Common Bamboo Species Identification using Machine Learning and Deep Learning Algorithms

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Abstract: Due to its growth rate and strength, bamboo's versatility is huge. Bamboo has been developed to replace hardwood naturally. But it can be difficult to recognize a bamboo as many appear in a cluster or singular. Each bamboo type has its applications. Because of the utility of bamboo, we have worked in Random Forest, naive bays, logistic regression, the SVM-kernel, CNN, and ResNET, amongst several machine-learning algorithms. A similar test was carried out and delineated using graphs based on uncertainty matrix parameters and training accuracy. In this paper, we have used the data of following five species such as Phyllostachys nigra, Bambusa vulgaris 'Striata', Dendrocalamus giganteu, Bambusa ventricosa, and Bambusa tulda which are generally found in north India. We trained, tested and validated the species from datasets using different machine learning and deep learning algorithms.

Keywords : Machine learning, Random forest, naive Bayes, logistic regression, kernel SVM, CNN and ResNet

I. INTRODUCTION

Bamboo belongs to the Bambusoideae subfamily of the Poaceae grass family, which contains over 115 separate genera and over 1400 species. It is common in Eastern and South-Eastern Asia and on the Indian and Pacific Ocean islands. Very few of the Arundinaria genus members are originally from the south of the US. Bamboos are the world's big, fast-growing plants, thanks to a special rhizome-dependent mechanism. Bamboo is a fast-growing, versatile and non-wood forest crop that has unmatched biomass production rates for all other plants. Bamboo produces higher yields of raw materials for use, as biomass rises by 10-30 percent annually versus 2-5 percent for trees. Each bamboo component can be used. It is used for the manufacture of paper, walls, furniture, wood, materials of construction. Many bamboo pieces can even be eaten.

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Bamboo also decreases runoff, avoids significant soil erosion and, because of its high consumption of nitrogen, helps minimize water pollution.

Dues to its height, regenerates, and is resilient, even after strong typhoons, the environment protects against typhoons. No other plant material could be competitive with the utility of bamboo. It is also a food source. It has been used in many ways in the early years, not to mention the traditional use of bamboo in early people's daily life, particularly in Asia. Being as important as that, it can allow both researchers and civilians to recognize quickly and easily. Different bamboos have various characteristics and we chose five bamboo species for this article: Phyllostachys nigra, Bambusa vulgaris'Striata',Dendrocalamus giganteus, Bambusa ventricosa, Bambusa tulda. Phyllostachys nigra: Phyllostachys nigra is a flora plant in the bamboo subfamily of the Poaceae family of plants, a member of China's Hunan province and is widely grown elsewhere. The common term i s black bamboo.

Bambusa vulgaris: The standard, open-clump type bamboo species is Bambusa vulgaris. It is native to Indochina and Yunnan, but is widely grown in many other parts of China. Dendrocalamus giganteus: The giant tropical or subtropical, dense-clumpant plant nativ e to Southeast Asia is commonly known as the Dragon Bamb oo or one of several species called Giant Bamboo.

Bambusa ventricosa: Bambusa ventricosa is a bamboo plant that is raised in southern China in both Vietnam and the province of Guangdong. The crop is cultivated widely for bulbous and ornamental peaks in subtropical regions throughout the world.

Bambusa tulda: Bamboo tulda is considered one of the most useful of the species in bamboo, or Indian timber bamboo. Originally from Indochina, Tibet and Yunnan, it is naturalized in Iraq, Puerto Rico and areas of South America. it is native to India.

The variations between the various bamboo species can be difficult. Image classification is one of the sublime and worthy approaches in the technological world from which we can see great results in the classification of an image in different fields, which is an element of computer vision. Computer Vision is a general perception of and contexts of visual settings. Classification of images refers to a computer vision mechanism that can identify the image by visual content. The classification of images is usually split into two categories, i.e. Supervised learning and unsupervised learning.

Supervised learning refers to an algorithm in which the given dataset is labelled, i.e. the output to be predicted is given whereas unsupervised algorithm refers to an algorithm in which the given dataset is unlabelled, i.e. the predicted output is not given.Various image recognition methods such as machine learning algorithms, profound learning algorithms and certain pretrained models such as Microsoft ResNet[1]. Machine Learning represents mathematical concepts based on some formulas and equation on probability and statics. Machine learning algorithms and deep learning algorithms for classification purposes are Logistic Regression [2], KNN [3], SVM [4], Random Forest [5], Naive Bayes [6], Convolutional Neural Networks [7], etc. These fall under the category of classification algorithms which uses the concept of hyper-plane, decision boundary, cost functions, etc.

This paper presents a comparative analysis of five algorithms and one pre-trained model logistic regression, support vector machine, naive bayes, random forest, convolutional neural networks and ResNet for 5 common species of bamboo collected from Forest Research Institute (FRI), Dehradun, India.

The organization of our work is as follows. Section II explains a brief literature survey of research which are already done on the merger of Technology and forest. Section III denotes overview of Bamboo species, machine and deep learning algorithms. Section IV describes the proposed methodology used for the proposed work with result analysis. Finally, section V gives a conclusion and its future scope.

II. LITERATURE SURVEY

The integration of the technology with forest analysis results to an expeditious in classification and detection of these floral and faunal species. Applications like classification and detection of species in the forest, forest cover classification using geo satellite images, GIS applications in forestry, Intelligent Navigation, and a lot more. A brief literature survey is given below. I. Gogul et al. [8] used convolutional neural networks and transfer learning for the flower recognition system. It helps to determine the flower from 28 classes. The combinations of convolutional neural networks

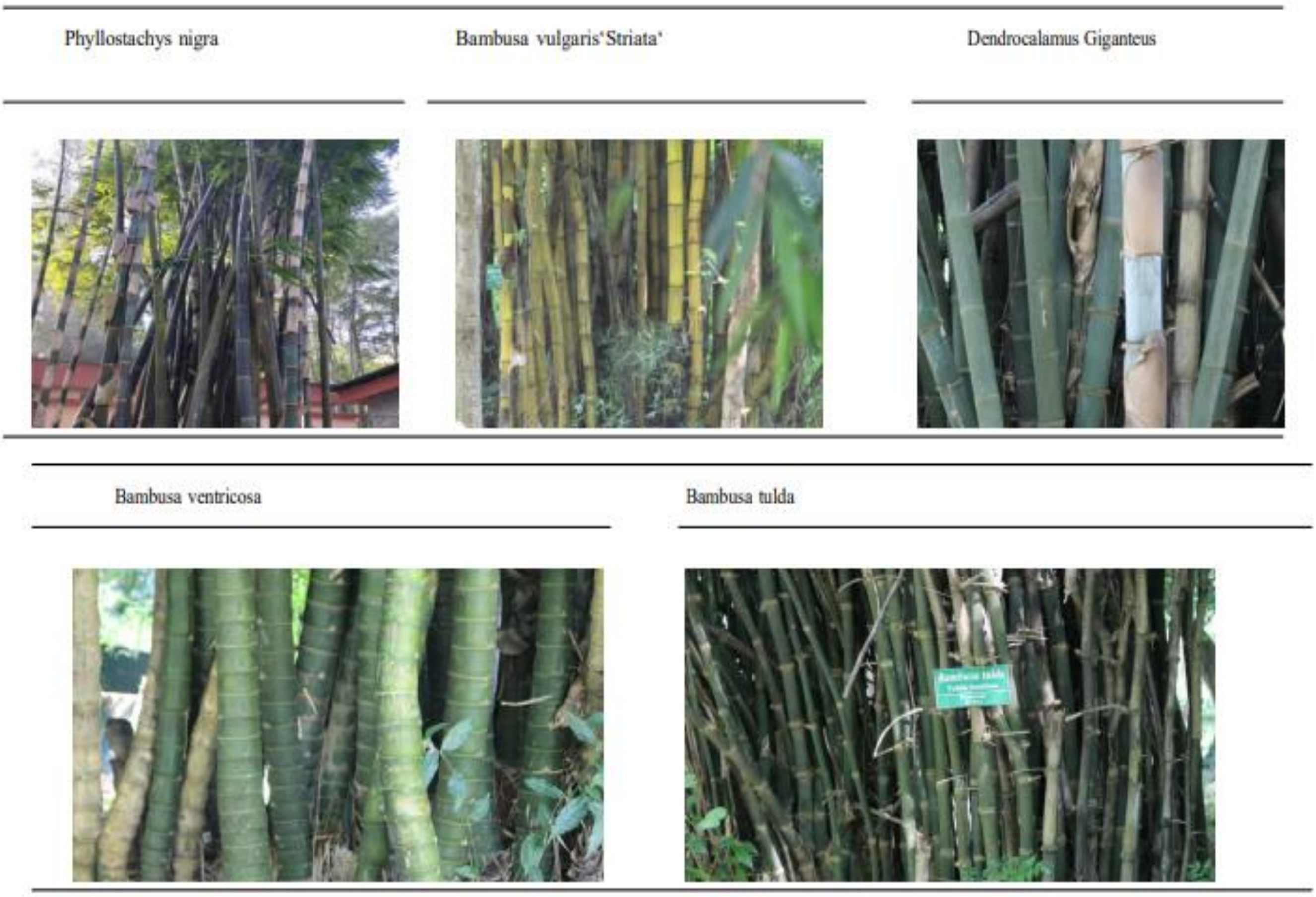

Fig. 1. Bamboo Species

and transfer learning used as a feature extractor such as Local Binary Pattern (LBP), Color Channel Statistics, Color Histograms, Haralick Texture, Hu Moments, and Zernike Moments. Niko S underhauf et al. [9] used CNN(Convolutional Neural Network) to extract the features from the image for classifying the plant of QUT from an image. It was trained initially for general object classification using millions of images from the ImageNet dataset. Luiz G. Hafemann et al. [10] constructs deep neural networks for forest species recognization. The idea behind this is to get the texture for texture classification in the two forest species with two forest species dataset, i.e., one with macroscopic images and another with microscopic images. Highresolution texture images are used. The achieved accuracy is 95.77% and 97.32% by beating the best result.

S. Natesan et al. [11] constructs a tree classifier using UAV Images using and ResNet. High-resolution RGB images are gathered from a camera mounted on a UAV platform over 3 years that varied in numerous acquisition parameters such as season, time, illumination and angle to train. Two pine species, namely red pine and white pine, were taken for the research by dividing it into two categories, i.e., one with three acquisition years and the second with one acquisition year. The achieved accuracy is 51 % over classification. K. Suzuki et al. [12] constructs a Convolutional Neural Network. Using simultaneously acquired airborne images and LiDAR data, they attempted to reproduce the 3D knowledge of tree shape, which interpreters potentially make use of geospatial features which support interpretation are also used as inputs to the CNN. They had shown that the multi-modal CNN works robustly, which gets more than 80 % user's accuracy and also 3D multi-modal approach is especially suited for deciduous trees.

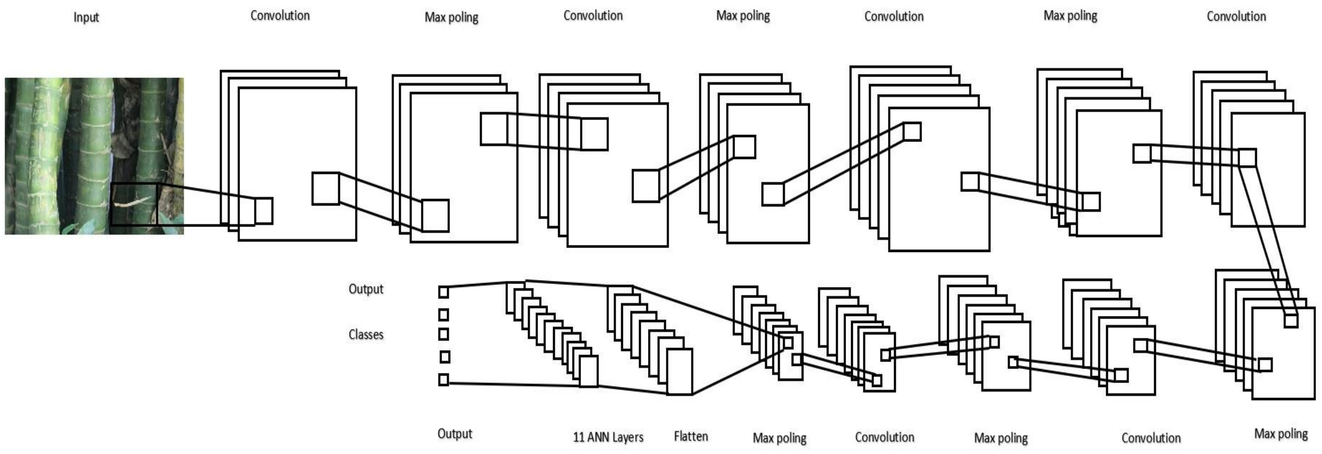

Fig. 2. Structure proposed convolution neural network.

III. PROPOSED METHODOLOGY AND RESULT ANALYSIS

For this paper, the images have been obtained from the botanical garden of FRI, Dehradun. The acquisition consists of five species of bamboos. These are Phyllostachys nigra, Bambusa vulgaris 'Striata, 'Dendrocalamus giganteus, Bambusa ventricosa, Bambusa tulda, for each species approximately 120 images were collected and augmented. The operations executed on the photos were 90-degree rotation, 180-degree rotation, sharpened, blurred. To keep uniformity within the dataset, we took photos from a distance of about 1 meter from the respective bamboo. Then the images are introduced to the selected classification algorithms. Classification is predicting the target class based on the training data. The classification algorithms that we have selected are: Logistic regression: It is a binary classifier which estimates discrete values based on a given set of independent variable/variables. It predicts the probability of the existence of an event by fitting data to a logit function. It is used when the dependent variable is categorical. For multiclass classification, the training process is also called one vs all classification. We train multiple logistic regression, i.e. one for each class in training dataset. While we are training, we grab a single class and treat it as +ve (y==1) and group the rest of the classes together and assign them with a negative value (y==0). The prediction process can be called as One vs all prediction. The probability is computed for each class then one-vs-all prediction function will pick out the class for which the corresponding logistic regression classifier outputs the highest probability and return the class label.

State Vector machine: Each data item is plotted as a point in n-dimensional space with the value of each feature being the value of a particular coordinate, where n is the number of features. Then, we perform classification by obtaining the hyper-plane that differentiate the two classes. This algorithm is very efficient in high dimensional spaces. It also conserves memory by using a subset of training points in the decision function.

Naive Bayes: This classifier works on the hypothesis that the existence of a particular feature in a class is conditionally dissimilar with the presence of any other feature. Initially, the algorithm identifies the prerequisites to train a Nave Bayes classifier. It calculates the prior probability for given class labels. The conditional probability with each attribute with each class is calculated by using Bayes theorem. It multiplies the same class conditional probability. Then it multiplies prior probability with a probability calculated in the previous step. Lastly, the algorithm checks for the class with the greatest probability.

Random forest: It is used for both classification as well as regression. However, it is mainly used for classification problems. We know that a forest is consists of trees and more the number of trees means more robust forest. Likewise, random forest algorithm generates decision trees on data specimens and then gets the prediction from all of them and finally selects the best solution using voting. It is an ensemble method which is much better than a single decision tree as it reduces the overfitting by averaging the result. It works well for a broad range of data items than a single decision tree does and has less variance than a single decision tree.

Convolutional Neural Networks: It is a variant of neural networks used massively in the field of Computer Vision. It receives its name from the type of hidden layers it consists off. The hidden layers of a CNN typically consist of convolutional layers, pooling layers, fully connected layers, and normalization layers. In this convolution and pooling functions are used as activation functions. Convolution: The main constituent of Convolutional Neural Networks is the convolutional layer. Convolution is a mathematical operation to merge two sets of information. By applying convolution to an image means we use a convolution filter, also known as the kernel to generate a set of feature maps to generate a feature map the kernel slides over the image, and we compute an element wise matrix multiplication and sum the results. We keep adding the results after each slide to the feature map. Pooling: It is performed after the convolution operation. ordinarily perform pooling to reduce the dimensionality. Pooling allows us to diminish the number of parameters, which shortens the training time and combats overfitting. Pooling layers down sample each feature map separately, reducing the height and width, keeping the depth intact. The most basic type of pooling is max pooling which takes the max value in the pooling. After the desired amount of convolution and pooling operations, the feature maps are flattened and attached to a fully connected layer which is nothing but an artificial neural network. Kernel or convolution filter detects various edges, i.e. convolution extracts feature from the image and makes artificial neural network capable of recognizing features common to a class. The proposed architecture of CNN is shown in Fig. 2.

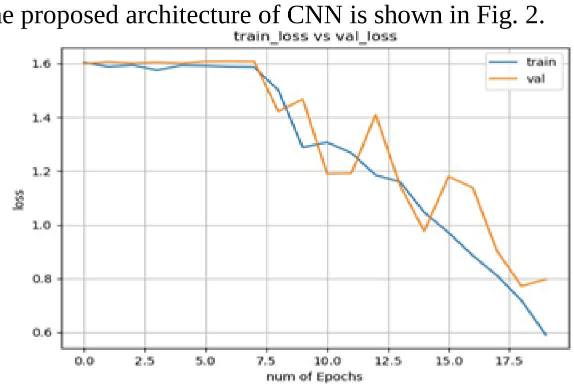

Fig. 3. Plot of training vs validation loss of CNN.

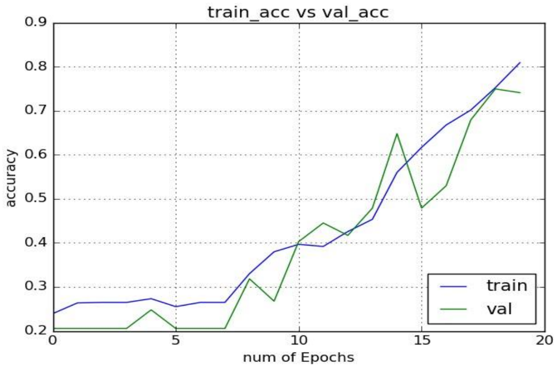

Fig. 4. Plot of training vs validation accuracy of CNN.

The input size for the first convolution layer is 224x224. It has six convolution operations, and every convolution operation is accompanied by a max pool operation. After last max pool operation feature maps are flattened and attached to an artificial neural network which has 11 layers. Fig. 3 illustrates the training loss vs validation loss of CNN. Fig. 4 illustrates the training accuracy vs validation accuracy of CNN. Residual Network (ResNet): This network provides a platform for residual learning, which promotes network education that is much broader than traditionally used. Even deep models have gained considerably from many visual recognition tasks. There is a desire to go deeper, to solve more complex tasks and also to improve the accuracy of classification. As the layers in the neural system increase, however, it becomes difficult to form the neural network, and precision also begins to saturate and then degrade. Both of these problems are overcome by residual learning. Several layers are stacked and trained for the task in a deep convolutionary neural network. At the end of its layers, the network tests many low / medium / high levels. We try to learn some residual in residual training instead of trying to learn some traits. The remaining material can be interpreted as a removal of the dimension learned from this layer's data. ResNet does this through shortcut links (directly connecting the nth layer input to a certain $(n+x)^{th}$ layer. It has shown that training this form of networks is more convenient than training simple deep neural networks. Instead of learning a ResNet from the ground up, we can use its pre-trained weights to train our model. Transfer learning is a technique in which a single workplace model is used to perform a second related task. Training a neural network such as ResNet will take a lot of computing time, so we can use their pre-trained weights instead of training them from scratch. These weights were trained in the wide and challenging task of classification of images such as the photographing competition ImageNet of 1000 class. We use ResNet50 as a state-of - the-art function transformer by cutting off its linear model, trained for various classes and applying our linear classification to it. The training process is going very quickly because we only train logistical regression. ResNet-50 is a CNN educated in the ImageNet database on more than a million images. The network is 50 deep layers in which images can be grouped into 1000 categories of objects. Fig. 5 illustrates the training loss vs validation loss of ResNet. Fig. 6 illustrates the training accuracy vs validation accuracy of ResNet. If we are predicting for Phyllostachys nigra then:- True Positives (TP): These are cases in which we predicted yes (Bamboo is Phyllostachys nigra), and it is Phyllostachys nigra. True Negatives (TN): We predicted no, and it is not Phyllostachys nigra Bamboo. False Positives (FP): We predicted yes, but it is not Phyllostachys nigra. (Also known as a “Type I error”) False Negatives (FN): We predicted no, but it is Phyllostachys nigra. (Also known as a “Type II error.”) Precision is a fraction of true positive and actual result, whereas recall is a fraction of true positive and predicted outcome. With the help of precision and recall, we get the accuracy of a model by the given formula.

Precision = TP/(TP + FP)

Recall = TP/(TP + FN)

A = (TP + TN)/(TP + TN + FP + FN)

Error rate can also be calculated by inverting the accuracy value as:

Error rate = (1− A)∗100

From the classification report in Fig. 7 and Fig. 8, we observed that the various algorithms have different precision and recall. Therefore, the F1 score is a harmonic mean of precision and recall from which we can analyze different algorithm more efficiently.

F1score = 2∗((Precision∗Recall)/(Precision+Recall))

The calculated F-Measure will be close to the smaller value of Precision or Recall. It is useful than accuracy in case of uneven class distribution [Fig. 7], [Fig. 8].

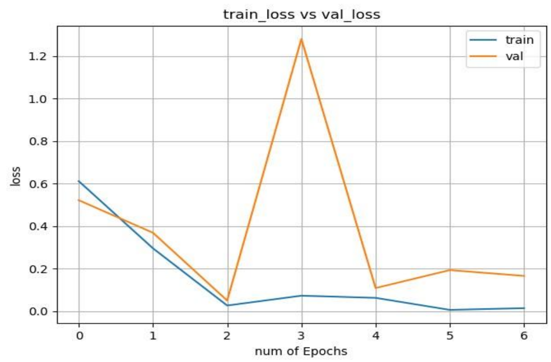

Fig. 5. Plot of training vs validation loss of ResNet.

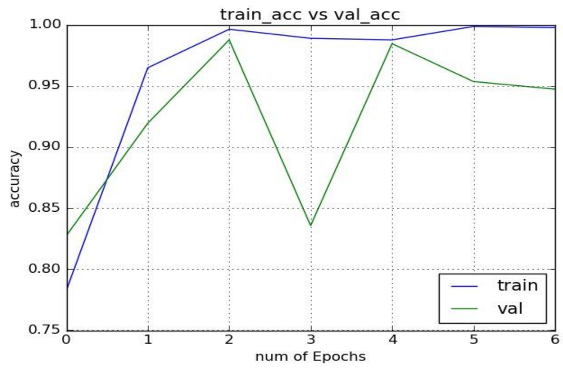

Fig. 6. Plot of training vs validation accuracy of ResNet.

	PHYLLOSTACHYS NIGRA			BAMBUSA VENTRICOSA			BAMBUSA TULDA		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score
RANDOM FOREST	0.58	0.51	0.55	0.60	0.60	0.60	0.56	0.69	0.62
NAÏVE BAYES	0.54	0.32	0.40	0.33	0.51	0.40	0.45	0.31	0.36
SVM	0.89	0.63	0.74	0.49	0.57	0.53	0.68	0.49	0.57
LOGISTIC REGGRESSION	0.88	0.73	0.80	0.66	0.84	0.74	0.81	0.64	0.71
CNN	0.89	0.157	0.69	0.72	0.84	0.78	0.80	0.91	0.85
RESNET	**0.90**	**0.81**	**0.85**	**0.71**	**0.98**	**0.83**	**0.93**	**0.79**	**0.86**

Fig. 7. Classification report of classes Phyllostachys nigra, Bambusa ventricosa and Bambusa tulda.

	DENDROCALAMUS GIGANTEUS			BAMBUSA VULGARIS 'STRIATA'		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
RANDOM FOREST	0.56	0.52	0.54	0.57	0.48	0.52
NAÏVE BAYES	0.39	0.45	0.42	0.43	0.36	0.39
SVM	0.69	0.60	0.64	0.47	0.79	0.59
LOGISTIC REGGRESSION	0.77	0.78	0.78	0.71	0.74	0.73
CNN	0.84	0.77	0.81	0.83	0.86	0.84
RESNET	**0.98**	**0.80**	**0.88**	**0.93**	**0.86**	**0.89**

Fig. 8. Classification report of classes Dendrocalamus giganteus and Bambusa vulgaris striata'

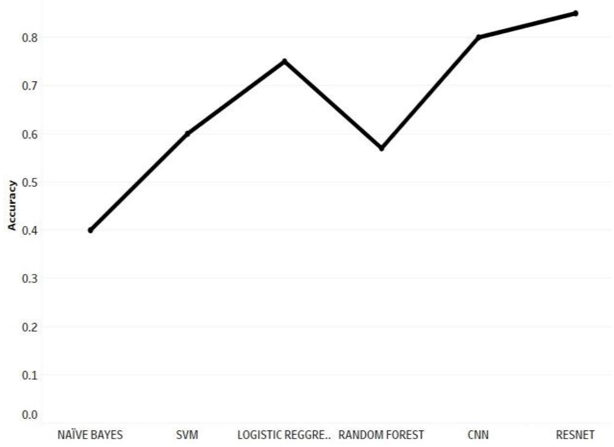

Fig. 9. Plot of accuracy of different algorithms.

The Calculated accuracy by Random Forest, Naive Bayes, SVM, Logistic Regression, CNN and ResNet are 57%, 40%, 60%, 75%, 80% and 86%. Fig. 9 represents that ResNet has achieved maximum accuracy, and Navie Bayes achieved the least. It is excellent to achieve 86 percent accuracy in the identification of bamboo species and can also be further improved for more bamboo groups. Fig. 10 illustrates F1-score performance plot of all class algorithms. We have observed that for all classes ResNet is extremely good compared to other algorithms.

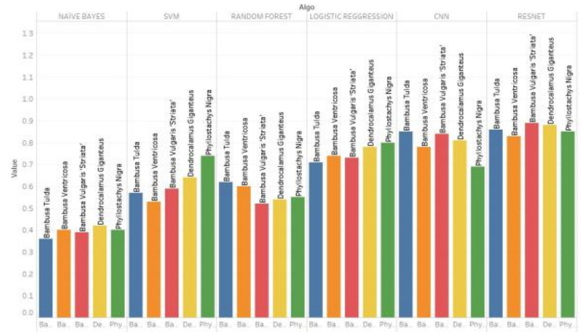

Fig. 10. Plot of F1-score of different algorithms and classes

IV. CONCLUSION AND FUTURE WORK

One of the major problems in the botanical field is the identification of bamboo species. Literature studies show the numerous work that has already been proposed in the combination of bamboo and technological organisms. However, only a digital picture is still required to identify bamboo. Machine learning and deep learning algorithms can have a more precise influence on the identification of bamboo species in the computer brain. It can help botanists and researchers to identify bamboo species in real time. If well implemented, the techniques are without a doubt effective method and a cohesive approach to high-precision identification of bamboo species. If more real-time information is available, it will be possible to explore the identification of bamboos with recent artificial intelligence (AI) developments and the advantages of AI diagnostics with more species.

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