PREDICTING PARTICIPANT COMPETENCE TEST RESULT USING MACHINE LEARNING APPROACH

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***Abstract*-- The 3in1 training for electronics operators aims to deliver competent participants. Therefore, it is necessary to improves the learning curriculum and materials. However, the organizer and teaching staff lack information about the factors that determined the success rate of participant's competence tests. Therefore, this paper aims to build a model for predicting participant competence test result. The data of participant's assessment scores were first collected and prepared as the dataset. The prediction model builds by applying a machine learning approach. These cover the use of ANOVA to ranked the course subjects towards the competency test results (C and NC) and build the prediction model using the Random Forest algorithm.**

From the results, we found that the competency test results are more affected by the practical subjects rather than theory subjects. From the ANOVA results, the most significant practical subject is the screwing lesson, while for theory subject is 5S-Kaizen. The prediction model obtains an accuracy of 94,6% for 5-subjects and 91,9% for 8-subjects from the original dataset. However, from the precision rate, it was found that the oversampling and hybrid sampling dataset shown better results. This confirms that the resampling technique is working to solve the imbalanced dataset problem.

***Keywords*: prediction model; random forest; data resampling; competency test; electronics operator.**

I. INTRODUCTION

Since the electronic industry is a technology-intensive industry, and in recent years, the progress of Industry 4.0 has been realized a certain breakthrough, the electronics industry poses new challenges to the practitioner’s professionalism and knowledge reserve [1]. The electronics industry is one of the priority industries in the Roadmap for Making Indonesia 4.0 Strategy launched in 2019 [2].

The electronics industry in Indonesia requires refreshing, especially in enhancing and developing human resources competencies. To adhere to these objectives, the Industrial Training Center of Surabaya has a role in organizing training and education for human resources operators in the electronics industry. The 3in1 training and education (training - certification - placement) for electronic operators is a form of strategic activity carried out to answer the needs of training in the electronics industry. This electronic operator training activity collaborates with the electronics industry with export-oriented audio products (active speakers).

The Industrial Training Center of Surabaya collaborate with one of the electronic industries held the 3 in 1 training for electronics operators. The training design is developed according to the competencies required by electronic operators in the electronics industry. The development includes curriculum creation, determining the learning methods and materials, and a strict evaluation that adheres to the industry standard.

The 3in1 training for electronic operators aims to establish the essential competencies of participants. These competencies include skills, behavior, and knowledge in operating equipment in the electronics industry. Large part of the training takes place in the workshop room. The target of the 3in1 training for electronic operators is to produce competent human resources to be placed to work in the electronics industry [3]. Therefore, all training participants are expected to receive Competent certification results by the competency test scheme performed at the end of the training.

The competency test scheme used in the 3in1 training for electronic refers to the Decree of the Minister of Manpower and Transmigration of the Republic of Indonesia Number KEP.249 / MEN / IX

/ 2009 concerning the Stipulation of SKKNI in the Processing Industry Sector, Radio, Television, and Communication Equipment Industry and Its Equipment in the Audio Video. Especially focus on the operator level 1 test scheme with the occupation of PCB Mounting Operator Manual [4]. In line with this, the design of appropriate curriculum and education and training materials is necessary for continuous evaluation.

According to Rivai [5] training is part of the learning process to acquire and improve skills outside the education system that applies in a relatively short time with methods that prioritize practice rather than theory. For continuous learning improvement of the training, we need the information of each course subject's impact on determining participant's success in achieving the final competency test. Unfortunately, the available data is only in the form of participant evaluations from the teachers during each subject's assessment.

At the end of each course session, the teaching staff (Instructor and Widyaiswara) assess the participant to collect the evaluation score. Besides the assessment at the end of each course session, participants must take part in the final competency test with the recommendation of Competence (**C**) or Not yet Competence (**NC**). However, the number of participants stated as C and NC was very unbalanced. Therefore, the rough data evaluation needs to be further processed to reveal compelling information related to the impact of course subjects on predicting participant's success in the final competency test.

Therefore, this paper aims to build the prediction model to determine the success factor of participants in the final competence test. The prediction model result was then used to identify which course subjects that significant to the success of participants in completing the competence test. The data used in this paper are the evaluation of participants in several batches of 3in1 training for electronic operators in 2019. Meanwhile, the participant's competence test results category target (class) was obtained from the report issued by the professional certification agency of Industrial Training Center of Surabaya.

II. METHOD

This section described the proposed method implement to perform the study. The proposed method consists of four main stages, there are: data collection and data preprocessing, ranking the course subjects using ANOVA, building the prediction model using random forest algorithm, and calculate the performance measures of accuracies and precision rate from the predicting model in testing dataset. Figure 1 shows the order of steps in the methodology.

More detailed description on each stage is given in the following subsection. The machine learning approach in this study is use to build the prediction model of participant's competence test results based on the course subject rank dataset obtain from the ANOVA f-score.

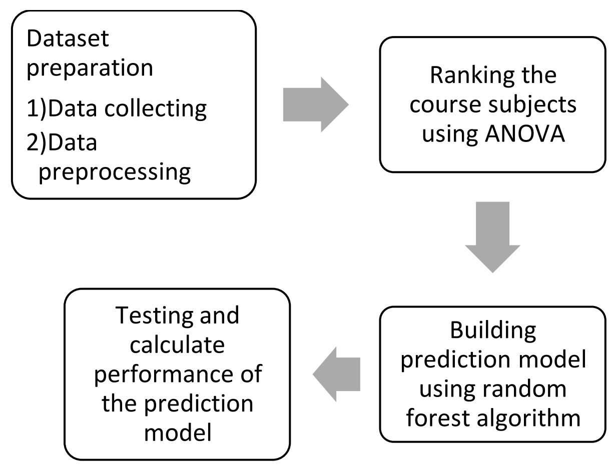


Fig. 1. Methodology of this study

A. Data collection

In this study, the raw data was obtained from the participant's assessment score at the end of each course subject. In 2019, the Industrial Training Centre of Surabaya held 12 batches of 3in1 training for electronics operators. Among those batches, we select 4 batches of 3in1 training data. This selection is made according to the completeness of the participant's evaluation score in entire course subjects. Moreover, these 4 batches of data also represent number of participant's data that are labeled as competent (C) and not yet competent (NC) participants. Table 1 shows the detailed description of the data that is collected for this study.

TABLE I
Raw data collected from 4 batches of 3in1 training

Batch number	Number of Participants: Competent (C)	Number of Participants: Not yet Competent (NC)	Total number of participants
4	1	40	41
5	1	47	48
6	5	45	50
9	3	46	49
∑ Data	10	178	188
% of Data / Total participants	5,3%	94,7%	-

There are two categories of course subjects delivered in the 3in1 training for electronics operators. These categories are practical subjects and theoretical subjects. We identify 8-course subjects that are related to the competency test material among the entire course subjects given in the training. Those 8-course subjects were shown in table 2.

TABLE II
Related course subjects to the competence test material

No	Course Subjects	Categories
1	5S-Kaizen	Theory
2	Basic of Electronics	
3	Quality Assurance	
4	Understanding Work Instruction	
5	Screwing	Practical
6	Inserting Component	
7	Soldering	
8	Fitting Assembly	

B. Data preprocessing

The raw data consists of 188 rows of participant's evaluation scores from 8-course subjects. This raw data becomes the original dataset for the training and the testing of the prediction model. the testing and training data division is done stratified randomly in each label of C and NC with a percentage of 20% of the total data. So that, the data used for the training process were 151 participants (8 NC and 143 C), and the data for testing the prediction model were 37 participants (2 NC and 35 C).

As seen in Table 2, the number of participants labeled Competent is much more than the data of participants labeled Not yet Competent. As a result, the percentage of data is not balanced for each label (C and NC). Therefore, in this step, the resampling process is carried out to balance the dataset.

In this study, we perform the resampling technique. The resampling technique includes oversampling, under sampling, and a hybrid combination of both [6]. Figure 2 illustrates how each resampling technique works for the dataset.

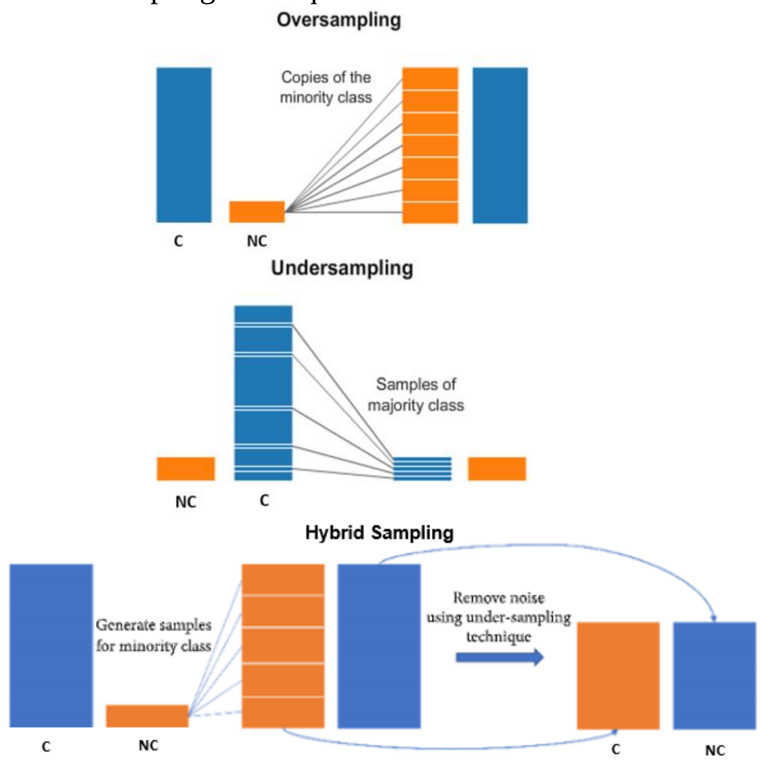


Fig. 2. The illustration of the resampling techniques

C. Course subjects ranking using ANOVA

For the organizer and the teaching staff, the information regarding the impact of each course subjects toward the participant's success in the competence test is essential. This information are beneficial for the teaching staff in preparing the lesson plan and improving the training curriculum. To address this problem, we propose the use of ANOVA (Analysis of Variance).

ANOVA is one of the statistical tests used to analyze the differences between the means in each category of the data sample. ANOVA calculates the f-score value between each course subjects against the target label [7]. The f-score score determines the difference between the mean scores of the features (in this case is course subjects) across the different target data labels (in this case, C and NC). The F-value score in ANOVA is then used to rank the importance of course subjects to determine the participant's competence test result.

D. Building prediction model using random forest algorithm

The training process aims to build a prediction model for UJK results based on input data that has been rated from the previous stage. Because the initial data used had an imbalance in the amount of data, a learning method was used that could handle unbalanced data, namely the ensemble classification method. In machine learning approach, the ensemble method uses multiple algorithms and learning techniques to obtain better performance than can be achieved from a single learning algorithm.

This research uses one of the algorithms known in ensemble learning, namely the Random Forest (RF). The prediction model in RF is built by combining many predictors to classify the data. The main classification algorithm in RF is a decision tree. RF is a combination of several trees which are then combined into one prediction model:

$$\{\, h_k = h(x, \theta_k),\ k = 1, \dots, N \,\} \quad (1)$$

Therefore, each tree in the RF model contributes one particular class category decision for each x data studied [8].

E. Calculation of accuracies and precision rate from predicting model

In this study, accuracy was used as the performance criterion. Accuracy is one metric for evaluating prediction models [9]. Therefore, the accuracy shows the fraction of the proposed models can correctly predict participant's competence test results. Accuracy is the proportion of the number of correct predictions from all categories (C and NC) divided by the total number of all data samples with the following formula:

$$Accuracy = \frac{Number\ of\ true\ positive + true\ negative}{Number\ of\ all\ data\ samples} \quad (2)$$

Other measures, such as precision is also used to show the results of performance predictions. The precision rate is given by the proportion of the number of correct predictions from the positive class (C or NC) divided by the total number of predicted samples from the positive class.

$$Precision = \frac{Number\ of\ true\ positive}{Number\ of\ true\ positive + false\ positive} \quad (3)$$

III. RESULTS AND DISCUSSION

In this section, we explore the implementation of the proposed method for predicting the participant competence test result using the ANOVA and Random Forest algorithm.

There are 151 participants data that available from 4 batch of electronics training course, the result of competence test recommended 143 participants as *Competence* **C** and 8 participants as *Not yet competence* **NC**. Therefore, in further processing 143 data labeled as **C** and 8 data labeled as **NC**. The dataset was used as original training dataset for the prediction.

Due to the imbalance size of each category in the dataset. We perform a resampling process. From the resampling process of the original dataset, we create two artificial data as the comparison in building the prediction model later, which are oversampling and hybrid sampling. However, we not performing the under-sampling technique because the total number of **NC** and **C** data was too small for building the prediction model. Table 2 shows the resampling results of the data. These three types of datasets were used across the experiments.

TABLE II
Resampling data results used in experiment

Dataset name and code	Number of rows		Percentage of Total Data (%)		Total Data
	NC	C	NC	C	
Original Dataset [ORI]	8	143	5%	95%	151
Oversampling [OS]	80	143	36%	64%	223
Hybrid Sampling [HS]	48	57	46%	54%	105

A. Course subjects rank from ANOVA

In each dataset, we compute the f-score from the ANOVA test for every course subject towards each category (**C** and **NC**). From the entire 8 course subjects, we select the best 5 course subject according to the f-score results. Those 5-course subjects are considered as the most impactful (significant) in determining the participant's success during the final competence test. Table 2 shows the f-score ANOVA results from the five best-ranked course subjects.

TABLE III
Course subjects rank results from ANOVA (f-score)

Rank	ANOVA (F-Score)					
	ORI		OS		HS	
1	Screwing	5,60	Screwing	39,91	Screwing	14,77
2	Inserting Component	5,38	Inserting Component	29,65	Inserting Component	12,03
3	Soldering	0,56	Soldering	3,67	Basic of Electronics	6,02
4	Basic of Electronics	0,37	Basic of Electronics	3,35	5S-Kaizen	3,26
5	5S-Kaizen	0,34	5S-Kaizen	2,69	Soldering	2,38

It can be seen from Table 3 that the results of the course subjects rank according to the ANOVA (f-score) are consistent for the three types of input data. From Table 3, it can be seen in general that there are 5-course subjects that have the highest importance on the participant competence test results, which are screwing, inserting components, soldering, basics of electronics, and 5S-Kaizen.

According to table 3, we can conclude that the practical course subjects were more take effect than the theoretical course subjects. Among the other practical course subjects, the screwing course obtains the highest f-Score value. It is because, in the screwing lessons, participants must focus on increasing their speed in doing work that also requires high concentration. So that participants who can get a good mark on screwing lesson practice tend to have the possibility of success during the final competency test.

This result is aligned with one of the principles of training according to William B Werther [10], the transference of knowledge and skills. The training programs designed following the implementation of the work will accelerate participants in learning and mastering the expected skills. In other words, the knowledge and skills conveyed during the training using the simulation or practice method will be easier to apply in actual situations while participants working in the related industry.

Meanwhile, the 5S-Kaizen was discovered to have an impact on the participant's competency test result, in addition to other theoretical subjects. It's because the 5S-kaizen course was not only taught in class but also as a practical habituation for participants before they started their daily activities in training. As a result, the 5S habits that participants have internalized have an impact on how they conduct the competency test. A prior study on the long-term effects of Kaizen training [11] backs up this conclusion. In the study, it was discovered that the Kaizen training program had a favorable impact on industry practices that lasted at least two years for the study's objects.

B. Prediction model from training dataset

To build a predictive model for participant's competency test results, we use the ANOVA result as a training dataset. In this stage, we apply the random forest algorithm. Based on the training dataset using the RF algorithm, we obtain the accuracy results of the prediction model for participant's competency test results in all types of experimental data input. Table 4 shows these results.

TABLE IV
Accuracies (%) and precision comparison from the prediction model in all data types

Dataset types	Accuracies (%)		Precision	
	8 Subjects	5 Subjects	8 Subjects	5 Subjects
ORI	91,9	94,6	0,893	0,895
OS	83,8	86,5	0,924	0,927
HS	73,0	75,7	0,916	0,918

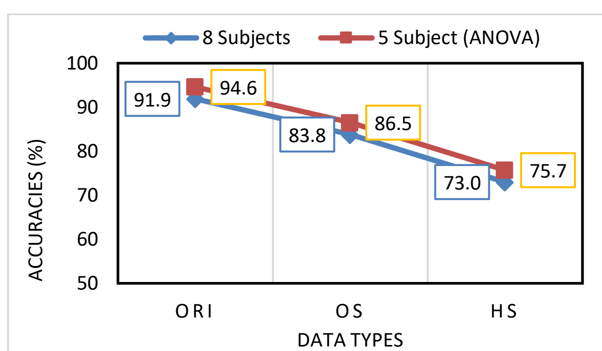


Fig. 3. The accuracies comparison from prediction model from all type of data input.

Table 4 shows the accuracy results of the participant's competence test prediction model for all types of data. Also shown in Figure 3, a comparison graph of the accuracies predictions using all training course subjects (8-subjects) and predictions using only 5 recommended course subjects from the ANOVA results.

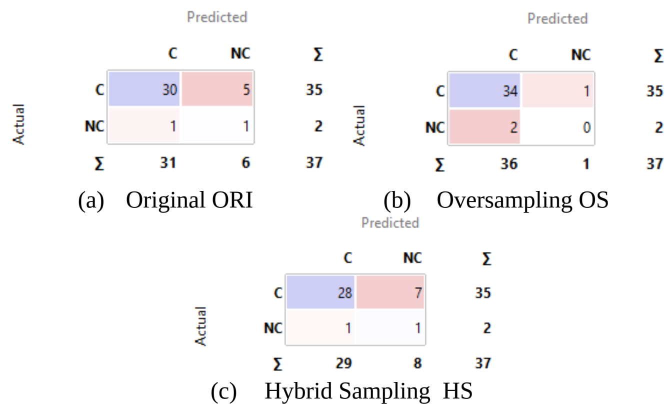
From table 4, we see that the accuracies in all data types obtained from 5-subjects (ANOVA) have slightly better than those of 8-subjects. It indicates that the 5-subjects recommend from the ANOVA were important in determining the participant's success during the final competency test.

The original dataset (ORI) achieves the highest accuracy of 91.9% for 8-subjects and 94.6% for 5-subjects (ANOVA). However, this accuracy itself does not guarantee that the prediction model is the most reliable. Based on the precision calculation shown in table 3, we see that the ORI data precision score is the lowest of 0.893 on 8-subject and 0.896 on 5-subject (ANOVA). This is due to an imbalance category in the ORI data. Meanwhile, the best precision results are in OS data and HS data. These results prove that the data resampling technique can overcome the problem of imbalanced data. At the same time, the accuracies and precision in table 3 show that the resampling techniques are beneficial to create predictive models with a balanced performance value between accuracy and precision.

C. Prediction model from testing dataset

For the validation of the prediction model of participants competence test result. We use the testing data which already design in the preliminary stage (see subsection A. Data Preprocessing of Method section). The total number of experimental data was 37 (2 C, 35 NC). Figure 4 shows the results of the prediction on the test data in all types of data experimental with the 5 most significant course subjects from the ANOVA results.

In Figure 4-a, the ORI data show that all trial samples were predicted as C class. This result proves that there are imbalanced data in the learning process so that all data are determined in the majority class (C). In contrast to the OS and HS data, there are several NC data that predicted correctly. These because there is an existing number of a minority class (NC) during the training process. As a result, the prediction model was relatively balanced. These indicate that the initial data resampling process was successful in dealing with the problem of imbalance in the amount of data per category.



(a) Original ORI (b) Oversampling OS (c) Hybrid Sampling HS

Fig. 4. The model prediction result confusion matrix on the testing data.

IV. Conclusion

In this study, a series of experiments were carried out on participant evaluation data. The goal is to build a prediction model for determining participant's competence test results.

Based on the results of predicting model on the original data, oversampling, and hybrid sampling dataset. It was found that practical subjects had a higher impact than theoretical subjects. From the results of the ANOVA test on the training dataset, with the respective target of C and NC, it was identified that 5-subjects have significant importance (based on f-score value). Those 5-subjects were screwing lessons, inserting components lessons, soldering lessons, basics of electronics, and 5S-Kaizen.

According to the ANOVA results, the 5-subjects which has a significant impact also proven in the prediction model participant's competence test result with better accuracy and precision performance compared to using the entire course subjects. Besides that, the data resampling process that was carried out in the data preprocessing also useful in reducing the imbalance in the number of data samples from each category (C and NC).

There are several benefits from the results of this paper. For the training organizers, they can make improvements to the curriculum by adjusting the duration of the lesson which is sufficient for the course subjects that have a significant impact on determining participant's success in the final competence test. As for teaching staff, they need to pay more attention to the course subjects which important for the participant's competence test, such as practical course subjects and 5S-Kaizen. Therefore, the intensive learning model is required. The learning model should focus on increasing the speed of work (in completing tasks) and the creation of daily habits in 5S-Kaizen.

V. ACKNOWLEDGMENT

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