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Prediction of Foreign Exchange (Forex) Market Using Support Vector Machines

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ABSTRACT

Foreign Exchange is the means of converting one currency to another and some problems within a county could affect fluctuations in the currency; recession in a countries economy for three consecutive quarters affects the country by causing a decline the exchange rate where one is buying the same product but has a lower purchasing power. The change of the political power causes a shift in the economy which could either stabilize the exchange rate or make it lose its value; a country with a depleted foreign reserve which is meant to back liabilities could affect a country greatly making investors back out to avoid severe losses. This paper therefore presents a predictive system using support vectors with the help of three technical indicators to better predict the exchange rate of the given currency. The predictive model designed for FOREX using SVM and sample datasets was gotten from the Central Bank of Nigeria (CBN), after Training and Testing, validation of the results using other predictive system. However, on theoretic grounds, it has been shown that SVM have a few motivating properties which may support the concept that SVM generally perform better in Classification and Regression. The significance of this study benefits the body of research by establishing a novel procedure for integration of technical analysis into the market prediction and such integrations can provide grounds for a much higher forecast rate.

Keywords – Artificial Intelligence, Waikato Environment for Knowledge Analysis, Foreign Exchange, Support Vector Machines, Technical Indicators

1. INTRODUCTION

Foreign Exchange (FX) or currency trading also known as FOREX, is a decentralized worldwide market where the entire world's currencies trade. The need for currency exchange is the primary reason why the forex market is the biggest most fluid monetary market in the world(Record 2004). Trading FOREX is all about making money, just because the transaction cannot be seen physically, does not mean it is not being traded.

Currencies have three symbolic letters (NGN), the first two identifies as the country's name (Nigeria) and the third identifies as the country's currency name (Naira). Box and Jenkins Auto Regressive Integrated Moving Average (ARIMA) technique is commonly used for time series forecasting and due to its general acceptance was used as a benchmark for future modeling approaches(Wang et al. 2015). In recent days, researchers have geared towards the SVM which emerged as a new and powerful technique for learning from data and in solving classification and regression errors with a much better performance margin (Kayal 2010). One benefit of the SVM is its ability to decrease structural risk as opposed to empirical risk employed by the ANN(Melchers & Beck 2018).

1.1 Statement of Problem

FOREX market is an issue of much interest employing numerous statistical approaches and data mining procedures, which makes it difficult to predict, though a few factors could influence the market positively. The factors are inflation rates, depleted foreign reserves and high interest rates which is determined by the Central Bank of the Country. However, this research considers these factors affecting the rise and fall of the prices of goods and services as well as the ratio of export to import.

1.2 Objectives

The objectives of this study is to accurately predict the dynamics of the foreign exchange market using Support Vector Machines by identifying the factors that brings about high interest rate, establishing the effects of inflation rates and interest rates to the volatility of FOREX.

2. RELATED WORKS

(Kamruzzaman et al. 2003) considered the effects of the four kernel functions- polynomial, radial basis, linear and spline on conjecture errors using several performance metrics. Forecasting analysis is assessed in terms of these commonly used statistical metrics that is, Normalized Mean Square Error (NMSE), Mean Absolute Error (MAE), Directional Symmetry (DS), Correct Up trend (CU) and Correct Down trend (CD), measuring accuracy and upward/downward trend of the market. They used the MNSE and AME polynomial kernel to reduce their prediction error. The radial basis and polynomial kernel seemed to be a better choice in forecasting forex market but to achieve an improved performance a complex or mixed kernel function should be selected.

(Okasha 2014) used real world datasets to create a two-month forecast with the aid of the Support Vector Machines, Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Network. The outcomes of applying SVM methods and the precision of projecting was calculated and compared to those of the ARIMA and ANN methods through the minimum root-mean-square error of the natural logarithms of the data. The yield of ANN, assuming linear output neuron, a hidden layer with h sigmoid hidden nodes, then an input variable (X_j), is given where H(.) is the linear transfer function of the output neuron k, G (.) is the transfer function of the hidden layer, b_k is its bias and wi is the connection weight between the output units and the hidden layers. The output from SVM are more accurate than both the ANN and ARIMA models.
(Madge & Bhatt 2015) used Support Vector Machines to analyze price unpredictability and momentum of stocks to predict whether future stock prices will be higher or lower at any given day.

The specific kernel used is the Radial Kernel. It has the capacity to handle several input sets to accommodate the few conditions on the geometry of the input data. Their classifications are based on similar training examples and use the patterns in data as a plus. In the short run, very little predictive ability was discovered but in the long run there were better definite predictions, which might not be directly translated to long- term profits. (Nwokorie & Nwachukwu 2015) new and improved model that provides a wider set of dynamic process information about the market prices was developed, which also took into consideration the fundamental and technical analysis of the FOREX market modeled with Neural Networks.

The networks predictions were integrated to get the market price movements, with the use of market sentiment and volatility values to develop a trading strategy using Marcov chain. A Markov chain which was named after Andrey Markov are mathematical systems that experience transitions from one state to another according to certain probabilistic rules(Ching & Ng 2006). The improved model is then implemented with the Meta-Quote scripting Language (MQL) of the meta-Trader platform. A relative benchmark with models based on only the technical data disclosed that the addition increased profit.

When the neural networks were used to examine, forecast and trade currencies in the FOREX market it also produced better result than was expected. A new strategy using Marcov chain that acknowledged eight market phases instead of the usual three has given rise to a range of substantial improvement on profitability.

3. METHODOLOGY

Constructive research method is adopted for this research because it integrates the area of theory and doesn't necessitate that your research be based on solidity, it is primarily based upon theories, hypothesis and case studies. The implementation of the system adopts the Object- Oriented Analysis &Design (OOAD).

3.1 Proposed System

The proposed system architectural model is shown in Figure 1. The system includes the following key modules;

- The Data Division
- Kernel Trick
- Machine Learning Algorithm
- The Classifier
- Forecast

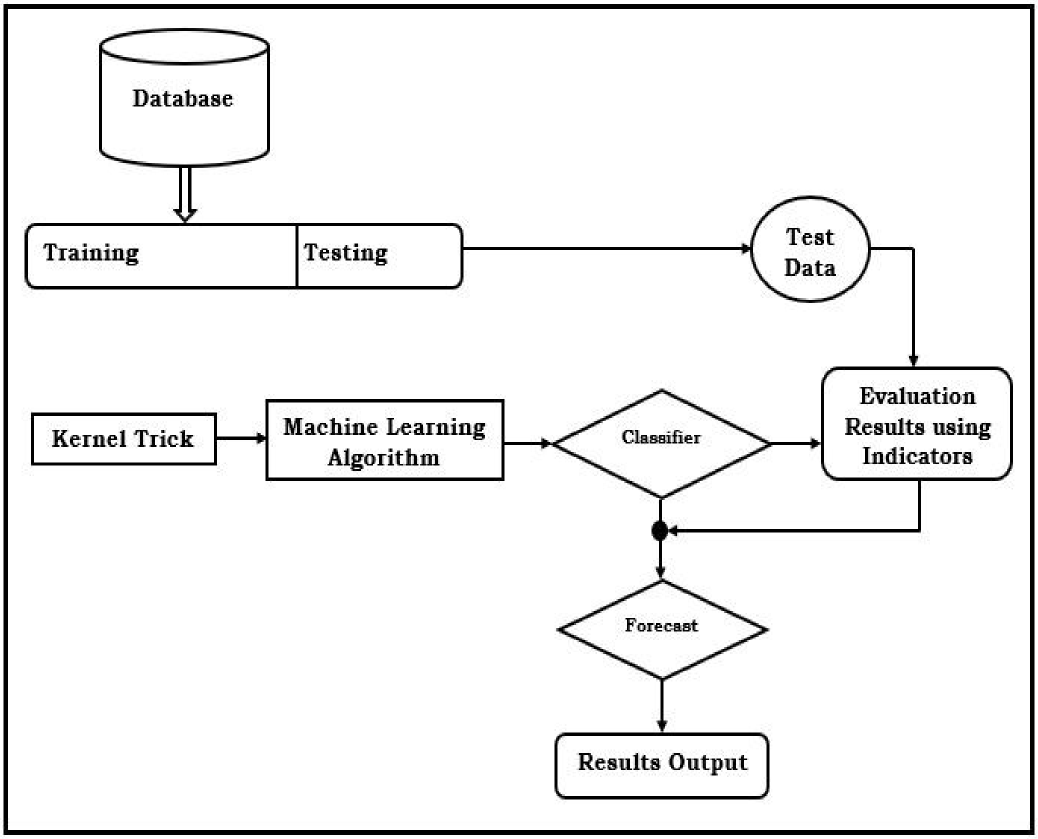

Figure 1: Architectural Design of the Proposed System

3.2 Description of Key Modules

The section describes the key modules used for the analysis and results generation.

The Data Division

This module divides the collected data sets into; Training set, testing set and validation set. It is important to know that only the training and testing sets were entered into the SVM, the validation set was kept back as a tool for checking and comparing the predictions made by the system.

Kernel Trick

The Polynomial kernel of degree 2 was used. The kernel trick determines the behavior of the machine learning algorithm and the pattern to be used in selection of support vectors.

Machine Learning Algorithm

The SVM governing equation is implemented to obtain the support vectors and WEKA uses the SMOreg function to carry out this task. The Sequential Minimal Optimization Regression (SMOreg) implements the support vectors and then uses them for regression.

The Classifier
After carrying out machine learning, the data is further classified to train on the test data. This simply uses the kernel trick on the test data as a way of experimenting the effectiveness of the machine learning that was carried out.

Forecast
This is the process whereby the user determines which kernel trick appears suitable to be used. This is based on the evaluations made.

3.3 Use Case Diagram of the Proposed System

The Use Case diagram shows the simple scenario illustrating the different tasks performed by the User. The Figure 2 shows the use case of the proposed system.

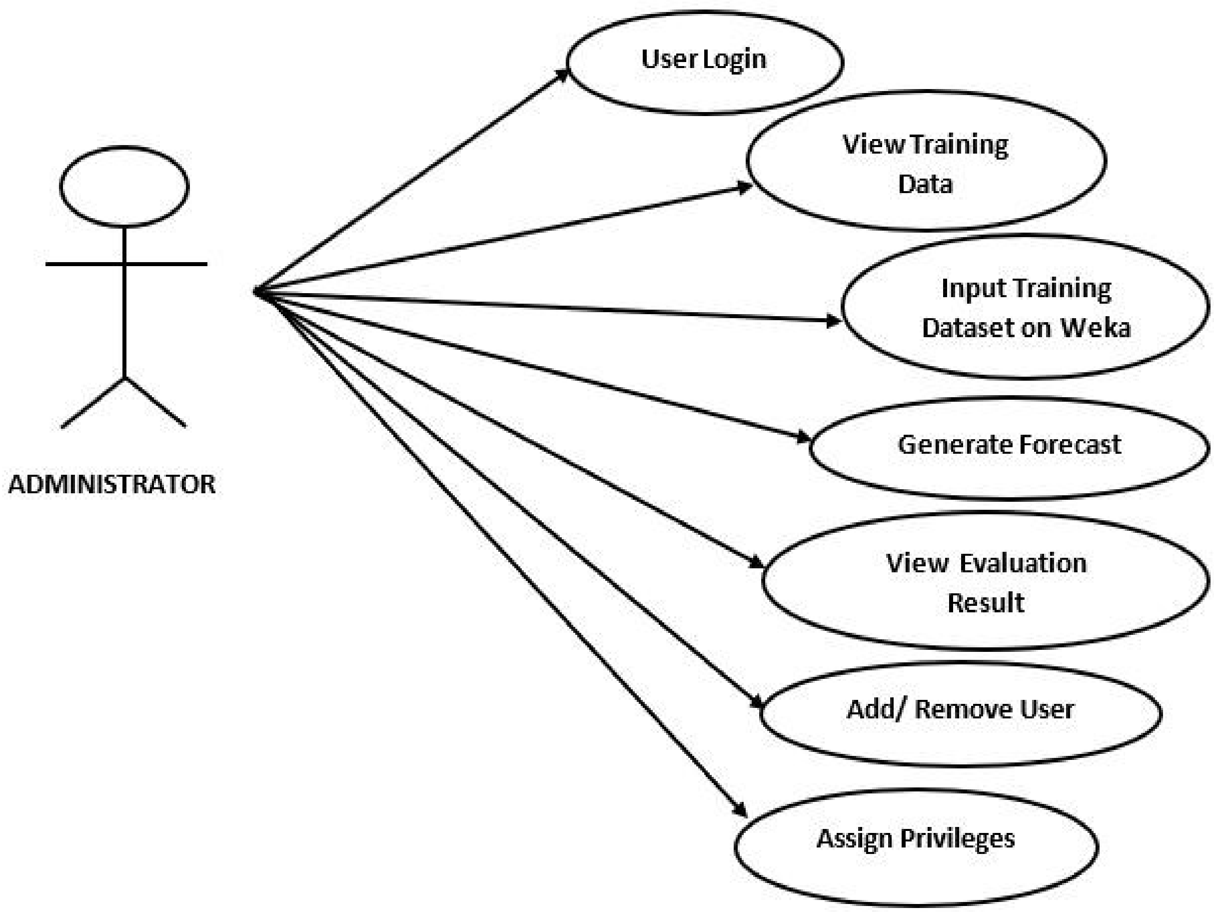

Figure 2: Use Case Diagram of the Proposed System

4. RESULTS AND DISCUSSIONS

4.1 Data Presentation

The exchange rates for the NGN/USD from January 2018 to December 2018, a total number of 365 data sets were collected. Following the percentages for Training, Testing and Validating data; 70% of the data was used for Training consisting approximately 256 instances which forms the values collected from January 1, 2018 to September 13, 2018, 25% of the data for Testing consisting of approximately 25 data and this forms the values collected from December 14, 2018 to December 31, 2018 and 5% of the data for Validation consists of approximately 18 instances and this forms the values collected from September 14, 2018 to December 13, 2018. The technical indicator used to compare the prediction was the delay moving averages; MA5, MA10, MA20, MA60 and MA90.

4.2 Modelling Approach

Consider an n-dimensional feature vector x = (X_1,.....,X_n). We can define a linear boundary (hyperplane) as

$$b_0 + b_1x_1 + \ldots b_nX_n = b_0 + \sum_{i=1}^{n} b_1x_1 = 0 \qquad \text{- - - - -} \qquad \text{Equation 3.1}$$

Then elements in one category will be such that the sum is greater than 0, while elements in the other category will have the sum be less than 0. With labelled examples, using the inner products, let

$$y = b_0 + \sum_{i=1}^{n} b_1x_1 = \sum \alpha_i y_i x_i * x. \qquad \text{- - - - - -} \qquad \text{Equation 3.2}$$

Where * represents the inner product operator and y is the label and can also be referred to as the margin, such that, $y \in \{-1,1\}$

Replacing the inner product with a more general kernel function K which allows the input to be mapped to higher-dimensions, we derive the SVM thus;

$$y = \sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b \qquad \text{- - - - - -} \qquad \text{Equation 3.3}$$

Where,

y = the scoring function used to compute the score for an input vector x.
α_i = coefficient associated with the i[th] training example
y_i= a class label, either -1 or 1.

If output of scoring function is negative, then the input is classified as belonging to class y = -1. Also, if the score is positive, the input is classified as belonging to class y=1.

K = The Kernel function.
x_i= coefficient associated with training data.

- This function operates on two vectors and the output is a scalar.
- There are different possible choices kernel function

x = The input vector that we are trying to classify
b = a scalar vector

Equation 3.3 is the governing equation to determine our support vectors. Thus, it is the basis for training the collected data. The data training will be carried out using Waikato Environment for Knowledge Analysis (WEKA) software version 3.8.3.

The software was developed by the University of Waikato, Hamilton, New Zealand, with the sole aim of solving very tedious regression problems. In this vein, three kernel tricks were used;

1) The Polynomial kernel of degree 2
2) The Pearson VII universal (PUK) kernel
3) The Radial Basis Function (RBF) kernel

The Mean Absolute Percentage Error (MAPE) between the actual data and the prediction on training and test instances were used to determine the best kernel trick to adopt. In doing this, the kernel trick function with errors nearing zero was chosen as the best kernel trick function to analyze the NGN/USD exchange rate.

4.3 Experimental Results

Three different experiments were carried out using the various kernel tricks; Polynomial Kernel, Pearson VII Universal Kernel, Radial Basis Function (RBF) Kernel. For each of the functions, a 10-fold cross validation method was used in a bid to obtain better results. Also, the normalization of data was carried out using the software. The Sequential Minimal Optimization (SMOreg), which is an algorithm for determining support vectors during training of support vector machines, was used to carry out regression on the collected data. The sequences of carrying out forecast using the WEKA software are shown in Appendix.

Table 1: Errors in machine prediction using Polynomial Kernel

S/N	Actual	Predicted	MAE	MSE	MAPE
1	364.9478	367.342	2.3942	5.7322	0.66%
2	363.6262	364.9342	1.3080	1.7109	0.36%
3	362.999	366.0437	3.0447	9.2702	0.84%
4	362.9918	367.4655	4.4737	20.0140	1.23%
5	363.1428	366.2951	3.1523	9.9370	0.87%
6	363.3364	365.9179	2.5815	6.6641	0.71%
7	363.6933	370.8911	7.1978	51.8083	1.98%
8	364.2376	368.8323	4.5947	21.1113	1.26%
9	363.979	361.68	2.2990	5.2854	0.63%
10	364.0002	367.471	3.4708	12.0465	0.95%
11	364.2481	370.1751	5.9270	35.1293	1.63%
12	363.0075	361.5365	1.4710	2.1638	0.41%
13	363.0068	364.9358	1.9290	3.7210	0.53%
14	363.5972	365.0523	1.4551	2.1173	0.40%
15	363.522	359.3766	4.1454	17.1843	1.14%
16	364.5027	357.6933	6.8094	46.3679	1.87%
17	364.5066	369.6484	5.1418	26.4381	1.41%
18	363.5532	380.5607	17.0075	289.2551	4.68%
	Average		**4.3557**	**31.4420**	**1.20%**
* MAE = Mean Absolute Error, *MSE = Mean Squared Error, *MAPE = Mean Absolute Percentage Error					

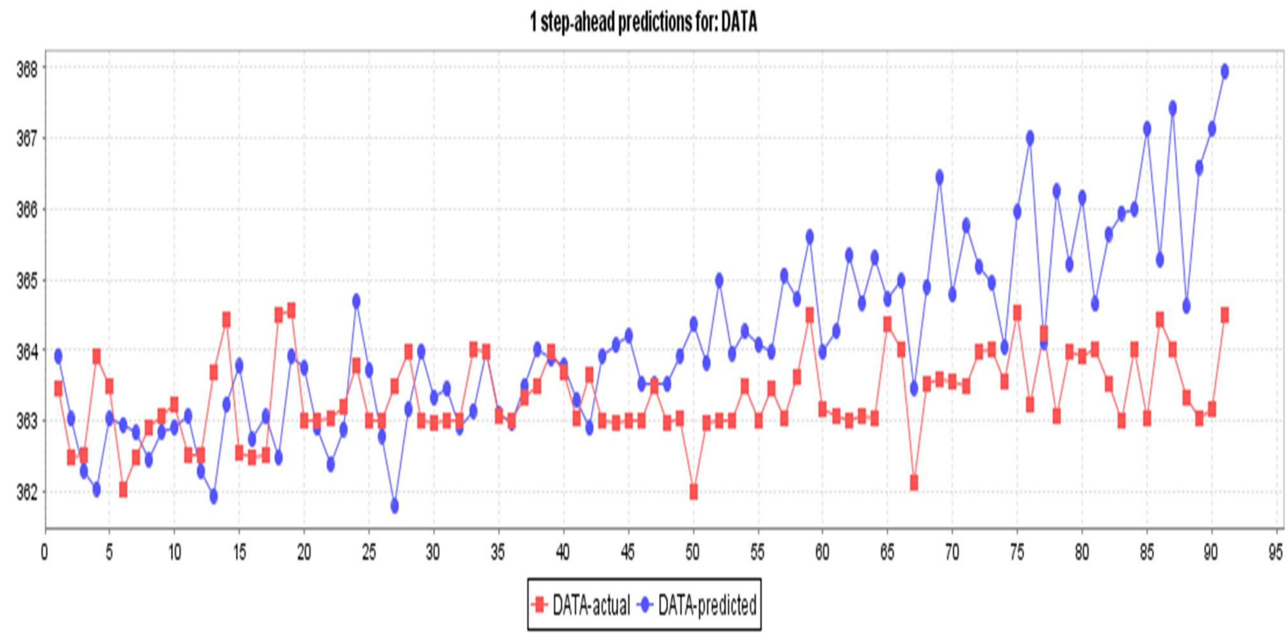

Figure 3: Line Graph of the Actual and Predicted Value from Table 1

4.4 Comparative Analysis of the various techniques using MAPE

To ascertain the best tool for prediction of foreign exchange in the Nigerian economy considering the timeframe in which the data was collected, a contrast between the support vector machines learning algorithm and the moving averages was made. Below is a summary of the various Mean Absolute Percentage Errors (MAPE) obtained from each of the experiments carried out and the Moving Averages. The Comparative analysis of the various techniques using MAPE is shown in Table 2 while Figure 4 is the Bar Chart representation of Table 2.

Table 2: Comparative Analysis using MAPE

TECHNICAL INDICATORS	MAPE
Polynomial kernel	1.20%
PUK	0.70%
RBF Kernel	0.24%
MA5	0.17%
MA10	0.14%
MA20	0.14%
MA60	0.14%
MA90	0.14%

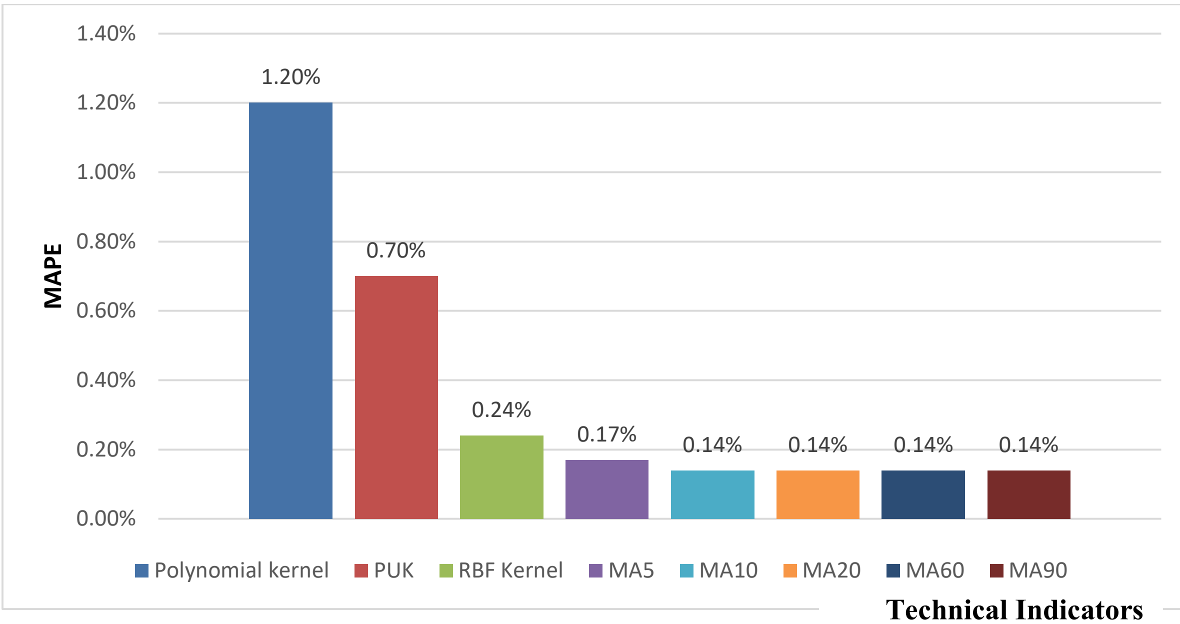

Figure 4: Bar Chart Representation of Table 2

5. CONCLUSION

This study investigates the performance of an SVM model for NGN/USD forex forecasting. Also, a combination of technical indicators was used to ascertain which model has the lowest error and examines which model followed the test data prediction closer from the charts. In doing this, it was discovered that using the RBF kernel trick on the SVM produces a more reliable forecast. The polynomial kernel also followed the path of the test results but delivered a rather questionable forecast. Thus, concluding that the various kernel tricks should be tried on subsequent data sets to know which one will be suitable for the data set because it is obvious that each data set has its unique trajectory, as such it might be misleading to use the RBF kernel trick as its forecast might not be as good as that of either the polynomial kernel or the PUK.

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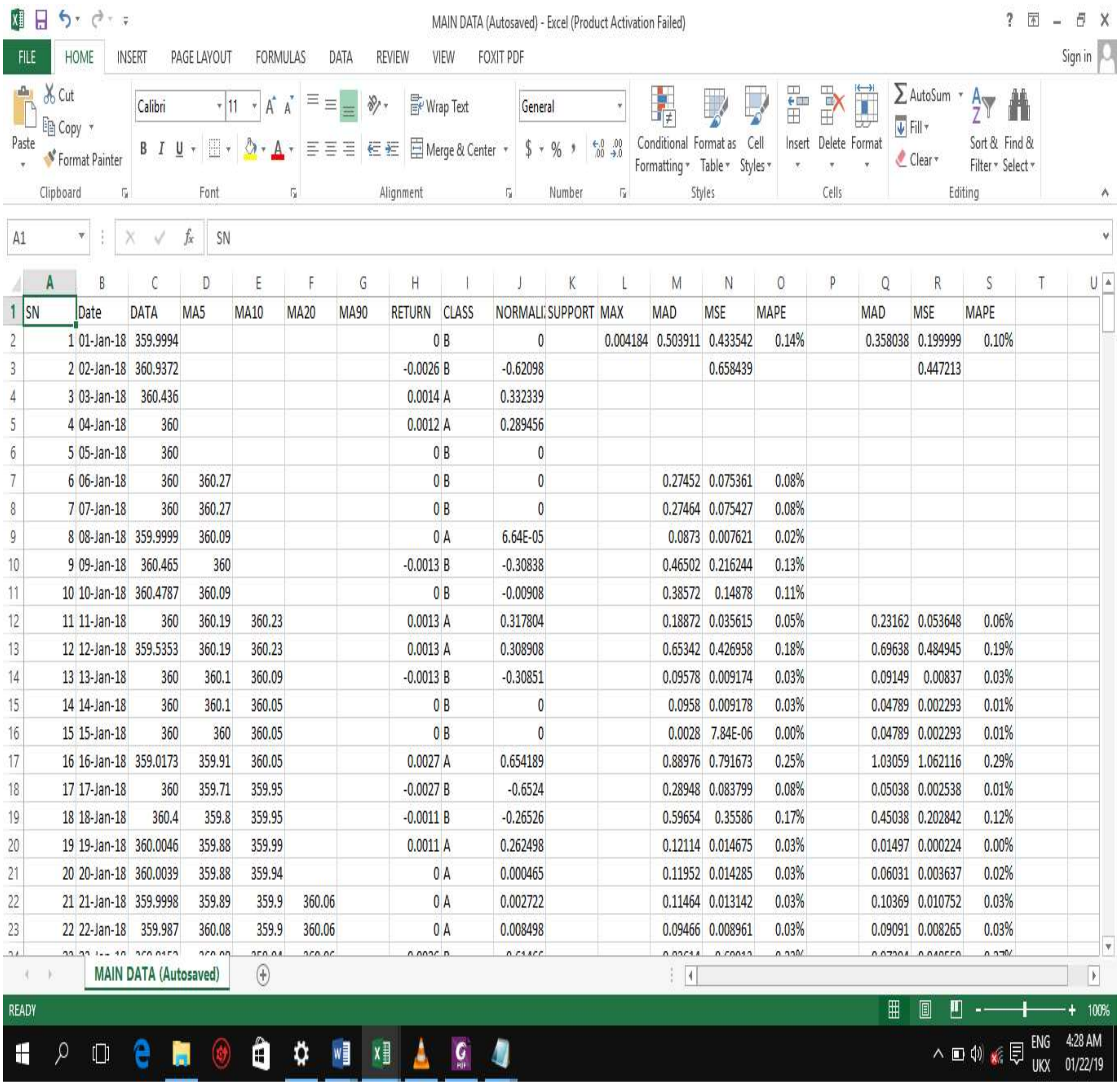
APPENDIX

APPENDIX A



SN	Date	DATA	MA5	MA10	MA20	MA90	RETURN	CLASS	NORMALI:	SUPPORT	MAX	MAD	MSE	MAPE		MAD	MSE	MAPE
1	01-Jan-18	359.9994					0	B	0		0.004184	0.503911	0.433542	0.14%		0.358038	0.199999	0.10%
2	02-Jan-18	360.9372					-0.0026	B	-0.62098				0.658439				0.447213	
3	03-Jan-18	360.436					0.0014	A	0.332339									
4	04-Jan-18	360					0.0012	A	0.289456									
5	05-Jan-18	360					0	B	0									
6	06-Jan-18	360	360.27				0	B	0			0.27452	0.075361	0.08%				
7	07-Jan-18	360	360.27				0	B	0			0.27464	0.075427	0.08%				
8	08-Jan-18	359.9999	360.09				0	A	6.64E-05			0.0873	0.007621	0.02%				
9	09-Jan-18	360.465	360				-0.0013	B	-0.30838			0.46502	0.216244	0.13%				
10	10-Jan-18	360.4787	360.09				0	B	-0.00908			0.38572	0.14878	0.11%				
11	11-Jan-18	360	360.19	360.23			0.0013	A	0.317804			0.18872	0.035615	0.05%		0.23162	0.053648	0.06%
12	12-Jan-18	359.5353	360.19	360.23			0.0013	A	0.308908			0.65342	0.426958	0.18%		0.69638	0.484945	0.19%
13	13-Jan-18	360	360.1	360.09			-0.0013	B	-0.30851			0.09578	0.009174	0.03%		0.09149	0.00837	0.03%
14	14-Jan-18	360	360.1	360.05			0	B	0			0.0958	0.009178	0.03%		0.04789	0.002293	0.01%
15	15-Jan-18	360	360	360.05			0	B	0			0.0028	7.84E-06	0.00%		0.04789	0.002293	0.01%
16	16-Jan-18	359.0173	359.91	360.05			0.0027	A	0.654189			0.88976	0.791673	0.25%		1.03059	1.062116	0.29%
17	17-Jan-18	360	359.71	359.95			-0.0027	B	-0.6524			0.28948	0.083799	0.08%		0.05038	0.002538	0.01%
18	18-Jan-18	360.4	359.8	359.95			-0.0011	B	-0.26526			0.59654	0.35586	0.17%		0.45038	0.202842	0.12%
19	19-Jan-18	360.0046	359.88	359.99			0.0011	A	0.262498			0.12114	0.014675	0.03%		0.01497	0.000224	0.00%
20	20-Jan-18	360.0039	359.88	359.94			0	A	0.000465			0.11952	0.014285	0.03%		0.06031	0.003637	0.02%
21	21-Jan-18	359.9998	359.89	359.9	360.06		0	A	0.002722			0.11464	0.013142	0.03%		0.10369	0.010752	0.03%
22	22-Jan-18	359.987	360.08	359.9	360.06		0	A	0.008498			0.09466	0.008961	0.03%		0.09091	0.008265	0.03%

Figure A.1: Data Formatting in MS Excel

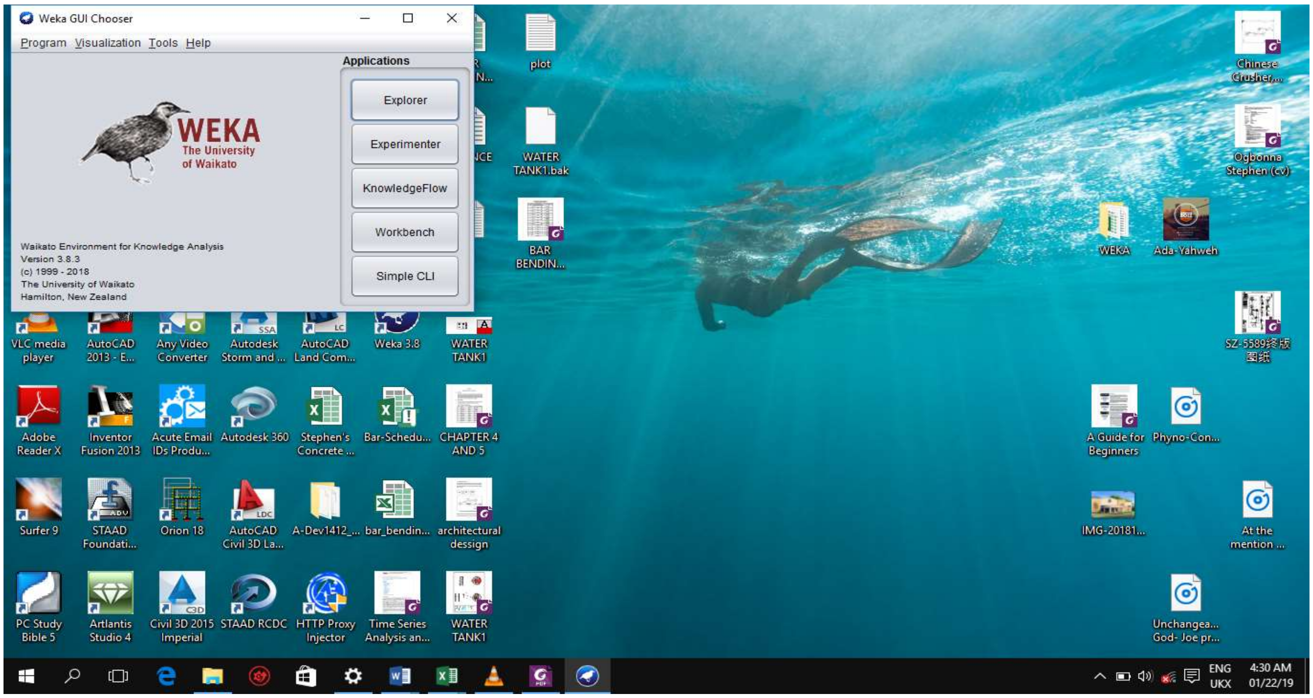


Figure A.2: Weka Graphic User Interface Selection

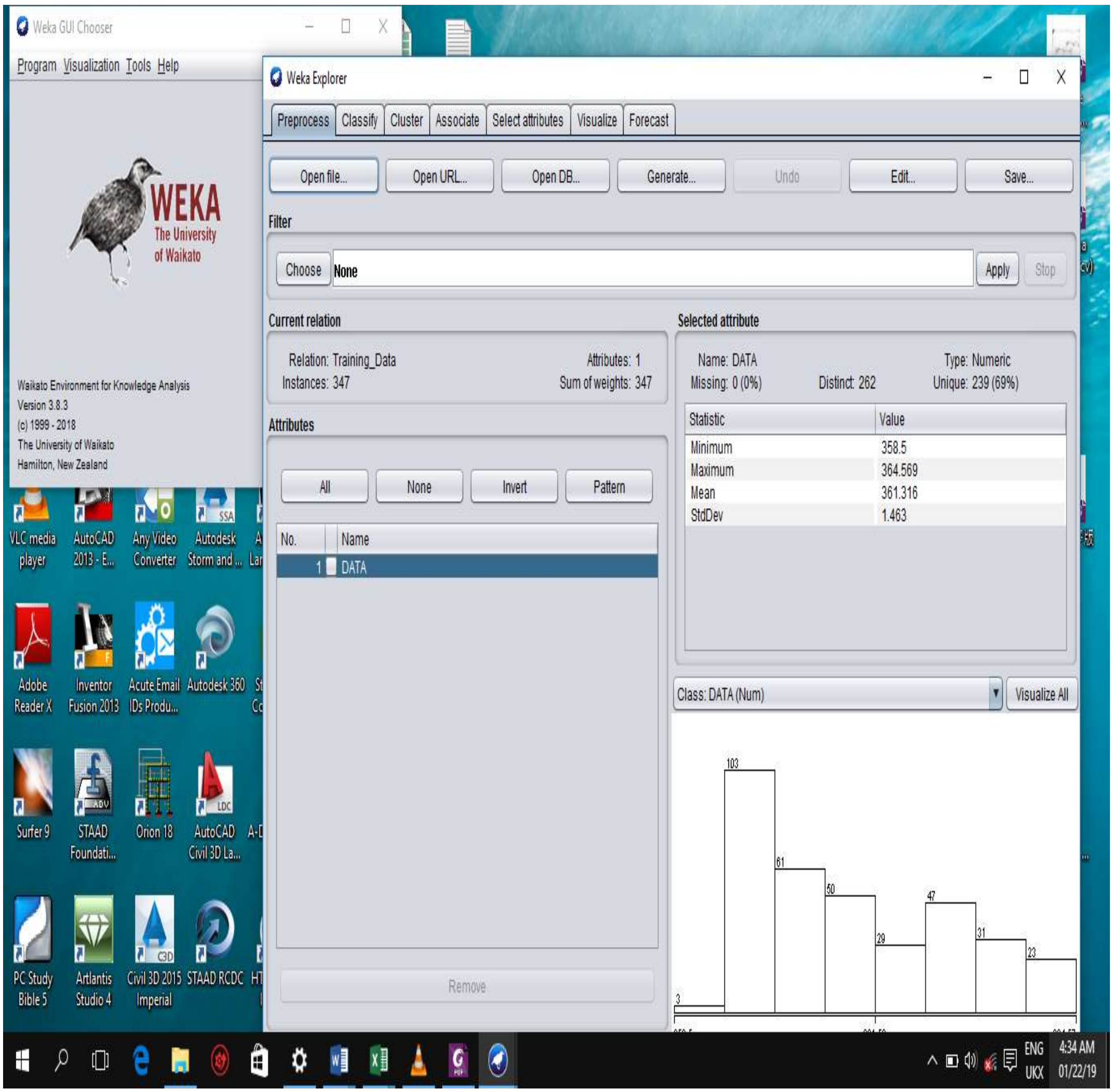


Figure A.3: Weka Explorer Page for Data Importation and Statistics

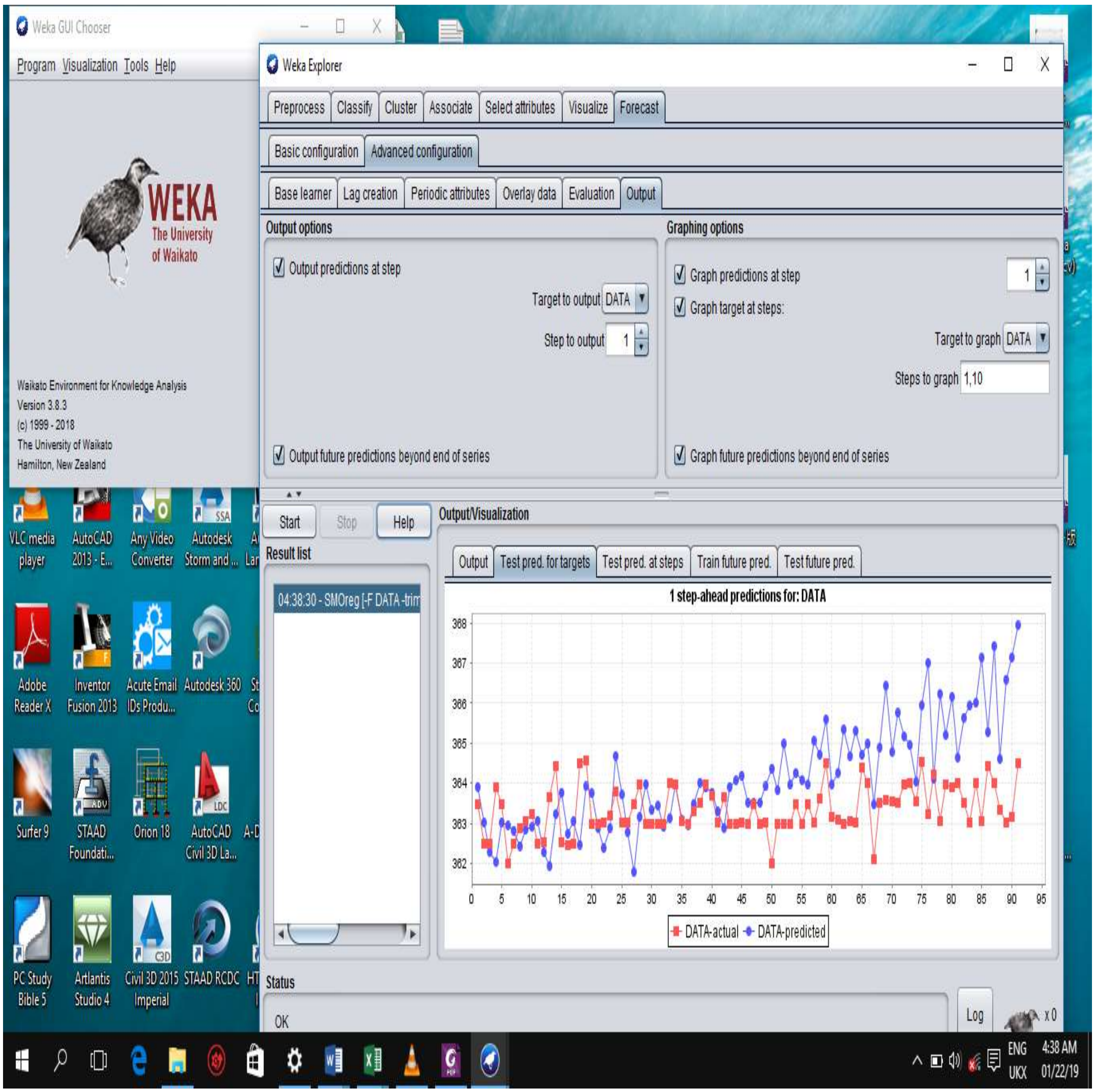


Figure A.4: Weka Data Output