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Multispectral Imaging Using BP Classifier for Plant Identification

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Abstract—With the technological advancements in the field of Computer Vision along with Machine learning, agricultural automation has an important role for small fields to achieve high efficiency and precision at low cost. Combined with deep learning techniques, every aspect of agricultural production and monitoring based on large datasets promotes more economic and robust performance for the production and development of agricultural automation systems in a more intelligent manner. This paper intends to focus on the applications of image processing techniques in agriculture, plant and fruit detection, weed detection using Multispectral imaging technique along with Backpropagation classifiers to improve the performance.
Keywords — BP Classifier, Machine Vision, Precision Agriculture, Plant identification, Wees Detection

I. INTRODUCTION

Agriculture, mainly the economic backbone globally for many countries, aids to meet the basic needs of the human beings across the world. The main objective to combine agriculture with various technologies is to increase the productivity of the crops and to protect it from deterioration and misuse. Machine Learning emerged with big data technologies and high-performance computing allows to understand data intensive processes in agriculture industry [1].

Machine learning in the operational agricultural environment [2] allows for species breeding, species recognition, field conditions management such as soil management, water management, crop management for yield prediction and crop quality, disease detection, weed detection, livestock management, animal welfare. Much of the literature review on popular models in agriculture reveals that Artificial Deep Neural Networks and Support Vector Machines[3] are used to predict yield and quality of crops as well as livestock production. Though ML algorithms at present are capable to solve individual problems, knowledge-based agriculture with the integration of automated data recording, data driven farming practices would increase production levels and quality of the crops.

Machine Learning, a sub-field of artificial intelligence dedicates to the study of prediction and inference algorithms. The question raises technically is that "How can we measure the prediction ability of the selected function of the training process?'.

There have been numerous research works carried out on how machine learning algorithms can be used to improve conventional agriculture. The techniques vary with the type of the crops, data they work with, geographic locations as well. These techniques vary from early detection of diseases, determination of the affected area based on the color, quality of foods, nutrient deficiencies in a particular crop based on the visible phenotypes in the crops. This paper presents applications of computer vision along with machine learning in various domains of agriculture.

II. Existing System

Manual systems tend to be error-prone. Machine Learning algorithms enables us to analyse massive volumes of data accurately and efficiently, for further implementation of Computer Vision and Machine Learning applications in agriculture. In Computer Vision, source of radiation plays an important role. These different sources of radiation can be categorized into Gamma Ray imaging, X-ray, UV band, Visible band and IR band, Microwave band imaging and Radio band.

Remote sensing techniques [4] with pattern recognition can be used for crop discrimination either by visual or digital interpretation techniques. Vegetation extraction in image processing can be done in two parts: First is preprocessing for radiometric and geometrical corrections. Second, image classification for supervised and unsupervised model will be reviewed. Commonly used image classification techniques include unsupervised clustering, multi-stage classification, density slicing with thresholds, decision tree-based classifications. In these techniques Green Index and relativity sensitivity index are calculated based on the reflectance and the extent of the irrigated crop lands. Remote sensing techniques have their own limitations in the context of incomplete, imprecise sensors, and very difficult to extract end members.

Thermal imaging [5], a passive technique (infrared range between 3 to 14 µm) focuses on an important parameter, Water Per Area. The thermal properties of the plants are much affected with the amounts of water per area a leaf contains. Thermal imaging techniques can be very much useful in post harvesting operations such as bruise detection, maturity evaluation, detection of foreign substances in food, etc. Though thermal imaging produces better results, but are not accepted as a standard as the climatic conditions vary from region to region in agricultural applications.

Classification of fruits and vegetables using fusion of features and classifiers were also proposed. For this classification, machine learning techniques such as Support Vector machine, Classification trees, Linear Discriminant Analysis, K-NN are used based on the variety of species and their production.

Machine Learning also finds its application in weed detection. Edge based classifiers are used to identify narrow and broad weeds. Color detection method [6] images captured are used to adjust color grains as well as shutter time to gray plates. To classify weeds into narrow and broad weeds, statistical methods such as mean, standard deviation are used. But the success rate of classification models for statistical methods is less compared to color method for classification. Symlet, Coiflet, Meyer, Daubechies, Biorthogonal and R-biorthogonal Wavelet analysis[7] can be used for Weed Infestation Rate which can be used for Image decomposition and reconstruction [8].

Principal Component Analysis (PCA), a classical dimensionality reduction method, can be used for identification of the seeds of the weeds [9]. Erosion and dilation segmentation algorithms are used to classify weeds into narrow and broad weeds.

Though there are many approaches to bring out the enhancements in conventional agriculture, automating the analysis of yield limiting factors save both time and money. Automated analysis of agricultural applications helps farmers with expert knowledge which is not readily affordable by them. With the technological advancements, there is a high-availability of quality measurements coupled with modern algorithms, fused with multiple sources of information from sensors placed in different fields, satellite imagery, etc.

Despite of many technological advancements, the major concerns of agriculture are quality of yields, water availability and stress, usage of pesticides. Along with the thermal properties of the plant, infrared imaging also provides additional means to analyse pre-harvesting operations, when to harvest and to monitor irrigation. Traditional edge-based machine learning classifiers can be used for foreign plant detection using color images [10]. Though the classification is based on plant color features, texture of plants also has been integrated to achieve classification accuracy. But all these techniques are partially successful.

As the fields and the extent of farming grow bigger, improvised monitoring systems are required for enhanced automated management. Precision agriculture [11] aims at providing optimized operational plan at minimizing the use of resources and maximizing the yield productivity and quality. Precision agriculture utilizes advanced technological hardware and algorithmic means to collect, integrate sensory data acquired at several scales from different fields: from ground, multispectral sensors, tractor-mounted, drones as well as satellites.

Image processing becomes a challenging task for Plant and Fruit Detection approaches. Firstly, the segmentation and the color information is affected by the extent of illumination. For example, if the given fruit is in green color, then it becomes difficult to extract the fruit from the background with leaves and branches. In this case, the algorithms deployed might not produce good results. For this problem to overcome, we need a robust segmentation algorithm, which operates regardless of the fruit color and the

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surrounding environment, thereby achieve higher accuracy. Also, there is a chance of misclassification due to varying light intensities. For this the algorithm should focus on the following:

a) Computation region

b) Fine Tuned neural network model

c) Application of dimensionality reduction and a good classification algorithm.

Also, the algorithm should be capable enough to perform well under different field conditions with different color backgrounds, light intensities, different stages of crop growth.

III. PROPOSED SYSTEM

This paper proposes a technique, a combination of color value feature with Backpropagation Classification. The ANN is trained for detecting the color of the fruit and the maturity levels based on the texture. These extracted features can be used for the classification of the fruit into ripe or unripe, healthy or unhealthy, leafy, ready to harvest or not. This kind of prediction for ripeness could be better helpful for the prediction of losses. For this, the selection of the appropriate camera equipment is a tedious task. to decide upon the specific camera equipment used for machine vision applications in agriculture [12], the following factors are to be examined:

a) Sensor resolution of the camera
b) Frame rate
c) Connectivity /Image transfer rate
d) Price

Machine Vision cameras can be divided into the following categories:

- RGB, Multispectral and Stereovision cameras.

RGB cameras are used as they are affordable for fruit/plant detection, segmentation, yield prediction, ripeness detection, weed detection, etc. Also, RGB cameras can be focused for image analysis rather than the image quality. But RGB cameras are not treated as appropriate if the algorithms use color processing. For Segmentation tasks [13], color information is very much crucial. The quality of the images, depends on the camera resolution and its properties that deals with sizes of objects, lighting conditions and the distance from the object.

With multispectral image (Hyperspectral, Ultrasonic, Thermal) technologies [14-15], the objects with similar color exhibit different reflectance in non-visible regions, which typically provide better results compared to conventional RGB Cameras. Machine Vision systems provide the simulation of technological characteristics similar to the eyes of a human. Multispectral imaging collects the light reflected from the plant of leaf surface. The physical and the biochemical interactions within the leaf changes when infected with a disease. Each pixel in the image has been represented as a vector, especially called spectral signature, where these images are collected at an optical range (350-1000nm).

The following figure explains how the input image is pre- processed and segmented, feature extraction and how BP classifiers are applied for prediction of the class of the plant.

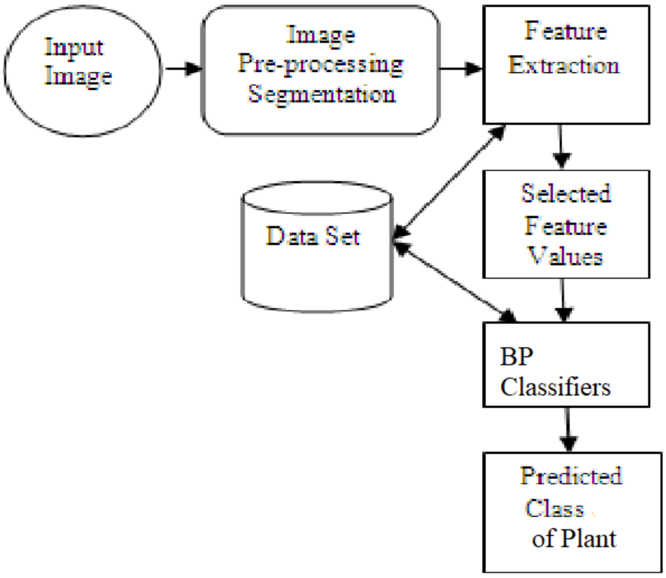

Fig. 1.1 Plant Detection using Multispectral Imaging with BP classifiers

The experiments were conducted on Ubuntu 16.04 Linux server with a 3.40 GHz i7-3770 CPU (16 GB memory) and a GTX 1070 GPU (8 GB memory). The plant dataset contains 100 samples of each class, with 1608 images of 1600x1200 pixels, which are split into 80 training samples and 20 test samples. The images are resized to fit to 224x224 pixels and the per-pixel value is divided by 255.

For training the algorithm using backpropagation, stochastic gradient descent has been used which can be expressed as below:

$$\delta_x = w_{x+1}\left(\sigma'\left(w_{x+1} \bullet c_x + b_{x+1}\right) \circ \mathrm{up}\left(\delta_{x+1}\right)\right)$$

$$\Delta w_x = -\eta \bullet \sum_{i,j}\left(\delta_x \circ \mathrm{down}\left(S_{x-1}\right)\right),$$

where up represents up sampling, down represents down sampling, δ_x represents sensitivity, w_{x+1} represents multiplicative bias, Δw_x represents the weight update, η can be termed as the learning rate.

The cross-entropy loss function for the stochastic gradient can be given as:

$$L_i = -\log\left(\frac{e^{f_{y_i}}}{\sum_j e^{f_j}}\right)$$

Where f_j can be taken as the jth element classification vector of f.

The learning rate is set to 0.001, and the decay rate observed is 10^{-6}. The test accuracy improves after the initial epochs and stabilizes after 50 epochs.

IV. CONCLUSIONS

Applications towards agriculture providing the earth observation data which supports increased area under agriculture, increased crop intensity and productivity, etc. RS data can provide the data related to groundwater helping in irrigation, flood management. Applications like environment assessment and monitoring, disaster monitoring and mitigation, weather climate, village resource center, etc. can also be better considered to improve the precision agriculture. As the machine learning technology advances, automatic plant identification really helps farmers for plant monitoring, ecological surveillance, etc., Further, integrating these advances into mobile-based plant identification can improve the performance and could gain much more attention from researchers.

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