A MACHINE LEARNING BASED SMART AGRICULTURE ARCHITECTURE FOR PLANT RECOGNITION AND CLASSIFICATION

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ABSTRACT

A plant's main component is water. In this way, changes in plant water content have a significant impact on how plants grow. Visual item identification is a straightforward skill for a human. Computer-based picture identification is still difficult, though. Recent developments in machine learning have led to the development of strong recognition and classification methods that can handle challenging settings. This research proposes a machine learning-based smart agricultural architecture based on plant detection and categorization. In order to improve plant development in a local water situation, this research seeks to organize and design an intelligent framework in light of Support Vector Machine (SVM) and machine vision. The strategy employs a powerful deep learning-based architecture for item identification in the context of Smart Agriculture. This architecture describes an approach for image recognition with a specific focus on the automated recognition of plants and flowers. It aims to automatically detect damages in leaves and fruits, locate them, classify their severity levels, and visualize them by contouring their exact locations. The mobile iOS (iPhone Operating System) application was described that was designed,and results can indicate a higher accuracy when theSVM was utilized as the classifier with high precision for plant conditions (Fresh and Wilted).

Keywords: Plant recognition and classification,machine learning, Support Vector Machine(SVM).

INTRODUCTION

Throughout the history of human agriculture, one of the key goals has always been to increase the economic efficiency of agricultural operations. Unfortunately, due to the challenges in achieving quality/cost balance, this target has not been met to the intended degree. Frequent visits to agricultural production sites are important; else, crop production safeguards may not be taken as needed. Farmers raise the price of the harvest by investing more time and money into each visit. Since those farmers spend a lot of time observing and assessing their crops, smart agriculture has become vital. Technologies based on the "Internet of things" (IoT) allow remote and accurate monitoring, supervision of crops that is not only cutting-edge but also economical [1].

The cycle of observation, diagnosis, decision, and action should guide smart agriculture. In this cycle of repetition cycle, data should be collected and used quickly to make changes that optimize the farming process. Data can be obtained and recorded using sensors that capture natural resources like crops, livestock, atmosphere, soils, water, and biodiversity during the observation phase. The sensor values are transmitted to a cloud-hosted IoT platform based on predefined decision models thatdetermine the object's state under investigation during the diagnostic phase. During the decision phase, the components based on machine learning techniques determine whether an action is required. During the action phase, the end-user evaluates the situation and applies the action. Then the cycle starts all over again [2].

Throughout the years, the ages of living creatures have increased, so incorporatetheir learning aptitudes. Nowadays, Machines get familiar with asimilar route as people do. This learning action of machines is additionally called the preparation of a machine to make it smart. Different computer vision calculations floor a path for building machines canny because of their capacity to translate the pictured information. The machine does this byutilizing two huge components known, for example, acknowledgment and arrangement.The recognizable proof of plants depends onmonitoring its morphological highlights, for example, the structure of the stem, roots,leaves, and natural products. There are manymachine learning techniques used for thispurpose. In this paper, SVM and CNN techniques shall be used to plant recognition and classification.

LITERATURE SURVEY

Providing automation of processes inprecision farming and detecting anomaliesin the system is a specific area of study. Anomaly detection canbe defined asdetecting unexpected items or unusualbehavior in data sets, which differ from thenormal situation. According to the notions inthe field of agriculture, elements that are notnatural for the environment are known asanomalies. Rong et al. [3] proposed twodifferent CNN structures for automatic segmentation and detecting foreign objectsof different sizes, natural or artificial. Theproposed structures were applied to walnutimages: Rasmussen and Moeslund [4]trained CNN models for kernel fragmentrecognition in RGB images of silage.Intelligent management and the automationof agricultural machinery are now realisticoptions, increasing agriculturalmechanization.

However, agriculturalmachinery recognition differs from plantrecognition in the data acquisition methodsused. For capturing agricultural machineryimages vehicle terminal camera is used, sothe images needpreprocessing. Zhang et al. [5] designed and trained the AMTNet network to recognize agricultural machinery images that produced acceptable results automatically. Ma et al. [6] proposed an unsupervised deep hyperspectral anomaly detector. An algorithm combining anomaly detection and deep learning proposed by Christiansen et al. [7] performed anomalydetection to exploit the homogenous characteristics.

Automatic plant image identification is the most promising solution for bridging the botanical taxonomic gap, which receives considerable attention in botany and the computer community. As machine learning technology advances, sophisticated modelshave been proposed for automatic plant identification. The research on automatic plant taxonomy has yielded fruitful results. One must note that those models are still far from the requirements of a fully automated ecological surveillance scenario [8]. The datasets above lack the mobile-based plant images acquired in natural scenesthat vary significantly in contributors, cameras, areas, year periods, individual plants, etc. The traditional classification models rely heavily on preprocessing to eliminate the complex background and enhance desiring features. Moreover, handcraft feature engineering is incapable of dealing with large-scale datasets consisting of unconstrained images.

Mobile-based automatic plant identification is essential to real-world social-basedecological surveillance [9], invasive exotic plant monitoring, and ecological science popularization. With the popularity of smartphones and the emergence ofPl@ntNet mobile apps [10], millions of plant photos have been acquired. Improving the performance of mobile-based plant identification models attracts increasedattention from scholars and engineers. Nowadays, many efforts have been conducted in extracting local characteristics of leaf, flower, or fruit. Most researchers usevariations on leaf characteristics as a comparative tool for studying plants, and some leaf datasets, including the Swedishleaf dataset, Flavia dataset, and ICL dataset, are the standard benchmark.

PLANT RECOGNITION ANDCLASSIFICATION MODEL

The framework of the plant recognition and classification model architecture using machine learning is given by Fig.1. The figure consistsof the input image module,feature extraction module, classifier module,and mobile application.

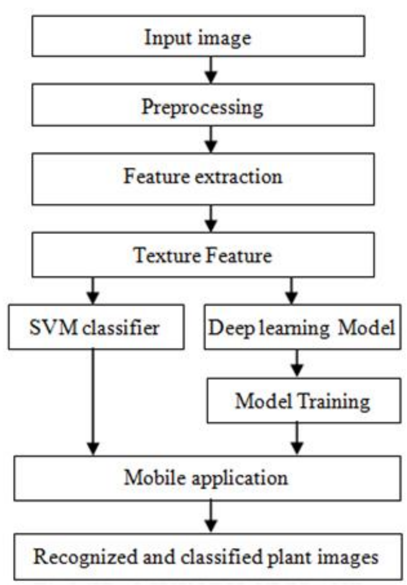

Fig.1. Framework of plant recognition and classification model

Input Image: The information and data of Images are increasingly significant in natural sciences. In this way, pictures can becaught from an advanced camera. Precisely, initially 20 (correct) images were manually selected representing each plant species. These manually chosen image sets were used for the initial deep learning modeling, i.e. to classify the downloaded dataset images to check whether the downloadedimages were in the proper dataset, i.e. they were in the manually classified image set forthe specific plant species.

Pre-processing: To improve imagerecognition accuracy and training efficiency,it is necessary to preprocess the images used.For recognition of images in the real world, consideration of images from many dimensions is essential. This includes image flipping (vertically and horizontally) to ensure that the trained neural network modelcan identify plants in different conditionsand from different angles. Noises occur as pixel values, which do not represent the true intensities of an image during the image acquisition. It is necessary to remove theimage noises to highlight or enhance the essential features of an image. The original images were resized and then retained in the RGB format. In this bilinear interpolationwas used to adjust the size of the image. Thecore of this algorithm is to determine thepixel values of the target image coordinates based on the pixel values of the coordinates from the original image. This background removed image is used for further processing. Data is transformed fromimage format(.jpg) to well-organizednumerical data, improves data quality, and protects applications from potentiallandmines such as null values, unexpected duplicates, incorrect indexing, and incompatible format.

Feature Extraction: Feature extractionis completely dependent on the three types of highlights: shading histogram, edge histogram, and Sobel edge bearing. Ashading histogram is utilized to produce the shading difference in the picture. There are diverse shading space models like RGB (Red Green Blue), HSV (Hue Saturation Value), YCbCr, etc. These diverse space models' portrayal changes habitually. The info picture is called RGB shading spacepictures, so changing RGB to HSV shading space can be got. The HSV shading space model is accustomed to gathering the shading histogram impeccably since H is thetone which means the genuine wavelength of the shading

Texture Feature: The surface is a component. It is utilized to change the pictures into the locales, and it will group these areas. There is parcel of surfaceexamination procedures utilized withdiscrete criteria for extraction: measurablestrategies; channel methods. Nearby picture highlights determine the different highlights.

Classification: Initially machinelearning-based SVM model is used to classify the downloaded dataset images to check whether the downloaded images were in the proper dataset, i.e., they were in the manually classified image set for the specific plant species. After the initial classification model finished (with all training models used just once), all images not classified into the suitable dataset were deleted. This process was repeated with deep learning model of Convolutional Neural Network (CNN). Consequently, these two processes are performedseveral times,including the newly identified (classified) plant species. The training data set was thus increased in size through deep learning approaches. It is noted that this procedure can be applied numerous times to increase the accuracy of the resultant plant prediction.

SVM:As the last step for an automated plantrecognition system, SVM is an intelligentalgorithm in training data to recognize each plant species' specific features andcategorize a new sample as the correct species. Support Vector Machines (SVM), a supervised machine learning approach, is conceded as one of the powerful classification methods due to its high capability in dealing with high dimensional space and data points that are not linearly separated. Applying linear SVM on feature-mapped data executes fast with low storage and improves classification performance.

Deep learning model: Only the trainedneural network can solve the classification problem, i.e., flower recognition. To addressthis, 80% of the dataset was used as thetraining set, 10% used as the validation set, and 10% percent of the dataset used as the test set. The training process is iterative. Before each iteration begins, a part of the training data is selected as an input batch. The forward propagation algorithm is then used to get the prediction results of the neural network. Since the training data has already been correctly classified, the gap between the predicted classification and the actual correct classification can becalculated. Finally, through the gap, the backpropagation algorithm is updated using the value of the neural network parameters. The prediction results of the neural network model on this batch can be assessed, e.g., to determine whether they are closer to the actual answer. In this way, the neuralnetwork shall be able to classify plants.

Mobile Application: The above machine SVM and deep learning algorithms were realized through a mobile application. Initially, the work has focused on the iPhoneiOS platform. For the implementation of the mobile application, the interface design was critical. The application was designed to be trivial, with no significant functions oroptions or a manual required. iOS devices have limited amounts of memory and hence limited processing ability. The iOS application uses the Tensorflow library. Thisprocess only supports operations that are commonly used for inference and do not have external dependencies. The classifier model trained previously thus needed some optimization to be used in the iOS devices.A Google build tool, Bazel was used to optimize the classifier model.

RESULTS

When applying the application for plant recognition, the overall results were divided into two case studies: one focused on 125 flower species classification and the otherfocused on 50 flower genera classification. This framework requires preparing the 50input pictures and computing the exact characterization dependent on the test picturesusing SVM. The arrangement precision is defined as the number of test pictures ordered appropriately by the absolute number of pictures increased by 100 using the CNN model.

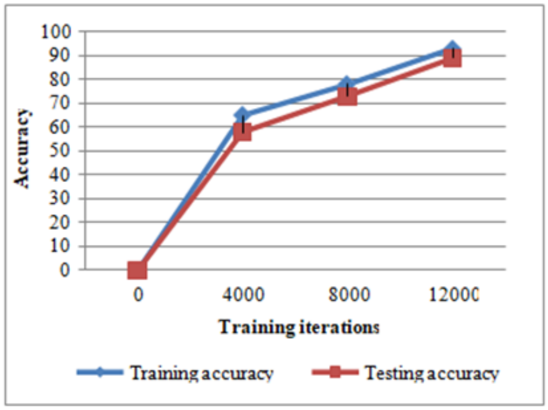

Fig.2. 125 Flowers species classification accuracy using CNN

Figures2 show that there was a rising trend intraining and testing accuracy for these case models. From the figure, as the training and testing increases, the accuracy increases. After 12,000 iterations of the training algorithm, the rising trend of accuracyincreases steadily.

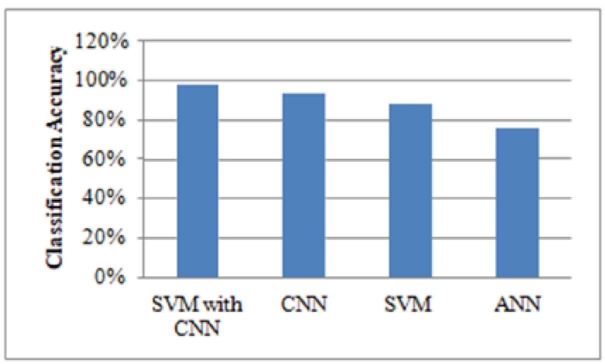

Fig.3. Final classification accuracy result of the 50 flower species

Figure 3 shows the final classification accuracy results of the 50 flower species classification case study for each species using SVM with CNN.A 98% classification accuracy was achieved with the proposed SVM with CNN technique compared to other individual performances and the ANN model. The generated feature sets are aided into Linear SVM, a supervised computing device learning algorithm usedfor classification and regression challenges. The classifier will assign the label to thephotograph, and it specifies which category it belongs to, from where the classifier is predefined primarily based upon the feature. This classification is used for each analysis and the trying-out phase. SVM makes use ofthe method referred to as the kernel. Theoverall results with a comparative graph are shown in Fig .4.

The mobile application is used to view the recognition and classification of plant results. The application has two main views:a prediction view and a category (classification) view. Users use their phones to video potentially unknown flowers in the prediction view and the data (classification and confidence level) shown. The application also offers an option to show the complete set of flowers that the mobile application has been trained to support. The mobile application itself is shown in Figure 4.

Fig. 4: MOBILE APPLICATION VIEW

CONCLUSION

This paper proposes a plant image recognition system that uses machinelearning to classify different plants and flowers.The machine learning technique used for the image recognition work, including image processing, to increase the size of the training dataset and ensure uniformity of input data have presented. It also presented how deep learning trained a CNN model to classify complex future inputimages. The development of an Android version of the mobile application is used for identifying the trained plant and flower species. The plant classification depends ona few essential aspects like color, a structureusing an SVM classifier. With this research paper, it can be concluded that the proposed plant recognition and classificationtechnique using SVM and CNN model isbetter than individual SVM,CNN, and ANN classifiers.Finally, abetter percentage of classification accuracy was obtained for theproposed SVM and CNN technique.

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