Hemp-Alumina Composite Radar Absorption Reflection Loss Classification

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Abstract— The Radar Absorption Material (RAM) method is a coating for reducing the energy of electromagnetic waves received by converting the electromagnetic waves emitted by radar into heat energy. Hemp has been studied to have the strongest and most stable tensile characteristics of 5.5 g/den and has higher heat resistance compared to other natural fibers. Combining the characteristics of hemp with alumina powder (Al2O3) and epoxy resin could provide a stealth technology system that is able to absorb radar waves more optimally, considering that alumina has light, anti-rust and conductive properties. The electromagnetic properties of absorbent coatings can be predicted using machine learning. This study classifies the reflection loss of Hemp-Alumina Composite using Random Forest, ANN, KNN, Logistic Regression, and Decision Tree. These machine learning classifiers are able to generate predictions immediately and can learn critical spectral properties across a wide energy range without the influence of data human bias. The frequency range of 2-12 GHz was used for the measurements. Hemp-Alumina composite has result that the most effective structure thickness is 5mm, used as a RAM with optimum absorption in S-Band frequencies of -15,158 dB, C-Band of -16,398 dB and X-Band of -23,135 dB. The highest and optimum reflection loss value is found in the X-Band frequency with a thickness of 5mm which is equal to -23.135 dB with an absorption bandwidth of 1000 MHz and efficiency of 93.1%. From this result, it is proven that Hemp-Alumina Composite is very effective to be used as a RAM on X-Band frequency. Based on the results of the experiments, the Random Forest Classifier has the highest values of accuracy (0.97) and F1 score (0.98). The F1 score and accuracy of Random Forest are 0.96 and 0.97, respectively, and do not significantly differ from KNN.

Keywords— Hemp-alumina; stealth technology; machine learning; reflection loss; electromagnetic classification.

I. INTRODUCTION

Since radar's inception, researchers have looked into ways to lessen the impact of microwave reflections on its sensitivity. Impedance matching and resonant absorbers are the two primary categories of radar absorbers. Materials that are capable of absorbing radar are made up of elements that are resistive and/or magnetic. More design options are available thanks to the availability of capacitive and inductive loss mechanisms in circuit analog materials. The absorption frequency of dynamic absorbers can be tuned by controlling the resistive and capacitive terms. Many conductive and magnetic materials, including carbon, metals, and conducting polymers, have been tested for absorption. On the other side, Indonesia is endowed with natural conditions that encourage the growth of various flora with high economic value, one of

which is Hemp (Boehmeria Nivea). Because of its ability to absorb radar (Radio Detection and Ranging) waves optimally, Hemp has the potential to be used as a coating for military equipment with a Stealth Technology system (stealth technology). Hemp Radar, satellite, mobile, and point-to-point communication all use the microwave spectrum in today's communication and technology. Researchers from all over the world have taken notice of the sharp rise in electromagnetic pollution and have responded by creating a variety of microwave absorbing materials. Agricultural residue-based eco-friendly and biodegradable microwave absorber is an intriguing and difficult subject for contemporary researchers. [1] offers a comprehensive analysis of literature based on agriculturally based microwave absorbers. According to the literature, agricultural-based microwave absorbers can take the place of traditional

commercial polyurethane, polyimide, etc., absorbers for anechoic chamber applications. Reviewing the design, fabrication, and absorption characteristics of microwaves on eco green materials, the Hemp-Alumina is a material that have the ability to absord microwaves effectively. Raising the fiber content can enhance the strength of the composite material made from Hemp fibers [2]. Therefore, in this research, the Hemp-Alumina Composite material will be thoroughly studied as an alternative material which is environmentally friendly and low cost for coating anti-radar objects. However, the Radar Cross Section (RCS), which is a target area that reflects the incoming signal, is very important in the radar system's ability to detect targets [3]. The Stealth Technology system will perform better if the target RCS is as small as possible for radar to read. The RAM (Radio Absorbent Materials) method is one way to reduce RCS [4].

Several parameters must be considered in the RAM method, including weight, thickness, microwave absorption, environmental resistance, and mechanical strength [5,6]. [7] research shows that hemp can be used successfully as a renewable resource for bio-composites with minimal impact on the environment. Hemp composites may be unrivaled in the composite industry for bio-composite demand due to the higher strength, heat resintance, and stable tensile properties of hemp fiber. Combining Hemp characteristics with alumina powder (Al2O3) and epoxy resin is expected to result in a Stealth Technology system that can absorb radar waves more effectively due to the alumina content's light, anti-rust, and conductive properties [8].

Research on the impact of using Hemp-Alumina Composites as radar wave absorbers has been done by [9]. Descriptive statistics were employed in this investigation even though the data's distribution did not clearly indicate a threshold. Analytical relationships between coating characteristics and electromagnetic properties would be challenging under such circumstances. Machine learning is expected to be able to predict the electromagnetic properties of absorbent coatings in order to solve this problem. According to [10,11], Machine Learning will play a dominant role in the next generation of wireless technology because it provides a faster solution in the Electromagnetic domain. To create a consistent method for evaluating Startle Reflex, [12] designed a machine learning program and process that can categorize Startle Reflex wave patterns across various animal models automatically. The spectrogram of the S-parameter is processed using a deep convolutional neural network (DCNN) by [13] to identify the necessary features and classification boundaries.

Although machine learning is extremely useful, implementing machine learning presents numerous challenges. The selection of learning algorithms is one of the challenges. It is difficult to decide which algorithm to use because there are so many. The algorithm chosen is directly related to what is predicted as well as the type of data obtained. As a result, several Machine Learning methods will be used in this study to classify the reflection loss of Hemp-Alumina Composite based on frequency.

This research will offer a classification method that corresponds to the pattern of the data obtained. In this research, Random Forest, ANN, KNN, Logistic Regression and Decision Tree are used to classify the reflection loss of Hemp-Alumina Composite. The main contribution of this research is the comparison between many machines learning to classify the reflection loss and choose the best scenario which one is the best machine learning that have the highest accuracy.

II. MATERIAL AND METHOD

A. Data Collection

In this work, reflection loss was measured using *Vector Network Analyzer* VNA ADVANTEST type-3770 at the Research Center for Electronics and Telecommunications, The Indonesian Academy of Sciences. The first step is the collection of parameter data related to the thickness of the tested composite, the frequency of the tested range, the S-Parameter (S11), and the absorption that occurs in the composite. The existence of S-Parameter is intended to be able to determine the percentage of power that can be absorbed by Hemp-Alumina Composite based on variations in thickness (3 mm and 5 mm) in the frequency range of 2 – 12 GHz. Composites are printed in 3 sizes, this is because the tests were carried out on 3 frequency ranges, namely the S-Band, C-Band, and X-Band ranges using a waveguide. Table 1 shows the type of waveguide used for testing on each frequency band.

TABLE I
WAVEGUIDE TYPE AND COMPOSITE SIZE

Frequency	Waveguide	Size
S-Band (2-4 GHz)	A-INFOMW tipe 284WCAN	7.65 x 3.9 cm
C-Band (4-8 GHz)	A-INFOMW tipe 137WCAN	3.8 x 1.91 cm
X-Band (8-12 GHz)	AINFOMW tipe 90WCAN	2.75 x 1.5 cm

The work steps in data collection are as follows:

1. Print the Hemp-Alumina Composite size based on the frequency range namely C Band, S band and X band, after that it is attached to the waveguide and then covered with a metal cover.
2. VNA calibration
3. Installation of the waveguide on the coaxial cable that connects to the VNA
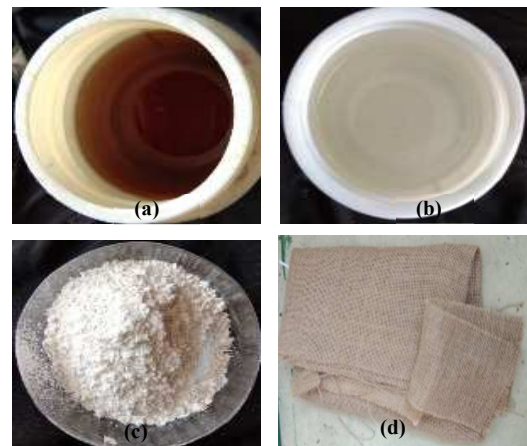4. Reflection loss data collection
5. Data validation

Fig. 1 Hemp-Alumina Composite Material: (a) Epoxy Hardener (b) Epoxy Resin (c) Alumina (d) Hemp Fiber in Woven Form
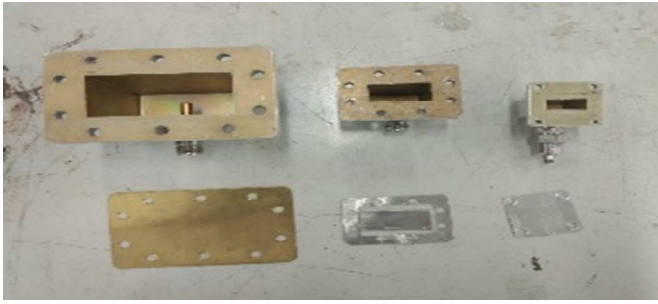
Fig. 2 Print Hemp-Alumina Composite Material Based on Thickness (3mm and 5 mm) and cut the according to the waveguide size: (a) S-Band: 7.65 x 3.9 cm (b) C-Band 3.8 x 1.91 cm (c) X-Band 2.75 x 1.5 cm

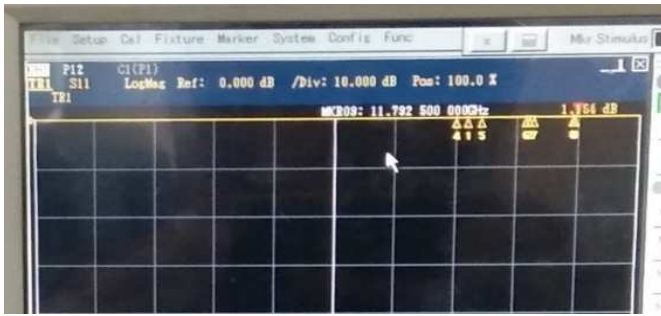

Fig. 3 Composite Installation on Waveguide

Fig. 4 VNA Calibration

Fig. 5 Connect Wave guide to VNA

Fig. 1. is the materials required to produce the Hemp-Alumina composite. Fig. 2. is waveguide used in the measurement process based on the frequency utilized. Figure 3 shows the composite installation during measurement on the waveguide. Figure 4 is the VNA calibration. The calibration process is using the manual dummy load provided by the manufacturer. Figure 5 presents the measurement process when the composite connected to VNA. These figures show how data is collected and the measurement framework, while Fig. 6. displays the data analysis framework.
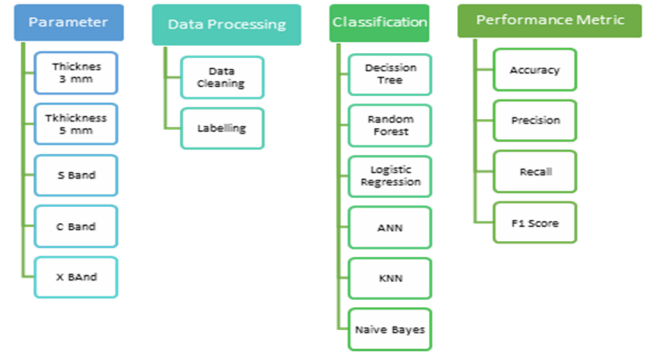

Fig. 6. Data Analysis Framework

B. Classification

Classification is a supervised learning technique used to identify new observation categories based on the classification model obtained from training data. In the classification algorithm, the program learns from datasets or observations, then new observations are classified into classes or groups such as yes or no, 0 or 1, spam or no spam, and so on. Classification algorithms that are frequently employed include the following: Decision Tree, Random Forest, Logistic Regression, Naïve Bayes, Artificial Neural Network (ANN) and K Nearest Neighbors (KNN).

Decision tree classifiers are widely recognized as one of the most commonly known approaches for representing data classification. Decision Tree is used to explore data by dividing a large data set into a smaller set of records and considering the destination variable. In general, the decision tree learning algorithm is a recursive process. The given data set is split so that the data is divided into several subsets and each subset is considered as a given data set in the next step. Split selection plays a very important role in the decision tree algorithm. In this study, the Gini index was used to split the data set. [14] takes a comprehensive approach to the decision trees.

In 2001, [15] introduced the Random Forest scheme. [15] used Random Forests to generate estimators along with a set of decision trees in this study. A random subset of the data is used to create the decision tree. The Random Forest classification method is a combined tree method for the development of the Classification and Regression Tree (CART) method by applying the bootstrap aggregating (bagging) and random feature selection methods. Random forest is a nonparametric analysis that can produce higher accuracy, can handle large amounts of training data efficiently, and there is no pruning of variables as in the decision tree algorithm (single classification tree).

NB classifiers are linear statistical classifiers that are regarded as being simplistic and extremely effective [16]. Bayes is a supervised learning algorithm that applies Bayes theorem. The classification method is done by predicting future opportunities based on previous experience. The main feature of the Naïve Bayes Classifier is a very strong assumption (Naïve) of the independence of each event/condition. One of the advantages of Naïve Bayes is that it does not require a lot of training data to predict the value of the classification parameter.

KNN is a machine learning method that aims at labeling previously unseen query objects while distinguishing two or

more destination classes [17]. KNN works by taking a number of k nearest data (neighbors) as a reference to determine the class of new data This algorithm classifies data based on similarity or proximity to other data. Following Euclidean distance equation method is used to calculate the distance between two points $X_1 = (x_{11}, x_{12}, ..., x_{1n})$ and $X_1 = (x_{21}, x_{22}, ..., x_{2n})$ in the KNN algorithm [18]

$$d(X_1, X_2) = \sqrt{\sum_{i=1}^{n}(x_{1i} - x_{2i})^2} \qquad (1)$$

Many studies use ANN because of their ease of implementation, ability to handle large amounts of data, and, most importantly, ability to learn from examples [19]. ANN is an information processing system that has characteristics similar to neural networks in living things. There are three different things that affect the characteristics of a neural network, namely architecture, learning algorithms and activation functions[20]. The Neural Network model usually use backpropagation neural network. Backpropagation consists of three constituent layers, namely the input layer, the hidden layer and the output layer.
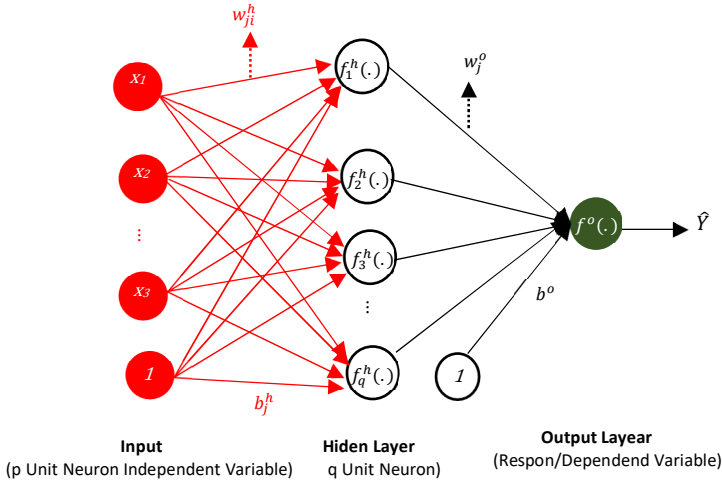

Fig. 7 Data Artificial Neural Network Architecture With One Hidden Layer

Logistic regression is a classifier with a classification method where each observation has a predictor variable related to the response variable [21]. Logistic regression as a classifier in classification analysis which classifies research subjects based on probability thresholds. The regression model used is based on training data which is then applied to the testing data.

Several classification algorithms are used in many studies to compare their performance. [22] Comparing Naïve Bayes and Decision Tree C.45 for hospital readmission diabetes patients. Research results [18] show that the Decision Tree gives better results than the Naïve Bayes algorithm. [23] compare the Naïve Bayes Algorithm, Decision Tree and Neural Network to classify the training course web pages. The study showed that Naïve Bayes gave the best performance with an F Score of 0.97. [24] compare the Random Forest, Logistic Regression and ANN algorithms to classify Bank Customer account closures. The results of this study indicate

that ANN provides the best performance with an accuracy of 0.86. In order to predict breast cancer, Nave Bayes and Random Forest were compared by [25]. According to the findings of this study, Random Forest has the best performance, with an accuracy of 0.98. [26] study the classification algorithms of Decision Tree, AODE, Naïve Bayes and KNN to analyze student's performance. The research shows that KNN provides the best accuracy than other algorithms. [27] use Naïve Bayes, Random Forest, and Decision Tree to classify customer profiling for bank telemarketing. In this study, it was found those three algorithms were able to improve performance even though using small number of features. Decision Tree provides the highest accuracy. Meanwhile Random Forest provide the highest precision and Naïve Bayes provide the highest recall. This study use only two feature, namely thickness and frequency, to classify reflection loss of Hemp-Alumina material. Therefore, the same classification algorithm in [28] used in this study. In addition, Logistic Regression, Artificial Neural Network (ANN) and K Nearest Neighbors (KNN) algorithms. The classification modelling was carried out with Python 3.

Intuitive performance indicators namely accuracy, precision, recall and F-1 score using a confusion matrix were used to validate the performance of the classification model. Calculation of the number of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) is required to create a confusion matrix. The calculation of the performance indicator is carried out using the following mathematical formula [29].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (2)$$

$$Precision = \frac{TP}{TP+FP} \qquad (3)$$

$$Recall = \frac{TP}{TP+FN} \qquad (4)$$

$$F1 - score = \frac{2 \times Precision \times Recall \, Precision}{Recall + Recall} \qquad (5)$$

The confusion matrix depicts the prediction made by machine learning algorithms and the actual situations. For each testing data, accuracy displays the ratio of true positives to true negatives. The accuracy determines how well the algorithm performs in making predictions. Precision is the proportion of correctly predicted positive test results to all predicted positive test results. Recall measures how often forecasts turn out to be accurate when compared to all test data. Precision and recall are weighted averaged to provide the F1 Score.

III. RESULT AND DISCUSSION

Visualization of reflection loss data against 2 - 12 GHz frequency at a thickness of 3 mm and 5 mm Hemp-Alumina composite material can be seen in the Fig. 8.

The graphic shows that the data does not follow a certain pattern and spreads non-linearly. Selecting the frequency range where the material works best as an absorber will be made easier with the use of Machine Learning. The

classification used in this study is binary classification with criteria in Table 2.
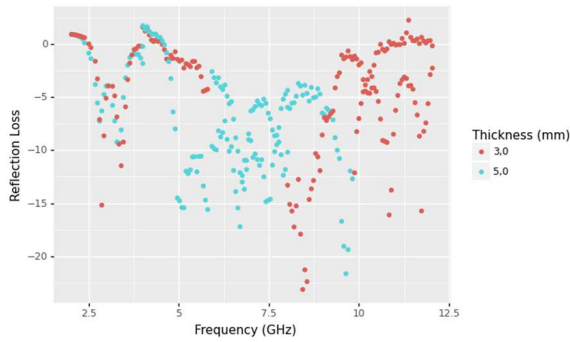

Fig. 8 Hemp-Alumina Composite Reflection Loss at 2-12 Ghz Frequency

TABLE II
ANALYSIS OF DATASET

Criteria	Classification
Reflection Loss < -10 dB	Good Absorber Material
Reflection Loss ≥ -10 dB	Poor Absorber Material

Summary data can be seen in Table 3.

TABLE III
SUMMARY OF REFLECTION LOSS DATA

Thicknes	Band	Count	Mean	Min	Max	Std
3 mm	S	31	-2.94	-9.32	0.93	3.18
	C	67	-4.43	-12.38	1.59	3.86
	X	68	-7.20	-21.65	-2.27	4.24
5 mm	S	31	-3.20	-15.19	0.90	4.25
	C	67	-8.66	-17.22	1.73	5.40
	X	68	-4.82	-23.14	2.25	6.61

The predictor variables used are material thickness and frequency. To get the classification model, the data is divided into two parts, namely 80% data as training data and 20% data as testing data. Table 4. lists the Decision Tree parameters.

TABLE IV
DECISION TREE PARAMETER

Parameter	Value
Criterion	Gini
Maximal Depth	20
Minimal Leaf Size	2
Minimal size for split	4
Random State	42
Minimal impurity decrease	0.001

Parameters used in Random Forest are same with Decision Tree parameter in Table IV, Material thickness and frequency are the input variables used in this paper for Logistic Regression model. While the output variable is Reflection Loss. Table 5. shows how output variables are classified.

TABLE V
LOGISTIC REGRESSION OUTPUT VARIABLE CLASSIFICATION

Criterion	Classification	Encoding
Reflection Loss < -10 dB	Good	0
Reflection Loss ≥ -10 dB	Poor	1

The same variable that was used in Logistic Regression is used in Naive Bayes Classification in this study. Likewise with the predictive variable encoding used.

TABLE VI
NAÏVE BAYES CLASS PROBABILITY

Class	Criterion	Value
Good	Posterior	$P(Good|Frequency, Thickness)$
	Prior	$P(Good)$
	Likelihood	$P(Frequency, Thickness|Good)$
	Evidence	$P(Frequency, Thickness)$
Poor	Posterior	$P(Poor|Frequency, Thickness)$
	Prior	$P(Poor)$
	Likelihood	$P(Frequency, Thickness|Poor)$
	Evidence	$P(Frequency, Thickness)$

The ANN has criteria as seen in the Table 7.

TABLE VII
ANN PARAMETER

Criterion	Value
Input Dimension	2
Hidden Layer	1
Activation	Sigmoid
Kernel Initializer	Uniform
Unit	10
Optimizer	Adam

The number of neighbors on KNN were tried from 1 to 40 with an error value that can be seen in the following figure 9.
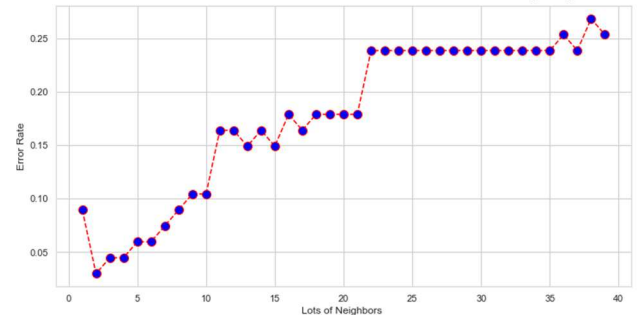

Fig. 9 Error Rate for 1 to 40 Neighbors in KNN

We can see in Fig. 9 that the closest average error value to 0 is when the neighbor values are 2. These results can be used as guidelines for determining the neighbor value that makes the KNN model high accuracy. From there we can minimize prediction errors.

Fig. 10. depicts the confusion matrix for the six methods used in this study. The model accuracy obtained from the Confusion Matrix is shown in Table 8.

TABLE VIII
MODEL ACCURATION

Algorithm	Accuracy
Decision Tree	0.90
Random Forest	0.96
Logistic Regression	0.82
ANN	0.88
KNN	0.97
Naïve Bayes	0.73

TABLE IX
MODEL PRECISION

Algorithm	Precision
Decision Tree	0.96
Random Forest	0.97
Logistic Regression	1
ANN	0.92
KNN	1
Naïve Bayes	1

a. Decission Tree   b. Random Forest   c. Logistic Regression
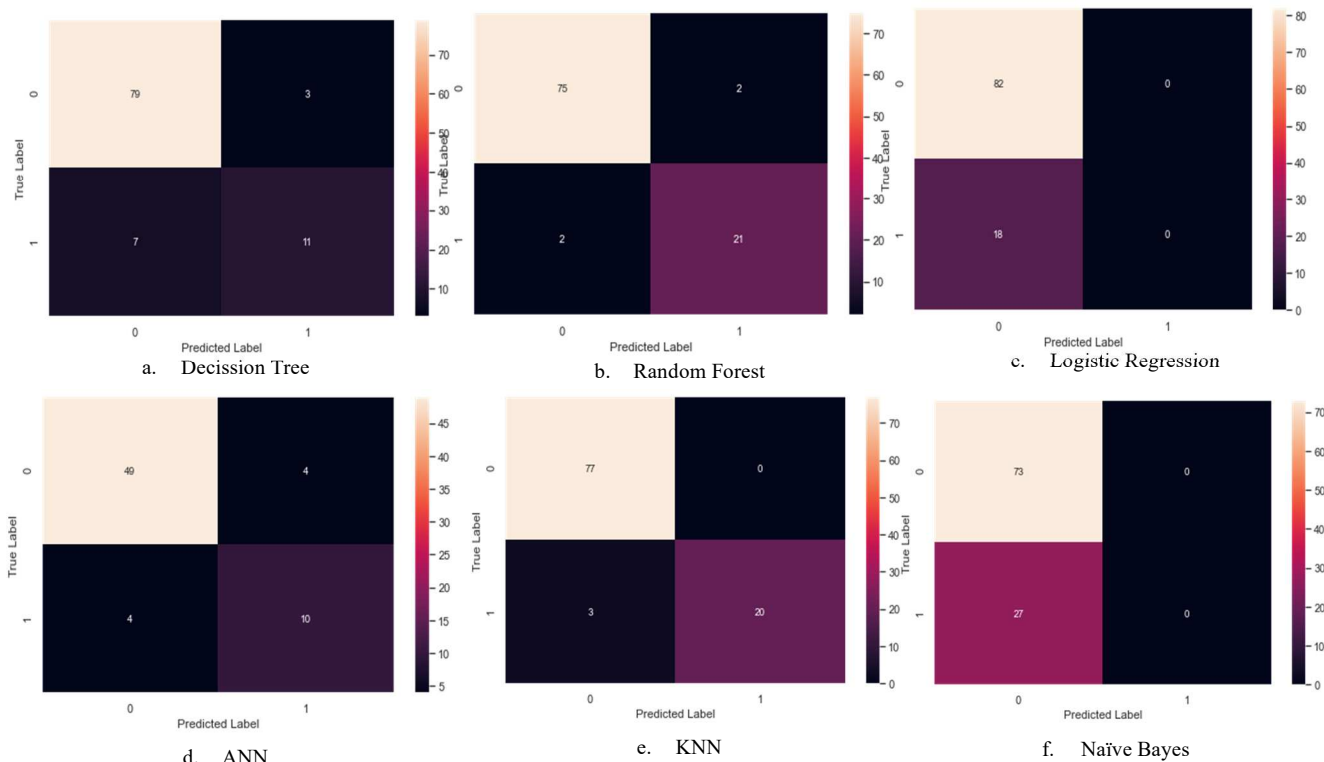
d. ANN   e. KNN   f. Naïve Bayes

Fig. 10. Confusion Matrix For Each Model

The precision of each model is presented in Table 9. The recall information for each model is presented in Table 10.

TABLE X
MODEL RECALL

Algorithm	Recall
Decision Tree	0.92
Random Forest	0.97
Logistic Regression	0.82
ANN	0.92
KNN	0.96
Naïve Bayes	0.73

The F1-Scores for each model are listed in Table 11.

TABLE XI
MODEL F1-SCORE

Algorithm	F1-Score
Decision Tree	0.94
Random Forest	0.97
Logistic Regression	0.90
ANN	0.92
KNN	0.98
Naïve Bayes	0.84

Fig. 11. reveals the high precision but low recall of the Naive Bayes method and Logistic Regression. This occurs when 100% of the testing data in both methods is labeled as a fair absorber even though it is actually a good absorber. To prevent this circumstance, [30] employed the performance metric F1 Score. In such circumstances, accuracy also provides better performance. KNN offers the best accuracy and F1 Score of the six algorithms studied, with values of 0.97 and 0.98, respectively. Similar to the accuracy and F1 Score values of 0.96 and 0.97, Random Forest likewise offers a high accuracy and F1 Score.
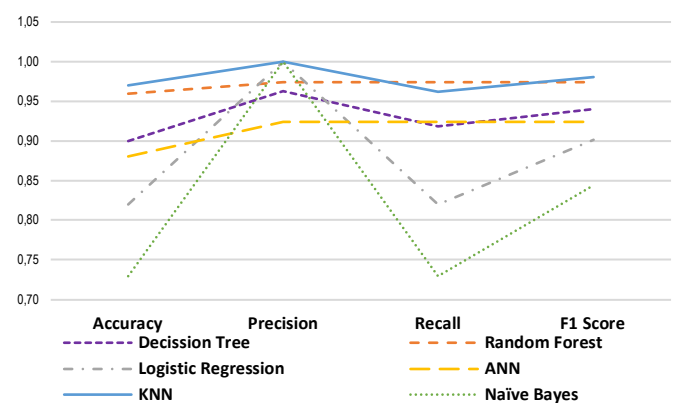

Fig. 11 Performance Indicator

IV. CONCLUSION

According to the results of the studies, the KNN provides the greatest accuracy and F1 score value, which are 0.97 and 0.98, respectively. Accuracy and F1 Score for random forest are 0.96 and 0.97, respectively, and do not substantially differ from KNN. Fig. 12. shows the classification tree created by a random forest. In future research, additional material thickness data will be carried out. The addition of this data is intended so that frequency absorption predictions can be made based on the thickness of the Hemp-Alumina composite material.

405

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