Classification of Plant Seedling Images Using Deep Learning

Catherine R. Alimboyong
Graduate Programs
Technological Institute of the Philippines
Quezon City, Philippines
catherine.alimboyong@sdssu.edu.ph

Alexander A. Hernandez
College of Information Technology Education
Technological Institute of the Philippines
Manila, Philippines
alexander.hernandez@tip.edu.ph

Ruji P. Medina
Grduate Programs
Technological Institute of the Philippines
Quezon City, Philippines
ruji.medina@tip.edu.ph

***Abstract*—*The agricultural sector has recognized that for crop management to thrive, acquiring relevant information on plants is needed. However, studies have shown that agricultural problems remain difficult in many parts of the world due to the lack of the necessary infrastructures. Using a public dataset of 4, 234 plant images from Aarhus University Signal Processing group in collaboration with University of Southern Denmark, that consist of descriptions under a controlled condition concerning camera radiance and stabilization. This paper uses a convolutional neural network for training and does data augmentation to identify 12 plant species using a variety of image transforms: resize, rotate, flip, scaling and histogram equalization. The trained model achieved an accuracy categorization of 99.74% during validation and 99.69% during testing, with specificities and sensitivities of 99%. In future works, we plan to utilize the model by training it to other types of plants like herbal-medicinal plants and other crops in other countries. Moreover, the proposed method can be integrated into a mobile application with the goal to provide farmers efficient farming practices.*

***Keywords*— Classification, deep learning, plant seedling images, convolutional neural network**

I. INTRODUCTION

An essential aspect of life on earth is the presence of plants. In fact, it gives us sustenance, medicines, protect, and provide us with a sound breathable climate [1]. However, with a bloating population, observed climate change and environmental changes [2], there is a growing risk to several ecosystems[3]. Identification of plant seedling is essential as it can help in recognizing different plant species. In most cases, identification is performed manually, either visually or by microscopy. Recently, manual identification of plant species made it difficult for human experts, and more so for amateurs as it may take several minutes, hours or even days to solve expert tasks. A good understanding of shapes, petal and leaf types, as well as the entire plants, are equally essential to help measure plant condition and even model climate change using machine learning algorithms [4]. Consequently, it is vital to categorize new or unusual plant classes [5]. Furthermore, the interests in image classification are growing [6], [4]. Given the availability of digital images from online databases [6], the need to create a fast method to classify plant species is urgent.

Recently, classical techniques have been extensively used for identification and classification of plant images [7]. However, these conventional techniques have been replaced by Deep Learning algorithms (DL) [8]. In DL, handcrafted feature extractors are unneeded. Previously, traditional methods of sorting images involved the use of hand-crafted approach [9]. Significant works have been done on speech [10], natural language [11] and image processing [12]. Opposing to outmoded machine learning procedures where features are manually selected and dig out through initiated processes, a class of deep learning technique called Convolutional Neural Networks (CNN) can quickly determine gradually sophisticated features from the available data [13], [14]. To this end, CNN becomes widespread and capable of realizing unique solutions to various concerns [15], [16], particularly plant classification within agricultural fields [3], [17], [18]. Currently, there have been a lot of researchers develop automated analysis to plant images. A review of the different techniques used [3], [17] has also been presented recently. As a result, they turned out to become feasible for more multifaceted image recognition issues. Currently, CNN's are utilized in various existing modernistic image sorting tasks [19] which can tackle exceedingly intricate image recognition with several entity classes to a remarkable gauge.

In this article, we intend to put forward deep learning-based convolutional neural systems for plant seedling classification of images. The plant classification model is tested to plant seedling images then evaluated using accuracy, specificity, and sensitivity. The results of this study will be an excellent contribution to the continuous development of crops management and towards providing a new technique to assist and ease farming practices.

The succeeding parts of the paper is structured as follows: Section II looks into the notion of Deep Learning, Plant Classifications, application, and challenges. Section III outlines the suggested technique for plant image classification through deep learning. Section IV sketches the experiments as well as the outcomes. Finally, inferences are offered in Section V.

II. LITERATURE REVIEW

A. *Deep Learning*

DL is a technique that attempts to assimilate "depth" (complex) behaviors and can solve problems that require complex highly-varying functions [8]. DL is based on algorithms for training neural networks, usually involving very large, and in most cases, non-labeled data set. Nevertheless, for machine vision jobs, the positive outcome of deep learning is anchored on the CNN which can be regarded as an efficient method for categorization of images [20]. CNN's are concurrently employed in agriculture mainly, for recognition and classification tasks [3], and have been proven to provide superior results. DL algorithm consists of various components (i.e., Deep Neural Networks, Convolutional Neural Networks, Recurrent Neural Networks, and Q-learning). The most popular is known as convolutional neural networks (CNN or ConvNet). CNN initially proposed in the 1980's by Kunihiko Fukushima as discussed in works of [8] are feed-forward ANN that has been expansively designed to exclude feature extraction process by inputting the network directly with normalized images [21]. The deep convolutional neural networks as described in works of [22] demonstrated outstanding performance in the large-scale image classification task of ILSVRC-2012 [23].

Moreover, CNN is also used as feature extractors. AlexNet uses pretrained CNN as feature extractor [18] for training an image classifier. AlexNet uses ImageNet as a source of images since it is a well-known and well-used images, with freely available training datasets and benchmarks. It is an ImageNet classifier with deep convolutional neural networks. The architecture, shown in Fig.1, is similar to that used by [24] for ImageNet classification.

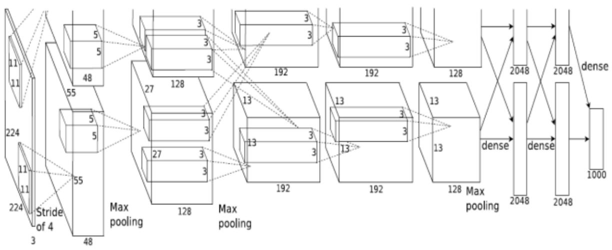

Fig. 1: Architecture of ImageNet Convolutional Neural Network [24]

The system contains 25x1 layers. The principal layer, Image Input, takes 227x227x3 images as input image with 'zerocenter' normalization. Succeeding layers are associated to one another deprived of some overriding merging or normalization sections. The last segment, Classification Output, which calculates a network performance is directed into entirely- connected layers, with optional performance weights and other parameters. It has five convolution layers (2, 6, 10, 12,14). After doing the convolution and merging in the final segment, the amount produced is directed into three fully-connected layers of 4096x4096x1000 neurons.

B. *Plants Classification, Application and Algorithms*

Significant works have been done for plant image classification tasks. These include classification between maize plants and weeds with 44580 segmented images at early growth with obtained training accuracy of 97.23% [20]. Another approach for classification of herbal leaves is demonstrated by [25] with modifications on local binary patterns. A Modified LBP is grounded on the consistency of texture features. In this case, replacement to a hard threshold was considered. Other researchers focus on developing applications such as the works of Johannes et al., [26] for plant disease classification in wild conditions. The system achieved excellent results for early recognition of three wheat diseases. An analysis was carried out using seven handheld devices of 3500 images across two sites - Spain and Germany. Another expert system was created for identification of various plant taxonomy by choosing the preeminent distinct features of the shape of leaves, color, and texture through ant colony optimization [27]. The research of [28] demonstrated superior results while utilizing CNN for learning unsupervised feature representations of plant species with 44 classes.

Very recently, Giselsson et al.,[29] proposed four classification approaches namely Template Matching, ANN, SVM, and DBN, for identifying plant stimuli from electrical signals using the combination of waveform-based feature extractor and PCA approach, which obtained a recognition rate of 96%. These experiments have underscored that such methods were able to outperform the classical techniques of identifying plant species which directs to a snowballing interest in mechanizing the procedure of species classification and associated works.

III. OUR PROPOSED APPROACH

This section describes our method from pre-processing to the classification of plant images using deep learning. Fig.2 shows our proposed approach. A description of the important pre-processing steps, training, and testing requirements are also discussed in this section. In figure 2, the inputs are pre-processed images of 12 plant species and the output are its classification or the types of plant.

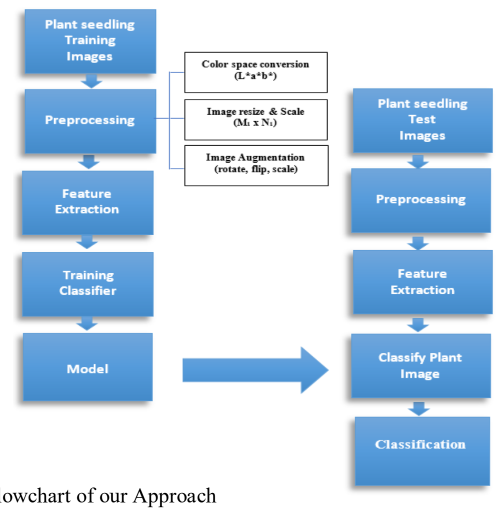

Fig. 2. Flowchart of our Approach

A. Datasets

Apt information is necessary to all the phases of image classification, starting at training stage to performance evaluation. A database of images of approximately 4,234 unique plants belonging to 12 plant species at several growth stages in seedling type from Aarhus University Signal Processing group, this is in collaboration with University of Southern Denmark. It comprises annotated RGB images with a physical resolution of roughly 10 pixels per mm. Shown in Table I are the plant seedling images based on the data set [30].

TABLE I. PLANT SEEDLING IMAGES FROM PUBLIC IMAGE DATABASE.

Plant	Data
Blackgrass	263
Charlock	390
Cleavers	287
Common Chickweed	611
Common Wheat	211
Fat Hen	475
Loose Silky-bent	654
Maize	221
Scentless Mayweed	516
Shepherds Purse	231
Small-flowered Cranesbill	496
Sugar Beet	385
TOTAL	**4, 234**

B. Image Preprocessing

At the image preprocessing step, we applied color space conversion and image enhancement. We performed color space conversion to determine the chromaticity and luminosity layers as well as for the enhancement of visual analysis. Since images are varied, we resized these from a 54x54 to as much as 3991x3557, MxN sizes of images. The RGB images of plants are transformed into L*a*b* color space by arithmetically manipulating the original color channel using (Eq.1) to generate a new color channel suitable for classifying each kind of plant species,

$$r_1 = R/(G + €) \text{ and, } r_2 = B/(G + €) \tag{1}$$

where:

Red, green and blue channels denoted as R, G, and B are the pixel values, while € is used to avoid divisions by zero. On the other hand, r1 and r2 denote the nonconformity of each pixel. To facilitate the same sizes of images for training, validation, and testing using the deep learning model, the dimensions of images should be of size MxM, where M=227. The images for all dataset are resized in 227x227, RGB color space. Image resize returns a new image that has the number of rows and columns specified by the two-element vector, [227 227], as shown in Fig. 3 and Fig. 4.

Fig. 3: Example of plant seedling images, the first row are Charlock, second-row Black-grass, the third row is Cleavers, the fourth row are Common Chickweed, the fifth is Common Wheat, and sixth are Fat Hen.

Fig. 4: Example of plant seedling images, the first row is Loose Silky-bent, second is Maize, third is Scentless Mayweed, fourth is Shepherds Purse, fifth are Small-flowered Cranesbill, and sixth are the Sugar beet seedling images.

C. Data Augmentation

Data augmentation is performed not only to enlarge our utilized dataset artificially but also to lessen the likelihood of overfitting throughout the training stage, and maximize the benefit of fine-tuning. And to reduce the data sets' overall noise. We use a variety of image transforms: flip, rotate, scale, flip-scale, and histogram equalization. Specifically, we modify the concentrations of the RGB channels in training images. After implementing data augmentation, the data set is now 118,750 images of which the 83,126 are for training, 23,750 for validation and 11,874 for testing. All experiments were carried out using MatLab 9.2 (MatLab 2017). Fig.5 shows a sample of original plant images, and Fig.6 displays an example of augmented plant images.

Fig. 5: Sample of original plant images [30].

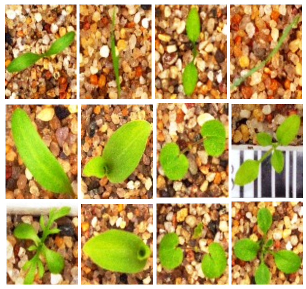

Fig. 6: Sample of augmented plant images.

D. Training and Classificaiton

In detail, the deep learning network classifier is done using AlexNet [23]. AlexNet was used in the study of Russakovsky et al., to categorize more than a million of images into 1000 classes using the Image net database for training. Using transfer learning, which is done by applying pre-trained models as a baseline to build CNN networks, we trained our network using AlexNet for the classifcation of plant images. Fine-tuning a network with transfer learning is usually more rapid and convenient than training a system from out of nowhere. This is done by reusing the network, the pre-trained networks learned the low-level features of images, and learn specific features. AlexNet has 25 layers, of which 1 is input layer for image data, 1 output layer for the classification, 5 are Convolution layer, 7 ReLU (Rectified Linear Unit) Activation Function, 2 are cross channel normalization with 5 channels per element, 3 are 3x3 max pooling with stride [2 2] and padding [0 0 0 0], 2 are 4096 fully connected layers, 1 layer for the 12 fully connected layer (plant seedling classification), 1 layer for dropout, 1 layer for softmax for a generalized logistic activation function which is used for multiclass classification and this is connected to the final output layer.

The training used the stochastic gradient descent with momentum (SGDM) optimizer, with an initial learning rate of 0.001, mini-batch size of 64 and 100 maximum number of epochs. Then the final layers are replaced with new segments to learn features specific to the plant seedling. The fewer the classes, the faster the training. Then training is done to 83,126 images of 12 classes. The Classifier Model is then saved and used for classification of 23,750 validation images, and 11,874 testing images. This is done by randomly using 70% of all images for training, 20% for validation and 10% for testing.

The performance of the model is evaluated using accuracy, specificity, and sensitivity. The overall efficiency is computed using (Eq. 2). In our case, we used the following terms to describe the evaluation criteria namely: true positive (TP), true negative (TN), false negative (FN), and false positive (FP). The TP indicates the current predicted plant seedling class category that is correctly classified. The TN pertains to other groups that do not belong to the existing plant seedling class category. The FP pertains to other plant seedling class category incorrectly classified as the current plant seedling class type. The FN relates to the current plant seedling class category that was incorrectly classified and did not belong to the existing class. As for Sensitivity, we used (Eq. 3). Sensitivity is the proportion of true positives that are correctly classified. Similarly, to get the true negative rate we used (Eq. 4) to compute the specificity. Specificity means the proportion of the true negatives. It suggests how good the test is for classifying plant seedling class category in normal (negative) condition.

$$Accuracy = \frac{(\mathrm{TP} + \mathrm{TN})}{(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN})} \qquad (2)$$

$$Sensitivity = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \qquad (3)$$

$$Specificity = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \qquad (4)$$

IV. RESULTS AND EVALUATION

The approach was implemented in MATLAB 9.2 (MATLAB 2017). A single PC with a 2.8 GHz Intel(R) Core(TM) i7-4790 CPU, 64-bit operating system, 20 GB RAM and NVIDIA GeForce GTX 1050 video RAM, running on a Windows 10 Home Edition, was used for the entire process of training and testing the model described in this paper. Table II demonstrates the classification performances of each plant seedling during validation and testing. The validation results have achieved a very high accuracy rate of 99.74% and 99.69% during testing.

TABLE II. PLANT SEEDLING IMAGES USED IN TEST AND CLASSIFICATION USING DEEP LEARNING.

Plant	Training Data	Validation	Validation Accuracy	Test Data	Testing	Testing Accuracy
Blackgrass	1315	1288	97.95%	657	642	97.72%
Charlock	1950	1949	99.95%	975	974	99.90%
Cleavers	1435	1431	99.72%	717	715	99.72%
Common Chickweed	3055	3053	99.93%	1527	1526	99.93%
Common Wheat	1105	1105	100.00%	553	553	100.00%
Fat Hen	2375	2370	99.79%	1187	1184	99.75%
Loose Silky-bent	3270	3256	99.57%	1635	1628	99.57%
Maize	1105	1104	99.91%	553	553	100.00%
Scentless Mayweed	2580	2579	99.96%	1290	1289	99.92%
Shepherds Purse	1155	1149	99.48%	578	577	99.83%
Small-flowered Cranesbill	2480	2480	100.00%	1240	1240	100.00%
Sugar Beet	1925	1925	100.00%	962	962	100.00%
TOTAL	**23750**	**23689**	**99.74%**	**11874**	**11843**	**99.69%**

Moreover, the best performance was achieved on Common Wheat, Maize, Small-flowered Cranesbill and Sugar Beet, of 100% during testing. These plants are herb, root and food crop. But almost all have more than 99% accuracy except for the Black-grass that is below 99%. The training, validation, and testing of images took 357,531.2 seconds for 118,750 images. With a 100 epochs, it took 129,800 iterations to complete. It started with a 3.68% training accuracy on the first epoch and first iteration to 100% accuracy to the last epoch and iterations.

TABLE III. MISCLASSIFIED PLANT SEEDLING IMAGES PER CATEGORY.

Plant	Validation	Testing
Blackgrass	27	15
Charlock	1	1
Cleavers	4	2
Common Chickweed	2	1
Common Wheat	0	0
Fat Hen	5	3
Loose Silky-bent	14	7
Maize	1	0
Scentless Mayweed	1	1
Shepherds Purse	6	1
Small-flowered Cranesbill	0	0
Sugar Beet	0	0
TOTAL	**61**	**31**

In Table III, the top 2 plants that have more than ten validation images that are misclassified are also the top 2 plant seedlings misclassified during testing. These plant seedlings are Black Grass and Loose Silky-bent, and both are of weed species. Majority of the misclassified plant seedlings are of weed status and monocot. This constitutes one of the major groups into which the plants' seedlings have traditionally been divided. And Black-grass are usually misclassified as Loose Silky-bent and vice versa. Fig. 7 presents a sample of incorrectly classified images, and Fig. 8 shows an example of correctly classified plant seedling images.

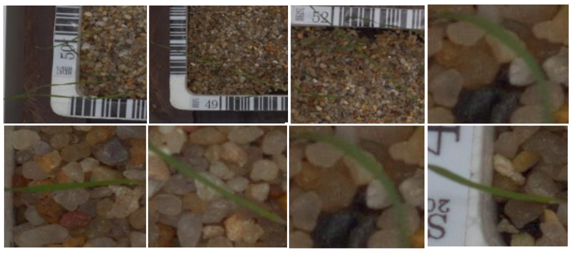

Fig. 7. Sample of plant seedling images incorrectly classified.

Fig. 8. Sample of plant seedling images correctly classified.

TABLE IV. CONFUSION MATRIX FOR THE CLASSIFICATION OF 12 PLANT SEEDLINGS LISTED IN TABLE 1. THE NUMBERS IN BOLD INDICATES THE CORRECT CLASSIFICATION FOR THE GIVEN CLASS.

Actual \ Predicted	'Black-grass'	'Charlock'	'Cleavers'	'Common Chickweed'	'Common wheat'	'Fat Hen'	'Loose Silky-bent'	'Maize'	'Scentless Mayweed'	'Shepherds Purse'	'Small-flowered Cranesbill'	'Sugar beet'
'Black-grass'	**642**	0	0	0	0	0	15	0	0	0	0	0
'Charlock'	0	**974**	1	0	0	0	0	0	0	0	0	0
'Cleavers'	0	0	**715**	2	0	0	0	0	0	0	0	0
'Common Chickweed'	0	0	0	**1526**	0	0	0	0	1	0	0	0
'Common wheat'	0	0	0	0	**553**	0	0	0	0	0	0	0
'Fat Hen'	1	0	0	1	0	**1184**	0	0	0	0	0	1
'Loose Silky-bent'	7	0	0	0	0	0	**1628**	0	0	0	0	0
'Maize'	0	0	0	0	0	0	0	**553**	0	0	0	0
'Scentless Mayweed'	0	0	0	1	0	0	0	0	**1289**	0	0	0
'Shepherds Purse'	0	0	0	0	0	0	0	0	1	**577**	0	0
'Small-flowered Cranesbill'	0	0	0	0	0	0	0	0	0	0	**1240**	0
'Sugar beet'	0	0	0	0	0	0	0	0	0	0	0	**962**

Table IV depicts the confusion matrix for the 12 class configuration during testing and validation. It consists of twelve rows and twelve columns that reports the number of false positives, false negatives, true positives, and true negatives. It detailed the output for analysis of correct classifications with 11,843 images. The rows specify the actual classification, and the columns determine the predicted rating. An average of 99.74% during testing, and 99.69% during validation gives an excellent overall classification. Thus, it is believed that more plant images used for training give a higher accuracy performance.

TABLE V. CLASSIFICATION RESULTS DURING FINAL TRAINING.

Plant	Accuracy	Sensitivity	Specificity
Blackgrass	99.81%	98.77%	99.87%
Charlock	99.99%	100.00%	99.99%
Cleavers	99.97%	99.86%	99.98%
Common Chickweed	99.95%	99.74%	99.99%
Common Wheat	100.00%	100.00%	100.00%
Fat Hen	99.99%	100.00%	99.99%
Loose Silky-bent	99.94%	99.09%	99.98%
Maize	100.00%	100.00%	100.00%
Scentless Mayweed	100.00%	99.85%	100.00%
Shepherds Purse	100.00%	100.00%	100.00%
Small-flowered Cranesbill	100.00%	100.00%	100.00%
Sugar Beet	100.00%	99.90%	100.00%

Table V presents the classification results during final training. After averaging, the final trained network yields an overall accuracy of 99.97%. This means to say that the proposed system was able to improve the classification performance with 100% accuracy on Common Wheat, Scentless Mayweed, Shepherds Purse, Small-flowered Cranesbill and Sugar beet. And almost all plant categories achieved an accuracy of more than 99%, of which some are often regarded as weed, and others are crop species. Moreover, an overall sensitivity of 99.77% and specificity of 99.98%, showed the feasibility and effectiveness of the proposed method. As noticed, Charlock, Common wheat, Fat Hen, Maize, Shepherds Purse, and Small-flowered Cranesbill got the highest percentage concerning Sensitivity, while Common Wheat, Maize, Scentless Mayweed, Shepherds Purse, Small-flowered Cranesbill and Sugar Beet, got the perfect percentage regarding Specificity. These results revealed a substantial performance and believed to be state-of-the-art in terms of classifying 12 different plant species.

V. CONCLUSION

In this paper, a new method for categorizing plant species at early growth stages was explored using deep learning-based convolutional neural networks. The developed model demonstrated a validation accuracy of 99.77% and 99.69% for testing, outperforming conventional approaches. This result is an excellent contribution to the continuous development in the agricultural research area and to the widespread objective of augmenting global agricultural yield.

However, some limitations should be noted. The first is that the performance of deep learning algorithm is dependent on large-scale datasets, containing millions of training samples. This means the smaller the training samples, the higher the possibility of overfitting throughout the training stage. To lessen the likelihood of overfitting, there's a need to increase the training data into hundreds of thousands or even millions of training data through augmentation. Other techniques such as the implementation of dropout can also help prevent overfitting. The second is that CNN requires high hardware demands and requires a massive amount of memory for training the model. Thus, we need to have an accelerated GPU or use Google's Tensor Processing Unit (TPU) for training to attain a much-reduced training time. Furthermore, the model is focused on considering twelve plant species. We can extend this model to other types of plants such as herbal-medicinal plants or other crops in other countries as well as considering other datasets from online databases. Finally, the proposed technique can be integrated into a mobile application with the goal to provide farmers efficient farming practices.

REFERENCES

[1] J. Chaki, R. Parekh, and S. Bhattacharya, "Plant leaf classification using multiple descriptors: A hierarchical approach," *J. King Saud Univ. - Comput. Inf. Sci.*, pp. 1–15, 2018.

[2] R. M. Prakash, "Detection of Leaf Diseases and Classification using Digital Image Processing," 2017.

[3] A. Kamilaris and F. X. Prenafeta-boldú, "Deep learning in agriculture : A survey," vol. 147, no. July 2017, pp. 70–90, 2018.

[4] M. Mehdipour, B. Yanikoglu, and E. Aptoula, "Neurocomputing Plant identi fi cation using deep neural networks via optimization of transfer learning parameters," *Neurocomputing*, no. April 2016, pp. 0–1, 2017.

[5] G. L. Grinblat, L. C. Uzal, M. G. Larese, and P. M. Granitto, "Deep learning for plant identification using vein morphological patterns," *Comput. Electron. Agric.*, vol. 127, pp. 418–424, 2016.

[6] S. P. Mohanty, D. Hughes, and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection," 2016.

[7] A. Picon, A. Alvarez-Gila, M. Seitz, A. Ortiz-Barredo, J. Echazarra, and A. Johannes, "Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild," *Comput. Electron. Agric.*, no. April, pp. 0–1, 2018.

[8] Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," 2015.

[9] J. Amara, B. Bouaziz, and A. Algergawy, "A Deep Learning-based Approach for Banana Leaf Diseases Classification," *BTW*, pp. 79–88, 2017.

[10] K. Osako, R. Singh, and B. Raj, "Complex recurrent neural networks for denoising speech signals," *2015 IEEE Work. Appl. Signal Process. to Audio Acoust. WASPAA 2015*, pp. 16–20, 2015.

[11] G. Sehgal, B. Gupta, K. Paneri, K. Singh, G. Sharma, and G. Shroff, "Crop Planning using Stochastic Visual Optimization," pp. 0–4, 2017.

[12] S. T. Hang and M. Aono, "Open world plant image identification based on convolutional neural network," *2016 Asia-Pacific Signal Inf. Process. Assoc. Annu. Summit Conf. APSIPA 2016*, 2017.

[13] L. Pearlstein, M. Kim, and W. Seto, "Convolutional Neural Network Application to Plant Detection , Based on Synthetic Imagery," pp. 1–4, 2016.

[14] D. Mishkin, N. Sergievskiy, and J. Matas, "Systematic evaluation of convolution neural network advances on the Imagenet," *Comput. Vis. Image Underst.*, vol. 161, pp. 11–19, 2017.

[15] C. Affonso, A. L. D. Rossi, F. H. A. Vieira, and A. C. P. de L. F. de Carvalho, "Deep learning for biological image classification," *Expert Syst. Appl.*, vol. 85, pp. 114–122, 2017.

[16] A. Saini, E. S. Kaur, and E. D. V Saini, "Satellite Image Classification using Artificial Neural Network," vol. 42, no. April, pp. 88–91, 2015.

[17] A. Kamilaris, A. Kartakoullis, and F. X. Prenafeta-Boldu, "A review on the practice of big data analysis in agriculture," *Comput. Electron. Agric.*, vol. 143, pp. 23–37, 2017.

[18] J. G. A. Barbedo, "A review on the main challenges in automatic plant disease identification based on visible range images," *Biosyst. Eng.*, vol. 144, pp. 52–60, 2016.

[19] J. Wang, Y. Yang, J. Mao, Z. Huang, C. Huang, and W. Xu, "CNN-RNN: A Unified Framework for Multi-label Image Classification," *2016 IEEE Conf. Comput. Vis. Pattern Recognit.*, pp. 2285–2294, 2016.

[20] C.-C. Andrea, B. B. Mauricio Daniel, and J. B. Jose Misael, "Precise weed and maize classification through convolutional neuronal networks," *2017 IEEE Second Ecuador Tech. Chapters Meet.*, pp. 1–6, 2017.

[21] "Deep Learning." [Online]. Available: https://www.mathworks.com/discovery/deep-learning.html. [Accessed: 02-May-2018].

[22] J. A. A. Salido and C. R. Jr, "Using Deep Learning for Melanoma Detection in Dermoscopy Images," vol. 8, no. 1, 2018.

[23] O. Russakovsky *et al.*, "ImageNet Large Scale Visual Recognition Challenge," *Int. J. Comput. Vis.*, vol. 115, no. 3, pp. 211–252, 2015.

[24] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," *Adv. Neural Inf. Process. Syst.*, pp. 1–9, 2012.

[25] Y. G. Naresh and H. S. Nagendraswamy, "Classification of medicinal plants: An approach using modified LBP with symbolic representation," *Neurocomputing*, vol. 173, pp. 1789–1797, 2016.

[26] A. Johannes *et al.*, "Automatic plant disease diagnosis using mobile capture devices, applied on a wheat use case," *Comput. Electron. Agric.*, vol. 138, pp. 200–209, 2017.

[27] W. W. Guo, "Expert Systems with Applications Incorporating statistical and neural network approaches for student course satisfaction analysis and prediction," vol. 37, pp. 3358–3365, 2010.

[28] S. H. Lee, C. S. Chan, P. Wilkin, and P. Remagnino, "Deep-Plant: Plant Identification with convolutional neural networks," pp. 3–8, 2015.

[29] L. Chen, Yang., Zhao, Dong-Jie., Wang, Zi-Yang., Wang, Zhong-Yi Wang., Tang, Guiliang., Huang, "Plant Electrical Signal Classificaton Based on Waveform Similarity," *Algorithms*, vol. 9, no. 4, 2016.

[30] T. M. Giselsson, R. N. Jørgensen, P. K. Jensen, M. Dyrmann, and H. S. Midtiby, "A Public Image Database for Benchmark of Plant Seedling Classification Algorithms," 2017.