Plant Seedling classification in Harsh Environment using Preprocessed Deep CNN

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***Abstract*— In developing and developed countries, farmers are struggling to reduce costs and provide organic produce. Farming large areas of land requires equipment, workers, and other material that burden farmers with increased costs to compete in the local, regional, and global markets. With the advent of new technologies in the field of Artificial Intelligence, Internet of Things (IoT), cloud computing, and others, there is a glimpse of hope for inventing new techniques in farming that will eventually reduce the cost of farming large areas of land. In this paper, a method is proposed that can automatically classify plant seedlings with great accuracy thus making it possible for automatic farming processes. In this paper, we propose a Deep CNN architecture for the automatic classification of plant seedlings using whole images and using segmented images as input. The test accuracies achieved outperform similar methods reported in previous studies. The experiments showed that the proposed method achieved an average accuracy of 97.27% when whole images are used as input and an average accuracy of 99.52% when segmented images are used as input to the proposed Deep CNN architecture. The segmented images increased the accuracy by 2.25%. The proposed Deep CNN architecture results are impressive for both cases of using whole images or segmented images as input. The dataset used in this work consists of 5000 images of 12 different species which are captured at various development phases.**

Keywords*— *Leaf Segmentation; IoT in Plantation; Convolutional Neural Network; Leaf Classification; Plant Seedling; Seed Planting Automation

I. Introduction

Plants play a significant role in maintaining a healthy ecosystem. They guarantee the survival of other organisms by supplying food and oxygen. In addition to this, they are the only vital resource that is responsible to provide us with essential products like medicine, coal, natural gas, etc. Hence, it is necessary to ensure the existence of plants which would in turn ensure the existence of other organisms. Unfortunately, it has been observed that lately many species of plants are already extinct or on the verge of extinction. This can be caused due to both natural and man-made reasons. Deforestation and urbanization are the two major factors that result in the declining population of plant species. The loss of plants leads to the environment dealing with various consequences such as land desertion, climate anomaly, floods, global warming, biodiversity loss, etc. People have now realized the importance and need for protecting plants. Apart from taking effective measures to protect plants, ordinary people need to identify plants to improve the consciousness of plant protection. It utilizes aspects such as Global Positioning System (GPS) as well as information technology to find out the best possible places to plant as well as the best possible times to plant. With the rapid change in the world's climate and the threat of global warming, now is the most important time to enhance the use of this type of agriculture. One aspect of precision agriculture that plays an important role in the plant seedling classification. Plant seedling classification enables the system to differentiate between the plant and weeds that exist within the crops through the incorporation of algorithms to help identify each through sets of image-related data. The technique utilizes technology and aims to allow for cheaper, higher quality plant life. This in turn will allow for the plant seedlings to be positioned more accurately and in more effective areas to gain the best possible result.

For novice readers, a seeding is baby plant sporophyte growing out of an embryo of the seed. The first phase in the seedling development if the germination of seeds. The baby seedling has three parts; radicle, hypocotyl and cotyledons. Flowering plants known as angiosperms are identified through the number of seed leaves. Other plants knowns as the gymnosperms have various number of seed leaves for example eight cotyledons for the pine seedlings. The portion of the seed embryo that develops as a shoot bearing is referred to as plumule. Plumule develops when the cotyledons grow above the ground referred to as epigeal germination. Hypogeal germination is a term used for seeds that have the plumule developing through the soil with cotyledons staying underground [1-3].

The motivation of this study is to automate the seed planting of various plants as well as automate some agricultural processes such as weed removals and others that will enhance the yield. The main aim of this paper is to propose a plant seed classification technique based on Convolutional Neural Networks (CNNs) using the dataset found in the Kaggle website. The proposed algorithm will be compared with other machine learning algorithms proposed in previous literature.

The novelty of this work is the use of a Deep Neural Network Architecture for the classification of plant seedlings before and after segmentation. The proposed Deep Neural Network Architecture consists of 10 convolutional layers plus a pooling layer, a flattening layer, and a dense layer.

The rest of the paper is organized as follows: Section 2 presents the literature review related to this research, section 3 details the proposed algorithm, section 4 contains the details of the dataset used, section 5 shows the obtained results, the paper concluded in section 6 while section 7 has the list of all references used.

II. Literature Review

In [3], the authors evaluated the feature selection methods and their effect on the performance of the machine learning inspection and classification of pot plant seedling. The tested the feature selection on the conventional machine learning algorithms and concluded that feature selection can increase the accuracy by up to 7.4%. In [4], the authors published a dataset of around 960 unique plants that belong to 12 different species within different stages of growth. RGB images with a resolution of 10 pixels/mm make up the images for the database. In [5], the authors proposed a drone-based automatic monitoring of seedling using neural networks. They used low altitude UAV images and object-based image software for the analysis and detection of target seeds and seedlings. They achieved above 90% accuracy for target seed classification and above 80% for target seedling classification. They found that the higher the altitude the lower the accuracy. In [6], the authors proposed an architecture consisting of 7 layers (5 convolutional and 2 fully connected) for the automatic classification of plant seedling images. They used a dataset consisting of 4,234 images for 12 plant species. They achieved an overall accuracy of 90.15% in 111 minutes and 36 seconds as they aimed to optimize speed and memory consumption as well. In [7], the authors present a comparative study using two traditional neural network algorithms, a CNN algorithm, and a deep learning technique for image recognition on a 4,275 image of 960 plants for 12 different species. They conclude that CNN-based seedling classification may potentially optimize the yield and enhance productivity and efficiency in agriculture. In [8], the authors propose a method for the recognition of plant species in color images using CNN. They used a dataset of 10,413 images of 22 crop and weed species at early growth stages. They obtained the images from 6 different datasets with variation in resolution, lighting, and soil type. They achieved an accuracy of 86.2% for the combined dataset. In [9], the authors propose a technique to predict the germination capacity in addition to discriminating Jatropha Curcas L. seeds in terms of germination speed and vigor of seedling through the means of x-ray analysis and machine learning. They obtained an average accuracy of 94.36% for seed viability, 83.72% for germination speed, and 89,72% for seedling vigor. In [10], the authors propose a Deep CNN method for the identification and classification of maize drought stress. They compared their proposed method with traditional machine learning algorithms. They reported an average accuracy of 98.14% for identification and 95.95% for the classification of maize drought stress. In [11], the authors propose a segmentation method SegNet based on a fully convolutional network (FCN) for recognition of weeds in rice seedling fields. Color images were used and they compared their proposed method of classical segmentation methods. They reported an accuracy of 92.7%. In [12], the authors propose a non-destructive technique for root system classification with different degrees of freezing injuries which is based on the impedance spectra measurement. In [13], the authors propose a technique for the classification of weed and crop species using CNN. A hybrid model of VGGNET and AlexNET was used. This was compared by both individually. The hybrid model outperforms AlexNet and VGGNET individually. In [14], the authors propose an image processing technique for plant leaf classification. The detection and classification techniques for leaf disease from 1997 to 2016 are covered in their paper. In [15], the authors propose a classification method for weed and vegetables from crop images taken outdoors through SVM. Above 90% classification was achieved. In [16], the authors propose a machine learning method for the segmentation of the weeds from images. The authors designed a dataset for this purpose. The poor performance of the machine learning algorithms was observed for grayscale images with changing light conditions and changing distance of the camera to the weeds. In [17], the authors propose the use of unmanned aerial vehicles (UAVs) in what is referred to as smart farming to monitor farmlands to minimize the number of pesticides and herbicides. The authors propose an automatic vegetation detection system based on extracted features and estimate the weed and crop distribution based on classification. The system was tested on two farms one in Germany and one in Switzerland to prove the concept.

Machine learning algorithms for classification and detection can also be used in various other industries. It can be used in Manufacturing, Medicine, pharmacology, education, and other fields. As examples, in [18] the authors propose a machine learning algorithm for license plate recognition. They use Raspberry PI and perform a feature extraction based technique for the recognition process. They reported an average accuracy of 90.6%. In [19], the authors use Machine learning for Education in particular for the automatic handwritten script recognition. They extracted 65 features and used several classifiers. Random Forest (RF) achieved the best accuracy of 96.73% for Multilanguage numeral recognition. In [20], the authors used machine learning for the medical industry. They proposed a brain tumor feature-based classification method. Another example of an image processing technique in the medical field was presented in [21]. The authors proposed a skin lesions segmentation technique and tested on 300 images. They reported an average accuracy of 96.6%. In [22], an example of machine learning in the manufacturing industry is used. The authors propose automatic monitoring and analysis of powder bed images.

III. PROPOSED SYSTEM

In this article, Deep Neural Networks based approach is proposed for the classification of original plant seedling images and the classification of the images after segmentation. The images are subject to two stages of processing: first stage is the preprocessing stage where images subjected to various preprocessing methods such as noise removal, centering images, etc. The second stage is the use of the proposed Deep Neural Network architecture. Segmentation is also done in the second experiment between the preprocessing stage and the Deep CNN stage.

A. Dataset Description

The data sheet incorporated is compiled of several different plant types during various stages of its growth cycle consisting of 12 different plants seedling having total 4751 images [23]. Through the application of the Imaging and seedlings calcification, these different pictures will be reviewed and assessed to see which ones have experienced the most growth based on how they were classified within the actual field. Figure 1 shows the sample images of plant seedling of different species captured at different parameters. The imaging shows plants within different areas and different types of soils. The goal of these images is to study them and find where they grew more promptly, as well as identifying how the application of geo-agriculture played a role in making these selections. Through these images, the plants show different qualities of their growth cycle, as well as different aspects of their growth that is otherwise slowed down through normal agricultural means. The images will help pinpoint the right location, as well as the most efficient way to plant and harvest these crops.

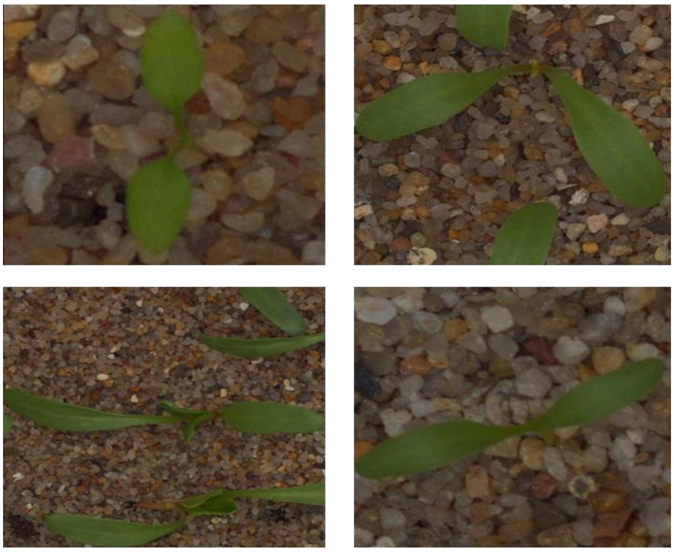

Figure 1. Sample Images of Plant Seedling Dataset

Figure 2. Sample Images of plant seedling with misleading background

B. *Preprocessing for Segmentation*

The segmentation of the plan seedling image from the whole image was done using the methods listed in [24]. The images with preserved edges are smoothed using Anisotropic Diffusion Filter (ADF) followed an Adaptive Thresholding to segment the plant seedling image through binarization. Other morphological operations are then applied to further enhance the image. The final segmented image is acquired through the application of the proposed boundary conditions for selecting objects based on distance. The sample outcome of the segmented plant seedling images are shown in Figure 3.

The preprocessing stage consists of subjecting the images within the dataset to various preprocessing methods which include the following:

- Noise Removal using Gaussian filters
- Centering the Image
- Conversion from RGB to grayscale
- Automated Thresholding for Binarization
- Removing the background of leaves
- Remapping the original image plant leaves

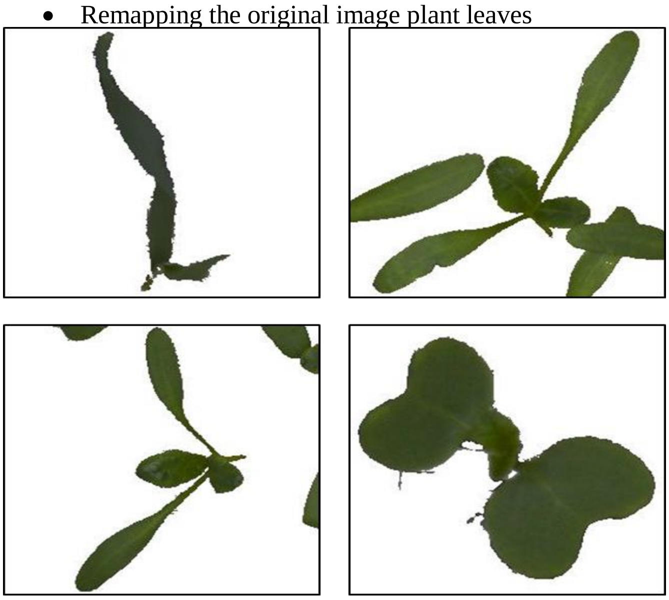

Figure 3. Processed Plant seedling samples with background removed

C. *Convolutional Neural Networks (CNN)*

Although the notion of Deep Learning Architecture has been introduced for a vast time duration, still the implementation of Deep Learning to its ultimate value has not been accomplished until lately with progress in computing potential, technological power, and computing assets. The algorithms proposed for deep learning architectures have accomplished novel success in various fields like speech and image recognition amidst numerous others [23].

The theory of Deep Learning is dependent upon what is regarded as Convolutional Neural Networks (CNN or ConvNets). A novel Convolutional Neural Network or CNN was introduced by Krizhevsky in the year 2012. It was deeper and broader than LeNet and eventually succeeded with the Image Net 2012.

In this paper, a Deep CNN architecture is proposed which consists of 10 convolutional layers, a pooling layer, a flatten layer, and a Dense layer. The convolutional layers start with an input patch of 64x64x 16 then reduce to 32x32x32 and eventually reduce to 16x16x64. The pooling layer pf 2x2x64 is used to down sample the features obtained from the convolutional layers. The flatten layer and Dense layer is then applied to output 12 outputs that represent the classes. Table 1 details the architecture of the Deep CNN proposed in this paper.

TABLE I. PROPOSED CNN MODEL FOR PLANT SEEDLING CLASSIFICATION

Input Plant Seedling Image (64x64x3)		
Conv. 1 (64x64x16)	Batch Norm. 1	Activation 1
Conv. 2 (64x64x16)	Batch Norm. 2	Activation 2
Conv. 3 (32x32x32)	Batch Norm. 3	Activation 3
⋮	⋮	⋮

Conv. 10 (16x16x64)	Batch Norm. 10	Activation 10
Avg. Pooling (2x2x64)		
Flatten Layer (256)		
Dense Layer (12 Output Layer)		

IV. Results and Analysis

Different experiments are performs using 80% for training and 20% for testing, the results are presented in Table 2. Results indicate that 97.27% accuracy was obtained using the whole image as input to the Deep CNN architecture. After segmenting the plant seedling portion of the image and feeding it to the Deep CNN architecture, a classification accuracy of 99.52% was achieved with an increase of 2.25% in accuracy. The 80% of images used for training are actually divided to two portions with 20% of the 80% used for validation and remaining images used for training.

TABLE II. Comparison of experimental results based on original images and segmented images

CNN Method	Train Acc.	Train Loss	Test Acc.	Test Loss
Original Images	97.27%	0.1845	91.58%	0.3929
Segmented Images	99.52%	0.1338	95.02%	0.2699

Figure 4 shows the validation and test accuracy results when using the whole image as input to the proposed CNN architecture with x-axis representing number Epochs of increasing size. It is observed that for Epochs less than 80, the test accuracies are somewhat unstable. However, for epochs of 80 and more the test accuracy is more stable and follows the trend of the validation accuracy.

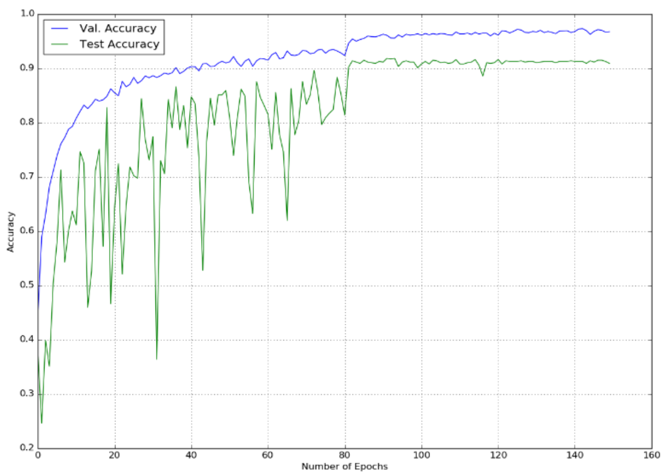

Figure 4. Train and validation accuracy using whole image as input to Deep CNN

Figure 5 shows the validation accuracy vs the testing accuracy when the segmented image of the plant seedling is used as input to the proposed Deep CNN architecture. Again the x-axis represents the number of epochs. Even below 80 epochs, it is observed that the testing accuracy is more stable and follows somewhat the trend of the validation accuracy with the similarity in trends increasing beyond 80 epochs. It is also observed that better test accuracy results are obtained for the segmented images.

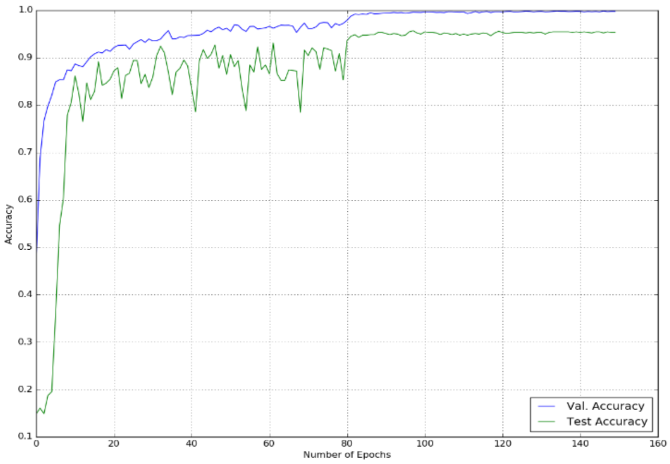

Figure 5. Train vs validation accuracy using segmented image as input to Deep CNN

V. Conclusion

In this paper, a classification technique was proposed for classifying the plant seedlings using both whole images and using segmented images as inputs to a proposed Deep CNN architecture. The proposed system consists of two stages; a Preprocessing Stage, and a Deep CNN stage for classification. The importance of this work is rooted with the importance of the agriculture industry in many countries both developing and developed. The increase cost of manual farming make it difficult for the agriculture industry to compete and make profit. The automated process of farming, weeding and other agriculture activities is needed to reduce cost and allow for farming large areas of land. Through the proposed technique, a classification accuracy of 97.27% was achieved for whole images of the plant seedlings and an average accuracy of 99.52% was achieved for segmented images of the plant seedling dataset with an increase of 2.25%. The results obtained in this study outperform similar methods reported in previous studies.

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