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Decision Tree Algorithm for Predicting Student Performance Based on Psychological Tests

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Abstract

It is essential to consider the psychological aspect of selecting new students to determine the success of prospective students. In this paper, we propose an approach to predict student performance based on their psychological test scores using the Decision Tree algorithm. The dataset used in this study was taken from the student admission process at the Institut Teknologi Del.

The admission dataset contains the scores of psychological tests and the Grade Point Average (GPA) of classes 2019, 2020, and 2021. Each class has its own attribute set. Therefore, we came up with two approaches. The first approach was to use as many records as possible, and the opposite of the second was to utilize more features.

Our results showed that the first approach was slightly better. The MAE value was 0.3654 to 0.4568. Moreover, none of the psychological test attributes strongly correlate to GPA and hence do not guarantee student performance.

Keywords

Decision Tree, Machine Learning, Psychological Test

INTRODUCTION

Student learning success is inseparable from the influence of various factors, such as the learning environment or other factors (both internal and external). This is supported by [1], which concluded that one factor that significantly influences student success is motivation and whether the student has learning talent. Another illustration is that student motivation and satisfaction positively correlate with student learning outcomes.

A psychological test is a test used to measure individual differences and individual reactions on different occasions. Psychological tests are used to get candidates according to the abilities expected to achieve organizational needs [2]. The application of psychological tests is very important to determine the suitability or eligibility of the individual for the organization or institution.

The Institut Teknologi Del (IT Del) student admission process includes academic tests after which a psychological test is used to measure the level of ability of prospective students in the social, emotional, personality, and potential fields. Psychological tests are provided at each entrance after the academic tests are carried out. The psychological test measurement is intended to see whether the candidate can adapt to the campus lifestyle.

Based on this, the admission is decided by examining both the psychological and academic aspects. The psychological test conducted at IT Del has several measurement categories such as General Intelligence Test (TIU), Emotional Stability, Work Achievement, Work Tempo, Accuracy, Consistency, Endurance and Intellectual Quotient (IQ) or Work Attitude and Intelligence. Furthermore, each aspect of the psychological test will be measured according to the applicable rating scale. Psychological test aspects are calculated using a letter scale (grade) with 2 format, the first format includes Very Poor (KS), Poor (K), Somewhat Poor (AK), Fair/Average, Somewhat Good (AB), Good (B) and Excellent (BS) while the second format includes Poor (K), Moderately Poor (S-), Moderate (S), Sufficiently Poor (C-), Sufficient/Adequate (C), Sufficiently Good (C+), Moderately Good (B) and Good (B).

The candidate's eligibility is decided by the Head of the Study Program where the candidate applies. In the Information Systems study program, the requirements for prospective students who are considered eligible are measured through the General Intelligence Test (TIU) with a range of scores greater than or equal to 10 (TIU >= 10), IQ greater than or equal to 105 (IQ>= 105). For the results of each aspect that has a Somewhat Poor (AK) value, there can be no more than 3, and there are no aspects with a Poor (K). This assessment has the potential to result in human error, as well as subjective decisions. In other words, the assessment can override the application of the prerequisite scale that has been determined by considering other aspects.

Based on the problems above, we need a machine learning model that can provide predictions for prospective students based on their academic achievements when they enter IT Del. The model will work by comparing aspects of the psychological test assessment and comparing the Grade Point Average (GPA) of the previous students while participating in active lectures at IT Del. The GPA has been studied through previous research [2], which predicted student GPA based on first-semester results. This study used computer science course data, followed by grades from six courses, one laboratory result, and GPA in the graduation year. The method used in this study is the Generalized Linear Model, Deep Learning, and Decision Tree.

This research will focus on developing a machine learning model using a decision tree algorithm to leverage the flexibility and interpretability of the algorithm while benefiting from the improved accuracy and generalization capabilities of machine learning. The machine learning algorithms help overcome the limitations of decision trees by optimizing the tree structure, reducing overfitting, and capturing complex patterns in the data. Thus, using machine learning models using decision tree will help predict the right prospective new Del Technology Institute students according to their academic achievements.

LITERATURE REVIEW

Psychology test

Psychological tests have various data collection techniques, such as tests, interviews, case studies, behavioral observations, and other procedures [2]. Based on research [3], the implementation of psychological data collection tests that are commonly used, such as paper and pencil tests, objective and essay tests, standard and non-standard tests, individual and group tests, verbal or nonverbal tests, personality tests, interest tests, aptitude tests, achievement test, intelligence test, and vocational test.

In applying psychological tests, several characteristics must be met [4], namely validity and reliability. Validity is the degree to which the measurement is accurate through a psychological test. At the same time, reliability is the level of consistency with the tests performed. This aims to set the level of Stability and relativity of the tests performed. Reliability is dependability, Stability, consistency, predictability, and accuracy. If it meets the reliability criteria, then the assessment results from the test can be interpreted as reliable.

Decision Tree

Supervise Learning algorithm, which can be used for regression or classification. In other words, *the decision tree* can be used for numerical and categorical data. The decision tree algorithm works like a tree, where class labels are leaves and features (or conditions) are branches. Decision trees are used to deal effectively with large non-linear data sets. The decision tree observes the characteristics of an object and trains the model in a tree structure to predict future data to produce meaningful continuous outputs. Continuous output means that the output/result is not discrete. It is not represented simply by a discrete set of known numbers or values. The decision tree divides the dataset into smaller subsets, and decisions are formed in stages [5]. Decision trees are used to deal effectively with large non-linear data sets. Besides that, decision tree algorithms are easy to understand, interpret and visualize [6].

Evaluation Metrics

Based on research [7], the evaluation metrics used to measure forecasting errors and assess predictive models in the regression model are MAE, MSE, RMSE, and MAPE. In what follows, we'll elaborate more on research-based error evaluation metrics used in this research.

1) MSE (Mean Squared Error)

MSE is the difference - the average square of the difference between the predicted and actual values [8]. The greater the MSE value, the worse the model performance will be, and vice versa.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (Xi^2 - X'i^2)$$

2) MAE (Mean Absolute Error)

MAE measures how well the regression model predicts the actual target value. MAE is calculated by taking the average absolute error (model prediction minus the true value). The greater the MAE value, the worse the model's performance in predicting the target value, and vice versa. MAE gives less weight to outliers [7].

$$MAE = 1/n\sum_{i=1}^{n} |Xi - X'i|$$

3) MAPE (Mean Absolute Percentage Error)

MAPE measures the average absolute percentage error between predicted and true values. The lower the MAPE value, the smaller the prediction error in the model.

$$MAPE = 1/n\sum_{i=1}^{n} |Xi - X'i/Xi| * 100$$

Further description of the evaluation in research will display the evaluation results. However, the evaluation using MAE is more emphasized. This is as described in research [7], suggesting that the MAE algorithms are more appropriate for determining the accuracy of predictions. In line with that study, research [9] suggests that the MAE evaluation metrics are better used to compare performance between different regression models.

Correlations Coefficient analysis

Correlation coefficient analysis is a statistical technique used to measure the strength and direction of the relationship between two variables. It provides a numerical value that indicates the extent to which the variables are linearly related. The following is interpretation of the range of correlations coefficient analysis.

Table 1: Correlations Coefficient analysis [10]

Positive	Negative	Interpretation
+1.00	-1.00	Perfect
+0.80 to +0.99	-0.80 to -0.99	Very Strong
+0.60 to +0.79	-0.60 to -0.79	Strong
+0.40 to +0.59	-0.40 to -0.59	Moderate
+0.20 to +0.39	-0.20 to -0.39	Weak
+0.01 to +0.19	-0.01 to -0.19	Very Weak

Positive correlation refers to the relationship between two variables where a change in the value of one variable is followed by a change in the same direction in the other variable. Conversely, negative correlation occurs when a change in the value of one variable is followed by a change in the opposite direction in the other variable.

METHODOLOGY

Data

The dataset will be taken from the student admission process at IT Del, which is presented with data on psychological test results and the GPA of active students majoring in Informatics and Information Systems until 2022/2023. In particular, the data used are for the 2019, 2020, and 2021 batches. The following is a description of the data used and the features/variables in it.

From the results of the Analysis carried out above, there are three categories related to the availability of column attributes in the dataset: Available, Limited, and None. Restricted categories will be removed in the future due to the limited availability of records in the 2020 dataset, which only contains 14 of the 50 records in the 2020 dataset. Also, another reason why these records will be deleted is the format is different from the rest of the 2020 data set. Thus it is not possible to do a combination of column attributes.

Table 2: Comparison of attribute datasets

Attribute	2019	2020	2021
Seq	Available	Available	Available
GPA1	Available	Available	Available
GPA2	Available	Available	Available
GPA3	Available	Available	Available
GPA4	Available	Available	None
GPA5	Available	None	Available
GPA6	Available	None	Available
GPA	None	None	Available
Batches	None	None	Available
TIU	None	Available	Available
TIU Category	None	Available	Available
Emotional Stability	Available	Available	Available
Work Achievement	None	Available	Available
Work Tempo	None	Available	Available
accuracy	None	Available	Available
Consistency	None	Available	Available
endurance	None	Available	Available
IQ	Available	Available	Available
IQ Category	None	Available	None
Intelligence	Available	Limited	None
work attitude	Available	Limited	None
IQ. 1	None	Limited	None
Emotional Stability.1	None	Limited	None

Based on the results of the Analysis, it will be divided into two analyses. Analysis based on records focuses on each attribute available in each dataset, namely the attributes 'Seq', 'GPA1', 'GPA2', 'GPA3', 'Emotional Stability,' and 'IQ.' While the second Analysis is an analysis that includes all available column attributes in the 2020 dataset and 2021 dataset or is categorized into Analysis based on features. For comparison, the second Analysis includes all available attributes in each dataset for 2020, and 2021. In this case, the available column attributes are TIU, TIU Category, Emotional Stability, Work Achievement, Work Tempo, Accuracy, Consistency, Endurance, GPA1, GPA2, and GPA3. This is done to enrich the features' availability in this study

Architectural Models

Based on the architectural design, the research was initiated with the *Data Understanding process*, which consists of the stages of *Data Collection, Describe Data*, and *Data Validation*. Furthermore, the data that has been validated will enter the *Data Preparation stage. Data preparation* consists of several phases: *Data Selection, Data Cleaning,* and *Data Transformation.* In the next stage, *Data Integration will be carried out based on the Analysis carried out, namely, Analysis based on records* development and *Analysis based on features* development which produces each dataset. Furthermore, the two datasets will be carried out in the *build test scenario stage*, the *modeling stage.* In this condition, split the data with a ratio of 80:20. As much as 80% of the dataset will be used for training *(train data)* and the remaining 20% for data testing *(test data)*.

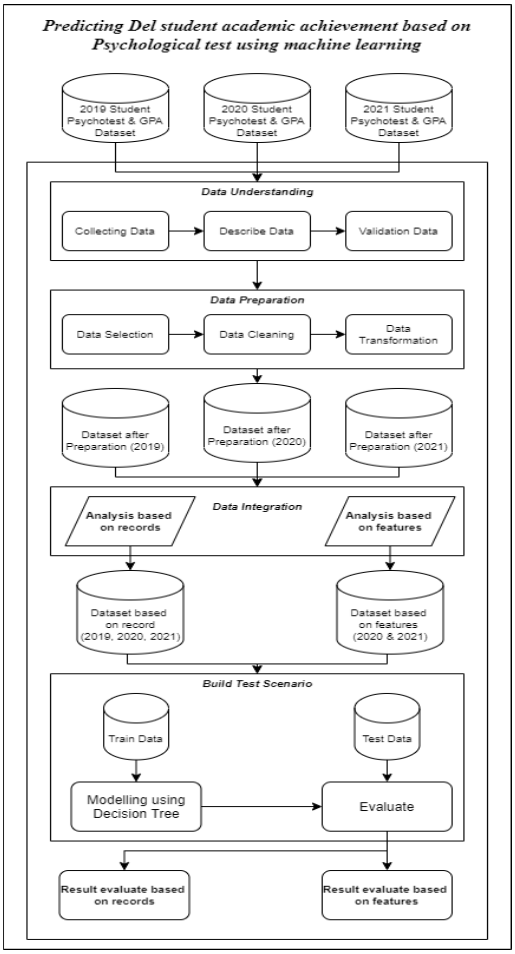

Figure 1: Architectural Design models

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Data Correlation

The following section aims to analyze the relationship of each attribute used based on the Analysis based *on records* and Analysis *based on features.* This stage aims to explain the relationship conditions for each attribute as the basis for *feature selection* to be used in model development using heatmap correlation.

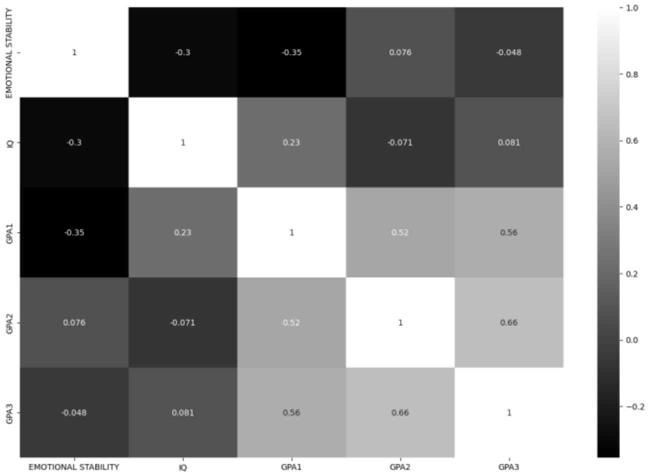

Figure 2: Heatmap correlation based on attributes

The image displays a heatmap correlation based on attributes that match *the Analysis based on records* showed a very weak correlation between the input feature and the target feature, specifically a correlation of 0.076 between emotional stability and GPA 2, indicating a very weak positive correlation. Additionally, there is a negative correlation of -0.071 between IQ and GPA 2, indicating a very weak negative correlation. The heatmap correlation ranges from zero (0) to one (1).

This section also shows positive values and negative values. A positive value means that the two attributes move in the same direction, while a negative value means the opposite. Zero value indicates that the two attributes have no correlation. On the heatmap, the GPA1, GPA2, and GPA3 attributes are displayed in white, which indicates a strong correlation between each of these attributes. Based on this, we will remove the columns for GPA1 and GPA3 due to the Analysis for feature selection. In addition, GPA2 will be used as a target feature to support the objectives of this study by using GPA as a reference, followed by psychological test scores. As a consideration, GPA1 is not used as a feature selection. It is because students are currently carrying out the adaptation process well in the form of lectures being held. Whereas GPA3 was chosen for data, this means that data for this study has yet to be available, compared to GPA2, which in the future can be used as a research comparison for the 2022 batch dataset if available.

In addition, if you use the GPA1 and GPA3 attributes as input features, this will conflict with research objectives which measure the performance of prospective students based on a combination of psychological tests by comparing GPA results taken by students during their active lecture period or in other words when using GPA1, GPA2, and GPA3 for student performance, there is no need to make predictions involving psychological test attributes. Based on these results, there will be two *input features,* namely 'EMOTIONAL STABILITY' and 'IQ,' and *a target feature*, GPA2. As a note, the attributes described in these results will be used in future datasets based on records.

All available attributes will be displayed after combining the 2019, 2020, and 2021 datasets *(datasets based on records).*

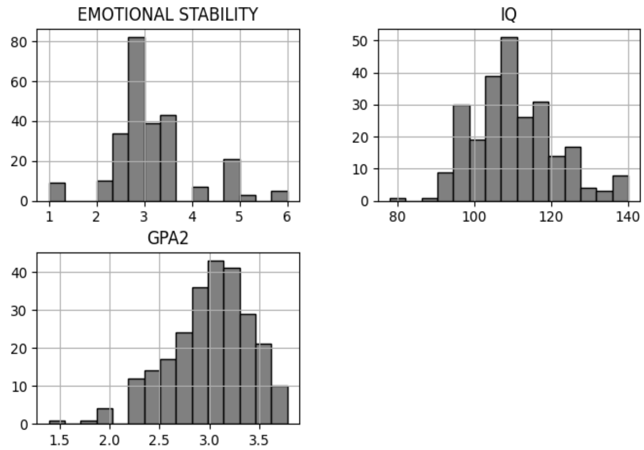

Figure 3: Available attribute of datasets based on records

The applied feature selection will have similar stages as was done in the Analysis based on records by deleted columns on the GPA1 and GPA3 attributes.

Heatmap analysis based on feature correlation showed that each psychological test input feature from 'TIU' to 'IQ', showed a very weak correlation with the target feature, namely 'GPA2' which is displayed with a heatmap color that tends to be dark.

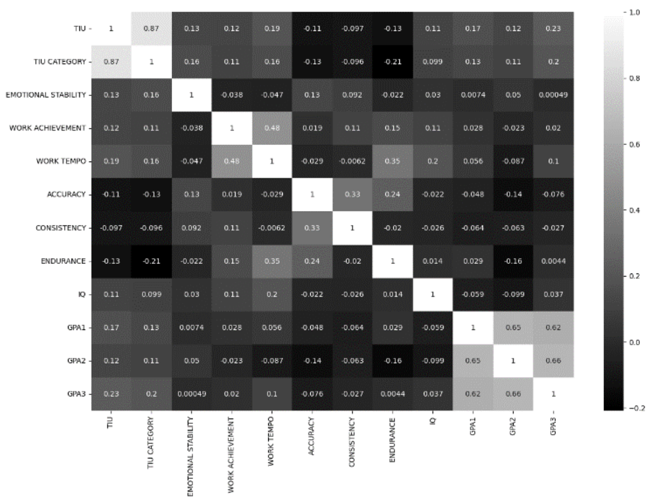

Figure 4: Heatmap correlation based on feature

The correlation heatmap indicates a very weak correlation between the input feature and the target feature, namely a correlation of 0.12 between GPA2 and TIU, a correlation of 0.11 between GPA2 and TIU category, a correlation of 0.05 between GPA2 and emotional stability, and negative correlations of -0.023 with work achievement, -0.14 with accuracy, -0.063 with consistency, -0.16 with endurance, and -0.099 with IQ. All available attributes will be displayed after combining the 2020 and 2021 datasets *(datasets based on features).*

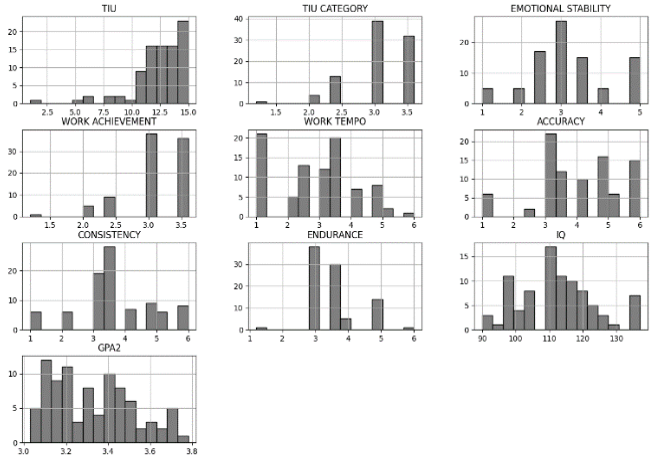

Figure 5: Available attribute of datasets based on features

So based on these conditions, there will be nine input features, namely TIU, TIU Category, Emotional Stability, Work Achievement, Work Tempo, Accuracy, Consistency, Endurance, IQ and GPA2 as target features. These attributes describe the attributes available in the dataset based on features. As an explanation, TIU is General Intelligence Test and TIU Category is labeling in letter form for TIU attributes.

RESULTS

The following will show a bar chart comparing the evaluation results of the first Analysis or *Analysis based on records* using 253 data with the results of the second Analysis or *Analysis based on features* using 168 data used to predict the results of GPA2.

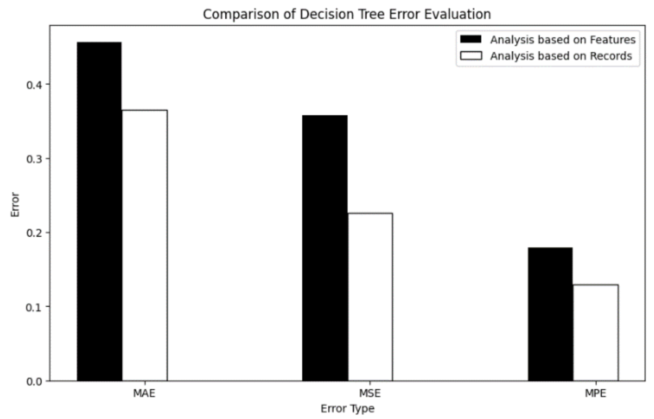

Figure 6: Comparison od Decision Tree Error Evaluation

For special values generated from the evaluation results will be displayed as follows.

Table 3: Evaluation Results

Metrics	Decision Tree based on Records	Decision Tree based on Features
MAE	0.3654	0.4568
MSE	0.2263	0.3577
MPE	0.1296	0.1797

Based on the evaluation above, the results show that decision tree algorithms tend to produce low error evaluations, or models with better performance are used when using more features during model training and testing. In more detail, the lowest error evaluation results can be measured through MAE. This aims to compare the smaller output of the two analyses carried out. Thus the development of the best model that produces the lowest error and by the research title Decision *Tree Algorithm for Predicting Student Performance Based on Psychological Test* is *Analysis based on features.*

CONCLUSION

Based on the research analysis that has been done, namely Analysis based on features and Analysis based on records, a comparison is made between the evaluation error of the decision tree algorithm. It can be concluded that the best performance is analysis based on records.

The Analysis based on records showed a very weak correlation between the input feature and the target feature, specifically a correlation of 0.076 between emotional stability and GPA 2, indicating a very weak positive correlation. Additionally, there is a negative correlation of -0.071 between IQ and GPA 2, indicating a very weak negative correlation. This is as shown in the correlation heatmap, which shows the level of correlation for each attribute is still classified as *very weak correlation*. Meanwhile the evaluation results show a relatively low and good relative error, with MAE of 0.3654, MSE of 0.2263, and MPE of 0.1296.

Even though the development of *machine learning models* has been successfully carried out in research, certain psychological test aspects are not a guarantee in determining each student's performance. Therefore, it is important to recognize that assessing student achievement should not solely focus on psychological tests or academic exams but should also consider aspects such as motivation, personality, interests, social skills, and creativity. Taking a holistic and comprehensive approach to evaluate student achievement can provide a more complete and accurate picture of their abilities and potential.

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