Deep Learning based Intelligence Cognitive Vision Drone for Automatic Plant Diseases Identification and Spraying

Ghazanfar Latif [a*], Jaafar Alghazo [a], R. Maheswar [b], V. Vijayakumar [c], Mohsin Butt [d]
[a] *College of Computer Engineering and Sciences, Prince Mohammad bin Fahd University, Saudi Arabia.*
[b] *Dean – Research (Assistant) & School of EEE, VIT Bhopal University, India.*
[c] *Cloud Computing Consultant, MIT Square, UK.*
[d] *College of Applied and Supporting Studies, King Fahd University of Petroleum and Minerals, Saudi Arabia.*

Abstract. The agriculture industry is of great importance in many countries and plays a considerable role in the national budget. Also, there is an increased interest in plantation and its effect on the environment. With vast areas suitable for farming, countries are always encouraging farmers through various programs to increase national farming production. However, the vast areas and large farms make it difficult for farmers and workers to continually monitor these broad areas to protect the plants from diseases and various weather conditions. A new concept dubbed Precision Farming has recently surfaced in which the latest technologies play an integral role in the farming process. In this paper, we propose a SMART Drone system equipped with high precision cameras, high computing power with proposed image processing methodologies, and connectivity for precision farming. The SMART system will automatically monitor vast farming areas with precision, identify infected plants, decide on the chemical and exact amount to spray. Besides, the system is connected to the cloud server for sending the images so that the cloud system can generate reports, including prediction on crop yield. The system is equipped with a user-friendly Human Computer Interface (HCI) for communication with the farm base. This multidrone system can process vast areas of farmland daily. The Image processing technique proposed in this paper is a modified ResNet architecture. The system is compared with deep CNN architecture and other machine learning based systems. The ResNet architecture achieves the highest average accuracy of 99.78% on a dataset consisting of 70,295 leaf images for 26 different diseases of 14 plants. The results obtained were compared with the CNN results applied in this paper and other similar techniques in previous literature. The comparisons indicate that the proposed ResNet architecture performs better compared to other similar techniques.

Keywords: Automatic Plant Identification, Residual Networks, Cognitive Vision Drone, Deep Learning, Automatic Spraying, Convolutional Neural Networks (CNN), Smart Devices, Plant Diseases.

1. Introduction

Plants play a major role in the cycle of nature. They guarantee the survival of all organisms since they manufacture both food and oxygen. However, due to an increase in deforestation and urbanization, there has been a significant decline in the growth of plant species. This has caused an increase in environmental problems like flood, global warming, climate anomaly, etc. Agriculture has long been an important aspect of the world we live in. Farming as well as planting various crops play an integral role in the agriculture industry as well as in many different industries. However, throughout the years many changes and developments have been introduced in this field. Initially, planting crops was done manually by farmers throughout different times of the year. The development of technology has allowed for a rapid change in the manner in which this is achieved. One of the newest aspects that have been introduced is what is referred to as precision agriculture. Precision agriculture incorporates technological aspect within the field to create more accurate and well thought of crops.

1.1. Motivation

With the nature of the world being severely threatened by different problems that exist such as poverty as well as climate change, its necessary to come up with a new means of differentiating crops in order to find the best possible outcomes for various reasons including but not limited to reducing the cost in agriculture, automatically removing weeds from within the crops, spraying infected crops with proper chemicals, etc. Human population is rapidly growing and there is a very high demand for food these days. Utilizing technology in the right manner and being able to incorporate new scientific techniques will drastically help secure a better future by cutting costs spent on conventional agricultural methods.

Currently, 270,000 from a total of 400,000 plant species are named and identified by professional botanists. Latest plant taxonomy methods like chemotaxonomy, serotaxonomy, cytotaxonomy, etc., are being developed to classify, name, and describe the plants. However, these methods can only be done by professional and they consume a lot of time. A good understanding of plants is crucial for recognizing rare or new plant species. This can help enhance the drug industry and boost the agricultural sustainability and productivity.

Computer vision techniques like image processing and machine learning can be utilized for classification of diverse plant genus. This eradicates the difficulty that novices face while identifying plants. Leaf-based features are usually used for plant classification. This is due to a variety of reasons; leaves are easier to analyze than flowers due to the 2D shape of the leaf as compared to the 3D shape of the flower and the availability of leaves at any time of the year unlike flowers which only grow in the blooming season. In addition, the seasonal characteristics of the flowers and fruits, the difference in stem and root structure makes leaf-based features a better option. Thus, leaves are extensively used for computer-aided plant identification.

To summarize, throughout the world, farming as a profession is declining because of increased costs of chemicals, unpredictable crop yields and excessive labor costs. Smart solutions need to be implemented to help provide better yield at a low cost. The field of image processing integrated with IOT technology and Drone technology can provide a means for smart farming that can cover large farming areas that will reduce manual farming processes and assist in producing crops for the continually increasing world population.

1.2. Contribution

In this paper, the aim is to design a precision agriculture system integrating the new technologies such as Drones and Image processing techniques for automatic identification of infected plants and spraying the necessary plants with the required chemical. Large areas of farmland make it very time consuming for humans to physically inspect each plant, identify if it is infected, and then spray. However, with drone technology, multiple drones can be used to cover large areas of farmland and orchards for inspection and make conclusive decision whether the plant or tree is infected so that necessary action can be taken. The whole process can be automated with minimal human interaction resulting in improved efficiency. The proposed system will consist of a drone equipped with high resolution cameras with sufficient computing power and network connectivity. The drones will capture images of the plant or tree leaves and based on the proposed deep learning method (residual networks), classify whether the leaf belongs to a tree/plant or just a weed leaf. In addition, the system will accurately identify whether the plant/tree is infected with a disease. Images will be sent to the cloud for further processing as well. If the tree or plant is identified to contain a disease, the drone system will automatically take the decision to spray either part of it or whole. The system proposed in this paper allows for the drones to periodically survey the farm area and send images to the cloud for further processing and decision making. In summary there are various advantages of automating the process. First, the system will periodically survey the farmed area which can be as large as hundreds of acres and send images in real time to the cloud. Secondly, the drone has access to all the portions of the plant or tree even if it is a high tree. Third, the drones can interact with each other and avoid covering or spraying areas repeatedly. The process of chemical spray can be automated and the precise amount of chemical spray can be calculated to reduce the overall cost of chemicals. Lastly, the use of the cloud will allow for Big Data processing in real time.

The rest of the paper is organized as follows: section 1 gives the overview introduction, section 2 is the related work, section 3 shows the details of the methodology, section 4 illustrates the experimental results, in section 5 a detailed discussion is presented, section 6 concludes the paper, section 7 gives possible enhancements that can be done the system in future and section 8 lists the references used.

2. Related Work

Plant identification is the process in which each plant is allocated to a known taxon. The images of the plant leaves are often used as the major element to differentiate one plant from another. A process called feature extraction is performed to ensure the effectiveness of the identification process. This process contains either quantitative or qualitative characters. The quantitative characters compromises of features that can be counted or measured, like plant height, flower width, the number of petals per flower, etc. Whereas, qualitative characteristics are features like leaf shape, color, leaf arrangement, etc. Since no two plants share the exact same features, certain plant identification approaches are required to identify the plant species.

Image processing and machine learning techniques are used in many applications for the detection, recognition and classification based on images or videos. Supervised and unsupervised techniques are used to accomplish these tasks. Feature extraction along with traditional methods are applied with innovation usually shown in the feature extraction or deep learning networks and its variations such as residual networks are applied to complete these tasks. These methods can be applied either on agriculture, medicine, education, transportation or other areas [1-7]. All these applications have one aim which is to automate the recognition process usually done by humans. The automation of the recognition process allows for electronic control of many other processes that follow the recognition process. In this paper, we concentrate on the use of image processing techniques and drone technology for applications related to the agriculture industry, in particular for automatically identifying infected plants or portions of plants and spraying them with the required chemical according to the disease.

In [6], the authors proposed an approach to identify plant using digital images of leaves. It consists of three stages: pre-processing, feature extraction, and classification. In the pre-processing stage, the input images are enhanced before performing computational processing. Whereas, during the feature extraction phase the features are extracted based on the color and shape of the leaf image. These features are sent as an input vector to the Artificial Neural Network (ANN) and Euclidean (KNN) classifier. The experimentation was carried on a sample of 1907 leaves of 33 different plant species that were obtained from Flavia dataset. The proposed approach achieved a 93.3% accuracy rate by using the ANN classifier. The ANN classifier takes less average time for execution as compared to the Euclidean distance method. In [7], the authors proposed a technique that uses deep learning to automatically recognize plants in a natural environment. The BJFU100 datasetwas used in this research and it was acquired through the use of mobile phone in natural environment. It consists of 10,000 images of 100 ornamental plant species. They proposed a 26-layer deep learning model called ResNet26 that resulted in an accuracy of 91.78%.

In [8], the authors presented an algorithm for identification using multiclass classification based on shape, color, volume and cell feature. A three-stage comparison was performed. The first stage consists of comparing the redness, greenness, and blueness index feature. Second stage compares the shape feature and finally the last stage compares cell feature and volume fraction feature. The experiment is implemented on a total of 1000 flower and leaf images. The accuracy achieved is 85% on an average. In [9], the authors proposed an algorithm to automatically identify a plant based on its leaves. The algorithm follows the pre-processing, feature extraction, and classification stage. The feature extraction stage uses the morphological features, Fourier descriptors and Shape-Defining Features (SDF) of the input images. In the classification stage, the extracted features are sent as an input vector to a ANN. The experimentation was performed on a dataset that consists of sample leaf images from 14 different fruit trees. The accuracy achieved for the experiment was above 96%. The same accuracy rate was also achieved for the Flavia and ICL datasets [9]. In [10], the authors propose a technique to classify plant leaves based on the texture and shape of the leaf. Two classifiers are used in this proposed method which are the: Neuro-Fuzzy Controller (NCF) and Multi-Layered Perceptron (MLP). Gabor filter and Gray Level Co-occurrence Matrix (GLCM) is used to model the leaf texture, whereas the leaf shape is modeled using Curvelet features and Invariant Moments. The leaf image is made invariant to transformations by using a pre-processing stage. A collection of seven predefined slots have been introduced to avoid distortion for the leaves that contains different aspect ratios. Experimental results indicate that the proposed method was successful in identifying leaves with differing texture, shape, size or even orientations till a certain degree. The method achieved a higher accuracy rate of 87.1% when the Multi-Layered Perceptron (MLP) classifier was used.

In [11], the authors developed a method for leaf classification that uses a feedforward neural network called Probabilistic Neural network (PNN) as a classifier. Unlike the traditional methods, this method also incorporated color as a feature along with shape, vein, and texture to classify a leaf. This added feature enhances the performance by achieving an average accuracy of 93.75%. The proposed method was tested on Falvia dataset that compromises of 32 different types of plant leaves. In [12], the authors proposed a general-purpose automated leaf identification method to classify plants. This method is accurate, fast in execution, efficient, and easy to implement. It uses a Probabilistic Neural Network (PNN) along with data and image processing methods. A total of 12 features are extracted and processed by Principal Components Analysis (PCA) to model the input vector of PNN. The method used a dataset consisting of 1800 samples which represents 32 different types of plant. The experimental results obtained has indicated that the accuracy achieved is over 90%. In [13], the authors introduced a k-Nearest Neighbor (K-NN) density framework for leaf classification. This method uses separate processing of the three basic features of the leaves, which is the shape, texture, and margin. Separate K-NN density estimators were used for each feature and a simple product of the three was then used to generate the final estimate. The estimation was applied on two datasets, which is the Iris dataset and another one consists of one hundred plant species. Each dataset yielded different results. Overall, the combination of three K-NN estimates an improvement with an accuracy of 96%.

In [14], the authors proposed a method that automatically identifies plant leaves by implementing feature extraction, pattern recognition, and classification of the leave images. The shape and color of the leaf is used as the features for the leaf classification. The software which was used for the system has been trained on a database containing 100 leaves and was then tested with 50 different plant species. The proposed algorithm resulted in an accuracy of 92%. In [15], the authors developed a multiscale shape-based method for leaf identification. The paper compared four types of multiscale triangle representation which are: Triangle Area Representation (TAR), Triangle Side Lengths representation (TSL), Triangle Oriented Angles (TOA), and Triangle Side Lengths and Angle representation (TSLA). This methodology was carried on four different leaf datasets and it was observed that the TSLA approach achieved the highest accuracy of 96.53%.

In [16], the authors introduced a new feature set for shape-only leaf recognition in which the fundamental shape and Local Area Integral Invariants (LAIIs) signal were used as the features. The proposed method was experimented on a publicly available leaf dataset. The methodology procedure contains a segmentation process that segments the given sample by a grey-level and LAII extraction measure samples individually. The obtained results were compared with similar datasets that contain over 100 leave samples. The highest accuracy acquired was over 98%. In [17], the authors explored a new method for the leaves recognition of medicinal plants. The features used in this paper compromises of grey textures, Grey Tone Spatial Dependency Matrices (GTSDM), and Local Binary Pattern (LBP). The dataset comprises of a total of 250 images of medical plant leaves of five species which belongs to the suburbs of Western Ghats region. The accuracy obtained in this study was 94.7%. In [18], the authors combined the LVQ and RBF classifiers. This resulted in a better performance as compared to other tested methods. The proposed algorithm resulted in 98.7% of accuracy. In [19], the authors present methods for the recognition of plant species based on images or videos using a traditional and deep learning approach. The features extraction approach extracts features using Hu moments shape features, Haralick texture features, color features using channel statistics and final texture features from the local binary pattern. Different classifiers are applied. The datasets used are Swedish leaf, folio, leaf12, and flavia. Random forest (RF) classifier achieved the highest recognition amongst the traditional methods with 82.38%. Deep learning method namely Very Large CNN (VGG) 16 CNN and VGG 19 CNN layers achieved even better performance. 16 CNN achieved 97.14% for leaf12. 19 CNN achieved an accuracy of 99.41%, 96.25%, and 96.53% for Swedish leaf, Falvia, and Folio respectively. In [20], the authors study the image segmentation methods namely maize rust, maize head smut, and maize smut in north east china. They propose a new method for image pre-processing for image background. Their method showed improved segmentation results.

In order to cover a wider area of planted fields, researchers have proposed the use of drones equipped with computing technology and agriculture processes such as pest spray in order to automate the agriculture industry reducing cost and increasing yield. A lot of research has been presented on the use of artificial intelligence (AI) based drones in the agriculture industry [21-22]. The concentration has been to equip drones with image processing techniques to make them smart devices that can detect and recognize different plants based on leaf classification and other variations. The use of the drones can be as simple as a monitoring system and as complex as identifying infected plants and spraying them with the required chemicals. Researchers have also proposed the integration of Internet of Things (IoT), Cloud computing, AI, and drones in the agriculture industry [23-25]. The use of IoT allows for remote smart sensing that can be communicated via the cloud to drones or any other device. The use of the cloud services allows for the processing of Big Data which is needed in the case of using AI based processing in plant identification and for processing still images or video images obtained from the drone. The integration of all technologies those that exist and those developing will lead to a cost-effective agriculture industry that can increase its yield and ensure healthier plants. Like image processing techniques, the use of IoT, Cloud Computing, remote sensing, drones and other technologies is used not only in agriculture but other industries as well [26-28].

3. Proposed Methodology

In this paper, we propose a SMART Precision Agriculture system consisting of Drones fitted with Cameras and SMART Image processing Algorithms. The system can accurately survey large fields of plants, identify plants with diseases based on captured leaf pictures, take the necessary decision to spray plants with a precise quantity of chemical, and decide on the portion of the plant where the chemical is to be sprayed. The SMART Precision Agriculture system is equipped with the communication tools to; **a.** upload images to the cloud and receive results from cloud-based algorithms, **b.** communicate with the base station to alert of any infected plant and provide the precise location, **c.** communicate with other drones for formation, territory, etc. The cameras on the drones are connected with a Raspberry PI module for processing the images and transferring them to the cloud. The system is also fitted with IoT sensors for evading obstacles like varying tree structures in the vast fields. The heart of the SMART system is the advanced Image processing algorithms proposed in this paper which are Residual Networks and CNNs. Based on the detection and classification algorithms, infected plants are identified to decide on the type and quantity of chemicals to be sprayed, and to where the chemical should be sprayed (Portion of the plant or complete plant).

Figure 1 shows the system model of the proposed SMART system. Each Drone within the multi drone configuration consists of Cognitive vision local processing through the use of Raspberry PI and camera modules. The camera captures the leaf images and identifies the infected plants using deep learning algorithms. Based on the identification, the SMART system decides to spray chemicals based on disease type, where to spray and how much to spray. Each Drone also consists of Cognitive Vision Cloud Processing so that captured images are uploaded to the cloud server that contains algorithms for data management, data analysis, crop analysis and reporting. The cloud system also contains long term decision support algorithms for the plant fields. The Drone base allows for human drone interaction with user friendly interface that allows communication between the drones and the humans in the base.

3.1. Residual Neural Networks

Convolution Neural Networks (CNN) have greatly aided the image processing field in the recent years. CNN can integrate different image features and classifiers in an end to end system that requires minimal preprocessing. Feature extraction in CNN can be enhanced by introducing multiple layers in the network that increases the depth of the network. The number of layers in a CNN model is significant and modern studies indicate that maximum performance is acquired by using very deep networks [29-30]. However, there are various issues that can affect the model if we keep increasing the depth. Firstly, the problem of vanishing gradients can affect convergence. This can be resolved by using initial and intermediate normalization layers with back propagation. A degradation problem also occurs when very deep networks start converging. It causes the accuracy to get saturated and start degrading quickly with further increase in layers [31]. Degradation results in high training error which can be resolved by using residual networks [32-33].

A Residual Neural Network (ResNet) is a special type of neural network that uses skip connections to exclude certain layers in the neural network. The skipped layers use non-linear activation function and batch normalization is applied between the skip layers. The weight of the jumps are formulated using a weight matrix.

Fig. 1. Workflow of the proposed Intelligence Cognitive Vision Drone for Automatic Plant Diseases Identification and Spraying

ResNet models containing numerous stacked skips are known as Dense ResNet's. The advantage of skipping layers is to avoid the problem of vanishing gradients by utilizing the activation functions from previous layers and prevent degradation. The procedure is repeated until the adjacent layers can learn their weights. Skipping layers help in reducing the speed of training in the learning stage and helps minimize the problem of vanishing gradients. Once the feature space of the input is learned, the skipped layers are expanded in the later stages.

The basic building block of a residual network is shown in Figure 2. This building block is repeated throughout the network. In a regular network we learn the mapping from $x \rightarrow F(x)$. In case of ResNet block the mapping from $x \rightarrow F(x) + G(x)$ is formalized by feed forward neural networks having shortcut connection which are also called jumps. If the input and output dimensions are similar i.e. $dim(x) = dim(F(x))$ then $G(x)=x$ is an identity function. In this case the connection is called identity connection. Having the added shortcut connections as identity mappings results in the network having the training error less than the regular neural network, which helps solve the degradation problem. If the input and output dimensions are not same then zero padding is used.

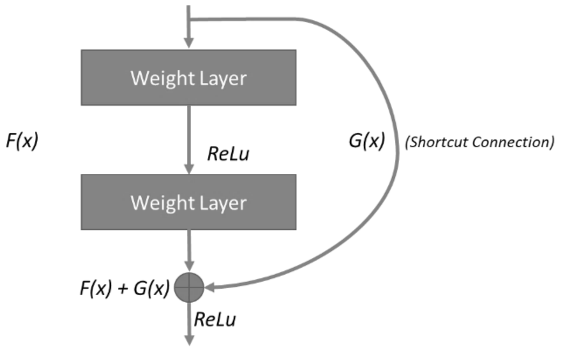

Fig. 2. The basic building block of a Residual Network

The resulting building block for each of the stacked layers in the network having same dimensions of ***F*** and ***x*** is given in Eq. (1).

$$y = F(x, \{M_i\}) + x \qquad (1)$$

The function $F(x, \{M_i\})$ is mapping which needs to be learned and can represent multiple fully connected or convolutional layers. If the dimensions of ***F*** and ***x*** are not same, a linear projection is formed using short connections to match the dimensions. Eq. (2) shows the resulting output function of the residual block. Here *Ms* is the linear projection.

$$y = F(x, \{M_i\}) + M_s x \qquad (2)$$

In this paper, we use the two modified ResNet models with varying number of layers and image parameters to evaluate the performance of the leaf diseases classification with other CNN architectures. In ResNet version 1 model, shown in figure 3, the shortcut identity connections are added to every block of two 3 x 3 filters. Identity mapping is used for all the shortcut connections (indicated by black line) and projection shortcut (using *1 x 1* convolution layer) is used in cases where the input and output dimensions do not match. The problem of vanishing gradients and degradation is avoided using the batch normalization and nonlinear activation for the shortcut connections. The depth of the convolution layers in the ResNet version 1 is dependent on the residualblock based on Eq. (3)

$$depth\_V1 = N * 6 + 2 \qquad (3)$$

Where N is the number of residual blocks e.g. *N=3 for ResNet 20.* The variable *i* in Figure 3 represents the number of stages in the model.

The ResNet version 2 model, presented in figure 4, introduces bottleneck connections whose filter size is calculated by increasing the block size of the shortcut connections to three. The three layers inside a residual function block are convolutional layers of size 1 x 1, 3 x 3, and 1 x 1. The 1 x 1 layers are responsible of decreasing and increasing the dimensions of the input while 3 x 3 layer becomes the bottleneck with smaller dimensions. Figure 4 shows the ResNet version 2 model. Eq. (4) shows the depth of the convolution layers dependency on the residual block.

$$depth = N * 9 + 2 \qquad (4)$$

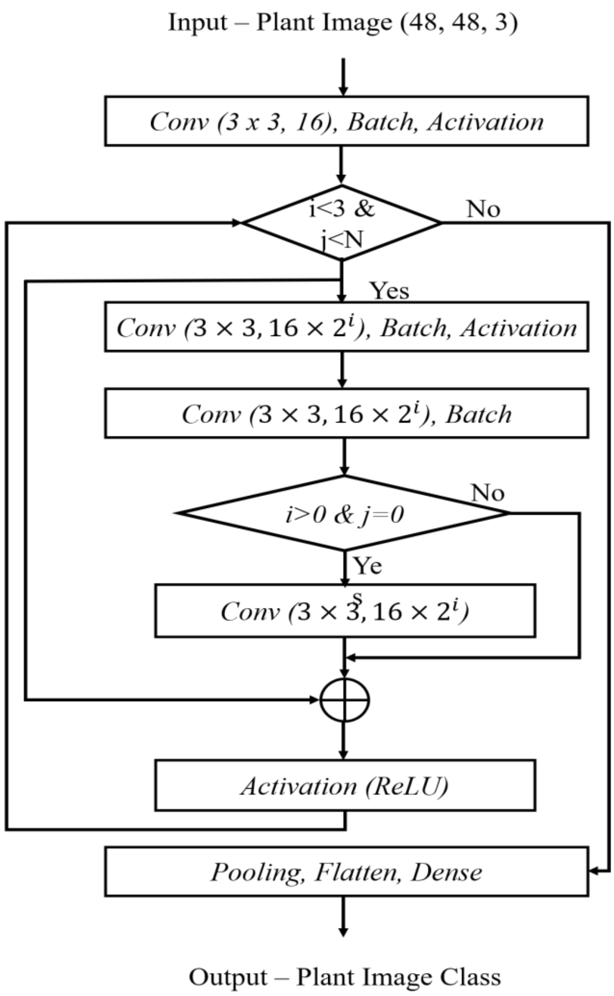

Fig. 3. Architecture of the ResNet Version 1

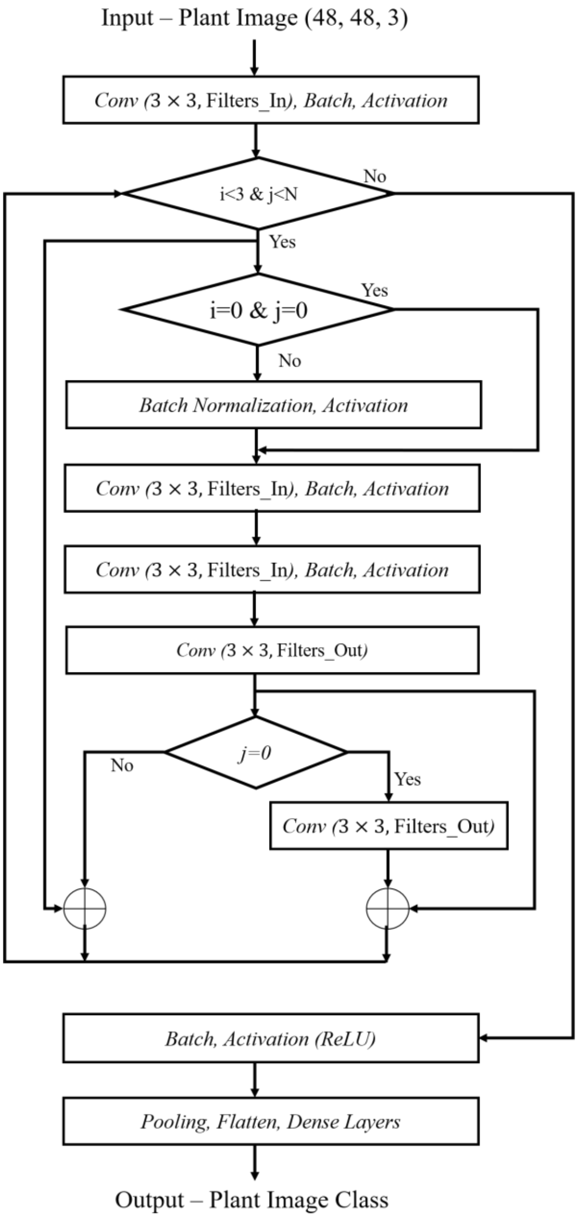

Fig. 4. Architecture of the ResNet Version 2

3.2. Experimental Dataset

The dataset used in this paper is the leaf classification dataset from a public database [34]. The dataset consists of 14 types of fruits and vegetable plants labeled into 38 different classes; 14 healthy crop leaf classes and 24 crop leaf disease classes. The dataset contains a total of 70,295 RGB labeled images. 80% of the images (56,295 images) are used for training, while the remaining 20% (14,000 images) are used for testing. The testing data is chosen randomly out of the 20% testing sample. Figure 5 shows the details of the dataset of the leaf image for different species. Each box in Figure 5 shows a different leaf species in a healthy state (title bold) followed by leaf disease of the same species. For each image, the number of sample images available for the particular leaf and class is stated; i.e. first image in the Figure shows APPLE in bold meaning it is a healthy leaf image and on top of the image the number 2008 indicates the number of sample images for healthy apple leaves.

4. Experimental Results

With 80% training and 20% testing data, the proposed ResNet models are trained and tested with various layer values and various parameter values with Epochs values (10,25,50, and 100) where Epochs is the number of training iterations. Version 1 of the proposed ResNet architecture used model depth of 8, 20, 32, and 44 layers shown in Table 1. The parameters varied between 80,486 and 667,814. The best accuracy was achieved using a model depth of 32 layers, 472,038 parameters, with 100 Epochs with an average Validation accuracy of 99.4% with a Validation loss of 0.0854. With these model parameters, the average testing accuracy achieved is 99.15% and testing loss of 0.0938. The results show that beyond a certain depth and parameter count, the accuracy does not improve significantly and sometimes even declines.

Version 2 of the proposed ResNet architecture used model depth of 11, 20, 56, and 83 layers shown in Table 2. The parameters varied between 306,374 and 1,680,934. The best accuracy was achieved using model depth of 56 layers, 856,198 parameters, with 100 Epochs with an average validation accuracy of 99.90% with a validation loss of 0.0465. With these model parameters, the average testing accuracy achieved is 99.78% and testing loss of 0.0529.

In this paper, the system was also tested using different CNN Architectures based on number of layers and parameters with Model 1 and Model 2 proposed in [35]. For each model, Epochs (10, 25, 50, and 100) were used. Table 3 shows the results of the experiment with the two CNN models. As shown in Table 3, the best accuracy is achieved using model 3 with Epochs 50 with an average validation accuracy of 98.65% and validation loss of 0.0417. The average testing accuracy in this case was 91.85% and testing loss of 0.4481.

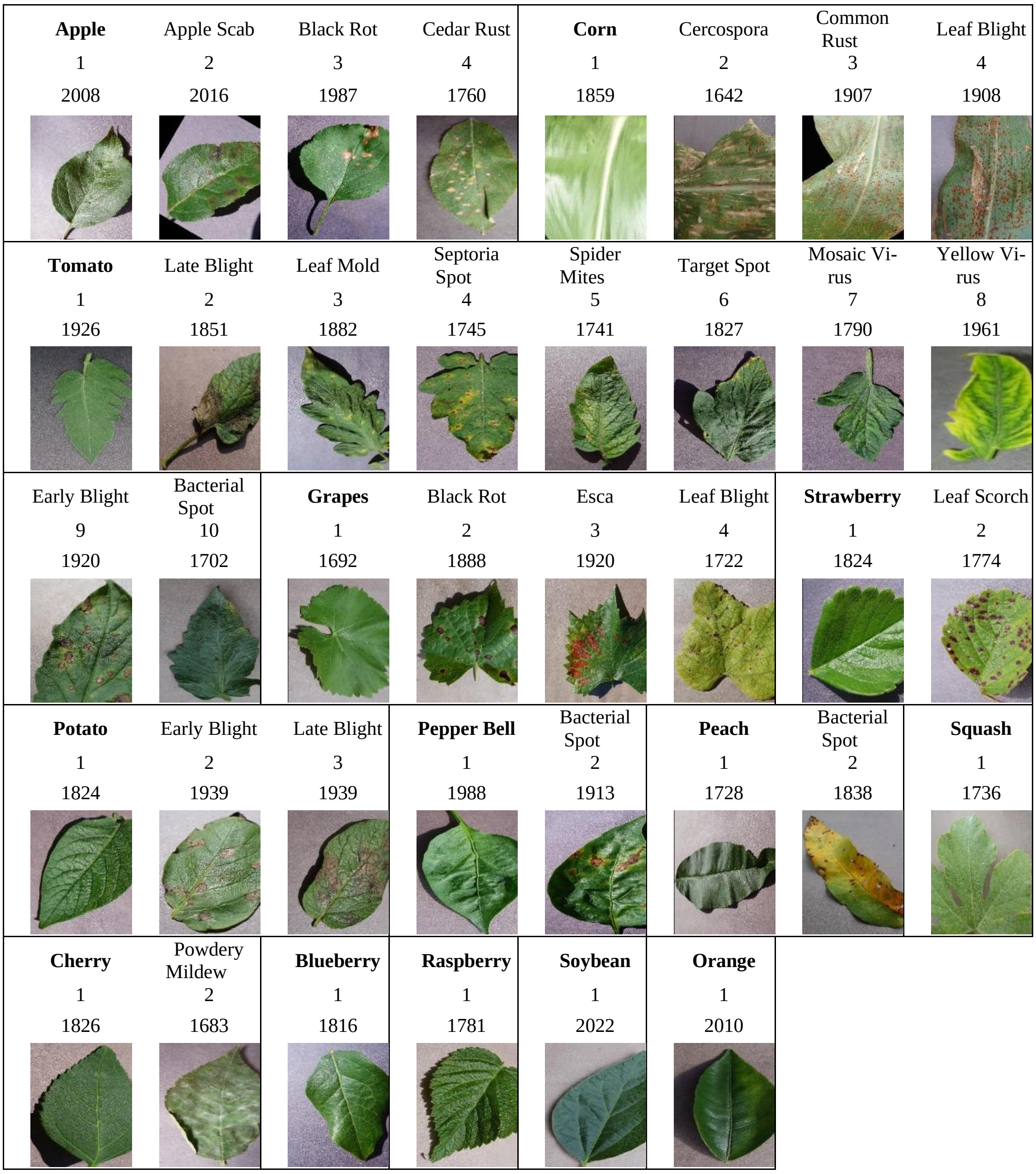

Fig. 5. Summary of the used dataset with their total number of images and samples

Table 1. Experimental results of different Proposed ResNet Architectures based on Version 1

Model Depth	Params	Epoch	Val. Acc.	Val. Loss	Test Acc.	Test Loss
8 Layers	80,486	10	93.21%	0.3225	87.38%	0.5333
		25	95.19%	0.2622	93.21%	0.3600
		50	96.15%	0.2316	95.92%	0.2409
		100	**99.16%**	**0.0951**	**98.80%**	**0.1062**
20 Layers	276,262	10	94.05%	0.3721	88.94%	0.5950
		25	95.69%	0.3809	89.39%	0.4913
		50	96.64%	0.2332	94.59%	0.2900
		100	**98.58%**	**0.1555**	**98.24%**	**0.1120**
32 Layers	472,038	10	93.47%	0.4093	90.49%	0.5071
		25	95.83%	0.2823	93.99%	0.3443
		50	96.58%	0.2261	94.80%	0.3000
		100	**99.40%**	**0.0854**	**99.15%**	**0.0938**
44 Layers	667,814	10	93.71%	0.4017	89.79%	0.5283
		25	95.72%	0.2796	91.54%	0.4292
		50	96.58%	0.2282	95.82%	0.2560
		100	**99.39%**	**0.0822**	**98.99%**	**0.0977**

Table 2. Experimental results of different Proposed ResNet Architectures based on Version 2

Model Depth	Params	Epoch	Val. Acc.	Val. Loss	Testing Acc.	Testing Loss
11 Layers	306,374	10	92.62%	0.4069	90.79%	0.4752
		25	94.65%	0.3164	92.73%	0.3820
		50	95.86%	0.2655	94.37%	0.3104
		100	**95.63%**	**0.2658**	**96.24%**	**0.2553**
20 Layers	581,286	10	92.64%	0.4525	88.22%	0.6521
		25	95.47%	0.2908	92.10%	0.4107
		50	96.11%	0.2477	95.88%	0.2524
		100	**99.22%**	**0.1035**	**98.94%**	**0.1087**
56 Layers	1,680,934	10	93.45%	0.4143	86.31%	0.6529
		25	95.57%	0.2916	92.36%	0.4162
		50	96.53%	0.2361	96.04%	0.2576
		100	**99.90%**	**0.0465**	**99.78%**	**0.0529**
83 Layers	2,505,670	10	93.77%	0.4024	91.00%	0.5119
		25	95.62%	0.2855	94.08%	0.3494
		50	96.72%	0.2239	95.59%	0.2714
		100	**99.38%**	**0.0870**	**99.05%**	**0.0960**

Table 3. Experimental results based on the proposed different CNN Architectures

Model Depth	Epochs	Val. Acc.	Val. Loss	Test Acc.	Test Loss
Model 1 (12 Layers)	10	92.45%	0.2230	85.79%	0.4483
	25	97.23%	0.0832	86.66%	0.5385
	50	98.12%	0.0624	88.85%	0.5174
	100	**98.76%**	**0.0502**	**89.44%**	**0.6695**
Model 2 (14 Layers)	10	93.14%	0.2015	87.50%	0.3995
	25	96.65%	0.0982	89.61%	0.4259
	50	**98.65%**	**0.0417**	**91.85%**	**0.4481**
	100	97.95%	0.0632	90.31%	0.4853

5. Discussions

In this paper, we propose two versions of the ResNet Architecture and two models of CNN Architecture that can equip drones for SMART precision farming. The models were tested thoroughly using the public dataset of 70,295 images [34]. Table 4 shows the comparison between the proposed architectures in this paper and those reported in previous literature. The Table 4 clearly shows that the proposed ResNet Architecture version 2 achieves the highest average testing accuracy of 99.78%, which is better than all previously reported results in the literature and also higher than the two CNN models used in this paper. There are various advantages to the proposed SMART Precision Agriculture system. The SMART features and automated multi drone system can cover vast areas of farmland periodically on a daily basis. This task alone is impossible for humans to achieve, even if there is a large number of labors employed on the farm. So, in essence, we can reduce employment costs. In addition, the system also lessens the cost of farming not only through saving on farmhand salaries but also through precise measurement of chemicals sprayed, which saves the amount of chemicals. The system also helps in monitoring plants and trees which may not be accessible to humans.

Table 4. Comparison of Proposed Method experimental results with existing techniques for Plants Diseases Identification

Authors	Classifier/ Method Used	Dataset	Accuracy (%)
Proposed ResNet	ResNet Version-2	70295 Images of 38 Classes	99.78%
Proposed CNN	Convolutional Neural Networks [35]	70295 Images of 38 Classes	91.85%
Mohanty et al. [34]	GoogLeNet CNN	70295 Images of 38 Classes	99.34%
Mohanty et al. [34]	AlexNet CNN	70295 Images of 38 Classes	85.53%
Satti et al. [6]	Artificial Neural Network (ANN)	Flavia (1907 images of 32 classes)	93.30%
Sun et al. [7]	A deep learning model called ResNet26	10,000 images of 100 plant species	91.78%
Mishra et al. [8]	Multiclass Classification	Collection of 1000 leaf and flower images	85.00%
Chaki et al. [10]	Multi-Layered Perceptron (MLP)	Flavia (1907 images of 32 classes)	87.10%
Kadir et al. [11]	Probabilistic Neural network (PNN)	Flavia (1907 images of 32 classes)	93.75%

The crop yield is further increased due to the constant monitoring of every plant or tree on the farm to ensure their health throughout the season. The direct advantages of this system are reducing production cost, increasing yield and making farms more profitable. This increases the interest in farming and encourages many to start farming in the vast areas of farmland that are not utilized. In addition, there are indirect advantages to the environment because increasing farming and plantation provides a positive impact on the environment.

As in any research, there are some limitations to the work presented, some of the limitation are listed below:

1- Solution Tested in lab and simulated environment with no access to field test for various reasons. Small field tests were done within the university campus.
2- Lack of funding for multiple drone tests.
3- Applied to one dataset only so far.
4- Computational power limitations

6. Conclusion

Throughout the world, farming as a profession is declining due to the increase in farming costs, unpredictable crop yield and unstable chemical prices. However, in recent years the concept precision farming has been proposed that utilizes the latest technologies in farming.

In this paper, we proposed a SMART precision farming system composed of cognitive vision drones equipped with enough computing power for automatically monitoring large areas of farmland to oversee the healthy growth of plants and trees through image processing. Plants automatically detected with the disease are sprayed with a suitable chemical. The system contains a cloud-based backend to generate smart reports and predict crop yield. With a user-friendly HCI interface, farmers have access to the information and are notified when an unhealthy plant is detected. The advantage of such a system includes reduced production cost and high crop yield while providing a positive impact on the environment. The proposed modified ResNet architecture in this paper achieved an average accuracy of 99.78% on a dataset of 70,295 images that outperformed different architectures proposed in recent literature.

Future work will include developing the system further so that it can identify more species of leaf/plant diseases and develop better image processing algorithms that increase detection and recognition accuracy. Also, future work will include the integration of IoT within the system to monitor areas of the farmland continually. In addition, the limitations of this current study will be addressed in future enhancements of the proposed system in this work that will be tested in the field as well with multiple drones.

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