DEVELOPING A PREDICTIVE MODEL TO PREDICT THE EXCHANGE RATE OF BANGLADESHI TAKA (BDT) AGAINST US DOLLAR (USD)

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Abstract

This study is concerned with applying machine learning to develop a predictive model to forecast the exchange rate of Bangladeshi Taka (BDT) against US dollar (USD). There are studies that showed that machine learning and deep learning methods fit well in predicting exchange rate and outperform traditional models. However, in Bangladesh, machine-learning based predictive modeling for the said purpose has remained an uncharted area so far and this paper attempts to fulfill this research gap. For this, the economic data of Bangladesh for 11 fiscal years (from 2009-10 to 2019-20) were collected from the central bank database and analyzed using the analytics tool-KNIME. The findings suggest that (1) decision tree makes a comparatively better predictive model with very high level of accuracy, (2) feature selection technique does not contribute to the improvement of accuracy, and (3) to get the optimal model, multiple experiments with different combinations of variables should be conducted. The findings of this paper can be of immense help to several stakeholders including the country's central bank, policymakers, academicians, and researchers as it can be the base point to explore novel avenues of research and to advance the application of predictive modeling in new areas.

Keywords : *Predictive Analytics, KNIME, Decision Tree, Naïve Bayes, SVM, Feature Selection, Exchange Rate*

JEL Classification : *C53*

1. INTRODUCTION

Bangladesh, being an emerging economy in South Asia, receives huge remittance from the workers working abroad, enjoys healthy Foreign Direct Investment (FDI), finances many mega projects partly from foreign borrowings, and imports more than exports. This developing country is one of the fastest growing economies in South Asia and is aiming to be a developed country by 2041. Over the last couple of years, this country has made significant progress in Gross Domestic Product (GDP) growth, foreign trade, USD reserve, poverty reduction, inflation, and other important socio-economic factors. One major driver of the economy's wheel is wage earners' remittance which has seen significant growth in last couple of fiscal years. Government is trying to ensure that the remittance comes in through formal channel.

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2% incentive by government and gradual depreciation of BDT against USD are few of the initiatives to ease the remittance inflow. The country's foreign exchange reserve depends heavily on the inward remittance too. For instance, the reserve has reached the record $39 billion, riding on the inflow of $4.56 billion in remittance in July and August of 2020.

Many researchers across the globe conducted studies to detect the relationship between exchange rate and FDI. One such study focused on the impact of exchange rate on the FDI inflow in the USA and found that when the FDI environment is favorable, the exchange rate plays a positive and significant role on the average level of FDI inflows. Because FDI is another key driver for economic growth of the country, the government of Bangladesh is reforming policies to attract FDI. Also, many international firms are planning to diversify their manufacturing locations to multiple countries. Therefore, a favorable exchange rate, i.e., weaker BDT will be an added advantage for Bangladesh. Again, one study shows that in South Asian countries, exchange rate volatility affects the FDI inflows negatively. However, openness of trade and increased GDP may counter this impact (Jannat, 2020).

Another notable factor is the country's export, which is mostly dependent on ready-made garments (RMG) sector. Hence, government is trying to boost exports by diversifying the basket into different sectors. In addition to that, to increase export, recently the central bank is planning to depreciate local currency, i.e., BDT against USD, driven by the demand from local exporters and the currency depreciation by competitor countries. Currency devaluation affects multiple other factors such as import, remittance, inflation, etc. Therefore, currency depreciation through managed floating should consider all the related factors. Although the fluctuation in the exchange rate does not impact the foreign trade of a country in the short run, it can affect in the long run (Nguyen & Do, 2020).

1.1 Research Motivation

Exchange rate has an impact on the FDI a country receives, the export it makes, the inflation it experiences, and the interest rate it maintains. Hence, forecasting the exchange rate has lasting impact on decisions made by multiple stakeholders: businessmen, government, policy makers, international lenders, and so on. To develop the infrastructure and ensure better connectivity for future, the government of Bangladesh has already taken multiple mega projects, with many more in the pipeline. Being a developing country, Bangladesh cannot afford to finance these projects on its own, rather depends on borrowing from international lenders. Exchange rate is crucial for these borrowings and repayment purposes as well. Moreover, as Bangladesh leans heavily towards imports than exports, exchange rate is always a crucial factor as import payments are made in USD. So, to boost exports, the central bank is planning to work on making the exchange rate favorable either by devaluing currency or by other measures through managed floating system. Again, a weaker BDT against foreign currencies means higher consumer spending for the imported items. Although this is good to demotivate imports, there are lots of products or services for which it is critical. Hence, even if the central bank plans to devalue currency, it must strike the right balance, taking this important factor into account. In addition to direct impacts, a weak exchange rate indirectly pushes inflation. To counter that, sometimes, the central bank intervenes by raising interest rate. Conversely, if the exchange rate is too strong, it lowers the interest rate to ease the contractionary monetary policy. Hence, exchange rate has indirect impact on interest rate too (Picardo, 2020). Since exchange rate plays a pivotal role for export, inflow of remittance, FDI, and other economic variables, the central bank always tries to maintain a stable and favorable rate. These are the motivating factors behind conducting this research as its completion will lead to outcomes and understanding that will be beneficial to multiple stakeholders including the central bank and other policy makers.

1.2 Research Objective

The major objective of this study is to develop a machine-learning based predictive model to predict the exchange rate of BDT against USD.

1.3 Organization of the Paper

The paper starts with the background of the study which discusses the relevant important variables followed by an extensive literature review to shed light on prior works in this area and to clearly pinpoint the research gap. In the next part, the methodology section talks about the data and explains the analysis tool used. The data analysis and discussion part elaborates on the findings resulted from the different classification techniques used and the rationale behind using each of the methods. The paper ends with highlighting the potential avenues of further research and the theoretical and managerial contributions this paper can make in this regard.

2. LITERATURE REVIEW

There are a good number of researchers who worked on issues such as factors affecting exchange rate (Uddin et al., 2013; Chowdhury & Hossain, 2014), determinants of exchange rate (Ogun, 2020), and the comparison of different econometrics models to forecast exchange rate (Mia et al., 2017; Mia & Rahman, 2019; Banik et al., 2013). However, there are relatively fewer works in Bangladesh that focused on developing a machine-learning based predictive model to determine the exchange rate of BDT against USD.

Alam et al. (2017) worked on finding an appropriate Artificial Neural Networks (ANN) model to forecast the exchange rates of BDT vs USD. They used the exchange rate data from 2004 to 2016. Using 80% of the data in the training set, 10% data in the test set, and the remaining 10% as validation set, they concluded that neural network model fits well for the intended purpose.

Ahmed and Keya (2019) did a time series analysis for predicting the exchange rate of BDT against USD. Calculating the trend of the yearly data from 1971-72 to 2014-15, they forecasted the exchange rate for the period 2015-16 to 2019-20. The researchers tested the stationarity of the data and finally identified the Autoregressive Integrated Moving Average (ARIMA) model to be the best fit model for predicting exchange rate.

A comparative analysis between the ANN model and the ARIMA model was furnished by Mia et al. (2017). The comparative analysis was based on the accuracy of these models. Analyzing the exchange rate data from 2004 to 2016, the study concluded that ANN models are a better predictor of exchange rate in comparison to the ARIMA models.

Another comparative analysis was conducted by Mia and Rahman (2019) where they evaluated a couple of econometrics model to identify the best one for forecasting the volatility for exchange rate. They used the exchange rate data (BDT vs USD) from 2004 to 2019 for this purpose. Their findings suggested that generalized autoregressive conditional heteroscedasticity (GARCH) model is the best fit model for the prediction.

Banik et al. (2013) worked with daily exchange rate data for the period 1992 to 2009. They used non-linear forecasting models: Markov Switching Autoregressive model (MS_AR), fuzzy extension of artificial neural network model (ANFIS), and generalized autoregressive conditional heteroscedastic (GARCH) model. They used 63% observation to train the models and the rest 37% for testing purpose. Using the statistical measures, they identified that ANFIS is a better predictor than the other two models.

The work of Barai et al. (2018) considered more variables than just the historical exchange rate. To forecast the nominal exchange rate of BDT, the researchers used an Autoregressive Distributed Lag (ARDL) version of an error correction model since this allows to check the long-term and short-term dynamics of the exchange rate. Their designed equation included the impact of national price level differences, interest rate differentials, and foreign currency reserves. To evaluate the predictive accuracy, they used the random walk and random walk with drift benchmarks. Their forecast accuracy analysis revealed that ARDL based forecasts are less accurate than the benchmark models.

To identify the factors affecting the exchange rate, Uddin et al. (2013) checked the impact of four different variables: currency reserve, stock of money, total debt, and political instability (represented by a dummy variable). They used the monthly time series data for the period 1984 to 2012. They concluded that all these factors matter in the determination of exchange rate. For example, if currency reserve goes up, exchange rate becomes favorable.

Chowdhury and Hossain (2014) worked on almost similar topic but with a different data set. They used the data for the period 1990 to 2011 and checked the importance of inflation, GDP growth rate, interest rate, and current account (CA) balance in the determination of exchange rate. Using simple linear regression analysis for data analysis, they concluded that GDP growth rate, current account balance, interest rate, and inflation rate are the major factors.

Ogun (2020) proposed a model that can determine the nominal exchange rate in a developing country. It mentioned that imports, capital outflow, and speculations influence the demand for foreign exchange whereas exports, foreign investments, shifts in foreign reserve, and speculations impact the supply side. Moreover, it emphasized that, in a typical developing economy, the nominal exchange rate is varied by some crucial factors: the weather condition, existence of parallel market exchange rate premium, and corruption.

Joshi et al. (2020) checked the suitability of ARIMA model to predict the exchange rate of Indian Rupee (INR) against three different currencies: USD, Euro, and Yen. They designed 4 different models and identified the most suitable one for forecasting the exchange rate in the context of India.

To forecast the foreign exchange rate between INR and USD, Kaushik and Giri (2020) made a comparative analysis among a traditional econometric model, a machine learning model, and a deep learning method. The data was collected and analyzed for the period 1994 to 2018. Their index used multiple variables: consumer price index, index of industrial production, rate of interest, money supply, reserves, stock market index, and net export. The analysis was advanced enough to develop three prediction models to forecast the exchange rate. Additionally, it covered the feature analysis to determine the important variables. The authors concluded that contemporary machine learning and deep learning methods outperform the econometric models.

2.1 Summary of Literature and Research Gap Identification

Table 1 : Summary of Literature Review

Researchers	Objectives	Models/Variables used
Alam et al. (2017)	To find an ANN model to forecast the exchange rates of BDT vs USD.	Artificial Neural Networks (ANN)
Ahmed and Keya (2019)	To predict the exchange rate of BDT against USD.	Autoregressive Integrated Moving Average (ARIMA)
Mia et al. (2017)	To compare ANN model and the ARIMA model to identify the better one.	ARIMA and ANN
Mia and Rahman (2019)	To identify the best model by evaluating a couple of econometrics model.	Econometrics models
Banik et al. (2013)	To identify the best model to forecast the exchange rate.	Markov Switching Autoregressive model; ANN model; GARCH model
Barai et al. (2018)	To forecast the nominal exchange rate of BDT.	Autoregressive Distributed Lag (ARDL) version of an error correction model

Researchers	Objectives	Models/Variables used
Uddin et al. (2013)	To identify the factors affecting the exchange rate.	Currency reserve, stock of money, total debt, and political instability
Chowdhury and Hossain (2014)	To identify the factors affecting the exchange rate.	Inflation, GDP growth rate, interest rate, and current account (CA) balance
Ogun (2020)	To identify the determinants of nominal exchange rate movements in less developed countries.	Weather condition, the existence of parallel market exchange rate premium, etc.
Joshi et al. (2020)	To check the suitability of ARIMA model to predict the exchange rate of INR.	4 ARIMA models
Kaushik and Giri (2020)	To forecast the exchange rate while conducting a comparative performance analysis of an econometric model, a machine learning model, and a deep learning method.	Granger Causality test; Vector Auto-regressive model; Support Vector Machine (SVM); Long Short-Term Memory RNN

In summary, the works of Alam et al. (2017) and Ahmed and Keya (2019) focused on finding the appropriate model for predicting exchange rate. Mia et al. (2017) and Mia and Rahman (2019) did comparative analysis of the models' accuracy and identified the best fit model. Banik et al. (2013) used the daily data series to determine the best non-linear forecasting model. However, all these five works used the historical exchange rates for different periods. Barai et al. (2018) worked on examining the model accuracy by using more variables. Uddin et al. (2013) and Chowdhury and Hossain (2014) worked on determining the significant factors that affect the exchange rate. If the papers of authors from other nearby countries are checked, a more extensive analysis is observed. For instance, the work of Kaushik and Giri (2020) utilized machine learning for the intended prediction. Again, Ogun (2020) emphasized on including unconventional variables.

In Bangladesh, relatively fewer studies have focused on developing prediction model to forecast the exchange rate. It is seen that the existing works to determine the exchange rate did not use advanced techniques with multiple variables. Hence, there is a clear gap to work on developing advanced predictive model.

3. METHODOLOGY

3.1 Data Source

This paper has used the economic data of Bangladesh for 11 fiscal years, starting from 2009-10 to 2019-20. There are couple of reasons behind choosing the data for this period only. Firstly, to work with a machine learning model, a sizable dataset is crucial so that the model can be adequately trained; a critical factor for the prediction accuracy. Secondly, during the chosen fiscal years, both the local and global economy experienced diverse economic events that impacted the exchange rate, making the sample representative. Having said so, undoubtedly, inclusion of more years of data would have been better but availability of the data in the required format, i.e., monthly data for the chosen variables, was a challenge which is another major rationale to consider the mentioned period only. Data has been collected from the following source:

✓ Monthly Economic Trend Reports published by Bangladesh Bank (the central bank of Bangladesh)

3.2 Variables Used

Independent variables: The independent variables derived from literature review include wage earners' remittance, balance of trade, foreign reserve, inflation, FDI, interest rate, and GDP. FDI data was available for 3 or 6 months combined. Hence, the total amount was equally divided in each month for that period. While preparing the paper, the FDI data for April, May, and June 2020 were not available. In the analysis using KNIME, these missing values were imputed using appropriate node. The interest rate considered here is the rate of interest on non-resident foreign currency deposit (NFCD) account offered by foreign banks operating in Bangladesh. Moreover, In Bangladesh, as GDP is calculated yearly, it was equally divided into 12 months.

Dependent variable: Exchange rate was used as the dependent variable. It is the equivalent value of one USD in BDT at a particular time. For this paper, period (month) average was taken.

3.3 Analytics Tool Used

This study utilized the KNIME analytics platform to build a predictive model. To identify the best classification method, the paper experimented couple of techniques in KNIME. Firstly, workflows were developed using Decision Tree, Naïve Bayes, and K-fold cross validation techniques. Secondly, to check whether the accuracy improves, workflows were built using feature selection methods. The techniques used with feature selection are Decision tree and Naïve Bayes. As part of the experiment, in Naïve Bayes, two workflows were constructed by creating 5 and 10 folds accordingly. Thirdly, the dependent variable was grouped into four and five class intervals respectively. Approximately equal number of observations were grouped in each class. But for that, the class width (the range of exchange rates) had to be compromised, i.e., they were different for each class. Then workflows were formulated using the Decision Tree, Support Vector Machine (SVM), and Naïve Bayes techniques. Apart from these, this paper utilized the followings:

Missing value: The missing values were imputed using the 'Missing value' node of KNIME. The condition was set as 'most frequent value' for strings and moving average by taking 6 values behind and 1 value ahead for number.

Partitioning: In KNIME workflows, the data need to be partitioned for training and testing. With the classification techniques- Decision Tree, Naïve Bayes, and SVM- 80% data were used to train the model and 20% to test it. Additionally, in feature selection with Naïve Bayes technique, data were split as 85% for training and 15% for testing.

X-partitioner: This paper utilized the x-partitioner node to create folds. In the K-fold cross validation, firstly 5 folds were created. Again, in feature selection using Decision Tree and Naïve Bayes, initially 5 folds were made. Then with Naïve Bayes, 10 folds were created. The main purpose of such variations in fold creation was to check which method helps develop the most robust predictive model.

Sampling technique: In KNIME workflows, data need to be sampled for training and testing the model. Initially, random sampling was used to select data for training. However, when the dependent variable was classified in different classes, stratified sampling was used. The main objective of choosing stratified sampling in the latter case was to ensure that each class group is properly represented to train the model.

4. DATA ANALYSIS AND DISCUSSION

4.1 Developing Predictive Model

First, this paper tried to develop a predictive model to predict the exchange rate (dependent variable) by using all the other independent variables. Table 2 summarizes the result of each method used.

Table 2 : Prediction Accuracy under Different Methods

Methods Used	Prediction Accuracy	Comment
Decision tree	29.6%	The accuracy may seem poor, but it actually is not so (exchange rate in each month was different. With each exchange rate representing one category, there were around 27 categories)
Naïve Bayes	22.2%	
K fold cross validation (k=5)	$R^2 = 0.921$	Good accuracy

In the workflow using Decision Tree and Naïve Bayes techniques, 80% data were used for training and 20% for testing. Random sampling method was used in both methods. Moreover, random seed was applied to ensure that the result remains same even if the workflow is run at different times. Although the accuracy seems low, it is not so because there were around 27 categories. More specifically, each row of the test dataset represented a category as exchange rate for each month was different. With Naïve Bayes, the accuracy fell to 22.2% from the 29.6% found with Decision Tree method. Then, the study used 5-fold cross validation technique. Here too, the random sampling method and random seed were used. The value of R-squared was found 0.921, indicating a comparatively better accuracy.

4.2 Feature Selection

At this stage, this paper experimented to improve the accuracy by using the feature selection method in KNIME. The output is summarized in Table 3.

Table 3 : Prediction Accuracy using Feature Selection

Methods Used	Accuracy (hold-out set)	Accuracy (last loop)	Mean (Accuracy)	Standard Deviation (Accuracy)	Comment
Decision tree	14.8%	4.8%	0.095	0.048	High variation in accuracy between the hold-out set and the last loop, and among the loops. Most important feature: Foreign reserve
Naïve Bayes (5-fold)	18.5%	9.5%	0.076	0.026	High variation in accuracy between the hold-out set and the last loop, and among the loops. Most important feature: Foreign reserve.
Naïve Bayes (10-fold)	15.0%	9.1%	0.098	0.091	High variation in accuracy between the hold-out set and the last loop, and among the loops. Most important features: Trade Balance, inflation.

4.2.1 Feature Selection using Decision Tree

This study used feature selection under Decision Tree method. Using the random sampling method, 80% data were used to train the model. Later, 5-fold cross validations technique was used to partition the data. In the 'Feature Selection Filter' node, the accuracy was 0.095 using one feature (Foreign Reserve). After that if other variables, such as Remittance, Trade Balance, GDP, and Current account were added, the accuracy remained unchanged, implying that the addition of these features did not contribute to the accuracy. But when more features such as Interest Rate, Capital Account, and Inflation were added, the accuracy fell to 0.048. Since one of the objectives of feature selection is to select minimum number of variables, 'Foreign Reserve' was identified as the most important feature. Again, using Decision Tree, the accuracy for the hold-out set was 14.8% whereas the accuracy for the last loop was 4.8%. Moreover, the performances of the five folds varied widely, ranging from 0.048 to 0.143. Additionally, the mean of accuracy was 0.095 with a standard deviation of 0.048 (too high for this mean). Therefore, it can be concluded that feature selection using Decision Tree did not improve the accuracy of the model and was not a reliable predictive model in this case.

4.2.2 Feature Selection using Naïve Bayes (5-fold)

Next, this paper employed feature selection by using the 'Naïve Bayes' method. Here also, using the random sampling method, 80% data were used to train the model. Later, 5-fold cross validation technique was used to partition the data. In the 'Feature Selection Filter' node, the accuracy was 0.095 when only one variable- 'Foreign Reserve'- was used. Later, with the addition of more variables, the accuracy remained the same, i.e., 0.095. More specifically, if variables such as FDI, Remittance, Trade Balance, GDP, Current Account, Capital Account, Inflation, and Interest rate were used, the accuracy did not improve, indicating 'Foreign Reserve' to be the most important feature. The accuracy of the hold-out set was 18.5% and that of the last loop was 9.5%, showing that the variation of performance was too high. On the other hand, the mean of accuracy was 0.076 with a standard deviation 0.026 (very high for the mean 0.076). Additionally, the variation among the performance of loops ranged from 0.048 to 0.095, meaning that the performances of the loops were not consistent among themselves. Altogether, this model too was not suitable enough to predict the exchange rate in this case.

4.2.3 Feature Selection using Naïve Bayes (10-Fold)

As the dataset was small, this paper checked whether the change in partition improves the accuracy. Therefore, using the Naïve Bayes classification technique, 15% data were kept aside as hold-out set. Instead of using 5 folds, 10 folds were used here. However, these changes had little impact on accuracy. For instance, the accuracy to predict the exchange rate for the hold-out set was 15% and the accuracy of the last loop was 9.1%. Again, the performances of different folds in 'Loop End' node had huge variations, ranging from 0% to 27.3%. Additionally, the mean of accuracy was 0.098 with a high standard deviation of 0.091. Altogether, changing the partitioning method and increasing the number of folds did not improve the accuracy. However, in the 'Feature selection filter', it was seen that the variable 'Trade balance' resulted in 11.8% accuracy but if the variable 'Inflation' was added, the accuracy reached 17.6%. But further addition of variables beyond these two did not change the accuracy anymore. So, two important features identified here were 'Trade Balance' and 'Inflation'.

4.3 Categorization of Dependent Variable (4 categories)

At this step, the dependent variable (Exchange rate) was categorized into four classes as shown in Table 4. Again, the main purpose of this classification was to help identify the range within which the exchange rate might fall. It is worth mentioning here that to keep the number of observations almost similar in each class, the class width had to be compromised.

Table 4 : Classification of Dependent Variable

Range (Exchange Rate)	Category	Number of Observations	Range (Exchange Rate)	Category	Number of Observations
69.06 to 77.52	1	33	77.59 to 78.40	2	35
78.45 to 81.88	3	31	82.55 to 84.95	4	33

Here, three different classification techniques were used. For all of these, stratified sampling method was chosen. 80% data were used to train the model and the rest to test it. Table 5 summarizes the accuracy under each method.

Table 5 : Summary of Output with 4 Categories (Accuracy)

Methods Used	Prediction Accuracy	Comment
Decision tree (with 4 categories)	**96.3%**	**Highest accuracy**
SVM (with 4 categories)	51.9%	Lower in comparison to accuracy in Decision Tree
Naïve Bayes (with 4 categories)	88.9%	Better but lower in comparison to that of Decision Tree

With four classes, accuracy above 25% is good. As shown in the above table, using the 'Decision Tree' resulted in an accuracy of 96.3% which is far better than the standard. Again, the accuracy fell to 51.9% using the SVM method. However, as mentioned earlier, if there are four classes, the accuracy above 25% is acceptable. Thus, the accuracy using SVM was also good. Finally, under the Naïve Bayes Classification technique, the prediction accuracy was 88.9%. Of these three methods, using categorization of dependent variable, the 'Decision tree' method provided the highest accuracy.

4.4 Categorization of Dependent Variable (5 categories)

While classifying the observations into four classes, one class (the first one) had higher width in comparison to the other three classes. Therefore, to make the class width comparatively more uniform, this paper classified the observations into five classes as shown in Table 6.

Table 6 : Classification of Dependent Variable

Range (Exchange Rate)	Category	Number of Observations	Range (Exchange Rate)	Category	Number of Observations
69.06 to 75.74	1	28	76.52 to 77.80	2	27
77.81 to 79.69	3	26	79.83 to 83.41	4	26
83.72 to 84.95	5	25			

Table 7 : Summary of Output with 5 Categories (Accuracy)

Methods Used	Prediction Accuracy	Comment
Decision tree	**88.9%**	Better but lower in comparison to Decision Tree's accuracy with 4 classes
SVM	70.4%	Better than SVM's accuracy with 4 categories but lower in comparison to Decision Tree's accuracy
Naïve Bayes	**88.9%**	Better but lower in comparison to Decision Tree's accuracy

Here, the method for sampling and partitioning was replicated as it was with four classes. As shown in Table 7, with decision tree, the accuracy was 88.9% which is less than the accuracy with decision tree using 4 categories. Again, using the SVM method, the accuracy was 70.4%. Therefore, it can be said that with exchange rate categorized into five classes, the SVM method improved the accuracy. However, in comparison to performance of the accuracy with Decision tree and Naïve Bayes method, the performance of the SVM method was relatively lower. Finally, using Naïve Bayes, the accuracy was 88.9% which is similar to the accuracy when the exchange rate was divided into four categories (Table 5), meaning that with this method, change in number of categories did not improve the accuracy. Now, compiling all the analysis results, the next part shows the summary of the methods used, accuracy of each of them, and the major findings.

4.5 Summary of Findings

Table 8 : Summary of Classification Methods used and Accuracy

Methods Used	**Prediction Accuracy**	**Comment**
Decision tree	29.6%	The accuracy may seem poor, but it actually is not so (Exchange rate in each month was different. With each exchange rate representing one category, there were around 27 categories)
Naïve Bayes	22.2%	
K fold cross validation (k=5)	$R^2 = 0.921$	Good accuracy
Feature Selection		
Feature Selection_ Decision tree	Accuracy for hold-out set = 14.8%; last loop = 4.8%	High variation in accuracy between the hold-out set and the last loop, and among the loops. Most important feature: Foreign reserve.
Feature Selection_ Naïve Bayes (5-fold)	Accuracy for hold-out set = 18.5%; last loop = 9.5%	
Feature Selection_ Naïve Bayes (10-fold)	Accuracy for hold-out set = 15%; last loop = 9.1%	High variation in accuracy between the hold-out set and the last loop, and among the loops. Most important features: Trade Balance, inflation.
Categorizing Dependent Variable	**Independent Variables used:** FDI, Remittance, Trade Balance, Foreign Reserve, GDP, Current Account, Capital Account, Interest Rate, and Inflation.	

Methods Used	**Prediction Accuracy**	**Comment**
Decision tree (with 4 categories)	**96.3%**	**Highest accuracy**
SVM (with 4 categories)	51.9%	Lower compared to Decision Tree's accuracy
Naïve Bayes (with 4 categories)	88.9%	Better but lower in comparison to Decision Tree's accuracy
Decision tree (with 5 categories)	**88.9%**	Better but lower in comparison to Decision Tree's accuracy with 4 classes
SVM (with 5 categories)	70.4%	Better than SVM's accuracy with 4 categories but lower in comparison to Decision Tree's accuracy
Naïve Bayes (with 5 categories)	**88.9%**	Better but lower in comparison to Decision Tree's accuracy

From Table 8, it is seen that of all the methods tried, decision tree made the most accurate prediction. However, a good idea would be to determine the range of exchange rates since it will help to predict the range within which the exchange rate may fall.

5. CONCLUSION

This paper is concerned with developing a model to predict the exchange rate of BDT against USD. It was found that the analytical tools help develop a robust predictive model to predict the exchange rate movement. This is consistent with the findings of Kaushik and Giri (2020). More importantly, in the analysis with machine learning, multiple pertinent variables can be incorporated and experimented. In this paper, Decision tree and Naïve Bayes were found to be more suitable techniques than other methods. Finally, use of feature selection did not improve the accuracy and could not constitute a better predictive model.

5.1 Future Research Directions and Managerial Implications

This paper has introduced a novel dimension of work with predictive modeling and thus has provided scope for both theoretical and managerial contributions. From the theoretical perspective, the methodology and predictive modeling used in this study may work as a base point to initiate and advance the application of machine learning based modeling to newer avenues of research. For instance, this study worked with a data set of 11 fiscal years. To arrive at the best model, future studies may conduct further trials with a wider range of data. To account for economic fluctuations, anomalies, and extreme events in the training model, data sets that reflect such diverse economic scenarios may be chosen. Doing so may boost the predictive accuracy of the model. Again, different training models (such as Random Forest, logistic regression, etc.)

may be experimented to check whether these methods enhance the accuracy. Last but not the least, different classifications of dependent variables can be made while ensuring similar class width and number of observations in each class. All these experiments will help train the workflow better, which is crucial for attaining desired accuracy.

Another area of further research may be to dive deep into the feature selection workflow and doing so can be worthwhile. For instance, addition of Variance Inflation Factor (VIF) node may identify the underlying problems in the poor performance of that workflow. Finally, more advanced studies may incorporate the sentiment analysis in the model as sentiment about the economy may ultimately impact the exchange rate. Analytics models are the best fit for that purpose.

From the managerial perspective, this paper will be insightful for the policymakers, central bank, and the businessmen since many of their decisions depend on the fluctuations of exchange rate. However, the concept and methodology used here can be customized based on the requirements of the respective firms and industries. Altogether, future researchers, academicians, and practitioners will find this paper valuable alike.

Data Availability Statement

The data used in the analysis were collected and compiled from here.

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