

Master’s Thesis

**Forecasting Currency Exchange Trend on USD/CAD**

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Degree Thesis

Big Data Analytics

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**Abstract**

Currency exchange rate forecast has been, and remains a challenging tasks. With unpredictable natural disasters, political instabilities, government policies, and many other factors, it becomes difficult to correctly forecast the currency exchange rate. Many researchers in the past have done great works on forecasting the exchange rate of the United State Dollar (USD)/Canadian Dollar (CAD) using statistical approach. Even the Fundamental approach of relying on macroeconomic factors of the two countries, such as GDP ratio, Import/Export, government revenue, etc. were considered at various points. But (while forecasting the USD/CAD exchange rate), none of the previous methods considered deeply the underlying market trends which forms the basics of Technical analysis. We have included various machine learning models and Time-sensitive indicators that directly aligns with the USD/CAD exchange rate movement so as to address this issue. These features will create a new dimension for researchers to predict and forecast the USD/CAD exchange rate. We have considered various types of models for predicting and forecasting the USD/CAD exchange rate, and realized that among all our models, Time Series models provides the best accuracy. While building our model, we relied of daily forex statistical data maintained by Yahoo Finance and Investing.Com. The later has more data (*almost time two compared to Yahoo Finance*), but were always downloaded manually to as .csv file before usage. On the other hand, the data from Yahoo Finance is read directly and automatically into a DataFrame via an API. While Yahoo Finance maintained this statistical data from September 2003 up till date, with over 5300 records, Investing.Com has been keeping this records since January 1982, and with over 10900 records. All our macroeconomics data (Consumer Price Indices (CPI), Interest Rates, Inflation Rates, Imports, Exports, Government Revenue, GDP Ratios, GDP Growths, and Un-Employment Rates) were automatically downloaded from the World Bank’s portal via an API. Due to huge data size available to me, I used 85% of my data for training my models, and the remaining 15% for my testing. At the end, we were able to come up with good results from our models, of which Random Forest Regressor (RFR) outperformed others based on accuracy.

**Keywords:**

Modelling, Forex, USD/CAD, Random Forest Regressor

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# Introduction

The foreign exchange (forex) market stands as one of the most dynamic and influential financial markets globally, facilitating the exchange of currencies and shaping international trade and investment. Among the myriad currency pairs traded in this market, the USD/CAD pair occupies a significant position due to its prominence in North American trade and its influence on the economies of the United States and Canada.

The USD/CAD exchange rate reflects the relative strength of the US dollar (USD) against the Canadian dollar (CAD) and is subject to various factors, including macroeconomic indicators, geopolitical events, central bank policies, and market sentiment. Understanding and accurately forecasting movements in the USD/CAD exchange rate are crucial for stakeholders ranging from multinational corporations and financial institutions to individual traders and policymakers.

Given the complexities and uncertainties inherent in the forex market, the development of reliable forecasting models for the USD/CAD exchange rate becomes imperative. Such models provide valuable insights into future exchange rate movements, enabling market participants to make informed decisions and manage risks effectively.

This thesis aims to contribute to the field of forex forecasting by proposing a robust and accurate model for predicting the USD/CAD exchange rate. Leveraging a combination of econometric techniques, statistical methods, and machine learning algorithms, the proposed model seeks to capture the underlying relationships and dynamics driving USD/CAD exchange rate fluctuations.

By incorporating a diverse set of predictors, including macroeconomic indicators, technical analysis indicators, and sentiment analysis metrics, the model endeavors to provide a comprehensive and holistic approach to USD/CAD forecasting. Additionally, the utilization of advanced modeling techniques, such as time series analysis, regression analysis, and machine learning algorithms, enables the model to adapt to changing market conditions and improve predictive performance over time.

The thesis will proceed by reviewing relevant literature on forex forecasting methodologies and exploring the key factors influencing the USD/CAD exchange rate. Subsequently, it will detail the methodology employed in developing the forecasting model, including data collection, feature selection, model training, and evaluation. Finally, the thesis will present empirical results, discuss implications for stakeholders, and offer recommendations for future research in the field of forex forecasting.

Through this research endeavor, we aim to contribute to the advancement of forex forecasting techniques and provide valuable insights into the dynamics of the USD/CAD exchange rate, ultimately assisting market participants in making more informed decisions and mitigating risks in the forex market.

## Literature review

The forecasting of currency exchange rates, particularly for the US dollar (USD) against the Canadian dollar (CAD) pair (USD/CAD), is of paramount importance in the realm of international finance and trade. This literature review aims to provide a comprehensive overview of existing research and methodologies related to forecasting trends in the USD/CAD exchange rate.

**Introduction to Forex Forecasting:** The forecasting of currency exchange rates plays a crucial role in facilitating international trade, investment decisions, and risk management strategies for businesses and financial institutions. The USD/CAD exchange rate, being one of the most widely traded currency pairs, attracts significant attention from traders, investors, and policymakers alike.

**Review of Exchange Rate Models:** Various theoretical models have been proposed to explain and forecast currency exchange rate movements. These include the Purchasing Power Parity (PPP) model, Interest Rate Parity (IRP) model, and the Asset Market Approach (AMA). While these models provide valuable insights into the determinants of exchange rates, empirical evidence suggests mixed results in forecasting the USD/CAD pair due to factors such as market inefficiencies and behavioral biases.

**Empirical Studies on USD/CAD Forecasting:** Numerous empirical studies have explored forecasting techniques for the USD/CAD exchange rate using a variety of methodologies. Time series analysis, econometric models, and machine learning algorithms have been employed to predict short-term and long-term trends in the currency pair. While some studies have reported promising results, others have highlighted the challenges of accurately forecasting exchange rate movements, particularly in the presence of volatile market conditions and geopolitical events.

**Role of Macroeconomic Factors:** Macroeconomic factors such as interest rate differentials, inflation rates, GDP growth, and trade balances play a significant role in driving USD/CAD exchange rate dynamics. Central bank policies, including those of the US Federal Reserve and the Bank of Canada, influence investor sentiment and market expectations, leading to fluctuations in the currency pair. Incorporating these macroeconomic factors into forecasting models is essential for improving prediction accuracy and capturing trend reversals.

**Technical Analysis and Market Sentiment:** In addition to fundamental analysis, technical analysis techniques and market sentiment indicators are widely used by traders and analysts to forecast USD/CAD trends. Chart patterns, moving averages, and momentum oscillators help identify support and resistance levels, trend direction, and potential reversal points in the currency pair. Sentiment analysis tools, such as sentiment indexes and news sentiment analysis, provide insights into market sentiment and investor psychology, complementing traditional forecasting approaches.

**Evaluation of Forecasting Accuracy:** Evaluating the accuracy and reliability of forecasting models is critical for assessing their effectiveness in predicting USD/CAD exchange rate trends. Studies have employed various performance metrics, including mean absolute error (MAE), root mean square error (RMSE), and directional accuracy, to measure forecasting accuracy and compare different models. While some models exhibit robust performance under certain market conditions, others may struggle to adapt to changing environments, highlighting the importance of ongoing model evaluation and refinement.

**Challenges and Future Directions:** Despite advancements in forecasting techniques, several challenges persist in accurately predicting USD/CAD exchange rate trends. These include data availability, model complexity, parameter estimation, and model validation. Future research directions may focus on integrating alternative data sources, developing ensemble forecasting models, and incorporating uncertainty measures into forecasting frameworks to enhance prediction accuracy and robustness.

**Conclusion:** In conclusion, forecasting currency exchange trends on the USD/CAD pair is a complex and challenging task that requires careful consideration of macroeconomic factors, technical analysis tools, and market sentiment indicators. While existing research provides valuable insights into forecasting methodologies and approaches, further research is needed to address remaining challenges and improve prediction accuracy in dynamic and unpredictable forex markets.

This literature review sets the stage for the subsequent research in this thesis, which aims to develop and evaluate forecasting models for predicting USD/CAD exchange rate trends using a combination of statistical data, macroeconomics data, and technical analysis techniques.

## Research question

**How do I mitigate against losing money in forex by being able to predict the price direction accurately most of the times?**

Ever since the world economy got heavily dependent on international trade, buying goods and services from a country requires an individual or an organization to buy them in the accepted local currency of that country. For example, if an organization purchases goods from Canada, that entity must pay in Canadian Dollar (CAD) despite having United States Dollars (USD). The currency exchange rate plays a vital role in this transaction. That organization can exchange US Dollars with Canadian Dollar depending on the exchange rates set by the central bank of Canada. So the Exchange rate means the value of one nation’s currency in terms of another. As exchange rates became a crucial element in international trade, predicting currency exchange rates became a demanding and a challenging process for businesses and individuals involved in the FOREX (foreign exchange market).

In the earlier days, economists tried to evaluate their mathematical exchange-rate models using the horse race approach, where they saw which model performed better in predicting the actual values of the exchange rate. Machine learning techniques have added a new dimension by making devices self-learner. Machine learning algorithms are capable of doing complex calculations faster and capable of making decisions more accurately. For that reason, predicting a currency exchange rate has shifted from manual accounting to machine learning algorithms, which have proven much more efficient and accurate than previous approaches. Over the last thirty years, the unanimity on the determinants of currency exchange rate movements has further broken down. The actual reason for the currency exchange movements can be explained partly by the world economy and the development of new theories of exchange rate determination.

The work done in this paper has focused on the perspectives of the world economy in the exchange rate movements of two big economies by taking into account the driving forces of the currency Supply versus Demand in the global market. Though the USD/CAD exchange rate prediction was made before using time series models, machine learning, and neural network models, much more inaccuracy still needs to be addressed in most previous research works. In the existing studies on the USD/CAD exchange rate, there was no inclusion of the underlying Technical features as well as macroeconomics indices, which are the dependent variables that will help predict the trend better. All the existing research just used the USD/CAD exchange rate pattern to train the models but ignored the factors that can directly suggest the exchange rate. None of them trained their models using the underlying features. The challenge is to improve the results even by a small margin to mitigate investment risk, and promote higher returns while maintaining an investment portfolio.

Due to lack of in-depth knowledge and proper analysis, many investors has lost so much in Forex. This triggered my interest in exploring ways of (fully or partially) automating this predictive analysis. I am using USD/CAD as a case model for other forex pairs. My approach to this study of forecasting the USD/CAD exchange rates stands on the combination of Statistical data, Technical features, and Macroeconomic indices, with deep learning, and machine learning algorithms. Every country has macroeconomics policies that drives her economy. Previously, researchers have trained their models by relying heavily on the exchange rate pattern only. Those approaches were much more statistical than considering the underlying reasons behind the fluctuation of the USD/CAD exchange rate. In this research work, I will be considering few macroeconomics indices of United States (USA) and that of Canada (CAN) that directly have large impact of their exchange rates. I will also consider statistical data as well as some established technical features like RSI, SMA, EMA, and MACD. I am convinced that pulling energy from these three reliable techniques will give me better forecasting compared to the existing works. This novel empirical approach has created a new dimension for the researchers to factor in their insights and develop models for better prediction and reduce investors’ risk in the FOREX market. Reducing investors’ risk in the FOREX market will significantly increase investment. For a fast growing country such as Canada, it is essential to increase investments in order to improve its economy. Therefore the main concept of this research can be described by these points:

1. Previously, researchers have forecasted the USD/CAD exchange rate by using the pattern of the market rate only. Those approaches were much more statistical than considering the underlying factors behind the change in the USD/CAD exchange rate.
2. To address this issue. First, we have studied the reasons behind the change in the USD/CAD exchange rate from an economic perspective.
3. Secondly, we identified the models that can be used for forecasting the USD/CAD exchange rate.
4. Then, we applied these interesting techniques to machine learning models in our research. We have trained our models using reliable macroeconomics indices, statistical data, and technical features, thus, found a better result than other existing research.
5. Finally, we have proposed a pipeline for improving the result further.

## Related research works

Before starting the implementation of our research work, we explored a lot of related research works in the field of machine learning, neural networks, and economics historical data. Some notable research works related to our USD/CAD currency exchange rate forecasting have been mentioned below:

Researchers like [*Saeed A, Awan RU, Sial MH,* and *Sher F*](#BM01)has analyzed the determinants of the exchange rate between USD and PKR within the framework of the monetary approach. They have taken stock of money, foreign exchange reserves, and total debts of Pakistan relative to the USA as the dummy variables and took them as the determinants of the exchange rate. They have applied the ARDL approach to the co-integration and error correction model. The results confirmed that stock of money, debt, and foreign exchange reserves are significant determinants of the exchange rate. [*Yao J,* and *Tan CL*](#BM02) have provided empirical evidence that a neural network model is applicable for predicting the exchange rate. The authors have fed time-series data, moving averages into the model to determine the underlying rules of exchange rate movements between different currencies. Their work further showed that foreign currency’s dynamic supply and demand factors made it difficult to predict the foreign exchange rates effectively. This aligns with the fundamentals of economics, which are that prices increase when the demand is greater than the supply and decrease when the demand is less than the supply. Since FOREX is a currency market, this fundamental aspect of economics stands true.

Using data mining techniques, [*Carbureanu M*](#BM03) have tried to predict the Romanian LEU/Euro. In that study, they mentioned that political, economic, and social events in a given timeline influence the supply and demand of a currency and have an instant effect on the currency exchange rate. Since there is no control over political and social events, our study looked into the economic factors that strongly impact currency exchange rates.

*[Ramasamy R,](#BM04)* [and](#BM04) *[Abar SK](#BM04)* have used the yearly currency rates of three countries along with their macroeconomic variables, such as relative interest rates, to verify their impact on exchange rate movements. They used the bootstrapping technique to increase the sample size and run regressions to study the effect. According to their study, macroeconomic variables such as tax rate, the balance of payments, inflation rate, interest rates, and other factors randomly influence the exchange rates. However, these macroeconomic variables might be unstable depending on the state of the economy within a country.

*[Twin A](#BM05)* has stated a few macroeconomic factors that influence the currency exchange rates: inflation rate, interest rate, current account deficit, public debt, terms of trade, and strong economic performance. According to the exchange rate regime, the floating exchange rate is influenced by the market’s driving forces of supply and demand, where the fixed/pegged exchange rate is determined and maintained by the government or central bank ([*Natto KI*](#BM06)).

*[Zwanger S](#BM07)* have conducted a study to outline the effects of modern exchange-rate theory on the exchange rate movements of Chili and the United States. Since the Chilean Peso (CLP) is pegged to the USD, they have considered the independent variables of the monetary policy interest rate, money supply, and inflation rates. However, they have mentioned that these independent variables might lose their explanatory ability when economic conditions change or in the case of switching in the foreign exchange rate policy dictated by the central bank.

A study by [*Cushman DO*](#BM08) has tested the risk effects of real exchange rates on U.S. bilateral trade flows during the floating period using a few of the new and previously used risk measures. They have mentioned that other factors affect the calculation of exchange rates in third-world countries. According to the law of the fixed price model, the prices of goods in different countries which are traded internationally are identical in the perfect market.

Studies by [*Akhtar MA,* and *Hilton RS*](#BM09) has found that the uncertainty of exchange rate significantly impacts the imports and exports in Germany and the USA. They have established a negative relationship between the volatility in the exchange rate and the volume of international trade.

In their study, [*Broil U,* and *Eckwert B*](#BM10) have mentioned that developing countries have insignificant access to international capital. Thus, the domestic inflation rate is connected with fixed/pegged exchange rates. A study by [*Kemal MA*](#BM11) has revealed that in the case of Canada, the exchange rate volatility is positively related to so much of imports with little exports. Furthermore, they have concluded that currency devaluation occurs by balancing the trade deficit.

*[Bouraoui T,](#BM12)* [and](#BM12) *[Phisuthtiwatcharavong A](#BM12)* conducted a study on Thailand THB/USD exchange rate where they explained how the Thai central bank intervenes in response to certain concerns and shocks in the managed floating regime. In this scenario, the study outlines six important factors that influence the THB/USD exchange rate: interest rates differential, manufacturing production index, terms of trade, monetary base, government debt, and international reserves.

*[Refenes AN, Zapranis A,](#BM13)* [and](#BM13) *[Francis G](#BM13)* conducted a study where they have proved neural networks could outperform the statistical forecasting techniques when the non-linearity approaches are applied in the dataset of stock indices. They have shown that using sensitivity analysis and neural networks can provide a rational explanation of their predictive behavior and model their environment more convincingly than regression models.

*[Rehman M, Khan GM,](#BM14)* [and](#BM14) *[Mahmud SA](#BM14)* used CGP and Recurrent Neural Network to predict the exchange rates between AUD and three other currencies. An approach of Recurrent Neuro-Evolution was taken to forecast the currency exchange rate. They have observed that the computational method outperformed other statistical methods due to the flexibility and ability to select the best feature in real-time, and effectively recognize the patterns.

*[Islam MS,](#BM15)* [and](#BM15) *[Hossain E](#BM15)* predicted the exchange rates of major currency pairs using the GRU-LSTM hybrid network. They tested the results with the standalone GRU and standalone LSTM models and found that the hybrid model outperformed the standalone models. This provides us with the idea of using a hybrid model to predict the USD/CAD exchange rate.

*[Pandey TN, Jagadev AK, Dehuri S,](#BM16)* [and](#BM16) *[Cho SB](#BM16)* have reviewed the neural network and statistical models to predict the exchange rate and also proposed a machine that identifies the shortcomings of both the neural network and statistical models. They have found that multilayer neural networks had BAYESIAN learning predictive accuracy performed better than neural networks using backpropagation learning.

*[Rout M, Majhi B, Majhi R,](#BM17)* [and](#BM17) *[Panda G](#BM17)* forecasted the exchange rates using an adaptive autoregressive moving average (ARMA) model with differential evolution-based training. They have compared the ARMA-DE model with other competitive models and found that it outperformed other models for the long and short time predictions. The performance was measured based on the model’s training time and accuracy. [*Panda MM, Panda SN,* and *Pattnaik PK*](#BM18) also used convolutional neural networks for multi-currency exchange rate prediction. They have proposed a model that can develop multivariate exchange rate information and use those features better. They have used the adaptive learning rate (ADAM) optimization technique to provide optimal weight for their proposed model.

*[Majhi R, Panda G,](#BM19)* [and](#BM19) *[Sahoo G](#BM19)* used low-complexity artificial neural network models for efficient exchange rate prediction. This study has developed two ANN models: functional link ANN (FLANN) and cascaded functional link ANN (CFLANN). The models involve nonlinear inputs and a simple ANN structure with one or two neurons. They have observed that CFLANN works better than FLANN having the least error.

*[Refenes AN, Azema-Barac M, Chen L,](#BM20)* [and](#BM20) *[Karoussos S](#BM20)* applied a multilayer perceptron network to predict the currency exchange rate and also discussed the convergence issues related to network architecture.

*[Galeshchuk S,](#BM21)* [and](#BM21) *[Mukherjee S](#BM21)* stated that time series models and shallow neural networks result in acceptable estimates in the future prices for exchange rates but perform poorly at predicting the direction of change. On the other hand, machine learning classifiers trained on input features curated based on domain knowledge produce better results.

*[Damrongsakmethee T,](#BM22)* [and](#BM22) *[Neagoe VE](#BM22)* implemented a deep learning model with Long Short Memory (DLSTM) to predict the currency exchange rate of USD/THB and took financial inputs such as interest rate, gross domestic product rate (GDP), balance account, inflation rate, and balance of trade also a finite set of previous exchange rates. [*Wang J, Wang X, Li J,* and *Wang H*](#BM23) have used the model of CNN-TLSTM for USD/CNY exchange rate prediction. So going forward with neural networks and deep learning models has been a credible approach for us.

*[Baffour AA, Feng J, and Taylor EK](#BM24)* integrated the GJR (Glosten Jagannathan and Runkle) model with Artificial Neural Networks (ANN) model for forecasting the volatility of five currency exchange rate. They have found a significant improvement by using the ANN-GJR hybrid model rather than using benchmark models. These findings influence us to use the CNN-LSTM hybrid model for forecasting the USD/CAD exchange rate.

In their research, [*Roy SS, Chopra R, Lee KC, Spampinato C* and *Mohammadi-Ivatlood, B*](#BM25) compared and analyzed the Random Forest, Gradient Boosting Model and Deep Neural Network for predicting the stock of South Korean companies. In their research, Random Forest performed better than other models, and possible reasons for Deep Neural Networks’ lower performance can be the relatively small data set and difficulties in data augmentation.

*[Bose A, Hsu CH, Roy SS, Lee KC, Mohammadi-Ivatloo B,](#BM26)* [and](#BM26) *[Abimannan S](#BM26)* proposed a hybrid model by cascading Multivariate Adaptive Regression Splines (MARS) and Deep Neural Network (DNN) for predicting the closing price of the stock. They have found an accuracy of 92% while predicting the closing price of the exchange rate.

Our study has focused on the connection between the USD/CAD exchange rate in connection to the underlying Technical and Macroeconomics factors of exchange rate movement. This has proved the concept using different models. Researchers are yet to follow our approach for forecasting the exchange rate of USD/CAD in a dual floating currency setup. While doing the entire research project, we have followed some modeling, evaluating, statistical, and research methods for implementing our neural network models from here.

# Research methodology

Forecasting the forex (foreign exchange) market is a challenging task due to its high volatility and complex dynamics. Various models and techniques can be used for forex market forecasting, each with its advantages and limitations. Below is a list of some commonly used models and techniques for forecasting the forex market:

1. **ARIMA (Auto Regressive Integrated Moving Average)**: ARIMA models are widely used for time series forecasting, including forex exchange rates. They can capture the autocorrelation and seasonality in the data, making them suitable for capturing short to medium-term trends.

2. **Exponential Smoothing Models**: Exponential smoothing models, such as Simple Exponential Smoothing (SES), Double Exponential Smoothing (Holt's method), and Triple Exponential Smoothing (Holt-Winters method), are effective for forecasting forex rates, especially when the data exhibit trend and seasonality.

3. **Machine Learning Algorithms**:

- **Linear Regression**: Simple linear regression models can be used to predict forex rates based on historical data and relevant features.

- **Random Forest**: Random forest models can capture complex relationships in the data and are suitable for both short and long-term forecasting.

- **Gradient Boosting Machines (GBM)**: GBM models, such as XGBoost and LightGBM, are powerful ensemble learning techniques that can handle large datasets and capture nonlinear relationships.

- **Recurrent Neural Networks (RNNs)**: RNNs, particularly Long Short-Term Memory (LSTM) networks, are effective for capturing sequential patterns in time series data and are suitable for forex market forecasting.

- **Ridge Regression**: Ridge Regression is a type of linear regression that includes regularization, which helps prevent overfitting by adding a penalty term to the loss function. This model approach corrects for multicollinearity in regression analysis.

- **LASSO Regression**: Least Absolute Shrinkage and Selection Operator is a linear regression that combines variable selection and regularization in order to enhance the prediction accuracy and interpretability of the resulting statistical model. It adds a penalty term to the loss function, which encourages sparsity in the model coefficients, effectively performing feature selection.

4. **Time Series Decomposition**: Decomposition techniques, such as Seasonal Decomposition of Time Series (STL) and Singular Spectrum Analysis (SSA), can decompose the forex time series into trend, seasonal, and residual components, making it easier to model each component separately.

5. **Vector Auto Regression (VAR)**: VAR models are used to model the interdependencies among multiple time series variables, making them suitable for forecasting forex rates along with other related variables, such as interest rates and inflation.

6. **Long Short-Term Memory (LSTM)**: This is a type of recurrent neural network (RNN) architecture that is capable of learning long-term dependencies in sequential data. This model type also addressed the vanishing gradient problem encountered in RNN.

7. **Kalman Filters**: Kalman filter-based models can dynamically update forecasts based on incoming data and are suitable for adaptive and real-time forex market forecasting.

8. **Hybrid Models**: Hybrid models combine multiple forecasting techniques, such as combining statistical models with machine learning algorithms or combining different machine learning algorithms, to improve forecasting accuracy.

9. **Support Vector Regression (SVR) Model**: The goal of SVR is to find a function that approximates the relationship between the input variables and a continuous target variable, while minimizing the prediction error. Support Vector Regression (SVR) is a type of Support Vector Machine (SVM) that is used for regression tasks. While SVM is traditionally used for classification, SVR adapts the principles of SVM to predict continuous values.

10. **Bayesian Ridge Regression Model**: This is a type of linear regression model that incorporates Bayesian inference principles to estimate the parameters of the regression model. Unlike traditional linear regression, which uses point estimates for parameters, Bayesian Ridge Regression treats parameters as random variables and calculates their posterior distributions given in the data. It automatically incorporates regularization, reducing the risk of overfitting.

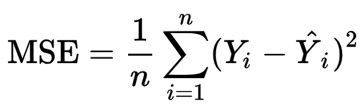
11. **AdaBoost Regression Model**: AdaBoost (short for Adaptive Boosting) is an ensemble learning method originally designed for classification but later extended to regression. The idea behind AdaBoost is to combine the outputs of multiple weak learners to create a strong predictor. A weak learner is a model that performs slightly better than random guessing. This is a meta-estimator that begins by fitting a regressor on the original dataset and then fits additional copies of the regressor on the same dataset but where the weights of instances are adjusted according to the error of the current prediction.

12. **Technical Analysis Indicators**: Various technical analysis indicators, such as Moving Averages, Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD), can be used for short-term forex market forecasting based on historical price and volume data.

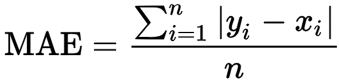
It's essential to note that no single model or technique is universally best for forecasting the forex market. The effectiveness of a forecasting model depends on factors such as the characteristics of the forex data, the forecasting horizon, the availability of relevant features, and the model's ability to adapt to changing market conditions. It's often advisable to use a combination of models and techniques and to continuously evaluate and update the forecasting models based on their performance and the evolving market dynamics.

## Performance metrics

We have forecasted the USD/CAD exchange rate by using various models, and the outputs of those models are continuous values. To make sure how good or bad our models are, we have calculated the error of our model. The badness of a model is how much error is generated by that model while predicting the USD/CAD exchange rate. For measuring the error of our models, we have used Root Mean Square Error (RMSE) which is used widely as a performance metric for regression analysis, forecasting, climatology, and so on. RMSE is known as the Standard deviation of residuals. RMSE penalizes the error more than the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) by squaring the error. For that reason, we have selected RMSE as our primary performance measurement metric, as well as Mean Absolute Error (MAE). Finally, to check how well our models fit the data, we have calculated the R-squire value (R2).

(1) 

(2) https://journals.plos.org/plosone/article/file?type=thumbnail&id=10.1371/journal.pone.0279602.e001

(3) 

(4) https://journals.plos.org/plosone/article/file?type=thumbnail&id=10.1371/journal.pone.0279602.e003

Where *y*i is the actual value of the USD/CAD exchange rate, https://journals.plos.org/plosone/article/file?type=thumbnail&id=10.1371/journal.pone.0279602.e004 is the predicted value of the USD/CAD exchange rate, and N denotes the total number of predictions or actual values. The model is better when the RMSE and MAPE are lower, and the model is bad when the RMSE and MAPE are high. The R2 takes values from –ve Infinity to 1. The closer the value of R2 to 1, the better the model is.

## Datasets

In the context of modeling, a dataset refers to a collection of data that is used for training, validating, or testing a predictive model. A dataset typically consists of multiple observations or instances, where each observation represents a single data point and is characterized by a set of features or variables. Below are some key aspects of datasets with respect to modeling:

**Features**: A dataset comprises one or more features (also known as independent variables or predictors) that provide information about each observation. Features can be numeric, categorical, or textual, and they capture the characteristics of the data that are relevant for modeling.

**Target Variable**: In supervised learning tasks, datasets often include a target variable (also known as the dependent variable or response variable) that the model aims to predict based on the features. The target variable represents the outcome or response of interest, and the model learns to make predictions about it based on the input features.

**Observations**: Each row or instance in the dataset represents a single observation or sample. Observations may correspond to individual data points, events, transactions, or entities depending on the specific application domain.

**Training, Validation, and Testing Sets**: Datasets are typically divided into subsets for training, validation, and testing purposes. The training set is used to train the model, the validation set is used to tune model hyperparameters and evaluate model performance during training, and the testing set is used to assess the final performance of the trained model on unseen data.

**Data Quality**: Ensuring the quality and integrity of the dataset is crucial for building reliable models. This includes handling missing values, checking for data consistency and correctness, and performing data preprocessing and normalization as needed.

**Size and Complexity**: The size and complexity of the dataset can vary depending on the specific modeling task and the amount of available data. Larger datasets may provide more representative samples of the underlying population and allow for more robust model training, while smaller datasets may require careful handling to avoid overfitting.

Overall, datasets play a central role in the modeling process, serving as the foundation upon which predictive models are built, trained, and evaluated. The choice of dataset, along with appropriate data preprocessing and feature engineering techniques, significantly impacts the performance and generalization ability of the resulting models. On this research work, we sourced our data from three major categories as explained in the following sub-sections.

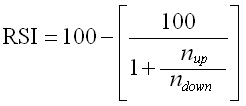
### Statistical data

Statistical data in the Foreign Exchange market is maintained at various degrees which include minutes, hourly, daily, weekly, and even monthly. On my research work, we relied on the daily data. My data were fetched from two different sources viz: Yahoo Finance and Investing.Com(<https://www.investing.com/currencies/usd-cad-historical-data>).

Data from YFinance is accessed directly through an API, while the data from Investing.Com has to be manually downloaded, transformed, before usage. However the data from Investing.Com is as twice bigger than that from YFinance, thus giving us the opportunity of coming out with better results. While YFinance maintained USD/CAD data from year 2003 till date (with over 5,385 records), Investing.Com maintained USD/CAD data from 1982 till date (with over 11,000 records).

### Technical data

**RSI (Relative Strength Index):** This is a popular momentum oscillator that measures the speed and change of price movements. It oscillates between 0 and 100 and is typically used to identify overbought or oversold conditions in a market. It is intended to chart the current and historical strength or weakness of a market based on the closing prices of a recent trading period. It is calculated as:



Where *nup* is the average of n-day up(gain) closes, and *ndown*is the average of n-day down(loss) closes.

**SMA (Simple Moving Average):** This is the average price over the specified period. It is a commonly used technical analysis indicator that helps smooth out price data by creating a constantly updated average price over a specific time period. It is calculated by adding up the prices of a security or asset over a certain number of periods and then dividing that total by the number of periods. That is to say, it is calculated by adding up the last "X" period's closing prices and then dividing that number by X



Where n = is the number of periods (e.g., days, hours, weeks) over which you want to calculate the average.

**Exponential Moving Average (EMA):** This is a type of moving average that gives more weight to recent data points compared to older data points. It is calculated by applying a smoothing factor to the previous EMA value and the current price. It places a greater weight and significance on the most recent data points. It is calculated as:



Where: EMA*t* is the Exponential Moving Average at time *t*

EMA*t- 1* is the Exponential Moving Average at the previous time period (*t - 1*)

*α* is the smoothing factor, which is calculated based on the number of period *n* used in the calculation. It is typically expressed as 2/(n + 1)

Closet is the closing price of the asset at time *t*

**MACD (Moving Average Convergence Divergence):** This is a popular technical analysis indicator used to identify trend reversals and momentum changes in financial markets, including stocks, currencies, and commodities. It consists of three components: the MACD line, the signal line, and the histogram. The MACD line is calculated by subtracting the 26-period exponential moving average (EMA) from the 12-period EMA. The signal line is a nine-period EMA of the MACD line. It is calculated thus:

MACD Line=EMA12−EMA26

Signal Line=9-period EMA of MACD Line

MACD Histogram=MACD Line−Signal Line

When the MACD line crosses above the Signal line, it's considered a bullish signal, indicating that the trend is potentially turning bullish and suggesting a buy opportunity.

When the MACD line crosses below the Signal line, it's considered a bearish signal, indicating that the trend is potentially turning bearish and suggesting a sell opportunity.

### Macroeconomics data

Macroeconomic factors refer to the broad economic indicators and variables that influence the overall performance of an economy. These factors provide insights into the health and direction of an economy and play a crucial role in shaping economic policies, investment decisions, and business strategies. These are some of the common macroeconomic factors which impacts the United State’s (USD) and Canadian (CAD):

**Gross Domestic Product (GDP):** GDP measures the total value of all goods and services produced within a country's borders over a specific period. It serves as a key indicator of economic growth and is often used to assess the overall health of an economy. While GDP Growth measures the marginal increase/decrease of the country’s economic performance, GDP Ratio measures the ability of a country being able to settle its debts.

**Inflation Rate:** Inflation measures the rate at which the general level of prices for goods and services is rising. It affects purchasing power, interest rates, and investment decisions, and central banks often target specific inflation rates as part of their monetary policy objectives.

**Interest Rates:** Interest rates, set by central banks, influence borrowing and lending activities, consumer spending, and investment decisions. Changes in interest rates can impact exchange rates, inflation, and economic growth.

**Unemployment Rate:** The unemployment rate measures the percentage of the labor force that is unemployed and actively seeking employment. It reflects the health of the labor market and has implications for consumer spending, government policies, and social welfare.

**Consumer Price Index (CPI):** The Consumer Price Index measures the average change over time in the prices paid by urban consumers for a basket of consumer goods and services. It is a key indicator of inflation and reflects changes in the cost of living. Central banks and policymakers closely monitor CPI to assess price stability and make monetary policy decisions.

**Imports and Exports:** Imports and exports refer to the goods and services a country buys from and sells to other countries, respectively. The balance between imports and exports affects a country's trade balance, current account balance, and overall economic growth. Trade deficits (when imports exceed exports) or surpluses (when exports exceed imports) can impact exchange rates, domestic industries, and employment levels.

**Government Revenue:** Government revenue includes all income generated by the government through taxes, fees, tariffs, and other sources. It funds public expenditures, such as infrastructure projects, social welfare programs, defense, and public services. Government revenue influences fiscal policy decisions, budget allocation, and economic development initiatives.

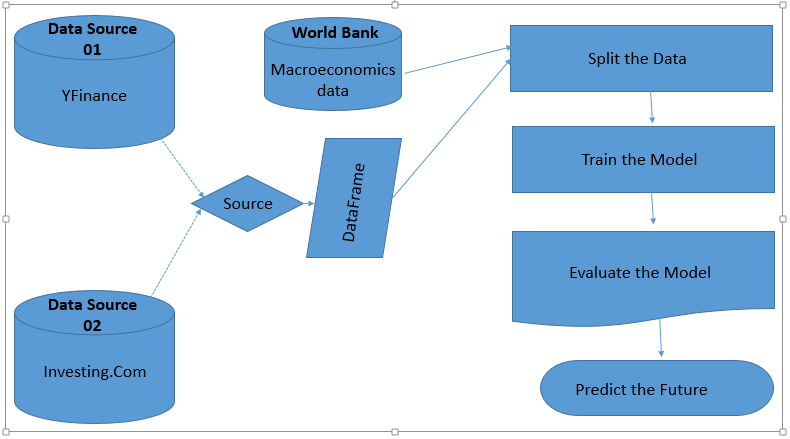
These macroeconomic factors are interconnected and play critical roles in shaping economic policies, influencing business decisions, and affecting the overall health of an economy. They can have complex and far-reaching effects on economies, financial markets, and individual businesses. Analyzing trends in CPI, imports, exports, and government revenue provides valuable insights into inflationary pressures, international trade dynamics, fiscal sustainability, and economic growth prospects. Policymakers, investors, businesses, and analysts closely monitor these factors to assess economic conditions and make informed decisions.

The Macroeconomics data were sourced from the World Bank’s(http://api.worldbank.org/) database through an API that was exposed as XMLs. We have considered the parameter “Price” as the target and the rest of the 18 macroeconomic factors as our features for training the models. Those macroeconomic factors are:

1. Consumer Price Indices (CPI) of USA
2. The Interest Rates of USA
3. The Inflation Rates of USA
4. GDP Ratios of USA
5. GDP Growths of USA
6. Imports of USA
7. Exports of USA
8. Government revenue of USA
9. Un-Employment Rates of USA
10. Consumer Price Indices (CPI) of Canada
11. The Interest Rates of Canada
12. The Inflation Rates of Canada
13. GDP Ratios of Canada
14. GDP Growths of Canada
15. Imports of Canada
16. Exports of Canada
17. Government revenue of Canada
18. Un-Employment Rates of Canada

We combined these eighteen macroeconomic factors with the technical tools to form a rich and comprehensive feature as an input to our model training and testing on USD/CAD exchange rate forecasting.

## Modelling



*Figure 1. Flow diagram*

The statistical data were supplied from two distinct sources (YFinance and Investing.Com). These are daily movements that tracks the changes in rates of USD against CAD. The basic information stored are **Open**, **High**, **Low**, and **Price**.

Open represents the exchange rate value at the beginning of each day.

High represents the highest rate recorded for the day.

Low represents the lowest rate recorded or the day.

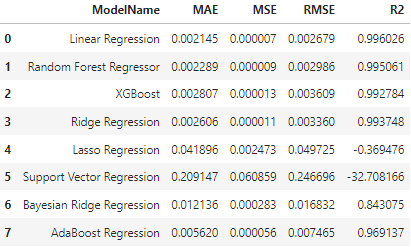
Price represents the exchange rate at the end of the day. For a business day that is still active, Price represents the rate at any moment of that day.

The Macroeconomics data were all fetched from the World Bank’s server through an API. For the purpose of this research, we concentrated on nine features which impacts the economy most, and thus affects the exchange rates. These features has been listed above in section 2.2.3 of this work.

The Technical data like RSI, SMA, EMA, and MACD were all calculated from the downloaded Statistical data using its formulas as was enumerated in section 2.2.2.

### Models considered

*Table 1. Models explored and compared*



As shown in Table 1 above, seven different Time series models were explored so as to get the best model suitable for predicting USD/CAD rate change. Linear regression, Random Forest Regressor (RFR), XGBoost, and Ridge Regressor models performed well based on the result above. The closer RMSE (Root Mean Square Error) is to zero, the more accurate the model prediction is.

### Modelling approach applied

As shown in Figure 1 above, the decision of the data source is made by the user. After which the data is downloaded into a DataFrame, and merged with the Microeconomics data using the **Date** field as a common column between the two DataFrames. For the purpose of this research work, I rely on the data from Investing.Com as it is more than twice the data from YFinance. It gives me more accurate forecasting results. At splitting stage, 15% of the data is reserved for testing, while the remaining 85% is used for training the model. The model is evaluated using different metrics as enumerated in section 2.1, and after which, forecasting follows.

### Adopted pipeline for predicting USD/CAD exchange rate

Among the top four in the models explored, RFR (Random Forest Regressor) is the most robust as it accepts unlimited number of features. RFR accepts Hybrid modelling approach such that Statistical data, unlimited Technical data, and unlimited Macroeconomics data can be combined together to come up with a high quality output. Random Forest Regressor mitigates the risk of overfitting, which is crucial when dealing with financial data where noise and outliers are common. By aggregating predictions from multiple decision trees trained on different subsets of the data, Random Forest Regressor reduces variance and generalizes well to unseen data, thus enhancing robustness and reducing the risk of overfitting. The dynamic of its operation makes it most acceptable. It adopts the Kalman filters approach, and operates in such a way that forecasting is iterated. The result of every forecast (n-1) forms part of the data that will be used in forecasting the next value. If for instance, if the RFR model is to predict the exchange rate value for next five days, day one is first predicted, and this rate value from day one will form part of the input for establishing the value or the next day, and so on. Take a look at SMA (Simple Moving Average) which is calculated as sum of the Closed Priced for *n* days divided by *n*. In this SMA instance, the predicted value is appended, while the oldest value in the series (based on Date) is popped off.

The time of training, validation, and testing data for Random Forest has been kept almost as the same as the time of our baseline models so that Random Forest can predict the fluctuations of the USD/CAD exchange rate for the same time as our baseline models have predicted the USD/CAD exchange rate. All hyperparameters have been set as default. After training Random Forest using the new dataset, this Random Forest model can predict the USD/CAD exchange rate fluctuations. These predicted fluctuations is a kind of noise generated from the fluctuations of features. If we can deduct some fluctuations from our baseline model predictions, the predictions will be closer to the actual values. First, the predictions of USD/CAD exchange rates provided by the baseline models have been calculated. Also, the fluctuations in the USD/CAD exchange rate predicted by Random Forest for the same time used for USD/CAD exchange rates prediction by our baseline models have been calculated. The baseline models provided the USD/CAD exchange rates for a particular time, and the Random forest provided the predicted fluctuations in the USD/CAD exchange rate for that same time.

Finally, the fluctuations have been deducted from the predicted USD/CAD exchange rates by our baseline models. The predicted fluctuations by Random Forest can be positive or negative. Suppose a single value of the USD/CAD exchange rate, predicted by our baseline models, is greater than the actual USD/CAD exchange rate. In that case, the fluctuation value predicted by Random Forest for that single value of the USD/CAD exchange rate should be positive. In that case, subtracting the fluctuation from the predicted USD/CAD exchange rate will drive the predicted USD/CAD exchange rate closer to the actual USD/CAD exchange rate. Suppose the predicted USD/CAD exchange rate is less than the actual USD/CAD exchange rate. In that case, the predicted fluctuation value should be negative so that it becomes positive while doing subtraction. As a result, the predicted USD/CAD exchange rate gets closer to the actual exchange rate.

Error is generated when there is a gap between the predicted and actual values. The main concept of our proposed pipeline is to make the predicted USD/CAD exchange rate closer to the actual exchange rate so that the error minimizes. But the problem is, let’s say, for example, for the first ten values, the predicted values are greater than the actual values. The predicted values for the next five values are less than the actual ones. Now, if we subtract a small fixed value from all the predicted values, the first ten predicted values will get closer to the actual values because those values were greater than the actual values. But the next five values will generate more error than the previous because those five values were less than the actual values, and subtracting a small value will create more distance from the actual values. Adding a small value will make the last five prediction values closer to the actual values, but again it will generate more distance for the first ten predicted values. So it is clear that adding or subtracting a small discrete value from the prediction value will not ensure that all the predicted values will get closer to the actual value. So it cannot ensure that the overall error will be reduced. Moreover, the gap between the predicted value and actual value is not equal and unidirectional everywhere, meaning predicted values are not either greater or less than actual values in all the situations. So choosing the small discrete value is also very critical. To address this issue, the small value we want to add or subtract will not be a fixed discrete value. Rather than considering a single small discrete value, we will consider different small values for different data points. Those different small values will be the predictions of Random Forest that we have introduced as predicted fluctuations. As we have mentioned earlier, the Random Forest model has been trained by using the features’ fluctuations, and the Random Forest’s prediction is the fluctuation in the USD/CAD exchange rate. That means the predictions of Random Forest describe how much the price of USD/CAD can fluctuate. So the USD/CAD exchange rate fluctuation will differ for every data point. Those fluctuation values can be both positive and negative. Now, if we deduct the fluctuation values from the predicted values, there is a chance that the predicted values will get closer to the actual values. Because now we are not using a small discrete value for all the data points. Each small value (fluctuation) is dedicated to a single data point as specific small values are predicted for specific data points by Random Forest. The unidirectional problem has been solved because the predicted small values (fluctuations) of Random Forest can be both positive and negative. So if the predicted small value (fluctuation) is positive, the predicted USD/CAD exchange rate will be reduced after subtracting. Again, if the predicted small value (fluctuation) is negative, then the USD/CAD exchange rate will be increased after subtracting. However, it is impossible to predict each fluctuation value correctly. In our experiment, we found an improvement in RMSE for all our models while applying this proposed pipeline. This indicates that most of the fluctuation predictions were correct. Therefore, after subtracting the fluctuations from the predicted USD/CAD exchange rates, the predicted USD/CAD exchange rates got closer to the actual price.

Random Forest Regressor (RFR) is a supervised learning algorithm belonging to the ensemble learning family, specifically the random forest method, used for regression tasks. It's an extension of the Random Forest algorithm for classification. Here is how Random Forest Regressor works:

**Ensemble of Decision Trees:** Like Random Forest for classification, Random Forest Regressor builds an ensemble of decision trees during training. Each decision tree is trained on a random subset of the training data and features.

**Decision Tree Construction:** Each decision tree in the ensemble is constructed by recursively partitioning the feature space into regions, where each region corresponds to a leaf node in the tree. The partitioning is done to minimize the mean squared error (MSE) of the target variable within each region.

**Bootstrap Aggregating (Bagging):** Random Forest Regressor uses a technique called bootstrap aggregating (bagging), where multiple decision trees are trained on different subsets of the training data. This helps reduce overfitting and improve generalization performance.

**Random Feature Subsampling:** In addition to sampling different subsets of the training data, Random Forest Regressor also randomly selects a subset of features at each split in the decision trees. This further increases the diversity among the trees in the ensemble and reduces correlation between them.

**Prediction:** During prediction, Random Forest Regressor aggregates the predictions of all decision trees in the ensemble to make the final prediction. For regression tasks, the predictions are typically averaged across the ensemble.

**Hyperparameters:** Random Forest Regressor has various hyperparameters that can be tuned to optimize performance, such as the number of trees in the ensemble, the maximum depth of each tree, the minimum number of samples required to split a node, and the maximum number of features to consider when looking for the best split.

Random Forest Regressor is known for its robustness, scalability, and ability to handle high-dimensional data with a large number of features. It often performs well across a wide range of regression problems and is less prone to overfitting compared to individual decision trees.

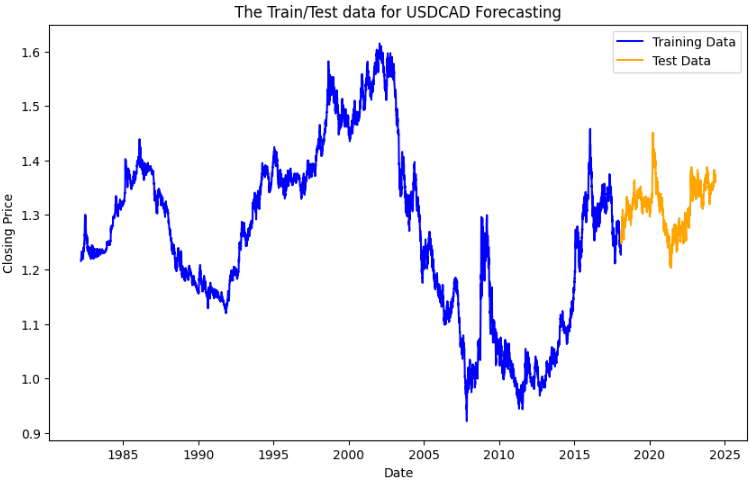
# Result

We have predicted the USD/CAD exchange rate using all our models and calculated the error of our models ([Table](https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0279602#pone-0279602-t003) 1) by using RMSE and MAE. Most of the researchers have used the RMSE for evaluating their models. For that reason, the RMSE has been considered the main evaluation metric. To check the fitting of our models, we have considered the R2 score. Then we plotted the actual value of the USD/CAD exchange rate price versus the predicted price (Figures [4](https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0279602#pone-0279602-g002), 5 and 6). After that, we applied our proposed pipeline to our models to check the effectiveness of the proposed pipeline. Finally, we have compared our results with other research.

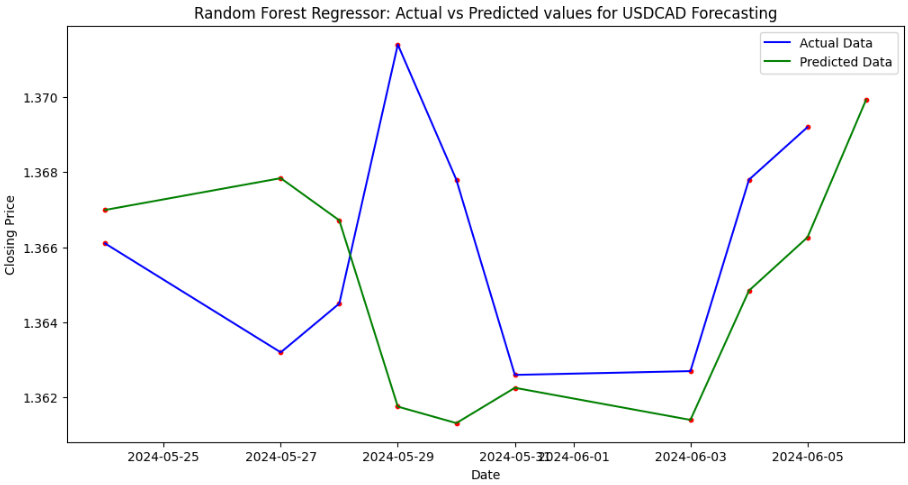


*Figure 2. Last fifty years data on USD/CAD*

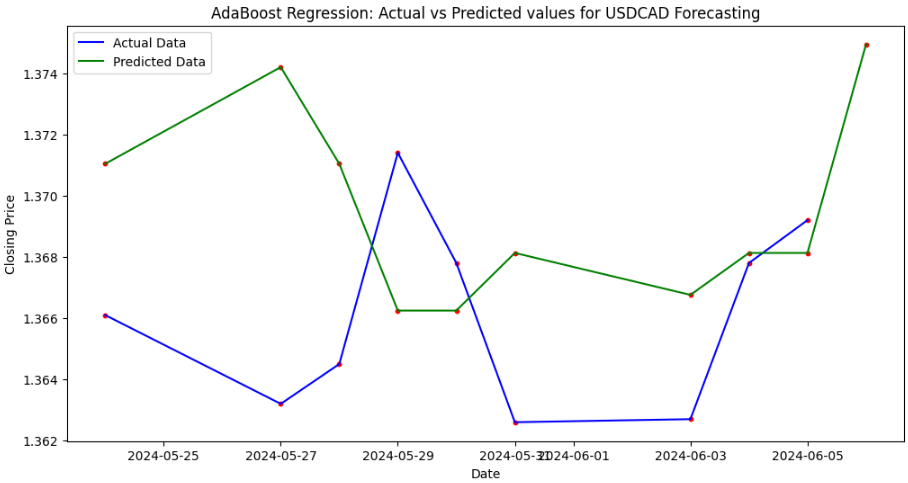
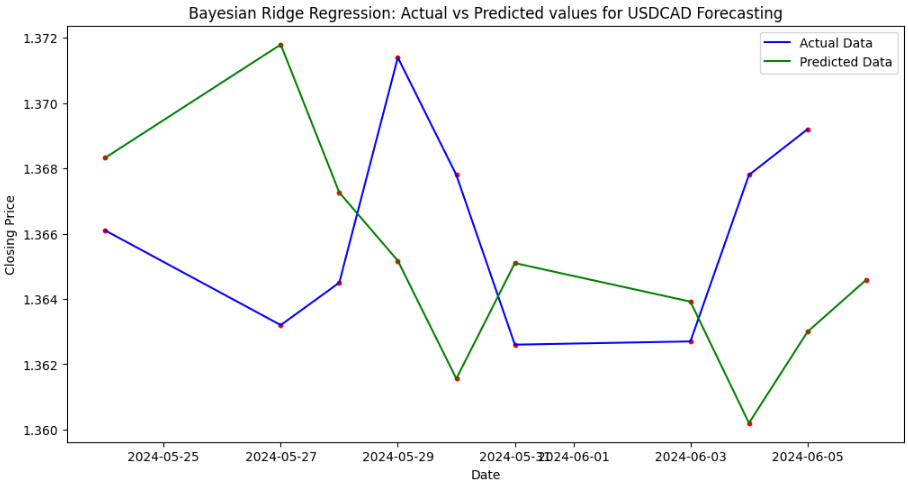
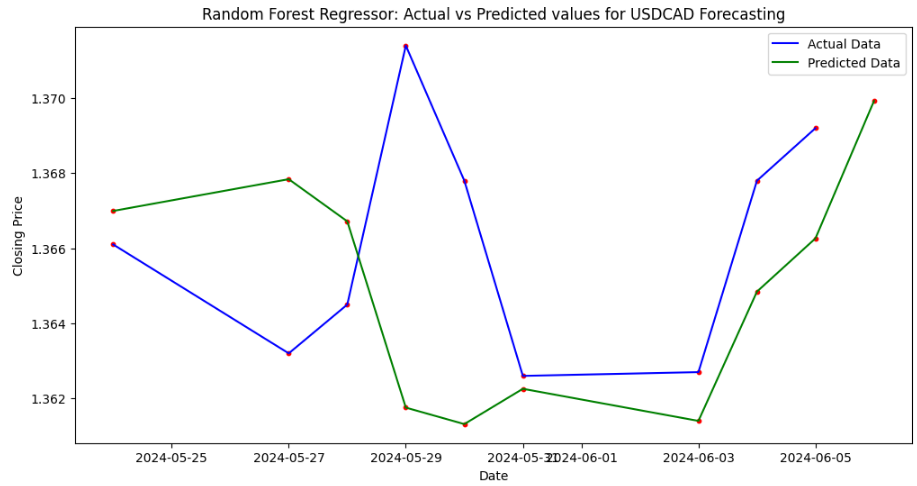
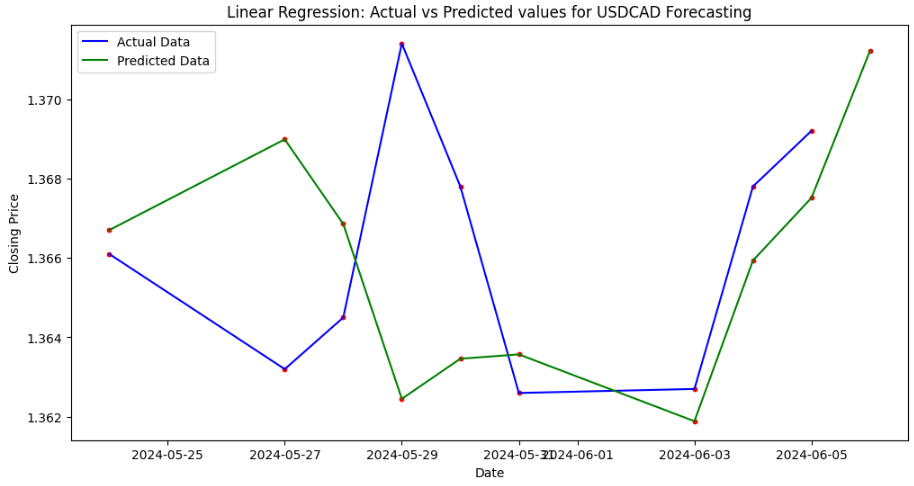
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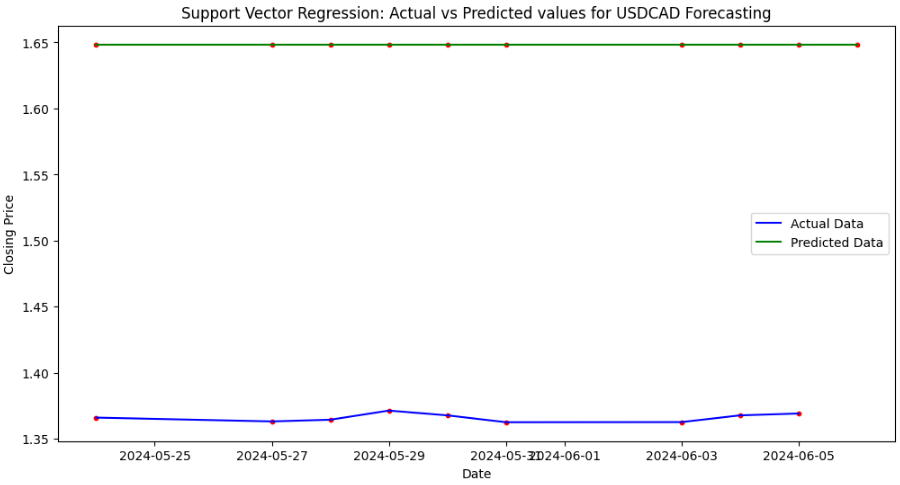
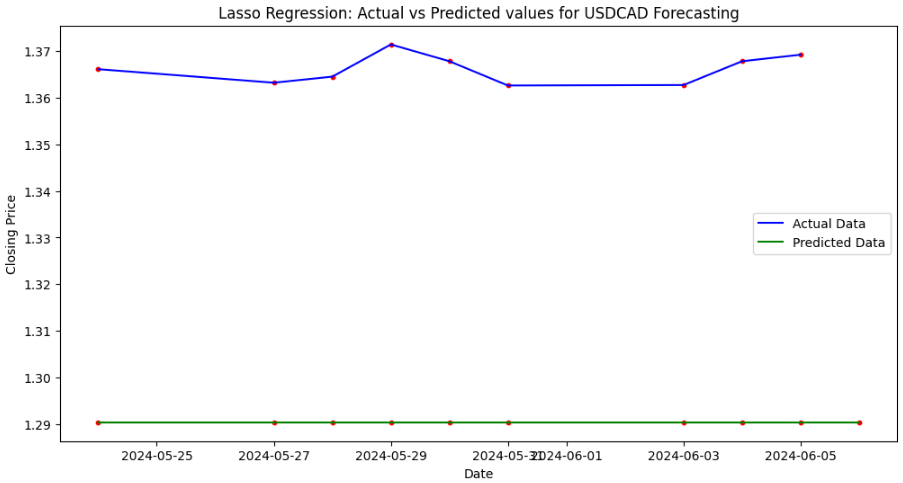
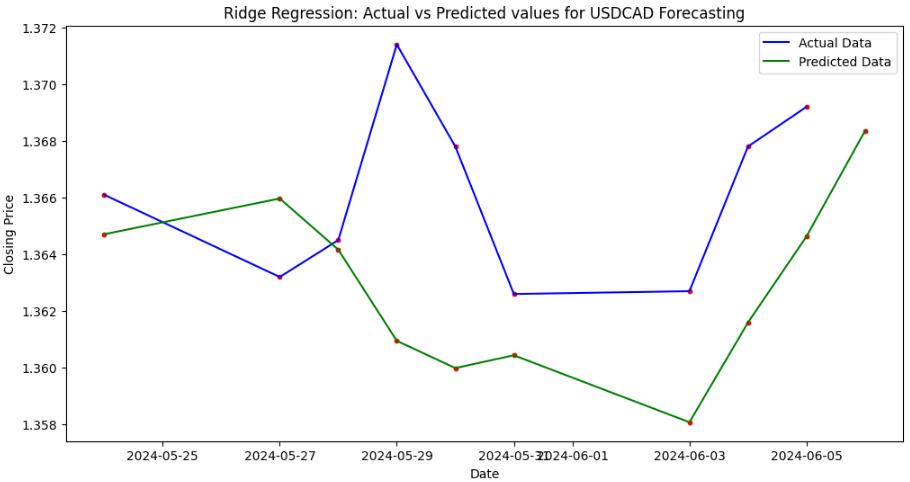
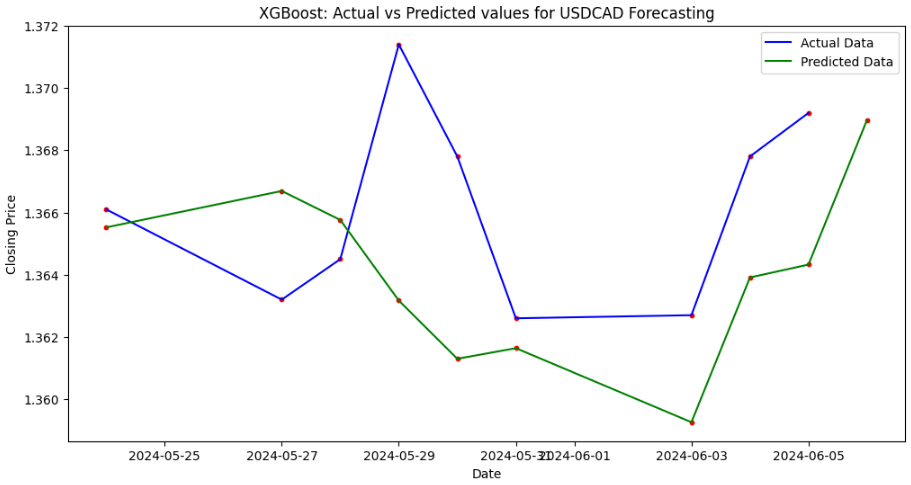
*Figure 3. Train-Test Data (Data downloaded as from 1982)*



*Figure 4. Actual vs Predicted values for* ***Random Forest*** *Regressor*



*Figure 5. Comparing* ***Actual*** *vs* ***Predicted*** *values for all the explored models - A*



*Figure 6. Comparing* ***Actual*** *vs* ***Predicted*** *values for all the explored models - B*

# Conclusion and Future proposals

Forecasting the exchange rate of USD/CAD more accurately can make the FOREX market a secure and reliable place for investors. Previously many researchers tried to forecast the exchange rate of USD/CAD by using time series models, machine learning models, and deep learning models but none of the research included factors that can directly affect the exchange rate of USD/CAD. To introduce a new scope for the researchers, we have included several Technical analytical metrics with 18 macroeconomic factors in our dataset. These macroeconomic factors are directly correlated with the USD/CAD exchange rate. In our research, we got a very good RMSE of 0.002679(Linear Regression) and 0.003007(Random Forest Regressor). In the future, research can be conducted using advanced models with these macroeconomic features to determine if the predictions are even more accurate. This study further triggered the need of brainstorming on the existing exchange rate forecast methodologies, and introducing more effective Technical indices and Macroeconomic factors.

As it is, our Macroeconomics feature were fetched from the World Bank’s database through an API. These data where maintained in yearly basis. Future research may help us by gaining access to these macroeconomics data where it is maintained at a more frequent intervals like quarterly or even monthly.

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