

Student Behavior Analysis to Predict Learning Styles Based Felder Silverman Model Using Ensemble Tree Method

Yunia Ikawati, M. Udin Harun Al Rasyid*, Idris Winarno

Politeknik Elektronika Negeri Surabaya

Jl. Raya ITS – Kampus PENS, Sukolilo, Surabaya, 60111

Corresponding Author: udinharun@pens.ac.id

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Abstract

Learning styles are very important to know so that students can learn effectively. By understanding the learning style, students will learn about their needs in the learning process. One of the famous learning management systems is called Moodle. Moodle can catch student experiences and behaviors while learning and store all student activities in the Moodle Log. There is a fundamental issue in e-learning where not all students have the same degree of comprehension. Therefore, in some cases of learning in E-Learning, students tend to leave the classroom and lack activeness in the classroom. In order to solve these problems, we have to know students' preferences in the learning process by understanding each student's learning style. To find out the appropriate student learning style, it is necessary to analyze student behavior based on the frequency of visits when accessing Moodle E-learning and fill out the Index Learning Style (ILS) questionnaire. The Felder Silverman model's learning style classifies it into four dimensions: Input, Processing, Perception, and Understanding. We propose a learning style prediction model using the Ensemble Tree method, namely Bagging and Boosting-Gradient Boosted Tree. Afterwards, we evaluate the classification results using Stratified Cross Validation and measure the performance using accuracy. The results showed that the Ensemble Tree method's classification efficiency has higher accuracy than a single tree classification model.

Keywords: E-Learning, Felder Silverman learning style model, Learning Style, Ensemble Tree Method.

1. INTRODUCTION

Education is one of the keys to human resource development. Advances in information technology make the education system also more developed. The rapid growth of Information Technology (IT), especially the internet, opens opportunities to develop better educational institutions' information services. E-Learning is a process of learning that uses technologies in the process of learning. Learning Management System (LMS) is one of the E-

Learning technologies [1]. Through LMS, students can access lecture materials, forums, chatrooms, and access lecture assignments given by lecturers [1]. Nowadays, one of the common learning management systems is Moodle. Moodle can record students' experiences and behaviors during online learning stored in the moodle log [2].

The problem in E-Learning is that students tend to leave the classroom and are less active. It is of particular concern; hence it is necessary to know students' preferences in the learning process by understanding each student's learning style. Students have different levels of understanding in the learning process [3]. The learning style refers to how students choose to be able to learn effectively. Along the students know the learning style, they will understand their needs in the learning process. Moodle unable to tell students' learning styles automatically. To determine the appropriate student learning style, it is necessary to analyze student behavior based on the frequency of visits when accessing Moodle E-learning and fill out a learning style questionnaire.

Based on these problems, this research uses the Felder Silverman model learning style approach based on four dimensions, namely Input, Processing, Perception, and Understanding, to map the learning style. We chose the Felder Silverman model because it is the most suitable learning style model in adaptive systems [4]. Felder & Silverman's learning style model divides students' learning styles into four dimensions, namely Process (Active / Reflective), Input (Visual / Verbal), Perception (Sensitive / Intuitive) and Understanding (Sequential / Global). Active Learners prefer to join a group to solve problems, but Reflective learners prefer to work independently or in a small group. Sensing students are more interested in learning concrete facts and learning materials, but Intuitive students prefer to learn abstract learning materials. Visual learners interest in learning materials such as diagrams, drawings, and graphs, but verbal learners like to learn by reading or listening to information. Sequential students' interest in information is expressed in linear measures, but Global Learners use systematic and global approaches.

We propose a prediction model using Ensemble Tree method, namely Bagging and Boosting-Gradient Boosted Tree. A decision tree is a single tree algorithm, while an ensemble tree is a combination of several classifications. Ensemble Tree method solves class imbalance problems in the classification process [5][6] and improves machine learning algorithms' stability and accuracy [7][8]. Stratified Cross Validation is a variation of Cross-Validation that considers a class or group of data points. So we use Stratified Cross Validation to evaluate model performance. We compared the accuracy value between the Ensemble Tree method and the single tree classification model.

The research consists of: Part I describes the introduction of the proposed research. Part II presents a review of previous research on the algorithms used to classify learning styles and their parameters. Part III shows a review of the author's contributions and the originality of the study.

Part IV describes the design system of research, data collection, data pre-processing, and applying the proposed methods. Part V discusses the performance of the proposed algorithm. Part VI contains conclusions.

2. RELATED WORKS

Some researchers have been conducted related to the prediction of student learning styles.

Hasibuan et al. [9] proposed to take into account the previous experience of students. The learning style prediction method uses the Neural Network algorithm and uses the Visual, Audio, Reading, and Kinesthetic (VARK) learning style. In this report, a total of 46 students participated.

Hoang et al. [10] suggested 3-layer Artificial Neural Networks (ANN) predict academic success based on learning styles.

Hasibuan et al. [11] implemented literature-based classification and predictive detection, regarded as a hybrid paradigm for identifying learning styles.

Wang et al. [12] proposed study to classify learning styles based on K-Means algorithms, analyze E-learning guidelines based on Page Rank algorithms, and analyze learning results.

Ouafae et al. [13] suggested an automated approach to identifying student learning styles based on web mining on moodle platforms. The process of classifying student log files corresponds to Felder and Silverman's learning style models. A total of 126 students have enrolled.

Ouafae et al. [14] implemented an adaptive e-learning framework. This study proposed an approach to the automated identification of learning styles based on the Felder and Silverman learning style models (FSLSM). The analysis consisted of two parts: the first part uses the K-means algorithm to divide it into sixteen FSLSM groups.

Manal et al. [15] proposed learning styles based on log data analysis using a Decision Tree relating to the FSLSM learning style. The study of this log data is focused on the navigation of the moodle students of e-learning. The result is a comparison of student quiz data and logs data. A total of 35 students participated. The accuracy result is 76%.

Ling et al. [16] suggested a Bayesian Tree augmented naive to enhance the identification of learning types. The detection process begins with defined learning types. In compliance with the Bayesian augmented naive tree, change and update the learning style, totalling 46 participants in this research for seven weeks.

Renato et al. [17] compared several classifiers such as Naive Bayes and the Decision tree in classifying students' learning styles in the Virtual Learning System. This study uses 108 students of Computer Programming courses using Moodle. They are using a model of the Felder-Silverman Learning Style. For its assessment, this analysis used ten cross-validations. They measure the performance of each classifier using kappa classification and accuracy.

Keeley et al.[18] suggested a new method that uses a fuzzy decision tree to construct a collection of fuzzy prediction models that combine these variables into all of the Felder Silverman Learning Style model dimensions. This study is focused on 75 undergraduate university students. This research compared the proposed approach to the decision tree. Get the best results when using the fuzzy decision tree process.

Sheeba et al.[19] proposed approach predicts student learning references based on three dimensions of FSLSM learning: processing, perception, and input. This experimented with 300 students. This approach uses an updated decision tree classifier, designed with strict decision-making guidelines, to be precise. The outcome shows that the modified decision tree's classifier produces better precision than the decision tree's standard classification.

Hanan [20] compared classification strategies such as ANN, Decision Trees, Support Vector Machines and Naïve Bayes to predict student results. Two thousand thirty-nine students are using this research at the Computer Science and Knowledge Campus. Artificial Neural Network (ANN) models achieve the best accuracy from other models.

Waropat et al. [21] suggested classification of Ensemble using voting to model learning styles by integrating Neural Networks and K-Nearest Neighbor. The ensemble approach is better than other classifications in terms of precision.

Many use classification algorithms, including Decision Tree, Neural Network, and Bayesian Network, based on several similar studies for learning style prediction. The Decision Tree algorithm is used in this research because it is an algorithm that is easy to apply and highly reliable based on decision rules. The decision tree is an algorithm for a single tree. It may be an issue to use one decision tree which may not be robust enough. Previous analysis has found that the precision of the decision tree is less significant [15][17-20]. Then it would be convenient to use to merge the approach with multiple decision trees. It is called ensembling [21] to combine multiple classifiers in a prediction model. In the classification process, the ensemble approach solves class imbalance problems [5][6] and increases the stability and accuracy of machine learning algorithms [7][8]. Therefore, this analysis suggests the Ensemble Tree approach to predict learning style, where other researchers have not used the Ensemble Tree method for prediction of learning style especially Boosting-Gradient Boosted Tree.

3. ORIGINALITY

This study proposes how to dynamically detect learning styles based on Moodle's student behaviour analysis. The results of the behavioral analysis will be compared with the results of the Index Learning Style questionnaires based on the Felder Silverman Learning Style Model. The process of mapping the learning style using the Felder Silverman model's learning style approach is based on four dimensions: Input, Processing, Perception, and

Understanding. Data mining is processed from student behavior analysis using Python programming. The mechanism of learning style prediction uses the Ensemble Tree system, respectively Bagging and Boosting-Gradient Boosted Tree. Ensemble Tree combines the classification of predictions from several models. The stability and precision of machine learning algorithms can be enhanced by this approach. Ensemble Tree can overcome instability in complex models with relatively small datasets. To evaluate model performance, Stratified Cross Validation is used. Stratified Cross Validation is a K-Fold variance that randomizes information based on a subset of training data and test data. It divides the data into n_splits that considers the class or group of data points. For example, the dataset is selected ten fold, divided into ten subsets, one subset as evaluation data, and the rest as training data. This method is replicated ten times, and the test data is different from the current subset. We compared the accuracy value between the Ensemble Tree method and the single tree classification model to measure performance.

4. SYSTEM DESIGN

In this study, we divided the process into four stages: (1) data collection, (2) data pre-processing, (3) classification model, and (4) analysis as shown on figure 1.

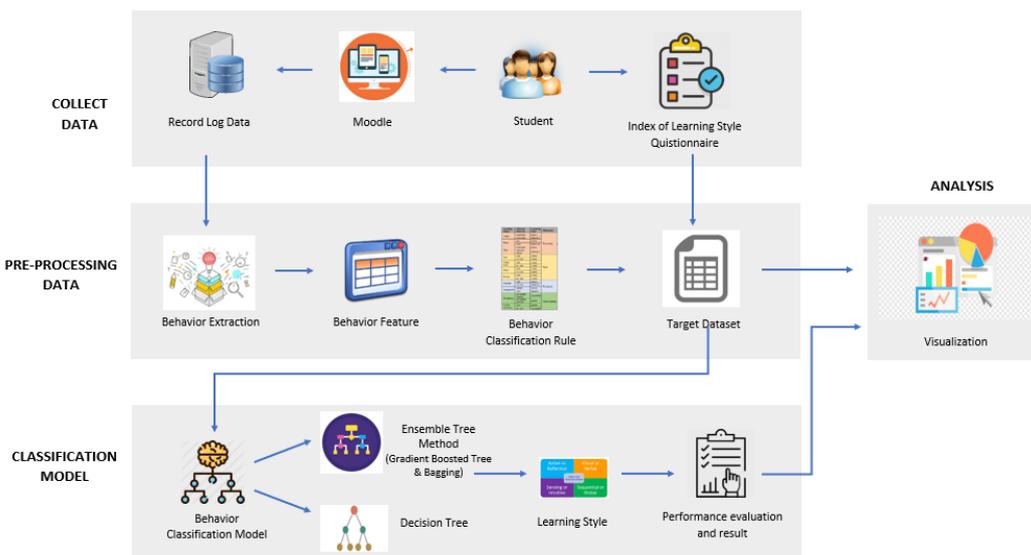


Figure 1. System Design

4.1 Data collection

The first step is the data collection process. To assess their preferred style based on the Felder and Silverman learning style questionnaire, for the first time, students have to fill out Index Learning Style questionnaires on the website <https://www.webtools.ncsu.edu/learningstyles/>. This questionnaire is made up of 44 questions. Besides, this research used the Moodle log data file at Lamongan State Community Academy (AKN Lamongan) for one

semester in the Wireless Network course at the site address <http://elearning.aknela.ac.id/moodle/>. There are 65 students interested in this study with a major in Informatics Engineering, and they have access to Moodle for one semester. During Moodle entry, all student activities will be stored in the log data (2048 records in total). The Index Learning Style (ILS) questionnaire data gathered from Moodle will also be correlated with learning style findings from students' actions towards e-learning in this research. Figure 2 shows the course content of the Moodle E-learning.

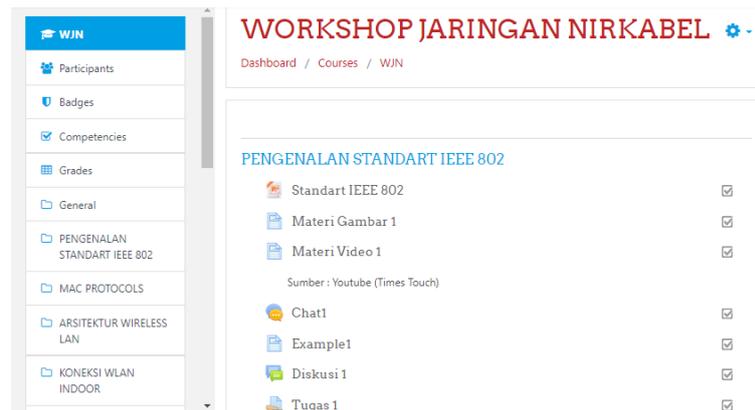


Figure 2. course content of the Moodle E-learning.

Based on figure 2, the material presented is adapted to Felder and Silverman's Model Learning Style Mapping.

4.2 Pre-Processing Data

It is a process to process raw data into quality data. The Pre-Processing process consists of three parts: Student Behavior Data Extraction, Behavior Feature, and Behavior Classification Rule.

4.2.1 Student Behavior Data Extraction

The extract process is the first stage of the pre-processing data system. The extract selects and retrieves data from one or more sources (e.g., database) and then accesses the data retrieved. Data extraction is a method for extracting information from the Moodle logs. There are nine attributes for each case documented in the Moodle logs: time, user full name, affected user, event context, component, event name, description, origin, IP address. This study focused only on the user attributes of full name, event context, event name, and description. It corresponds to student behavior analysis based on the rules of learning style in table 1. Event context attributes and event names reflect student behavior on different objects accessible from Moodle, such as chats, assignments, course content, and forum discussions. Figure 3 shows the performance of the log data.

Time	User full name	Affected user	Event context	Component	Event name	Description	Origin	IP address
15 June 2020, 5:42 AM	Moch. Syahri Wicaksono	Moch. Syahri Wicaksono	File: Studi Kasus EIGRP	System	Course activity completion updated	The user with id '58' updated the completion state for the course module with id '30' for the user with id '58'.	web	112.215.154.74
15 June 2020, 5:42 AM	Moch. Syahri Wicaksono	-	File: Studi Kasus EIGRP	File	Course module viewed	The user with id '58' viewed the 'resource' activity with course module id '30'.	web	112.215.154.74
15 June 2020, 5:42 AM	Moch. Syahri Wicaksono	-	Course: WORKSHOP JARINGAN NIRKABEL	System	Course viewed	The user with id '58' viewed the course with id '3'.	web	112.215.154.74

Figure 3. Moodle Log Data

4.2.2 Behavior Feature

Behavior Feature is the collection process of features appropriate for research purposes. This process is one of the data mining methods commonly used in the pre-processing stage. This technique is to reduce the complexity of the attributes to be used in the analysis process. This technique is to find out the most crucial feature subset of the data set. This process selects features that fit the FLSM learning style's dimensions from Logs file data. We choose three features based on the research needs: user full name, event context, and event name.

4.2.3 Behavior Classification Rule

Behavior Classification Rule is a rule for classifying learning patterns based on student behavior. The features are mapped according to the Felder-Silverman Model [22]. Based on the Learning Style Classification Rules, we can get a dataset pattern based on learning objects used as attributes/features based on FLSM. FLSM-based learning style divided into four dimensions, namely processing (active / reflective), input (verbal / visual), perception (sensor / intuitive) and understanding (sequential / global). Students who are classified to Processing dimension prefer to access learning object forums, demos, and chats. Students classified to Input dimension prefer to access the text of learning objects, pictures, videos, and powerpoint. Students who are classified to Perception dimensions prefer to access examples and assignments. Finally, students who are classified to Understanding dimensions based on navigation learning objects and course overview.

The target dataset is formed from data extraction based on the learning style classification rules in table 1. Attributes in a data set are based on learning objects. The value of each variable is the cumulative frequency of visits by students to each learning object. Furthermore, identify the class based on their conduct towards e-learning for each student. Class are estimated based on the rules of classification of learning types in table 1, with the largest number of frequencies of each student on Moodle.

Table 1. Proposed rules of learning style based on student actions

The object of learning	Related behaviour	Learning Style	Dimension
Forum	post/reply	active	Processing
	view/read	reflective	
Demo	run	active	
	view	reflective	
Chat	post/reply	active	
	view/no-action	reflective	
Text	visit	verbal	Input
	no visit	visual	
PowerPoint	visit	visual	
	no visit	verbal	
Video	visit	visual	
	no visit	verbal	
Picture	visit	visual	
	no visit	verbal	
Example	visit	sensor	Perception
	no visit	intuitive	
Assignment	submit	sensor	
	view	intuitive	
Navigation	navigating linearly	sequential	Understanding
	navigating globally	global	
Course Overview	view	global	
	no view	sequential	

4.2.4 Classification Model

Data Classification is the process in data mining to find a model or function that describes and distinguishes data into classes. Classification involves checking an object's characteristics and inserting an item into one of the previously defined categories. The classification process uses a supervised learning algorithm. In this study, data classification using Ensemble Tree is Gradient Boosted Tree and Bagging. We will compare Ensemble Tree Algorithm and Decision Tree Algorithm.

A. Decision Tree

Prediction models use tree structures or hierarchy structures. A Decision Tree is a classification method in data structures to analyze, recognize, and decide on unique behaviors [23], [24].

The tree's decision steps start by transforming the training data to the tree, the tree consisting of nodes, to decide the location of each node using the Entropy value S defined in equation 1.

$$\text{Entropy}(S) = \sum_{i=1}^k -p_i \log_2 p_i \quad (1)$$

Where:

S = set (dataset) of cases

k = number of partitions S

p_i = proportion S_i to S

Choosing the right segmentation variable from a data attribute in the decision tree can be calculated using each attribute-depending gain on the different values taken by this attribute, as shown in equation 2.

$$G(S, Q) = E(S) - \sum_{i=1}^k \frac{|S_i|}{|S|} * \text{Entropy}(S_i) \quad (2)$$

Where:

G = gain

S = set (dataset) of cases

k = number of partitions S

$|S_i|$ = proportion S_i to S

$|S|$ = number of cases in S

B. Bagging

Bagging can enhance the accuracy of learning algorithms by building a series of predictive functions and then combining them into predictive functions in a certain way [25]. Bagging proved sensitive to minor changes in training sets that were useful for improving classification accuracy from early decision tree classifiers by reducing variant misclassification.

In Bagging, large data sets are divided into smaller segments. Bagging uses equation 3 to calculate the final result of the classification.

$$e = \frac{1}{N} \sum_{i=1}^N e_i \quad (3)$$

Where:

e = final result of classification

N = number of classification models

i = classification order

C. Gradient Boosted Tree

Gradient boosted tree is the ensemble method of the classification tree. The ensemble comes from a decision tree model. The tree was added one by one to the ensemble and adapted to correct prediction errors made by

previous models [26]. It is an advanced learning ensemble method that obtains predicted results through gradually improved estimation.

Gradient Boosting Tree uses equation 4 to calculate the final result of the classification.

$$e = \sum_{i=1}^N w \cdot e_i \quad (4)$$

Where:

e = final result of classification

N = number of classification models

w = weight (weight calculated by considering the last iteration)

i = classification order / iteration

Boosting trains models whose classification results are weak to be optimal. So it can be said that boosting combines some weak data to obtain vital data by training models sequentially.

4.2.3 Analysis

This section analyzes the results of new data sets from previous processes and analyzes model classification results. Several parameters are analyzed, namely each student's learning style, learning objects that are often accessed by each student, and the comparison of several classification algorithms to predict learning styles.

5. EXPERIMENTS AND ANALYSIS

This section outlines Moodle's approach to detecting learning styles based on an interpretation of student behavior. Next, compare the results of learning style detection to the ILS results of student questionnaires and analyze the results of learning style predictions using the proposed algorithm.

5.1 Analysis of the proposed learning style detection

To evaluate the learning model outcomes using the suggested approach, to classify FLSM-based learning styles by evaluating student activity based on the number of visits to Moodle. Furthermore, comparing the results of student behavior analysis with ILS questionnaire as the reference [27]. It is because ILS questionnaires are instruments often used to identifying learning patterns based on the FLSM.

The process of extracting Moodle logs in E-Learning produces a target dataset of learning style detection results focused on the frequency of student visits to E-Learning. The dataset labels are the largest total number of frequencies of each student on the Moodle. Figure 4 shows the target dataset formed.

Student	Forum	Demo	Chat	Text	PowerPoint	Video	Picture	Example	Assignment	Navigation	Course Overview	Class
Achmad Munulij Ilhami	0	0	0	3	8	4	5	0	0	0	0	input
Aida Riski Firman Syah H.	0	0	0	5	3	4	3	0	1	0	0	input
Aji Santoso	6	2	7	0	1	0	0	1	0	0	0	processing
Ayu Ambarwati	0	0	0	1	5	2	6	0	0	0	0	input
Bagas Hadi Prastyo	0	0	0	0	1	0	1	3	6	0	0	perception
Bayu Ibrahim	0	0	0	1	5	2	3	0	0	2	2	input
Dian Anggraini Indah Puspita Sari	0	0	0	2	3	4	5	0	1	0	0	input
Gebby Citra Prastika	3	1	5	0	0	0	0	0	0	0	0	processing
Haffiddudin Ilham Pratama	0	1	0	0	0	0	0	5	2	0	0	perception
Harim Hawara Al Abid	0	0	0	2	4	3	2	0	2	0	0	input

Figure 4. Overview of the Target Dataset

Here is a visualization of learning style results using analysis dashboard.

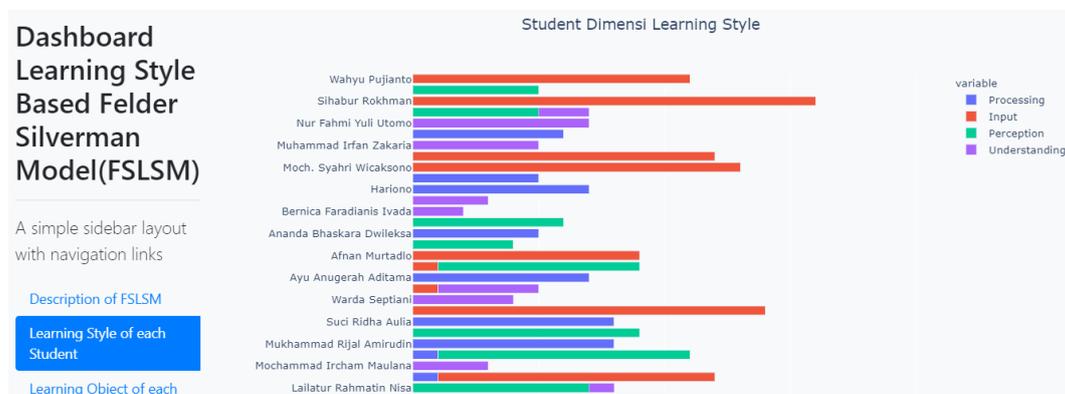


Figure 5. A Dashboard of the Student Learning Style

Figure 5 shows each student's learning style based on the dimensions of FLSM. There is more than one dimension of learning style in the picture for each student. The learning style is selected based on the most significant number of measurements of the learning style. On the dashboard, when the pointer goes to one of the students, there will be data on the learning style dimensions, the frequency of grades, and the student's name.

5.2 Evaluation of the proposed algorithm for predicting learning styles

This study proposed the Ensemble Tree algorithm, Gradient Boosted Tree, and Bagging for the learning style prediction process. Next, match the results of the ensemble tree with a single algorithm Decision Tree. The classification process uses Python in Jupyter Notebook programming language. For performance evaluation of classification model/algorithm using Stratified Cross Validation. Stratified Cross Validation is a cross-validation variant that splits data into two subsets: learning method data and validation data. that considers classes or groups of data points. It is suitable for small data samples consisting of more than one target class. We compared

the number of K-Folds used in the classification process to determine which one is best: Fold 3, 5, 10.

The accuracy is calculated to measure the classification model performance using equation 5.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} * 100\% \tag{5}$$

Where:

TP = True Positive

TN = True Negative

FP = False Positive

FN = False Negative

Table 2 and figure 6 show a comparison of the accuracy results of the proposed algorithm.

Table 2. Comparison of accuracy results

Algorithm	Accuracy using Stratified K-Fold		
	k=3	k=5	k=10
Decision Tree	82.10%	84.20%	84.30%
Gradient Boosted Tree	87.80%	88.90%	89.80%
Bagging	88.90%	89.10%	90%

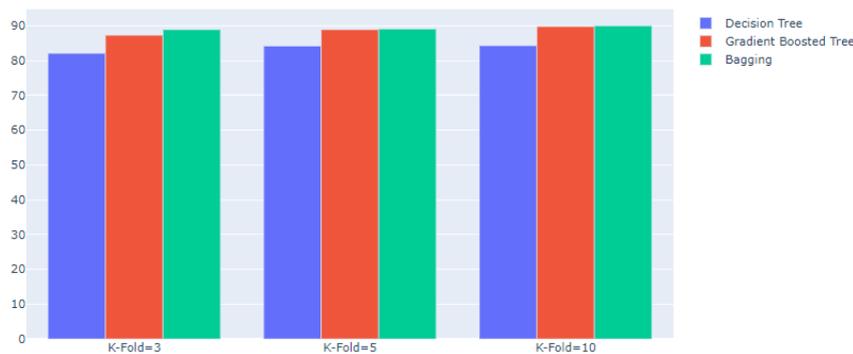


Figure 6. Comparison of measurement accuracy

Based on table 2, after conducting a classification experiment using the Decision Tree algorithm, Gradient Boosted Tree and Bagging using Stratified K-Fold. The k value or the number of iterations is altered by the values 3, 5, and 10. The highest accuracy is achieved when K = 10 with result using decision tree is 84.30%, accuracy with gradient boosted tree is 89.80%, and accuracy with Bagging is 90%. The highest accuracy is achieved when using Bagging algorithm with k= 10 and gain accuracy 90% from these results. Based on the results of experiments in table 2 and figure 6, comparisons between single Decision Tree algorithms and ensemble tree algorithms

(Gradient Boosted Tree and Bagging) for prediction showed that predictions using Ensemble Tree get higher accuracy value than a single algorithm. The Ensemble Tree method incorporates several classifiers in a prediction model that can reduce errors by reducing variance.

6. CONCLUSION

Students tend to leave the classroom and are less active when attending E-Learning. It is a problem in E-Learning, therefore it is necessary to know students' preferences in the learning process by understanding each student's learning style. Moodle can't automatically tell students' learning styles. To determine the appropriate student learning style, we can analyze student behavior based on the frequency of visits when accessing. In this research, we focus on analysis to determine learning patterns for students based on the learning styles of Felder and Silverman, which consist of 4 dimensions, namely Processings (Active / Reflective), Input (Visual / Verbal), Perception (Sensor / Intuitive), and Understanding (Sequential / Global). A simple web dashboard represents analytics defining learning styles to make it easier to visualize. Data analysis comes from log data in Moodle and compares the results of the study to ILS questionnaires. Furthermore, for learning style prediction, we propose an Ensemble Tree (Gradient and Boosting Tree) method using Stratified K-Fold, with values $k = 3, 5,$ and 10 . It is more efficient for relatively small amounts of data and more than one target class if using a Stratified K-Fold. The results obtained are very satisfactory, namely the highest accuracy value when using $k = 10$ with Ensemble Tree Bagging algorithm that is 90% accuracy. It proves that the use of the Ensemble Tree method is better than the Single Decision Tree Algorithm. For future research, we plan to increase the number of students involved in this research and develop research with other Ensemble Tree methods such as XGBoost Classifier, AdaBoost Classifier, and Extra Tree Classifier.

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