Implementation of CNN for Plant Identification using UAV Imagery

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***Abstract*—Plants are the world's most significant resource since they are the only natural source of oxygen. Additionally, plants are considered crucial since they are the major source of energy for humanity and have nutritional, therapeutic, and other benefits. Image identification has become more prominent in this technology-driven world, where many innovations are happening in this sphere. Image processing techniques are increasingly being used by researchers to identify plants. The capacity of Convolutional Neural Networks (CNN) to transfer weights learned with huge standard datasets to tasks with smaller collections or more particular data has improved over time. Several applications are made for image identification using deep learning, and Machine Learning (ML) algorithms. Plant image identification is a prominent part of such. The plant image dataset of about 300 images collected by mobile phone and camera from different places in the natural scenes with nine species of different plants are deployed for training. A five-layered convolution neural network (CNN) is applied for large-scale plant classification in a natural environment. The proposed work claims a higher accuracy in plant identification based on experimental data. The model achieves the utmost recognition rate of 96% NU108 dataset and UAV images of NU101 have achieved an accuracy of 97.8%.**

***Keywords*—Convolutional Neural Networks (CNN); Machine Learning (ML) algorithms; plant image identification; plant image dataset**

I. Introduction

When it comes to the matter of food, pharmaceuticals, and other raw materials, the first name that comes to our mind is Plant. Plants directly or indirectly provide benefits to humanity's progress. As a result, our ability to recognize the characteristics of a wide range of plant species was critical for our prosperity and survival. Thousands of plant species are scanned and cataloged by various researchers and academic practitioners [1] to better recognize their features, value, and prospective applications [2]. The majestic feature of the plant kingdom is that no two are alike. Every tree is beautiful and has possession of divergent characteristics. As no fingerprint in the world is identical, no venation pattern of a plant is similar. Different species have seemingly many varieties of shapes, sizes, textures, and effervescent colors. With the change in seasons, every tree changes its appearance to adapt to the environment. Automated plant identification is the most prominent remedy for bridging the environment with today's rapidly developing technology that has substantially improved in recent years. Both environmentalists and techies are showing considerable attention to plant identification for its never-ending applications. All this is possible because of the instigation of Deep Learning (DL) models, which can automatically learn to extract higher-level features from unrefined data [3]. Machine learning (ML), a branch of AI, is a technique in which a computer is taught, through the analysis of data, to carry out a particular activity, such as prediction. It has garnered a lot of interest in recent years from researchers in many different areas, including object recognition [4-5], natural language processing, speech recognition [6], and smart manufacturing [7-8]. Machine learning algorithms can be broken down into three distinct classes denoted by whether they rely on an external observer to provide feedback on the learning process: unsupervised learning, supervised learning, and semi-supervised learning. Unsupervised learning trains using unlabeled data, unlike supervised learning. Semi-supervised learning, in contrast to these other two types, uses both labeled and unlabeled data during training. The advancement in machine learning helped in developing innovative automated image identification models are proposed. With the evolution of smartphones throughout the previous two decades, mobile-based applications have become an important part of this development. Mobile phones play an important role in image identification in real-world and natural environments. Millions of images have been acquired through mobiles. The awareness of people on maintaining ecological balance and the crucial role of plant identification in many other platforms drives modern scientists to focus on improving the performance of mobile-based image identification models. DL networks can overcome prior challenges related to handcrafted feature extraction from massive volumes of data by utilizing parallel computing architectures [9]. DL models may learn which traits are most important for feature extraction using multi-level representations, demonstrating their efficacy [10].

In the modern-day, variations in leaf characteristics are used by researchers as a comparative tool for identifying plants. Many efforts have been put on to extract the features of flower, fruit, or leaf for identifying the plant. The research about automated plant identification has started about two decades ago. In [11], Söderkvist classified the trees from images of the leaf using a computer vision classification system. Different features of the leaf are defined as different descriptors for comparison. Backpropagation was used on 15 different Swedish tree classes to investigate features such as leaf shape and moment for the feed-forward neural network. In [12], Fu et al. believed that leaf venation contains important genetic information. Due to the high diversity in leaf veins, conventional thresholding-based methods may not extract information accurately. Features such as edge gradients, local contrasts, and statistical features are extracted to define the characteristics of the veins' surrounding pixels. The experiment shows that, when compared to traditional thresholding, the neural network is more efficient to identify vein images. Li et al. [13] presented an effective leaf vein extraction approach by using the snakes' method along with cellular neural networks. Using prior knowledge similar features were obtained from both implicit and parametric models for acceptable results on leaf segmentation. A probabilistic neural network as a classifier was employed for identifying the leaf images of plants that performed better than the BP neural network in terms of accuracy [14]. The concept of natural-based leaf recognition and a contour segmentation technique based on the polygon leaf model was used to obtain the contour images [15].

Deep learning has been a hot topic since 2010, and many scientists are focusing their efforts on deep learning for image recognition. Many researchers work on flowers for classifying ornamental plants. As leaves and flowers also have different features to distinguish, Nilsback and Zisserman proposed a model for foreground and background and a light generis shape model for identifying petal structures. This technique describes the shape, color, texture features, and other characteristics of the flowers [16]. A deep learning model with 26 layers and 8 residual building components was developed for identifying plants at a large scale in the natural environment. The suggested model achieved a recognition rate of 91.78% for the BJFU100 dataset, suggesting that deep learning is an encouraging approach for smart forestry [17]. A system to detect and recognize a variety of plant species was designed by Militante et al. [18]. The system was able to detect a variety of plant diseases too. A deep learning model was trained using 35,000 images of healthy and infected plant leaves and finally, a 96.5% of accuracy rate was achieved by the trained model. Liu and Kan proposed a classification model which has a combination of texture combination and shape features, using deep belief network architecture. Local binary patterns derive the texture of a leaf. The combination is maintained by gray level co-occurrence matrix and Gabor filters [19]. In the year 2022, Haq [20] applied a machine learning-based Random Forest (RF) classification model for comparing the vegetation extent. To identify leaf images, Zhang et al. [21], created a deep learning system that included eight layers of Convolution Neural Networks (CNN) and achieved a better recognition rate. Zhang et al. combined the Harr-like transformation of local features with SIFT features of flower images, classifying them by the k-nearest neighbor method. His conjecture of concentrating on local features hindering performance proved right. In 2020, Yang et al. employed shallow CNN in place of DCNN for identifying the disease on the images of a leaf. A significant performance improvement was achieved with their method in comparison to the DCNN models. The use of PCA helps in performance improvement and reduces computational complexity too [22].

All this research paved a path for nowadays plant recognition technology. Various mobile applications like Pl@ntNet [23], LeafSnap [24], Microsoft Garage's Flower Recognition app [25], iNaturalist [26], and Plantsnap [27] are the most prominently used mobile applications for plant identification. Although there are numerous kinds of research on terrestrial plant identification there are barely any with UAV imagery. Automatic plant taxonomy has had rapid growth in recent years but image identification using UAV [28] is the newborn interest of the researchers. Popescu D and Ichim have proposed an image recognition model based on texture analysis. Two types of texture statistical and fractal characteristics were considered on images of forests, buildings, grassland, and flooding zone. All the research done prior to date hinders their performance in a natural environment. The traditional models used for classification rely on preprocessing of the image to delete the background and enhance it. Preprocessing the dataset consumes time and might not be as accurate as natural environment identification. The main advantages of the UAV (unmanned aerial vehicle) are the collection of the terrestrial dataset is more time taking than the aerial dataset. The traditional classification of aerial images is expensive for monitoring the evolution of the research area.

To overcome all these challenges, we acquired the NU108 a terrestrial dataset using a mobile phone in a natural environment. A UAV dataset NU101 is another prominent part of this research. A five-layer deep learning model is applied to the proposed model and a recognition rate of 97% was achieved on the NU101 dataset.

II. Dataset

A. Terrestrial Imagery

The terrestrial dataset NU108 contains 300 images of nine plant species within the campus of NIIT University (See Fig. 1). These images were collected by mobile phone in the natural environment with the help of a camera of 12 megapixels. The size of the image is 4032x3024. Drone imagery in the same vicinity NU101 dataset is collected by UAV (DJI SPARK). The images were taken from an altitude of 24m. The drone is equipped with a camera of 12 megapixels with an equivalent focal length and an RGB sensor image of a size 960 × 1280 as shown in Fig. 2.

B. Drone Imagery

The dataset NU101 was collected through DJI SPARK from an altitude of 24m. A total of 15 images covering an approximate distance of 300m have been collected and made into a mosaic image using Drone2 map software. ROIs of each tree species in the image are detected using MATLAB and used as training data for our model. A total mosaic image is used for validation.

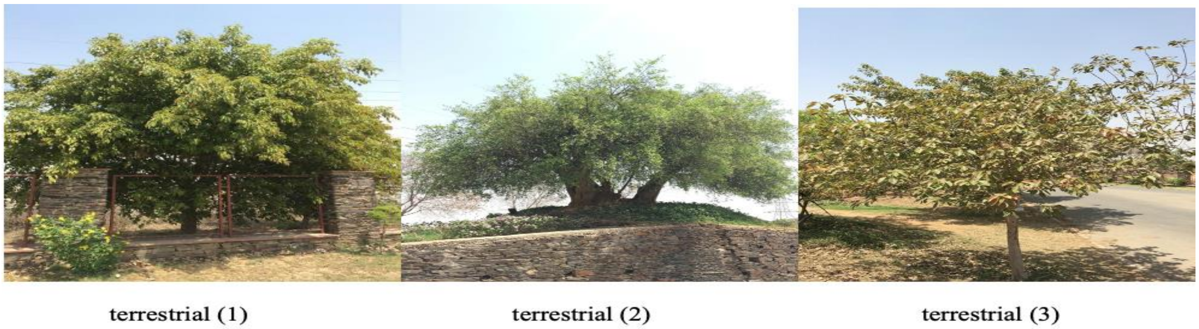

Fig. 1. Terrestrial images of plant species from the NU108 dataset.

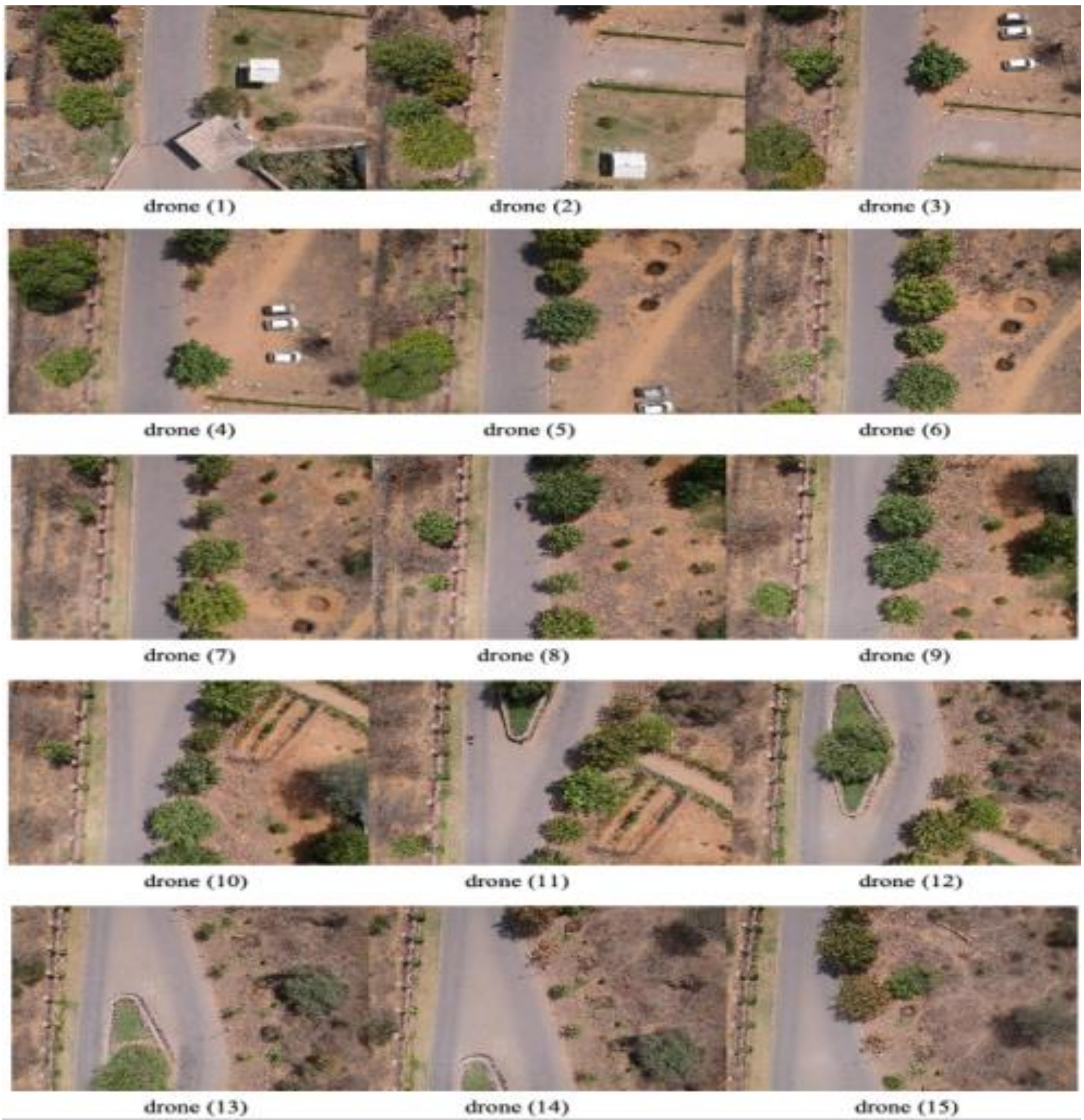

Fig. 2. The drone images of plant species were collected using DJI SPARK from an altitude of 24m.

III. METHODOLOGY

A. *Convolution Neural Network*

While ML has many applications, its success is highly dependent on the features chosen to train the model. Due to their ability to automatically extract higher-level features from the raw input data, deep learning algorithms have garnered a lot of attention in recent years. When it comes to deep learning, the most popular technique is the convolutional neural network (CNN) algorithm, which is built on the ANN foundation. Convolutional networks were inspired by early findings of biological processes; the connectivity pattern of CNN neurons resembles the organization of an animal's visual cortex. A CNN allows elements to be identified and classified with minimal pre-processing [32-37]. The CNNs are regularized multilayer perceptron variants. The term "multilayer perceptron" usually refers to networks that are fully connected, meaning that each neuron in one layer is linked to all neurons in the next layer. In comparison to other image classification techniques, CNN requires extremely little pre-processing. Difficult image-driven pattern recognition problems can be solved easily by the simple architecture of CNNs that require minimum input parameters [38]. When other algorithms need to be hand-engineered this neural network learns about the filters which help in natural scene image classification. This is the best feature of CNNs that they do not need any prior knowledge about the classification and most little human efforts are needed.

1) Convolution: The convolution layer, which is connected to local portions of the input, will determine the output of neurons by calculating the scalar product of a set of weights with the region related to the input volume represented in the form of metrics. The operation of convolution is shown in Fig. 3. The rectified linear unit (abbreviated as ReLU) is applied as an 'elementwise' activation function like a sigmoid to the output of the previous layer's activation.

2) Pooling: It is one of the building blocks of CNN that simply reduce the input size with the help of the downsampling process. Thus, it reduces the computation for the given problem (See Fig. 4). Multiple polling layers (i.e., Max Pooling Layer and Average Pooling Layer) can be applied to reduce the number of parameters within that activation.

3) Fully connected layer: The input data to CNN layers cannot be inserted as shapes or pictures. Therefore, the process of flattening is performed to construct a single-dimensional feature vector from the output of the convolutional layers as shown in Fig. 5. Furthermore, it is linked to the final classification model, which is referred to as a fully connected layer. The fully connected layers produce the final output class scores from the activations in the same way that normal ANNs do. The generated class scores can be utilized for classification. It is also possible that ReLU might be employed between these layers to improve performance.

4) Architecture: A convolutional neural network consists of a convolution layer in which the input image is convoluted with multiple kernels (feature detectors) and then connected to the polling layer where features are magnified and then connected to the fully connected layer. The activation functions help in the classification of the data. The architecture of our model has five-layered deep neural networks (See Fig. 6 (a)), and the second model with three neural network layers (See Fig. 6(b)). The convolution layer model is applied to terrestrial data NU108 for image identification.

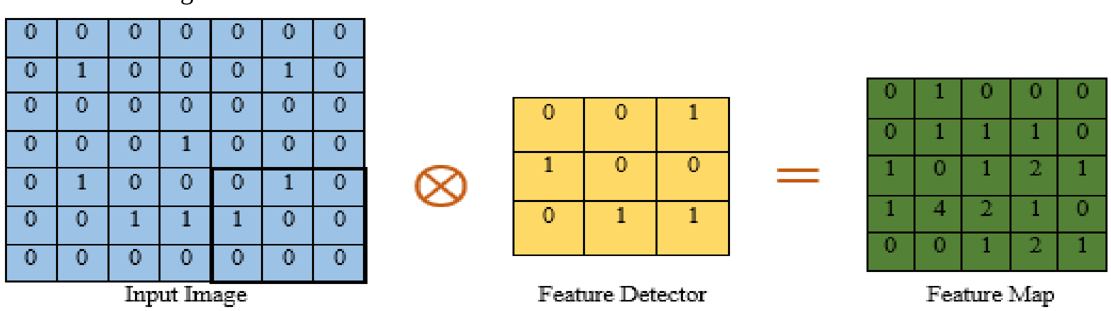

Fig. 3. Convolution operation using the scalar product of a set of weights with the related region.

Fig. 4. Illustration of max polling layer.

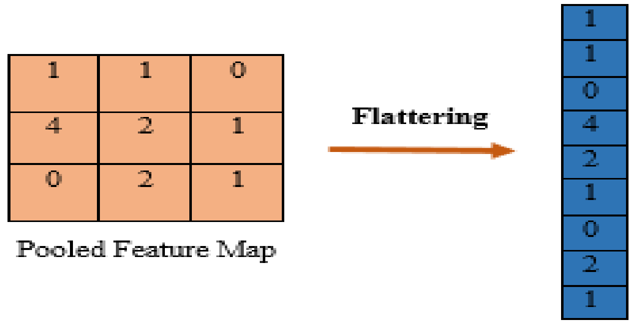

Fig. 5. Process of flattening to convert the data into a 1-dimensional feature vector.

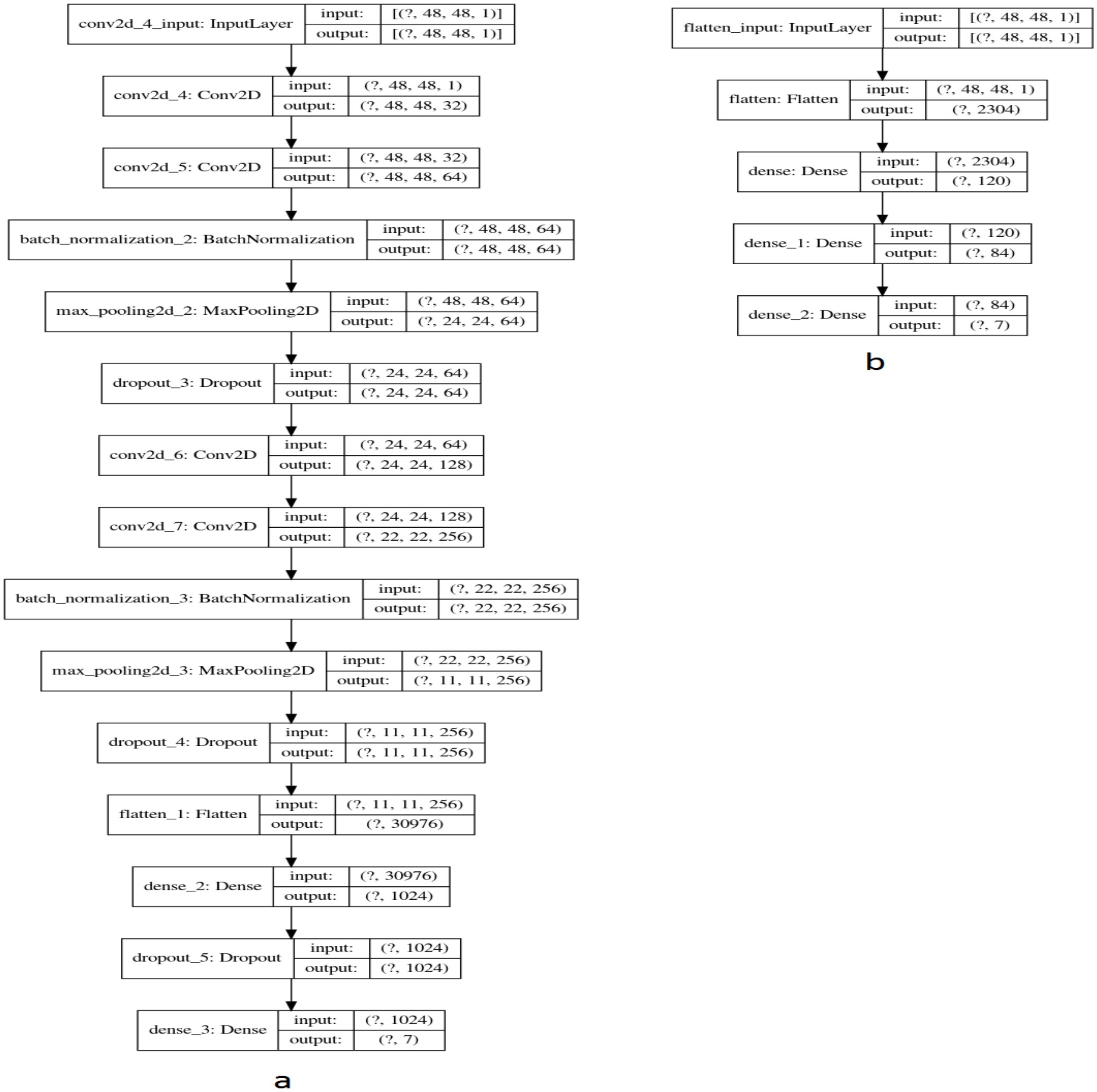

Fig. 6. The architecture of the models with (a) five layers of deep neural networks, (b) three layers of neural networks.

5) ReLU: The activation function ReLU is used mainly to remove the negative values. The standard way of model a neuron's output is f as a function of its input x is with f(x) = tanh(x) or f(x)=1/(1+e−x). These saturating nonlinearities are significantly slower than the non-saturating nonlinearity in terms of training time with gradient descent and are described mathematically as f(x) = max (0, x). A visual Illustration of the ReLU activation function is shown in Fig. 7. Following [29], refer to neurons with the nonlinear property as ReLUs. Deep CNNs with ReLUs perform better than their tanh unit counterparts in terms of training time. When compared to other activation functions, such as sigmoid or tanh, RELU does not experience the vanishing gradient problem that these other activation functions do.

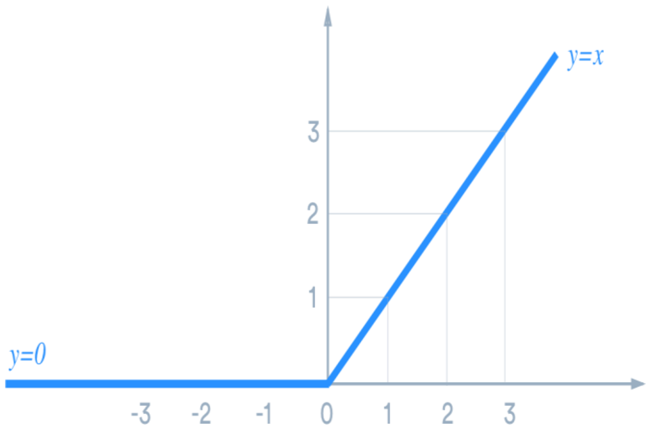

Fig. 7. A visual Illustration of the ReLU activation function.

6) Sigmoid function: A sigmoidal function in the form of a hyperbolic tangent is consistently preferred theoretically and experimentally for deep learning models. It is used in neural networks to give logistic neurons with real-valued output which is a bounded function of their total input. Having the advantage of nice derivatives, it facilitates learning the weights of a neural network much easier. Sigmoid activation function S(x) is defined by equation (1) and is illustrated in Fig. 8.

$$S(x) = \frac{1}{1+e^{-x}} = \frac{e^x}{e^x + 1} \quad (1)$$

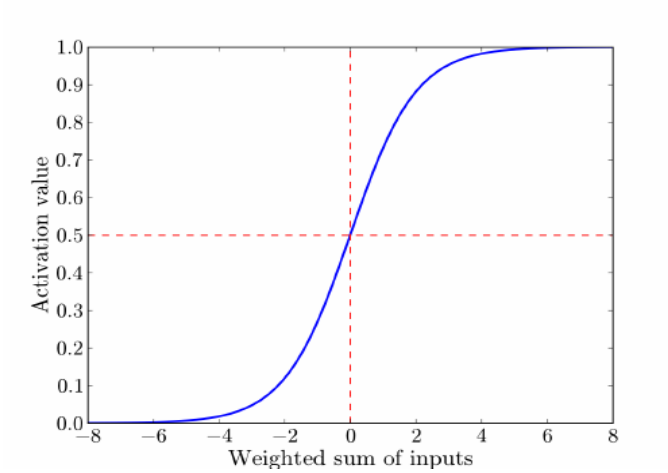

Fig. 8. Sigmoid activation function.

B. PCA Method

After the input image is processed further the image has a natural scene with trees and other objects in it. Tree identification is carried out as the first step toward classification and identification. Tree identification is done through the Primary Component Analysis method which is one of the dimensionality reductions. The mosaic of the input image is shown in Fig. 9.

1) Decorrelation: Decorrelation stretch enhances the visual perception of the image so that the objects can be differentiated due to enhanced color separation of the image (See Fig. 10).

2) Principal component analysis: Principal Component Analysis (PCA) is a technique used for dimensionality reduction. It directly decreases the number of feature variables by saving only the required variables. PCA is used to obtain a single-band image. First, compute the covariance matrix of the data and further calculate the eigenvalues and vectors for the computed covariance matrix. Select only the most significant feature vectors using the eigenvalues and vectors, and then convert the data onto those vectors to reduce dimensionality (See Fig. 11).

Fig. 9. Mosaic of the input image.

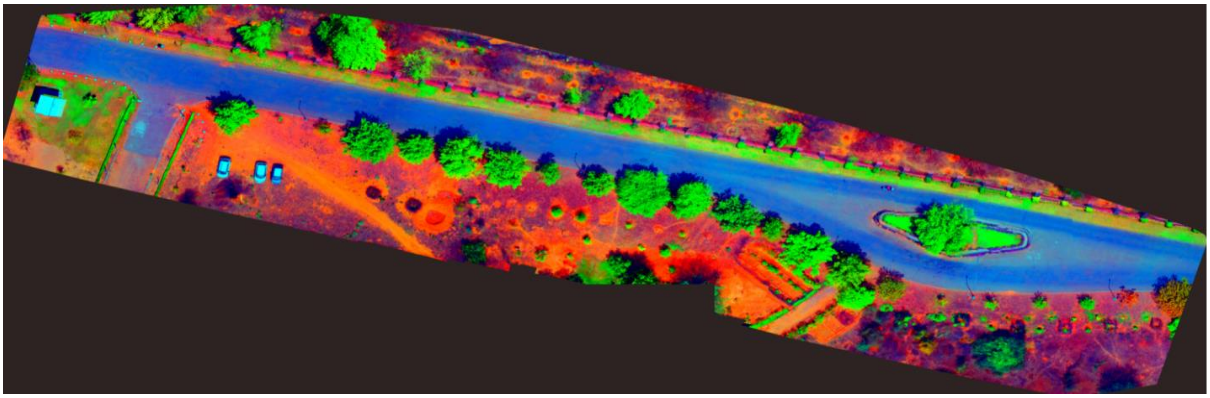

Fig. 10. Image after decorrelation stretch image.

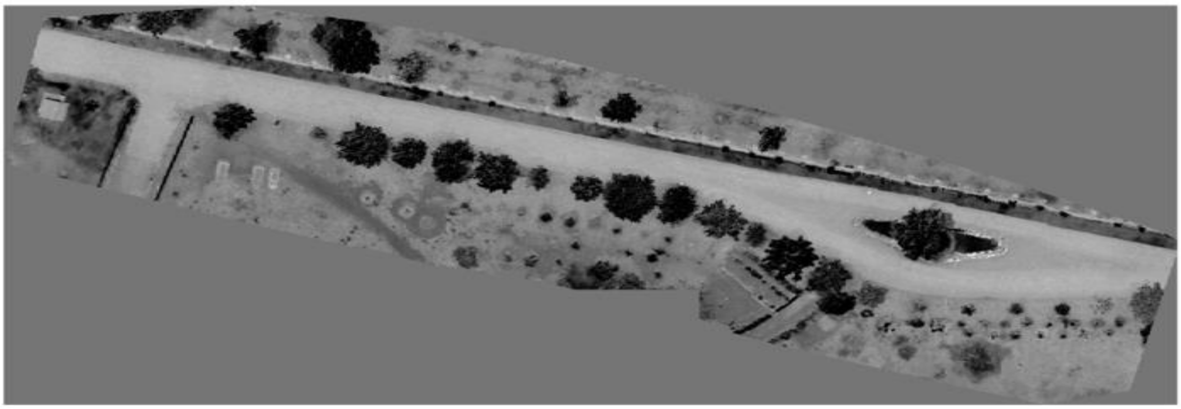

Fig. 11. Image after applying the PCA technique.

3) Thresholding: Thresholding is done by using Otsu's Method in our model. Otsu's thresholding approach iterates through all the threshold values and calculates a measure of pixel-level spread on each side [30] of the threshold, categorizing the pixels as foreground or background. The goal is to discover the threshold value at which the sum of foreground and background spreads is the smallest.

4) Edge detection: Edge detection is an image processing approach for detecting object boundaries within images. It works by sensing brightness discontinuities. It's utilized for data extraction and image segmentation. Edge detection in our model helps define the tree's outline and separate the tree from the background for further analysis. Noise in the form of unwanted background and shadow of the trees can be removed using the Gaussian Filter method. This helps in reducing false detection. The Gaussian filter is represented as equation (2).

$$H_{ij} = \frac{1}{2\pi\sigma^2} exp(-\frac{(i-(k+1))^2+(j-(k+1))^2}{2\sigma^2}) \quad (2)$$

$$1 \leq i, j \leq (2k+1)$$

Two methods namely Sobel and Canny can be applied to detect the edges. Canny has four different filters to detect edges in different directions in blurred images. The output of Sobel is taken as the input of canny. Canny gives an output of an image with thicker outer lines and thinner inner edges.

5) Implementation and preprocessing: Tree crowning is followed by Dataset Processing after the edge detection of the vegetation. Trees and plants are cropped from the resultant image of tree crowning and are stored in a folder for further processes. Multiple images are cropped from a single image using Matlab. Several trees are counted by the application of the PCA method and that helps in the training of the model. All the trees that are cropped and stored are now sorted. Identification of the species is done manually. The data set folders thus obtained are divided into the testing set and training set.

Keras is a Python based open-source deep learning framework that is used to implement the model. All the experiments were run on a Windows server with a GTX 1050Ti GPU (8 GB memory) and a 3.40 GHz i7-8750H CPU (16 GB memory).

6) Training algorithm: A feed-forward neural network is like a logistic regression algorithm, but the input values get more linearly separable with the addition of hidden layers. A gradient descent-based strategy was used to train this model by minimization of backpropagated error. The backpropagation algorithm is used to iteratively discover a local optimum of the loss function [31]. The error backpropagation through the output layer L to layer $l < L$ will be done via a recursive computation as equations (3, 4, 5).

$$\frac{\partial L}{\partial {w_k}^{(l)}} = \frac{\partial \eta^{(l)}}{\partial {w_k}^{(l)}} \frac{\partial h^{(l)}}{\partial \eta^{(l)}} \frac{\partial \eta^{(l+1)}}{\partial h^{(l)}} \frac{\partial L}{\partial \eta^{(l+1)}} \tag{3}$$

$$= - \frac{\partial \eta^{(l)}}{\partial {w_k}^{(l)}} \frac{\partial h^{(l)}}{\partial \eta^{(l)}} \frac{\partial \eta^{(l+1)}}{\partial h^{(l)}} \Delta^{(l+1)} \tag{4}$$

$$= - \frac{\eta^{(l)}}{{w_k}^{(l)}} \Delta^{(l)} \tag{5}$$

IV. Result Analysis

A series of experiments were done to find the best accuracy and improve the quality of the result. The comparison between accuracy and epochs of the validation accuracy and testing accuracy has been measured. The proposed model results in 97.8% accuracy over the UAV dataset and 96% accuracy in the terrestrial dataset (See Fig. 12). The output image after applying the proposed CNN model is shown in Fig. 13. For the size of the dataset, this five-layered CNN is the best tradeoff between model capacity and accuracy.

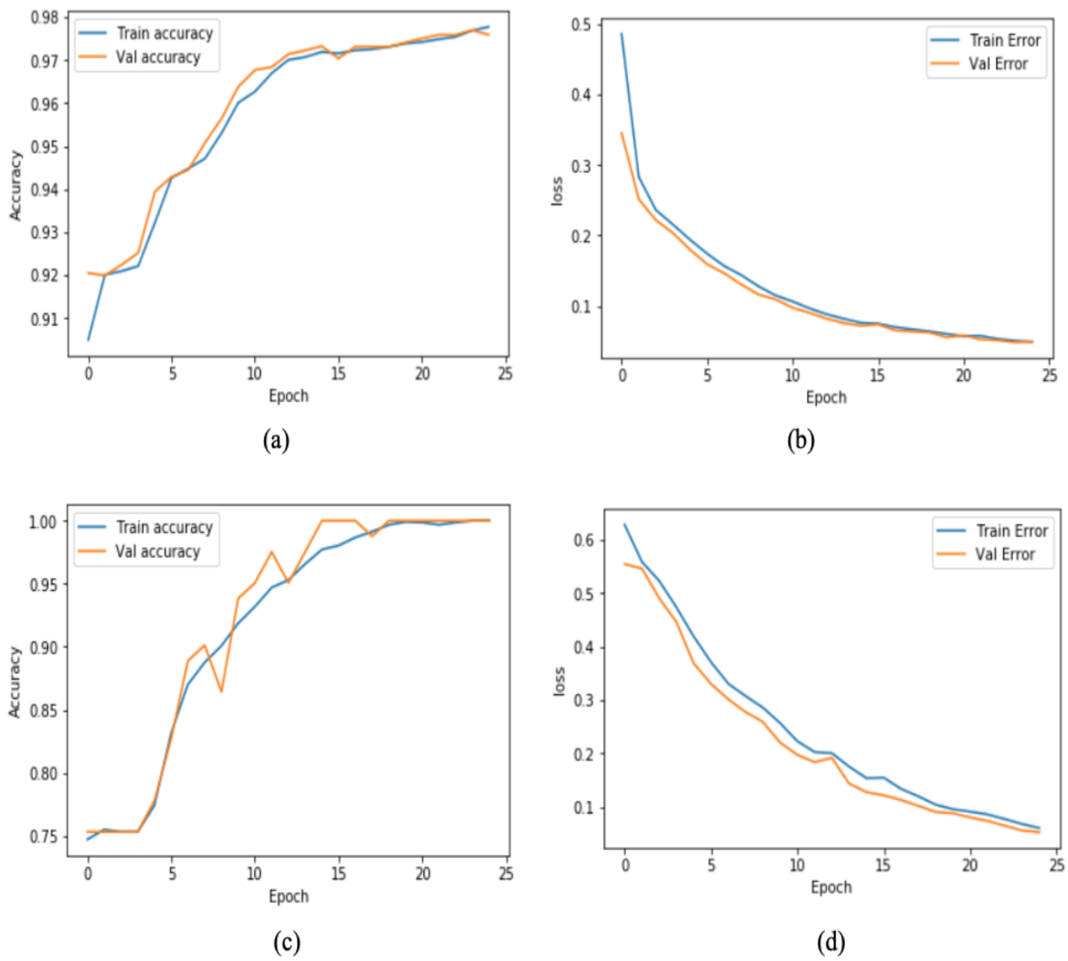

Fig. 12. Performance of the model.

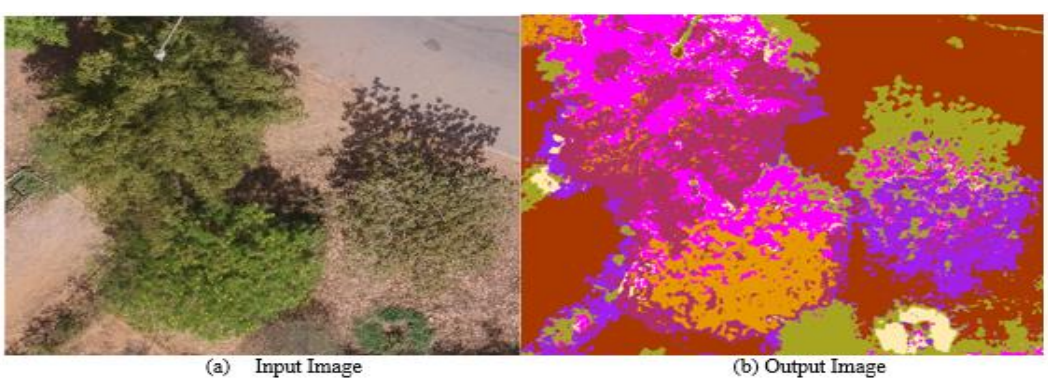

Fig. 13. Resultant image after applying the proposed CNN model.

V. Conclusion

The first mobile device acquired the NU108 dataset containing 300 images of nine plant species and the NU101 UAV data set which paves a path for further plant identification studies on UAV imagery. The proposed model achieves an accuracy of 97.8%, proving that deep learning is an encouraging technology for classifying plants in the natural environment. The NU101 database will be expanded in the future to include more plant species at various stages of their life cycles, as well as more thorough annotations. The drone imagery will be widened and work on more sophisticated systems for higher accuracy over a larger area will be done in future research work. The future scope of the present work will be utilizing the advanced DL models with additional datasets.

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