Deep Convolutional Neural Network Model for Tea Bud(s) Classification

Iromi R Paranavithana, Viraj R Kalansuriya

Abstract— **Tea production exerts a huge impact on the economy of countries like China, Kenya, and Sri Lanka as they are involved in the world-wide tea production in a substantial manner. They are also amongst the countries, where production of tea is done in a huge scale. However, there is a myriad range of problems associated with tea picking. For instance, there is no proper procedure for selecting tea leaves, inability to guarantee the integrity of tea buds and inability to achieve the picking standards of conventional standards. Further, conventional tea should be plucked at a precise time. The convolutional neural network (CNN) is a deep learning method that performs better in image processing and classification tasks and widely used in the recent literature. Therefore, this study proposes an approach, based on CNN to develop a model that identifies and predicts the suitability of tea buds for the plucking as a solution to the aforementioned problems. First, the suitable and unsuitable tea buds are identified visually before the process of picking. The image samples used here, are created, and preprocessed to identify the hyperparameters. After that, the best combination of hyperparameters was identified for the optimal model. Then, the optimal trained model was evaluated using test data. Finally, an interactive software was developed for tea bud(s) classification. The experimental results show that the accuracy of the CNN model is 70.15% for 10000 image samples, while the accuracy of Support Vector Machine (SVM) and Inception V3 is 65.86% and 68.70% respectively. Hence, the CNN based classification performs better in classification and can improve the classification efficiency of tea buds effectively.**

Keywords— **Deep Convolutional Neural Network, Deep Learning, Image Classification, Tea Buds Classification**

I. INTRODUCTION

TEA is one of the favorite drinks all over the world that has a rich nutritional value and health benefits. Tea is considered as a healthy drink in many countries. It is imperative to maintain the good quality of tea leaves under the commodity economy. For that, it is necessary to identify the tea buds which is good for picking at the initial stages to improve the economic value of the tea [1]. Countries like Kenya, China, and Sri Lanka are the global giants in the list of countries that produce tea. The required workforce for tea plucking accounts for more than one second of the total in the whole tea production process [2].

Most tea plucking equipment available in the market is based on traditional mechanical mechanisms. The issues related to tea plucking are lack of selectivity for tea leaves, inability to guarantee the integrity of tea buds, and inability to achieve the plucking standards of conventional tea.

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The conventional tea must be collected at a specific time.

The skilled workforce in the industry is insufficient compared to the growing percentage of the industrial economy in the gross national product in tea producing countries.

The countries can produce substantial economic benefits with the advancement of the efficiency of plucking tea during the tea plucking period. The gap of skillful effort regards to tea plucking exists in the tea industry leads to fewer profit margins. This creates a high demand for human resources. Many planters exit the tea plantation industry because they cannot fulfill the demand. Few studies focus on the fresh tea leaf classification problem. But, to date, no study is focused on the tea bud classification before harvesting. Therefore, it is imperative to research on automate classification on tea buds as a step of the tea process automation.

The researchers investigated on classification of plants using leaves as a relative tool [3]-[4]. The features such as shape [5]-[6], texture [7]-[8], and venation [9]-[10] are utilized widely to separate the leaves. Deep learning technologies improve the current state-of-art level of pattern recognition in computer vision [1]. Our objective is to develop a model, which can classify the tea buds effectively and accurately prior to harvesting. In this study, we develop a Deep Convolutional Neural Network (CNN) model to classify the tea buds. Deep CNN is a type of deep learning concept that shows better performance in image classification and recognition problems [11].

II. RELATED WORK

A. Tea Bud(s) Classification

Tea bud classification is a major technology for the enhancement of automated tea plucking. Existing tea classification methodologies can be classified into raw tea and gross tea classification approaches.

The gross tea classification approaches involve classifying tea grades: grade Fanning's (FANN); Dust one (D1); Pekoe Fanning's (PF) [12]and green and black tea [13]. The authors use techniques such as principal component analysis (PCA), Fourier-transform near-infrared spectroscopy (FT-NIRS), [12] and Olfactory System Model with a multi-layer structure that is connected by feedforward and feedback lines with scattered delays and Back-Propagation network (BP) [13].

Many researchers use Machine Learning (ML)/Deep Learning (DL) techniques to classify the raw tea. Reference [2] proposed a method based on an improved K-means clustering algorithm to identify tea buds using HIS (hue (H), saturation (S), intensity (I)) color model. Saturation compared the tea bud and the background contrast. The squared Euclidean distance used as the similarity distance between the pixels, and the mean square error used as the clustering criterion function to classify the color. The accuracy of the model is improved using morphology operations [2]. Several studies use texture analysis-based feature extraction classification methods to classify the fresh tea leaves [14][15]— Gray Level Co-occurrence Matrix (GLCM) with Support Vector Machines (SVM) [15] and GLCM and Local Binary Patterns (LBP) [14]. The other techniques used for this purpose were Faster RCNN Inception 2 [16], inception 3 model [1], VGG16[16] and CNN [16]. All these techniques applied to harvested fresh tea leaves. But identifying the suitable tea leaves from the big tea plantations is a difficult task to deal with. To date, no study investigates classifying tea buds from the tea plantations as it is before harvesting.

B. Neural Networks in Image Classification

The CNN performs well in classifying and recognizing problems in image processing and has improved accuracy in many Machine Learning tasks.

Al-Saffar, Tao and Talab [17] proposed a classification framework called region-based pluralistic CNN, which can encode semantic context-aware representations. The study combined a set of different discriminant appearance factors. Because of that, the representation based on CNN represents the spatial-spectral contextual sensitivity that is critical for accurate classification of pixels.

Said, Jemel and Ejbali [18] proposed ensemble MLP-CNN classifier and it acquires supplementary findings obtained from CNN based on deep spatial feature representation and MLP based on spectral discrimination. The ensemble MLP-CNN classifier was tested in urban and rural areas using aerial photography and additional satellite sensor data sets. The results show that MLP-CNN classifier performs better than spectral and texture-based MLP, pixel-based MLP, and context-based CNN in classification accuracy.

Lee, Chan, Wilkin and Remagnino [19] investigate CNN to learn new feature representations for 44 different plant species gathered at the Royal Botanic Gardens, in England. They obtain an intuitive understanding on the selected features of the CNN model using a visualization technique based on the Deconvolutional Networks (DN). The study found the venations of different orders explicit each plant species in a unique manner. The outcomes of using CNN features with different classifiers imply stability and transcendence which can be compared to the solutions that depends on hand-made features.

Soderkvist [20] categorized the shape characteristics and moment features of the leaves and analyzed the 15 different Swedish tree classes by using the backpropagation for the feed-forward neural network. Fu, Chi, Chang, and Fu [21] selected the local contrast and other parallel factors to explain the features of the neighboring pixels of veins. The artificial neural network used to divide the veins and other leaves. The experiment suggests that the neural network is more effective in recognizing the vein figures. Li, Zhu, Cao, and Wang [22] suggested an efficient leaf vein extraction method by combining snake's technique with cellular neural networks, which obtained satisfactory outcomes on segmenting leaf.

Moreover, He and Huang [23] utilized the probabilistic neural network as a dimension to recognize the plant leaf images, which has better identification veracity comparing to BP neural network. [23]-[24] The results suggested the texture features associated with the shape characteristics. Reference [25] created a deep learning approach that formulates eight layers of CNN to classify leaf images with a higher recognition rate.

Ghazi, Yanikoglu and Aptoula [26] use deep CNN to recognize the plant species captured in a photograph and quantify the various factors which have an impact on the functioning of the networks. They use deep learning architectures, namely AlexNet, GoogLeNet, and VGGNet, and utilized the data augmentation procedures built on the image transforms including translation, rotation, reflection, and scaling with the purpose of deducting the possibility of overfitting.

III. Methodology

A. Dataset

The data was collected from tea estates under different weather and lighting conditions and by covering a large area of tea plantation. Further, the images were captured through different lighting conditions such as the high contrast images in the Morning light, normal condition in the daylight and low conditions in the evening. After taking the images in the natural environment, the images were processed for suitable chunks. The format used is JPEG with 24 bitmaps.

As for the different sizes and shapes of tea buds of the tea estates, it is needed to detect and cut off the images of tea buds. Interfering the background data in tea bud images with high definition can be reduced by cutting the image. As a result, the target area of the image becomes clearer which provides more convenience to extract the features for the neural network. Thus, this study segments the image automatically using image processing technology as follows:

1) Use Gaussian Smoothing low pass filter to remove noise.

2) Convert images into grayscale to detect the image outline.

3) Employ the Sobel edge detector to extract the edges and to further reduce the noise. The formula as follows.

$$G = \sqrt{G_x^2 + G_y^2} \tag{1}$$

The square root of the total of the horizontal and vertical squares of each pixel of the point is equal to the Gray value of a point

$$|G| = |G_x^2| + |G_y^2| \tag{2}$$

The gray value of the point is equal to the approximation value without square to enhance the efficiency of the computation.

$$\Theta = arctan\left(\frac{G_x}{G_y}\right) \tag{3}$$

Calculate the direction of antimony degree

4) Convert into Binary image

5) Employ the horizontal and vertical scanning methods to locate the tea buds and cut it.

Likewise, a data set was formed with a collection of 10000 images that cover a range of tea buds that are suitable (5000) and unsuitable picking (5000). This method made it possible to train the low detailed images in the training process.

These images contained substantial varieties of quality and a fixed dimension which is 200 x 200 pixels. These images are arbitrarily partitioned into two sections for training and testing which compromised with 6400 training and 1600 test images.

B. Proposed Model Architecture

The classification model to classify the tea bud(s) proposed in this study is based on the D-CNN. Fig 1 illustrates the preprocessing, network design, and evaluation phases for the created dataset, classifying them into two categories: (1) Suitable for picking and (2) Not suitable for picking.

The CNN architecture used in this experiment has four layered architecture that are three convolutional-pooling and one completely connected layers except the last layer of output neurons as depicted in the Fig.2.

1) Convolution Layer

In this experiment, the input consists of 200x200x1 neurons representing the Gray scale matrix of 200x200x1 tea bud image. The primary convolutional layer employs a convolutional kernel of a size of 9x9 and a stride length of 4 pixels to separate 64 feature maps. Then max pooling task is applied, and it was directed in a 9x9 region. The next convolutional-pooling layer additionally uses 9x9 convolutional kernel that brings 128 feature maps, and the remaining parameters stay unchanged. The third convolutional-pooling layer again uses a 9x9 convolutional kernel that fetches 128 feature maps.

2) Pooling Layer

The pooling layer chooses a maximum layer with a size of 9 x 9 and a step size of 3 x 3 for data processing. The maximum pool size in this study does not consistent with the step size, which can lead to more data richness.

3) Full connection layer and output layer

The fully connected layer connects all the features and send the output value to the classifier. This layer consists of 512 rectified linear units (ReLU) neurons that are completely a connected layer. The final layer has binary neurons that are related to the classification of tea buds which are suitable or unsuitable for picking. The ReLU activation function is utilized by the three convolutional pooling layers.

The optimal hyper parameters need to be identified, to train a best model out of the identified hyper parameters. The hyper parameters used were;

1. Dataset – 6000, 8000, 10000 images
2. The number of Epochs - 3, 10, 20, 100, 500.
3. The Optimizers - Stochastic Gradient Descent, Adam, and RMSProp.
4. The number of layers.

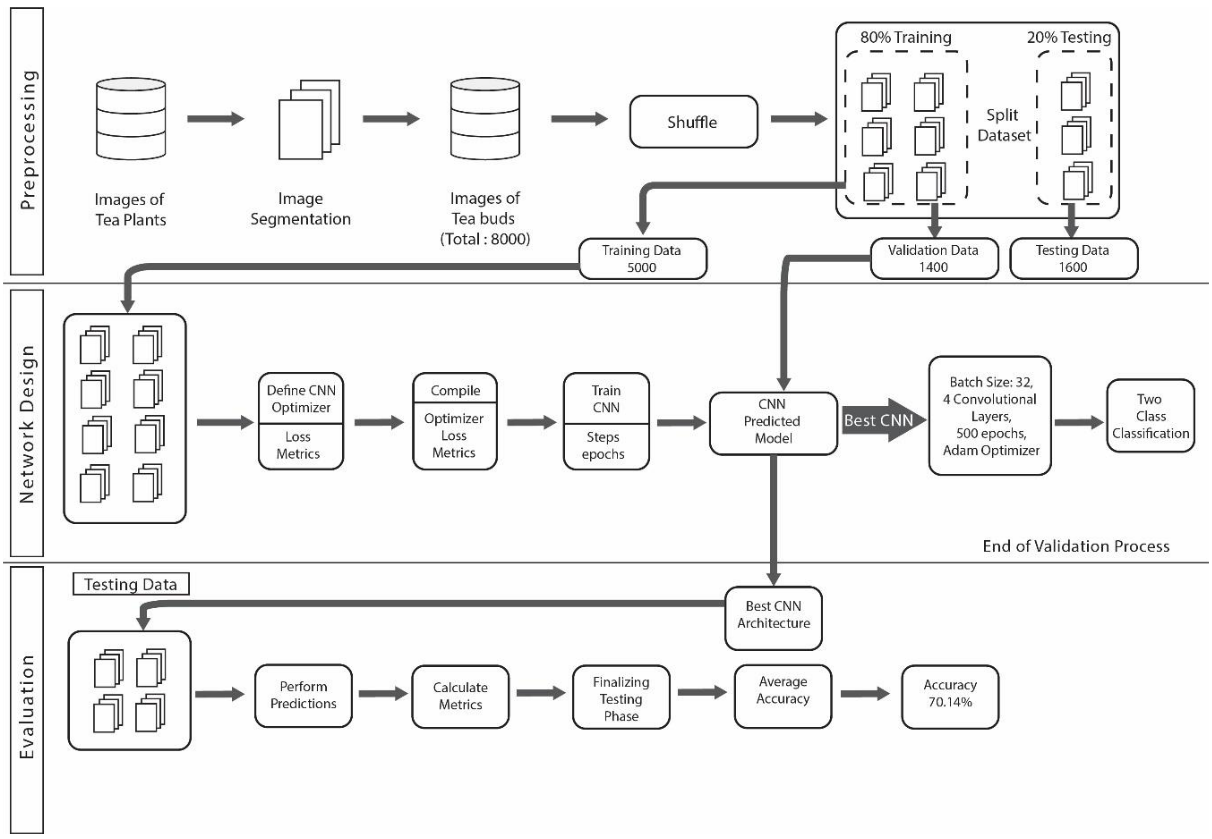

Fig. 1. The stages of the proposed methodology

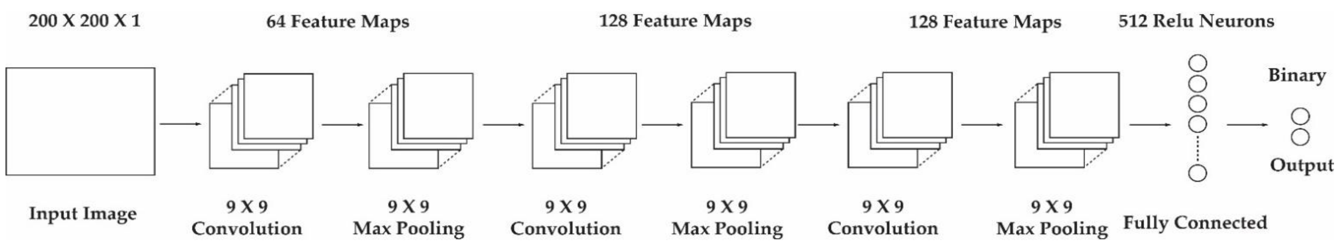

Fig. 2. Proposed CNN Architecture

This study uses an image set of 10000 images, 500 epochs, Adam optimizer and four layers as optimal hyper parameters to train the model.

IV. Results

This section summarizes the findings of this study based on the outcomes of the methods used. Each process was repeated three times for the classification accuracy of the calculations.

This study uses Keras, Tensorflow deep learning frameworks and the ReLU activation function. The frameworks have been installed through Anaconda Navigator which is a desktop Graphical User Interface (GUI) that permits to launch applications and helps to oversee packages, environments, and channels effortlessly.

The common deep learning libraries used are the Theano, Torch and Caffe. Even though Theano is faster than TensorFlow, it depends on the mathematical aspect of deep learning. But TensorFlow creates a higher level of abstraction for implementation. [27]-[28]. Torch is written with a scripting language called Lua which is simpler than python. Torch is difficult in adapting to this study as majority of other libraries written in Python instead of Lua [29]. Caffe performs better in developing applications which involve vision, speech, and multimedia. But Caffe cannot be used in this research because it involves using texts only. TensorFlow is suited better for the model creation.

Keras is a highlevel neural network API with the potential of running applications on top of TensorFlow, CNTK or Theano. [30].

Activation function is a node added to the output of the neural network which is the core of the deep neural network structure. It is used to decide whether the output of the neural network is yes or no, by mapping the output values between 0 and 1 or between -1 and 1 depending on the activation functions between two different layers. The most used activation functions at present include the Sigmoid function, ReLU function, Leaky ReLU function etc. However, the sigmoid function has a gradient vanishing problem that usually occurs in the backward transferring. This causes to a greater reduction in the training speed and the convergence results. The ReLU function can effectively lessen the gradient vanishing problem. The deep neural networks can be trained in the supervised manner without relying on the unsupervised layer-by-layer pre-training by using ReLU function that significantly improves the performance of the D-CNN. Therefore, it is proved that the performance of the ReLU function is better than the sigmoid function [12].

An optimal CNN model was created after experiments with various volumes of datasets, epochs, optimizers, convolutional layers, and batch sizes as below.

1. Dataset – 6000, 8000, 10000 images
2. The number of Epochs - 3, 10, 20, 100, 500.
3. Batch sizes – 8,16,32
4. The Optimizers - Adam, Stochastic Gradient Descent and RMSProp.
5. The number of layers.

The optimal CNN design was a CNN with an image set of 10000 images, 500 epochs, 32 batch sizes, Adam optimizer and four layers.

The Table 1 illustrates the performance analysis and outcomes for optimal CNN configuration for three runs.

The graphs in Fig. 3 depicts the accuracy and loss for the optimal CNN model, respectively.

A comparative analysis between SVM, Inception V3 and, our best model was performed to further examine the performance of the proposed CNN model. The comparison results are shown in Table 2.

TABLE II
CLASSIFICATION ACCURACIES BETWEEN PROPOSED CNN, SVM AND INCEPTION V3 ALGORITHMS

Model	Accuracy
CNN	70.15%
SVM	65.86%
Inception V3	68.70%

The classification accuracy and learning efficiency of tea buds are significantly improved when feature extraction and classifier training combined in the deep learning technology. The SVM and Inception V3 require a set of methods to pre-process the images prior to the extraction of shape and texture features. Then, the classification is done using the feature selection classifiers. The experimental time will increase due to extracting features and adjusting parameters. However, the classification results can be improved to a certain extent. The key benefit of the CNN, when compared with SVM and Inception V3, is the original image can input directly into the network without preprocessing which leads to save time and reduce the limitations of artificial design features. The findings demonstrate that the accuracy of CNN model is 70.15%. The efficacy of the CNN method is higher when compared with other machine learning algorithms.

V. Discussion of results and Conclusion

The problem of classifying the fresh tea before harvesting was solved using the CNN algorithms, which considered as a powerful method for image identification and classification tasks. In this study, a total of 10000 images of tea bud(s) were collected including both suitable and not suitable tea buds. Several architectures including SVM and Inception V3 were tested and classification accuracies ranging from 65.86% to 70.15%. The Deep CNN model with 4 convolutional layers, 32 batch size, 500 epochs and Adam optimizer is the optimal CNN when compared to accuracy and loss of the testing phase.

The classification performance of the proposed model further assessed through comparing with SVM and Inception V3 algorithms, which were applied in the specific problem in the literature.

Past literature that are highly related to this study are those conducted in [14],[15] and [16], regarding raw tea classification. These works use CNNs and SVM for classifying the tea leaf. However, there is no study focus on the fresh tea bud(s) classification before harvesting in the literature.

Accuracy of the model is compared with SVM and Inception V3 to highlight the performance of the proposed CNN model. From the results listed in the Table II, it occurs that the proposed model performs better or like other applied methods in the problem.

This study validates that CNN algorithms can have higher accuracy in tea leaf classification problems and can be directly applied to the classification of tea buds where automatic classification is needed to automate the tea harvesting process.

The main benefits of the proposed CNN architecture are described as below.

1. Deep- CNN can perform better in training models with small datasets irrespective of the related literature which reported CNN works effectively only with large datasets. The proposed CNN model has demonstrated the capability of training small datasets efficiently in the tea classification problem.

2. Deep-CNN reduces the complexity of the architecture. It has a simple architecture and better performance in the problem of tea classification. The model had less execution time due to its simple architecture.

Overall, the proposed CNN method is proven to be sufficiently effective in the tea classification domain, outranking the SVM and Inception V3 models.

The limitations of this study are (1) the Utilization of a small dataset because deep learning approaches perform better on large datasets, and (2) The classification process has less interpretability and transparency. The future works will address these limitations by (1) Performing further investigation using a larger dataset and (2) Increase the accuracy of the model while improving the interpretability and transparency in the classification process. with the investigation of new efficient Artificial Intelligence architectures.

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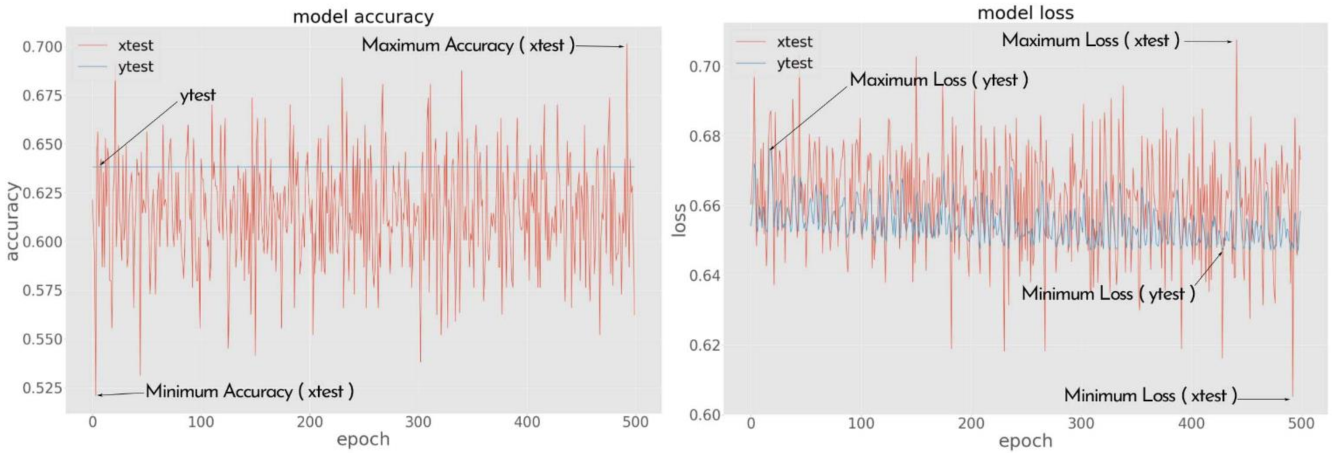
TABLE I
ACCURACIES OF THE MODELS; ACC. VALID—ACCURACY VALIDATION; LOSS VALID—LOSS VALIDATION; ACC. TEST—ACCURACY TESTING; LOSS TEST—LOSS TESTING.

	Batch Size=8				**Batch Size=16**				**Batch Size=32**			
	Acc. Valid	Loss Valid	Acc. Test	Loss Test	Acc. Valid	Loss Valid	Acc. Test	Loss Test	Acc. Valid	Loss Valid	Acc. Test	Loss Test
1st Run	60.15	39.85	60.75	39.25	64.42	35.58	63.85	36.15	69.99	30.01	70.14	30.5
2nd Run	66.13	33.87	66.02	33.98	68.15	31.85	68.29	31.71	70.12	29.88	70.13	29.92
3rd Run	62.04	37.96	63.14	36.86	69.88	30.12	68.17	31.83	70.14	29.86	70.14	29.86
Average	62.77	37.22	63.30	36.69	67.48	32.51	66.77	33.23	70.08	29.91	70.1366	30.09



(a) (b)

Fig. 3 Accuracy and Loss of the best CNN model

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