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Decision support system in machine learning models for a face recognition-based attendance system

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ABSTRACT

This research aims to develop a predictive model using face recognition-based attendance data and integrating decision support system (DSS) theory with machine learning (ML) techniques to identify high-performing teachers at vocational high schools (SMKs). The novelty of this research lies in integrating theory with the use of face recognition data and ML algorithms to predict and identify high-performing teachers, thereby enhancing decision-making processes and teacher performance management in SMK schools. The dataset consists of SMK teachers' attendance data obtained through a face recognition attendance system, totaling 998 entries. This research employs sensitivity analysis concepts from DSS theory and classification approaches from ML models utilizing support vector machine (SVM), decision trees (DT), and random forest (RF). The models are trained and tested on Google Colab using Python, with data distribution guided by the Pareto principle. The research findings indicate that integrating DSS theory with ML contributes to innovation and benefits in improving decision-making and teacher performance management by successfully predicting high-performing teachers. Evaluation results show the highest accuracy rate of 98% with the RF model, making it the best predictive model compared to the other two models.

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1. INTRODUCTION

The use of technology in optimizing human resource management processes has become a primary focus in various fields. Especially in the current digital era, where technology-based attendance systems have been widely adopted, such as fingerprint, smart cards, radio frequency identification (RFID), QR code, and face recognition. Recently, face recognition technology has become a popular alternative for monitoring individual attendance. This is evidenced by the increasing number of studies focusing on the implementation of face recognition across various fields and institutions. In the financial sector, Srivastava and Bag [1] used face recognition as a modern marketing tool, Joo *et al.* [2] developed face recognition for payment method confirmation, and Khaparde *et al.* [3] used face recognition for fraud detection. Additionally, bibliometric analysis data using Vosviewer related to the use of face recognition shows that this topic has gained significant attention in recent years, particularly in the area of attendance systems. This is indicated by several emerging studies such as [4]-[7] which utilize face recognition technology for attendance in various institutions. Face recognition is also starting to be integrated with new technologies like machine learning (ML) for specific needs. Several recent studies [6], [8]-[13] use ML for accuracy tasks in face recognition detection. Additionally, research by [14]-[17] use various machine-learning models as tools for analysis in face recognition.

About predictive models, ML has brought significant benefits in various contexts, including employee performance prediction, sales prediction, risk analysis, and more. Several recent studies [18]-[20] utilized ML as a predictive model for the sales and purchase of goods, while [21] employed ML as a tool for predicting customer purchasing habits. Additionally, research by [22]-[24] used ML to predict and analyze risks. Furthermore, studies focus on developing more complex predictive models to predict individual attendance by considering various factors such as weather conditions, employee schedules, and other external factors. Research by [25], [26] combined various data with weather data using ensemble learning techniques to predict attendance and purchases with higher accuracy. However, there has been no research utilizing employee attendance data from attendance systems themselves, indicating that the use of attendance data is still an area that needs to be explored further.

In the context of secondary education, having accomplished teachers and efforts to support their development are vital aspects in ensuring the quality of education provided. Additionally, the use of attendance data in school attendance systems to predict the performance of vocational high school (SMK) teachers has not been studied. On the other hand, there are not many studies that integrate these analytical results into systems that directly support decision-making. In this regard, the appropriate use of theory will support the development of predictive models to become more holistic and efficient. Decision-making requires a set of concepts, principles, and methods to design, develop, and implement systems, one of which is the decision support system (DSS) theory. The main goal of this theory is to provide effective support for decision-makers in dealing with complex and unstructured problems. Concerning ML, this theory can support the development of predictive models to become more holistic and efficient. DSS theory itself has been applied in various fields, for instance, in the financial sector, DSS is used to investigate components in the fintech ecosystem [27]. In decision-making, DSS is implemented on computers for automated decision-making [28]-[32] also utilized DSS to assist web-based decision-making. In newer technology, several studies [33]-[35] integrated DSS theory with artificial intelligence (AI) as a tool for disease detection or diagnosis.

Although the application of DSS theory is evident in various fields, no research has been found that uses this theory in conjunction with ML for predictive tasks simultaneously. Additionally, the use of DSS in the field of education has not been explored. In the context of secondary education, the use of attendance data for strategic decision-making is still very limited. Many schools record teacher attendance using face recognition systems, but the stored data is rarely utilized for data-driven decision-making. To fill this gap, this study aims to develop a predictive model to identify outstanding teachers and those who need further development using ML techniques based on attendance data obtained through a face recognition-based attendance system, integrating concepts from DSS theory. DSS can provide a structured framework for analyzing data and offering informative recommendations for school management. Through the integration of the selected theory, the resulting predictive model is expected to optimize performance management and prediction accuracy in teacher classification while providing more holistic and applicable insights in the context of educational organizations. Thus, this research aims not only to fill a gap in the academic literature but also to make a tangible contribution to improving the effectiveness of teacher and staff performance management in the educational context.

2. METHOD

2.1. Approach and technique

This research employs a sensitivity analysis approach (DSS theory) and ML classification techniques for predictive tasks. DSS theory is a collection of concepts, principles, and methods used to design, develop, and implement systems that aid in decision-making. The primary goal of this theory is to provide effective support for decision-makers in addressing complex and unstructured problems. DSS encompasses several approaches with different purposes and functions, including sensitivity analysis, risk analysis, and multi-criteria analysis [36]. In this study, the sensitivity analysis approach from DSS theory is chosen for the development of a predictive model using ML. This approach is capable of understanding how sensitive the ML model is to changes in input parameters, which is very helpful in identifying the most influential variables or features in the prediction results. Additionally, sensitivity analysis in DSS theory allows for adjustments or improvements to the model if there are variables with significant impacts on the prediction or if weaknesses are revealed during sensitivity analysis. The ML classification technique is used to predict outstanding SMK teachers and those who need further development based on the attendance system dataset obtained through face recognition. Classification is a task where the system is given an input and subsequently classifies that input into the appropriate category or class [37]. The classification approach in the ML model developed in this research uses support vector machine (SVM), decision tree (DT), and random forest (RF) models. These three models are chosen due to their performance accuracy, ability to handle various types of data (including categorical and numerical data), model flexibility, and scalability.

2.2. Integration of decision support system theory in the development of machine learning predictive models

Integrating concepts and techniques from DSS theory into the development of ML models can enhance the system's ability to provide better decision-making support. Figure 1 shows the integration steps performed in the ML model. In the identification phase, research needs and existing problems are identified and understood for decision-making regarding which ML model to use. Once the problem is identified, data characteristics, problem complexity, and analysis objectives are considered when selecting the ML model. During the data collection step, teacher attendance data is gathered through a face recognition-based attendance system implemented in SMKs. Subsequently, the data undergoes several processing stages to generate relevant features through preparation, cleaning, and feature extraction as needed for model training and testing. Following this stage, the development of the ML model proceeds with training and testing, and predictions are made using the prepared data.

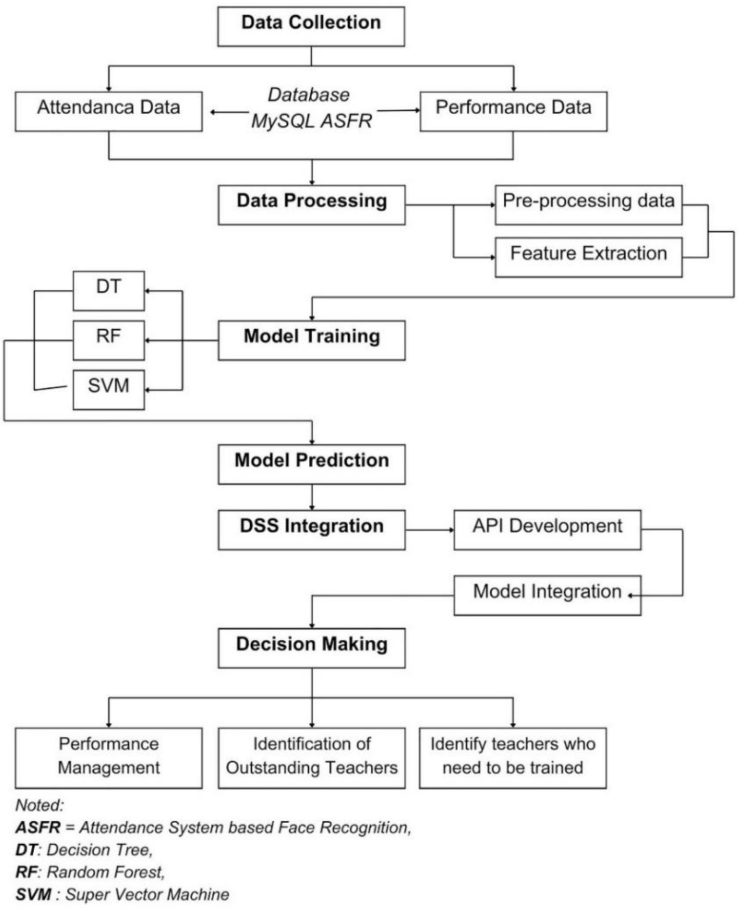

Figure 1. Integration model of DSS theory into the developed ML model

2.3. Dataset

The dataset consists of data extracted in MySQL database format, stored using Excel format, and subsequently processed according to research needs before being saved in CSV format to support data usage in the training and testing of ML models. The dataset extracted from the system for research purposes totals 998 entries. Additional data includes performance data of SMK teachers obtained from performance evaluations, classroom activities, and interviews conducted with several staff members including teachers, principals, and SMK students. The dataset used in the research undergoes preliminary analysis and processing before use. Data cleaning involves filling in missing values to avoid skewed data distribution and prevent overfitting. Subsequently, the data is labeled and separated according to the required features.

The dataset is then divided into training and testing data using the Pareto principle or the 80/20 rule [38], where 80% of the data is used for model training and 20% for model testing and evaluation of the developed model's performance. In this model development step, 80% of the dataset is trained using SVM, DT, and RF models to enable the models to learn patterns present in the dataset. Various model parameters are adjusted to enhance performance and prevent overfitting. Next, model testing is conducted using the remaining 20% of the dataset to evaluate model performance, involving measurement metrics such as accuracy, precision, recall, and F1 score.

2.4. Evaluation metrics

2.4.1. Accuracy

This is a metric for evaluating the performance of classification models, especially when the target classes are balanced. This metric measures how many correct predictions are made out of the total predictions made by the models (SVM, DT, and RF), providing an overall picture of how well the models predict. The accuracy metric is calculated using the (1):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

where true positive (TP) is the number of correct predictions for the positive class. True negative (TN) is the number of correct predictions for the negative class. False positive (FP) is the number of incorrect predictions for the positive class. False negative (FN) is the number of incorrect predictions for the negative class.

2.4.2. Recall

This metric will measure the model's ability to find all positive samples and show how well it effectively identifies high-performing teachers. The recall metric will be calculated using (2), which ensures that the model's capability to identify relevant samples is quantified precisely. High recall indicates that the model is successful in minimizing false negatives, ensuring that most high-performing teachers are correctly identified.

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

2.4.3. Precision and F1-score

The precision metric measures how accurate the model is in predicting the positive class, i.e., how many of the positive predictions are positive. F1-score is a harmonic mean of recall and precision that will provide a comprehensive overview of the developed model's performance by considering recall and precision simultaneously. Precision metric is calculated using (3), and for the F1-score metric, it is calculated using (4).

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$F1 - Score = 2 \times \frac{Presisi \times Recall}{Presisi+Recall} \quad (4)$$

2.5. Training and testing environment

The training and testing of the model are conducted using the Python programming language with the scikit-learn library in the Google Colab environment. Python is a highly capable programming language for data analysis in AI. Meanwhile, the scikit-learn library is powerful and easy to use for various machine-learning algorithms. This library will be used to implement SVM, DT, and RF algorithms. Loading datasets in comma separated value (.CSV) format in Google Colab is facilitated using Pandas, an open-source software library used in the Python programming language for data manipulation and analysis. This library provides data structures and data analysis tools that are easy to use, especially in the form of DataFrames. Pandas enable users to clean, manipulate, and analyze data more efficiently.

2.6. Training and testing dataset

Figure 2 shows the training and testing dataset using a ML model. In Google Colab, the required libraries are imported first (pandas, sklearn, SVM model, RF, DT, and also the necessary metrics). Using the CSV format, the dataset is uploaded into Google Colab using Python. In this case, the dataset was prepared using separated labels and features ready for pandas using "&(cell)&" in Excel in CSV format. This dataset contains attendance data of SMK teachers for the last 3 months obtained through a face recognition-based attendance system. Besides labels, the dataset also includes several features such as frequency of attendance, late arrival date, number of working days, and others. For separating features and labels in the uploaded dataset, the command ‘data’ becomes #Features and #Labels, X=data.drop(‘Performance’, axis=1) # Features and y=data[‘Performance’] # Labels, where ‘Performance’ is the label in the table with a value of 1 for high-performing SMK teachers and 0 for those needing support. Regarding the division of data for training and testing, this research follows the Pareto principle (80/20 rule) [38].

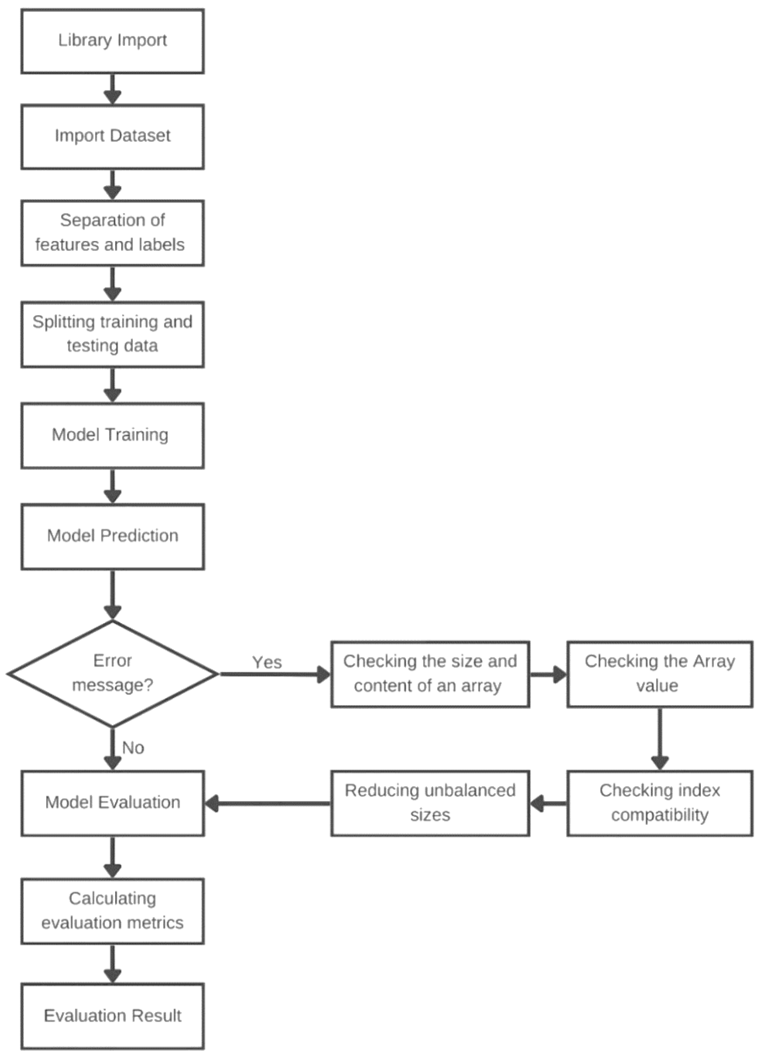

Figure 2. Training, testing, and prediction process of the developed ML model in the research

In model training, SVM, DT, and RF models are initialized and then trained using the training data. During model prediction, the testing data is used. If no error message appears, the model evaluation step can proceed. However, if an error message appears in the prompt, the size and content of the array are checked using the ‘shape’ attribute. If there is an imbalance in the data at the indices that appear, the size is adjusted to balance it. Further in model evaluation, each model is evaluated using predefined metrics to determine accuracy, recall, precision, and the F1-score value of each model. If no further issues arise, the evaluation results are displayed. The ValueError that occurs during model prediction indicates a mismatch in the number of samples in the input variables provided to the “accuracy_score()” function. When using the function accuracy_score(y_test, svm_pred), both arguments y_test and svm_pred for the SVM model being used must have the same number of samples. In this normalization test, several analyses are conducted including descriptive analysis, outlier tests, and non-parametric analysis until the data is normally distributed and ready for training, testing, and predicting results as needed. Additionally, Shapiro-Wilk and Kolmogorov-Smirnov tests are conducted to assess the normality of the data distribution.

3. RESULTS AND DISCUSSION
3.1. Machine learning model
Table 1 shows the results of evaluating 3 ML models in this study, showing an interesting performance comparison in predicting the performance of SMK teachers who excel and those who need development. According to the findings presented in Table 1, the SVM model achieved high accuracy, reaching 97.2%, and perfect precision of 100%. This indicates that the model correctly classifies teachers approximately 97.2% of the time and identifies all teachers who are excelling or in need of development. The recall score of the SVM model is 95.7%, slightly below that of RF and DT. Meanwhile, the F1 score for SVM is the lowest at 97.8%. On the other hand, the DT model achieved the same accuracy level as the RF, at 98.3%, with precision and recall reaching 100% and 96.4%, respectively. Although its precision and recall are slightly lower than RF, the DT F1 score is 97.7%, indicating good overall performance.

Table 1. The results of the metric measurements on the three machine-learning models used

ML model	Measurement metrics			
	Accuracy	Precision	Recall	F1-score
SVM	0.972	1.0	0.957	0.978
RF	0.983	1.0	0.974	0.987
DT	0.983	1.0	0.964	0.977

Figure 3 shows the heatmap diagram regarding the performance metrics of the models. In the RF model, despite having equally high accuracy as SVM at 98.3%, this model shows slightly lower precision and recall compared to SVM, with precision and recall reaching 100% and 97.4% respectively. Additionally, the F1 score for the RF model reaches 98.7%, indicating very good overall performance. Therefore, although all three models have high accuracy, RF stands out with higher precision and F1 score, indicating that RF is the most effective model in identifying high-performing employees based on attendance data.

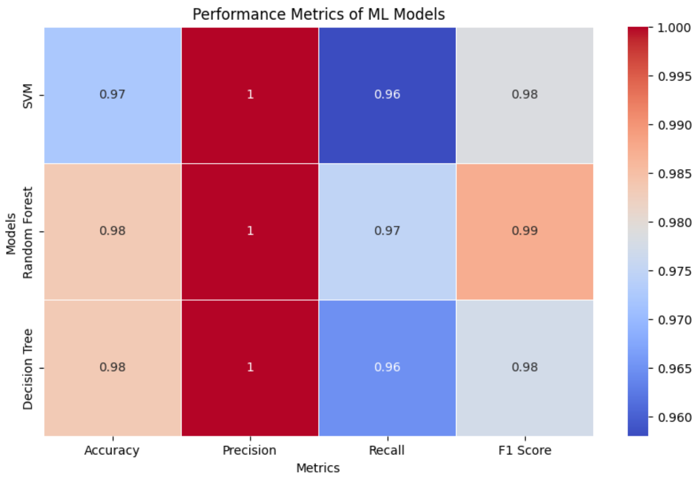

Figure 3. Heatmap diagram regarding the performance metrics of the ML models used for predicting high-performing teachers

3.2. Sensitivity analysis of the decision support system concept
Figure 4 shows the sensitivity analysis results of this study. Sensitivity analysis of the DSS theory was conducted using key parameters on three ML models: SVM, RF, and DT. Figure 5 shows the sensitivity analysis for each model. For the SVM model, variations were performed on the parameter C, which controls the decision boundary hardness. The results show that SVM accuracy tends to remain stable and quite high across most tested values of C, with slight decreases at smaller C values. This suggests that SVM may not be overly sensitive to the C parameter in this case. In contrast, for RF, variations were done on the number of trees (n_estimators). It was found that RF accuracy tends to increase with higher numbers of trees, indicating that an ensemble of many trees generally provides better performance, making RF advantageous for classification problems. Meanwhile, for the DT, variations were conducted on the tree depth. The results indicate that DT accuracy tends to increase with deeper trees up to a certain point, but beyond that point, accuracy starts to decrease, suggesting overfitting. Therefore, the trade-off between increasing accuracy and

the risk of overfitting when determining tree depth needs to be carefully considered. Overall, these findings highlight the sensitivity of each model to its respective parameters and emphasize the importance of parameter tuning for optimizing model performance in practical applications.

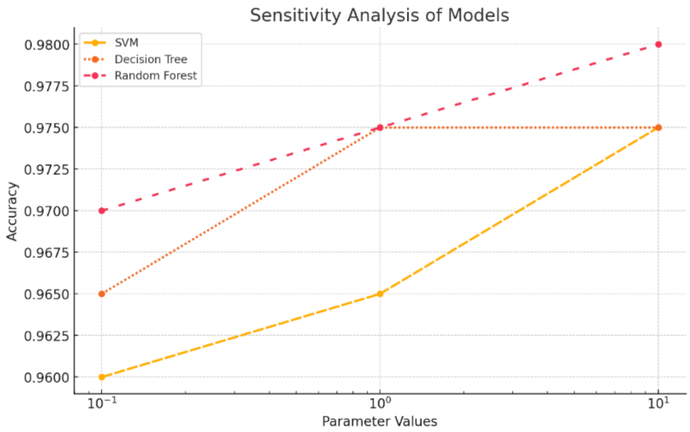

Figure 4. The result of sensitivity analysis for ML model used for high-performing predictions using DSS theory

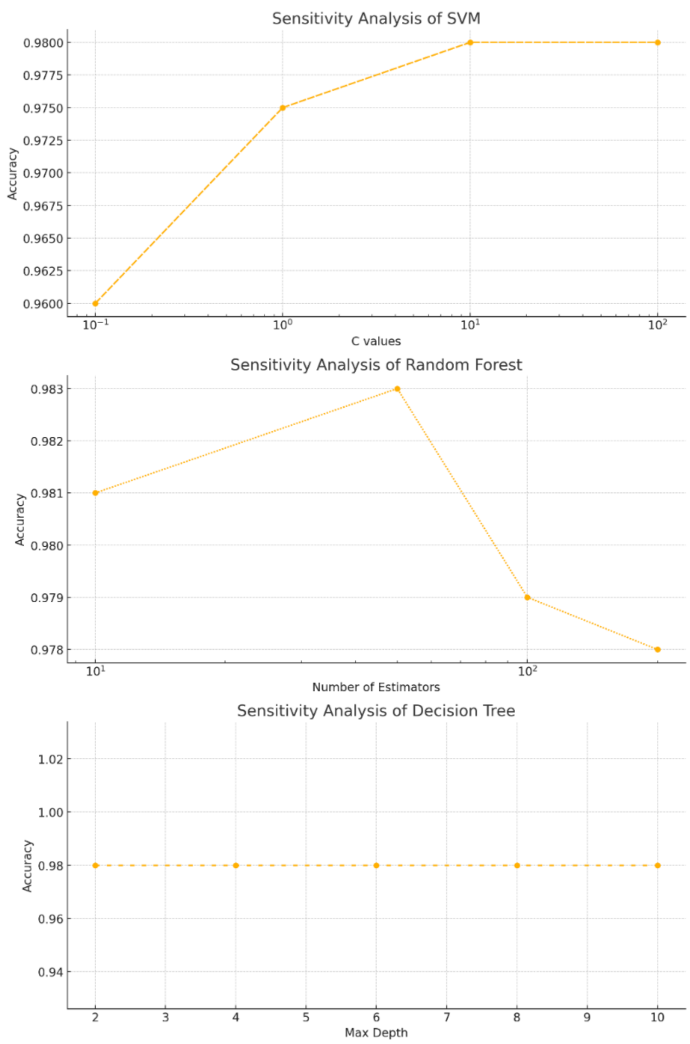

Figure 5. The result of sensitivity analysis for each model

The sensitivity analysis further indicates that the SVM model demonstrates the most consistent performance, exhibiting an increase in accuracy with adjustments to the C parameter. This increase underscores the model's robustness, particularly in high-stakes predictions where precision is critical. Conversely, the DT model reveals that its accuracy is optimal at certain depths, necessitating careful parameter tuning to avoid overfitting. The RF model, characterized by its ensemble approach, shows improved accuracy with an increased number of trees, reinforcing the notion that ensemble methods can enhance predictive performance. These insights collectively emphasize the necessity of understanding model sensitivities in the context of DSS theory, highlighting the significance of strategic parameter adjustments to optimize ML outcomes in practical applications.

3.3. Normality test

In the previously used dataset consisting of 998 data points, it was found that the data was not normally distributed, prompting further analysis. In this study, data normalization was conducted using an outlier function to remove unnecessary data points. Subsequently, tests and analyses were performed to ensure the success of normalization and to verify if the data met the assumptions required for further analysis. In this case, the dataset initially containing 998 data points was reduced to 876 data points ready for use. Descriptive analysis was then carried out to understand the characteristics of the normalized data distribution post-outlier removal. Table 2 shows the Shapiro-Wilk and Kolmogorov-Smirnov p-value tests on the models used. The normality of the residual distribution was assessed through regression analysis to fulfill the assumptions required by the method used. Next, Shapiro-Wilk and Kolmogorov-Smirnov tests were conducted on the evaluation data from each model. The Shapiro-Wilk test results showed that the p-values for all three models (SVM, RF, and DT) were well above the significance level of 0.05, indicating that the evaluation data from all three models tended to follow a normal distribution.

Table 2. Shapiro-Wilk and Kolmogorov-Smirnov p-value tests on the models used for prediction with the integration of DSS theory

No	Model	Shapiro-Wilk p-value	Kolmogorov-Smirnov p-value
1	SVM	0.890903	0.001633
2	RF	0.899373	0.001476
3	DT	0.899373	0.001476

On the other hand, the Kolmogorov-Smirnov test indicated that the p-values were significantly below the 0.05 significance level, suggesting that the evaluation data from all three models did not significantly differ from a normal distribution. Therefore, it can be concluded that the evaluation results indicate very good performance from all three classification models, while the evaluation data tends to follow a normal distribution based on the Shapiro-Wilk test, despite minor differences indicated by the Kolmogorov-Smirnov test. This provides additional confidence in interpreting the evaluation results and the reliability of the conclusions drawn from the model performance analysis.

3.4. Recommendation

From the research findings, SVM showed an accuracy of 97.2%, with a maximum precision of 100%, identical to the other two models, and a recall value of 95.7%. However, its F1 score was quite high, reaching 97.8%. On the other hand, DT achieved an accuracy of 98.3% with a recall score of 96.4% and an F1-score of 97.7%. In this context, RF exhibited the highest accuracy compared to the other two models, at 98.3%, with a recall of 97.4%. This indicates that the RF model can provide very good predictions in identifying SMK teachers who excel and those who need additional guidance. While SVM and DT also performed well, RF strikes an optimal balance between accuracy, precision, and recall. Therefore, it is highly recommended to use a RF as the most suitable model for this prediction task. Moreover, this model can also be employed in cases where maximizing accuracy and precision is crucial, while a DT may be considered if computational speed is a primary factor and there is tolerance for slight decreases in the F1 score.

3.5. Discussion

The results of this study indicate that the RF model outperforms others in predicting the performance of high-performing vocational school (SMK) teachers and those who require further development. The highest accuracy achieved by this model was 98.3%, with near-perfect precision and recall values of 100% and 97.4%, respectively. This positions RF as the most effective predictive model compared to the SVM and DT models. Several previous studies have highlighted the advantages of RF in handling large datasets and decision-making tasks. For instance, Khiavi [26] used RF to predict base flow generation potential in flooded areas and found that RF outperformed other methods such as linear regression and DT models in terms of accuracy. This aligns with our findings, where RF demonstrated superior reliability in handling complex data like face recognition-based attendance data. Additionally, a study by [10], which developed a face recognition algorithm for fraud detection systems, revealed that integrating ML with RF provided more accurate and reliable results compared to other standalone models. These findings support our results, where RF effectively handled variations in attendance data and produced more stable predictions.

While the SVM model showed close accuracy to RF at 97.2%, it appeared less sensitive to data variations, particularly with a slightly lower recall of 95.7%. This is consistent with the findings of [8], who found that SVM was less efficient in handling complex or nonlinear features such as attendance data. Their study highlighted that although SVM performs well in binary classification tasks, the model requires precise parameter adjustments to function optimally, especially with heterogeneous datasets. The DT also demonstrated solid performance with an accuracy of 98.3%, but this model is more prone to overfitting, particularly with high-dimensional data. Chavan and Sherekar [9] observed similar issues in their use of DT for face recognition ML tasks, where the model performance degraded when faced with highly variable data. In our study, the DT achieved the same precision as the RF, but with a slightly lower recall of 96.4%, indicating that the model was less effective at identifying all teachers requiring development.

Integrating DSS theory in developing ML models has significantly enhanced prediction accuracy and decision-making capabilities. DSS helps identify the most influential input parameters, allowing dynamic model adjustments based on input data variations. A study by [32] demonstrated that integrating DSS in web-based systems improved decision-making accuracy by offering better sensitivity analysis to changing inputs. Our research corroborates these findings, showing that DSS improves prediction performance by guiding model parameter selection, particularly for critical variables such as teacher attendance and lateness.

The findings of this research have significant implications for school management, particularly in improving teacher performance in vocational schools. The integration of face recognition-based attendance systems with ML models and DSS can assist schools in identifying high-performing teachers and providing recommendations for further development for those needing support. This aligns with research by [1], which identified that using face recognition technology in education can enhance human resource management efficiency, particularly in monitoring and evaluating staff performance. Our study emphasizes the importance of utilizing existing attendance data for more strategic decision-making, an area that has not yet been widely adopted in the Indonesian education system.

While this study provides valuable insights, several limitations should be noted. The dataset is limited to SMK teachers' attendance data over the last three months. Future research should incorporate a larger and more diverse dataset, considering other factors such as performance evaluations from students and principals. Additionally, this study used three ML algorithms, exploring other models such as neural networks or ensemble learning could offer deeper insights into model reliability in different scenarios.

4. CONCLUSION

In this study, sensitivity analysis of the DSS theory was applied to ML prediction models using a classification approach to analyze the performance and predict SMK teachers who excel and those who need additional support. The three ML models used in this study were SVM, DT, and RF. The results showed that all models achieved a high precision level of 100%, indicating that the models rarely make mistakes in classifying teachers who excel and those who need additional support. However, in terms of accuracy, RF and DT performed better compared to SVM. The accuracy rates for RF and DT were both 98.3%, while SVM was slightly lower at 97.2%. This suggests that both RF and DT have advantages in predicting teacher classifications. On the other hand, all three models also showed balanced results between recall and precision, as indicated by their F1 scores. In this case, the F1 scores for all models were above 97%, indicating that all tested models were able to achieve a good balance in identifying teachers who need additional support (recall) and minimizing errors in classifying teachers who excel (precision). Therefore, for the prediction task in this study, RF and DT can be considered excellent choices over SVM.

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