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Electronic Money Transactions Forecasting with Support Vector Regression (SVR) and Vector Autoregressive Moving Average (VARMA)

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Abstract

In today's digital era, the trend of payments with electronic money is rising. Some people have switched to do their way to the modern method such as electronic money. This is to improve the efficiency of the financial system. However, with the convenience and speed provided, if electronic money is not being controlled properly, this can cause an unmanageable price of goods. In managing the risk of using electronic money, it is required to forecast the nominal of electronic money in Indonesia. This paper implements multivariate data analysis with variables such as nominal electronic money transaction, volume electronic money transaction, and Money supply (M1) to forecast nominal electronic money transactions. The methods used are Vector Autoregressive Moving Average (VARMA) and Support Vector Regression (SVR). The results of the forecasting model were compared using Mean Absolute Percentage Error (MAPE). According to the research, the SVR model had a better outcome than VARMA model, with a MAPE value of 3.577 %. Its shows that the forecast data of the SVR model is close to the actual data.

Keywords: Electronic money, forecasting, multivariate time series, SVR, VARMA.

I. INTRODUCTION

IN the current digital era, transaction activities are not only carried out by using cash. Some people have switched to making payments with electronic money. This innovation in the field of financial technology improves efficiency in the financial system. Transactions with electronic money have been widely applied to various industrial areas, and various merchants or shopping outlets have integrated payment systems with electronic money, supported by the rising mobile lifestyle in the digital era. The mobile transaction lifestyle is used, such as shopping, paying electricity, and telephone bills using electronic money [1].

Currently, the popularity of digital payments with electronic money in Indonesia is increasing. Bank Indonesia noted that the volume of digital banking transactions continues to increase, whereas, in March 2021, it grew 42.47 percent, reaching 553.6 million transactions [9]. The increase of the transaction by using electronic money can be influenced by several monetary instruments, one of them is the money supply (M1). The results show that money supply (M1) positively affects the demand for electronic money in Indonesia [2]. However,

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the convenience and speed provided by electronic money can cause people's purchasing power to rise if it is not monitored correctly. Thus, this can increase the prices of goods unmanageably [3].

In the context of risk prevention and supervision of the use of electronic money, forecasting electronic money transactions in Indonesia is needed in the future. In previous research, the data analysis used to predict the use of electronic money was univariate, and the method used was backpropagation with genetic algorithms [4]. Falentino Sembiring (2021) uses a Simple Moving Average (SMA) statistical approach to predict the movement of bitcoin electronic money. This method provides an accuracy rate of 63% [5]. Meanwhile, Saad Ali (2021) uses the SVR model to predict the price of Cryptocurrency. The RBF kernel on the SVR model has the best predictive results for the price of Cryptocurrency [6]. In previous studies, the lack of supporting variables caused the error value of the model prediction results to rise. The statistical methods used in previous studies still used a simple MA model, which could not accommodate all-time series variables. Therefore, in this study, multivariate data analysis is used with variables such as the nominal of electronic money transactions, the volume of electronic money transactions, and the money supply (M1) to forecast the nominal of electronic money transactions. The method used is VARMA as an MA model development combined with a VAR model involving more than one variable and SVR with time series data. The two methods are compared, and the model with the lowest error rate is selected to forecast the nominal electronic money transaction.

II. LITERATURE REVIEW

A. Electronic Money

Electronic money is defined as a means of payment in electronic form where the value of the money is stored in certain electronic media. The user must first deposit the money to the issuer, and it is stored in forms of electronic media before being used for transaction purposes. When it is being used, the value of electronic money stored in electronic media will be reduced by the value of the transaction, and after that, it can be refilled (top-up). Electronic media to store the value of electronic money can be in the form of chips or servers. The use of electronic money as an innovative and practical means of payment is expected to help pay for mass economic activities, so that its development can help accelerate transactions on toll roads, in the field of transportation such as trains and other public transportation or transactions at minimarkets, food courts, or parking [9].

B. Money Supply M1

The money supply is the total value of money in the hands of the public, which consists of currency and demand deposits. In economics (in general), what is meant by money is a generally accepted medium of exchange for transactions. The public widely agrees with the medium of exchange as an exchange for goods and services [2]. The money supply is divided into M1 (money in the narrow sense), which consists of currency and demand deposits, and M2 (money in the broad sense), which consists of M1 plus quasi-money. Currency (currencies) is money issued by the government and or the central bank in the form of paper money or coins. Demand deposit (deposit money) is money issued by a commercial bank. Examples of demand deposits are checks and any transfer forms (such as giro). Quasi money includes savings accounts, time deposits, and foreign exchange accounts [2]. Understanding (M1) is purchasing power that can be used directly for payments, can be expanded, and includes payment instruments that are close to the money, for example, time deposits and savings deposits in banks or can also be interpreted as money as well as currency plus demand deposits [2]. Electronic money is a stored-value or pre-paid product where a certain amount of money is stored in an electronic media owned by a person, the value of which will decrease when used for payments for various types of transactions. Based on these characteristics, the nature of electronic money float is very liquid or can be equivalent to cash or demand deposits. Then electronic money can be counted as part of M1 [2].

C. Multivariate Time Series

Time series is a series of variable values ordered based on the time of occurrence, where the values are interconnected. Time series data can be annotated as follows

$$Xi(t); [i = 1,2,3, \dots n, t = 1,2,3, \dots m] \quad (1)$$

i is the number of variables, and t is the time series [10]. Time series analysis includes analysis involving one variable (univariate) and analysis involving many variables (multivariate) [7]. Multivariate time series analysis can also be defined as a collection of Univariate Time Series data that forms a single unit [8]. Multivariate time series analysis explains the interaction and joint movement (co-movement) among a group of time series variables. In finance, multivariate time series analysis models asset return systems, asset prices, exchange rates, interest rate term structures, and economic variables [11]. Multivariate Time Series data is represented in the following matrix form:

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \dots & a_{1m} \\ a_{21} & a_{22} & a_{23} \dots & a_{2m} \\ a_{31} & a_{32} & a_{33} \dots & a_{3m} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ a_{n1} & . & . & a_{nm} \end{pmatrix} \quad (2)$$

Matrix A is n x m in size, where n indicates the number of observed variables and m indicates observations on the variate [8].

D. Vector Autoregressive Moving Average (VARMA)

The Vector Autoregressive Moving Average model is a combination of Vector Autoregressive (VAR) and Vector Moving Average (VMA) [12]. VAR is the development of the AR model by involving more than one variable. In the VAR model, all variables are considered endogenous and interrelated. In general, the VAR (p) model can be written as follows [14]:

$$y_t = v + A_{1yt} - 1 + \cdots + A_{pyt-p} + \varepsilon_t \quad (3)$$

By assigning an error term to _t. Then _t is white noise with a mean of 0, a variance of 1, and a limited representation of the moving average (MA) model. The following is the formula for the VMA [14]:

$$\varepsilon_t = u_t + M_1 u_{t-1} + \cdots + M_q u_{t-q} \quad (4)$$

The equation for the combination of VAR and VMA models is as follows.

$$y_t = v + A_{1yt} - 1 + \cdots + A_{pyt-p} + u_t + M_1 u_{t-1} + \cdots + M_q u_{t-q} \quad (5)$$

where y_t is the observation vector sized $k \times 1$ containing k variable at time t, v as intercept vector, u_t is a vector error of size k × 1, which has a mean of 0 and a variation of 1, A_i relates to VAR coefficient parameter matrix, with $i = 1, 2, \dots, p$ with size k × k, and M_j shows the VMA coefficient parameter matrix, with $j = 1, 2, \dots q$

The following is an example of VARMA (p, q) for 2-variables :

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} = \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} + \begin{pmatrix} A_{11,1} & A_{12,1} \\ A_{21,1} & A_{22,1} \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} + \cdots + \begin{pmatrix} A_{11,p} & A_{12,p} \\ A_{21,p} & A_{22,p} \end{pmatrix} \begin{pmatrix} y_{1,t-p} \\ y_{2,t-p} \end{pmatrix} + \begin{pmatrix} u_{1,t} \\ u_{2,t} \end{pmatrix} + \begin{pmatrix} M_{11,1} & M_{12,1} \\ M_{21,1} & M_{22,1} \end{pmatrix} \begin{pmatrix} u_{1,t-1} \\ u_{2,t-1} \end{pmatrix} + \cdots + \begin{pmatrix} M_{11,p} & M_{12,p} \\ M_{21,p} & M_{22,p} \end{pmatrix} \begin{pmatrix} u_{1,t-p} \\ u_{2,t-p} \end{pmatrix} \tag{6}$$

In the VARMA method, it is necessary to do a stationary test of the data to determine whether the data used meets the average stability and variance. Stationary data is a state where the data is on average and constant from time to time. The data can be considered stationary when no significant growth or decline pattern [18]. The stationary testing process was carried out using the *Augmented Dickey-Fuller* (ADF) test with a significance value (α) = 5% [7]. The ADF testing procedure is carried out with the following steps [18]:

1. Hypothesis

H_0: Data is not stationary
H_1: Data is stationary

2. Required magnitude (parameter)

Significance level (α), δ, and SE (δ)

3. ADF test statistic

$$t = \frac{\delta}{SE(\delta)} \tag{7}$$

Where the *AR* parameter, SE (δ), is the standard error of the δ *and t* statistical test.

4. Criteria for ADF rejection

If $|t\delta| \geq |t\,(n-1;\alpha)|$ or $p - value \leq \alpha$, then H_0 is rejected.

E. Order of Vector Autoregressive Moving Average (VARMA)

1) ACF and PACF

ACF (Autocorrelation Function) is the relationship between data related to observation data at the time + and data 1 with time deviation [3]. The ACF equation or graph can be used to determine the order in the MA [3]. The following is the equation of ACF [13]:

$$r_k = \frac{\sum_{t=k+1}^{n}(Y_t - \hat{Y})}{\sum_{t=1}^{n}(Y_t - \hat{Y})^2} \tag{8}$$

Where r_k is the coefficient of ACF, Y_t is the value variable Y at time t, and Y_{t-k} is the value of variable Y at time t-k, $\hat{Y}$ is the average of the variable Y, and n is the amount of data. Meanwhile, PACF (Partial Autocorrelation Function) is the correlation between and by eliminating the relationship between linear variables $Y_{t-1}, Y_{t-2},\ldots Y_{t-k+1}$ [7]. Moreover, PACF is used to determine the order of AR. The following is the equation of PACF [13]:

$$r_{kk} = Corr(Y_t, Y_{t-k} | Y_{t-1}, Y_{t-2}, \ldots Y_{t-k+1}) \tag{9}$$

Where is the correlation in the bivariate distribution and is conditional with $Y_{t-1}, Y_{t-2},\ldots Y_{t-k+1}$

2) Akaike Information Criteria (AIC)

We also calculate AIC for each der combination according to ACF and PACF results. Thus, the optimum combination orders of p and q are determined by choosing the minimum AIC. The following is the equation of AIC [20]:

$$AIC = -2ln(L) + 2p \tag{10}$$

which L is a likelihood and p shows the number of VARMA parameters.

F. Support Vector Regression (SVR)

SVR is an implementation of Support Vector Machine (SVM) specifically for regression cases. The basic idea of SVM is to map training data from the input space to a higher dimensional feature space via functions and then build a separate hyperplane with maximum margins in the feature space. SVR aims to create a dividing line close to a lot of data, then reduce the distance between the dividing lines with the data [15]. The SVR concept is based on risk minimization, which is to estimate a function by minimizing the generalization error's upper limit so that SVR can overcome overfitting. SVR for non-linear data can be formulated in equation 11.

$$f(x) = \sum_{i=1}^{l} (a_i^* - a_i)\,(K(x_i, x) + \lambda^2) \tag{11}$$

a_i^* and a_i are the value of the Lagrange multiplier variable, $K(x_i, x)$ is the kernel function used, and is the scalar variable. Lagrange Multiplier is useful to determine the value of a function that is limited by a constraint condition to find a relative minimum or maximum [17]. Value of Lagrange multiplier a_i^* and a_i can be found by doing the sequential learning as follows:

$$E_i = y_i \sum_{j=1}^{l} (a_i^* - a_i)\, R_{ij} \tag{12}$$

$$\delta\alpha_{i\,1}^* = min\{max[\gamma(E_i - \varepsilon) - \alpha_i^*], C - \alpha^*\} \tag{13}$$

$$\delta\alpha_i = min\{max[\gamma(E_i - \varepsilon) - \alpha_i], C - \alpha_i\} \tag{14}$$

$$a_i^* = a_i^* + \delta\alpha_{i\,1}^* \tag{15}$$

$$a_i = a_i + \delta\alpha_i \tag{16}$$

E_i = the value error of i
y_i = the value of the actual data to i
$\delta\alpha_i^*, \delta\alpha_i$ = change in the value of α_i^* and α_i
ε = epsilon
C = complexity
γ = learning rate
We can estimate γ using the *Hessian matrix R* through the following equation:

$$[R]_{ij} = K(x_i, x) + \lambda^2 \tag{17}$$

Then we have

$$\gamma = \frac{cLR}{max([R]_{ij})} \tag{18}$$

Some methods in data analysis use the linear function. However, non-linear data are more often encountered. Thus, data transformation is carried out into higher spatial dimensions [16]. In SVR, kernel functions can convert non-linear input data to a higher dimension. By implementing kernel functions, we have linear relationships among the feature space. There are three kernel functions in SVR: linear, polynomial, and Gaussian Radial Basis Function (RBF). The RBF kernel function is the most frequently used [15].

1. Linear Kernel

$$K(x, x') = xx^T \tag{19}$$

2. Polynomial Kernel

$$K(x, x') = (1 + x_i x^T)^d \tag{20}$$

3. Gaussian Radial Basis Function (RBF) Kernel

$$K(x, x') = exp(-\frac{||x - x_i||}{2\sigma^2}) \tag{21}$$

Where x and x_i id the used, $||x - x_i||$ Euclidean distance and σ is an SVR parameter value that must be defined first.

III. RESEARCH METHOD

The system generally consists of two approaches, VARMA and SVR, to forecast electronic money transaction data. The following is a flowchart of both models.

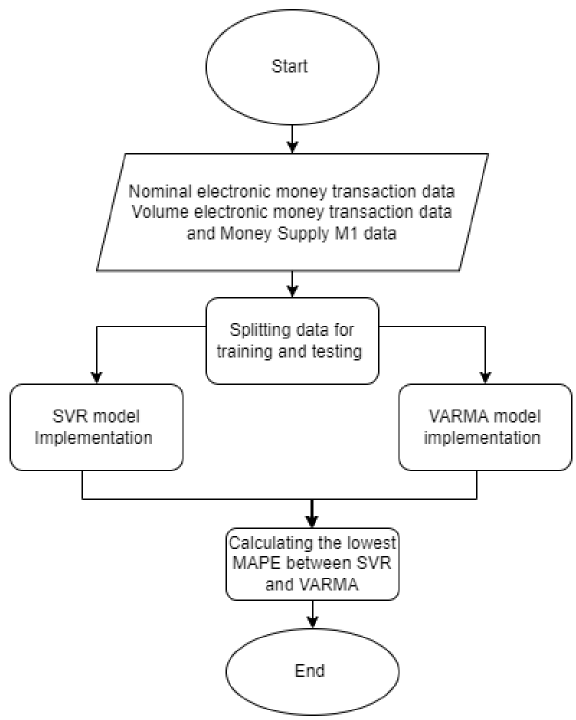


Fig. 1. System design flowchart

In Fig. 1, the data processing process passes through several stages. The following is an explanation of each stage:

1) Nominal electronic money transaction, Volume electronic money transaction and Money supply M1 Dataset

The dataset used is the monthly data on electronic money transactions in Indonesia from 2010 to 2021, which was obtained from the official website of Bank Indonesia https://www.bi.go.id and the dataset of the Money Supply (M1) from 2010 to 2021, which was obtained from the website of the Indonesian Central Statistics Agency https://www.bps.go.id. The volume of electronic money transactions is the number of shopping transactions carried out using electronic money in a certain period, while the Nominal electronic money transaction is the value of the shopping transaction [9]. The result of standardized data can be seen in Table I.

TABLE I
ELECTRONIC MONEY TRANSACTION AND MONEY SUPPLY (M1) DATASET

Date	Volume electronic money transactions	Nominal electronic money transactions	Money Supply (M1)
Jan-10	2.019.147	57.412,87	490083,79
Feb-10	1.914.662	55.147,91	494460,84
Mar-10	1.993.607	64.639,68	494717,69
Apr-10	2.065.037	48.985,27	514005,04
….	….	….	….
Sep-21	470.906.025	27.637.429,79	1968434,37
Oct-21	514.266.736	29.231.098,99	2071417,83
Nov-21	530.022.350	31.297.757,70	2114754.18
Dec-21	602.293.039	35.100.099,84	2282157.25

From the correlation analysis that is conducted between the variable Money Supply (M1) and electronic money transactions, the following results were obtained:

TABLE II
CORRELATION TABLE BETWEEN VARIABLES IN THE DATASET

	Volume electronic money transactions	Nominal electronic money transactions	Money supply (M1)
Volume electronic money transactions	1.000000	0.913344	0.888666
Nominal electronic money transactions	0.913344	1.000000	0.851435
Money supply (M1)	0.888666	0.851435	1.000000

Based on Table II, we can see the correlation between variables in the dataset. The variable of money supply (M1) with the volume of electronic money has a positive correlation of 0.888666, while the nominal electronic money with the money supply (M1) has a high positive correlation of 0.851435.

2) Splitting data for training and testing

The dataset is divided into training data and test data. The training data is used to model the nominal electronic money transactions, while the test data is used to evaluate the performance of the trained model. A comparison of the results of the forecast data with the test data can be used as a reference in hyper-parameter tuning. In the distribution of training data and test data, the test data used are the last 12 rows in the dataset, and the rest is used for modeling training data on the use of electronic money. This decision is based on the range of forecast data, and because the data is monthly, the test data range is used for 12 months.

3) Implementation of the VARMA model

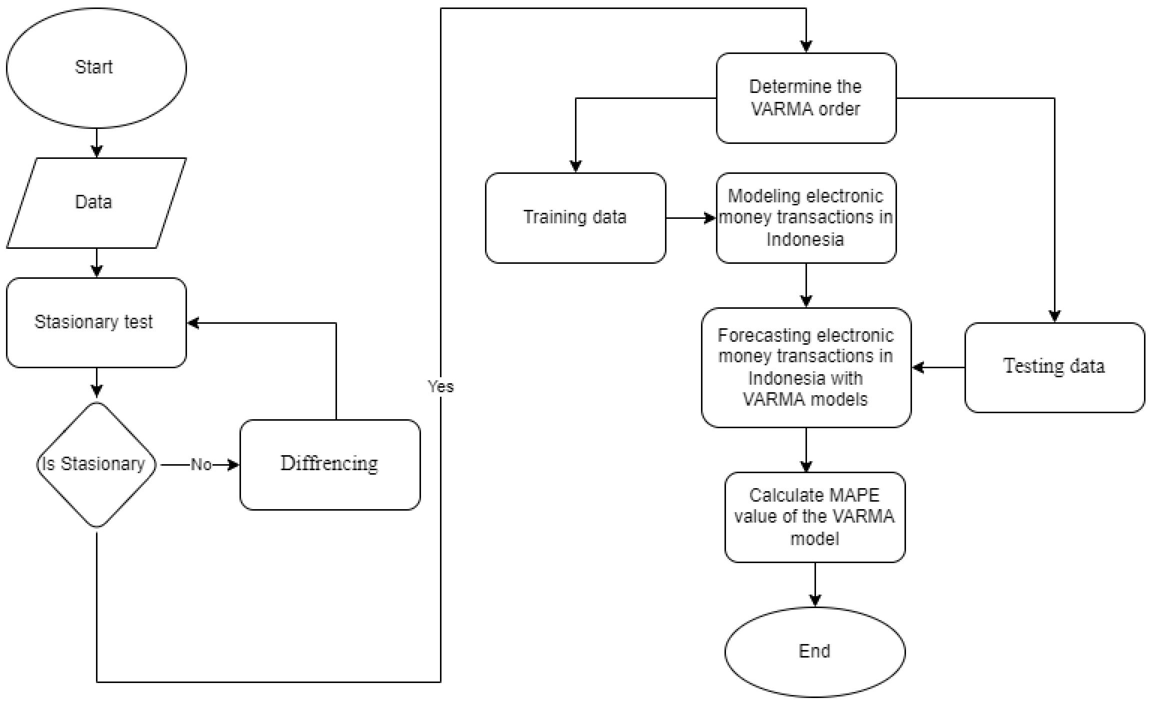


Fig. 2: Flowchart of VARMA model implementation

The flowchart in Fig. 2 shows the steps in forecasting electronic money transactions. The following are the explanation:

- Stationary Test

  A stationary test is carried out using the ADF test to see whether the data is stationary or not. If the data is not stationary, then differencing is carried out until the data becomes stationary.

- Order of VARMA model

  Determine the optimum lag of the VARMA model begins by determining the order of AR and MA first using the ACF and PACF plots. From the results of the ACF and PACF plots, the order of p and q can be obtained. Then the best model is determined based on the order obtained from ACF and PACF by combining p and q, considering the optimum model using the smallest AIC.

- Forecasting the nominal of electronic money transactions with VARMA model

  We compare the forecasting results and test data to calculate MAPE. We also consider the parameter combinations to analyze the best performance of VARMA model.

4) Implementation of the SVR model

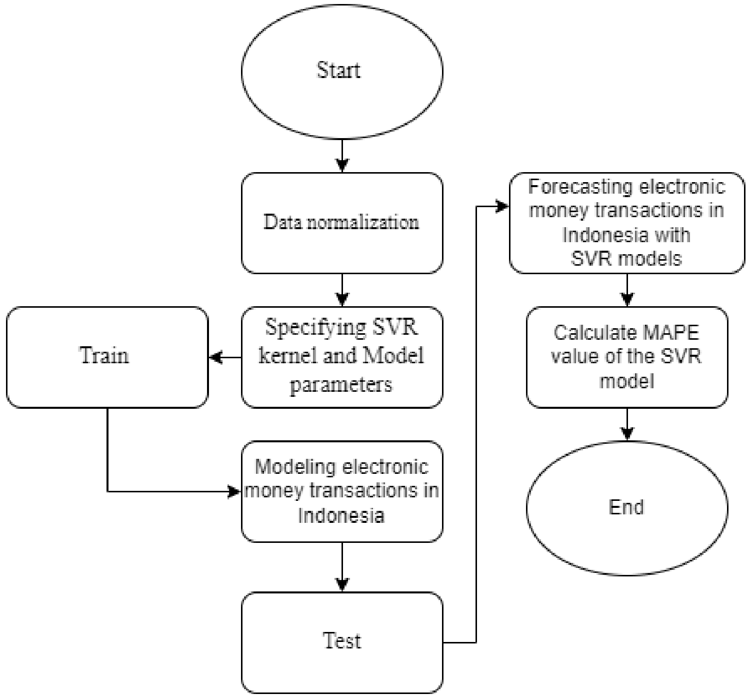


Fig. 3: Flowchart of SVR model implementation

Fig. 3 reveals the steps in forecasting electronic money transactions using SVR. The following is an explanation of each of the steps:

- Data normalization
  Data normalization is the preprocessing of data to convert the value of data into a similar range to reveal the relationship between the variables. One of the normalization methods is Min-Max transformation.

$$x_{new} = \frac{x_{old} - x_{min}}{x_{max} - x_{min}} \tag{22}$$

- Determining the SVR kernel and the parameters
  In the SVR model, there are several parameters used. To produce the best model, we consider such tuning parameters. One of the scenarios is changing the SVR kernels. We allow three kernels: RBF, linear, and polynomial.

- Modeling electronic money transactions in Indonesia
  The training data is used to construct an electronic money transactions model. The result of SVR model can be used to forecast nominal electronic money transactions.

- Forecasting the nominal of electronic money transactions with SVR model

  The forecasting results are compared with test data for model evaluation. Each parameter combination is tested, and the error value that we get can be used as a reference for performing hyper-parameter tuning.

4) Calculating the lowest MAPE between SVR and VARMA

The forecasting results of the two models are compared using Mean Absolute Percentage Error (MAPE) to find the best model. MAPE measures the error of the model's predictive value, which expresses an average absolute percentage of residual. The following is the MAPE equation:

$$MAPE = \frac{\sum_{t=1}^{n} \left| \frac{Y_t - \widehat{Y}_t}{Y_t} \right| \times 100\%}{n} \tag{23}$$

which

n : Number of forecasting periods

Y_t : Original data at time t

$\widehat{Y}_t$: Data from forecast results at time t

IV. RESULTS AND DISCUSSION

In this section, we evaluate the forecasting performance of electronic money transactions using the SVR and VARMA models. The two models were compared to determine the best model based on the MAPE values. The model with the lowest error rate is the model with the best performance.

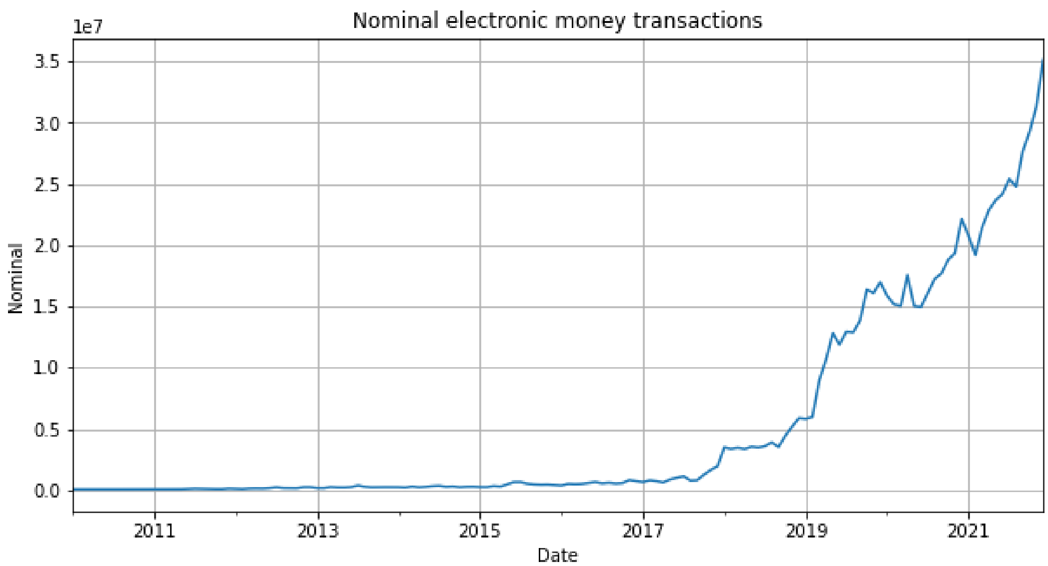


Fig. 4 Nominal electronic money transaction monthly data graph

Figure 4 shows the monthly data movement of nominal electronic money transactions from 2010 to 2021. From 2010 to 2016, there was no significant increase or decrease. This was due to many factors, one of which was inadequate financial technologies. However, in February 2019, there began to be a significant increase in nominal electronic money transactions. Many factors can cause this increase, one of which is due to financial technology that has begun to develop in Indonesia.

1) Results and analysis of forecasting electronic money transactions using the SVR method

The process of forecasting the SVR method begins with the selection of a kernel. The kernel used is linear, RBF, and polynomial with a value of $\boldsymbol{\varepsilon}$ = 0.01. The three kernels were chosen to see which kernel can provide a good forecasting model and give a small error value on MAPE.

TABLE III
MAPE VALUE OF EACH KERNEL

Kernel	MAPE
Linear	4.782 %
RBF	18.917 %
Polynomial	6.383 %

Based on Table III, the linear kernel shows the best results because it gives a smaller error value than other kernels with a MAPE value of 4.782%. After determining the kernel, the next step is to perform hyper-parameter tuning. This stage aims to obtain optimal parameters so that the forecasting results are better than before. The parameters used include C and epsilon. Each value of the parameter affects the results of the forecast.

TABLE IV
MAPE VALUE OF EACH SVR KERNEL AFTER HYPER-PARAMETER TUNING

Kernel	$\boldsymbol{\varepsilon}$	$\boldsymbol{C}$	MAPE
Linear	0.01	0.01	49.842 %
	0.01	0.1	16.354 %
	0.01	1	4.782 %
	0.01	**10**	**3.577 %**
	0.1	0.01	45.397 %
	0.1	0.1	25.619 %
	0.1	1	14.272 %
	0.1	10	14.272 %
RBF	0.01	0.01	18.917 %
	0.01	0.1	7.898 %
	0.01	1	31.706 %
	0.01	10	18.917 %
	0.1	0.01	31.706 %
	0.1	0.1	18.953 %
	0.1	1	9.409 %
	0.1	10	31.706 %
Polynomial	0.01	0.01	18.796 %
	0.01	0.1	18.186 %
	0.01	1	6.382 %
	0.01	10	8.951 %
	0.1	0.01	7.419 %
	0.1	0.1	7.419 %
	0.1	1	7.419 %
	0.1	10	7.419 %

In this study, the SVR kernel parameters have been standardized so that if kernel parameters are not found in other kernels, they are left in the default condition. The parameters used are C and $\boldsymbol{\varepsilon}$. In Table IV, the combination of C and $\boldsymbol{\varepsilon}$ values causes the MAPE values to change. This is because the $\boldsymbol{\varepsilon}$ parameter controls the width of the regression zone used in studying the data. The greater the $\boldsymbol{\varepsilon}$ value, the more flat the regression estimate. The C value affects the deviation of $\boldsymbol{the\ \varepsilon}$ parameter, which can still be tolerated. When the C value is greater, the tolerance for $\boldsymbol{\varepsilon}$ is greater, and the width of the regression zone can be optimized. From the study results, it can be concluded that the best kernel for making a forecast is a linear kernel with a value of C = 10 and $\boldsymbol{\varepsilon}$ = 0.01, which obtained results of MAPE 3,577%. The following is a visualization of the best forecasting results of the SVR model with the linear kernel.

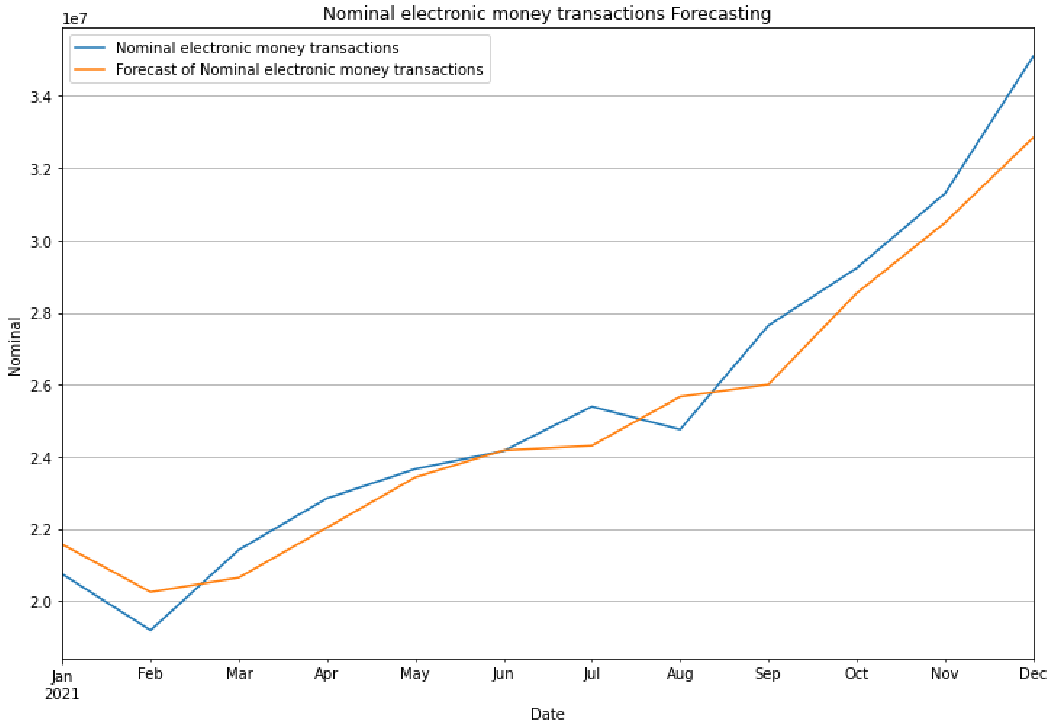
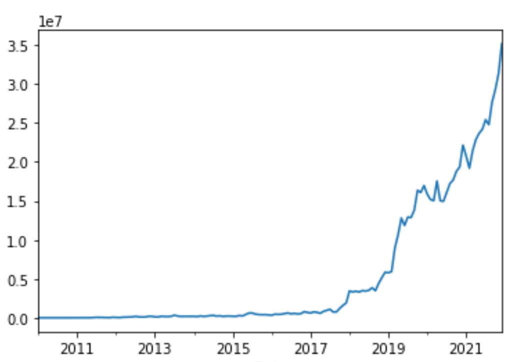


Fig. 5: Graph comparison between actual data with forecasted data using the SVR model

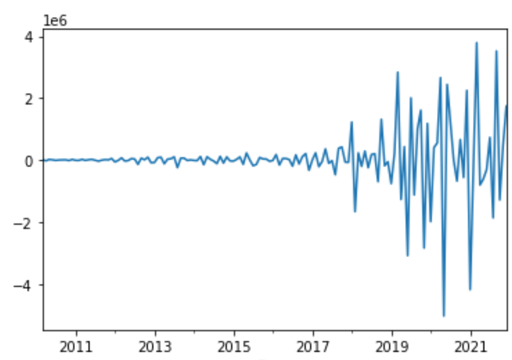
Based on Fig. 5, it can be seen that the trend shown in the forecasting data has a pattern that is almost the same as the actual data. One example is the transition from January to February. In the actual data, nominal electronic money transactions decreased by 7.51%, and in forecasting data, the decline occurred by 6.12%. The percentage difference in value between the actual and forecasted data in February is 5.52%. This shows that the forecast value is relatively close to the actual value.

2) Results and analysis of forecasting electronic money transactions using the VARMA method.

Before the data is entered into the VARMA model, the data is tested using the Augmented Dickey-Fuller Test to ensure the stationary of the data. If the data is stationary, then the VARMA process can be continued. This study showed that the data was not stationary, and the differentiation was carried out twice until all the data became stationary.



Non-stationary data graph



Stationary data graph

Fig. 6: Graph comparison between stationary data and non-stationary data

The next step is determining the order of the VARMA model by looking at the ACF and PACF plots. The ACF plot is used to find the VAR order, and the PACF plot is used to find the VMA order.

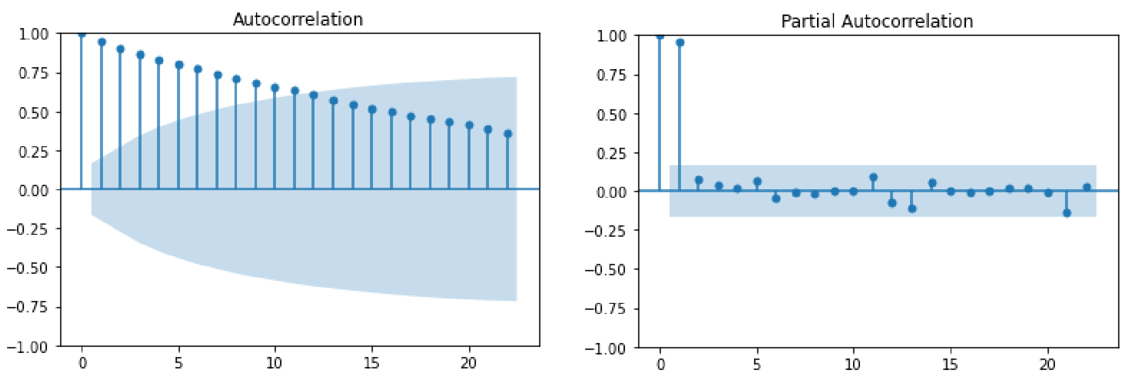


Fig. 7 Plot ACF and PACF non-stationary data

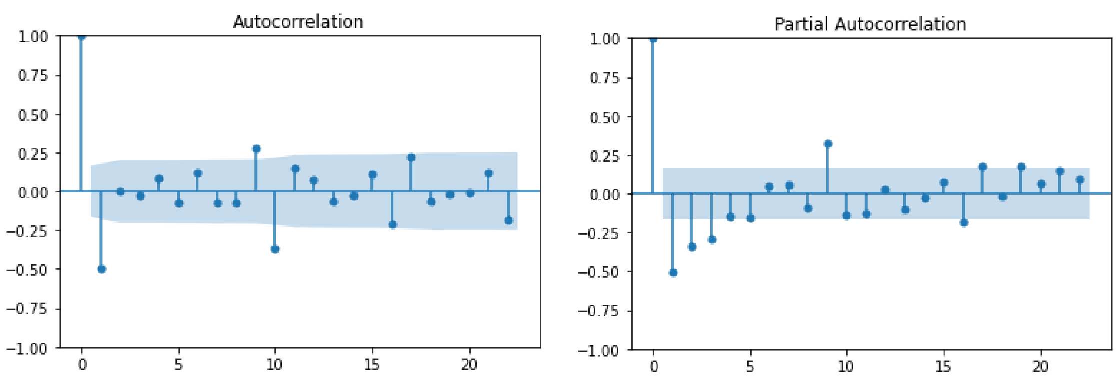


Fig. 8 Plot ACF and PACF stationary data

To determine the VARMA model, the ACF and PACF plots used are plots on stationary data. In Fig. 7, the ACF and PACF plots are performed on non-stationary data, so the results of the plots are not used. While the plots in Fig. 8, the ACF and PACF plots are carried out on stationary data to determine the order of the VARMA model. Based on the ACF plot in Fig. 3, the first cut-off in the 2nd lag can be interpreted that the data in the 3rd lag and so on are not correlated with the 1st lag, and data with a distance of 2 periods are not correlated with each other anymore. Meanwhile, figure 8 shows the first PACF cut-off plot in the 6th lag, indicating that the data in the 7th lag and so on are no longer correlated with the data in the 1st to 5th lag. This can be considered to find the optimal lag with the maximum value of the VARMA order combination (5,1) using AIC in Equation (10).

TABLE V
THE AIC VALUE OF EACH ORDER VARMA MODEL

Order VARMA	AIC values
VARMA(1,1)	12929.76
VARMA(2,1)	12905.30
VARMA(3,1)	12943.12
VARMA(4,1)	12872.56
VARMA(5,1)	**12847.57**

Based on Table V, each VARMA order gives an AIC value that is not much different from each other. This shows that the dataset used is compatible with each order of the VARMA model. The AIC values in table V provide the maximized likelihood estimate and the number of parameters for estimating information lost in the model. The smallest AIC value means that less information is lost. Order VARMA (5,1) gives the smallest AIC value, so it is used in this study.

The data is divided into training data and test data. The number of test data is the last 12 rows in the dataset. The amount of test data is determined based on the range of values to be forecast. In this study, the data used is monthly data, so the time span is 12 months. Then the training data is implemented in the VARMA(5,1) model. The implementation of the model produces variable coefficients used for forecasting, and these results can be seen in Table VI.

TABLE VI
VARMA MODEL VARIABLE VALUE

Parameter	Equation result of nominal electronic money transaction	Equation result of volume electronic money transaction	Equation result of money supply (M1)
intercept	8.226e+04	1.354e+06	2440.4460
L1. volume electronic money transaction	0.0020	-1.2207	-9.375e-05
L1. nominal electronic money transaction	-1.4944	-11.3103	-0.0201
L1. money supply (M1)	4.9225	-10.0125	-0.5556
L2. volume electronic money transaction	0.0105	-1.0523	0.0003
L2. nominal electronic money transaction	-1.2929	-8.9248	-0.0314
L2. money supply (M1)	4.0299	-16.1745	-0.3859
L3. volume electronic money transaction	0.0087	-0.7311	7.944e-05
L3. nominal electronic money transaction	-0.9757	-5.7388	-0.0236
L3. money supply (M1)	-0.0554	-75.8489	-0.3095
L4. volume electronic money transaction	0.0089	-0.3801	5.945e-05
L4. nominal electronic money transaction	-0.6653	-2.1207	-0.0077
L4. money supply (M1)	-1.5384	-78.7138	-0.4555
L5. volume electronic money transaction	0.0076	0.0945	6.816e-05
L5. nominal electronic money transaction	-0.2767	0.1907	0.0003
L5. money supply (M1)	0.6665	-25.6299	-0.4306
L1.e(volume electronic money transaction)	0.0097	0.6841	0.0002
L1.e(nominal electronic money transaction)	0.6203	-1.6607	0.0291
L1.e(. money supply (M1))	-0.8097	26.7960	-0.7991

In Table VI, each row shows the coefficients generated by VARMA (5,1) model to be multiplied by each predictor variable, and each column indicates the variable to be forecast. By using these parameters, nominal electronic money transactions are forecasted for 12 months. The following is a visualization result of the nominal forecast of electronic money transactions using VARMA.

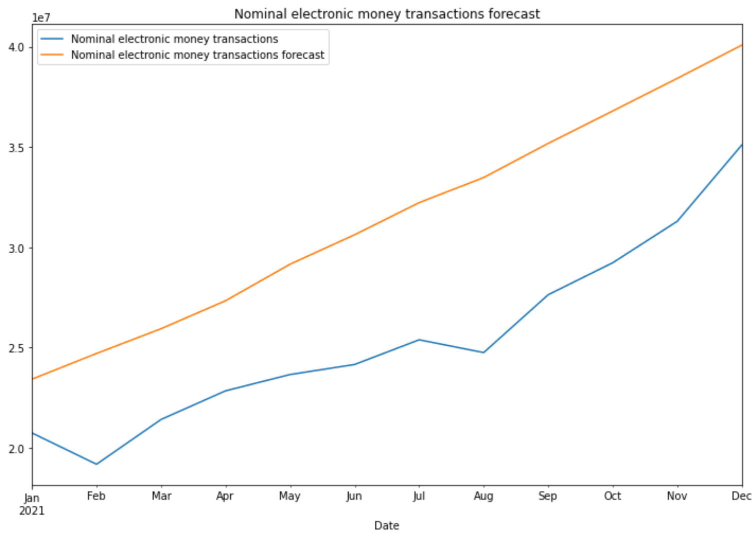


Fig. 9: Graph comparison between actual data with forecasted data using VARMA model

Based on Fig. 9, the results of forecasting using the VARMA model have a trend pattern that follows the trend pattern from the actual data, but the forecasted data has a value that is quite far from the actual data. One example is the transition between January and February. On actual data, nominal electronic money transactions decreased by 7.51%, while on forecasting data, there was an increase of 5.47%. The percentage difference between the actual and forecasted data in February is 28.77%. From the VARMA error rate, MAPE, is 23.728%

3) Evaluation result

This study focuses on comparing the performance of the SVR and VARMA models in forecasting the nominal electronic money transactions in Indonesia by involving the supporting variables for the volume of electronic money transactions and the money supply (M1) with time series data types.

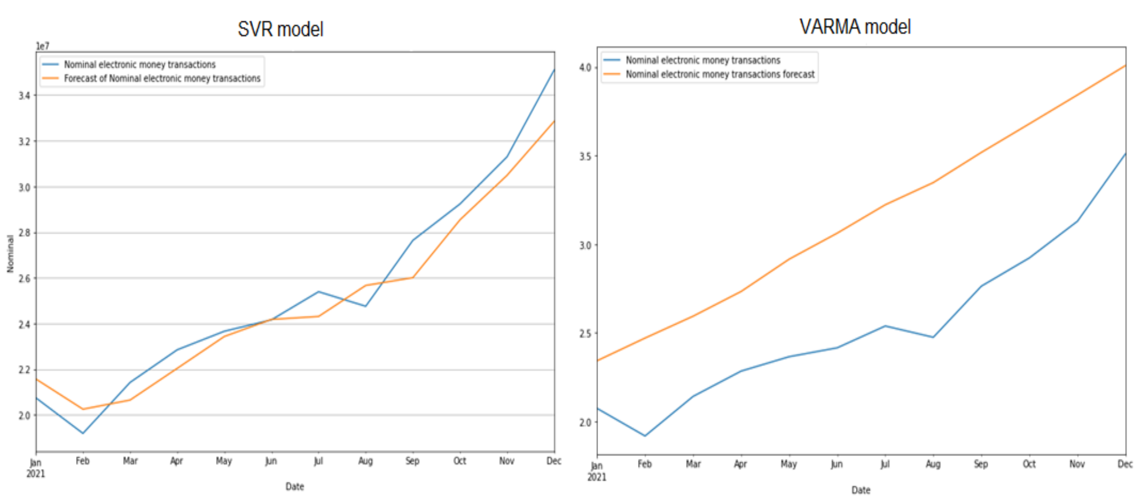


Fig. 10 Comparison of the evaluation results of the SVR model and the VARMA model

Based on Fig. 10, it can be seen that in the evaluation of the error comparison between the SVR model and the VARMA model, both models show good results by showing the same trend as the actual data, but based on the MAPE value, the best evaluation results are shown in the SVR model which gives a MAPE value of 3.577% with the best kernel is linear obtained after tuning hyper-parameters. While the VARMA model provides a MAPE with the value of 23.728%, these results are obtained from the VARMA (5.1) order model based on the smallest AIC calculation. The two error measurement results show that the SVR model has a smaller error value than the VARMA model.

V. CONCLUSION

Based on the evaluation results of the nominal forecasting of electronic money transactions, the VARMA model has a MAPE value of 23.728%, while the SVR model has a MAPE value of 3.577%. From both results, it can be concluded that the SVR model is better than the VARMA model in forecasting electronic money transactions because it provides a lower error rate. This shows that the forecast data of the SVR model is close to the actual data. In future research, it is hoped that other supporting variables that have a positive correlation with the nominal electronic money transactions can be added, for example, such as the money supply (M2), the level of public consumption, and community mobility. In the SVR model, minimal sequential optimization can be implemented to optimize the SVR model and change the parameters such as ɣ and C values.

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