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MACHINE LEARNING CLASSIFICATION MODELS FOR DETECTION OF THE FRACTURE LOCATION IN DISSIMILAR FRICTION STIR WELDED JOINT

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Abstract:
Data analysis is divided into two categories i.e. classification and prediction. These two categories can be used for extraction of models from the dataset and further determine future data trends or important set of classes available in the dataset. The aim of the present work is to determine location of the fracture failure in dissimilar friction stir welded joint by using various machine learning classification models such as Decision Tree, Support Vector Machine (SVM), Random Forest, Naïve Bayes and Artificial Neural Network (ANN). It is observed that out of these classification algorithms, Artificial Neural Network results have the best accuracy score of 0.95.

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1. INTRODUCTION

Machine learning is the sub-domain of artificial intelligence, which gives ability to a computer system to perform a certain task without being programmed exhaustively. The main focal point of machine learning is to provide a particular algorithm, which can be further trained to perform a given task or an objective. Machine learning is adjacently related to fields of mathematical optimization and computational statistics [1-3]. Machine learning can be classified into four categories, i.e. Supervised Learning, Unsupervised Learning, Semi-Supervised Learning and Reinforcement Learning [4]. With help of Supervised Learning, the data can be processed and classified by using a powerful machine language. Supervised Learning is further sub-divided into two techniques, i.e. Regression and Classification techniques. The main focus of this research work is on Classification technique to be implemented in the Friction Stir Welding process. In supervised machine learning, Classification is one of the most important aspects. Classification technique is used for dataset categorization into a distinct and desired number of classes where labels are assigned to each class. Machine learning classification models find various applications in manufacturing industries. Zaghloul et al. [5] used machine learning classification approach for classifying electrical measurement results from a custom-designed test chip. Kim et al. [6] trained the models with Fault Detection and Classification (FDC) data for detection of the faulty wafer in semiconductor manufacturing process. Sudhagar et al. [7] used Support Vector Machine (SVM) classification model for classification and detection of defective welds by using surface images. Du et al. [8] studied the void formation conditions by using a decision tree and a Bayesian neural network classification models. Machine Learning is finding various applications in Friction Stir Welding process which is a solid-state joining technology mainly finds application in the joining of the alloys which are difficult to weld by conventional welding process.

In the present work, the dataset is used from the research work carried out by Chinnakannan et al. [9] for implementing various Machine learning classification models for determining the fracture location of dissimilar Friction Stir Welded austenitic stainless steel with the copper material.

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2. MATERIALS AND METHODS

Friction Stir Welding process was carried out to join dissimilar combinations of austenitic stainless steel (304L) to copper material. The main input parameters, used for carrying out the Friction Stir Welding process were tool rotational speed (rpm), burn off length (mm), upset pressure (Mpa) and friction pressure (Mpa). The experimental dataset is shown in Table 1. In Fracture location column, 0 indicates fracture at the copper location, while 1 indicates fracture at the weld location. The dataset is converted into a comma-separated values (CSV) file and it is futher imported into a Google Colaboratory platform for subjecting it to different Machine Learning classification algorithms.

Firstly, the dataset is subjected to the Support Vector Machine (SVM) algorithm. The SVM is a supervised machine learning algorithm, which gives a good accuracy for a limited available dataset and further uses less computational power. It is able to categorize two available set of classes. The main objective of the SVM algorithm is to find the best hyperplane for distinguishing the two available classes in the given dataset.

In the SVM models, instead of a simple line, there is a tube and a regression line in the middle. The tube shows a width ε and the width is measured vertically and along the axis, as shown in Fig.1, not perpendicular to the tube but vertically and this tube itself is called the ε-Insensitive tube indicated by yellow highlighted part in Fig.1. If any points in this dataset that fall inside the tube, their respective error will be disregarded. So, this tube can be thought of as a margin of error that are allowing the model to have and not caring about any error inside it. For the points outside the ε-tube, the error is given care. The distance between the tube and point is measured. Those distances have marks, $\in_i^*$ if the point lies below the tube and $\in_i$ if the point lies above the tube. So, the circled variables, shown in the Fig.1 are called slack variables. Equation (1) shows the relationship between the space parameter w and the above discussed distances.

$$\frac{1}{2}\,||w||^2 + c\sum_{i=1}^{m}(\in_i + \in_i^*) \qquad (1)$$

The value obtained from Equation (1) should be the minimum and the sum of the distances $\in_i$ and $\in_i^*$ should be thr minimum, as well.

Table 1. Experimental Dataset

Friction Pressure (Mpa)	Upset Pressure (Mpa)	Burn off length (mm)	Rotational Speed (RPM)	Fracture Location
22	65	1	500	0
22	65	2	1000	0
22	65	3	1500	0
22	87	1	1000	0
22	87	2	1500	0
22	87	3	500	0
22	108	1	1500	0
22	108	2	500	0
22	108	3	1000	0
33	65	1	500	0
33	65	2	1000	0
33	65	3	1500	0
33	87	1	1000	0
33	87	2	1500	1
33	87	3	500	0
33	108	1	1500	1
33	108	2	500	0
33	108	3	1000	1
43	65	1	500	0
43	65	2	1000	1
43	65	3	1500	1
43	87	1	1000	1
43	87	2	1500	0
43	87	3	500	1
43	108	1	1500	0
43	108	2	500	1
43	108	3	1000	0

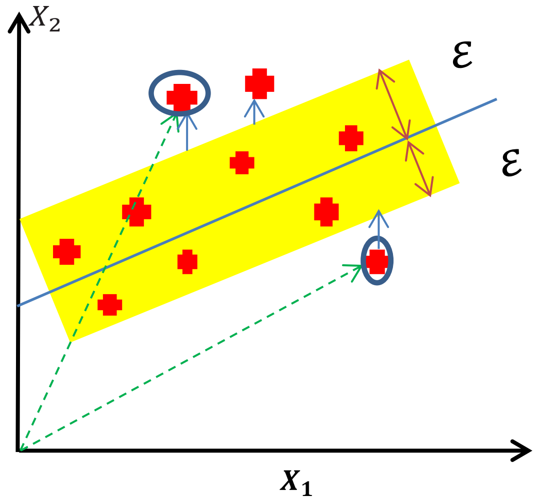

Fig. 1 Support Vector Machine Classification Model

Secondly, the dataset is subjected to Naïve Bayes classification algorithm. The working principle of Naïve Bayes is based on Bayes theorem, which further works on the conditional probability. With help of the conditional probability, probability of an occurrence of event can be calculated by using prior available knowledge.

Equation (2) represents the conditional probability where P (A|B) is the probability of the hypothesis given that the evidence is there, P (B) is the probability of the evidence (regardless of the hypothesis), P (B|A) is the probability of the evidence given that hypothesis is true and P (A) is the probability of hypothesis A being true, which is also known as the prior probability. The Naïve Bayes algorithm has many categories, but Gaussian Naïve Bayes algorithm has been used in the present work.

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)} \tag{2}$$

Thirdly, Decision tree classification algorithm is implemented on the dataset file. Decision tree is a supervised machine learning algorithm, which has a pre-defined dataset and is mostly used for the classification problem. The dataset is divided into two or more homogenous classes, based on the best splitter in input variables. There are two types of the decision tree i.e. continuous variable decision tree and categorical variable decision tree. In the present work, categorical variable decision tree has been used, because the target variables are 0 and 1. Important terminology regarding decision tree algorithm is shown in Fig. 2.

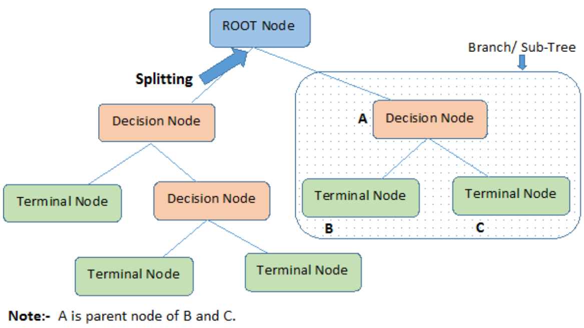

Fig. 2 Decision Tree algorithm structure [10]

The entire sample of dataset is represented by a Root Node, which is sub-divided into two or more sub-nodes by the process of Splitting. When the sub-nodes are divided into more sub-nodes, then the Decision Node is obtained. When the nodes do not split further then it is called the Leaf or Terminal Node.

Fourthly, the dataset is subjected to Radom Forest classification algorithm. The Random Forest is a supervised machine learning algorithm, which is formed by ensembling of decision tree and is further trained by bagging method. Multiple decision trees are built up by the Random Forest and are further merged together in order to give more accurate predicted value. Fig.3. shows the working principle of the Random Forest algorithm.

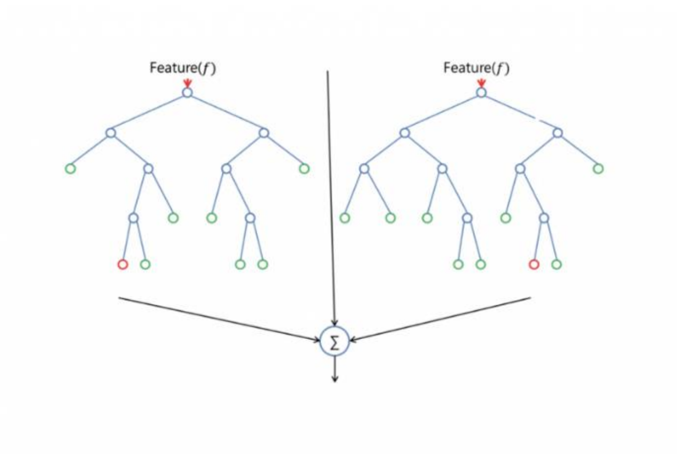

Fig. 3 Working method of Random Forest algorithm [11]

Fifthly, the Artificial Neural Network (ANN) is used for determination of the fracture location in the given dataset. The ANN model, used in the present work, consists of an input layer, two hidden layers and an output layer. The Input layer consisted of Friction Pressure (MPa), Upset Pressure (MPa), Burn off length (mm) and Rotational Speed (RPM) as input parameter nodes. Both hidden layers consisted of 11 nodes each of which are subjected to ReLu activation function and the output layer has the Fracture location as an output node, which is further subjected to sigmoid activation function as shown in Fig.4.

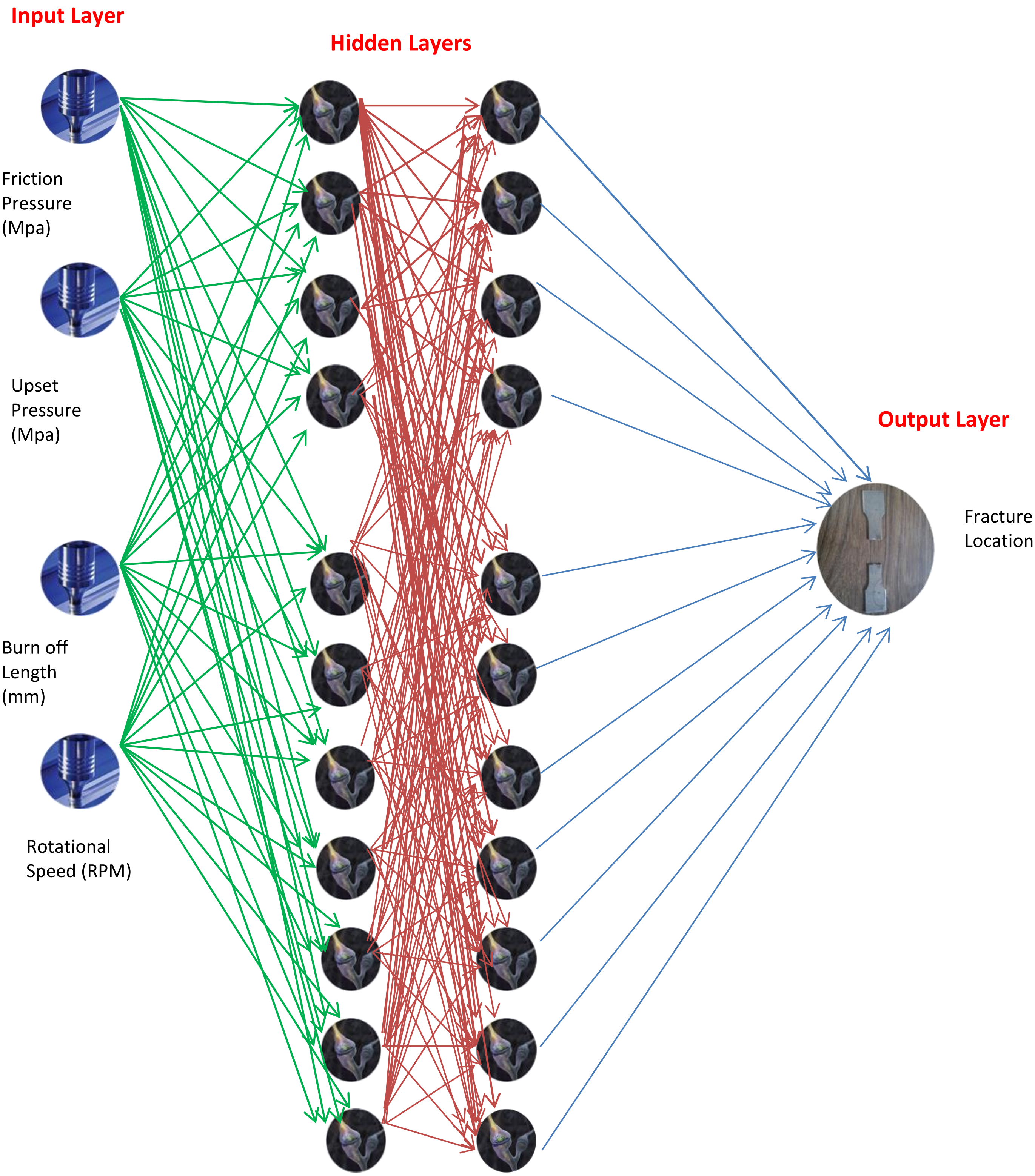

Fig. 4 Artificial Neural Network architecture implemented on the dataset

3. RESULTS AND DISCUSSION

The accuracy score obtained is 0.66 when the dataset is subjected to Support Vector Machine algorithm. The confusion matrix obtained in the case of the Support Vector Machine learning algorithm is shown in Fig.5.

From the confusion matrix is observed that values of Trues positives, True negatives, False positives and False negatives are 4, 0, 0 and 2, respectively.

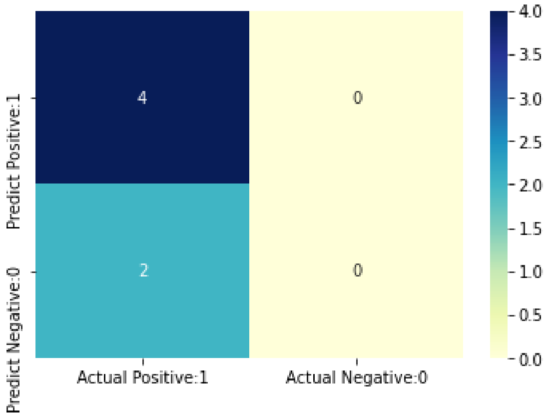

Fig. 5 Confusion Matrix for Support Vector Machine

The accuracy score obtained is 0.67 when the dataset is subjected to the Naïve Bayes Machine learning algorithm. The confusion matrix obtained in the case of Naïve Bayes algorithm is shown in Fig.6.

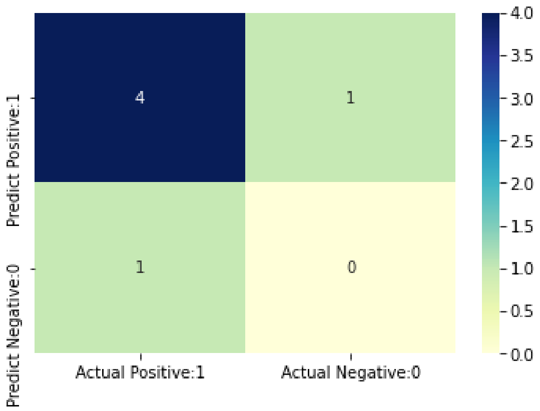

Fig. 6 Confusion matrix for Naïve Bayes Algorithm

From the confusion matrix obtained is observed that values of True positives, True negatives, False positives and False negatives are 4, 0, 1, and 1, respectively.

The accuracy score obtained is 0.50 when the dataset is subjected to decision tree machine learning algorithm. The confusion matrix obtained in the case of the Decision Tree Machine learning algorithm is shown in Fig.7.

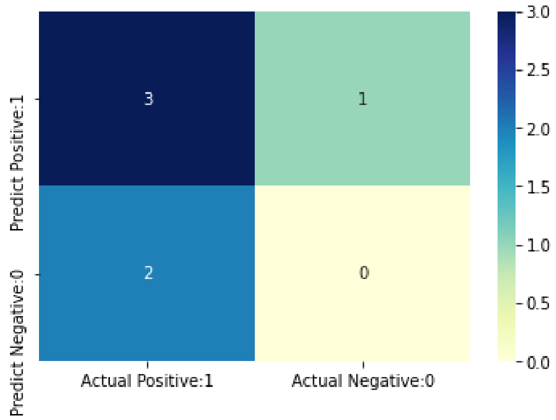

Fig. 7 Confusion Matrix for Decision Tree algorithm

From the confusion matrix is observed that the values of True positives, True negatives, False positives and False negatives are 3, 0, 1 and 2, respectively. The plot of the Decision Tree obtained when Gini criterion is used is shown in the Fig.8.

The decision tree obtained when Entropy criterion is used is shown in the Fig.9.

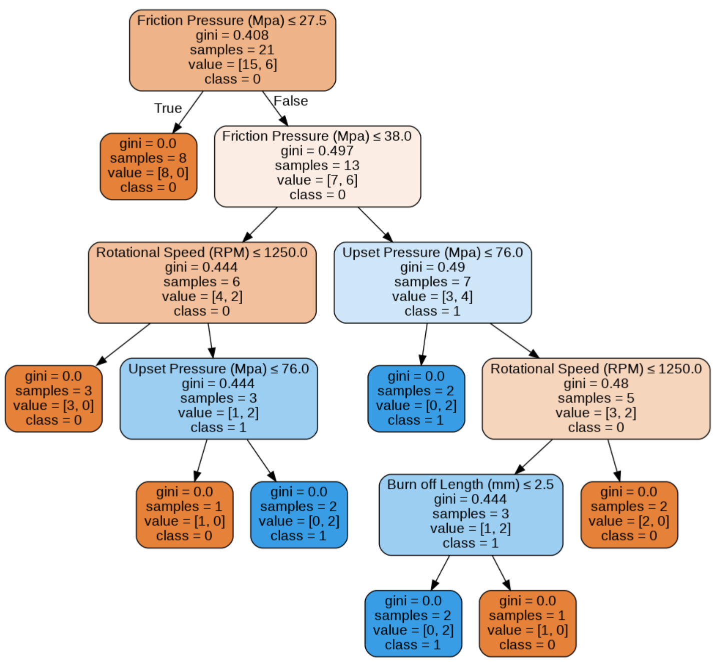

Fig. 8 Decision Tree obtained for the given dataset due to Gini Criterion

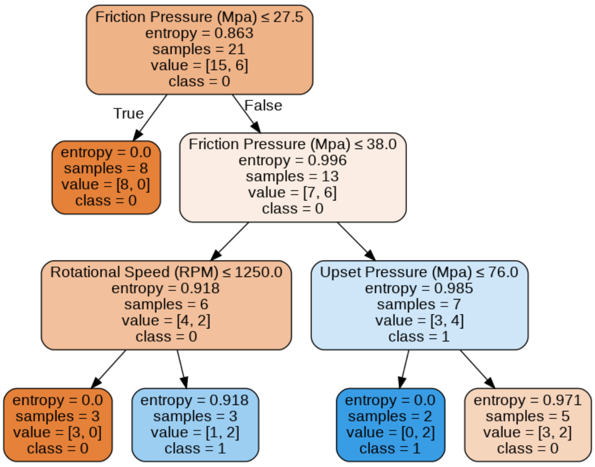

Fig. 9 Decision tree obtained from the given dataset due to Entropy Criterion

The accuracy score obtained is 0.50 when the Random Forest algorithm is subjected to the given dataset. The confusion matrix obtained in the case of the Random Forest algorithm is shown in Fig.10. From the confusion matrix is observed that the values of True Positives, True Negatives, False positives and False negatives are 3, 0, 2, and 1, respectively.

The accuracy score obtained is 0.95 when the Artificial Neural Network is subjected to the given dataset. The heat map is shown Fig.11. The confusion matrix obtained in the case of the Artificial Neural Network is shown in Fig.12.

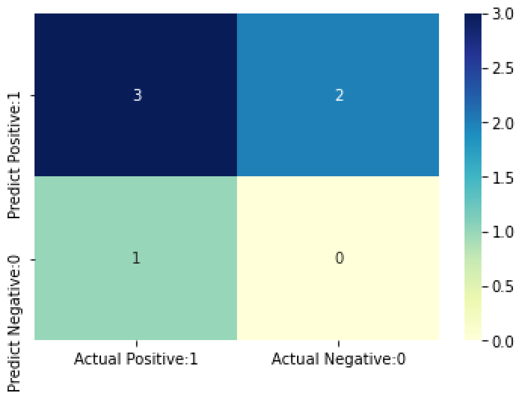

Fig.10 Confusion matrix for Random Forest algorithm

Fig.11 Heat Map of the given dataset

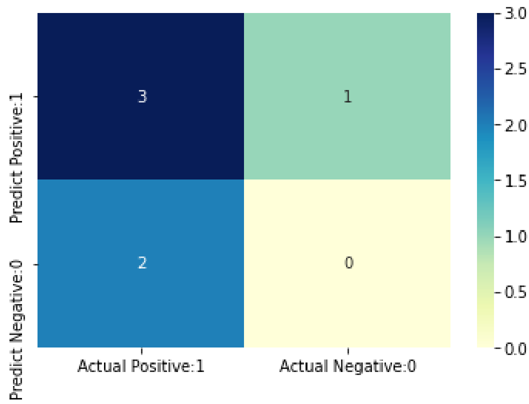

Fig.12 Confusion matrix for Artificial Neural Network

From the confusion matrix is observed that the values of True positives, True negatives, False positives and False negatives are 3, 0, 1 and 2, respectively.

CONCLUSIONS

Machine learning classification algorithms are successfully implemented for prediction of the fracture location in the Friction Stir Welded dissimilar joint. It is observed that the best accuracy score is obtained from the Artificial Neural Network algorithm, i.e. 0.95, while the lowest accuracy score is obtained from both Random Forest and Decision Tree algorithm, i.e. 0.50. The accuracy score can be increased if the number of given dataset is increased.

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