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Classification and Detection of Herbs Based on Shape and Texture Features using Deep Learning and YOLO V2

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***Abstract:* -** By using traditional methods recognizing herbs will takes a lot of effort and time to identify the desired plant from among the thousands of herbs. Because the pharmacist and botanist do not need to collect plants using traditional methods, identification of herbs via a vision system is advantageous. Here we are proposing Classification and Detection of Herbs Based on Shape and Texture Features Deep Learning and YOLO V2. In the proposed system, we'll use convolutional neural networks to categorize herbs. According to experimental findings, this model is superior to the machine learning technique known as the Support Vector Machine feature classifier. This approach of categorization turns out to be more effective for classifying and detecting herbs. Here we will investigate and build an efficient classifier and detector better than previous that is Deep Learning Neural Network (DLNN) and YOLO V2 Object detector.

***Keywords:* - Herbs classification, machine learning, feature extraction, support vector machine, deep neural networks, YOLO V2 Object detector, Object Detection.**

I. Introduction

Herbs have long been used by humans in daily activities, including food preparation, medicine, and the cosmetics business. There are countless numbers of herbs, and because of their similarities, some of them are difficult to categorize, making classification crucial for herb users. Most specialists still classify herbs using the conventional methods in several nations, including India, Thailand, and Malaysia, depending on their understanding. Consider Malaysia as an example. There, herbs are categorized based on scent, leaf form, and/or leaf color. Researchers continue to find the classification of plants to be an intriguing subject.

However, because there are so many different colors and shapes of plant species, it is a difficult topic. Leaf is one of the many classification techniques for herbs that have been suggested in the literature. This is because the leaves of different herbs differ from one another and are distinctive to each plant. As a result, using leaves as a technique of classification is still effective. This is why such information is offered in easily accessible botanical reference sources. Due to the similarities of many herbs' leaves, categorizing them based solely on their leaf photos is insufficient. Thus, a feature-based approach to classifying herbs was suggested to address the issue of accuracy. Some studies have employed shape, texture, venation, and color features to distinguish between the various plants for various uses.

Herbs are plants that have savoury or aromatic qualities and are frequently utilised in cuisine, medicine, and perfume. Over the past few decades, the usage of herbal medicines for medical purposes has expanded on a global scale. Recognizing the various herb species is difficult due to their diversity. This has sparked intense interest among researchers in developing artificial intelligence techniques for classifying herbs.

II.RELATED WORKS

The first and most crucial stage in computer vision research [1] is to transform the captured object into a mathematically altered feature vector that has the appropriate shape, texture, and/or color information for the classification. Studied about leaf shape identification.

In this paper, [2] We outline a technique for identifying plants that uses various image organ queries. Preprocessing, feature extraction and description, classification methodology, and fusion approaches are only a few of the difficulties that the proposed system addresses. Studied about plant identification application

In this paper [3], a leaf database from different plants is firstly constructed. Due to the difficulty in identifying certain important curvature spots, the suggested method is more reliable than the one based on contour features. Finally, experiments are used to show how effective and efficient the suggested strategy is at differentiating between plants. Studied about Recognition

Different plants' leaves have various traits that can be used to categorize them. This paper [4] presents a simple and computationally efficient method for plant identification using digital image processing and machine vision technology. Studied about machine vision technology

Identification of medicinal plants is regarded as a crucial step in the creation of herbal medications in the Ayurvedic medical system. This paper [5] presents edge and color descriptors that have low-dimension, effective and simple. Studied about texture and edge features-based approach

This research [6] is for plant classification based on leaf identification is becoming a popular trend. The result of this study is that when testing real-world sampling for leaf recognition and classification, more external characteristics will be taken into account. Studied about features extraction and recognition

III.METHODOLOGY

Here we are proposing a new method for classification and detection of herbs using CNN and YOLO V2 object detector. First the input image is taken and apply preprocessing for the image and input the image to the convolutional neural network which is CNN net classify the image with herb name and then leaf is detected in that image using object detector.

YOLOV2: Yolo is efficient and speedy for processing right now. A single network, containing item locations and classes, is used to create predictions. Accuracy can be totally taught to improve. In YOLOv2, you can find out more about a block by hovering over it. Each convolution block, with the exception of the final convolution block, first passes through BatchNorm normalization before Leaky Relu activation. The supplied image is used by YOLO to generate an SS grid. Each grid cell predicts a single object. For instance, an attempt is made to anticipate the "person" item in the yellow grid cell below, whose center (the blue dot) is within the grid cell.

Every grid cell is projected to have a certain number of border boxes. In this image, the yellow grid cell locates the person using two border box predictions (blue boxes). There is a distance restriction imposed by the one-object rule on how adjacent detected items can be.

For each grid cell,

- Each box has a box confidence score, and it predicts B boundary boxes.
- No matter how many boxes B there are, it only detects one object,

It projects probability for the C conditional class (one per class for the likeliness of the object class). Box confidence score is contained in the boundary boxes. The confidence score represents the boundary box's accuracy and the likelihood that the box includes an object (or is objectless). We divide the image's width and height by the bounding box's width and height. x and y are the offsets to the relevant cell. Consequently, all of x, y, w, and h are between 0 and 1. There are 20 conditional class probabilities in each cell. The likelihood that the identified object belongs to a specific class is represented by the conditional class probability (one probability per category for each cell).

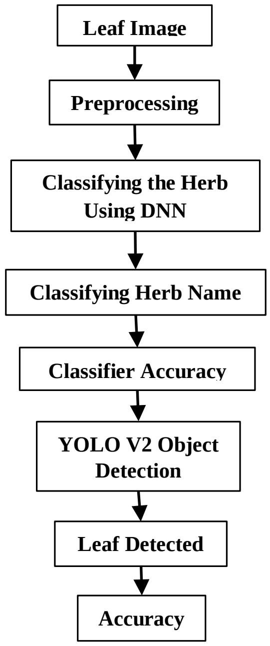


Fig 1: Block Diagram of Proposed Method

Each prediction box's class confidence score is calculated as follows:

Class confidence score is equal to box confidence score time's conditional class probability.

It gauges the level of certainty for both the classification and the location (where an object is located). Those score and probability phrases are easy to conflate. For your future reference, listed below are the mathematical definitions

$$\text{box confidence score } = P_r(object).IoU$$

$$\text{conditional class probability} = \mathrm{P}_r\left(class_i \,\middle|\, object\right).IoU$$

$$class\ confidence\ score = P_r(class_i).IoU$$

$$= \text{box confidence score} \times \text{conditional class probability}$$

Where $P_r(object)$ is the probability, the box contains an object

The intersection over union, or IoU, between the projected box and the actual data is the ground truth.

$\mathrm{P}_r\left(class_i \,\middle|\, object\right)$ is the probability the object belongs to $class_i$ given an object is presence.

$\mathrm{P}_r(class_i)$ is the probability the object belongs to $class_i$

Multiple bounding boxes are predicted by YOLO for each grid cell. One of them should be in charge of the object in order to calculate the loss for the real positive. For this, we choose the one that has the highest intersection over union (IoU) with the actual data. The forecasts for the bounding box specialize as a result of this tactic. With each forecast, accuracy in predicting specific sizes and aspect ratios increases.

Sum-squared error between the forecasts and the actual data is used by YOLO to determine loss. Assembled into the loss function are:

- The classification loss.
- The loss of localization (errors between the predicted boundary box and the ground truth).
- The drop in confidence (the objectness of the box).

Classification loss

The classification loss in each cell, provided an object is found, is equal to the squared error of the class conditional probability for each class:

$$\sum_{i=0}^{s^2} \mathbb{1}_i^{obj} \sum_{c \in classes} \left(p_i(c) - \hat{p}_i(c)\right)^2$$

Were

$\mathbb{1}_i^{obj} = 1$ if an object appears in cell i, otherwise 0.

$\hat{p}_i(c)$ denotes the conditional class probability for class c in cell i.

The projected border box sizes and locations are measured by the localization loss. We only include the box that detects the object in our count.

$$\lambda_{coord} \sum_{i=0}^{s^2} \sum_{j=0}^{B} 1_i^{obj} \left[\left(x_i(c) - \hat{x}_i(c)\right)^2 + \left(y_i(c) - \hat{y}_i(c)\right)^2\right] + \lambda_{coord} \sum_{i=0}^{s^2} \sum_{j=0}^{B} 1_i^{obj} \left[\left(\sqrt{x_i} - \sqrt{\hat{x}_i}\right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i}\right)^2\right]$$

Where $\mathbb{1}_i^{obj} = 1$ if the j th boundary box in cell i is responsible for detecting the object, otherwise 0.

λ_{coord} increase the weight for the loss in the boundary box coordinates.

Absolute errors in large boxes and tiny boxes should not have the same weight. For example, a 2-pixel mistake in a large box has the same effect as one in a tiny one. Yolo forecasts the square root of the width and height of the bounding box rather than the width and height to partially address issue. Additionally, we double the loss by λcoord to place a greater focus on the border box precision (default: 5).

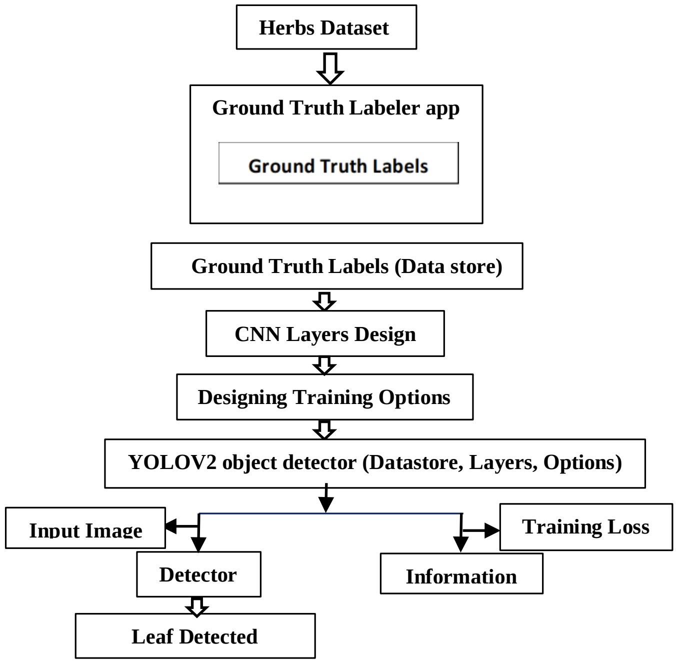


Fig 2: Yolo V2 Architecture

IV.EXPERIMENTAL RESULTS

The below figures are the experimental outputs of the proposed method

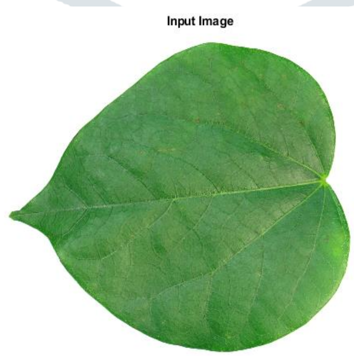


Fig 3: Input Image

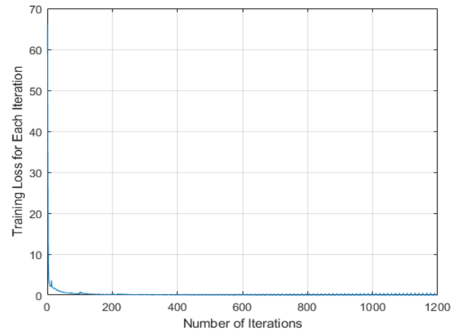


Fig 4: Training Loss

While training the CNN network with images the above image is the training loss for the network. Above plot which is between the number of iterations and training loss for each iteration.

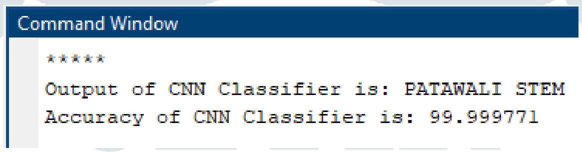


Fig 5: Leaf Classification and Classifier accuracy

The above figure shows the classified leaf name and accuracy of CNN classifier.

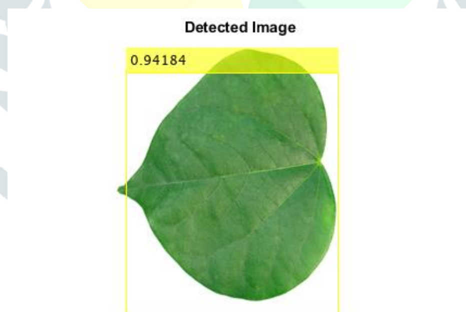
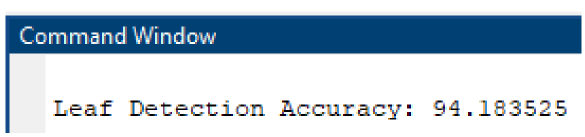


Fig 6: YOLOV2 Detection Image

The above figure is the detected leaf image with boundary box in which leaf is detected.



The above figure shows the detected leaf accuracy of YOLO V2 object detector.

Fig 7: Leaf Detection

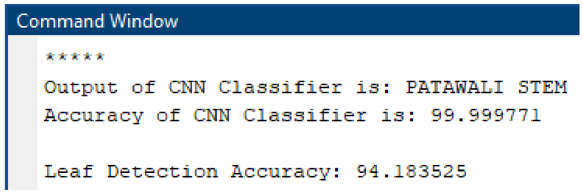


Fig 8: Command window results

S. No	Existing Method	Proposed Method
1	64.2957	97.09165
2	60.690491	98.06103
3	64.146019	95.56739
4	58.273315	97.49483
5	75.479233	97.53475
6	57.435154	98.06437
7	61.331146	95.37027
8	75.492775	96.55573
9	57.162399	99.12314
10	68.209412	98.21062

Fig 11: Accuracy Comparison Table

The above table is comparison between proposed and existing system with improved accuracy in proposed system

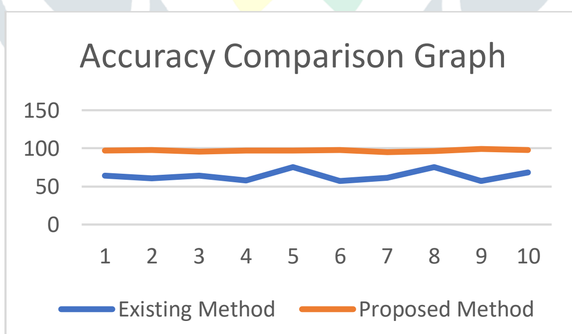


Fig 12: Accuracy Comparison Graph

The above graph is comparison graph between proposed and existing system with improved accuracy in proposed system which represented graphically.

V.CONCLUSION

In this study, we proposed an efficient and automated herbs classification and detection approach based on shape and texture features using deep learning. Convolutional Neural Networks, also known as CNNs, are a subset of artificial neural networks used in deep learning and are frequently used for object and picture recognition and categorization. After classifying herb and detecting leaf using a pretrained network YOLO V2 which is used for object detection. This method of categorization proves to be more useful for grouping herbs. Here, we have implemented a Deep Learning Neural Network (DLNN) classifier and detection using YOLO V2, which is more effective than SVM classifier. Here we are seeing the output as classification of 5 different herbs, classified output as the name of herb and the accuracy of the proposed classifier.

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