Rupiah Exchange Prediction of US Dollar Using Linear, Polynomial, and Radial Basis Function Kernel in Support Vector Regression

Mufni Alida[1], Metty Mustikasari[2]
[1]Magister Information System Program, Gunadarma University, Indonesia
[2]Faculty of Computer Science and Information Technology, Gunadarma University, Indonesia

Article Info	ABSTRACT
	As a developing country, Indonesia is affected by fluctuations in foreign exchange rates, especially the US Dollar. Determination of foreign exchange rates must be profitable so a country can run its economy well. The prediction of the exchange rate is done to find out the large exchange rates that occur in the future and the government can take the right policy. Prediction is done by one of the Machine Learning methods, namely the Support Vector Regression (SVR) algorithm. The prediction model is made using three kernels in SVR. Each kernel has the best model and, the accuracy and error values are compared. The Linear Kernel has $C = 7$, $max\_iter = 100$. The Polynomial Kernel has $gamma = 1$, $degree = 1$, $max\_iter = 4000$ and $C = 700$. The RBF kernel has $gamma = 0.03$, $epsilon = 0.007$, $max\_iter = 2000$ and $C = 100$. Linear kernels have advantages in terms of processing time compared to Polynomial and Radial Basis Function (RBF) kernels with an average processing time of 0.18 seconds. Besides that, in terms of accuracy and error, the RBF kernel has advantages over the Linear and Polynomial kernels with the value R2 = 95.94% and RMSE = 1.25%.

Corresponding Author:

Mufni Alida,
Magister Information System Program,
Gunadarma University Campus A,
Jl. Kenari No. 13 Jakarta Pusat, Indonesia
Email: mufnialida@gmail.com

1.   INTRODUCTION

In the economic world, the global market has an important role as an international forum of transactions between countries in selling or buying goods or services internationally. In these markets, money is used as a legal payment instrument and in the international financial system requires the exchange of currencies of each country or with global currencies. In addition to inflation and interest rates, currency exchange rates are often used to measure the level of a country's economy. The tool used to facilitate transactions between countries on global markets is the US Dollar (USD), and each country has a different exchange rate with the USD. Financial time series data (Exchange Rate) are affected by various events such as demonetization, politics, war, natural disaster, etc. [1]. According to the Oxford Dictionary of English, Exchange Rate is the value of one currency for conversion to another [2].

The nominal exchange rate is defined as the price of a currency in terms of another currency. In parallel, the real currency exchange rate should be defined as the price of the currency in real terms. In the literature and textbooks, however, it is defined as the relative price levels between two countries, rather than how much the currency can purchase in real terms [3]. As a developing country, foreign exchange rate fluctuations are very influential in the Indonesian economy, so the determination of foreign exchange rates must be profitable and the country can run its economy well. The prediction of the exchange rate is done to know the large exchange rates that occur in the future; however, the government can take the right policy. The economic sector is one of the mainstay sectors in competition and achievement with other countries. For this reason, it is very important to pay attention to issues related to the global economy and Indonesia. At present,

the issue of the exchange rate prediction is one of the best important problems in economics and finance. Exchange rate prediction is urgently required in the exchange rate management for both government and investors.

On the one hand, predicting the evolution of the exchange rate can help investors worldwide to make portfolio decisions. On the other hand, it plays a significant role for the government to make macroeconomic policies [4]. The instability of the exchange rate can make investors discouraged from investing, this will cause a setback in development in Indonesia because so far, the role of foreign investors has been very large in economic growth.

Based on the description above, we need to be able to process currency exchange rate data to make the right policy in the future with artificial intelligence. Artificial Intelligence (AI) makes human problems easier to solve and can predict future problems [5]. Using analysis and the best method in AI will reduce the effects of errors and also increase profitability and Machine Learning is one of Artificial Intelligence that could solve a problem from known based on the learning or training data that has been inputted [6-9]. One of the machine learning methods is the Support Vector Regression method. This method is the development of SVM (Support Vector Machine) for regression cases [10]. The purpose of the SVR is to find a function $f(x)$ as a hyperplane (dividing line) in the form of a regression function that corresponds to the input data with an error ε and makes ε as thin as possible. The SVR method is used to solve non-linear problems. SVR is successfully applied in several problems in time series prediction [10]. This is what drives this research to use SVR to predict the rupiah exchange rate.

This study refers to several previous studies, including Abdul Aziz, Nurhana, and Mohd Fauzi Bin Othman who conducted Binary Classification research using Support Vector Machines [11]. The object classified is a chicken's excrement image, which will be classified as healthy and sick chickens. This study compares more and less extracted features, less extracted features and also applies the Gabor filter to these features to see the effect it has on classification accuracy. Results show that having more features extracted using GLCM techniques allows for greater classification accuracy. Then Saeed, Sana, and Hong Choon Ong conducted a study of the Support Vector Machine algorithm to see the performance results of each kernel in SVM and the merging of several kernels [12]. The results obtained in this study are said that by merging the existing kernel can help improve the results or performance of Support Vector Regression.

Based on some of the above research and an explanation of the importance of the movement of the Rupiah exchange rate against the US Dollar, this paper that discusses the prediction of the Rupiah exchange rate against the US Dollar will be examined using the Machine Learning method, namely SVR. However, the method is divided into three, namely Linear, Polynomial, and Radial Basis Function (RBF) kernels in the SVR. Besides, this study also aims to compare kernels. Comparison is measured using the accuracy value of R2 Square and the value of the error RMSE (Root Mean Square Error).

2. METHOD

This section will explain some of the methods used and also evaluation calculations from the models that have been made. Then It will be explained about the data used and finally, the analysis stages of this paper will be explained.

2.1. Support Vector Regression

Support Vector Regression (SVR) is an adaptation of the previous machine learning theory used in classification problems, namely Support Vector Machine (SVM). SVR is the application of the SVM method for regression cases. SVM is applied to the classification case and produces output in the form of integers or discrete, while SVR is applied in the case of regression which produces output in the form of real or continuous numbers [13].

The concept of SVM can be explained simply as an attempt to find the best hyperplane that functions as a separator of two classes in the input space. Figure 1 shows some data that is a member of two classes. Class -1 is symbolized in red while class +1 is yellow. On the left of figure 1 shows some alternatives to the dividing line.

The best hyperplane can be found by measuring the margin of the hyperplane and finding the maximum point of the margin. Margin is the distance between the hyperplane and the closest data from each class. The data closest to the margin is called a support vector. In Figure 1 on the right, a solid line showing the best hyperplane is located right in the middle of the two classes. Red and yellow dots that are in the black circle are support vectors.
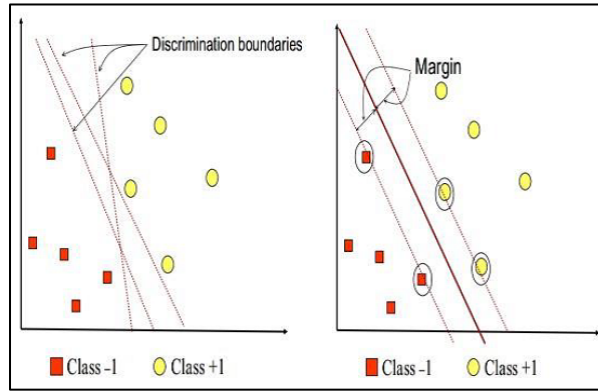
Figure 1. Hyperplane

2.2. Kernel Tricks

SVM can only be used on linear data, so we need a development to make SVM that is able to separate non-linear data, one of them is by adding kernel functions (Kernel Tricks). By using the kernel function, data that cannot initially be separated linearly will be brought to a higher dimension so that in the new dimension, the hyperplane can be constructed to separate non-linear data [14].

Many data mining or machine learning techniques were developed with the assumption of linearity, so the resulting algorithm is limited for linear cases. With the kernel method, an x data in the input space is mapped to feature space with higher dimensions through.

$$\varphi: x \to \varphi(x) \tag{1}$$

where x are separate data points, φ is what would map our data onto higher dimensional space [15].

Applying kernel tricks means just to replace the dot product of two vectors by the kernel function. The kernel functions used in this study are [15, 17]:

1) Linear Kernel

The linear kernel is the simplest of all the kernels. Technically the data isn't projected onto higher dimensions when this kernel is used, so it is just the inner product of x and y with an optional constant term c.

$$K(x,y) = x^T y + c \tag{2}$$

The benefit of the linear kernel is that it is incredibly simple and only has the constant term c as a parameter.

2) Polynomial Kernel

Unlike the linear kernel, the polynomial kernel does involve taking the inner product from a higher dimension space. The polynomial kernel can be expressed as

$$K(x,y) = (\alpha x^T y + c)^d \tag{2}$$

where the three parameters are α, c, and d. The most common degree (d) used is 2 as larger degrees can lead to overfitting.

3) Radial Basis Function (RBF) Kernel

$$K(x,y) = exp(-\gamma||x-y||^2)$$

$$||x-y|| = Euclidean\ distance\ between\ \text{x \& y} \tag{4}$$

where γ is a free parameter that scales the amount of influence two points have on each other. Unlike the polynomial kernel, which looks at d extra dimensions, RBF expands into an infinite number of dimensions. This is due to the expansion of the exponential.

2.3. Evaluation Metrics

Evaluating the algorithm of Machine Learning is one of the important things. Evaluation can show that the model used has satisfactory results or not. Therefore, it is necessary to evaluate several types of evaluation metrics that exist to get a conclusion on which model is the best. In this paper, several evaluation metrics will be used, including the following:

1. R2 Square

$$R^2 = 1 - \frac{SS\ Error}{SS\ Total} = 1 - \frac{\Sigma(y_i - y_i')^2}{\Sigma(y_i - y'')^2} \tag{5}$$

Information:
y_i = Observation of the ith response
y''= Average
y_i'= Forecast of the ith response
$SS\ Error$= Variation values of the model residues
$SS\ Total$= The value of total variation in data

2. RMSE (Root Mean Square Error)

$$RMSE = \sqrt{\frac{\Sigma(Y_t - Y_{t+1})^2}{n}} \tag{6}$$

Information:
Y_t = Actual value in period t
Y_{t+1}= Forecast value in the period $t\ +\ 1$
n = Number of observation

2.4. Research Data

In this study, the dataset was obtained from a web-based financial market platform that used to provide real-time data, price quotes, financial tools, the latest news, and analysis from 250 exchanges around the world with 44 international editions. The platform is called investing.com [18]. On this platform, a dataset of Rupiah to US Dollar is obtained from May 1998 to April 2019. The dataset consists of 5 attributes, namely Open, Close, High, Low, and Change. The dataset has a total of 1096 data. The flow of steps in taking the Rupiah exchange rate dataset against the US Dollar is: The first step is to access the investing.com platform. The second is to choose which dataset will be taken according to research needs. The third is to get raw data that has not been processed. The file obtained is in CSV format.

2.5. Proposed Method

This section describes the proposed method used in this paper and in general can be explained in Figure 2. The proposed method is divided into 5 stages. The first stage is data collection. The second stage is preprocessing data, which is useful for preparing data before it is applied to the algorithm. The third stage is implementing data into the kernel model in SVR. The fourth step evaluates the model using accuracy testing and error testing. The fifth stage is to display the results of the performance of each kernel that has been tested and compare which kernels have the best accuracy values.
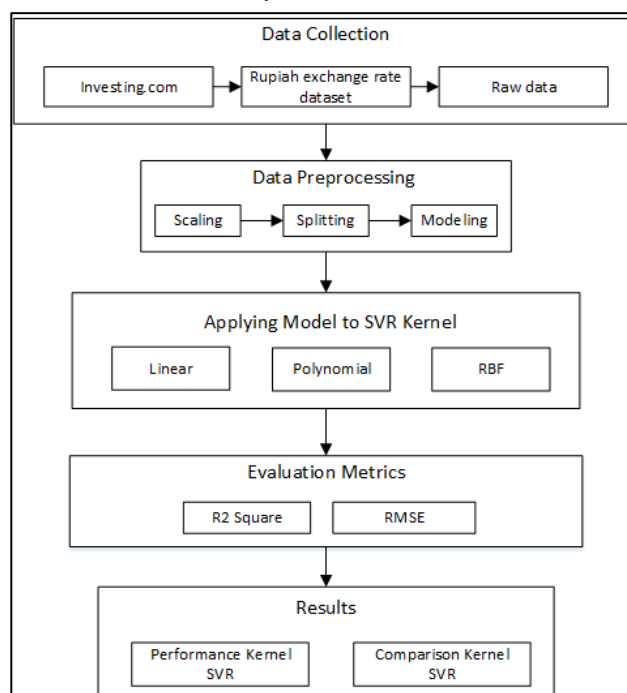

Figure 2. Research Stage

Figure 2 shows the steps of this study which are divided into 5 main stages, namely:
1. Collect data on the Rupiah exchange rate against the US Dollar from May 3, 1998, to April 28, 2019. The dataset displayed in the form of weekly data.
2. Preprocessing data include:
   - Scaling Data uses the MinMax Normalization technique with a range of 0-1.
   - Splitting Data. The dataset is divided into x and y data. Data x as the independent variable and data y as the dependent variable. Then the x and y data are subdivided using the Cross-Validation 10 Fold method into x_train, y_train, x_test, and y_test data.
   - Data Modelling. At this stage, searching for the best model of each kernel. This model search also uses 10 Fold Cross-Validation.
3. Implement the best model of each SVR kernel with test data.
4. Evaluate the metrics on the model by using R2 Square for accuracy values and RMSE for error values.
5. Showing the results of the best model, the accuracy and error values of each kernel, and their comparison.

3.   RESULTS AND DISCUSSION
In this section, it is explained the results and discussion on applying the SVR method to the prediction process. Besides, the application of the Linear kernel, Polynomial, and Radial Basis Function (RBF) will be discussed as well. After that, we will discuss the comparisons between kernels in the SVR. This chapter also discusses the performance of each kernel based on the calculation of R2 Square for accuracy values and RMSE (Root Mean Square Error) for error values.

3.1. SVR Kernel Prediction Model
This research gets the best model from each kernel. The model is visualized with a line graph. The graph shows the movement of the Rupiah exchange rate against the US Dollar based on time. Horizontal lines as time and vertical lines as exchange rates. On the graph, there are 2 lines. The red line is the representation of the predicted data, and the blue line is the representation of the actual data (y_test). The two lines are close together, which shows the accuracy of the prediction data and the actual data. The closer the two lines, the higher the accuracy. The model was obtained from trial and error scenarios for forming SVR equations in more than 100 scenarios.

3.1.1 Prediction Model of the SVR Linear Kernel
From the experiment, it was obtained 3 best models from the Linear SVR kernel. The best model is obtained from trial and error scenarios for forming SVR equations for Linear kernels in more than 100 scenarios. In this Linear kernel equation, there are 2 parameters used, the parameter 'C' and 'max_iter' parameter. C is the penalty parameter of the error term, and 'max_iter' is the maximum iteration at the time of the prediction process. Besides measuring the accuracy and error values of each of the models, this study also measures the prediction time of each of these models. Prediction time is the length of time of the model takes to predict a value. This prediction time is used to measure the performance of each model. The comparison of 3 best models can be seen in Table 1.

Table 1. Comparison of the Best Linear Kernel Models

No.	C	Max Iter	R2	RMSE	Prediction Time
1	7	100	90.37%	1.93%	0.08 seconds
2	7	90	89.65%	2.00%	0.1 seconds
3	8	90	88.29%	2.13%	0.09 seconds

Based on the comparison above, the linear kernel has the best model with a combination of parameters $C = 7$, $max\_iter = 100$ with an accuracy value of 90.37% and an error value of 1.93% (see Figure 3).
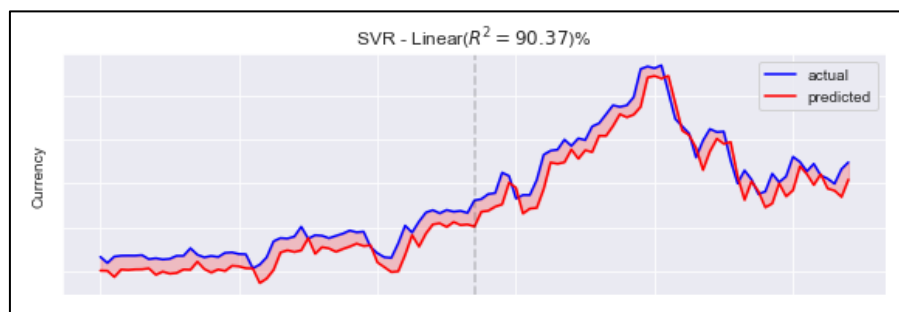

Figure 3. Linear Kernel Prediction Model

3.1.2 Prediction Model of the SVR Polynomial Kernel

From the experiment, it was obtained 3 best models from the Polynomial SVR kernel. The model was obtained from trial and error results to get the best model. Trial and error are done with various scenarios for forming SVR equations for the Polynomial kernel. These scenarios number more than 100. Some of these scenarios produce the 3 best models with Polynomial kernel parameters consisting of gamma, degree, max_iter and C. Gamma is a parameter for non-linear hyperplanes. The degree is the degree of the Polynomial used to find the hyperplane to split the data. Max_iter is the maximum iteration during the prediction process. C is the penalty parameter of the error term. Besides measuring the accuracy and error values of each of the models, this study also measures the prediction time of each of these models. Prediction time is the length of time of the model takes to predict a value. This prediction time is used to measure the performance of each model. The comparison of 3 best models can be seen in Table 2.

Table 2. Comparison of the Best Polynomial Kernel Models

No.	Gamma	Degree	Max Iter	C	R2	RMSE	Prediction Time
1	1	1	4000	700	93.05%	1.64%	0.99 seconds
2	1	1	4000	400	86.04%	2.32%	0.69 seconds
3	1	1	4000	100	70.82%	3.36%	0.25 seconds

Based on the comparison above, the Polynomial kernel has the best model with a combination of parameters $gamma = 1$, $degree = 1$, $max\_iter = 4000$ and $C = 700$ with an accuracy value of 93.05% and an error value of 1.64% (see Figure 4).
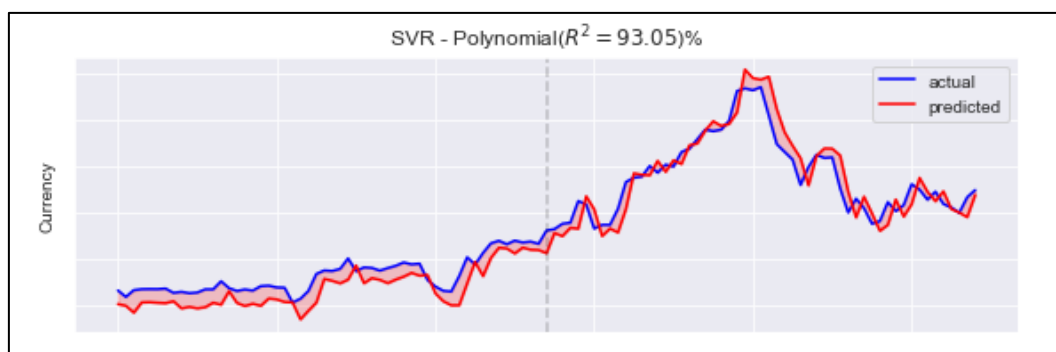

Figure 4. Polynomial Kernel Prediction Model

3.1.3 Prediction Model of the SVR Radial Basis Function (RBF) Kernel

From the experiment, it was obtained 3 best models from the Radial Basis Function (RBF) kernel. The model was obtained from trial and error results of more than 100 scenarios that have been made. This scenario contains the formation of an SVR equation for the RBF kernel consisting of parameters gamma, epsilon, max_iter, and C. Gamma is a parameter for non-linear hyperplanes. Epsilon controls the width of the regression zone used in studying data. The greater the epsilon value, the regression estimate will be more flat (approaching linear regression). Max_iter is the maximum iteration during the prediction process. C is the penalty parameter of the error term. Besides measuring the accuracy and error values of each of the models, this study also measures the prediction time of each of these models. Prediction time is the length of time of the model takes to predict a value. This prediction time is used to measure the performance of each model. The comparison of 3 best models can be seen in Table 3.

Table 3. Comparison of the Best RBF Kernel Models

No.	Gamma	Epsilon	Max Iter	C	R2	RMSE	Prediction Time
1	0.03	0.007	2000	100	96.57%	1.15%	0.99 seconds
2	0.03	0.007	2000	11	96.44%	1.17%	0.69 seconds
3	0.03	0.01	5000	11	96.38%	1.18%	0.25 seconds

Based on the comparison above, the RBF kernel has the best model with a combination of parameters $gamma = 0.03$, $epsilon = 0.007$, $max\_iter = 2000$ and $C = 100$ with an accuracy value of 96.57% and an error value of 1.15% (see Figure 5).
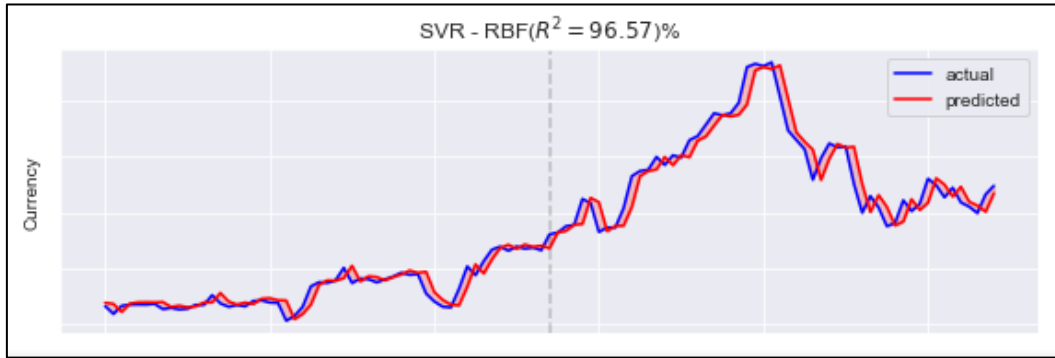
Figure 5. RBF Kernel Prediction Model

3.2. SVR Kernel Performance

In this study also calculated each performance owned by the SVR kernel. This calculation is done from the 10 best scenarios of each kernel. This research has conducted more than 100 scenarios created when testing accuracy, error, and time values for each kernel. This scenario consists of a combination of each parameter in the Linear, Polynomial, and RBF kernels which include the parameters C, max_iter, $gamma$, $degree$, and $epsilon$. However, in this section, only the prediction time will be displayed to display the performance of each kernel. The performance results can be seen in Table 4.

Table 4. SVR Kernel Performance (seconds)

	Performance		
Scenario	Linear	Polynomial	RBF
1	0.33	1.79	1.22
2	0.32	0.40	1.39
3	0.26	0.26	0.58
4	0.26	0.44	0.93
5	0.17	0.27	1.48
6	0.08	0.69	1.12
7	0.07	0.27	1.40
8	0.09	0.25	0.35
9	0.10	0.69	1.01
10	0.08	0.99	1.29
Average	0.18	0.60	1.08

3.3. Evaluation Metrics of SVR Kernel

Evaluation is obtained when performing various scenarios for forming SVR parameters for each kernel. There are 100 more scenarios done for each kernel, but only 10 best scenarios per kernel are calculated and get the average results in this paper. Evaluation is measured based on the accuracy value using R2 Square and the error value using RMSE (Root Mean Square Error). The results of the average evaluation metrics of each kernel are shown in Table 5.

Table 5. Comparative Evaluation Metrics

	R2	RMSE
Linear	80.46%	2.71%
Polynomial	71.82%	3.24%
RBF	95.94%	1.25%

Table 5 shows a comparison of each of the Linear, Polynomial, and RBF kernel evaluations with the following explanation:
1. Accuracy. The average percentage of Linear Kernel is 80.64%. The average percentage of Polynomial Kernel is 71.82%. The average percentage of RBF Kernel is 95.94%.
2. Error. The average percentage of Linear Kernel is 2.71%. The average percentage of Polynomial Kernel is 3.24%. The average percentage of RBF Kernel is 1.25%.

4. CONCLUSION

The implementation of the prediction of the Rupiah exchange rate against the US Dollar using a Linear, Polynomial, and Radial Basis Function (RBF) kernel in Support Vector Regression (SVR) was successfully carried out. This implementation produces 3 best models in each kernel. In the Linear kernel, the best model is obtained with a combination of parameters C = 7, max_iter = 100. In the Polynomial kernel, the best model is obtained from a combination of parameters gamma = 1, degree = 1, max_iter = 4000 and C = 700. The RBF kernel has the best model with the parameters of gamma = 0.03, epsilon = 0.007, max_iter = 2000 and C = 100.

The average time for predictions for each kernel is different. Linear kernels have an average time of 0.18 seconds. The Polynomial kernel has an average time of 0.60 seconds. The RBF kernel has an average time of 1.08 seconds. Evaluation of Linear, Polynomial, and RBF kernel metrics are measured with accuracy and error. Linear kernels have an average yield of 80.46% for accuracy and 2.71% for errors. The Polynomial kernel has an average yield of 71.82% for accuracy and 3.24% for errors. The RBF kernel has an average yield of 95.94% for accuracy and 1.25% for errors.

Based on the results obtained, this study managed to get the best model of each kernel. Then in terms of processing time when predicting Linear kernels have advantages over the others. Different results are obtained in terms of accuracy and error because the RBF kernel has advantages over the others.

Future studies are expected to get more data so that they can perform performance tests for each kernel with a different amount of data. After getting the best model from this research, it is hoped that it can continue the comparison with other methods available in the Deep Learning algorithm so that it can get to know the performance of the Support Vector Regression algorithm.

5. REFERENCES

[1] Richa Handa, A.K. Shrivas, and H.S. Hota,"Financial Time Series Forecasting using Back Propagation Neural Network and Deep Learning Architecture", *International Journal of Recent Technology and Engineering (IJRTE)*, 2019.

[2] A. Stevenson, "Oxford Dictionary of English", *OUP Oxford*, 2010.

[3] Bill Z .Yang, and Zeng Tong, "A Note on the Real Currency Exchange Rate: Definitions and Implications", *Journal of International Business and Economics*, 2014.

[4] Feng Ziang and Wenjun Wu, "Hybrid Genetic Algorithm and Support Vector Regression Performance in CNY Exchange Rate Prediction", *International Conference on Engineering Science and Management*, 2016.

[5] A. P. Sidik, "Diagnosis of Types of Diseases in Cassava Plant by Bayes Method", *Jurnal Online Informatika (JOIN),* 2019.

[6] D. S. K. Chandar, D. M. Sumathi, and D. S. N. Sivanandam, "Forecasting of Foreign Currency Exchange Rate using Neural Network", *International Journal of Engineering and Technology (IJET)*, 2015.

[7] M. I. Jordan and T. M. Mitchell, "Machine learning: Trends, perspectives, and prospects," *Science*, 2015.

[8] N. M. Samsudin, C. F. binti Mohd Foozy, N. Alias, P. Shamala, N. F. Othman, and W. I. S. Wan Din, "Youtube spam detection framework using naïve bayes and logistic regression," *Indones. J. Electr. Eng. Comput. Sci.*, 2019.

[9] N. Alias, C. F. M. Foozy, S. N. Ramli, and N. Zainuddin, "Video spam comment features selection using machine learning techniques," *Indones. J. Electr. Eng. Comput. Sci.*,2019.

[10] R.P. Furi, Jondri, and D. Saepudin, "Prediksi Financial Time Series Menggunakan Independent Component Analysis dan Support Vector Regression Studi Kasus: IHSG dan JII", *e-Proceeding of Engineering,* 2015.

[11] Nurhana Abdul Aziz and Mohd Fauzi Bin Othman, "Binary Classification using SVM for Sick and Healthy Chicken based on Chicken's Excrement Image", *Pertanika Journal Science and Technology*, 2017.

[12] Sana Saeed, and Hong Choon Ong, "Performance of SVM with Multiple Kernel Learning for Classification Tasks of Imbalanced Datasets", *Pertanika Journal Science and Technology*, 2019.

[13] Vladimir Vapnik, "The Nature of Statistical Learning Theory", *Springer-Verlag*, New York, NY, 1995.

[14] M. Athoillah, "Pengenalan Wajah Menggunakan SVM Multi Kernel dengan Pembelajaran yang Bertambah ", *Jurnal Online Informatika (JOIN),* 2017.

[15] Steven Dye, "An Intro to Kernels", Retrieved Juni 22, 2020, from *https://towardsdatascience.com/an-intro-to-kernels-9ff6c6a6a8dc*, 2019.

[16] Tian Xia, "Support Vector Machine Based Educational Resources Classification", *International Journal of Information and Education Technology*, 2016.

[17] Ajay Yadav, "Support Vector Machines (SVM)", Retrieved September 15, 2019, from *https://towardsdatascience.com/support-vector-machines-svm-c9ef22815589,* 2018.

[18] Investing.com, "Data Historis USD IDR", Retrieved Juli 7, 2019, from *https://id.investing.com/currencies/usd-idr-historical-data*, 2019.