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Bamboo Species classification Using Deep Convolutional Neural Network (DCNN)

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Abstract: **In Asia, bamboos are the most significant forest product used by rural communities. Different bamboo species are utilized for various purposes. The categorization and identification of bamboo plant species are one of the more challenging tasks in agriculture because of the variety and various field circumstances. The traditional system, which relies on skilled hand labeling, takes a lot of time. Therefore, this study uses deep learning techniques to recognize these kinds of bamboo. In this paper, initially convert the original input image into a gray scale image, then remove the noise from the input images to better predict. Secondly, extracts the features of bamboo culm sheaths such as blade, auricle, ligule, and hairs from the culm sheath using the DenseNet-169 technique. Thirdly, utilizing the YOLOv5 technique to detect the sheaths from bamboo for better classification. And finally, classify the bamboo with its category type using the Deep Convolutional Neural Network (DCNN) technique. For experiments, it collects the input data from the user and the process on our dataset with those collected data, if the input image is matched with our collected data then it will show the category of the bamboo species to the user. This experiment achieves the "state-of-the-art" classification outcomes with 96.17% classification accuracy. The accuracy, sensitivity, specificity, and precision metrics will be utilized with manually gathered data to assess the efficacy of the proposed methodology.**

Keywords: Bamboo species identification, classification, deep convolutional neural network, culm sheaths.

I. Introduction

The utilization of bamboo has a long and well-established history throughout the tropical and subtropical parts of the world. The development and research done over the past few years have developed and adequately proved that bamboo may be a suitable alternative to wood and numerous other heritage products for the building and house building industry as well as several infrastructure projects [1-3]. Bamboo has been used in a variety of infrastructure projects and is being used to replace wood in many other places. The high-quality of bamboo are planned to plant soon [4, 5]. Its utilize in industrial processing has demonstrated that there is great potential for producing inexpensive composite components and materials that work well in both non - structural and structural applications.

The most significant forest product used by rural communities in Asia is bamboo. Different bamboo species are utilized for various purposes. In housing, agriculture, horticulture, fishing, basket making, land- and water-based transportation, handicrafts, and the growth of edible shoots are justified [6-8]. Therefore, it is essential to be able to precisely identify specific bamboo to determine its value. The botanist has been doing the identification for a lengthy decade. Bamboos are often categorized visually using microscopic characteristics like vascular bundles and exterior morphological traits like shoot apices and culm sheaths. Bamboo may be classified by the Culm sheath's shape, which is useful information. By observing the size, form, kind of hairs, and cilia, the culm sheaths are studied to confirm the species [9]. Botanists used to spend a lot of time identifying the species of plants, how it was done in the past. The Culm sheaths are the most crucial component of the plant and are readily available when identifying bamboo species through image processing. Figure 1 depicts an example of culm sheaths [10]. A bamboo leaf transformed to form the culm sheath the most crucial component of bamboo for differentiating between species is the culm and culm sheaths. It has been proven that the Culm sheath is a trustworthy source for identifying bamboo species, although several additional characteristics are also employed by botanists. Since all Culm sheaths are typically green and brown in color, the texture and color features are not taken into consideration [11-13]. Color and texture are therefore unreliable characteristics for identifying bamboo species.

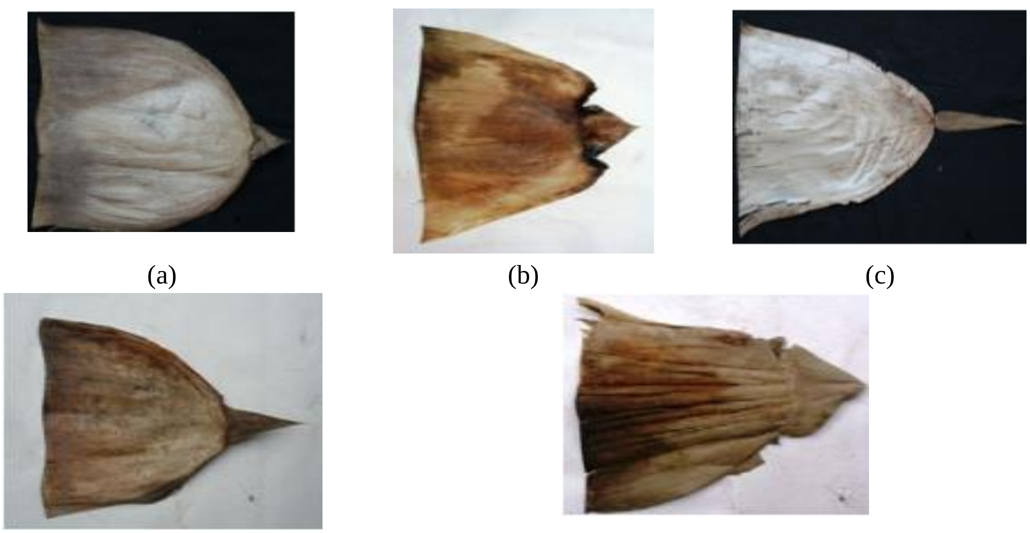

Figure 1. Sample of bamboo species such as (a) Dendrocalamus Longipathus, (b) Bambusa Vulgaris, (c) Dendrocalamus Melingensis, (d) Bambusa Balcooa, and (e) Bambusa Tulda.

The culm sheaths are the most essential part of the plant for recognizing bamboo species. The sheath completely encircles the new shoot in its early stages of development and resists it. Later, the sheath dries out and eventually falls off in most bamboo [14]. The sheaths open on different sides of the culm and are linked at the nodes. A bamboo culm's modified sheath, which determines whether the culm stands upright or bent backward, as well as whether it will come off early or stay attached, are significant factors. The most essential part of bamboo for differentiating between species is the culm sheath [15-17]. Other characteristics, like flowers and fruits, can also be used to identify different species of bamboo, although it takes a while roughly 30–40 years. Therefore, the goal of this research is to identify the species of bamboo by detecting the culm sheaths and categorizing those using deep learning techniques. In this work, methods for categorically identifying bamboo species were introduced. Initially, the input image is converted into a grey scale level, then reduce the noise for better identification using the mean filtering method. Then extracts the features such as Blade, Auricle, Ligule, and Hairs from bamboo sheaths using the DenseNet-169 technique. Furthermore, utilizing the YOLOV5 detection method to detect the bamboo sheath by collected features. To classify the bamboo species, using the Deep Convolutional Neural Network technique. The key components of this research are,

- In a pre-processing step, the first raw input image converts into a grayscale image and then removes the noise from the mean filter.

- To Feature extraction, we utilize the DenseNet-169 approach to extract the features such as Blades, Auricle, Ligule, and Hairs from bamboo culm sheaths.
- Utilizing the YOLOv5 technique to detect the sheath to get better classification results. Then classify the bamboo species into their category using a Deep Convolutional Neural Network.

This article's remaining sections are organized as follows. The relevant research on the classification of Bamboo species is included in Section 2. The proposed technique and its components are fully explained in Section 3. The experimental strategy is explained in Section 4. Section 5 reviews the research and offers suggestions for additional research.

II. Literature Survey

We read several papers for the literature study, which are listed below. [18] Suggested tests of bamboo materials include bending, longitudinal compression, and longitudinal tensile, longitudinal shear, transverse tensile, and transverse compression, while taking the influence of the bamboo nodes into account. The entire bamboo stalk's mechanical characteristics, including the wall thickness and outside circumference, are investigated. The link between mechanical qualities and perimeter and wall thickness is fitted using univariate and multiple regression analysis, and the conversion parameters between various mechanical properties are generated.

The Artificial Neural Network (ANN) method was suggested by [19] to evaluate the stiffness and behavior of the BRC beam findings. Errors in experimental data are typically brought about by a variety of factors, including human error, outdated tool calibration, incorrect test methodology, and mismatched test materials. The outcomes of the ANN approach are thus compared with the experimental data after being analyzed. The experimental data in this study are believed to deviate significantly from the outcomes of the ANN approach. Then, a powerful computational method based on ANN is proposed to predict the load vs. deflection of BRC. [20] Recommended that to overcome the low efficiency of manual identification, knowledge vision methodology is utilized to rapidly and effectively recognize and categorize the surface flaws of processed bamboo. The datasets are made up of 6360 images of defective bamboo mats from four different categories that the author took while standing in the same spot. They are divided into training and testing groups in an 8:2 ratio. To better partition the datasets for classification and comparison, we upgraded the U-net and used VGG16, GoogleNet, and ResNet50 with attention mechanisms.

III. Proposed Methodology

The culm sheaths are the most crucial components of the plant for recognizing bamboo species. The sheath completely encircles the new shoot in its early stages of development and resists it. Later, the sheath dries out and eventually falls off in most bamboo. The sheaths open on different sides of the culm and are linked at the nodes. A bamboo culm's modified sheath, which determines whether the culm stands upright or bent backward, as well as whether it will come off early or stay attached, are significant factors. The most crucial component of bamboo for differentiating between species is the culm sheath. So, here we use deep learning techniques to identify the bamboo species. This research has 4 steps to identify and classify the bamboo species. Initially, converted to a grey scale, then remove the noise from the input images for better prediction. In addition, extracts the features of bamboo culm sheaths such as blade, auricle, ligule, and hairs from input culm sheath images using the DenseNet-169 technique. Furthermore, utilizing the YOLOV5 technique to detect the sheaths from bamboo for better classification. And finally, classify the bamboo with their category type using the Deep Convolutional Neural Network (DCNN) technique such as Bambusa balcooa, Bambusa vulgaris, Dendrocalamus Longipathus, Dendrocalamus Melingensis, and Bambusa tulda. This process structure is shown in below Figure 2.

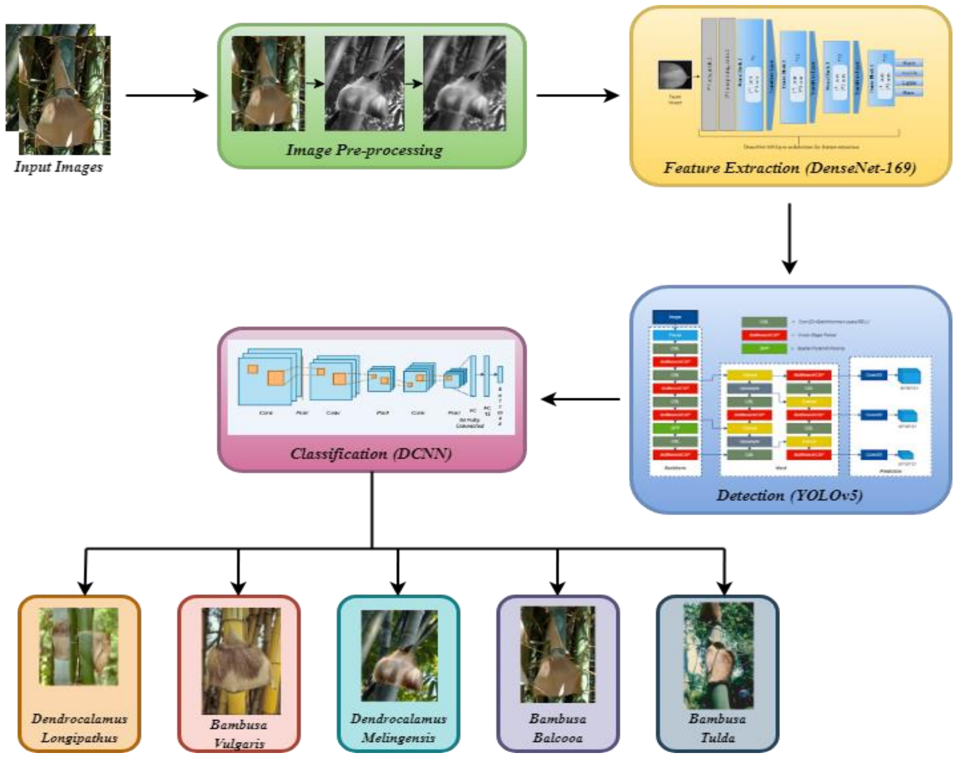

Figure 2. Proposed Methodology Architecture

A. *Image Pre-Processing*

Initially, in the pre-processing stage, we converted the raw input image to a grey scale level. Mean filtering is initially used in the pre-processing stage to reduce the noise from input images. Using different image smoothing templates for image convolution processing to reduce or eliminate noise is a traditional method of image de-noising in the spatial domain. Mean filtering's fundamental premise is to replace a pixel's single grey value with the combined grey values of multiple adjacent pixels. The image after smoothing and mean filtering is g(x, y), and g(x, y) is determined for a pixel point (x, y) in a given picture with f (x, y), its neighborhood S comprises M pixels by the following formula:

$$G(x,y) = \frac{1}{M}\sum_{(i,j\in S)} f(x,y)(x,y) \notin S$$

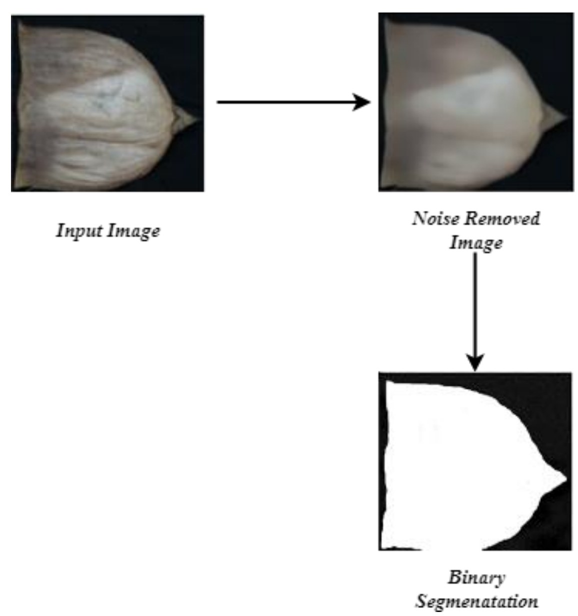

Figure 3. Pre-Processing step.

Figure 3 shows the processing of how our proposed pre-processing methods work.

B. *Feature Extraction*

After pre-processing, proposed a technique to extract the features of the culm sheath to find the category of bamboo trees. Here, we utilize the DenseNet-169 method to feature the extraction step. This extracts the features such as blade, auricle, ligule, and hairs from the sheath. As a result, this step goes through the DenseNet-169 methods structure and its function in feature extraction. Figure 4 displays the sample features of bamboo culm sheaths.

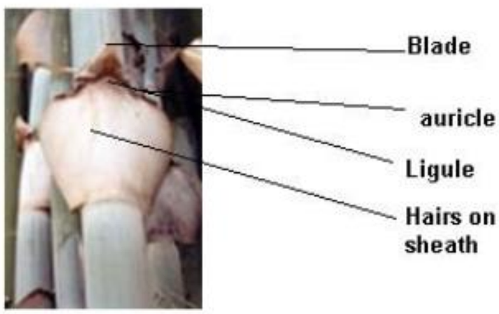

Figure 4. Culm Sheath

Deep Convolutional Networks is the most efficient frameworks for the recognition of image because they contain unusual types of pooling and convolutional layers. However, the gradient or input data that was available in the largest layers by the time, and the final layer was attained disappears as the network gets deeper. DenseNet gets over the gradient diminishing problem by connecting all other layers with the equal feature sizes together directly [21]. Since more generic characteristics can be found deeper in the network, utilizing the DenseNet structure as a feature extractor is primarily motivated by this fact. The pre-trained 169-layer densely connected convolutional neural network (DenseNet-169) was utilized for the process of feature extraction. This method was developed utilizing the extensive ImageNet dataset, which is publicly available. The DenseNet-169 structure have 4 dense blocks, 3 transition layers, and a pooling and convolution layer. After the first convolutional layers, a max pooling of 3x3, and 7x7 convolutions with stride 2 is used. The network then has 3 sets, every of which includes a transition layer before a dense block, with a dense block at its core. To achieve the dense connection proposed for DenseNet, direct connections from layer to another layer are provided to the network. To accomplish this, the feature maps of the preceding layers must be concatenated. However, since convolutional neural networks are primarily used to downsample the feature-maps size, the DenseNet structure is separated into the numerous dense blocks, densely connected mentioned above. Figure 5 demonstrates a flowchart showing how our methodology was used.

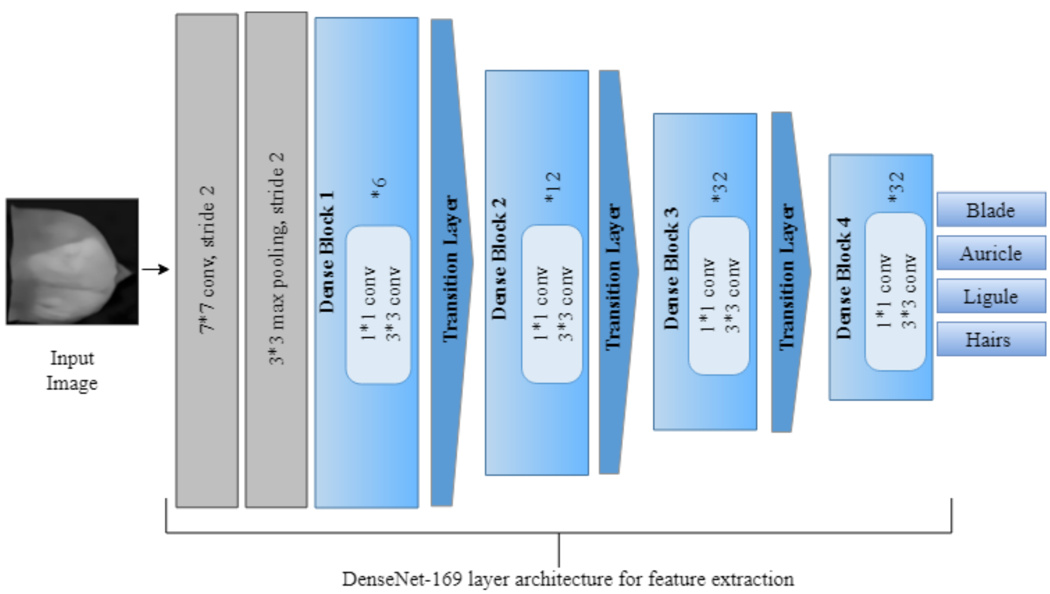

Figure 5. Represents a flowchart showing how our methodology was used.

Table 1. Structure of DenseNet

Layers	DenseNet-169	Outcome Size
Convolution	7x7 convolution, stride 2	112x112
Pooling	3x3 max pool, stride 2	56x56
Dense Block (1)	$\begin{bmatrix} 1 \times 1 \text{ convolution} \\ 3 \times 3 \text{ convolution} \end{bmatrix} \times 6$	56x56
	1x1 convolution	56x56

Transition Layer (1)	2x2 avg pool, stride 2	28x28
Dense Block (2)	$\begin{bmatrix}1\times 1\text{ convolution}\\ 3\times 3\text{ convolution}\end{bmatrix}\times 12$	28x28
Transition Layer (2)	1x1 convolution	28x28
	2x2 avg pool, stride 2	14x14
Dense Block (3)	$\begin{bmatrix}1\times 1\text{ convolution}\\ 3\times 3\text{ convolution}\end{bmatrix}\times 32$	14x14
Transition Layer (3)	1x1 convolution	14x14
	2x2 avg pool, stride 2	7x7
Dense Block (4)	$\begin{bmatrix}1\times 1\text{ convolution}\\ 3\times 3\text{ convolution}\end{bmatrix}\times 32$	7x7
Fully Connected Layer	7x7 global avg pool	1x1
	1000D fully-connected softmax	1000

These large blocks are separated by layers known as transition layers. In the network, every transition layer has a batch normalization layer, a 2x2 average pooling layer, a 1x1 convolutional layer, and a stride of 2. There are four thick blocks, each with two convolution layers, as already mentioned. The first layer is 1x1, while the second layer is 3x3. The sizes of the four dense blocks in the DenseNet-169 designs are 6, 12, 32, and 32 respectively [22]. The fully connected layer, the next layer after this, conducts the global average pooling of 7x7 and is considered by a last fully connected layer that utilizes "softmax" as the activation. Table 1 displays the structure of the DenseNet approach.

C. *Detection*

YOLOv5 is a region-based object identification network and a one-stage detector. The YOLO reconsiders object recognition as a regression issue that requires quick processing. Using extracted features, this detection method locates the sheath. The classification of the bamboo species into their category depends more on this detection step.

Figure 4 shows the three components of the YOLOv5 network structure: the backbone, the neck, and the outcome. The input image, which has a resolution of 640x640x3 pixels, passes via the Focus framework in the backbone. It first becomes a 320x320x12 feature map using the slicing process, and then, following a convolution operation using 32 convolution kernels, it finally becomes a 320x320x32 feature map [23]. A fundamental convolution module is the CBL module. A CNN serves as the framework, gathering and sculpting image features at various granularities. To create image features, the YOLOv5 utilizes the CSP Bottleneck. The head is composed of several layers that aggregate image features before forwarding them to a forecasting algorithm. To aggregate features, the YOLOv5 additionally uses the PA-NET. The detection procedure uses information from the head and includes processes for box and class prediction [24]. Figure 4 displays a diagram of the YOLOv5 architecture.

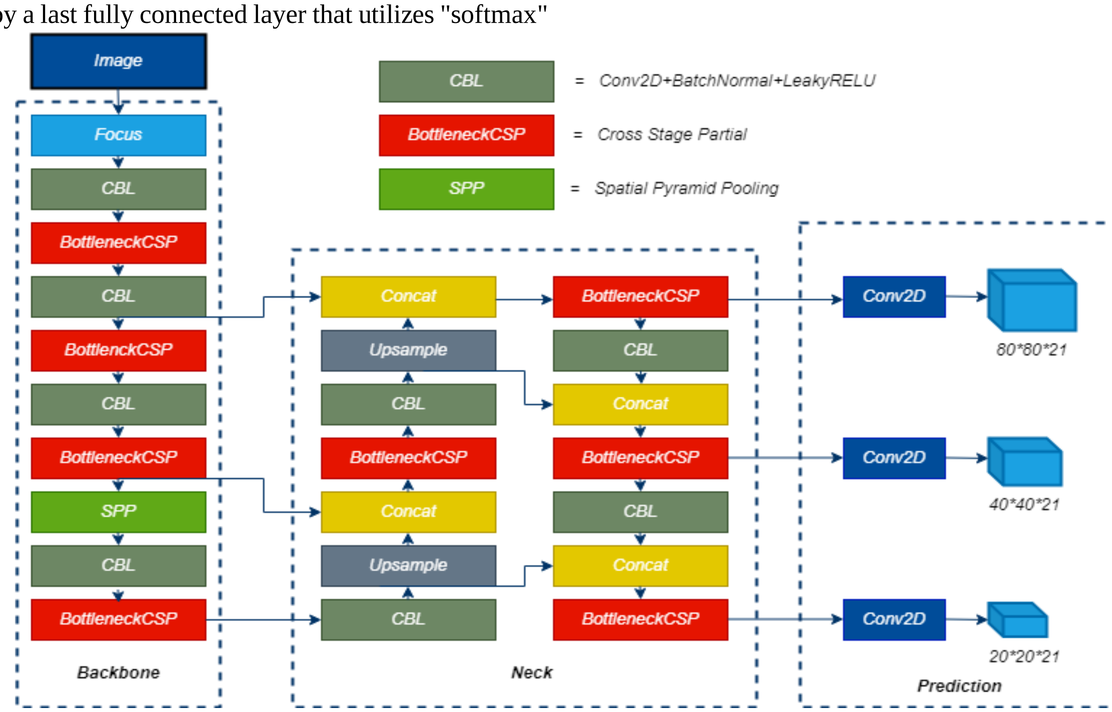

Figure 6. YOLOv5 network structure

Figure 6 shows the network structure of YOLOv5. This study aimed to identify the YOLOv5's ideal epoch for the created training model. This detection method is used for getting a better classification purpose.

D. Classification

After detecting the sheaths, we proposed a deep-learning technique to categorize the various species of bamboo. Five separate species are categorized here. They are Dendrocalamus Melingensis, Dendrocalamus Longipathas, Bambusa Vulgaris, Bambusa Balcooa, and Bambusa Tulda. We proposed a two-track DNN model architecture. Deep convolution neural networks (DCNNs) with max-pooling are used in the first track to improve system performance, while fully connected layers are used in the second track. The network consists of four layers of neurons in the hidden layer (one fully connected and three convolutional-pooling), except for the output neuron's final dense layer. The input of data is not counted as a layer. A 150x150 image's RGB value is represented by 150x150 neurons in the input. The first convolution-pooling layer extracts 32 feature maps, considered by a maximum pooling operation carried out in a 2x2 region. While other parameters are left unaltered, the 2nd and 3rd convolution-pooling layers employ the same 3x3 local receptive field (kernel) to generate 64 and 128 feature maps, respectively [25]. The outcome layers consist 15 Softmax neurons that correspond to the 15 different types of species, and the fourth layer is a fully linked layer with 64 ReLU neurons. ReLU activation functions are also used in the three convolutional-pooling layers. Figure 7 illustrates Conv.Net's primary operations.

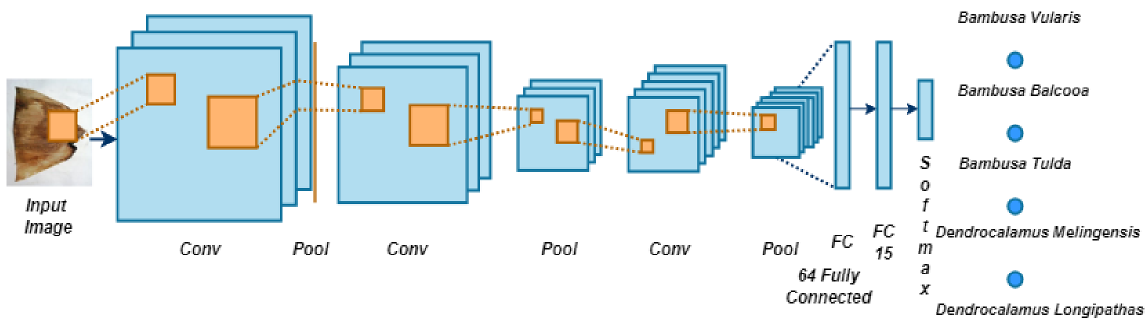

Figure 7. Proposed Deep Convolutional Neural Network Structure

By utilizing tiny squares of the input picture to learn picture attributes, convolution preserves the spatial relationship between pixels. In our model, convolved features were computed using a 3x3 filter. Rectified linear unit, or ReLU, is a nonlinear procedure. Since Conv.Net must learn non-linear real-world data most frequently, ReLU's aim is to give non-linearity to Conv.Net. Because the ReLU activation function trains neural networks considerably more quickly without sacrificing much in the way of generalization accuracy, we used it in our network. In contrast to tanh/sigmoid neurons, which need time-consuming calculations. This is a useful feature. A conventional multi-layer perceptron called the fully connected layer utilizes a softmax activation function in the outcome layer. To identify the input images, the max pooling and convolutional layers retrieve high-level attributes from the pictures. It classified the bamboo species by their category.

IV. Results and Discussion

By categorizing bamboo species using our dataset's analysis and our method for retrieving bamboo culm sheath properties, the first half of this section compares our methodology to "state-of-the-art" techniques. In the next subsections, provide the assessment results based on experimental data to evaluate our methods.

A. Dataset Description

Because there isn't a standard data set for bamboo species identification, so our dataset using Google images and other bamboo species that were available for free download at the time the data was collected. A 5500 image-balanced dataset is produced, with 1100 photos placed in each of the following five categories:

(1) Dendrocalamus Melingensis
(2) Bambusa Balcooa
(3) Bambusa Tulda
(4) Bambusa Vulgaris
(5) Dendrocalamus Longipathus

The dataset for bamboo species (5500) is split into a training data set (4850, i.e. 80%) and a test data set (650, i.e. 20%). Training data use (3980 of training data, i.e. 80%) and validation data usage are further separated from the training data set (870 of training data, i.e. 20%).

B. Quantitative Metrics

In this paper, the raw input image is converted to greyscale from the input image, then remove the noise from the input image to better prediction. Secondly, extracts the features of bamboo culm sheaths such as blade, auricle, ligule, and hairs from input culm sheath images using the DenseNet-169 technique. Thirdly, utilizing the YOLOV5 technique to detect the sheaths from bamboo for better classification. And finally, classify the bamboo with its category type using the DCNN deep learning technique. For experiments, we collected the images from our dataset images.

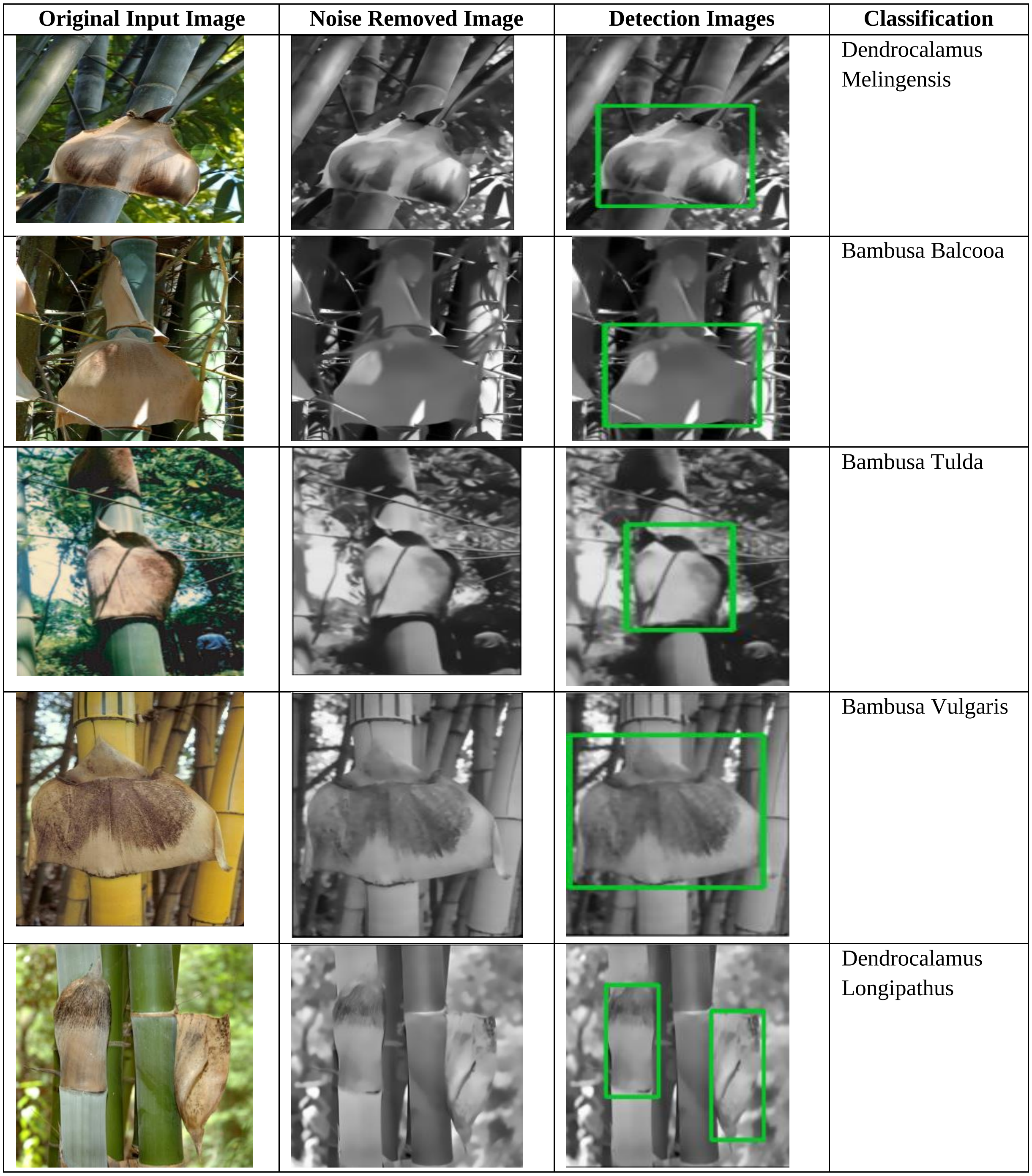

Figure 8. Results images of Bamboo species (a) Dendrocalamus Melingensis (b) Bambusa Balcooa (c) Bambusa Tulda (d) Bambusa Vulgaris (e) Dendrocalamus Longipathus

Figure 8 demonstrates the classification results from input bamboo images and places them into their category.

C. *Evaluation Metrics*

The proposed method's Precision (P), Accuracy (A), Recall, and F1-score (F) were examined as performance indicators (R). These measurements show:

1) *Accuracy*

To determine whether the classification of bamboo species is accurate, the accuracy measure is calculated.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{(Eq.8)}$$

2) *Precision*

The proportion of accurately forecasted positive outcomes to all forecasted positive observations is called as precision. The ability to carry out the following actions is precision.

$$Precision = \frac{TP}{TP+FP} \quad \text{(Eq.9)}$$

3) *Recall*

The terms for the recall are the True Positive Rate (TPR) and Sensitivity. The classifier's capacity to find all positive samples is shown by the recall score. It is the total divided by TP, including FN. As an example, consider the following:

$$Recall = \frac{TP}{TP+FN} \quad \text{(Eq.10)}$$

4) *F-Measure*

The harmonic mean of recall and precision is calculated utilizing F-Measure.

$$F1\ Score = 2 \times \frac{precision \times recall}{precision + recall} \quad \text{(Eq.11)}$$

D. *Performance Evaluation*

Comparing the proposed with other existing techniques in experimental performance, the proposed methodology has the highest categorization accuracy. Table 2 illustrates the results for CNN [18], DNN [19], ResNet50 [20], and the proposed DCNN on the bamboo species images from our collected data in terms of recall, accuracy, f-measure, and precision. For the five groups of bamboo species Dendrocalamus Melingensis, Bambusa Balcooa, Bambusa Tulda, Bambusa Vulgaris, and Dendrocalamus Longipathus, it is compatible with experimental results. The data demonstrate that the network model is rather accurate. The result shows that the proposed technique performs well in our dataset. Our results based on recall, accuracy, f-measure, and precision are presented in Table 2. These experiments improved our classification results and performances.

Table 2. Calculate the percentages of Recall (%), Precision (%), Accuracy (%), and F-Measure (%) utilizing the proposed and existing methodologies.

Approaches	**Accuracy (%)**	**Recall (%)**	**F-Measure (%)**	**Precision (%)**
CNN [18]	92.05	90.68	89.53	90.15
ANN [19]	89.12	88.45	86.09	90.89
ResNet50 [20]	84.91	85.26	81.94	83.87
Proposed (DCNN)	96.17	92.12	90.54	92.49

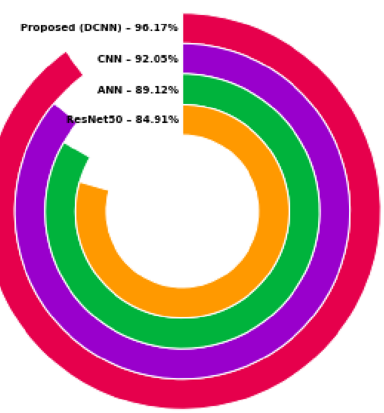

Figure 9. Analysis of Accuracy based on different techniques.

The proposed technique's accuracy analysis in comparison to other techniques in use was shown in Figure 9. Additionally, Figure 10 compares the precision, recall, and f-measure graphs for the categorization outcomes of the proposed method with those of other existing techniques. Our proposed model improved the classification accuracy with less computation time.

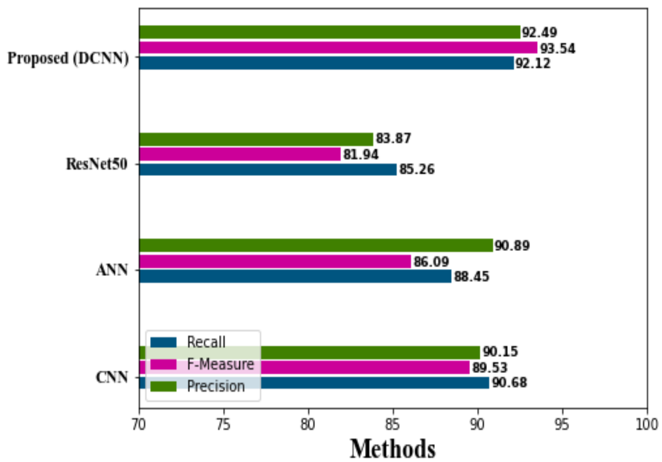

Figure 10. Comparison of the categorization outcomes of the proposed strategy with those of earlier methods for Recall (%), Precision (%), and F-Measure (%).

The achieved higher Precision for the proposed technique is 92.49%, compared to 90.15% for CNN [18], 90.89% for DNN [19], and 83.87% for ResNet50 [20]. Additionally, the recall of the proposed technique is better than that of other existing technology. ResNet50 [20] has the lowest accuracy, at 84.91 percent. Comparing with other existing methods the proposed DCNN technique achieves higher accuracy. According to the analysis of the experiment, implementing the proposed approach increased classification performance and less computing time for training the images.

E. Computation Time

The concept of computation time is another one that is covered. Deep learning approaches aims to simplify computations. Table 3 compares the computation times of our proposed DCNN technique to those of other previously used techniques. Improved classification accuracy is provided with little computational effort. The computation time utilizing is the most recent techniques and the proposed model is demonstrated in Figure 11.

Table 3. Utilizing the proposed and existing methods.

Methods	Computation Time
CNN [18]	0.23
ANN [19]	0.19
ResNet50 [20]	0.20
Proposed (DCNN)	0.16

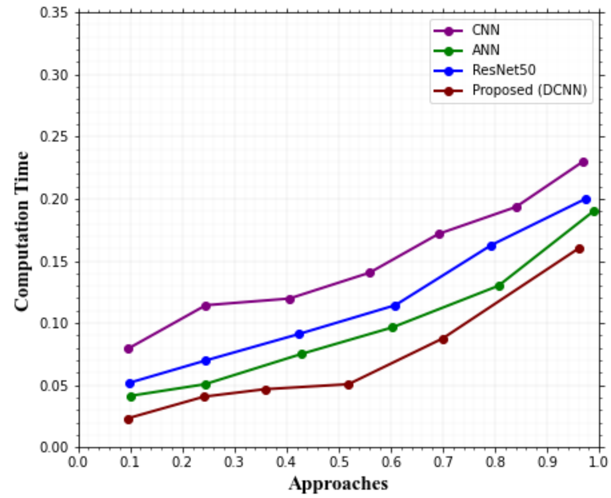

Figure 11. The computation time for the proposed methodology and existing methodologies.

F. Evaluation of training results

Validation and accuracy of trains, our accuracy after 100 epochs was 96.17%, which is amazing accuracy curves eventually converge. Figure 12 shows the accuracy of training and validation.

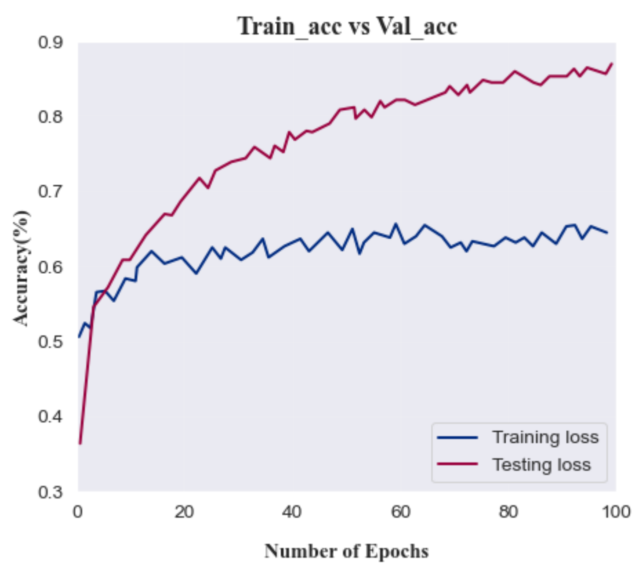

Figure 12. Training Vs Validation accuracy.

For a brief moment, the validation loss curve rises and falls. It implies that having more test findings can be beneficial. This might be acceptable, though, due to the low variance between Test and Train Loss and the flattening of the curve over epochs. Figure 13 shows the training and validation loss.

Figure 13. Training Vs Validation loss.

The accuracy and loss during training are shown in Figures 12 and 13. The DCNN offers better accuracy and loss estimations. In both the training and validation phases of the bamboo species classification process, our methodology performs better than earlier methods.

V. Conclusion

Bamboo has gained recognition as a multipurpose plant since it can be grown as a flowering plant in gardens and parks as well as utilized for building, making furniture, and producing biofuel, textiles, and paper. Its rapid growth, root system, and leaves can also help the environment. In this paper, first, we convert the input image to a gray scale image, then remove the noise from the input images to better predict. Secondly, extracts the features of bamboo culm sheaths such as blade, auricle, ligule, and hairs from input culm sheath images using the DenseNet-169 technique. Thirdly, utilizing the YOLOv5 technique to detect the sheaths from bamboo for better classification. And finally, classify the bamboo with its category type using the Deep Convolutional Neural Network (DCNN) technique. This experiment gives the "state-of-the-art" classification result with 96.17% classification accuracy. This manuscript's research could help in the development of a technique for low-shot categorization using deep learning in agriculture.

Acknowledgements

We declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere

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