PREDICTION OF SKINCARE SALES TURNOVER USING THE SUPPORT VECTOR METHOD AT THE WIDYA MSGLOW SIDOARJO COMPANY

^{1*}OKTAVIANA ISBIROTIN, ²WIWIET HERULAMBANG, ³RAHMAWATI FEBRIFYANING TIAS, ⁴RANGSANG PURNAMA, ⁵AHMADI AHMADI

^{1,2,3,4}Study Program of Informatics Engineering, Universitas Bhayangkara Surabaya

Jl. Ahmad Yani no. 114, Surabaya, 60231, Jawa Timur

⁵Study Program of Electrical Engineering, Universitas Bhayangkara Surabaya

Jl. Ahmad Yani no. 114, Surabaya, 60231, Jawa Timur

e-mail: ¹informatika@ubhara.ac.id, ²herulambang@ubhara.ac.id, ³rahmawati@ubhara.ac.id, ⁴rangsang.purnama@ubhara.ac.id, ⁴ahmadi@ubhara.ac.id

*Corresponding author

ABSTRACT

Every entrepreneur will certainly follow technological developments in the business world. MsGlow is one of the skincare businesses. The skincare business is one of the businesses that must compete with rapid and complex changes, and this very competitive makes business people have to think of strategies for business continuity in order to compete and also survive. One way that can be done is to utilize existing sales data. The importance of fast and precise operational data processing, information system facilities can be an alternative to solving problems in data processing, minimizing errors and accelerating the data processing process. As the number of sales transactions increases, there will be a buildup of data that has not been processed optimally. With the above problems, a forecasting system was created that can forecast skincare sales turnover using the Support Vector Machine (SVM) method. So far the SVM method has never been used to estimate sales turnover, especially skincare turnover. In this study, turnover in several areas will be forecasted. The kernel function variations used in Support Vector Machine (SVM) are RBF, Linear, and, Polynomial Degree 2. The results obtained from this research trial show that the overall forecasting model is good. The accuracy of the three areas obtained with the RBF kernel has a relatively good MAPE. In the accuracy test to predict skincare sales turnover, the three areas got a fairly good accuracy value of 94.46%. In the Sidoarjo area, it is predicted that there will be a lot of decrease in turnover in 2023-2024. These data prove that the way given in the research could solve the problem.

Keywords: Prediction, Turnover, Skincare, Support Vector Machine, MAPE.

1. INTRODUCTION

Currently, skincare is a basic need for women, both teenagers and adults. Of the various types of skincare available, there is one skincare that is quite well known, namely MsGlow. MsGlow has distributors spread throughout Indonesia. Widya MsGlow Sidoarjo is one of the official distributors of MsGlow which was founded in 2016 and is located at The Taman Dhika Housing Block 07 No.1 Sidoarjo. Currently, Widya MsGlow Sidoarjo's sales data processing still uses a manual data recording system written in books. There are always lots of sales every day. Each sale must be recorded one by one so that you can know the income earned within a certain period of time.

With so many distributors popping up, there is competition, which forces owners to make the right decisions in determining their sales strategy. To be able to do this, companies need sufficient sources of information to be able to analyze further in the future. One way that can be done is by utilizing existing sales data. The importance of fast and precise operational data processing means that information system facilities can be an alternative for solving problems in data processing, reducing errors and speeding up the data processing process. As the number of sales transactions increases, data will accumulate that has not been processed optimally.

One method that can be used is a relatively new artificial intelligence method in prediction, namely the Support Vector Machine method. The Support Vector Machine (SVM) method is one of the many methods that can be used to solve various types of problems, including forecasting. In solving a problem, Support Vector Machine (SVM) is able to handle non-linear problems with the kernel function which makes this method can be used for time series forecasting [11]. There are several researches talking about the use of SVM method in area of *prediction*, such as the the prediction of stroke with influential attributes [1], analysis of sales prediction [2], predicting visitor satisfaction [3], predicting rainfall and water discharge [4], predicting the number of Tuberculosis sufferers [6], the forecasting of foreign tourists coming to Indonesia [7], predicting client interest in deposit products [8], predicting crime rates based on news articles [9], predicting share price movements [10], and the diabetes prediction [12].

These studies inspired us to apply the SVM method to the problem of increasing sales turnover of skincare products at the MsGlow company. The aim of this research is to help improve the marketing of MsGlow skincare products by predicting future sales results based on previous sales data.

2. RESEARCH METHODOLGY

2.1 Research flow

Our research flow is shown in Figure 1. We use *Waterfall* method to describe the process conducted in every step of the research.

2.2 System Flowchart

In Figure 2, we show the flowchart of the process to compute the skincare sales turnover. To start the process, we must enters input data for modeling training. After that, the system will initialize the C parameters to get the optimal C parameter values. The next step is to test the Support Vector Machine (SVM) model using testing data. Based on this test process, an analysis of the results of the calculation, namely in the form of the Mean Absolute Percentage Error (MAPE) value, will be obtained. The MAPE value used to evaluate which parameter value is good to use.

2.3 Master Data

In this research, we used data obtained from Widya MSGlow Sidoarjo. The marketing area of the products are Sidoarjo, Surabaya, and Gresik. The data used is for a 3 year marketing period, shown in Table 1..



Figure 1. Research Methodology



Figure 2. System Flowchart of Skincare Sales Turnover at Widya MSGlow Sidoarjo Company

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No	Month	Voor	Turnover	i urnover at Marketing Area (Rp)				
110	wonth	I cai	Sidoarjo	Gresik	Surabaya			
1.	January	2020	109,500,000	112,500,000	120,600,000			
2.	February	2020	101,700,000	117,300,000	147,600,000			
3.	March	2020	96,000,000	112,500,000	132,600,000			
4.	April	2020	105,600,000	109,200,000	146,100,000			
5.	May	2020	118,800,000	120,600,000	114,900,000			
6.	June	2020	108,300,000	114,300,000	125,700,000			
7.	July	2020	106,200,000	108,000,000	124,500,000			
8.	August	2020	117,900,000	106,200,000	120,300,000			
9.	September	2020	123,600,000	102,600,000	135,600,000			
10.	October	2020	115,800,000	107,100,000	125,700,000			
11.	November	2020	107,400,000	108,000,000	121,800,000			
12.	December	2020	100,800,000	116,100,000	116,700,000			
13.	January	2021	113,400,000	123,600,000	129,600,000			
14.	February	2021	119,400,000	116,400,000	139,200,000			
15.	March	2021	118,500,000	120,600,000	135,000,000			
16.	April	2021	125,700,000	124,200,000	131,100,000			
17.	May	2021	114,300,000	116,100,000	132,000,000			
18.	June	2021	120,000,000	118,500,000	137,100,000			
19.	July	2021	116,700,000	123,600,000	132,600,000			

Table 1. Skincare Turnover of All Marketing Area Sidoarjo

No	Month	Voor	Turnover at Marketing Area (Rp)				
INU	WOITT	Tear	Sidoarjo	Gresik	Surabaya		
20.	August	2021	114,900,000	116,400,000	134,700,000		
21.	September	2021	125,100,000	118,200,000	141,900,000		
22.	October	2021	126,000,000	124,500,000	136,500,000		
23.	November	2021	132,900,000	116,700,000	126,300,000		
24.	December	2021	128,100,000	123,600,000	132,300,000		
25.	January	2022	136,800,000	126,000,000	129,300,000		
26.	February	2022	129,900,000	135,600,000	136,500,000		
27.	March	2022	125,700,000	129,300,000	134,400,000		
28.	April	2022	129,000,000	126,000,000	138,600,000		
29.	May	2022	137,100,000	132,300,000	137,700,000		
30.	June	2022	143,700,000	126,300,000	130,800,000		
31.	July	2022	135,600,000	134,700,000	132,000,000		
32.	August	2022	142,800,000	129,600,000	135,300,000		
33.	September	2022	133,800,000	132,000,000	129,600,000		
34.	October	2022	125,700,000	131,700,000	135,000,000		
35.	November	2022	133,200,000	125,700,000	128,700,000		
36.	December	2022	128,100,000	129,600,000	126,000,000		

3. RESULTS AND DISCUSSION

4.1 Pre-processing

At the data pre-processing stage, the data is changed from univariate form to multivariate form where the multivariate explains that the future turnover/ target (Yt) is influenced by the turnover of the previous period. Table 2 shows the sample of the univariate data from the marketing area Sidoarjo on marketing period January until December 2022.

Based on the univariate data above, now we create a multivariate data, as shown in Table 3 below. This multivariate table uses data marketing period from July 2022 to December 2022.

4.2 Normalization

Normalization is a process of grouping data attributes to minimize data redundancy in a database so that it can work optimally. The formula used to compute normalization is shown below:

 $normalizeValue = \frac{xValue - minValue}{maxValue - minValue}.$ (1)

No	Month	Turnover
1.	January	136,800,000
2.	February	129,900,000
3.	March	125,700,000
4.	April	129,000,000
5.	May	137,100,000
6.	June	143,700,000
7.	July	135,600,000
8.	August	142,800,000
9.	September	133,800,000
10.	October	125,700,000
11.	November	133,200,000
12.	December	128,100,000

Table 2. Univariat Data of Marketing Area Sidoarjo on period January – December 2022

 Table 3. Multivariate Data of Marketing period July 2022 to December 2022

Month	Yt	Yt-1	Yt-2
July	135,600,000	143,700,000	137,100,000
August	142,800,000	135,600,000	143,700,000
September	133,800,000	142,800,000	135,600,000
October	125,700,000	133,800,000	142,800,000
November	133,200,000	125,700,000	133,800,000
December	128,100,000	133,200,000	125,700,000

Table 4. Data Normalization									
Month	Yt	Yt-1	Yt-2						
July	0.550	1.000	0.633						
August	0.950	0.550	1.000						
September	0.450	0.950	0.550						
October	0.000	0.450	0.950						
November	0.417	0.000	0.450						
December	0.133	0.417	0.000						

where:

xValue = the value that will normalized

minValue = the lowest value of all variables

maxValue = the highest value of all variables

For example, now we will compute normalize the turnover value of period data from January 2022 to June 2022. We use this 6 month data, January to June, to predict the data of July 2022, as shown on Table 2. Based on this data, we can determine:

minValue = $125,700,000 \rightarrow$ the lowest turnover among January to June

maxValue = $143,700,000 \rightarrow$ the highest turnover among January to June

xValue = $135,600,000 \rightarrow$ the turnover value on July

So the normalize value of July 2022 computed as follows:

 $normalizeValue = \frac{135,000,000 - 125,700,000}{143,700,000 - 125,700,000} = 0.550$

By using the same way, we can compute data normalization of all multivariate data (Table 3). The result is shown in Table 4.

4.3 Training Process

4.3.1 Hessian Matrix

In the training process, a polynomial kernel of degree 1 will be used with the gamma parameter C=0.1. By using matrices multiplication of data normalization (Table 4), we compute Hessian matrix as follows:

 $X_{11} = ((Yt_1 * Yt_1) + (Yt-1_1 * Yt-1_1) + (Yt-2_1 * Yt-2_1) + C)^1$ $X_{11} = ((0.550 * 0.550) + (1 * 1) + (0.633 * 0.633) + 0.1)^1$ $X_{11} = 1.804$

By using the same way, we can compute data for Hessian Matrix of all normalization data (Table 4). The result is shown in Table 5.

4.3.2 Class Matrix

Class matrix is used for determine whether there has been an increase or decrease in sales in previous month. If in the previous month there was an increase in sales then the matrix content is 1, whereas if there was a decrease in sales then the matrix content is -1, as presented in Table 6.

Class Matrix is formed by using this formula:

	Table 5. Value of Hessian Matrix											
Data	1	2	3	4	5	6						
1	1.804	1.806	1.646	1.152	0.614	0.590						
2	1.806	2.305	1.600	1.298	0.946	0.456						
3	1.646	1.600	1.508	1.050	0.535	0.556						
4	1.152	1.298	1.050	1.205	0.528	0.288						
5	0.614	0.946	0.535	0.528	0.476	0.156						
6	0.590	0.456	0.556	0.288	0.156	0.291						

Ta	able	6.	Va	lue (of	Clas	s Ma	trix

Ζ	-1	1	-1	-1	1	-1			
-1	1	-1	1	1	-1	1			
1	-1	1	-1	-1	1	-1			
-1	1	-1	1	1	-1	1			
-1	1	-1	1	1	-1	1			
1	-1	1	-1	-1	1	-1			
-1	1	-1	1	1	-1	1			

Table 7. The result of Hessian Matrix * ClassMatrix

Data	1	2	3	4	5	6
1	1.804	-1.806	1.646	1.152	-0.614	0.590
2	-1.806	2.305	-1.600	-1.298	0.946	-0.456
3	1.646	-1.600	1.508	1.050	-0.535	0.556
4	1.152	-1.298	1.050	1.205	-0.528	0.288
5	-0.614	0.946	-0.535	-0.528	0.476	-0.156
6	0.590	-0.456	0.556	0.288	-0.156	0.291

 $Y = \begin{bmatrix} -1 & 1 & -1 & -1 & 1 & -1 \end{bmatrix}$ where :

$$Z = Y * Y$$

Then the Hessian matrix is multiplied by the Class matrix to form a class matrix aspresented in Table 7. Add up the values of each column and get the following results:

Column 1 : 1.804 + (-1.806) + 1.646 + 1.152 + (-0.614) + 0.590 = 2.771Column 2 : (-1.806) + 2.305 + (-1.600) + (-1.298) + 0.946 + (-0.456) = 1.890Column 3 : 1.646 + (-1.600) + 1.508 + 1.050 + (-0.535) + 0.556 = -2.599Column 4 : 1.152 + (-1.298) + 1.050 + 1.205 + -0.528 + 0.288 = 1.869Column 5 : (-0.614) + 0.946 + (-0.535) + (-0.528) + 0.476 + (-0.156) = -0.41Column 6 : 0.590 + (-0.456) + 0.556 + 0.288 + (-0.156) + 0.291 = 1.113Total Matrix Kernel = 6.059Alpha = 6 / 6.059 = 0.99Perform a Weight Search: W1 = Alpha * Column 1 * Y1 W1 = -2.774

l	W1	W2	W3	W4	W5	W6
	-2.744	-1.889	-2.698	-1.85	-0.406	-1.102

Then do a search for the bias value by taking each example class for the class Label 1 August and Label 1 July:

Calculation: $b = -\frac{1}{2} (W * Xk1 + W * Xk - 1)$ $b = -\frac{1}{2} * ((-2.744*1.806) + (-1.889*2.305) + ... + (-1.102*0.59))$ $b = -\frac{1}{2} * -1.057$ b = 0.528

After obtaining the bias value, you can then calculate the modeling pattern from the previous 6 months to get the predicted value for the next month. To calculate K (Xjanuary, Xt1) as follows:

$$\begin{aligned} \alpha 1 y1 \ K(xjuli,xt1) &= 1.0000 * -1 * (0.55*1*0.633) \\ &= -0.344 \\ \alpha 1 y1 \ K(xagu,xt1) &= 1.0000 * 1 * (0.95*0.55*1) \\ &= 0.5172 \\ \alpha 1 y1 \ K(xsep,xt1) &= 1.0000 * -1 * (0.45*0.95*0.55) \\ &= -0.232 \\ \alpha 1 y1 \ K(xokt,xt1) &= 1.0000 * 1 * (0*0.45*0.95) \\ &= 0 \\ \alpha 1 y1 \ K(xnov,xt1) &= 1.0000 * -1 * (0.417*0*0.45) \\ &= 0 \\ \alpha 1 y1 \ K(xdes,xt1) &= 1.0000 * -1 * (0.133*0.417*0) \\ &= 0 \end{aligned}$$

After calculating all the α iyi K(x1,xi) values against the first testing data values, the next step is to look for the modeling results. The modeling results are the sum of the data results that have been entered into the SVM model.

$$\Sigma \alpha iyi K(x1,xi) = (-0.344) + 0.5172 + (-0.232) + 0 + 0 + 0$$

= (-0.06)

And, Sign($\Sigma \alpha iyi K(x1,xi) + b = (-0.06) + 0.528 = 0.468$ These results are then denormalized to find out the forecasting results from July. Denormalization value = (0.468 * 18.000.000) + 125.700.000 Denormalization value = 134.124.400

From the denormalization process a function will be produced $f(\Phi(Xt))$ obtained from the value sign($f(\Phi(Xt))$).

 $f(\Phi(Xt)) = 134,124,400 - 128,100,000$

 $f(\Phi(Xt)) = 6,024,000$

Class prediction results are obtained from the results of the classification function. If the result is more than 0 then you enter class 1 and if the result is less than 0 then you enter class -1. The calculation results above show a Sign value of 6,024,000. This value is more than 0 so this result is in category 1. Therefore, this testing data is in the increasing category. Based on these results, the turnover value for January 2023 is predicted to increase with forecast results of 134,124,400.

4.4 Implementation

The process of predicting skincare sales turnover is carried out by optimizing parameters with different values in each test. The data processed comes from 3 (three) sales areas, namely Sidoarjo, Gresik, and Surabaya in the sales period 2020 to 2022. Prediction results are displayed in table form.

Table 8 shows that the smallest MAPE is obtained at the value of Gamma 0.860, Lambda value 0.7, and maximum iteration of 10. There are 4 (four) rows of data that contain the smallest MAPE values, where the epsilon value is different for each row of data. Table 9 shows that the smallest MAPE is obtained at the value of Gamma 0.590, Lambda value 0.4, and maximum iteration of 10. There are 3 (three) rows of data that contain the smallest MAPE values, where the epsilon value is different for each row of data. Table 10 shows that the smallest MAPE is obtained at the value of Gamma 0.270, Lambda value 0.7, and maximum iteration of 10. There are 4 (four) rows of data that contain the smallest MAPE is obtained at the value of Gamma 0.270, Lambda value 0.7, and maximum iteration of 10. There are 4 (four) rows of data that contain the smallest MAPE values, where the epsilon value is different for each row of data.

No	Training	Testing	Gamma	Lamba	Epsilon	Max.	MAPE			
	Data	Data				Iteration	(%)			
1.	24	12	0.070	0.2	0.00010	10	3.27264			
2.	24	12	0.280	0.4	0.00010	10	3.27264			
3.	24	12	0.440	0.5	0.00010	10	3.27418			
4.	24	12	0.860	0.7	0.00010	10	3.27131			
5.	24	12	0.070	0.2	0.00100	10	3.27264			
6.	24	12	0.440	0.5	0.00100	10	3.27418			
7.	24	12	0.630	0.6	0.00100	10	3.27264			
8.	24	12	0.860	0.7	0.00100	10	3.27131			
9.	24	12	0.860	0.7	0.01000	10	3.27131			
10.	24	12	0.860	0.7	0.10000	10	3.27131			

Table 8. Sidoarjo Area Test Results

Table 9. Gresik Area Test Results

No	Training	Testing	Gamma	Lamba	Epsilon	Max.	MAPE
	Data	Data				Iteration	(%)
1.	24	12	0.320	0.3	0.00010	10	2.36329
2.	24	12	0.330	0.3	0.00010	10	2.35825
3.	24	12	0.590	0.4	0.00010	10	2.35730
4.	24	12	0.920	0.5	0.00010	10	2.35765
5.	24	12	0.330	0.3	0.00100	10	2.35825
6.	24	12	0.330	0.3	0.01000	10	2.35825
7.	24	12	0.590	0.4	0.01000	10	2.35730
8.	24	12	0.920	0.5	0.01000	10	2.35765
9.	24	12	0.590	0.4	0.10000	10	2.35730
10.	24	12	0.900	0.5	0.10000	10	2.36128

No	Training Data	Testing Data	Gamma	Lamba	Epsilon	Max. Iteration	MAPE
1.	24	12	0.050	0.3	0.00010	10	1.76863
2.	24	12	0.090	0.4	0.00010	10	1.77488
3.	24	12	0.140	0.5	0.00010	10	1.77263
4.	24	12	0.200	0.6	0.00010	10	1.76863
5.	24	12	0.270	0.7	0.00010	10	1.76451
6.	24	12	0.350	0.8	0.00010	10	1.76620
7.	24	12	0.450	0.9	0.00010	10	1.76863
8.	24	12	0.270	0.7	0.00100	10	1.76451
9.	24	12	0.270	0.7	0.01000	10	1.76451
10.	24	12	0.270	0.7	0.10000	10	1.76451
9. 10.	24 24	12 12	0.270	0.7	0.01000	10 10	

Table 10. Surabaya Area Test Results

WILAYAH		TAHUN UJI	
SIDOARJO	~	2022	~
AHUN LATIH		JENIS KERNEL	
2020	~	RBF	~
2021	~	LAMBDA λ	
àamma λ		0.1	~
0.01000	~	Nilai Epsilon (e)	
Aax Iterasi		0.00010	~
10	v		
		PROSES	

Figure 3. Front Design of the System

The testing phase done uses the Black Box method. Black box testing is a test that does not look at the coding structure of a program. This testing usually covers program performance and functional testing is testing based on case studies that will be given to a component, module or feature that will be tested. Functional testing is carried out by providing input to components, modules or features and then checking the output results. If the resulting output matches expectations or is correct, if it is not appropriate then the part contains an error.

In this Figure 3 and Figure 4, testing will be carried out in the three areas by entering data into the system which will be processed using the Support Vector Machine (SVM) algorithm to determine the results of the values that have been entered.

The results of testing for each area will show the lowest MAPE value, which means the parameters used are the best for the process of predicting skincare sales turnover using the Support Vector Machine (SVM) method. In terms of system testing results, 12 test data experiments will be carried out in 2022. This test is carried out to ensure the feasibility of the system and compare the output values of the system and the original results.

Support Ve	ctor Machine							NANA 🧶 🤇
Nama	Tahun(Latih)	/ Jumlah Data Latih	Tahun(Testing)	Jumlah Data Testing	Jenis Kernel	MSE	RMSE	MAPE(%)
SIDOARJO	2021	24	2022	12	RBF	9.338.099,64083	3.055,83043	6.42916
SIDOARJO	2021	24	2022	12	RBF	4.998.165,81400	2.235,65780	3.88273
SIDOARJO	2021	24	2022	12	RBF	12.868.894,60867	3.587,32416	10.68717
SIDOARJO	2021	24	2022	12	RBF	19.635.919,69067	4.431,24358	17.24408
SIDOARJD	2021	24	2022	12	RBF	24.542.028,90425	4.953,99121	22.51490
SIDOARJO	2021	24	2022	12	RBF	28.096.919,61467	5.300,65275	26.64618
SIDOARJO	2021	24	2022	12	RBF	30.675.776,81900	5.538,57173	29.82560
SIDOARJO	2021	24	2022	12	RBF	32.540.950,09458	5.704,46756	32.22861
SIDOARJO	2021	24	2022	12	RBF	33.891.958,07542	5.821,68000	34.02672
SIDOARJO	2021	24	2022	12	RBF	34.876.320,12092	5.905,61767	35.36862
SIDOARJO	2021	24	2022	12	RBF	35.581.027,57942	5.964,98345	36.34628
SIDOARJO	2021	24	2022	12	RBF	36.103.386,52142	6.008,60937	37.08032
SIDOARJO	2021	24	2022	12	RBF	36.474.683,06467	6.039,42738	37.60702
SIDOARJO	2021	24	2022	12	RBF	36.728.764,50017	6,060,42610	37.96983
SIDOARJO	2021	24	2022	12	RBF	36.938.587,33442	6.077,71234	38.27093
SIDOARJO	2021	24	2022	12	RBF	37.088.376,63600	6.090,02271	38.48669
SIDOARJO	2021	24	2022	12	RBF	37,156,380,40808	6.095,60337	38.58485
SIDOARJO	2021	24	2022	12	REF	37.238.911,54300	6.102,36934	38.70424
SIDOARJO	2021	24	2022	12	RBF	37.45(1000,00000	6.119,64051	39.01042

Figure 4. Forecasting Result

Area	Trial	Accuration	Error	Precision	Recall
Sidoarjo	1	91.7%	8.3%	85.7%	100%
Sidoarjo	2	91.7%	8.3%	85.7%	100%
Sidoarjo	3	100%	0%	100%	100%
Gresik	1	83.3%	16.7%	83.3%	83.3%
Gresik	2	91.7%	8.3%	100%	83.3%
Gresik	3	100%	0%	100%	100%
Surabaya	1	100%	0%	100%	100%
Surabaya	2	91.7%	8.3%	100%	100%
Surabaya	3	100%	0%	83.3%	100%
	Average	94.46%	5.54%	93.11%	96%
	Sidoarjo	94.47%	5.53%	90.47%	100%
	Gresik	91.67%	8.33%	94.43%	88.87%
	Surabaya	97%	3%	94%	100%

The table explains that the highest accuracy value in each area was in the third experiment. After obtaining the average accuracy value, the system was able to predict skincare sales turnover using the Support Vector Machine (SVM) method quite well.

4.5 Presentation of Forecasting Result

To see the comparison results of skincare sales predictions in the Sidoarjo, Gresik and Surabaya areas, you can see the results of the following line graph Figure 5.

The comparison results of Skincare Sales Turnover Predictions in 2023 can be seen in the line graph of the predicted turnover results for the three regions. The Sidoarjo region is shown in blue, the Gresik region is a green line, and the Surabaya region is purple. In the comparison graph, it can be seen that the Sidoarjo region will experience quite a large increase in turnover in 2023. Meanwhile, the Gresik region will experience a decrease in turnover in 2024.

The results of the comparison of skincare sales turnover predictions in 2024 can be seen in the line graph of the predicted turnover results for the three regions, as presented in Figure 6. The Sidoarjo region is shown in blue, the Gresik region is a green line, and the Surabaya region is purple. In the comparison graph, it can be seen that the Sidoarjo region will experience quite a large increase in turnover in 2024. Meanwhile, the Gresik region will experience a decrease in turnover in 2024.

4. CONCLUSION

Based on the research that has been carried out, we can conclude that the using of the Support Vector Machine (SVM) method could solve the problem of skincare sales turnover prediction. This method helps the owner of the skincare company to predict their future profit based on previous data.

Based on the results of the research we conducted, it is hoped that future research will add more training data, both in terms of sales periods and additional marketing areas.



Figure 5. Comparison of Year 2023 Forecasting Results



Figure 6. Comparison of Year 2024 Forecasting Results

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