Review Article

The Relationship of Teacher Activity in the Teaching and Learning Process to Elementary Student Learning Outcomes Using Bootstrap Machine Learning

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Abstract:
Often, after the learning and teaching process is over, students will be tested with quizzes, midterm exams, and even end-of-semester exams, but these exams still take time after the teacher has taught several weeks or months that have passed; what if after teaching, for example, a math lesson, and students immediately understand or do not understand at all, and this can be detected using Machine Learning. The variable that can be raised is the value or quiz grade of a particular subject; for example, mathematics is one of the disliked subjects for most elementary school students, but how to find out that the student is able or unable to solve math problems and predict the end of semester grades for mathematics, this can be determined using Machine Learning, using the KNN Algorithm or K-MEANS method, or other methods that are deemed appropriate to the existing case study. In this case study, it is predicted whether a variable affects each other or affects other variables; this is done by doing or drawing relationships between variables. This research successfully concluded from the performance of machine learning in predicting students' understanding of math lessons after teaching and learning activities ended. The parameters that will be used for testing are population and sampling, and then data analysis, validity, and reliability tests are carried out.

Keywords: KNN-Algorithm, K-MEANS, Machine Learning, Teaching and Learning, Grade Prediction

1. INTRODUCTION

The teaching and learning process in elementary school is an essential foundation so that children can get an early introduction that determines future quality; mastery of a lesson will lead to an understanding that a child can use the left brain and right brain properly and a tendency to the left or right brain. The left brain tends to be used for logic and reasoning, including Physics, Chemistry, and mathematics, mostly using the left brain to solve arithmetic problems, while the right brain is used for creativity, such as singing, dance movements or dances such as regional dances, and music, such as playing drums, trumpets, pianos, even painting and drawing, all of these types of creativity are born from the right brain.

The success of teaching can be measured by various indicators, including [1] Students' ability to achieve learning objectives. This indicator is the most important indicator because the overall success of the teaching teacher can be seen from the extent to which students can achieve the learning objectives that have been set. [2] Students' enthusiasm and motivation in learning. This indicator shows how much students are interested and motivated to learn. Enthusiastic and motivated students will more easily understand the subject matter and achieve learning objectives. [3] Students' ability to apply the subject matter in daily life. This indicator shows how students can understand and apply the subject matter in everyday life. Students who are able to apply the subject matter in everyday life will find it easier to remember and understand the subject matter.

Primary school life is inseparable from children's self-development, so teachers are constantly teaching about how to educate children in many ways, not only in certain subjects, but also in moral guidance, such as religious studies and even sports, so that children's mentality will grow from physical and mental, body and soul, and spirituality are all well maintained. However, what is relatively difficult is how to understand children who have finished being taught are able to parse and solve a problem; for example, in math lessons, sometimes the teacher does it with a quiz exam at that time; this is where the child's mentality is tested, whether they are ready to take the exam, whether they will cheat on friends, and many more things that can be done, children tend to cheat when taking the quiz exam process, as well as midterm exams, or end of semester exams. This research developed a method using Machine Learning and a special case using Bootstrap [1-8]. For example, in telecommunications science, methods that have been used can be analyzed using the K-NN Algorithm or Bootstrap with RSSI and SNR data [9-10].

In various cases, what is especially being discussed in this research is how the output of learning that has been carried out at school by the teacher as a teacher and students as taught objects can be processed and accurate data obtained using machine learning. One of them is Bootstrap. Machine Learning Bootstrap, also known as bagging, is a machine learning technique used to improve the stability and accuracy of machine learning models. This technique works by creating several machine-learning models from bootstrap training data samples. Bootstrap samples are samples of data taken from the training data with returns, which means that each example in the training data can appear more than once in the bootstrap samples. Machine Learning Bootstrap techniques can be used for various types of machine learning algorithms, including decision trees, artificial neural networks, and linear regression. This technique can help reduce the variance of machine learning models, improving model accuracy. It can also help avoid overfitting, a problem that can occur when a machine learning model fits the training data too well and does not generalize well to new data.

2. THEORY

Some of the essential parameters used in the analysis include population and sampling. Some of the essential parameters used in the analysis include population and sampling. The population is essential when this research is carried out; the population will determine the sampling that will be carried out; there are several sampling techniques, including [1] Random sampling or random sampling, which is a sampling that uses a lottery against the population. Next is regular random sampling (ordinal sampling), which is taking subject numbers with the same distance. For example, multiples of 3, 4, 10, and so on. And random sampling with random numbers which is by making a table arranged in a certain order of the subject. Examples made are with certain graphs or percentages. [2] Group sampling or cluster sampling takes samples by characterizing population groups. For example, the first grade of junior high school with the background of the work and education of his parents. Next, the things that are considered in determining the sample include Determining the right research object, Determining the appropriate research population, Determining the correct size and sampling technique, and Taking samples accurately.

Furthermore, after the data is collected, the next step is data analysis, which is carried out by testing the validity and reliability of the data. Reliability relates to the reliability of the data, while validity relates to the truth of the data. Data analysis is carried out according to research needs and research methods, whether it requires data normality, data linearity, or data description, before conducting analysis (e.g., chi-squared, correlation, regression, and so on). The data analysis techniques and procedures used by the researcher and the reasons need to be explained. Data analysis can be done manually or with computer assistance (using statistical programs that are recognized nationally and internationally). Furthermore, things that need to be considered in data processing are Variable, Measurement Scale (nominal scale, ordinal scale, interval scale), Scale Type (Likert scale, Guttman scale, Semantic differential, and rating scale), Research instruments, validity and reliability of instruments.

The validity test relates to measuring what should be measured, the extent to which the accuracy of a measurement instrument in performing its measuring function, the extent to which the measurement results can be trusted, and the extent to which the measurement results can be trusted when measurements are taken at different times on the same group of subjects, the results are relatively the same. The high and low reliability is empirically indicated by a number called the reliability coefficient value. High reliability is indicated by a value of 1.00; reliability that is considered satisfactory or high is> 0.70.

Table 1. Differences of Bootstrap as supervised learning with Unsupervised Learning and Reinforcement Learning

Characteristics	Bootstrap/Supervised Learning	Unsupervised Learning	Reinforcement Learning
Definition	A machine learning technique is used to improve machine learning models' stability and accuracy.	A machine learning technique used to solve various machine learning problems with unlabeled data.	A machine learning technique used to solve various machine learning problems with agents that interact with the environment.
Data used	Labeled data	Unlabeled data	Unlabeled data
Output	Machine learning model	Patterns	Policy
Algorithm used	Bagging, bootstrap aggregating	Various machine learning algorithms include clustering, dimensionality reduction, and others.	A wide variety of machine learning algorithms, such as Q-learning, policy gradients, and others.
Benefits	It improves accuracy, helps to avoid overfitting, and is easy to implement.	Find patterns in data, reduce data dimensionality, etc.	Improves agent performance in interacting with the environment, such as maximizing rewards or achieving certain goals.
Limitations	It may increase model complexity and require more training data.	It can require more training data and can be difficult to interpret the results.	Training can require more time and resources, and it can be difficult to control agent behavior.

Characteristics	Bootstrap/Supervised Learning	Unsupervised Learning	Reinforcement Learning
Implementation example	Natural language processing, recommendation, fraud detection.	Clustering, dimensionality reduction, etc.	Robotics, game playing, and more.

3. METHOD

The method used in this research is Bootstrap [17-23]. The bootstrap method is a resampling technique used to estimate statistics on a population by sampling the dataset with replacement. It can be used to estimate summary statistics such as the mean or standard deviation, and It is used in Machine Learning to estimate the skill of machine learning models when making predictions on data not included in the training data. One of the methods used is Bootstrap [15-18], as shown in Figure 1. Bootstrap is a widely used statistical tool that is very powerful in quantifying the uncertainty associated with a given estimator or statistical learning method. As a simple example, Bootstrap can be used to estimate the standard errors of linear regression coefficients even though standard statistical software such as R can automatically output the standard errors [11-14]. However, the advantage of Bootstrap lies in the fact that it [19-20] can be easily applied to a variety of statistical learning methods, including measuring variability from other methods where it is difficult to output the standard error. Suppose we wish to invest some money into two assets that produce returns, X and Y, where X and Y are random data. We will split the amount of money into two, α for X and the remaining 1-α for Y. We will choose the value of α that will minimize the risk or variance of our investment. In other words, we want to minimize Var(αX+(1-α)Y). The value of α can be shown in equation 1, and then formula two is used to calculate the coefficient of variation. The command in R is shown in Equation 3.

$$\alpha = \frac{\sigma_Y^2 - \sigma_{XY}}{\sigma_X^2 + \sigma_Y^2 - 2\sigma_{XY}} \quad (1)$$

$$cv = \sqrt{Var/}\bar{x} \quad (2)$$

$$cv < \ -function(x)sqrt(var(x))/mean(x) \quad (3)$$

With σ_X^2 is a variable x or var (X) and σ_Y^2 is a variable Y or var (Y), and σ_{XY} is a Cov (X, Y). Moreover, the bootstrap dataset is created by randomly picking objects from the original dataset. Also, they must be the same size as the original dataset. However, the difference is that a bootstrap dataset can have duplicate objects. Here is a simple example to show how it works, along with the illustration in Figure 2.

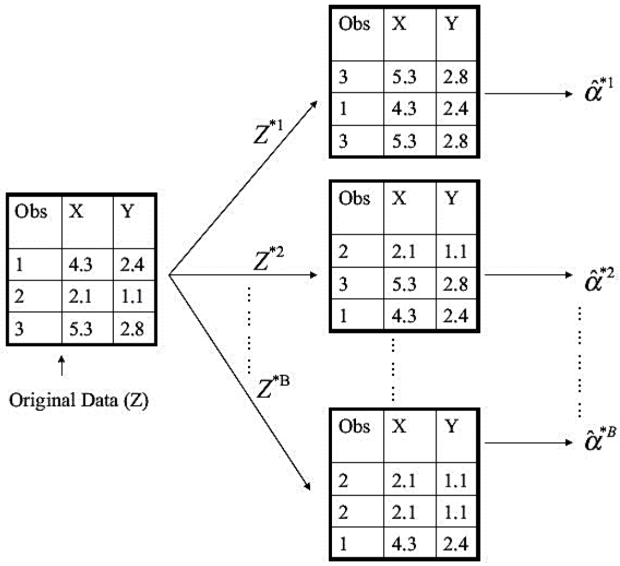

Figure 1. Statistics Learning Methods use Bootstrap

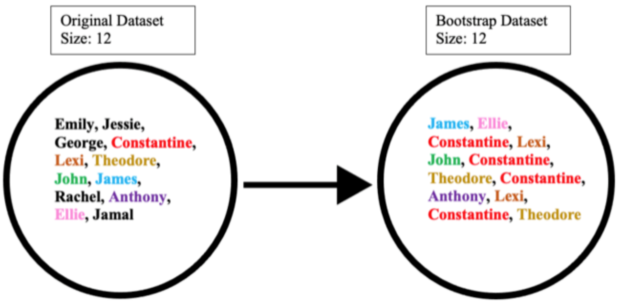

Figure 2. Bootstrap case study example

The next step is to create the out-of-bag dataset. The out-of-bag dataset represents the remaining people who are not in the bootstrap dataset. It can be calculated by taking the difference between the original and bootstrap datasets. In this case, the remaining unselected samples are Emily, Jessie, George, Rachel, and Jamal. Keep in mind that since both datasets are sets when taking the difference, duplicate names are ignored in the bootstrap dataset. The illustration in Figure 3 shows how the math does this process.

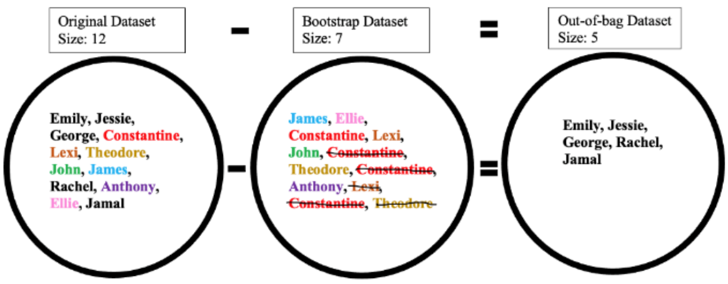

Figure 3. Dataset out-of-bag Bootstrap

Furthermore, the next step is to make a Decision Tree Generation. The next step of the algorithm involves creating a decision tree from the bootstrap dataset. The process examines each gene/feature and determines how many samples the presence or absence of the feature produced a positive or negative result. This information is then used to calculate a confusion matrix, which lists the true positive, false positive, true negative, and false negative values of the feature when used as a classifier. These features are then ranked according to various classification metrics based on their confusion matrix. Some common metrics include estimated positive correctness (calculated by subtracting false positives from true positives), "goodness" measure, and information gain. These features are then used to partition the samples into two sets: those with the top features and those without. The diagram in Figure 4 shows the two-depth decision tree used to classify the data. For example, a data point that shows Feature 1 but not Feature 2 would be assigned "No." Other points that do not show Feature 1 but show Feature 3 will be given a "Yes."

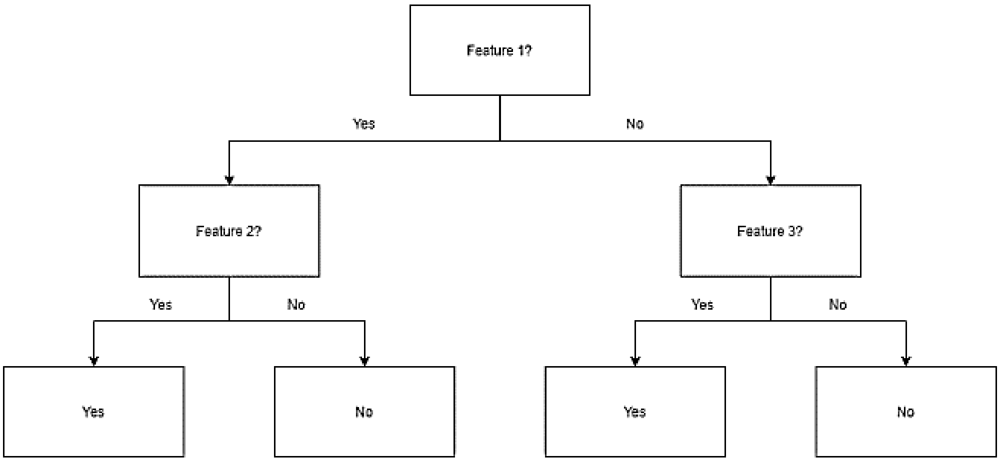

Figure 4. Decision Tree

4. RESULT AND ANALYSIS

The steps performed in the bootstrap analysis in this research are shown in the Pseudocode, and the flow of a series of programs run:

1. First, there is data x, and this is a sample cut from dataset x.
2. From the calculation of the coefficient of variation, the resulting CV (x), the value as in equation 3 is as follows, so the resulting CV (x) is 0.2524712.
3. If a single bootstrap sample is used on the x array, then as follows, the result is 0.3246178.
4. Next, create a bootstrap dataset with 1000 samples.
5. Then, determine the value (below) of the 5% confidence interval. And determine the value (above) of the 95% confidence interval.
6. For example, if the value of i is 1000, it can be replaced by boot numeric(i), where the i value can be changed depending on the project.
7. This boot value is always changing; now, we can see with the boot command, and if it changes, this boot value is not always the same.

Next is to do command 7 to see the number of element parameters, sum all samples, calculate the mean value, calculate the variance value, calculate the standard deviation, and calculate the mean and variance values of the bootstrap dataset. It can use the following commands in command seven while displaying the histogram using the hist (boot) command.

8. After plotting the Boot histogram, it will appear in Figure 5, Figure 6, and Figure 7. These percentile values are close to the previous results of 0.3092094 and 0.1602328.

Moreover, the following points show the step-by-step code on Machine Learning bootstraps to generate analysis data on the case of student assessment results from the classroom learning process.

```
1. dataset x<-c(8.6, 6.33, 10.4, 5.27, 5.35, 5.61, 6.12)
2. Command 1 CV <-function(x) sqrt(var(x))/mean(x)
3. CV function(x) sqrt(var(x))/mean(x)
4. CV(x) [1] 0.2524712
5. Command_2> CV(sample(x,replace=T)) [1] 0.3246178
6. Command_3> boot<-numeric(1000) > for(i in 1:1000)boot[i]<-
CV(sample(x,replace=T)) > quantile(boot,0.05) 5% 0.1591731
7. Command_4> quantile(boot,0.05) 5% 0.1591731 > quantile(boot,0.9)
90% 0.2940871
8. Command_5> boot <-numeric(1000)
9. Command_6> for(i in 1:1000) boot[i] <- CV(sample(x,replace=T))>
boot[i][1] 0.2644668
10.Command_7> length(x),[1] 25,> sum(x), [1] 171.44, > mean(x) [1]
6.8576, > var(x), [1] 2.997561, > sd(x), [1] 1.731346
> mean(boot), [1] 0.2407525, > var(boot), [1] 0.001994018, >
hist(boot)
11.Command_8, > library(bootstrap), > library(boot), > ratio<-
function(d, w) sum(d$x*w)/sum(d$u*w)
> mydata<- boot(city, ratio, R=999, stype="w"), > mydata, ORDINARY
NONPARAMETRIC BOOTSTRAP
Call:boot(data = city, statistic = ratio, R = 999, stype = "w"),
Bootstrap Statistics: original    bias    std. error, t1* 1.520313
0.0332888   0.2105707
12.Command_9 > CV<-function(x, id){ + xs<-x[id], +
sqrt(var(xs))/mean(xs), + }, > CV
function(x, id){, xs<-x[id], sqrt(var(xs))/mean(xs) }
13.Command_10, > CV(x), [1] 0.2524712 > bootdata<-
boot(data=x,CV,R=1000)
> bootdata ORDINARY NONPARAMETRIC BOOTSTRAP, Call: boot(data = x,
statistic = CV, R = 1000)
```

```
Bootstrap Statistics : original      bias    std. error
t1* 0.2524712 -0.01234132  0.04518137
14. Command_11 > boot.ci(bootdata)
BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
Based on 1000 bootstrap replicates
CALL :
boot.ci(boot.out = bootdata)
Intervals :
Level      Normal              Basic
95%   ( 0.1763,  0.3534 )   ( 0.1880,  0.3591 )
Level     Percentile            BCa
95%   ( 0.1459,  0.3170 )   ( 0.1796,  0.3468 )
Calculations and Intervals on Original Scale
Warning: BCa Intervals used Extreme Quantiles
Some BCa intervals may be unstable
Warning messages:
1: In boot.ci(bootdata) :
bootstrap variances needed for studentized intervals
2: In norm.inter(t, adj.alpha) :
extreme order statistics used as endpoints
     ---------------Step by Step Code of Bootstrap --------------
```

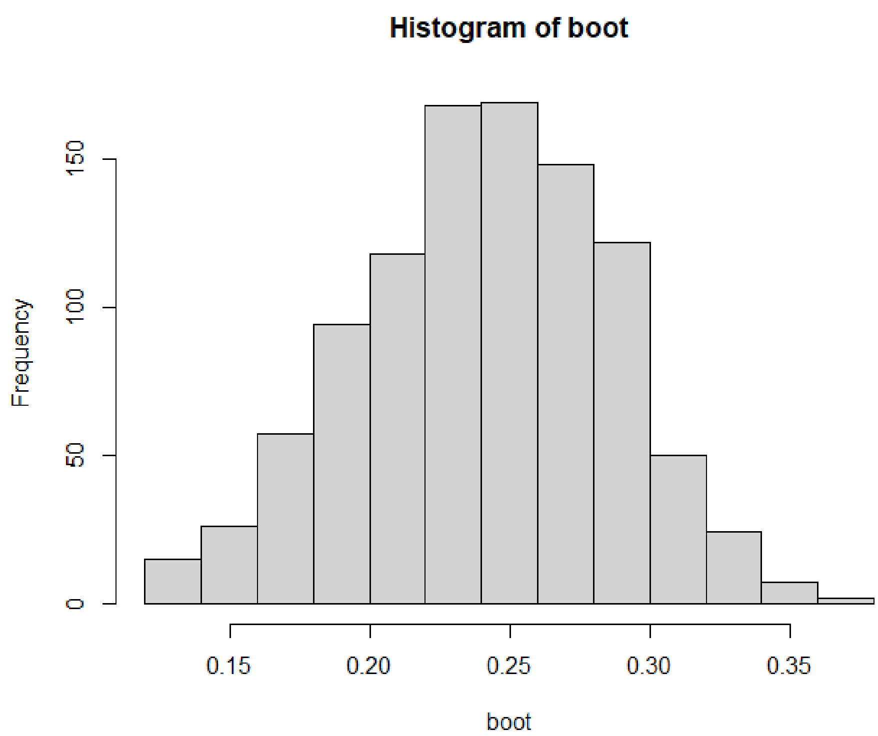

Figure 5. Histogram of boot 1 (Frequency versus boot)

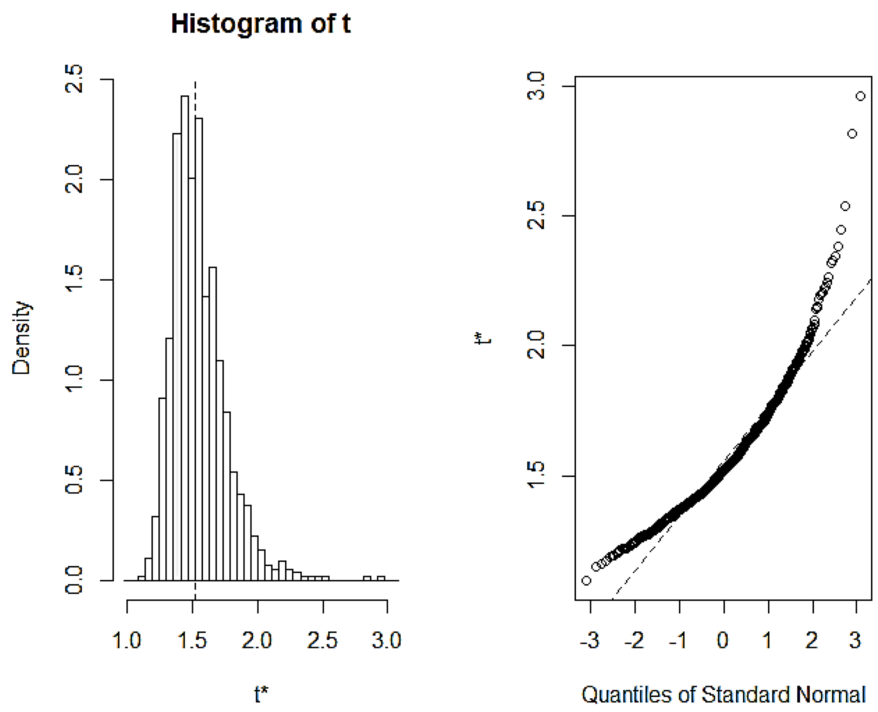

Figure 6. Histogram data boot 2 and t vs Quantiles of Standard Normal

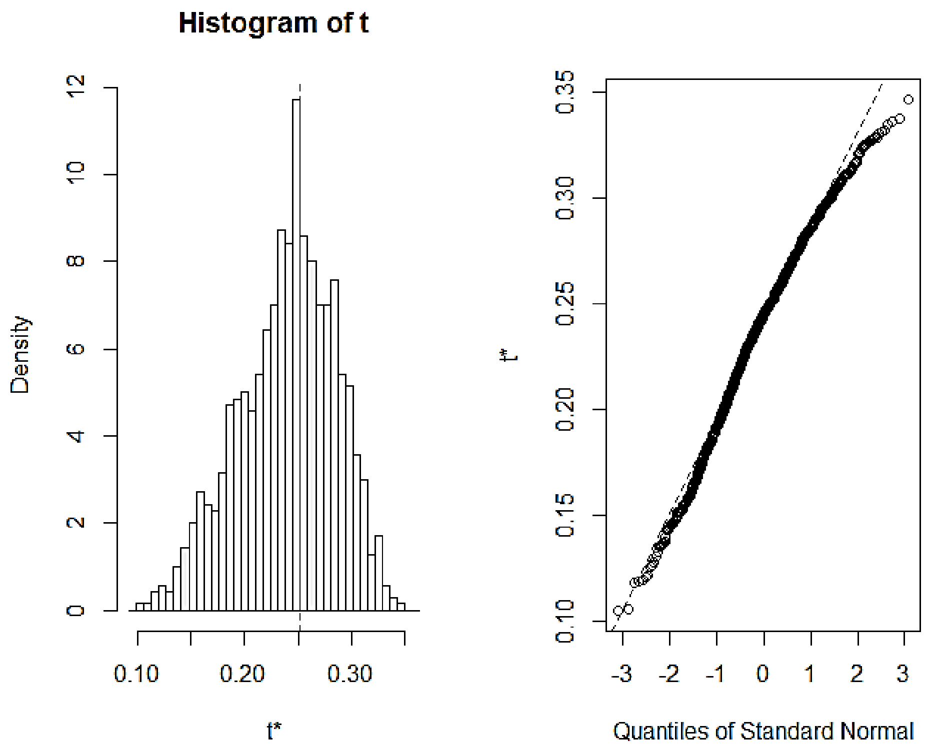

Figure 7. Histogram data boot 3 and t vs Quantiles of Standard Normal

5. CONCLUSION AND SUGGESTION

By using Bootstrap, we can determine the interval calculations that show the percentage (%) prediction value of the inputted data values, and these values can be obtained from the results of quiz scores done by students and recorded into raw data, which is then processed using Machine Learning and Bootstrap to get a certain interval value, for example, boot data has an interval value level 95% normal 0. 1762, 0.2494 and basic 0.1845, 0.3549. from the t histogram, the maximum density is obtained at 2.5 with quantities of standard normal maximum at 3.0, while the bootdata histogram has a density value of 12 maximum, and the Quantities of standard normal is 0.35.

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AUTHOR CONTRIBUTIONS

All Author is responsible for building Conceptualization, Methodology, analysis, investigation, data curation, writing—original draft preparation, writing—review and editing, visualization, supervision of project administration, funding acquisition, and have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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