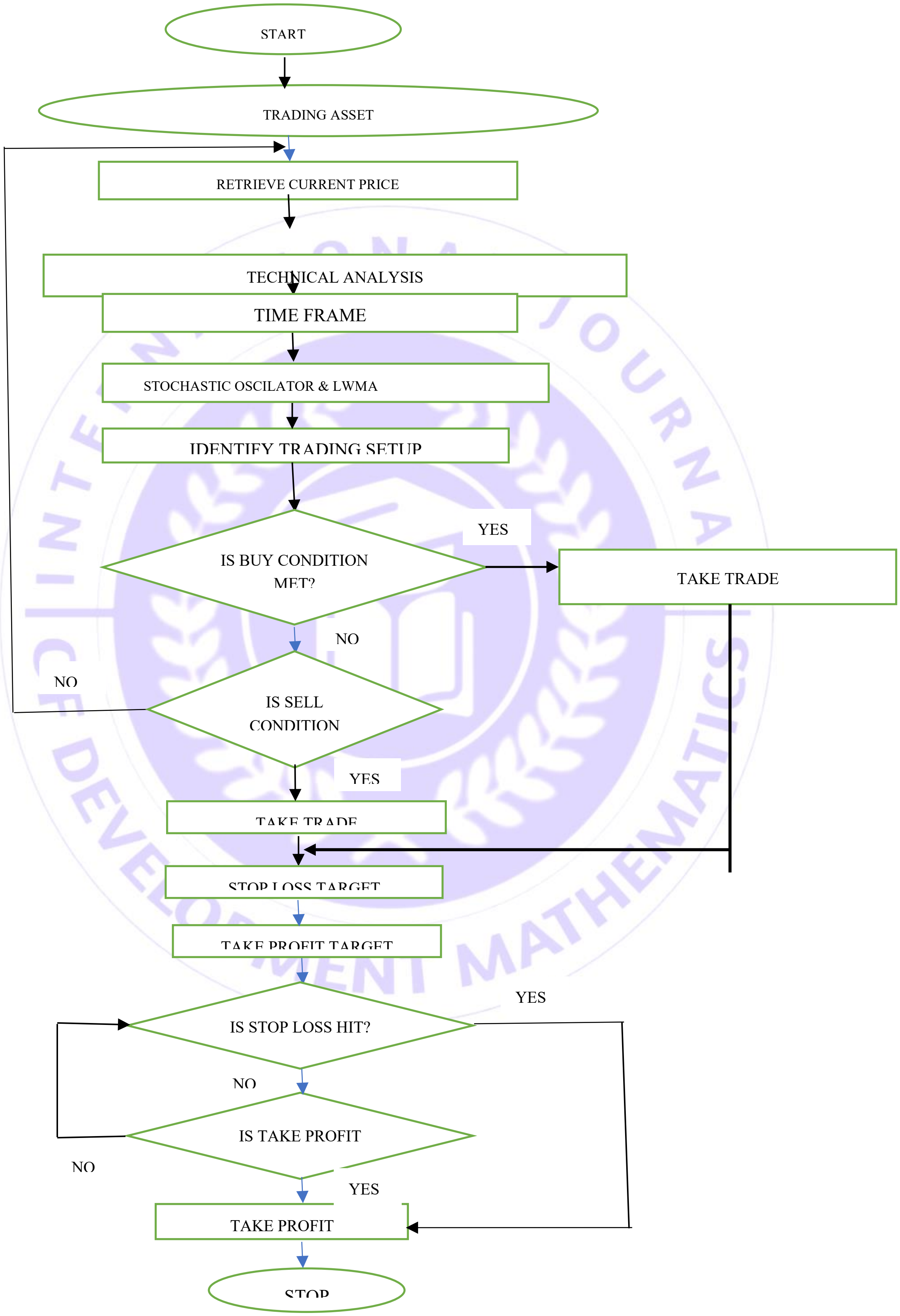
LWMA: Linear Weighted Moving Average

W1, W2, W3, ... WN: Weights assigned to each price data point

P1, P2, P3, ... PN: Price data points within the specified period

The LWMA assigns higher weight to recent price data points, providing a smoother line compared to other moving averages, it was utilized to identify trends in the market. An upward sloping LWMA indicates an uptrend, while a downward sloping LWMA indicates a downtrend. Trading signals were generated based on the LWMA crossover strategy. When the price crosses above the LWMA, a buy signal is generated, indicating a potential bullish trend. Conversely, when the price crosses below the LWMA, a sell signal is generated, indicating a potential bearish trend. The LWMA crossovers served as entry and exit points in the trading strategy. A machine learning approach incorporated with stochastic oscillator and Linear weighted moving average is very important in predicting forex prices. Stochastic Oscillator and Linear Weighted Moving Average were derived from the dataset collected and are used as independent variables (features), and the signal was used as the dependent variable which the model predicted as either Buy or Sell depending on the trading strategy.

This trading strategy used here utilizes a Moving Average Crossover (MAC) approach, leveraging two Linear Weighted Moving Averages (LWMA) with different time periods to identify trends and potential entry points. The strategy employs a short-term LWMA 15 and a long-term LWMA 50 to generate buy and sell signals. When the LWMA 15 crosses above the LWMA 50, it indicates a potential uptrend, triggering a buy order. Conversely, when the LWMA 15 crosses below the LWMA 50, it suggests a potential downtrend, prompting a sell order. However, if the moving averages are not crossing, it implies an unclear trend, and no trade is entered. This approach allows traders to capitalize on potential trend reversals while avoiding trades during uncertain market conditions. By combining the responsiveness of the LWMA 15 with the stability of the LWMA 50, traders can make gainful transactions.


START
TRADING ASSET
RETRIEVE CURRENT PRICE
TECHNICAL ANALYSIS
TIME FRAME
STOCHASTIC OSCILATOR & LWMA
IDENTIFY TRADING SETUP
IS BUY CONDITION MET?
YES
TAKE TRADE
NO
IS SELL CONDITION
NO
YES
TAKE TRADE
STOP LOSS TARGET
TAKE PROFIT TARGET
IS STOP LOSS HIT?
YES
NO
IS TAKE PROFIT
NO
YES
TAKE PROFIT
STOP

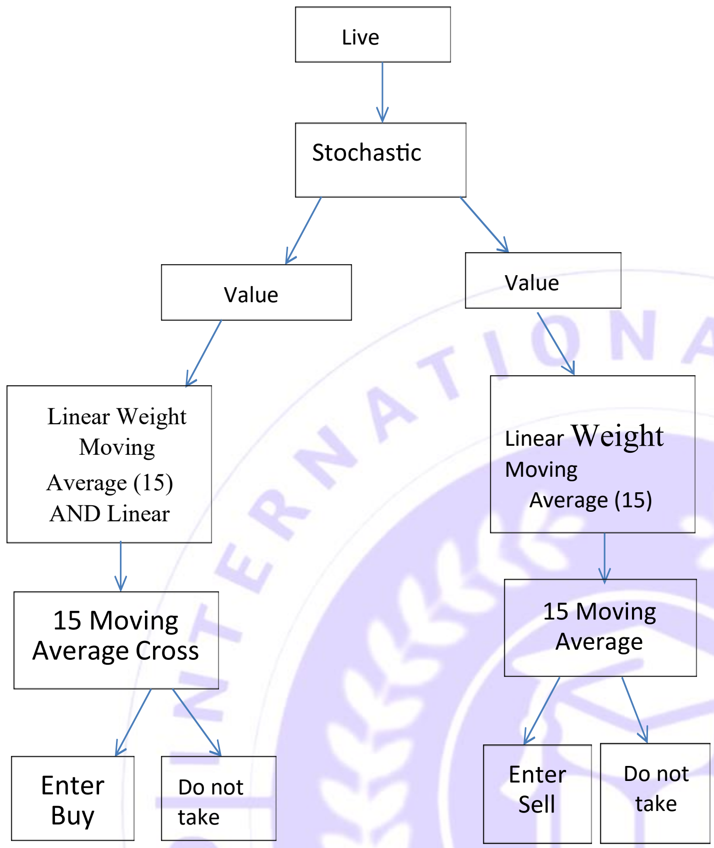


Figure 3: Decision Tree for the Trading Decision

3.11 The Decision Tree for the Trading Decision

This is the decision tree for the trading decision which is an Expert advisor tool and is based on Machine Learning with emphasis on decision tree algorithm. The proposed system generates trade strategy based on BUY/SELL decision trees that consists of technical indicators that are connected by logical operators. The below decision tree depicts the system. As shown from Figure 3, every decision can either by Buy or Sell. This is represented as two decision trees; one is responsible for Buy Signal and the other for Sell Signal recognition. Each of the decision tree is a trading rule. It consists of logical functions binding leaves, which are technical analysis indicators. The Forex Expert Advisor (EA) tool with a decision tree algorithm incorporates Stochastic Oscillator and Linear Weighted Moving Average as indicators for decision-making. The Decision tree algorithm is integrated into the EA to enhance the decision-making process. The algorithm combines multiple indicators, including the Stochastic Oscillator and Linear Weighted Moving Average to generate more sophisticated and informed trading decisions. The Stochastic Oscillator and Linear Weighted Moving Average serve as inputs to the decision tree, providing a systematic and unbiased approach to analyzing market conditions and generating trading signals. The EA further automates the decision-making process using the decision tree algorithm. This ensures quick analysis of market conditions and prompt execution of trades. The integration of the Stochastic Oscillator and Linear Weighted Moving Average enables the EA to generate trading signals efficiently, taking advantage of timely opportunities without delays. Extensive backtesting was conducted using the historical market data to evaluate the performance of the EA.

The decision tree algorithm's parameters and the indicators' settings are optimized to enhance the EA's effectiveness.

This iterative process helps fine-tune the algorithm and improve the EA's profitability potential. Another important factor was considered i.e. Risk Management. The decision tree algorithm incorporates risk management techniques into the EA. Based on the inputs from the Stochastic Oscillator and Linear Moving Average, the EA determines appropriate entry and exit points, stop-loss and take-profit levels, and position sizes. This enables effective risk management and capital protection. Consistency and Discipline was well considered in the model design. The decision tree algorithm ensured consistent and disciplined trading by following predefined rules and parameters. It eliminates human errors and emotional biases, promoting a systematic approach to generating trading signals and maintaining consistency in the trading decisions.

4. Results

Decision tree algorithm was used in this study for the prediction of forex prices based on FOREXTIME MT4 dataset. The dataset started from 11-23-2018 up to 05-22- 2023. The model was tested. Three performance metrics, Accuracy, Precision, and Recall were used to evaluate the model performance. The result is presented in the following section.

Table 2 Model Metric values

Metric	0	1	2	Accuracy %	
	%			Training set	Testing set
Precision	100	100	100		
Recall	97	100	100	96	98

Table 2 displays the tabulated results for the accuracy, precision, and recall metrics obtained from testing the model on the dataset. These metrics provide a comprehensive evaluation of how well the model performed in predicting forex market movements. As shown in table 4.1 the model achieved an accuracy of 96% on the training set. This high level of accuracy indicates that the model was able to learn the patterns and relationships within the training data effectively, making correct predictions for the majority of the instances. While on the testing set, the model achieved an accuracy of 98%. This suggests that the model generalizes well to unseen data, maintaining high performance when applied to new forex market data. The slight increase in accuracy from the training set to the testing set may indicate the robustness and reliability of the model in real-world scenarios. Also displayed on the table is the precision. The precision measures the proportion of true positive predictions among all positive predictions. In this study, precision values for all classes (buy, sell, hold) were 100%, which implies that the model did not produce any false positives. This is a critical metric in financial predictions, as false positives can lead to unnecessary trading actions, potentially causing financial losses. Another important performance metric was the recall, also known as sensitivity, measures the proportion of true positive predictions among all actual positives. The recall values were 97% for class 0 and 100% for classes 1 and 2. This indicates that the model successfully identified almost all actual positive instances. High recall is essential in ensuring that the model captures all opportunities for profitable trades without missing significant events. The high performance of the model across these metrics is illustrated with specific examples from the dataset:
Example 1: On May 1, 2023, the actual trading action was "buy", and the model accurately predicted "buy".
Example 2: On May 10, 2023, the actual trading action was "sell", and the model accurately predicted "sell".
Example 3: On May 15, 2023, the actual trading action was "hold", and the model accurately predicted "hold".
.

4.1 Result Implementation

MQL4 is an integrated development environment (IDE) that comes with a user-friendly integrated development environment that includes a code editor, compiler, debugger, and strategy tester for efficient development and testing of trading applications. MQL4 offers traders a powerful platform to automate their trading strategies and implement complex trading algorithms. The model was implemented on MT4 using MQL4 programming language on MT4 platform of two different brokers ForexTime and KOT 4X Demo Accounts

4.1.1 User Interface

Below is the user interface where user input parameters for the trading logic. This gives the user the opportunity to change the parameters of the decision logic if not satisfied with the input value. This gives the tool the flexibility of adapting to any given value. If a user is not satisfied with the outcome or the performance of the tool, he/she can decide to change the input parameter and observe the outcome until the result is satisfied. Figure 4 shows the interface of the implemented model.

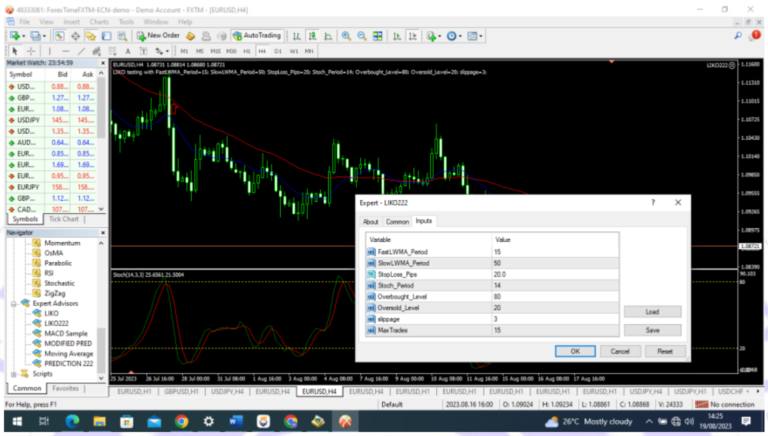


Figure 4: User Interface

In order to ensure the efficacy of the tool, a backtest was carried out using historical data as well as live data. The results are presented and discussed below.

Buy Signal

Figure 5: Buy signal EUR/USD on a 30 minutes chart

The above image shows a buy signal generated on the 4th of May, 2023. The system predicted correctly base on the set conditions given. It opened and closed automatically because it has met the take profit condition set. The entry price on the EUR/USD was 1.10420, the stop loss was 1.10390 and the take profit was 1.10420 at the end interest of 2pips was made which can say is profitable transaction.

Sell Signal

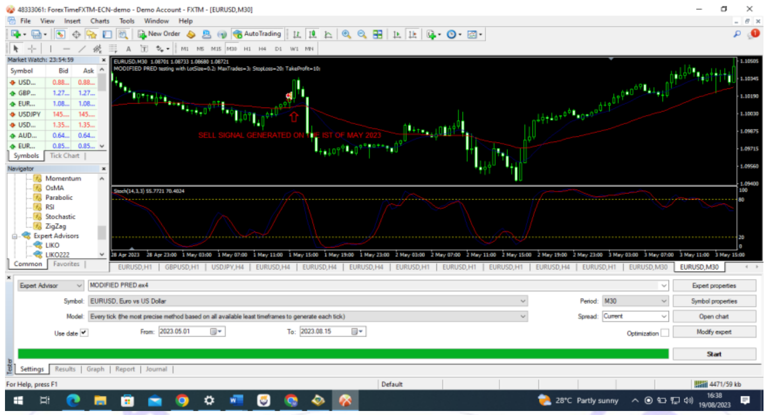


Figure 6: Sell signal generated on the 29th May, 2023 on a 30m minutes chart

The above image shows a sell signal generated on the 1st of May, 2023. The system generated the sell at exactly 3:00pm base on the set conditions given. It opened and closed automatically because it has met the take profit condition set. The entry price on the EUR/USD was 1.10182, the stop loss was 1.10212 and the take profit was 1.10182 at the end interest of 2pips accrued to the account.

Table 3. Trading Transactions

S/N	DATE/TIME	TYPE	SYMBOL	PRICE	STOP LOSS	TAKE PROFIT	PROFIT
1	2022.07.01 09:36	BUY	EUR/USD	1.04407	1.04387	1.04417	2pips
2	2022.07.04 05:00	SELL	EUR/USD	1.04335	1.04355	1.04325	-1pip
3	2022.07.04 06:00	SELL	EUR/USD	1.04336	1.04356	1.04326	2.00pips
4	2022.07.04 10:08	BUY	USD/JPY	136.469	136.449	136.479	-2.93pips
5	2022.07.04 10:08	BUY	USD/JPY	136.468	136.448	136.478	-2.93pips
6	2022.07.04 10:08	SELL	USD/JPY	135.389	135.409	135.379	-4.35pips
7	2022.07.04 10:08	SELL	USD/JPY	135.391	135.411	135.381	-4.35pips
8	2023.04.11 20:00	BUY	GBP/USD	1.24101	1.24081	1.24111	0.60pips
9	2023.04.11 20:00	BUY	GBP/USD	1.24104	1.24084	1.24114	O.60pips
10	2023.04.11 20:05	SELL	GBP/USD	1.24092	1.24092	1.24122	5.40pips
11	2023.04.11 20:06	SELL	GBP/USD	1.24090	1.24090	1.24120	5.40pips
12	2023.05.29 09:01	BUY	USD/CHF	0.90471	0.90451	0.90481	1pip
13	2023.05.29 09:02	BUY	USD/CHF	0.90462	0.90442	0.90472	1.10pips
14	2023.05.29 09:02	SELL	USD/CHF	0.90451	0.90451	0.90481	-5.82pips
15	2023.04.06 12:00	BUY	USD/CAD	1.34800	1.34780	1.34810	1pip
16	2023.04.06 12:00	BUY	USD/CAD	1.34801	1.34781	1.34811	1pip
17	2023.04.06 12:00	SELL	EUR/USD	1.10181	1.10211	1.10181	2pips
18	2023.04.06 12:04	SELL	USD/CAD	1.34782	1.34782	1.34812	4.37pips
19	2023.05.30 03:00	BUY	AUD/USD	0.65294	0.65274	0.65304	3pips
20	2023.05.30 03:01	SELL	AUD/USD	0.65275	0.65275	0.65305	-4pip

Total number of transactions = 20
Total number of profitable transactions = 13
Total number of failed transactions = 7
% of profitability = 65%
% of loss = 35%

Table 3 above shows twenty transactions that were carried out on the signal generated by the system on different time frames and currency pairs, out of this number, 13 (65%) of the transactions were profitable and 7 representing 35% were loss. It was observed that out of the failed transactions two of them hit stop loss before heading to a profitable point. Also, some of the generated signals were late due to the lagging on the 50-moving average. This affected the signal generated, if this barrier is not present most of the negative profit would have been positive and those that are profitable would have generated more pips that as presented in the table above.

5. Discussion

Classes (target) used are 0,1, and 2 representing different market movements such as "sell," "buy," or "hold" respectively. Model precision, and recall per class tested on 4000 dataset is shown in Table 2. These metrics provide an overview of how well the model perform overall and for each class. The precision is 100% for each of the target class, and model recall is 100% for 1,2 (buy, and no trade), and 97 for 0 (sell). Decision rule of the model was based on the target entropy. Entropy is a measure of disorder or impurity in a dataset. In the context of decision trees, it calculates the uncertainty associated with the class labels at a given node. Entropy ranges from 0 to 1. 0 perfectly pure, all samples belong to one class and 1 perfectly impure, samples are evenly distributed across all classes.

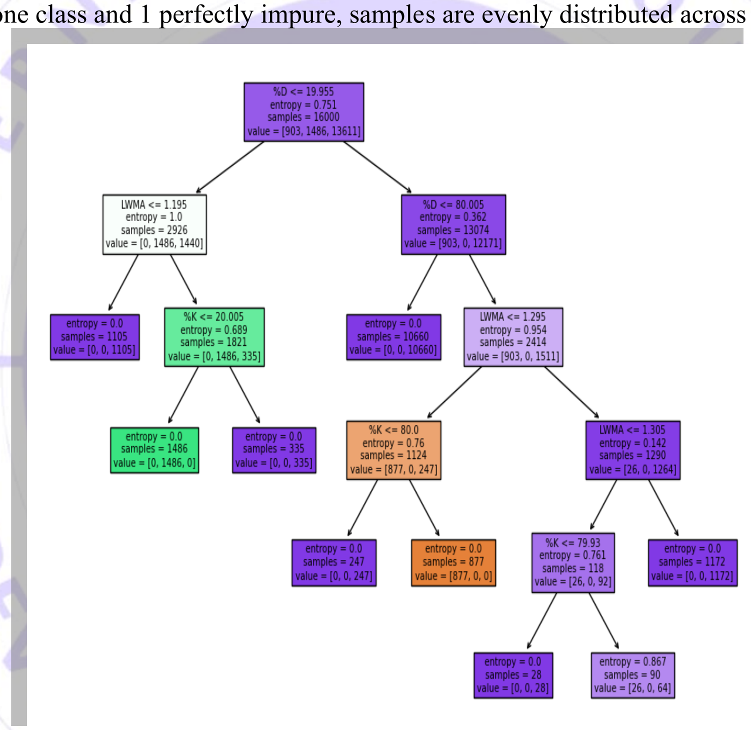


Figure 7: Model of node selection

From Figure 7 above, the top node was split based on the slow-stochastic oscillator %D, and has entropy of 0.751 on a sample of 16000, in which 903 is classify "sell"; encoded as 0. 1486 classify as "buy" also encoded as 1, and 13611 classify as "no trade". The next split was on the Slow stochastics oscillator %D which representing leave note of the model, the tree indicates that %D is more important in the initial decision. If a leaf node contains mostly positive samples, it suggests that the majority of trading with certain strategy in that leaf node tend to make a transaction of either sell, buy or no trade. The rule goes on to the last leaves.

The model performance accuracy was found to be 98%, and it was evaluated using confusion matrix as shown in figure 5.2 below. The figure shows actual prediction value and predicted values of the model. The model predicted 219 as "0 ", with 6 wrong predictions of O. Model should have predicted the 6 as "0" but predicted it "2". Therefore 6 is the true negative classification of "0"., Also the model predicted 393 as 1 and has miss classification 1. This means

1 is the true negative classification of 1. Similarly, the model predicted 3381 as "2 ", and it was so with no miss classification. Precision is the proportion of true positive predictions out of all positive predictions made by the model. It measures the accuracy of positive predictions while Recall is the proportion of true positive predictions out of all actual positive instances in the dataset. It measures the ability of the model to identify all positive instances correctly, regardless of the negative predictions.

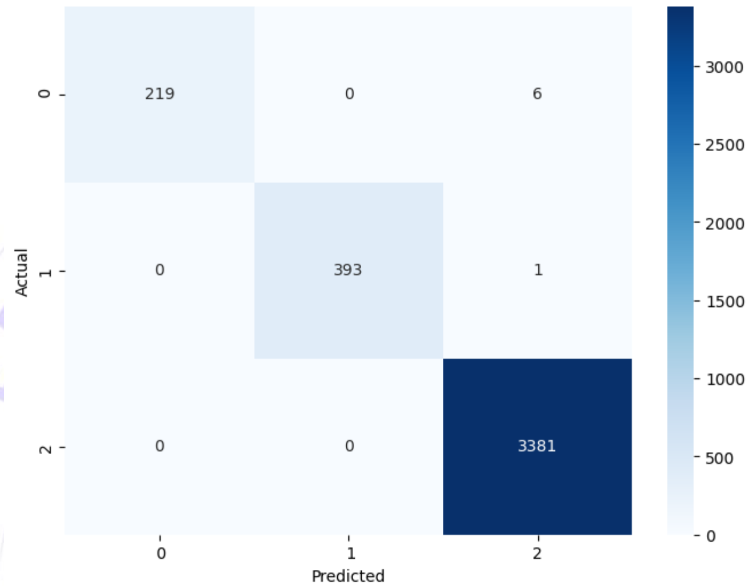


Figure 8: Model of confusion matrix

The decision tree model's high accuracy in predicting forex market movements is commendable, but understanding the underlying reasons behind these results is crucial for a comprehensive analysis. Several factors contribute to the model's performance: Quality data, feature selection and decision tree algorithm. Quality of data, the dataset used was comprehensive, covering a period of over five years, which provided the model with a rich source of historical information. High-quality data is fundamental to training effective machine learning models, and the detailed historical data from the FOREXTIME MT4 platform likely played a significant role in the model's success. Feature Selection also played a significant role, proper selection of features is vital in any predictive modelling task. Including relevant economic indicators and market sentiment data would have enhanced the model's ability to capture complex relationships within the data. The features selected were likely critical factors influencing forex prices, thus improving the model's predictive power and another major factor is the Decision tree algorithm, decision trees are effective at capturing complex patterns and interactions in data. They are capable of handling both numerical and categorical data and are robust to outliers, which can be beneficial in the volatile forex market. The algorithm's inherent ability to model non-linear relationships likely contributed to the high accuracy observed.

While the results are promising, it is essential to acknowledge the potential limitations of the study to provide a balanced perspective. The limitations include Risk of overfitting, Market dynamics, Execution risks, specific forex data used and the Assumptions in the research process. Risk of Overfitting, despite the high accuracy on the testing set, there is always a risk of overfitting. This occurs when the model performs well on historical data but fails to generalize to future, unseen data. Overfitting can lead to significant financial losses in live trading if the model's predictions do not hold up under new market conditions. other factors that cannot be ruled out are the Market Dynamics, forex markets are influenced by numerous unpredictable factors such as geopolitical events, economic announcements, and sudden changes in market sentiment. The model may not account for all such variables, leading to unexpected performance drops in real-world scenarios. Even with accurate predictions, actual trading involves challenges such as slippage, transaction costs, and latency, which can impact the profitability of the trades suggested by the model. These execution risks are not captured in the backtested model performance. Specific Forex data used, the dataset from the FOREXTIME MT4 platform, while comprehensive, may have inherent biases or limitations. The model's performance is heavily dependent on the quality and representativeness of this data. If the data does not capture certain market conditions or anomalies, the model may struggle in those scenarios. Various assumptions were made during the research process, such as the selection of features and the division of data into training and testing sets. These assumptions, while necessary, can introduce biases that affect the model's performance.

To strengthen the model and its applicability in real-world forex trading, several areas warrant further exploration:

i. Ensemble Methods: Exploring ensemble methods, such as Random Forests or Gradient Boosting, which combine multiple decision trees, could enhance model robustness and accuracy by mitigating the limitations of a single decision tree.
ii. Incorporating Real-Time Data: Integrating real-time data and testing the model in a live trading environment would provide insights into its performance under actual market conditions. This could help identify and address practical challenges not evident in backtesting.
iii. Feature Engineering and Selection: Further refinement of feature engineering techniques and incorporating additional relevant features, such as advanced technical indicators or macroeconomic variables, could improve the model's predictive power.
iv. Model Interpretability: Enhancing the interpretability of the model's predictions can provide traders with more actionable insights. Techniques such as SHAP (Shapley Additive Explanations) values can be used to explain the contribution of each feature to the model's predictions.
v. Exploring Other Algorithms: While the decision tree algorithm has shown promising results, exploring other machine learning algorithms such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN) could provide comparative insights and potentially uncover more effective approaches for forex prediction.

The results indicate that the decision tree model is highly effective in predicting forex market movements, with high accuracy, precision, and recall metrics demonstrating strong predictive capabilities. However, understanding the limitations and challenges in real-world applications is crucial for its successful deployment in live trading environments. Future research should focus on enhancing model robustness, incorporating real-time data, and exploring new algorithms and techniques to improve performance and reliability in dynamic forex markets. These steps will ensure the model's long-term effectiveness and profitability.

6. Conclusion

The research work is a milestone in the field of forex trading. The study was able to build a robust machine learning model, in the form of a decision tree, to predict forex market prices accurately. The insight derived from this model will help in the way investors will approach trading by providing them with a powerful tool to make informed decisions. The dataset used in this research is from 2018 to 2023. A comprehensive dataset was sourced from ForexTime, a reputable broker platform, the model was trained on the historical data and the decision tree model developed demonstrated exceptional accuracy, achieving a remarkable 98% success rate in predicting forex market prices, this underscores its efficacy and reliability as a predictive tool in the world of forex trading. Furthermore, the success of this research reaffirms the power of machine learning techniques, such as decision trees, in capturing complex patterns and relationships within financial data. It highlights the potential for leveraging advanced technology to gain deeper insights into the forex market's dynamics, enabling traders to navigate the market with greater confidence. The development and testing of our decision tree model have demonstrated its practical utility as a valuable predictive tool for forex trading. The model's outstanding 98% accuracy rate showcases its potential to enhance trading strategies, optimize investment decisions, and ultimately contribute to the financial success of investors in the forex market. This will in a way contribute to the understanding of how technology and data-driven approaches can enhance trading strategies. It has equally shown that the combination of decision tree algorithm, stochastic oscillators and linear weighted moving average and trading strategies has demonstrates how multiple methodologies can be used to create an effective trading tool. Exploration and analysis of historical data, as well as the preprocessing and normalization techniques employed has shown how data quality and preparation are crucial in developing a good forecasting model. Moreover, the use of cross-validation techniques to evaluate the model's performance has further enhanced the process and contributes to the methodology's reliability. The implementation of the model in both Python and MQL4 programming languages has shown the practicability of the research findings and it has shown how ideas can be translated into real-world tools. The research has contributed to academic discussions and professional communities in the financial markets, machine learning, algorithmic trading, and programming. This research paves the way for further exploration of machine learning methodologies in financial markets and underscores the importance of data-driven approaches in modern trading practices. Furthermore, the study recommends the following;

i. Traders should conduct a comprehensive evaluation of the performance of the Expert Advisor in a demo trading account before deploying real capital, a deep understanding of the EA's behavior and its historical performance data is significant.
ii. Traders should conduct thorough backtesting across various currency pairs and timeframes to build confidence in the EA's historical performance. Additionally, I recommend they continue with forward testing, using a modest portion of their capital, to assess the EA's real-time performance in current market conditions.
iii. Depending on the specific trading strategy in use, I suggest the integration of fundamental analysis indicators as complementary elements to the existing technical analysis within the EA. This integration can enhance the EA's trading approach by providing a more comprehensive and holistic perspective on the market.
iv. The integration of price action analysis into the existing trading strategy of the EA is highly recommended. Price action analysis involves studying and interpreting the historical price movements of assets to identify patterns, trends, and potential reversals. By incorporating this approach, the EA can gain valuable insights into market sentiment and enhance its decision-making process. This addition can lead to more robust and effective trading strategies, improving the overall performance and adaptability of the EA in various market conditions.
v. That traders and investors consider integrating the Expert Advisor into their trading activities. However, it is essential to exercise caution and conduct thorough due diligence before fully relying on the EA for trading decisions.
vi. Enhanced Feature Engineering: Future work should focus on refining the feature selection process. Incorporating additional relevant features such as macroeconomic indicators, sentiment analysis from news articles, and advanced technical indicators could provide the model with more comprehensive insights, thereby improving its predictive accuracy

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Appendix 1 Sample of historical data collected

DATE	TME	OPEN	HIGH	LOW	CLOSE	VOLUME
2018.11.23	10:00	1.28888	1.29095	1.28875	1.29057	2767
2018.11.23	11:00	1.29057	1.29087	1.28768	1.28809	4071
2018.11.23	12:00	1.2881	1.29142	1.28749	1.2902	4099
2018.11.23	13:00	1.29019	1.29033	1.28885	1.28915	3156
2018.11.23	14:00	1.28915	1.29058	1.28894	1.28993	2749
2018.11.23	15:00	1.28991	1.2909	1.28946	1.2909	2394
2018.11.23	16:00	1.29091	1.29324	1.29056	1.29311	4099
2018.11.23	17:00	1.2931	1.29431	1.29241	1.29427	3965
2018.11.23	18:00	1.29426	1.2968	1.29408	1.29579	4456
2018.11.23	19:00	1.2958	1.29673	1.29546	1.29578	2851
2018.11.23	20:00	1.29579	1.29896	1.29569	1.29853	3397
2018.11.23	21:00	1.29854	1.29854	1.29703	1.29719	1660
2018.11.23	22:00	1.29719	1.29743	1.2968	1.29694	1028
2018.11.23	23:00	1.29695	1.29778	1.29674	1.2976	1021
2018.11.24	00:00	1.29759	1.2977	1.29685	1.29724	1241
2018.11.24	01:00	1.29718	1.29729	1.29718	1.29729	2
2018.11.26	02:00	1.29731	1.29768	1.29631	1.29721	1348
2018.11.26	03:00	1.29721	1.29732	1.29599	1.29621	1663
2018.11.26	04:00	1.29622	1.29655	1.29519	1.29522	1476
2018.11.26	05:00	1.29526	1.29554	1.29501	1.2953	1347
2018.11.26	06:00	1.2953	1.29613	1.29517	1.29605	1358
2018.11.26	07:00	1.29607	1.29609	1.29527	1.29577	985
2018.11.26	08:00	1.29578	1.29617	1.29524	1.29551	1140
2018.11.26	09:00	1.29552	1.29582	1.29435	1.29565	1808
2018.11.26	10:00	1.29564	1.29836	1.2955	1.29711	3035
2018.11.26	11:00	1.29711	1.29746	1.29505	1.29518	3730
2018.11.26	12:00	1.29517	1.29683	1.2946	1.29678	3489
2018.11.26	13:00	1.29679	1.29699	1.29517	1.2966	2700
2018.11.26	14:00	1.29659	1.29799	1.2963	1.29656	3017
2018.11.26	15:00	1.29654	1.29702	1.29523	1.29602	2933
2018.11.26	16:00	1.29603	1.29745	1.29552	1.29713	3152
2018.11.26	17:00	1.29714	1.29727	1.29558	1.29631	3354

(ForexTime, 2023)

Appendix 2 Extracted dataset with target values

Lowest Low	Highest High	%K	%D	LWMA	Signal
1.2874	1.29896	85.44	86.20	1.30	0

1.2888	1.29896	82.69	84.38	1.00	0
1.2889	1.29896	72.55	80.23	1.30	2
1.2894	1.29896	60.63	71.96	1.30	2
1.2905	1.29896	56.43	63.21	1.30	2
1.2938	1.30077	7.68	18.78	1.30	1
1.2935	1.30077	21.32	13.23	1.30	2
1.2935	1.30077	38.51	22.51	1.30	2
1.2935	1.30077	13.76	24.53	1.30	2
1.2929	1.29978	15.31	22.53	1.29	2
1.2915	1.29978	19.08	16.05	1.29	1
1.2915	1.29978	28.62	21.00	1.29	2
1.2915	1.29978	27.90	25.20	1.29	2
1.2915	1.29978	21.98	26.17	1.29	2
1.2915	1.29978	21.01	23.63	1.29	2
1.2915	1.29978	16.55	19.85	1.29	1
1.2915	1.29948	33.71	23.76	1.29	2
1.2915	1.29801	33.64	27.97	1.29	2
1.2915	1.29684	40.45	35.93	1.29	2
1.2915	1.29684	42.51	38.87	1.29	2
1.2915	1.29684	30.71	37.89	1.29	2
1.2915	1.29684	36.52	36.58	1.29	2
1.2915	1.29479	53.50	40.24	1.29	2
1.2915	1.29448	72.15	54.05	1.29	2
1.2920	1.29448	10.42	45.35	1.29	2
1.2911	1.29448	18.02	33.53	1.29	2
1.2911	1.29448	31.53	19.99	1.29	2
1.2911	1.29448	48.05	32.53	1.29	2
1.2911	1.29448	32.73	37.44	1.29	2
1.2911	1.29448	27.63	36.14	1.29	2
1.2889	1.29448	2.91	21.09	1.29	2
1.2889	1.29425	7.03	12.53	1.29	1
1.2881	1.2939	22.96	10.97	1.29	2
1.2881	1.29386	18.74	16.24	1.29	1
1.2879	1.29386	50.17	30.62	1.29	2
1.2879	1.29379	72.56	47.15	1.29	2
1.2879	1.29433	96.08	72.93	1.29	2
1.2879	1.29433	80.69	83.11	1.29	0
1.2879	1.29433	79.75	85.50	1.29	2
1.2879	1.29435	98.28	86.24	1.29	0

1.2879	1.29537	97.98	92.00	1.29	0
1.2879	1.29606	86.42	94.22	1.29	0
1.2879	1.29606	86.54	90.31	1.29	0
1.2879	1.29606	78.77	83.91	1.29	2
1.2944	1.30125	74.30	63.81	1.30	2
1.2944	1.30125	76.37	73.76	1.30	2
1.2944	1.30125	76.51	75.73	1.30	2
1.2944	1.30058	92.79	81.89	1.30	0
1.2951	1.30072	80.04	83.11	1.30	0
1.2974	1.3046	89.92	89.34	1.30	2
1.2981	1.3046	87.31	88.78	1.30	2