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Implementation of Support Vector Machine Algorithm for Busy Day Classification at Manggala Motor Workshop

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ABSTRACT

This study addresses the problem of unpredictable customer surges at Manggala Motor Workshop, which often lead to long queues, inefficient resource allocation, and reduced service quality. To overcome this problem, the Support Vector Machine (SVM) algorithm was applied to classify workdays into two categories: busy and not busy. The dataset consisted of 400 simulated data points designed to represent real workshop operational conditions by incorporating attributes such as day, weather, promotions, holidays, number of bookings, and number of vehicles. The data acquisition process was carried out through simulation based on average service capacity and external factors that typically influence customer arrivals. Before modeling, preprocessing steps were performed, including one-hot encoding for categorical features and normalization for numerical features. The dataset was then split into 80% training data (320 entries) and 20% test data (80 entries). Using a linear kernel, the SVM model was implemented in Google Colab with the Scikit-learn library. The results showed an accuracy of 96.25%, with high precision and recall scores in both classes. These findings indicate that SVM is effective for binary classification of busy and non-busy days, enabling Manggala Motor Workshop to optimize technician scheduling, manage workloads, and allocate resources more efficiently, thereby improving service quality and customer satisfaction.

Keywords: Support Vector Machine, Binary Classification, Busy Day, Manggala Motor Workshop, Google Colab

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1. INTRODUCTION

In the era of digital transformation(Rifki et al., 2022), the automotive sector has also experienced developments in terms of services and operational management. One important entity in this sector is the car repair shop, which plays a vital role in maintaining vehicle performance(Epriliani et al., 2022). As the vehicle population increases, especially in urban areas, the public's need for repair shop services is also increasing(Sagala et al., 2024). However, the unpredictable surge in the number of customers often poses a challenge for workshop managers in managing resources, particularly technicians and service time(Nugroho et al., 2021).

A classic problem faced by car workshops is the inability to predict days with high visitation rates (busy days). Inadequate preparation for customer surges can lead to long waiting times, customer dissatisfaction, and a decline in service quality. Therefore, the ability to predict busy days is crucial for improving operational efficiency and customer satisfaction(Almunthaza et al., 2024).

Advancements in artificial intelligence (AI) and machine learning technology offer promising solutions to address this prediction challenge(Eka Patriya, 2020). One popular and proven effective algorithm for classification tasks is the Support Vector Machine (SVM)(Muttaqien & Hartono, 2022). This algorithm can optimally distinguish between two classes based on hyperplane separation(Jalil et al., 2024) and is well-suited for binary prediction cases such as "busy" and "not busy."

Previous studies have shown that the SVM algorithm can be effectively implemented in various sectors, including healthcare, finance, and transportation(Ditami et al., 2022). However, the specific application of SVM in predicting the busyness of car workshops is still rare(Anggraini & Alita, 2024). This opens up opportunities to develop a prediction system based on historical workshop operational data such as visit days, weather, promotions, holidays, number of bookings, and number of vehicles.

This study aims to develop a classification model using the Support Vector Machine (SVM) algorithm to predict busy days at Manggala Motor Workshop This research is based on data collected from workshop operations over several months, covering various factors considered to influence busyness levels. The results of these predictions are expected to provide useful recommendations for workshop management in work planning and service provision.

The selection of the SVM algorithm is based on its ability to handle high-dimensional data and optimal classification margins(Wulandari & Anubhakti, 2021). Additionally, SVM is relatively resistant to overfitting on datasets that are not too large, which is suitable for the context of this study using 400 observations. With this approach, the predictive model built can be relied upon to assist in automated decision-making.

With this SVM-based prediction system, car workshops can be better prepared to handle days with high visitation. Management can adjust the number of technicians, operational hours, and promotional strategies more effectively. Ultimately, accurate predictions will directly impact service quality and customer loyalty.

2. LITERATURE REVIEW

2.1. Support Vector Machine (SVM)

The Support Vector Machine (SVM) algorithm has been applied to build a stroke prediction model based on medical data(Tang, 2024). SVM is known for its ability to find the optimal hyperplane that effectively separates data classes, even in high dimensions. The model achieved an accuracy of 95% after 15 trials with an 80:20 split between training and testing data, demonstrating excellent performance in classifying complex medical data(Alexsander et al., 2024).

SVM was also used to analyze public sentiment toward the 2024 Presidential Election by utilizing data from Twitter. In its implementation, four types of kernels were used: linear, polynomial, RBF, and sigmoid. Among the four, the linear kernel provided the best results with an accuracy of 95.43%. With a total of 3,938 tweets, this model was able to accurately classify positive and negative sentiments, demonstrating the effectiveness of SVM in processing text data based on public opinion(Anggraini & Alita, 2024).

In the classification of student academic data, SVM was implemented to predict graduation timeliness. This study used the Radial Basis Function (RBF) kernel and compared it with other algorithms such as Decision Tree and Naïve Bayes. The test results showed that SVM outperformed with an accuracy of 92%, reinforcing the reliability of this algorithm in handling data with many attributes and non-linear distributions(Wulandari & Anubhakti, 2021).

In addition, SVM is also applied in classifying employment status based on demographic data. The main advantage of SVM in this study lies in its ability to process non-linear data using kernels such as polynomial and RBF. The preprocessing stage and the selection of appropriate features also play a major role in improving accuracy, resulting in a strong and reliable classification model in field data analysis(Ditami et al., 2022).

2.2. *Application of SVM in Vehicle Service Prediction*

Support Vector Machine (SVM) is applied to predict the arrival time of motor vehicle service customers based on historical customer visit data. This study aims to assist vehicle dealers in implementing Customer Relationship Management (CRM) strategies by leveraging machine learning to estimate when customers will return for service. By processing 11 features extracted from historical data such as visit frequency and the time interval between visits, the SVM was trained using several kernels linear, polynomial, RBF, and sigmoid and evaluated using K-Fold validation. The results show that the linear kernel provides the best prediction accuracy, reaching 92.5% on the training data and an average of 97.33% on the test data based on accuracy, precision, and recall metrics. These findings reinforce the potential of SVM, particularly with the linear kernel, in handling customer behavior prediction in the context of vehicle after-sales service(Nugroho et al., 2021).

2.3. *Comparison of SVM with Other Algorithms*

The Support Vector Machine (SVM) algorithm was used to analyze sentiment toward social assistance during the COVID-19 pandemic, with a classification approach based on age groups. SVM was chosen for its ability to handle subjective and inconsistent data, such as tweets. In this study, SVM was compared with the Naïve Bayes algorithm, which had previously been used in analyzing public figures' opinions on social media. The comparison results show that although Naïve Bayes is widely used, SVM is considered superior in handling the complexity of text data with high and varied opinion polarity(Muttaqien & Hartono, 2022).

The application of SVM in classifying stunting status in toddlers shows promising results with an accuracy rate of 82%. The use of a linear kernel in this algorithm effectively manages high-dimensional data and forms a robust classification model. Although this study does not explicitly compare it with Naïve Bayes, conceptually, SVM is considered more capable of handling correlated features, whereas Naïve Bayes often performs poorly under such conditions(Jalil et al., 2024).

On the other hand, the Naïve Bayes algorithm was used to predict motorcycle damage based on symptoms. The results are quite effective in probabilistic-based classification and easy to implement in web systems. However, due to the assumption of feature independence inherent in Naïve Bayes, accuracy tends to decrease when there is correlation between attributes. In such contexts, algorithms like SVM tend to perform better as they do not rely on such assumptions(Epriliani et al., 2022).

In sentiment analysis regarding electric vehicles on Twitter, the Naïve Bayes algorithm was compared with K-Nearest Neighbor and Decision Tree. The test results showed that Naïve Bayes had the lowest accuracy, at 63.50% with Word2Vec and 81.50% with TF-IDF. Although SVM was not used directly in this study, the results indicate that Naïve Bayes is less than optimal in handling the diversity of natural language on social media. Based on the advantages of SVM in similar studies, it can be assumed that this algorithm has the potential to produce higher accuracy in complex text analysis cases(Prasetyo et al., 2025).

2.4. Advantages of SVM

Support Vector Machine (SVM) is one of the most effective algorithms in machine learning for prediction tasks, both in the form of classification and regression. The advantage of SVM lies in its ability to handle both linear and non-linear data through the use of kernel functions. In a study predicting house prices in Bandar Lampung City, SVM demonstrated high performance, particularly in the regression model using a polynomial kernel, which achieved a coefficient of determination (R^2) value of 95.99%. This achievement indicates that the model can explain nearly all variations in the target data, making it highly suitable for predicting complex variables such as property prices(Lumbanraja et al., 2021).

Not only that, SVM also showed optimal performance in processing data with many features and an unbalanced class distribution. Classification results using Gaussian and Linear kernels showed high accuracy, reaching 91.18% in eight-class classification. This reflects SVM's ability to map data into appropriate groups. Combined with techniques such as feature selection and cross-validation using k-fold cross validation, the resulting model is not only accurate but also generally applicable. These advantages make SVM highly relevant for use in decision-making related to price prediction, where accuracy is crucial to minimize the risk of loss(Oktafani & Prasetyaningrum, 2022).

3. METHODS

This research is classified as quantitative experimental research, which aims to develop and evaluate a classification model using the Support Vector Machine (SVM) algorithm(Setyawan et al., 2024). The main objective of this study is to predict busy days at car repair shops based on daily operational variables, so that the results can be used as a tool to aid in managerial decision-making.

3.1. Dataset

The dataset used in this study consists of 400 simulated data entries that were specifically designed to represent the real operational situation of Manggala Motor Workshop. The data acquisition process was carried out by simulating daily workshop activities based on operational patterns, such as service capacity, working days, number of available mechanics, and common external factors influencing customer visits (e.g., weather conditions, promotions, and holidays). The workshop operates from Monday to Saturday with a total of four mechanics, and these operational characteristics were used as the basis for constructing the dataset.

Table 1. Dataset Description

No	Attribute	Data Type	Information
1	Days	Categorical	Monday–Saturday
2	Weather	Categorical	Sunny or Rainy
3	Promo	Numeric	0 = no promo, 1 = there is a promo
4	Holiday	Numeric	0 = not a holiday, 1 = national holiday
5	Booking	Numeric	Number of vehicles that have made reservations
6	Number of Vehicles	Numeric	Total number of vehicles arriving
7	Target (Label)	Binary	1 = Crowded, 0 = Not Crowded

The Target label is determined based on a specified threshold, namely a day is considered busy if the number of vehicles exceeds the average daily service capacity, which is more than eight vehicles per day.

Table 2. Dataset

No	Days	Weather	Promo	Holiday	Booking	Number of vehicles	Target
1	Monday	Sunny	1	1	4	12	0
2	Tuesday	Sunny	1	1	9	7	1
3	Wednesday	Rain	1	0	4	12	0
4	Thursday	Sunny	1	1	9	18	1
5	Friday	Sunny	0	1	1	10	0
6	Saturday	Rain	0	1	4	15	0

3.2. *Data Pre-processing*

Before training the model, several data preprocessing steps were performed to improve input quality and model performance. These steps included:

1. Categorical feature encoding: The 'Day' and 'Weather' features were converted into numerical form using the One-Hot Encoding technique so that they could be processed by the SVM algorithm.
2. Numeric feature normalization: Columns such as 'Booking' and 'Number of Vehicles' are normalized using the Min-Max Scaler technique, which converts values to a range of 0 to 1 to avoid scale dominance in model learning.
3. Data cleaning: The dataset is checked for the presence of missing values (NaN). All data containing missing values is cleaned or adjusted so that the training process runs without errors.

3.3. *Algoritma Support Vector Machine (SVM)*

The use of the Support Vector Machine (SVM) algorithm in predicting busy days at the workshop aims to classify workdays into two categories: busy days and non-busy days. The implementation process utilizes previously collected customer visit data, such as daily vehicle counts, types of services provided, and visit time information. SVM works by constructing the best hyperplane that can separate the two categories with maximum margin, even though the analyzed data does not always follow a linear pattern. The advantages of SVM in handling data with many variables and its ability to prevent overfitting make it the right choice for building an accurate and stable prediction system. In this study, the entire model training and testing process was carried out using the Google Colab platform, which provides flexibility and ease in data processing and the implementation of Python-based machine learning algorithms(Budiantoro et al., 2024).

Additionally, the SVM algorithm was applied to recognize visit patterns based on time and service type, thereby supporting decision-making processes in workshops, such as workforce allocation and operational scheduling. The model was trained using labeled data through supervised learning and successfully predicted busy days with high accuracy. The Google Colab platform also supports integration with various data analysis libraries such as Scikit-learn and Pandas, enabling efficient and interactive analysis processes. The predictions generated have a direct impact on improving service effectiveness and vehicle queue management, and help workshops avoid work backlogs on certain days. Thus, the use of SVM running on Google Colab has proven to be technically effective and useful in improving workshop operational efficiency(Setyawan et al., 2024).

3.4. Split Data

The data is divided into two subsets:

- 80% training data (320 data points)
- 20% test data (80 data points)

The division is done randomly, but using the random_state parameter to ensure consistency of results if the training process is repeated.

3.5. Model Evaluation

The model's performance was evaluated using a number of binary classification evaluation metrics, namely:

1. Accuracy: Measures how many predictions are correct compared to the total data. In this context, accuracy indicates how accurately the model classifies days as “busy” or “not busy” overall. A high accuracy value indicates that most predictions align with the actual conditions(Jalil et al., 2024).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP: True Positive (busy day correctly classified as busy)
- TN: True Negative (not busy day correctly classified as not busy)
- FP: False Positive (not busy day misclassified as busy)
- FN: False Negative (busy day misclassified as not busy)

2. Precision: Indicates the model's accuracy when predicting a day as “busy.” A high precision value means that most “busy” predictions are indeed busy days. This is important to avoid unnecessary resource allocation on days that are not actually busy(Jalil et al., 2024).

$$Precision = \frac{TP}{TP + FP}$$

3. Recall: Measures the model's ability to recognize all days that are truly “busy.” A high recall value means the model can accurately detect most busy days, which is crucial to prevent labor shortages or stock shortages on those days(Anggraini & Alita, 2024).

$$Recall = \frac{TP}{TP + FN}$$

4. F1-Score: A measure of the balance between precision and recall. This value is useful when both the accuracy and completeness of predictions need to be considered. In this study, a high F1-score indicates that the model is not only accurate but also consistent in recognizing both categories(Anggraini & Alita, 2024).

$$F1 = 2 \times \frac{Precision\ x\ Recall}{Precision\ x\ Recall}$$

5. Confusion Matrix: Presents prediction results in tabular form, showing the number of correct and incorrect predictions for each class(Oktafani & Prasetyaningrum, 2022). This helps in analyzing the types of errors that occur, such as whether the model more often misclassifies "busy" days as "not busy," or vice versa.

Table 3. Confusion Matrix

	Predicted Busy	**Predicted Not Busy**
Actual Busy	TP	FN
Actual Not Busy	FP	TN

6. Mean Absolute Error (MAE): MAE measures the average magnitude of errors between predicted and actual values, without considering direction. The smaller the MAE, the closer the model predictions are to the actual values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Where:

- y_i: actual value
- $\hat{y}_i$: predicted value
- n: total number of data points

7. Root Mean Square Error (RMSE): RMSE measures the square root of the average squared errors between predicted and actual values. Unlike MAE, RMSE penalizes larger errors more strongly, making it useful for detecting significant deviations.

$$RMAE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

4. RESULTS AND DISCUSSION

4.1. *Model Evaluation Results*

Model testing was conducted by dividing the dataset into two parts, namely 80% training data and 20% testing data, with a total of 400 entries. The Support Vector Machine (SVM) model used in this study implemented a linear kernel for binary classification: whether a day was busy or not busy at the workshop. The model testing results on 80 test data showed an accuracy rate of 0.9625 or 96.25%. In addition to accuracy, the model performance evaluation using precision, recall, and f1-score metrics produced the following details:

Table 4. Classification Report

Class	Precision	Recall	F1-Score	Support
0 (Tidak Ramai)	0.98	0.96	0.97	49
1 (Ramai)	0.94	0.97	0.95	31

- Overall accuracy: 0.9625
- Macro Average: Precision = 0.96, Recall = 0.96, F1-Score = 0.96
- Weighted Average: Precision = 0.96, Recall = 0.96, F1-Score = 0.96

```
Akurasi Model: 0.9625

Laporan Klasifikasi:
              precision    recall  f1-score   support

           0       0.98      0.96      0.97        49
           1       0.94      0.97      0.95        31

    accuracy                           0.96        80
   macro avg       0.96      0.96      0.96        80
weighted avg       0.96      0.96      0.96        80

Mean Absolute Error (MAE): 0.0375
Root Mean Square Error (RMSE): 0.19364916731037085
```

Figure 2. Classification Report

4.2. *Discussion*

The Support Vector Machine (SVM) model shows excellent performance in distinguishing between days with high ("busy") and low ("not busy") workshop visit rates. The high precision value of 0.98 in class 0 (not busy) reflects that the system is able to predict not busy days with a high degree of accuracy. Additionally, the recall of 0.96 indicates that most days that are truly not busy are successfully identified by the model.

In class 1 (busy), the model's precision is recorded at 0.94 with a recall of 0.97. This high recall value is crucial in the operational context of a workshop because it allows management to prepare resources optimally when a surge in visits is predicted. Accurate identification of busy days enables better planning in terms of workforce allocation, spare parts availability, and customer service.

The macro average values for precision, recall, and F1-score, which reached 0.96, indicate that the model performs consistently across both classes regardless of data distribution. On the other hand, the weighted average value, also 0.96, shows that the model remains consistent in handling data imbalance between classes. This consistency indicates that the model works evenly and is not biased towards a particular class.

The advantages of this model are inseparable from the systematic data preprocessing process, including the use of one-hot encoding for categorical features, normalization of numerical features, and proportional division of training and testing data. The selection of a linear kernel has also proven effective because the data can be separated linearly. Therefore, this SVM model is worth considering as a key component in an automated prediction system to support more accurate and efficient operational decision-making in workshops.

5. CONCLUSION

This study aims to apply the Support Vector Machine (SVM) algorithm in building a prediction model for busy days at a car repair shop based on several operational parameters, such as day, weather, promotions, holiday status, number of bookings, and number of vehicles. The dataset used consists of 400 data points, with 320 data points used for training and 80 data points for testing.

The experimental results show that the SVM model with a linear kernel can predict busy days with an accuracy rate of 96.25%, as well as high precision and recall values in both classes. This indicates that the model is sufficiently reliable in identifying operational conditions of a busy workshop. Some key points that can be concluded are:

1. The SVM algorithm is effective in handling binary classification problems in the context of workshop workload prediction.
2. Attributes such as day, weather, and number of vehicles have a significant influence in helping the model understand busy patterns.
3. With high accuracy and an F1-score above 0.95, this system can be used as a tool for daily operational decision-making in workshops.
4. The model also provides practical benefits in workshop resource planning efforts, such as mechanic scheduling, spare parts procurement, and queue management.

REFERENCES

Alexsander, Ahmad Nazri, Rio Agus Panbudi, & Junadhi. (2024). Implementasi Algoritma SVM dalam Memprediksi Penyakit Stroke. *Journal Zetroem*, *6*(2), 1–5. https://doi.org/10.36526/ztr.v6i2.3676

Almunthaza, R., Abdullah, D., & Darmi, Y. (2024). Perancangan Aplikasi Pencarian Bengkel Mobil Dengan Implementasi Algoritma Location Based Service Di Kota Bengkulu. *Jurnal Media Infotama*, *20*(1), 350–354.

Anggraini, J., & Alita, D. (2024). Implementasi Metode SVM Pada Sentimen Analisis Terhadap Pemilihan Presiden (Pilpres) 2024 Di Twitter. *Jurnal Informatika: Jurnal Pengembangan IT*, *9*(2), 102–111. https://doi.org/10.30591/jpit.v9i2.6560

Budiantoro, H., Sumijan, & Hendrik, B. (2024). Implementasi SVM dan KNN pada Sistem Penunjang Keputusan Kenaikan Pangkat Guru. *Jurnal KomtekInfo*, *11*(4), 380–389. https://doi.org/10.35134/komtekinfo.v11i4.588

Ditami, G. R., Ripanti, E. F., & Sujaini, H. (2022). Implementasi Support Vector Machine untuk Analisis Sentimen Terhadap Pengaruh Program Promosi Event Belanja pada Marketplace. *Jurnal Edukasi Dan Penelitian Informatika (JEPIN)*, *8*(3), 508. https://doi.org/10.26418/jp.v8i3.56478

Eka Patriya, E. (2020). Implementasi Support Vector Machine Pada Prediksi Harga Saham Gabungan (Ihsg). *Jurnal Ilmiah Teknologi Dan Rekayasa*, *25*(1), 24–38. https://doi.org/10.35760/tr.2020.v25i1.2571

Epriliani, L., Mayadi, & Pamungkas, R. W. P. (2022). Implementasi Algoritma Naïve Bayes Untuk Memprediksi Kerusakan Sepeda Motor Pada Bengkel Citra Djaya Motor. *Journal of Informatic and Information Security*, *3*(1), 59–72. https://doi.org/10.31599/jiforty.v3i1.1268

Jalil, A., Homaidi, A., & Fatah, Z. (2024). Implementasi Algoritma Support Vector Machine Untuk Klasifikasi Status Stunting Pada Balita. *G-Tech: Jurnal Teknologi Terapan*, *8*(3), 2070–2079. https://doi.org/10.33379/gtech.v8i3.4811

Lumbanraja, F. R., Saputra, R. A., Muludi, K., Hijriani, A., & Junaidi, A. (2021). Implementasi Support Vector Machine Dalam Memprediksi Harga Rumah Pada Perumahan Di Kota Bandar Lampung. *Jurnal Pepadun*, *2*(3), 327–335. https://doi.org/10.23960/pepadun.v2i3.90

Muttaqien, D. D., & Hartono, P. P. (2022). Implementasi Support Vector Machine pada Analisis Sentimen mengenai Bantuan Sosial di Era Pandemi Covid-19 pada Pengguna Twitter. *Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer*, *6*(1), 163–171. https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/10396

Nugroho, B. A., Pradana, A. K. A., & Nurfarida, E. (2021). Prediksi Waktu Kedatangan Pelanggan Servis Kendaraan Bermotor Berdasarkan Data Historis menggunakan Support Vector Machine. *Jurnal Edukasi Dan Penelitian Informatika (JEPIN)*, *7*(1), 25. https://doi.org/10.26418/jp.v7i1.42964

Oktafani, M., & Prasetyaningrum, P. T. (2022). Implementasi Support Vector Machine Untuk Analisis Sentimen Komentar Aplikasi Tanda Tangan Digital. *Jurnal Sistem Informasi Dan Bisnis Cerdas*, *15*(1), 10–19. https://doi.org/10.33005/sibc.v15i1.4

Prasetyo, T., Adhyaksa Waskita, A., Taryo, T., Raya Puspitek, J., & Pamulang Kota Tangerang Selatan, K. (2025). Analisis Sentimen Pengguna Seputar Kendaraan Listrik Di Twitter Dengan Penerapan Algoritma Naïve Bayes, KNN, dan Decision Tree untuk Klasifikasi. *Jurnal Sistem Komputer Dan*

Kecerdasan Buatan, *VIII*(2), 108–117. www.dataindonesia.com,

Rifki, M. I., Ikhsan, M., Nasution, R. H., & Handira, D. (2022). Analysis of Wlan Network Handover Performance Using Rssi and Threshold on Mobile Devices. *JURNAL INFOKUM*, *10*(4), 146–156. http://infor.seaninstitute.org/index.php/infokum/index

Sagala, J. R., Hasugian, P. S., Kumar, P., & Aispriyani, A. (2024). Pengembangan Model Predictive Maintenance Untuk Kendaraan Menggunakan Algoritma Pembelajaran Mesin. *Jurnal Sistem Informasi Dan Teknologi Jaringan*, *2*, 37–41. https://doi.org/10.63703/sisfotekjar.v5i2.53

Setyawan, M. F., Devgan Oktawijaya, J., & Agustin, S. (2024). Implementation of SVM in Soil Type Classification Using RGB Features. *Jurnal Ilmiah SISFOTENIKA*, *14*(2), 175–184. https://stmikpontianak.org/ojs/index.php/sisfotenika

Tang, W. (2024). Application of support vector machine system introducing multiple submodels in data mining. *Systems and Soft Computing*, 200096. https://doi.org/10.1016/j.sasc.2024.200096

Wulandari, R. F. T., & Anubhakti, D. (2021). Implementasi Algoritma Support Vector Machine (Svm) Dalam Memprediksi Harga Saham Pt. Garuda Indonesia Tbk. *INDONESIA JOURNAL INFORMATION SYSTEM (IDEALIS)*, *4*(2), 250–256. https://doi.org/10.36080/idealis.v4i2.2847