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Predictive Maintenance on Dry 8 Production Machine Line Using Support Vector Machine (SVM)

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ABSTRACT

Machines are the main element in manufacturing companies, and the role of machine performance is vital in the production process. Downtime problems caused by machine damage can significantly affect company productivity. This research implements the support vector machine (SVM) method for predicting Dry 8 production machine line maintenance, which aims to reduce downtime and increase productivity. The SVM method is known for its high accuracy and low error rate. The evaluation process used four kernel functions: linear, radial basis function (RBF), polynomial and sigmoid. The linear kernel function performed best with 99.8% accuracy, 83% precision, recall, and f1-score. These results show that the SVM method can be a viable solution to improve the efficiency of machine maintenance.

Keywords: Confusion Matrix, Machine Learning, Predictive Maintenance, Support Vector Machine

Introduction

PT XYZ is one of the companies engaged in the manufacturing industry that produces noodles. Some products produced include dry noodles, instant noodles, and vermicelli noodles. To maintain the quality of the products produced, the company has an ISO 22000:18 certificate for food management and continues to make improvements consistently and continuously to meet consumer needs. In the production process, the company has a line of instant, dry, and vermicelli machines. In machine maintenance management, the company implements preventive maintenance, breakdown maintenance, and scheduling maintenance [1].

In the manufacturing industry, maintaining optimal machine performance is essential for productivity. The company's main problem is frequent Dry 8 machine breakdowns, resulting in significant downtime. The workload is too heavy on the dynamo engine as the main drive and unexpected damage to the dough-making machine. The average damage ratio to the Dry 8 machine occurs six times each month and reduces the average working hours by 0.71 hours per day. Another problem is the availability of machine components and the waiting time for repairing damaged machines, which impacts downtime. Implementing maintenance prediction on Dry 8 machines can prevent the occurrence of machine breakdowns through early detection in an effort for continuous improvement [2].

Previous research on predictive maintenance to support this research has been conducted by Haliza, who states that the SVM method can produce high accuracy values in the predictive maintenance of motorised vehicles [3]. In contrast, Saputra's research states that the SVM algorithm can have linear kernel functions, radial basis functions (RBF), polynomials, and sigmoids [4]. Meanwhile, Kusumaningrum's research states that SVM and random forest algorithms can predict EPFAN motorbike maintenance using sensor data [5]. While [6] research states that prediction of aircraft engine maintenance can be made with machine learning methods, research is conducted to find solutions for maintenance prediction by comparing classification and regression results between random forest, SVM, and long-short-term methods.

Based on the problems that occur, the support vector machine (SVM) method is chosen as an alternative to solve these problems. SVM is known to provide high accuracy in predicting potential data. This has been proven in many SVM implementations to find globally optimal solutions that provide the best results in terms of classification and regression. With the implementation of SVM, it is hoped that companies can provide solutions for machine maintenance efficiency and increase productivity. [7]. This research aims to create a support vector machine (SVM) model as predictive maintenance that can be used as one of the considerations for evaluating machine maintenance. In addition, the SVM implementation is also evaluated by measuring the accuracy and error values of the test results.

Research Methods

Flow of Research

At this stage, explain the flow of the system creation process using a support vector machine with the help of Google Collab software. **Figure 1** is a flowchart for creating a support vector machine (SVM) model.

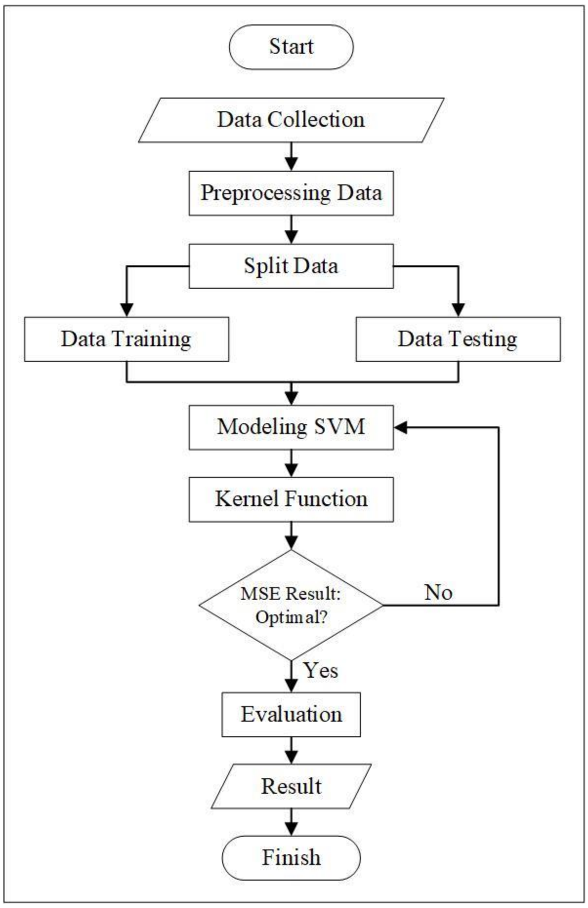

Figure 1.Flow Chart of Support Vector Machine

Data Collection

The initial stage in this research is data collection. The data to be used is maintenance prediction data that can be accessed through the website www.kaggle.com. The data collected amounts to 10,000 rows and ten columns. The features used in this research are Type, Air Temperature, Process Temperature, Rational Speed, Torque, Tool Wear, Target, and Failure Type. **Table 1** is a description of the data feature [8].

Table 1. Feature Data

No	Feature	Description
1	UDI	Attribute variants as data sequence number clues
2	Product ID	The data variant is an instruction code consisting of diverse numbers.
3	Type	Data variants consisting of the letters L, M, and H as product quality variables, low (20% of the data), medium (30% of the data), high (50% of the data)

4	Air Temperature	The air temperature around the machine obtained through the random walk process normalised to a standard deviation of 2 K and defined as 300 K
5	Process Temperature	The air temperature generated in the work process is normalised to a standard deviation of 1 K plus an ambient temperature of 10 K.
6	Rotational Speed	A value that indicates the number of revolutions of a machine in a given period
7	Torque	The value of the force produced by a machine in units of newton meters (Nm)
8	Tool Wear	The rate of wear and tear of a tool or machine by adding 2/3/5 minutes during use
9	Target	The labelling of whether the machine is damaged or not consists of the number 0, which defines a normal machine, while the number 1 defines a damaged machine
10	Failure Type	Labelling the type of machine condition, whether it is normal or damaged

Preprocessing Data

The preprocessing stage is the most important in data mining because it converts raw data into data suitable for mining procedures [9]. There are several stages in preprocessing. The first stage is data cleaning to find missing values, which refers to changing, modifying, or deleting data that is considered incomplete, inconsistent, inaccurate, or incorrect to produce high-quality data [10]. Furthermore, data transformation encoding, this stage is carried out to convert categorical variables into numeric ones through the label encoding method. For data reduction, at this stage, unnecessary data is removed in the mining process and data that will be removed at the name and symbol attributes [11].

Modelling SVM

The modelling stage in this study uses the support vector machine (SVM) algorithm. Support Vector Machine (SVM) is a supervised learning method that can be used in regression and classification [12]. This algorithm can solve prediction or classification problems by dividing data classes with dividing lines [13]. This algorithm has higher performance than other systems [14]. The basic theory of SVM is derived from a combination of existing computer science theories [15]. The basic principle of this algorithm is linear classification. In its application, it can be extended to non-linear classification [16]. Those working in data mining and machine learning highly value the SVM algorithm. Its actual performance in predicting new data types is very accurate [17]. SVM aims to design a more computationally efficient learning method for separating hyperplanes in a high-dimensional feature space [18].

SVM classification performance is highly dependent on the kernel function. The use of kernel functions can result in higher accuracy. The kernel's role is useful for moving the feature space to a high-dimensional space called kernel space. Kernel space can separate data into different classes with a linear hyperplane [19]. Kernels used include linear, sigmoid, radial basis function (RBF), and polynomial. [20]. The equation that can be used to calculate the linear kernel function is in equation (1), the RBF kernel function is in equation (2), the sigmoid kernel function is in equation (3), the polynomial kernel function is in equation (4) [21].

$$K(x,y) = x^T \cdot y + c \tag{1}$$

$$sigmasK(x,y) = exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right) \tag{2}$$

$$K(x,y) = \text{Tanh}(ax^+ \cdot y + c) \tag{3}$$

$$K(x,y) = (ax^T y + c)^d \tag{4}$$

Evaluation

The evaluation stage in this research is used to measure performance and evaluate the system that has been created [22]. In this study, the method used for evaluation utilizes a confusion matrix that places the prediction class at the beginning of the matrix and then the observation data on the left side of the matrix. Each matrix cell contains a number that indicates the actual number of cases in the observed class [23]. Confusion matrix is one of the methods used in the performance evaluation process of classification data mining models by predicting the correctness of objects [24]. The parameters used in the confusion matrix can be presented according to **Table 2**.

Table 2. Confusion Matrix

		Prediction	
		Positive	**Negative**
Actual	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Positive (TP)

True positive (TP) is a positive actual value and a positive prediction value. False Positive (FP) is a negative actual value but a positive predicted value. True Negative (TN) is a negative actual and predicted value. False Negative (FN) is a positive actual value, but the predicted value is negative [25].

Based on the confusion matrix evaluation, the accuracy, precision, recall and f1-score values are calculated. The accuracy score shows how accurately the system can classify the data. In other words, the accuracy score is the ratio of correctly classified data to the total data [26]. Precision is the degree of accuracy between the information requested by the user and the response provided by the system [27]. Recall is the percentage of positive category data correctly classified by the system [28]. F1 score is a weighted average comparison between precision and recall [29]. The equation that can be used to calculate accuracy is in equation (5), precision is in equation (6), recall is in equation (7), and f1-score is in equation (8) [30].

$$\text{Accuracy} = \frac{\mathrm{TP + TN}}{\mathrm{TP + TN + FP + FN}} \tag{5}$$

$$\text{Precision} = \frac{\mathrm{TP}}{\mathrm{TP + FP}} \tag{6}$$

$$\text{Recall} = \frac{\mathrm{TP}}{\mathrm{TP + FN}} \tag{7}$$

$$\text{F1-Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

Results and Discussion

Data

The data used is a maintenance prediction dataset with a total of 10,000 rows of data with 10 columns. **Figure 2** is a graph of failure type features. This figure shows that the machine is in the condition of no failure 965 data, heat dissipation failure 112 data, power failure 95 data, overstrain failure 78 data, tool wear failure 45 data and random failure 18 data.

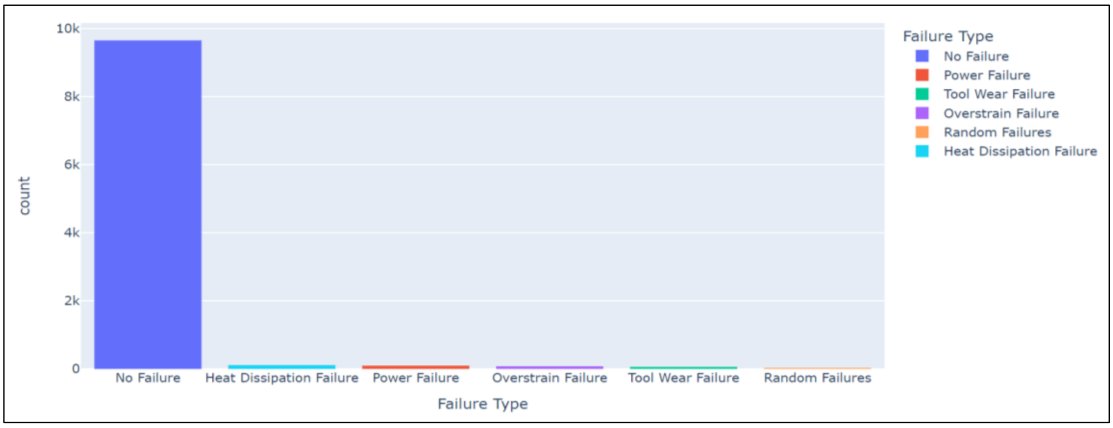

Figure 2. Failure Type

Preprocessing Data

The preprocessing stage is divided into several stages. In the first stage, missing value analysis is performed using 'isnull' and visualisation using 'msno.bar'. **Figure 3** is a visualization of missing values, it can be seen that there are no missing values in the data set.

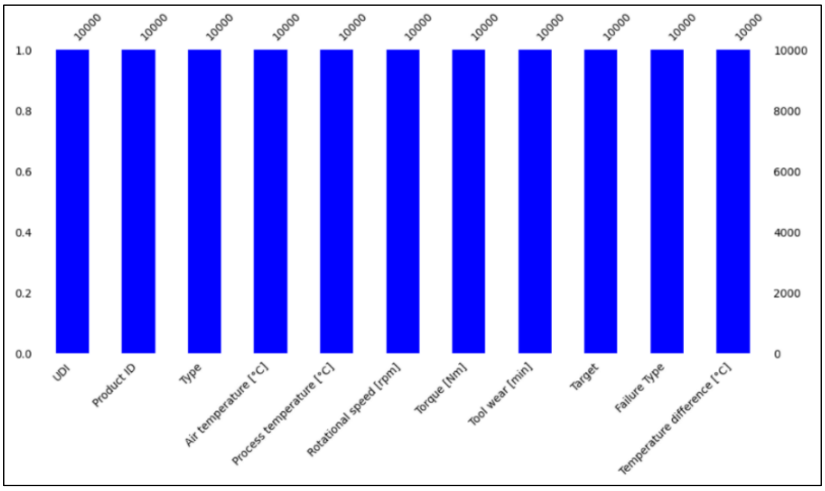

Figure 3. Missing Value Visualization

The next stage is data reduction. This stage aims to eliminate data features that are not used in testing. The command used is 'df. drop' with the features removed, namely 'UDI' and 'Product ID'. **Figure 4** is the output of data reduction.

	Type	Air temperature [°C]	Process temperature [°C]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Target	Failure Type	Temperature difference [°C]
0	M	25.95	36.45	1551	42.8	0	0	No Failure	10.5
1	L	26.05	36.55	1408	46.3	3	0	No Failure	10.5
2	L	25.95	36.35	1498	49.4	5	0	No Failure	10.4
3	L	26.05	36.45	1433	39.5	7	0	No Failure	10.4
4	L	26.05	36.55	1408	40.0	9	0	No Failure	10.5
...	...	...	...	...	...	...	...	...	...
9995	M	26.65	36.25	1604	29.5	14	0	No Failure	9.6
9996	H	26.75	36.25	1632	31.8	17	0	No Failure	9.5
9997	M	26.85	36.45	1645	33.4	22	0	No Failure	9.6
9998	H	26.85	36.55	1408	48.5	25	0	No Failure	9.7
9999	M	26.85	36.55	1500	40.2	30	0	No Failure	9.7

Figure 4. Output Data Reduction

The next stage is data transformation, this stage aims to convert categorial data into numeric with the label encoding method. The command that can be used is 'category_encoders' and the features to be changed are 'Type' and 'Failure Type'. **Tables 3** and **4** are a comparison of features before and after data transformation.

Table 3. Data Transformation Feature Type

Feature	**Data Transformation**	
	Before	**After**
Type	M	1
	L	2
	H	3

Table 4. Data Transformation Feature Failure Type

Feature	**Data Transformation**	
	Before	**After**
Failure Type	No Failure	1
	Power Failure	2
	Tool Wear Failure	3
	Overstrain Failure	4
	Random Failure	5
	Heat Dissipation Failure	6

Split Data

The data split stage divides the data into two types: training data and testing data. Before the data split stage, the feature selection (x) is used as input to the model that correlates with engine damage, while the label (y) variable is used as a prediction. **Table 5** is the separation of features and labels.

Table 5. Feature and Label Separation

Feature (x)	Label (y)
Air Temperature (°C)	
Process Temperature (°C)	
Rational Speed (Rpm)	
Torque (Nm)	Failure Type
Tool Wear (Min)	
Target	
Temperature Difference (°C)	

In this study, the training and testing data division ratio is 90%: 10% with a random state value of 13. Sample data to be used as 'x_train' and 'y_train' 9000 data, while data used as 'x_test' and 'y_test' 1000 data. **Table 6** shows the data parameters.

Table 6. Parameter Data

Test_size	0,1
Random state	13

Modelling Support Vector Machine

After the preprocessing and data division stages, the next process is to create an SVM model using 'SVC' in the Python 'sklearn' library. The hyperparameters used are 'C=1.0', 'gamma=scale', kernel 'linear', 'RBF', 'polynomial', and 'sigmoid'.

```
svm_model = SVC()
svm_model.fit(X_train, y_train)
preds = svm_model.predict(X_test)
```

Figure 5. Source Code Modeling SVM

Figure 5 is the source code for creating SVM models, where the 'SVC' algorithm is the command to create a classification model, the '.fit' algorithm is the command to train the model, the '.predict()' algorithm is the command to make predictions on test data and evaluate model performance using accuracy.

Evaluation

After the testing process, the next step is the evaluation process, which measures the performance of the created model. The evaluation is done using the confusion matrix by calculating the accuracy, precision, recall, and f1-score values. In addition, the mean square error is also evaluated. The following are the results of the confusion matrix using the kernel function, as shown in **Figures 6, 7, 8, and 9**.

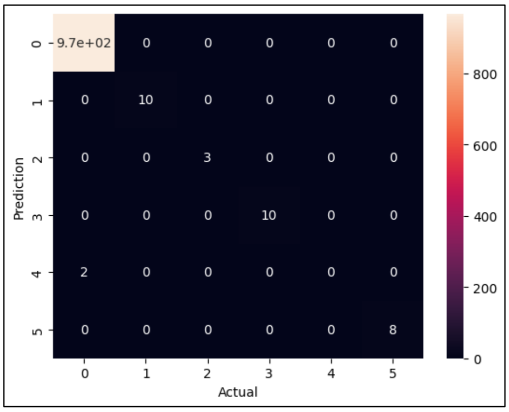

Figure 6. Confusion Matrix Linear

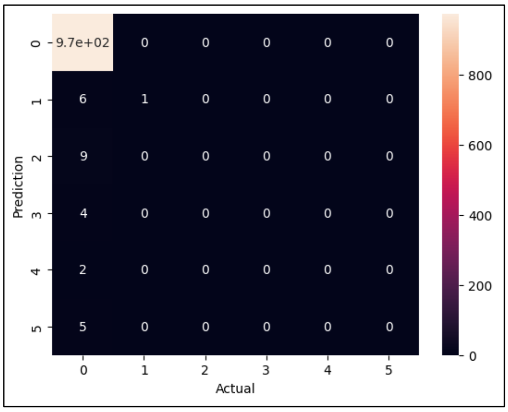

Figure 7. Confusion Matrix RBF

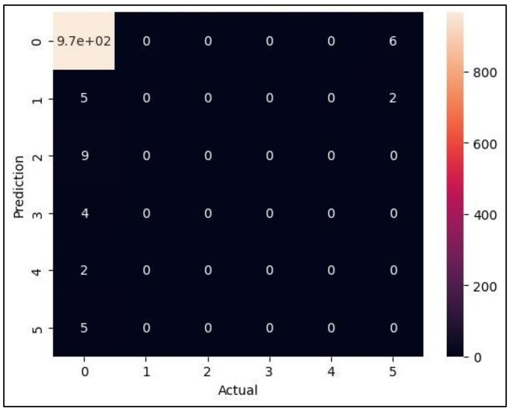

Figure 8. Confusion Matrix Sigmoid

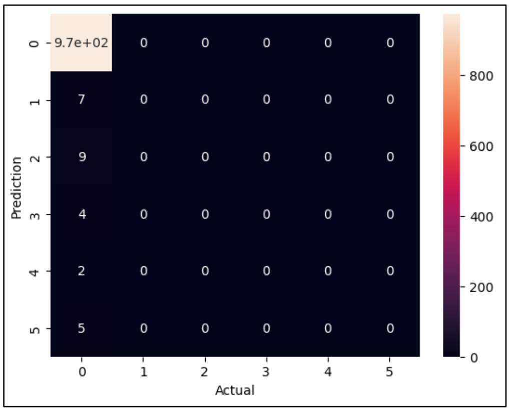

Figure 9. Confusion Matrix Polynomial

This research was conducted to calculate the classification and regression data of SVM method implementation with Python. Modeling is done by utilising several kernel functions, namely linear, radial basis function (RBF), polynomial, and sigmoid. The output generated by the model consists of accuracy, precision, recall, f1-score, and mean square error (MSE) values.

Table 7. Model Performance Result

Kernel	Accuracy	Precision	Recall	F1-Score	MSE
Linear	99,8%	83%	83%	83%	3,2%
RBF	97,4%	33%	19%	21%	23,5%
Sigmoid	96,7%	16%	17%	16%	41,6%
Polynomial	97,3%	16%	17%	16%	23,6%

Table 7 shows the model performance results, the linear kernel obtained an accuracy value of 99.8%, precision, recall, and f1-score of 83%, and MSE of 3.2%. The RBF kernel obtained an accuracy value of 97.4%, precision of 33%, recall of 19%, f1-score of 21%, and MSE of 23.5%. While the sigmoid kernel obtained an accuracy value of 96.7%, precision, and f1-score of 16%, recall of 17%, and MSE of 41.6%. While the sigmoid kernel obtained an accuracy value of 97.3%, precision, and f1-score of 16%, recall of 17%, and MSE 23.6%.

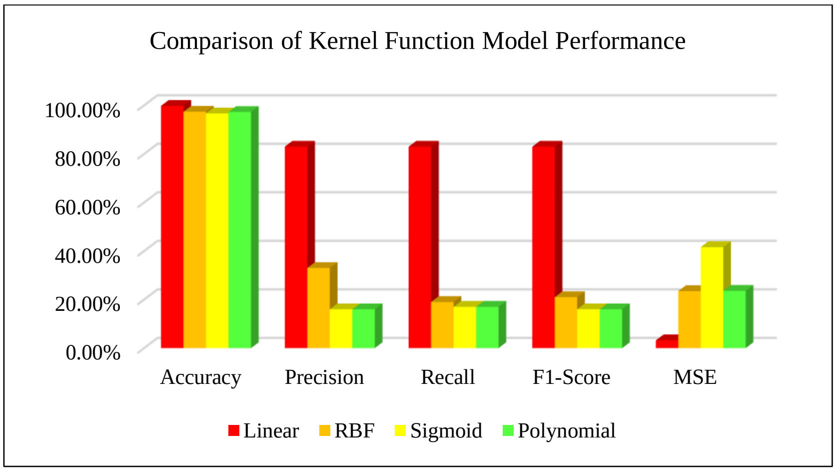

Figure 10. Comparison of Kernel Function Model Performance

Figure 10 shows the performance comparison of the prediction results. The best performance results are obtained by using a linear kernel with an accuracy value of 99.8%, precision, recall, f1-score of 83%, and MSE of 3.2%. Therefore, it is recommended to use a linear kernel for maintenance prediction because it can produce the best performance with optimal error values. Predictive models with classification help researchers in making predictions because the data is in a continuous format. Since the data can be transformed into labels, the prediction process is more accurate and faster than regression techniques. All the above factors determine the recommendation of using classification techniques to model predictive maintenance.

Manual Calculation of Accuracy Value

At this stage, the accuracy value of the kernel function is calculated manually based on the confusion matrix. The calculation process is as follows.

1. Linear

The following is a manual calculation of the accuracy value of the linear kernel function.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$
$$\text{Accuracy} = \frac{967+10+3+10+8}{967+10+3+10+8+2}$$
$$\text{Accuracy} = \frac{998}{1000}$$
$$\text{Accuracy} = 0{,}998$$

Based on this calculation, the accuracy value of the linear kernel function is 0,998 or 99,8%.

2. Radial Basis Function

The following is a manual calculation of the accuracy value of the radial basis function kernel.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$
$$\text{Accuracy} = \frac{973+1}{973+1+6+9+4+2+5}$$
$$\text{Accuracy} = \frac{974}{1000}$$
$$\text{Accuracy} = 0{,}974$$

Based on this calculation, the accuracy value of the radial basis function kernel is 0,974 or 97,4%.

3. Sigmoid

The following is a manual calculation of the accuracy value of the sigmoid kernel function.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$
$$\text{Accuracy} = \frac{967}{967+6+5+2+9+4+2+5}$$
$$\text{Accuracy} = \frac{967}{1000}$$
$$\text{Accuracy} = 0{,}967$$

Based on this calculation, the accuracy value of the sigmoid kernel function is 0,967 or 96,7%.

4. Polynomial

The following is a manual calculation of the accuracy value of the polyno kernel function.

$$\text{Accuracy } = \frac{\text{TP+TN}}{\text{TP + TN + FP + FN}}$$
$$\text{Accuracy } = \frac{973}{973+7+9+4+2+5}$$
$$\text{Accuracy } = \frac{973}{1000}$$
$$\text{Accuracy } = 0{,}973$$

Based on this calculation, the accuracy value of the sigmoid kernel function is 0,973 or 97,3%.

Conclusion

After modelling and testing the system, it is concluded that a support vector machine (SVM) can be implemented in maintenance prediction. This research uses kernel functions to find the best performance in prediction cases. The best performance is found using linear kernel function with an accuracy value of 99.8%, precision, recall, f1-score 83%, and mean square error (MSE) of 3.2%. So the recommendation for implementing the linear kernel function SVM method for maintenance prediction is because it can produce the best performance with optimal error values. Suggestions for further research development are exploring other machine learning such as random forest, decision tree analysis and deep learning. Recommend investigating the impact of additional features or alternative data sources on model performance. Propose a long-term study to evaluate the practical implementation and benefits of SVM models in real-world settings.

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