

# MACHINE LEARNING ANALYSIS IN IMPROVING THE EFFICIENCY OF THE STUDENT ADMISSION DECISION MAKING PROCESS NEW AT PANCA BUDI MEDAN DEVELOPMENT UNIVERSITY

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## Abstract

*The decision-making process in admitting new students is a crucial aspect that can influence the quality and efficiency of academic administration in higher education. This research aims to analyze the role of Machine Learning methods, especially Support Vector Machines (SVM), in increasing the efficiency of the decision-making process for new student admissions at the Panca Budi Development University, Medan. The data used in this research includes information from the student admissions process for the odd semester of the 2022/2023 academic year, which includes various variables such as Registration Number, School of Origin, Registration Payment, and others. The data is divided into a training set (70%) and a testing set (30%). The Support Vector Machine (SVM) model that was built was evaluated using metrics such as accuracy, precision, recall, and F1-Score. The research results show that the SVM model achieves an accuracy of 100%, with high precision and recall for both classes. Precision for both classes reached 1.00, while recall for the minority class (class 1) reached 0.91, indicating excellent model performance in classification. The conclusion of this research is that the Support Vector Machine (SVM) model can significantly increase efficiency and accuracy in the decision-making process for new student admissions at the Panca Budi Development University in Medan compared to conventional methods. These findings indicate that the application of Machine Learning methods can provide substantial benefits in the context of academic administration.*

**Keywords:** *Machine Learning, Support Vector Machine, New Student Admissions, Decision Making, Panca Budi Development University Medan.*

## 1. INTRODUCTION

The process of admitting new students is one of the most crucial stages in the operations of a university. Success in this stage greatly influences the quality of education offered by the institution. Panca Budi Development University Medan, as one of the higher education institutions in Indonesia located in North Sumatra, faces significant challenges in ensuring the process of admitting new students runs efficiently and effectively.

The main challenges faced in the new student admissions process include the large volume of applications, varying admission criteria, and limited human resources to assess each application in detail. This condition can result in delays in decision making, as well as potential errors in the selection of prospective students. Therefore, a solution is needed that can increase efficiency and accuracy in this process.

In the current digital era, the development of machine learning technology offers innovative solutions to overcome these challenges. Machine learning is a branch of artificial intelligence (AI) that allows systems to learn from data and make decisions with little or no human intervention. The application of machine learning in various fields has shown impressive results, including in big data analysis and complex decision making. Universities that are able to utilize advanced technology such as machine learning in their operations, including in the process of admitting new students, can increase their competitive advantage. This technology enables faster

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and more accurate analysis of prospective student data, helping to identify prospective students who have the best potential. In addition, the use of machine learning can reduce administrative workload, allowing Panca Budi Development University Medan staff to focus on other strategic tasks.

This research focuses on the Panca Budi Development University in Medan, which faces similar challenges in the process of admitting new students. By studying how machine learning can be applied to increase the efficiency of this process, it is hoped that this research can provide relevant and practical solutions for the Panca Budi Development University, Medan. The application of machine learning is expected to not only increase the speed and accuracy of decision making, but also improve the quality of student selection accepted.

Previous studies have shown the successful use of machine learning in various sectors, including education. However, there is still a lack of specific research on the application of this technology in the context of new student admissions at the Panca Budi Development University in Medan. Therefore, this research aims to fill this gap with an in-depth analysis of how machine learning can optimize the process of admitting new students to this university. It is against this background that researchers propose the title "Analysis of Machine Learning in Increasing the Efficiency of the Decision Making Process for New Student Admissions at the Panca Budi Development University, Medan".

## **2. PROBLEM FORMULATION**

- 2.1** How is the Support Vector Machine (SVM) method applied in the decision-making process for new student admissions at the Panca Budi Development University in Medan and how effective is this method in increasing process efficiency when compared to conventional methods?
- 2.2** What factors influence the performance of the Support Vector Machine (SVM) method in the decision-making process for new student admissions, and how to optimize the performance of this method so that it can produce more accurate and efficient decisions?
- 2.3** What challenges or obstacles are faced in applying the Support Vector Machine (SVM) method for the decision-making process for new student admissions, and how can they be overcome?

## **3. METHOD**

### **3.1 Types of Research**

The type of research that is appropriate for the title "Analysis of Machine Learning in Increasing the Efficiency of the Decision Making Process for New Student Admissions at the Panca Budi Development University in Medan" using the Support Vector Machine (SVM) method is experimental quantitative research. For the following reasons:

### **3.2 Quantitative Research**

- a)** This research involves structured and numerical measurements, such as processing time, accuracy level, precision, recall, and F1 score.
- b)** Data on student admissions, attributes of prospective students, as well as Support Vector Machine (SVM) prediction results can be measured numerically and analyzed using statistics.

### **3.3 Place and Time of Research**

#### **a) Research Place**

This research was conducted at the Panca Budi Development University, Medan, which is located at Jl. General Gatot Subroto Km 4.5 Sei Sikambing Medan.

#### **b) Research Time**

This research was conducted from November 2023 to August 2024.

### **3.4 Data Collection Techniques**

QRelevant data collection techniques may include some of the following approaches:

#### **Secondary Data Collection**

- a. Historical Data on Student Admissions Collect historical data regarding new student admissions from previous years. This data can include information such as entrance exam scores, report cards, interview results, and other relevant personal data.
- b. Documents and Archives Access archives and documents related to the student admissions process at the university.

### **3.5 Primary Data Collection:**

- a) Surveys and Questionnaires Distribute surveys or questionnaires to parties involved in the student admissions process, such as the admissions committee, prospective students, and lecturers involved. Questions can include experiences, opinions and suggestions regarding the student admissions process.
- b) Interview Conduct interviews with the admissions committee, lecturers, and prospective students to obtain more in-depth information regarding the student admissions process.

## **4. RESULTS AND DISCUSSION**

### **4.1 Application of the Support Vector Machine (SVM) method in the decision-making process for new student admissions at the Panca Budi Development University in Medan and how effective this method is in increasing process efficiency when compared to conventional methods**

#### **1. Data Collection and Preparation**

- a. Data on new student admissions is collected from the previous academic period, including various variables such as Registration Number, School of Origin, Registration Payment, Re-Registration Payment, and Semester 1 Payment.
- b. The data is then cleaned and prepared for use in training the SVM model. This process involves handling missing data, normalization, and transformation of relevant features.

#### **2. Data Sharing**

- a. The data is divided into two sets: training data (70%) and testing data (30%). Training data is used to build the SVM model, while testing data is used to evaluate the model performance.

#### **3. SVM Model Building**

- a. The SVM model is built using training data. SVM was chosen because of its ability to handle classification problems with clear boundaries between different classes.

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- b. Parameters such as C (regularization) and gamma (kernel coefficient) are adjusted to optimize model performance.

#### **4. Model Evaluation**

- a. The SVM model that has been built is evaluated using test data. The evaluation metrics used include accuracy, precision, recall, and F1-Score.
- b. The evaluation results show that the SVM model has 100% accuracy, with high precision and recall for both classes. This indicates that the SVM model is able to make very accurate and efficient predictions in classifying student admissions data.

#### **5. Comparison with Conventional Methods**

- a. Conventional methods previously used in the student admissions decision-making process usually involved simple manual or rule-based evaluations without in-depth data analysis.
- b. When compared with SVM, conventional methods may have disadvantages in terms of consistency, accuracy, and ability to handle large volumes of data as well as complex patterns in the data.
- c. The SVM model is proven to be more efficient because it can automate the decision process, increase prediction accuracy, and minimize human error in evaluation.

#### **6. Effectiveness of SVM in Increasing Efficiency**

- a. With 100% accuracy results, the SVM model clearly increases the efficiency of the new student admissions process. This model can handle large volumes of data with high accuracy, which is difficult to achieve with conventional methods.
- b. The model's effectiveness is also reflected in its ability to consistently provide accurate and reliable results, thereby speeding up the admissions process and reducing administrative burdens.
- c. In addition, SVM models offer flexibility in parameter adjustment and adaptation to changing data patterns, which conventional methods do not have.

### **4.2 Factors that influence the performance of the Support Vector Machine (SVM) method in the decision-making process for new student admissions, and how to optimize the performance of this method so that it can produce more accurate and efficient decisions**

#### **1. Feature Selection**

- a. **Influence:** SVM performance is strongly influenced by the quality and relevance of the features used. Irrelevant or redundant features can cause noise, which reduces model accuracy.
- b. **Optimization:** Perform feature analysis to select only those features that are relevant to student admissions decisions. Techniques such as feature importance or PCA (Principal Component Analysis) can be used to identify and reduce insignificant features.

#### **2. Data Scalability (Data Scaling)**

- a. **Influence:** SVM is sensitive to different feature scales. If features have very different scales, this can cause the SVM to perform suboptimally.
- b. **Optimization:** Use data normalization or standardization techniques so that all features are on the same scale, for example by using Min-Max Scaling or Z-score Standardization.

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### 3. Handling Class Imbalance

- a. **Influence:** Class imbalance occurs when the amount of data in one class is much greater than in other classes. This can bias the SVM model towards the majority class.
- b. **Optimization:** Use resampling techniques such as oversampling for minority classes or undersampling for majority classes. Another alternative is to use class weights to balance the influence of each class in training.

### 4. Kernel Selection (Kernel Selection)

- a. **Influence:** The choice of kernel (linear, polynomial, RBF, sigmoid) greatly influences the SVM's ability to separate complex classes.
- b. **Optimization:** Test different types of kernels and use cross-validation techniques to determine which kernel best fits the existing data. The RBF kernel is often used because of its flexibility, but other kernels can also be considered depending on the data distribution.

### 5. Parameter Adjustment (Hyperparameter Tuning)

- a. **Influence:** Parameters like C (regularization) and gamma (for RBF kernels) have a big influence on SVM performance. The parameter C controls the balance between model complexity and training error, while gamma regulates how far the influence of one training data reaches another.
- b. **Optimization:** Use grid search or random search techniques to find the optimal parameter combination. Cross-validation must be applied to ensure that the selected parameters provide the best performance on unseen data.

### 6. Data Size (Dataset Size)

- a. **Influence:** The amount of data used can affect the generalization of the model. SVM can work well on relatively small datasets, but performance can drop if the dataset is too large without hardware upgrades.
- b. **Optimization:** Make sure the dataset is large enough to support good generalization, but also consider using kernel approximation or linear SVM if the dataset is very large.

### 7. Outlier Handling

- a. **Influence:** The presence of outliers in the data can significantly affect the SVM results, especially if the outliers do not represent the true data pattern.
- b. **Optimization:** Identify and, if necessary, remove outliers from the data. Another method is to use robust SVM which is less sensitive to outliers.

### 8. Performance Evaluation (Performance Evaluation)

- a. **Influence:** Using proper evaluation metrics will help in assessing the overall performance of the model. Focusing solely on accuracy may not be enough, especially in the context of imbalanced data.
- b. **Optimization:** Apart from accuracy, consider other metrics such as precision, recall, F1-Score, and AUC-ROC for a more thorough evaluation. Use the confusion matrix to understand in detail the performance in each class.

### 9. Data Quality (Data Quality)

- a. **Influence:** Poor data quality, including missing data or irrelevant data, can reduce model performance.
- b. **Optimization:** Perform thorough data cleaning to handle missing values and eliminate inconsistent or incorrect data. Data cleaning should be the first step in the model training process.

## 10. Model Maintenance

- a. **Influence:** Built models may become less effective over time if data and environmental conditions change.
- b. **Optimization:** Routinely update and retrain the model with new data to ensure that the model remains relevant and accurate in the face of changing data patterns.

By optimizing these factors, the performance of the SVM method in the decision-making process for new student admissions can be significantly improved, resulting in more accurate and efficient decisions.

### 4.3 Challenges or obstacles faced in applying the Support Vector Machine (SVM) method for the decision-making process for new student admissions, and how to overcome them

#### 1. Class Imbalance (Class Imbalance)

- a. **Challenge:** New student admissions data may have an unbalanced class distribution, where the number of accepted students is much greater than those rejected (or vice versa). This imbalance can cause the SVM to be biased towards the majority class, reducing its ability to accurately detect the minority class.
- b. **Solution:**
  - Use resampling techniques such as minority class oversampling or majority class undersampling.
  - Apply different class weights to different classes to give more weight to minority classes.
  - Use evaluation metrics such as F1-Score or AUC-ROC that are more sensitive to class imbalance.

#### 2. Selection of the Right Kernel

- a. **Challenge:** Proper kernel selection is critical for SVM performance. The wrong kernel can cause the model to be unable to capture the complexity of the data, or vice versa, cause overfitting.
- b. **Solution:**
  - Test various kernels (linear, polynomial, RBF, sigmoid) using cross-validation to determine which one best fits the data.
  - If the data is linear, use a linear kernel to avoid unnecessary complexity. For non-linear data, RBF kernels are often a good choice.
  - Use grid search or random search to find optimal kernel parameters.

#### 3. Sensitivity to Outliers

- a. **Challenge:** SVM is very sensitive to outliers in the data. The presence of outliers can significantly influence the hyperplane selected by the SVM, causing the model to not be generalizable.
- b. **Solution:**
  - Perform outlier detection and consider removing or modifying outliers before training the model.
  - Use a robust version of SVM or add slack variables to reduce the impact of outliers.
  - Implement better data preprocessing to ensure cleaner and more representative data.

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#### 4. Computational Complexity

- a. **Challenge:** SVMs can be very computationally expensive, especially with large datasets or when using non-linear kernels such as RBF. High computing times can be an obstacle in applications that require fast responses or when working with large amounts of data.
- b. **Solution:**
  - Consider using Linear SVM if the data is linear enough or can be approximated well by linear SVM.
  - Use kernel approximation techniques to reduce the computational complexity of non-linear kernels.
  - Optimize feature selection to reduce input dimensions, thereby reducing model complexity.

#### 5. Hyperparameter Selection and Tuning

- a. **Challenge:** Hyperparameters such as C and gamma in SVM greatly influence the model performance. However, finding the optimal combination can be challenging because SVM is very sensitive to these values.
- b. **Solution:**
  - Use grid search or random search with cross-validation to find the optimal hyperparameter combination.
  - Experiment with C and gamma values on various scales (e.g., log scale) to find the balance between underfitting and overfitting.

#### 6. Difficulty of Model Interpretation

- a. **Challenge:** SVM models, especially those with non-linear kernels, tend to be difficult to interpret compared to simpler models such as decision trees. This can be an obstacle if interpretability is an important factor in decision making.
- b. **Solution:**
  - Use Linear SVM if interpretability is preferred and if the data is fairly linear.
  - Visualize SVM decision boundaries to get a clearer picture of how the model makes decisions.
  - Combine SVM with interpretation techniques such as LIME or SHAP to provide deeper insight into model decisions.

#### 7. Limitations in Data Scale and Dimensions

- a. **Challenge:** SVM may not work well with data that has very many features (high dimensions) or when these features are not relevant. Overfitting can occur if the number of features is too large compared to the number of samples.
- b. **Solution:**
  - Apply dimensionality reduction such as Principal Component Analysis (PCA) to reduce the number of features.
  - Perform feature selection to select only the most relevant features before training the SVM model.

#### 8. Reliance on Provided Data

- a. **Challenge:** SVM is highly dependent on the data used for training. If the training data is not representative or has bias, the SVM model may not be generalizable to new data.
- b. **Solution:**
  - Make sure the training data reflects the actual distribution of future data.

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- Use data augmentation whenever possible to enrich training data.
  - Apply cross-validation to ensure that the SVM model is able to generalize well on unseen data.

By understanding and overcoming these challenges, the application of the SVM method in the decision-making process for new student admissions can be optimized, resulting in more accurate, efficient and reliable decisions.

## 5. CLOSING

### 5.1 Conclusion

Based on the results of research and evaluation of the Support Vector Machine (SVM) model applied in the decision-making process for new student admissions at the Panca Budi Development University in Medan, it can be concluded that:

#### 1. Support Vector Machine (SVM) Model Performance

The Support Vector Machine (SVM) model shows excellent performance with accuracy reaching 100%. This shows that the model is able to classify student admissions data very accurately.

#### 2. Precision and Recall

Precision for both classes is 1.00, which indicates that every prediction made by the model for class 0 and class 1 is correct. Recall for class 0 also reached 1.00, while recall for class 1 was slightly lower at 0.91. This indicates that the model is very effective in detecting class 0 and quite good at detecting class 1, although there are some missed cases.

#### 3. F1-Score

*F1-Score* The high values for both classes indicate that the model not only has high precision but also good recall, with a good balance between the two.

#### 4. *Macros* and Weighted Average Value

*macros* and weighted average shows that the Support Vector Machine (SVM) model overall performs very well, both on all classes and on imbalanced data.

The Support Vector Machine (SVM) model has proven effective in improving the efficiency of the decision-making process for new student admissions, with very promising results in terms of accuracy and performance of evaluation metrics.

### 5.2 Suggestions

1. Further Data Collection To improve model performance and reduce potential bias, it is recommended to collect more data, especially for underrepresented classes. Additional data can help in increasing recall and reducing the possibility of overfitting.
2. Explore New Features Consider adding additional features that may be relevant to the student admissions process. More in-depth feature analysis can provide more insight into the factors that influence acceptance decisions.
3. Parameter Adjustment Perform a more careful parameter search for the Support Vector Machine (SVM) model, such as tuning the C and gamma parameters, to ensure that the model functions optimally.
4. Outlier Handling Identify and handle outliers in the data to prevent negative impacts on model performance. Better data cleaning techniques can improve model quality.



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5. Periodic Evaluation Conduct regular evaluations of the model with newer data to ensure that the model remains relevant and accurate as student enrollment patterns change.
6. Further Model Development Consider combining the Support Vector Machine (SVM) model with other methods or using ensemble techniques to further improve the performance and generalization capabilities of the model.
7. Model Interpretability If model interpretability is important, explore other techniques that can provide more insight into how the model makes decisions, such as more easily interpretable models or decision visualization techniques.

By following these suggestions, it is hoped that the decision-making process for new student admissions can be further improved, providing greater benefits for the Panca Budi Development University Medan.

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