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Research Article

Smartphone assist deep neural network model to recognize the high-quality tea using leaf maturity and its effect on leaf chlorophyll

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Abstract

Immature and tender tea leaves always produce high-quality tea than mature tea leaves. Depending on the maturity and age of the leaf, the colour and texture of the tea leaf are different. The photosynthesis capacity of the tea leaf also changes with the change of leaf maturity. Though the tea farmer plucks, classifies, and recognizes the best tea leaves (immature and tender) by viewing the visual symptoms and position of the leaves, the method is not authentic all time and leads to the overall degradation of the tea quality. The present study presents a smartphone assist tea leaf recognition system by analyzing the colour and texture properties of the tea leaf. The six different colour features and 4 Haralick texture features were extracted in the colour and grey domain of the leaf images. Three types of tea leaves, i.e., mature, immature, and tender, were classified using Deep Neural Network (DNN) with ADAM (Adaptive Moment Estimation) optimizer. With an accuracy of 97%, the DNN outperformed the Support Vector Machine (SVM) and K Nearest Neighbor (KNN). The SVM and KNN reported a total of 94.42% and 95.53% accuracy, respectively. The investigated system using DNN with an average precision and recall value of 98.67 and 98.34, respectively, may detect and classify the tea leaf maturity status. The system also can be used in AI-based tea plucking robotic systems or machines.

Keywords: Agri-informatics, ANN, DNN, Leaf maturity, Precision Farming, Smartphone

INTRODUCTION

Assam is known for tea farming (Baruah, 2015). The immature and tender tea leaves are best for the tea industry and it produces more high-quality tea than mature tea leaves (Baruah, 2015). The tea farmer and gardener recognize the immature and tender tea leaves by viewing the visual symptom or by touching the leaf. Though the gardeners or workers are already well trained in this field, they may make mistakes during tea leaves plucking. Nowadays, artificial intelligence (AI) based agricultural robot is used by farmers in their farming. The application of modern technology such as machine learning in Agri-informatics has been broadly used for the last 5 years. Researchers have tried to use machine learning algorithms in the different areas of Agri-informatics such as soil texture analysis (Barman and Choudhury, 2019), soil pH prediction (Barman *et al.*, 2008), chlorophyll prediction (Barman and Choudhury, 2020), and plant disease detection(Barman *et al*., 2020; Sood and Singh, 2020), etc.

The application of machine learning and deep learning algorithms for plant leaf maturity status recognition and classification is very limited. The researchers are found in fruit maturity status classification using machine learning techniques. Najeeb and Safar (2018) classified fruit maturity based on colour and texture. With an accuracy of 95.11% using deep learning, Mubin *et al.* (2019) classified young and mature oil palm trees. By extracting the colour and texture features. Behera *et al.* (2020) classified the maturity status of the papaya fruits using Artificial Neural Network (ANN). The use of K Nearest Neighbor (KNN) was reported by Pourdarbani *et al.* (2020) for fuji apple and mango fruit classification by extracting the colour and texture features. Sudana *et al.* (2020) reported the application of the Convolutional Neural Network (CNN) for mangosteen fruit maturity status classification

Along with the change of colour and texture of the fruit, the above literature also focused on the extraction of colour and texture features of the fruits. Like fruit, the colour and texture features of the tea leaf also change with its maturity. The colour of the tender and immature leaves is lighter green than the mature leaves and these leaves have a smoothy texture than the mature leaves. Wicaksono *et al.* (2019) reported extracting YCbCr colour features to classify the tea leaf maturity. Like other farming, Artificial intelligence-enabled modern technology can be used in the tea plucking industry to increase the overall productivity of tea farming by reducing human error in the tea plucking process. Keep in mind the above issues, the present study presents a smart farming system to recognize the best tea leaf by classifying the maturity of tea leaves using image processing and Deep Neural Network (DNN).

MATERIALS AND METHODS

Assam tea sample collection

The tea images used in this study were collected from the tea gardens of lower Assam, especially the Kokrajhar tea estate. The tea farmers usually recognized and classified the maturity status of the leaves by using naked eyes and expertise. Anwar *et al.* (2017) reported the three classes of leaves of *Aquilaria Beccariana* based on the position of the leaves from the branch. Barman and Choudhury (2020) reported that

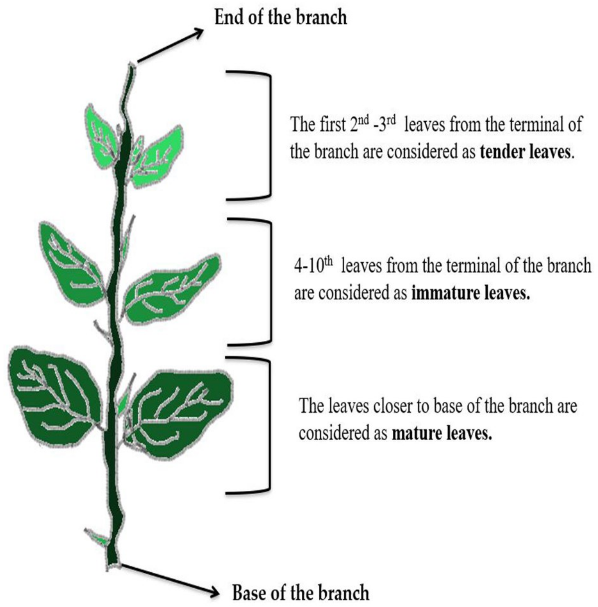

Fig. 1. *Visual texture of the mature, immature, and tender tea leaf*

the leaves closer to the branch's base are considered tea mature leaves, whereas 4 – 10th leaves from the terminal of the branch are usually considered immature tea leaves. The first 2 – 3rd leaves from the terminal of the branch are considered tender tea leaves. In the present study, the tea leaves were plucked based on the study of Barman and Choudhury (2020) and reported three different categories of tea leaves by analyzing the visual texture of the leaves (Fig. 1).

After plucking, the images of the tea leaves were snapped using a smartphone by maintaining a 12-inch distance between the camera lens and tea leaf with the help of an easy measure distance-measuring app. In the dataset, out of 360 images, each of 120 tea images belonged to the mature, immature, and tender category of the tea leaves (Fig. 2). For the classification, the leaves were labelled as 0 for tender, 1 for immature, and 2 for mature (Fig. 2). For the training and testing of tea leaf images, an 80:20 (288:72 images) ratio was used. The overall process of the system was followed as Fig. 3.

Fig. 2. *a) Tender b) Immature c) Mature*

Tea leaf maturity and its chlorophyll

By analyzing the visual texture of the tea leaf, one can say that the greenness of the mature leaves was more than the immature and tender leaves, but the greenness of the immature and tender leaves was the same. The chlorophyll of each leaf was estimated using a Soil Plant Analysis Development (SPAD) meter (Barman, 2021; Barman *et al.*, 2021; Barman and Choudhury, 2020). Most of the tender leaves' chlorophyll was in the range of 16 to 25, whereas the immature leaves' chlorophyll values were in the range of 27 to 35. The mature leaves' chlorophyll values were in the range of 40 to 60. It was shown that the range of leaf chlorophyll was changing with the change of leaf maturity. The tender leaves have low chlorophyll compared to the mature leaves. It means that leaf maturity has a great effect on chlorophyll value. So, the age of the leaf changes the chlorophyll indexes of a leaf.

Tea image pre-processing and feature extraction

Farmers often check the maturity status of the tea leaves with naked eyes by analyzing the colour and texture of the leaves. During the dataset collection, it was found that the texture of the tea leaf varies from leaf to leaf. Before the texture extraction, images were converted to BGR to RGB format using CV2 of python. Then RGB images were again converted to GRAY scale to find the Haralick texture of the images. After the image conversion into colour and gray domain, the features were calculated by defining the 10 different features in the colour and gray domain. In the colour domain, the mean and standard deviation of red, green, and blue colours were determined. In the gray domain, the contrast, correlation, inverse difference moments (IDM), and entropy of the Haralick were calculated. The equations of the feature extraction method are presented below.

Mean of RGB: $$\sum_{i,j=0}^{N-1} i.p_{i,j} \qquad \text{.....Eq.1}$$

Standard Deviation of RGB: $$\sum_{i,j=0}^{N-1} (i-Mean)^2 P(i,j))^{1/2} \qquad \text{.....Eq.2}$$

Contrast: $$\sum_{i,j=0}^{N-1} (i,j)^2 P(i,j) \qquad \text{.....Eq.3}$$

Correlation: $$\sum_{i,j=0}^{N-1} P_{ij} \frac{((i-\mu)(j-\mu))}{\sigma^2} \qquad \text{.....Eq.4}$$

IDM: $$\sum_{i,j=0}^{N-1} \frac{1}{1+(i-j)^2} P(i,j) \qquad \text{.....Eq.5}$$

Entropy: $$\sum_{i,j=0}^{N-1} P(i,j)\ln P(i,j) \qquad \text{.....Eq.6}$$

The algorithm of the feature extraction is given below.

Algorithm: Haralick Feature of the tea Leaf image

Step 1: Convert the colour image into RGB format.

Step 2: Convert the RGB image into a gray format

Step 3: Compute the Haralick Texture Feature

Step 3.1: Compute colour feature from the RGB image i.e., the Mean of Red, Green, and Blue.

Step 3.2: Compute the 2nd colour feature i.e., the Standard Deviation of Red, Green, and Blue.

Step 3.3: Compute the texture feature from the gray image i.e., contrast, correlation, inverse difference moments, and entropy.

Step 4: Compute the final feature vector by taking 6 colour features and 4 texture features from the Haralick definition.

From the single tea leaf, a total of 6 colour features were extracted in the colour domain(Barman, 2021) and the size of the feature vector of a single tea image was 1x6. The length of the Haralick texture feature for a single tea image was 1x4. The total feature vector size of a single tea image was1x10. The mean values of the different features are shown in Table 1 and Fig. 4.

In the present study, 288 tea leaf images were used for training purposes, so the size of the training feature vector of the maturity status classification was 288x10 with a testing size of 96x10.

Tea maturity status classification using DNN

In the present study, the DNN was used to classify the maturity of tea leaves. The DNN was introduced by considering 4 dense layers. The first dense layer received the 10 input feature parameters and it contains 512 hidden neurons. The second hidden layer and third

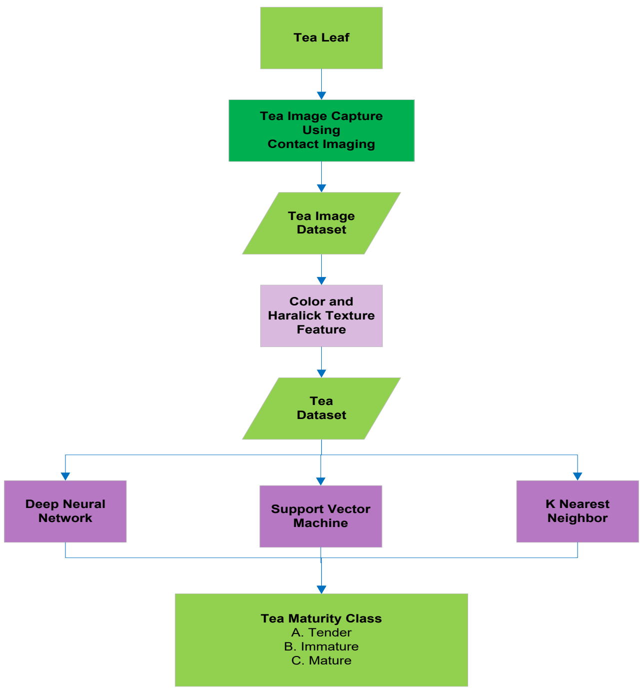

Fig. 3. *Flow chart of the proposed system*

Table 1. Feature values of the tea leaf

Leaf types	Immature	Mature	Tender
Mean_r	108.0347	91.30356	93.80403
Mean_g	200.18	202.517	201.4312
Mean_b	12.01872	11.14845	11.57137
Stddev_r	8.49844	10.13689	8.314974
Stddev_g	8.936729	9.610005	9.191333
Stddev_b	2.420448	4.413765	2.896424
Contrast	5.616073	11.19486	7.653708
Correlation	0.942483	0.91271	0.918703
IDM	0.476161	0.382073	0.431297
Entropy	7.904473	8.579689	8.106591

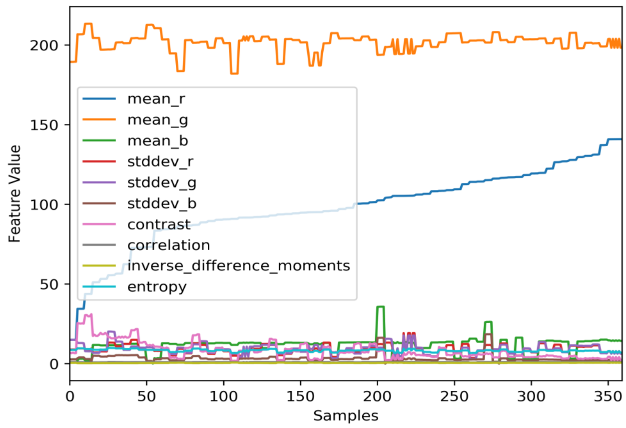

Fig. 4. *Scatter plot of the different features of the tea leaf images*

hidden layer contain the again 512 and 256 hidden neurons. The final dense layer contains 3 hidden layers for the classification of tea maturity. Except for the final dense layer, a relu activation function was added in the other layers to get the desired output. By applying two dropouts with a dropout rate of 0.2 and 0.3, the model was tried to reduce the overfitting. With a learning rate of 0.001, batch size = 10, and epoch = 10, the model was optimized with the ADAM (Adaptive Moment Estimation) optimizer. The loss of the DNN was calculated using the sparse categorical cross-entropy loss. For the better evaluation of the DNN model, another 20% (29 samples) of the training feature (288 samples) were used for validation.

Tea leaf maturity classification using SVM and KNN

The other state-of-the-art models, such as Support Vector Machine (SVM) and K Nearest Neighbor (KNN) were also applied to classify the tea leave's maturity. Two kernel parameters, such as liner and RBF were tunned with the SVM. The SVM-linear was applied by considering the C (Cost of misclassification) = 1 whereas the results of the SVM-RBF were checked for the gamma values of 0.0001, 0.001, 0.01, 0.1, 1, 10, and 100.

The KNN classifier is a lazy classifier that follows the instance-based learning process. The KNN is a memory-based algorithm, so the classification was also done for the different K values of 1to 9 by considering the euclidian distance metrics and leaf size =30. Both the algorithms were implemented in the python environment using the Keras library.

RESULTS AND DISCUSSION

In the first phase, the classification of tea leaf maturity is done using a deep neural network. In the next step, the results are compared with other states of art algorithms.

Earlier in the above section, it is mentioned that the DNN model is optimized with the ADAM optimizer, and trained with a learning rate of 0.001 for 10 epochs. The overall validation of the model with the training set is presented below in Fig. 5. The performance of the DNN

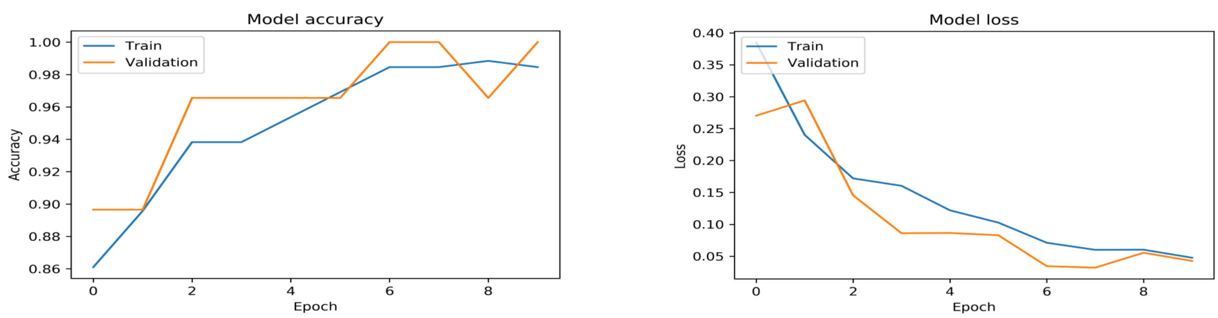

Fig. 5. *Train and validation accuracy and error of the DNN model.*

Table 2. Results of the DNN

Model	Class	Precision	Recall	F1 Score	Accuracy	Confusion Matrix		
	0	0.96	1	0.98		26	0	0
DNN	1	1	1	1	97	0	25	0
	2	1	0.95	0.98		1	0	20

Table 3. Results of the SVM

Model	C Value	Gamma Value	Accuracy
SVM-Linear	1	Auto	42%
SVM-RBF	1	0.0001	30.55%
SVM-RBF	1	0.001	40.27%
SVM-RBF	1	0.01	45.83%
SVM-RBF	1	0.1	83.33%
SVM-RBF	1	1	94.42%
SVM-RBF	1	10	92.41%
SVM-RBF	1	100	90.44%

model is also evaluated using the confusion matrix (Table 2). In Table 2, 100% perfect classification is reported in tender and immature tea leaves, whereas 1 image of mature tea leaf was misclassified as tender tea leaf. Along with the confusion matrix, the results of the DNN model are evaluated by calculating the precision, recall, and f1 score (Table 3). With a recall value of 0.98, 1, and 0.98, the precision value of the model, for class 0,1, and 2 is 0.96,1, and 1. The overall result of the model is 97%.

The other state-of-the-art models, such as Support Vector Machine (SVM) and K Nearest Neighbor (KNN), are also applied in the model. By considering the C = 1 and different gamma values, the SVM is tunned linear and RBF kernels and the results are presented in Table 3. Along with the decreasing performance of SVM Linear, the SVM RBF performance also decreases with the increasing value of gamma from 1 to 100 (Table 3). Table 3 indicates that the SVM model performs best (94.42%) at C =1 and gamma =1

The KNN algorithm is already reported by Behera et al. (2020) for papaya fruit maturity status classification with an accuracy of 100%. Based on the study presented by Behera et al. (2020), the KNN algorithm was also applied to classify the maturity of the tea leaves with different K values. The classification accuracy of the different K values is presented in Table 4, which shows that the KNN algorithm performed well at K =5 with an accuracy of 95.53%. Initially, the accuracy of the KNN was stable for K= 2 to 4. But after that, the testing accuracy of the KNN changed with the value of the K. The maximum testing accuracy of the KNN is at K =5. After K= 5, the testing accuracy decreased.

The DNN algorithm has already been used as a primary model for tea leaf maturity status classification. Apart from the DNN, the SVM and KNN models are also used to classify the maturity of the tea leaves. From Table 2, it is shown that the accuracy of the DNN model is 97%, whereas the accuracy of the SVM-linear, SVM-RBF, and KNN are 42%, 94.42%, and 95.53%, respectively. The comparisons of models and their precision, recall, f1 score, and confusion matrix are presented in Table 5.

From Table 5, the precision of the SVM-RBF is more in each class than the SVM-linear. With a precision value of 1 for classes 1 and 2, the DNN reports a 0.96 precision value than SVM and KNN. The DNN reports 1 recall value for the class mature and immature tea class. The f1 score of the DNN is higher than the f1 score of the SVM and KNN. The KNN reports the second-highest precision than the SVM. The SVM linear is not performing well due to the scattered nature of the data features. The confusion matrix of the SVM-RBF denotes that the complete 22 testing mature tea leaf images are perfectly classified as mature leaf whereas the 2 immature tea leaf is classified as mature tea leaf

Table 4. Results of the KNN for different K values

KNN	Training KNN	Testing KNN
KNN at K=1	1	1
KNN at K=2	99.65	94.44
KNN at K=3	99.65	94.44
KNN at K=4	99.65	94.44
KNN at K=5	99.65	95.53
KNN at K=6	95.48	83.33
KNN at K=7	91.31	72.22
KNN at K=8	80.2	59.72
KNN at K=9	82.29	63.83

Table 5. Comparative analysis of the DNN, SVM, and KNN algorithms

Model	Class	Precision	Recall	F1 Score	Support	Accuracy (Round Off)	Class	Confusion Matrix		
	0	0.85	1	0.92	22		0	22	0	0
SVM-RBF	1	1	0.92	0.96	24	94%	1	2	22	0
	2	1	0.92	0.96	26		2	2	0	24
	0	0.36	1	0.53	22		0	22	0	0
SVM-Linear	1	0.67	0.25	0.36	24	42%	1	18	6	0
	2	1	0.08	0.14	26		2	21	3	2
	0	0.88	1	0.94	22		0	22	0	0
KNN at K =5	1	1	0.88	0.93	24	96%	1	3	21	0
	2	1	1	1	26		2	0	0	26
	0	0.96	1	0.98	26		0	26	0	0
DNN	1	1	1	1	25	97%	1	0	25	0
	2	1	0.95	0.98	21		2	1	0	20

out of 24 immature tea leaf images. 2 tender leaves also show misclassification and reports as mature in case of SVM-RBF. A total of 4 tea leaf shows the misclassification in SVM-RBF. The total misclassification of tea leaf images in SVM-linear is 11, where 6 are immature and 5 are in the tender. In KNN, only 3 images are in the misclassification category and that is immature. With only 1 image as misclassification, the DNN model classifies 26 images as mature, 25 images as immature, and 20 images as tender. So, the Confusion matrix also reports that the DNN model outperforms. Wicaksono et al., (2019) reported 80% accuracy for the teal leaves maturity status classification by extracting the YCbCr colour values from the leave images. In the present study, the DNN reported an accuracy of 97%, which is more than the accuracy of the study reported by Wicaksono et al., (2019) while this accuracy is similar to the accuracy (97.1%) reported by Sudana et al., (2020) using CNN in the mangosteen fruit.

Conclusion

The present study showed the change of tea leaf chlorophyll with the change of leafage. The DNN algorithm with an accuracy of 97% is reported as the best model for tea leaf maturity classification. This study provides a new direction to tea farming by categorizing the tea leaf images. The system will help the small-scale tea farmer to find the best tea leaf for better productivity. The system presents a new low-cost image acquisition method for tea leaf maturity classification. The overall system is authenticated and acceptable than the visual system classification. The system can be loaded into a smartphone application and can be used by any tea farmer to select the best tea for better tea productivity. The system can also be used in tea farming robots.

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Conflict of interest

The authors declare that they have no conflict of interest.

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