Mobile-computer Vision Model with Deep Learning for Testing Classification and Status of Flowers Images by using IoTs Devices

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Abstract

Many commonplace issues may be addressed with the help of the Internet of Things (IoTs). We provide an efficient solution to test classification and status of flowers images by combining Deep Learning (DL) and IoTs. Due to the diversity of flower species, classifying and determining the status of flowers is a difficult undertaking. in this study, two-phase DL to differentiating between flowers of several species are developed into the application of mobile that discovers the type of flower so that describing the amount of water required for the daily irrigation for every kind of flower. First, the flower region is automatically segmented using Markov Random Fields (MRF) approach. Second, build a robust DL by using four models such as VCG-16, inception-V3, MobileNet-V2, and RestNet-18 to distinguish the different flower types. In this way, the system keeps track of the amount of water in the soil and uses water wisely while appreciating the user. To evaluate the flower's state, which is being tracked by nearby sensor devices, a cloud-based server and a mobile application are used in the flower status tracker implementation. The results show that the VCG with segmentation has the highest accuracy than other models but it has longer time in implementing.

Keywords: Classification, IoTs, Deep Learning, Markov Random Fields, Status of Flowers.

1 Introduction

Flowers are a great example of how the IoT may be used to enhance crop yields by providing instantaneous access to data on environmental conditions (Zhang, J., 2016), by integrating different sensors can discover information of humidity, temperature, carbon dioxide concentration, soil PH value, and light intensity, etc. (Lai Wang Feng., 2010). Flower classification & recognition is a challenging

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task because there are so many different kinds of flowers that all look relatively the same: several flowers of various kinds have similar appearance, colour, and form. Additionally, photos of many flowers often share common background elements like leaves, grass, etc. There are many other uses, such as content-based image retrieval for representing & indexing flowers, floriculture industry, plants monitoring systems, live plant educational and identification resources on flower taxonomy based on successful classification of flower. Manual classification is an option, but it can be laborious and time-consuming when dealing with many images, and it has the potential to be inaccurate for some flower classifications, especially when the background of image is complicated. Because of this, effective methods of floral segmentation, detection, and categorization are of paramount importance. The flower classification task was proposed to be taken on by DL approaches, particularly CNN-based methods. Due to its improved accuracy compared to classical approaches, CNNs have lastly attracted a lot of interest in solving numerous learning issues. Recently, they have been utilised in a number of natural image classification applications (Li Xue Bao, 2010) (Krizhevsky, A., 2017) (Simonyan, K., 2014) (He, K., 2016). However, only a small number of published publications have used CNN to solve the classification flower problem (Szegedy, C., 2015) (Xie, L., 2017) (Song, G.H., 2016). For instance, the work in (Xie, L., 2017) used a deep CNN and two levels of hierarchical feature learning (HFL) to solve the problem. They first initialised a pre-trained model of deep CNN for the novel target data using the transfer-learning technique HFL. Afterwards, we trained several depths of deep feature extractors. Comparing this method to other classification methods, the accuracy is successfully increased. It was suggested to use an online version of nearest-neighbor estimation (ONE) for both image classification and retrieval (Xie, G.S., 2017). This approach computed similarity between image candidate or each category and the query, which required regional description, manual item definition. and closest neighbor search of extracted CNN features. With reasonable computational overheads, the results demonstrate state-of-the-art accuracy in a variety of classification of image and retrieval data. In (Xie, L., 2015), a standard CNN representation dubbed Over Feat was applied to a variety of recognition tasks, one of which was flower classification. In the numerous classification tasks on multiple data, the experimental study demonstrates meaningful outcomes. The authors in (Szegedy, C., 2015), on the other hand, suggested RI convolution (RI-Conv) layers and reversal-invariant deep features (RI-Deep) to improve the capacity of CNN without affecting the complexity of model. This method improves accuracy on a number of picture categorization tasks including fine-grained object recognition, scene understanding, and visual recognition of large-scale. A method to extract deep convolutional activation features (DeCAF) for applying with a k-NN was put forth by the authors in (Sharif Razavian, A., 2014). Their data analysis demonstrates that the proposed strategy outperforms current methods in terms of precision and efficiency. In (Qian, Q., 2015), a model of task-driven pooling (TDP) for implicitly learning pooled representation from data was introduced. To improve the pooled representation in CNN models, TDP was employed instead of average or max pooling. For the purpose of maximising accuracy on a flower dataset, the suggested approach was expanded to multi-task classification of (mTDP). The right way to transfer features of CNN to perform a specific assignment was explored in (Xie, G.S., 2015). Their analysis revealed cutting-edge advancement on numerous datasets, including a dataset of flowers. Recently, in (Zheng, L., 2016), a method was published for leveraging winner takes all (WTA) hashing to shorten the duration of the action backward and forward propagation steps of a CNN. An alternative method employs a hierarchical deep semantic representation (H-DSR), which integrates semantic context modelling with visual data (Bakhtiary, A.H., 2017). Grids of fixed-location images were mined for Deep Neural Network features, and those features were then utilised to determine a response map with the help of trained classifiers. Then, a hierarchical deep semantic model was created by extracting semantic representation from the response map and combining it with visual representations. A CNN based approach to classify the flowers in (Zhang, C., 2017). To choose the flower region, they used saliency and luminance map approaches. A flower dataset was used to test the approach.

2 Materials and Methods

2.1. Proposed Method

The suggested system integrates DL ideas to determine the type of flower, and using the IoTs, data about flowers may be transmitted so that mobile devices can be used to monitor their health and manually or automatically adjust their watering schedules. The CNN architectures (MobileNet-V2, Inception-.VCG-, and RestNet-) are primarily used by the DL models for image classification. Also, we use important step, which is called MRF segmentation (Liu, Y., 2016) (Keskin, R., 2021).

2.2. VCG-16 Deep Learning

K. Simonyan and A. Zisserman from the University of Oxford suggested the CNN model known as VGG16. The Cov1 layer accepts a 224x224 RGB image. A series of convolutional (conv.) layers are applied to the image. If a very narrow receptive field was employed with the filters: 3×3 (If a very narrow receptive field was employed with the filters of up/down, left/right, and center). The 1×1 convolution filters, which may be thought of as the linear transformation of the input channels, are also used in one of the setups (Nilsback, M.E., 2008). Figure 1 shows the VCG-16 architecture.

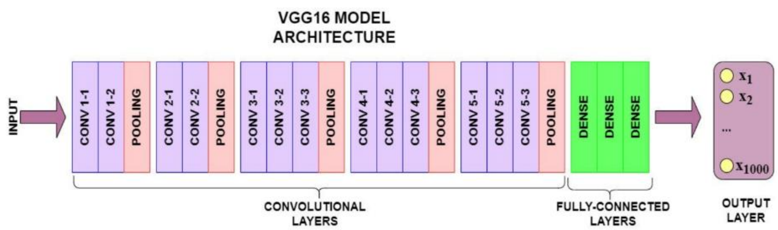

Figure 1: The VGG16 Model

2.3. Inception-V3 Deep Learning

The Inception V3 DL model is a CNN-based DL model employed in classification of images. The advanced model Inception V3 replaces the entry-level Inception V1, which was called Google Net in 2014 This Inception V1 module is referred to as the Naive form, which is shown in Figure 2. This naïve technique suffers from the drawback that even the 5x5 convolutional layer is CPU-intensive, time-consuming, and costly. Obviously, it was created by a group at Google. In 2015, the conception v3 model was released, with 42 layers and a reduced error rate, it is an improvement over its forerunners (Das, M., 1999).

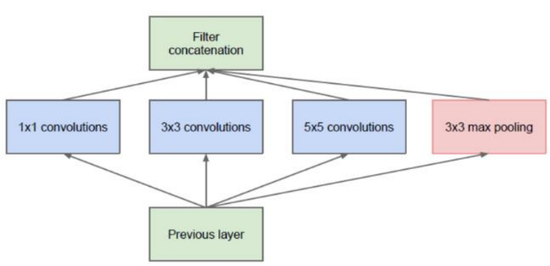

Figure 2: Inception-V3 Deep Learning

2.4. MobileNet-V2

MobileNetV2 is a CNN architecture designed to operate effectively on mobile devices. It is predicated on a residual structure that has been turned on its head so that the bottleneck layers are now connected by the residual links. The intermediate expansion layer makes advantage of lightweight depth wise convolutions as a source of non-linearity to filter features. MobileNetV2's overall structure is made up of a fully convolutional layer with 32 filters, followed by 19 residual bottleneck layers (Nilsback, M.E., 2006). MobileNet-V2 model has been shown in Figure 3.

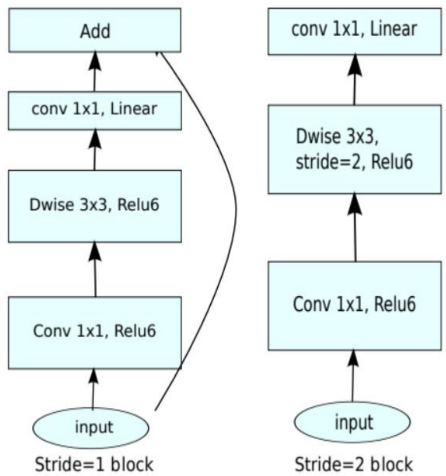

Figure 3: MobileNet-V2 Deep Learning

2.5. ResNet-18 Deep Learning

ResNets, also known as residual neural networks, employ a method called identity mapping. By-passing one layer and feeding its input into another. Think about the basic residual block in the illustration of Figure 4. Clearly, the idea of a shortcut (or "skip connection," as depicted in the diagram) is crucial to this scenario. In essence, a skip connection is an identity mapping in which the output of one layer is added to the input of the previous layer. ResNet-18 is a CNN that has been trained on more than a million images from the ImageNet collection the architectural structure of this object has 18 layers. It's highly practical and effective at its designated task, and it can divide an image into one of a thousand distinct kinds of objects. The network accepts images with a 224x224 resolution (Nilsback, M.E., 2007).

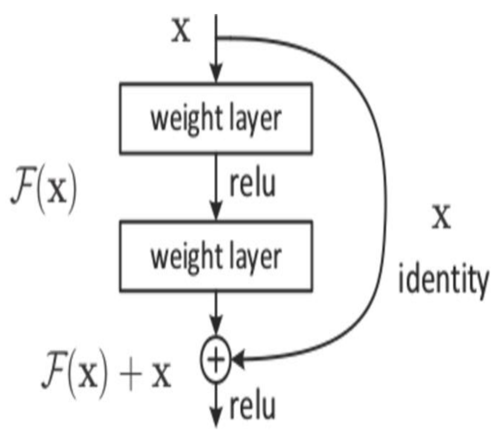

Figure 4: RestNet-18 Deep Learning

2.6. MRF Probabilistic Approach

It is possible to divide an image into regions because adjacent pixels always share the same characteristics. MRF is a probabilistic method that can identify pixel-related restrictions. Furthermore, it offers a solid theoretical foundation for formally defining concepts. Additionally, several building blocks are required for processing the image like a labeling field, observation field, defining pixels, and their neighbors in Figure 5 as 1^{st}, 2^{nd}, 3^{rd} order (Saitoh, T., 2004).

The most typical test in imaging studies is to see if a subject correctly identified an image anomaly. Usually, the investigator insists user; make a mark on the image to indicate the abnormality's location. There are several errors combined with the presentation, the magnitude of the marked abnormality, the user experience, etc. Assessments are often made using a way too simplistic of a procedure, estimating the distance in pixels from the target's focal point is used to determine if the user has successfully "struck" the target in order to determine whether or not a hit has been made, the designated area uses a predetermined amount of pixels to display an area of interest (AOI) surrounding the primary focus of the shot (Boykov, Y.Y., 2001).

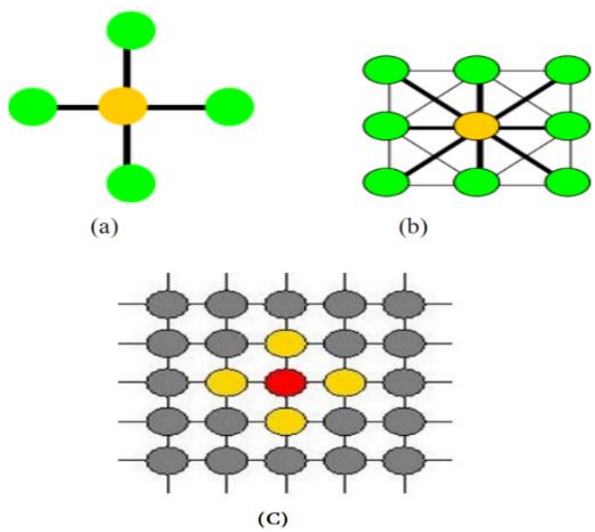

Figure 5: (a) 1st Order (b) 2nd Order (c) 3rd Order Neighbors in Random Fields

2.7. Segmentation

Many studies have suggested techniques explicitly to automatically separate a flower image into the flower in the foreground and the rest of the image in the background. In this case, we employ the method of segmentation described in. The plan of moves forward iteratively: First, a segmentation of the flowers is obtained using non-class-specific colour distributions for the foreground and background. In a few training images from each class in the data, pixels are labelled as foreground or background to learn these distributions, or background, and the distributions across all classes are then averaged. Given these public background or foreground distributions, by optimising the contrast dependent prior MRF cost function from, we first acquire a binary segmentation. Even while this segmentation may not be complete, it is frequently enough to extract at least some of the flower's external boundaries. Next, we fit this segmentation with a generic flower form model to look for petals. The model uses an affine invariant Hough-like method to choose petals with a loose geometric consistency.

A novel image-specific foreground colour model is gained by analysing the portions of the image that have petals judged to be geometrically consistent. Then, the general foreground model is blended with the image-specific foreground model to update the foreground colour model. Using this updated colour scheme, we repeated the MRF segmentation. The usage of the foreground tailored to the image frequently harvests more of the flower in situations when the initial segmentation was imperfect. The steps of learning the foreground of an image and fitting the shape model can be repeated until convergence is reached and very little change occurs between iterations. A 13-class flower dataset (out of a total of 17) was used to debut the technique in. On our dataset of 103 classes, Figure 6 displays sample segmentations that were produced using this approach. It's clear that it's effective even with flowers that have a considerably different shape from the ones used in.

Figure 6: Example Segmentations [29]

2.8. Performance Measures

To help evaluate the efficacy of segmentation, detection, and classification techniques, we suggest a number of metrics. We employ the pixel overlap score, also known as intersection over union (IoU), for flower segmentation. IoU is a percentage metric based on the union of the overlap between human and automatic segmentation. We focus on the flower in the foreground and only consider the overlap between it and the surrounding pixels. Some flower segmentation techniques, including those found in (Keskin, R., 2021), have utilised overlap score. The overlap value is a number between 0 and 1, and the greater the number, the more precise the segmentation.

$$\mathrm{IoU} = \frac{|\text{ manual} \cap \text{automatic}|}{|\text{ manual} \cup \text{automatic}|} \tag{1}$$

where | is the cardinality of a set. Since we only need a rough detection of the flower region to make a classification, our method is not overly sensitive to the quality of the segmentation, we assessed flower detection's precision. To compare the accuracy of manual and automated segmentation, we propose using the area of overlap between the two boxes as a metric. To assess the box overlap between the manually entered boxes and the detected boxes, we compute the box IoU (BIoU). When determining the optimal BIoU threshold, that is, the level of IoU at which the two boxes are deemed to have overlapped sufficiently, it is also essential to consider the following, we find $B_{\text{overlap}}^{\text{th}}$ which calculates the percentage of images having $B_{\text{IoU}} \geq$ th. The value of threshold is different between 1 (complete overlap) and 0 (no overlap).

$$B_{\text{overlap}}^{\text{th}} = \frac{|\text{ images} : B_{\text{IoU}} \geq \text{th}|}{|\text{ images }|} \tag{2}$$

The proportion of correctly classified images over all the images used to calculate accuracy is as follows:

$$acc = \frac{|\text{images: predicted class = manual class}|}{|\text{ images }|} \quad (3)$$

3 Simulation Results and Discussion

3.1. Dataset

In this study, we present a dataset of 8189 flower photos labelled with 103 different classification. These have been selected as examples of typical British flowers. The majority of the images were gathered from the web. We took a few shots for a few of the images that were collected. There are 40-250 image in each class. The distribution of the number of images across all classes is shown in Figure 7. The size of the images is changed so that the smallest size is 500 pixels. The dataset is divided into a validation set, a test set and a training set. Ten images per class are used in both the training and validation sets (totaling 1030 images each). The remaining 6129 images make up the test set (minimum 20 per class).

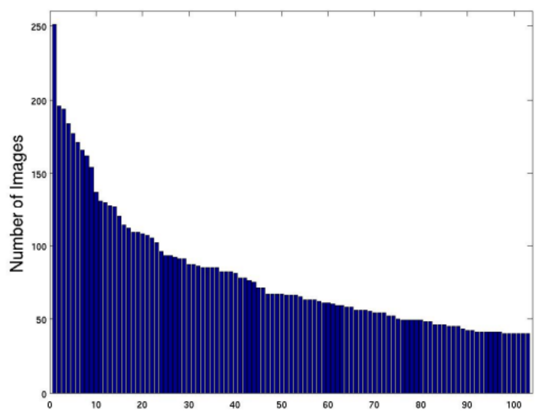

Figure7: The Breakdown of How Many Photos there are Throughout the 103 Classes

3.2. Implementation of Mobile Application

The dataset is divided into two parts, with 30% being used as a validation set and 70% being used as a training set. Each of the aforementioned four models was chosen for use in image classification as Mobile Net V2, ResNet-18, VCG-16, and Inception V3. The Stochastic Gradient Descent optimizer is used to train these models using a 0.002 percent learning rate and a batch size of 32. In 40 epochs, all of the models have been trained, and the validation accuracy is at its highest point. The system is then converted to a TensorFlow-Lite model and integrated into the application, where it successfully detects flowers via classification on Android-based smartphones. Models trained using transfer learning are evaluated for their precision. The VCG-16 model is used in the Android application since it has the highest validation accuracy.

On the Flower Dataset, a comparison of the various models is also carried out. Figures show that our suggested VCG-16 model significantly outperforms other approaches in terms of accuracy. The system configuration login page is shown in Figure 8. The name of the flower is determined by taking a snapshot with the smartphone's camera from the application menu. The image is forecasted as "petunia", "Artichoke", and "Garden Phlox" offered by the application.

The server is then used to relay the names of the flowers to the controller. Geraniums need damp soil since that's the average soil moisture level recorded for each flower kind. In this study, three groups are chosen to alert the user and provide water to the plant. These are described as normal, excessive water, and need water. As can be seen in Figure 9, normal notification occurs when the flower is irrigated and its moisture level rises to 52%. The message that more water is needed appears in Figure 10 when the measured value is 20%. Excessive water alerts are triggered when the Garden Phlox's moisture level reaches 62%, which is above the plant's optimal range as shown in Figure 11.

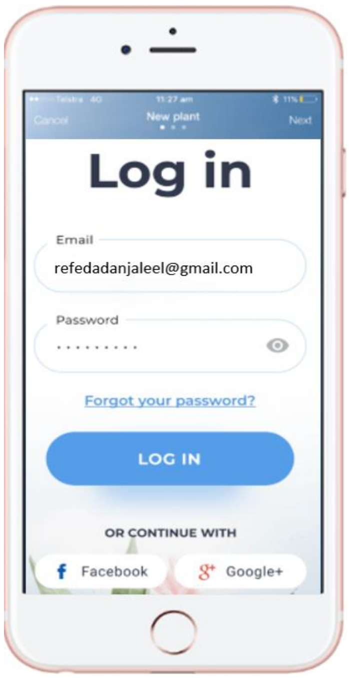

Figure 8. Login page of Mobile application Figure 9. Water statues of Petunia

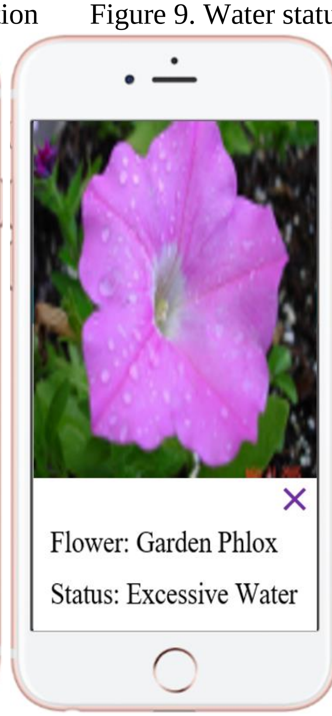

Figure 10. Water statuses of Artichoke Figure 11. Water statuses of Garden Phlox

3.3. Effect of Segmentation on Accuracy of Classification

To determine if segmentation might increase the precision of classification detection, the assessment of the DL in flower classification status discovering was examined. Using ResNet18, MobileNetV2, VGG-16, and Inception-V3 as the basic structure of the network, the experiment to determine flower types was conducted. The transfer learning method was applied throughout the training of the three networks. Network learning can be made more efficient and accurate by loading the relevant model. Images of flowers were first utilised for classification detection experiments without segmentation. Data was transferred to a size of (224 × 224 × 3) for experiments with the MobileNet-V2, VGG-16, Inception-V3, and ResNet18 networks, and to a size of 299 × 299 × 3 for experiments with the network of Inception-V3. Due to the addition of segmentation, the input size of the data was 224 × 224 × 4 for VCG-16, MobileNet-V2, and ResNet18, and 299 × 299 × 4 for Inception-V3. In this study, we employed the cross-entropy loss function for training and a batch size of 32 for our experiments. The rate of learning was set to 0.02 for ResNet-18, VGG-16, Inception-V3, and MobileNet-V2. The four network models with and without segmentation were compared based on the validation sets with the highest accuracy.

It can be seen from Figures 12, 13, 14, and 15 that the accuracies of ResNet-18, VGG-16, Inception-V3, and MobileNet-V2 were enhanced by adding segmentation.

Figures also show that VGG-16's accuracy increased noticeably after being segmented. The accuracy impact of VGG16 was comparable to ResNet18 when segmentation was not applied.

Measured in hours, this is how long it takes to train four different network models and evaluate a single sample. It is evident that VGG-16 and Inception-V3 need more training time. As expected, there was no variation in the average time needed to test the data across the four networks; it was only 0.9 s. ResNet-18 used around 20 ms for each piece of data, while Inception-V3 needed around 28 ms.

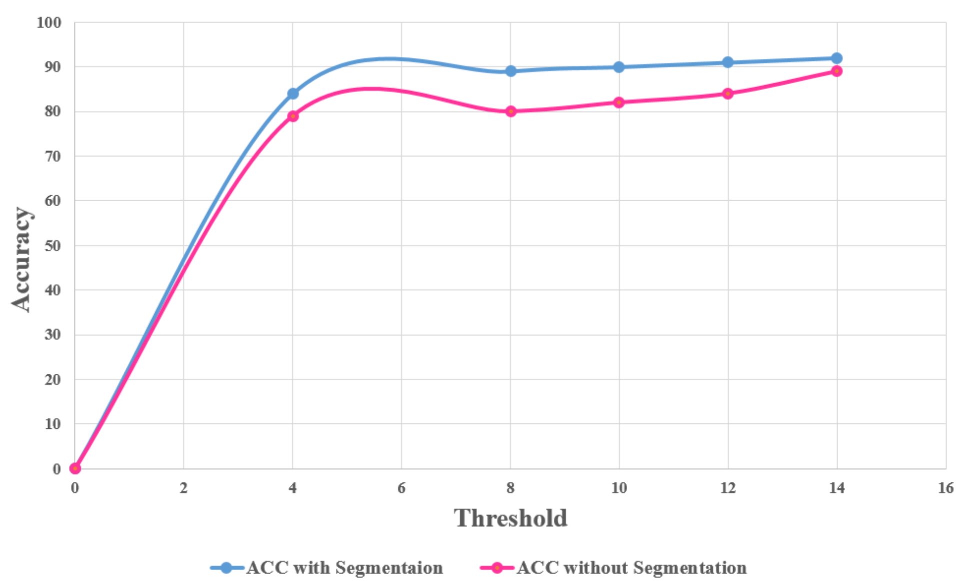

Figure 12: VCG 16

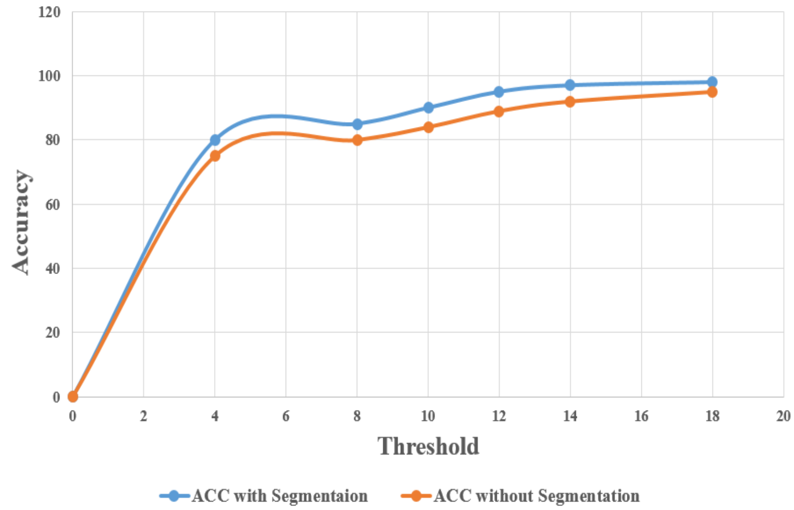

Figure 13: Inception V3

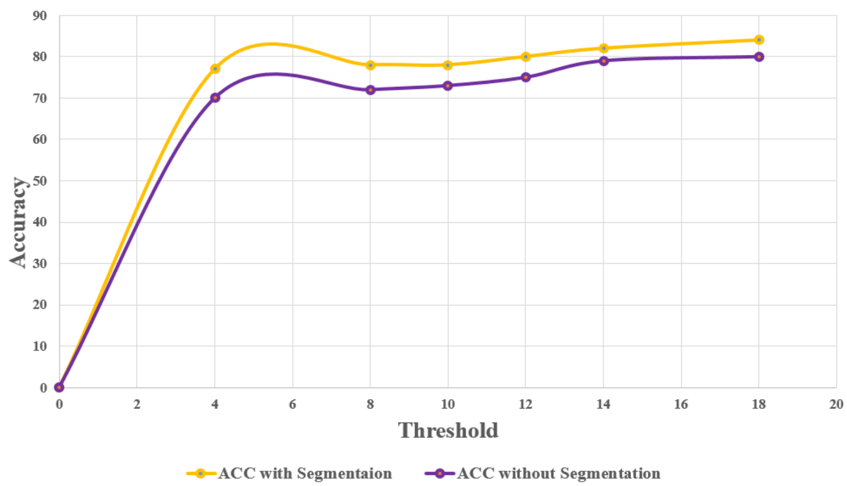

Figure 14: Mobile Net V2

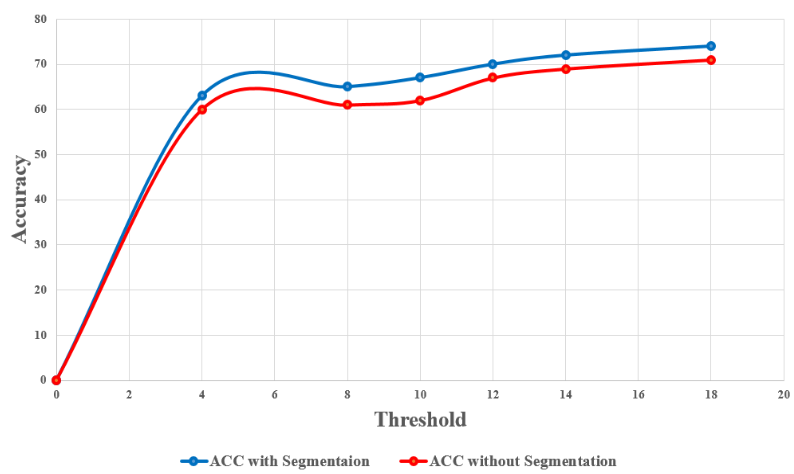

Figure 15: ResNet-18

4 Conclusions

In this study, we provide a DL with IoTs-based approach to flower image segmentation, detection, and classification. The mechanism for tracking flower state is used. It combines DL architectures (MobileNet-V2, VCG-16, Inception-V3, and RestNet-18) to classify and identify the flower, then give the plant with the appropriate amount of water and, in doing so, prevent overwatering, into a mobile device app. The system's advantage is that it uses image recognition to identify the type of bloom and then provides the appropriate watering instructions for each type of flower. The intuitive application shows the flower's related water levels as it manages and records the system to maintain the proper levels. Effectiveness of the proposed strategy was indicated by high accuracy scores in a comparison of categorization algorithms. Each network model has been combined with the MRF segmentation method to increase accuracy. The VCG-16 model is the most accurate, but it also takes the longest time to run. Also keep in mind that these were pre-trained algorithms that, whenever accessible, can be applied with ease to a larger number of images. As a result, the proposed technology can be used on a massive scale in agriculture, owing to the current circumstances and water limitations, in particular for water conservation. Jointly training the classifier with visually comparable classes is a promising avenue for future research.

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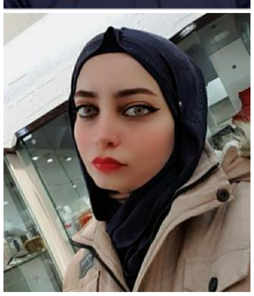

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