IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Leaf Based Plant Recognization on Mobile Devices

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Abstract: Leaf-based plant identification is becoming one of the most exciting and popular trends. Each leaf carries unique data that can be used to identify plants. The leaf images need to be pre-processed accordingly to extract the different critical features in the identification of plants based on leaves. The procedure for classification is carried out through a number of sub-procedures. An identification or classification problem is handled by mapping one of the unique classes to input data. In this procedure, a database of leaf images comprising images of test leaves with their equivalent plant information is initially created. Using image processing methods, essential characteristics are extracted. To make the identification system robust, the characteristics have to be stable. In addition, on servers or desktop computers, most current deep learning applications run. Considering there are a lot of mobile computing devices available, this paper discusses the implementation of the CNN-based object detection algorithm on Android devices.

***Index Terms* - plant recognition, machine learning, classification, CNN, Android Devices.**

I. INTRODUCTION

Plants are significantly vital for the safeguarding of the environmental. Nevertheless, it is a tricky and chief mission to identify the plant varieties on earth. The critical condition is that many plants are at the threat of extermination. According to the hypothesis of plant categorization, plants are fundamentally classified based on the shapes of leaves, flowers and fruits. However, flora and fruits are three dimensional items and increases complication [1]. Leaf recognition plays a vital responsibility in plant classification. To implement the plant identification system based on leaf, several critical features of leaf such as shape, vein, and texture features are extracted. The extracted crucial features are used as inputs to the classifier for the categorization of plants.

Considering the vast number of existing species in the world, identifying plants is a difficult task. The similarity of the interspecies and the variability of the intraspecies make the identification task especially difficult and time consuming for humans. For mobile devices, the application is intended to allow a consumer to recognize plants on the spot. It can also be used to enrich the information database as an observation collector unit. Using the database more to enrich the user experience.

Deep learning-based object detection has been very successful in recent years. Especially the CNN (convolutional neural network) model has significantly improved the recognition accuracy on large data-sets. For the ImageNet benchmark data set, the CNN based model has been dominating the leader-board since it's introduced by Krizhevsky in 2012 for the first time.

While CNN based model can achieve higher accuracy, they have following disadvantages:

- **High computation cost**. The CNN based model are usually very deep with tens or hundreds of layers and each layer takes a lot of computation.
- **Large memory demand**. The CNN based model has a lot of parameters that usually take hundreds of Megabytes of memory space.
- **Low efficiency**. Most CNN based model are designed without efficiency improvement.

As mobile computing devices are very popular and comparatively powerful, people want to embrace the benefits of CNN with their mobile devices. However, to enable their mobile application, new CNN architectures need to be developed to overcome the above issues. Also, most deep learning frameworks have provided interface for mobile platforms, including iOS and Android. In this paper, this paper discusses a development of a CNN based model and then implementation with Tensorflow and Android.

This paper intends to present an automated plant identification system with the following goals.

1. **Usability**: Develop a mobile application that users can conveniently carry to take photographs of leaves.
2. **Robustness**: Variations in leaf images such as rotation and scaling should not affect the outcome of the result.
3. **Portability**: Expose key capabilities of this application as a Web Service to facilitate faster future development across platforms.

By using a CNN in deep learning, a model class can be created to enable powerful and often correct assumptions by changing various parameters. There are several libraries used in deep learning studies.

II. Related Work

This section talks about CNN related work in object detection and the trend towards smaller CNN models [7].

1. CNN Architectures

Convolutional Neural Network (CNN) usually stands for the neural network which contains one or more convolutional neural layers. Each neural layer can be regarded as combination of several spatial filters. These filters are used for extracting features from pictures. Some well-known filters are Histogram of Oriented Gradients (HOG) and colour histograms, etc.

A typical input for an convolutional layer is a 3dimensionalgrid.They are (H) height, (W) width and (C) channels. Here in the convolution layer, each channel represents a filter. The first layer input typically has a (H, W, 3) form, where 3 stands for the raw images of the RGB channels.

CNN became popular in visual recognition field when it is introduced by LeCun et al. for handwritten zip code recognition in the late 90s. In their work, they used (5, 5, C) size filters. Later work proved that smaller filters have multiple advantages, such as less parameters and reducing the size of network activations. In a VGG network proposed by Karen Simonyan et al., (3, 3, C) - size filters are extensively used, while the networks such as Network-in-Network and GoogLeNet widely adopt (1, 1, C)-size filters, the possibly smallest filters and used for compressing volume of the networks.

With the networks go deep, the filter size design gradually become a problem that almost all the CNN practitioners have to face. Hence, several schemes for network modularization are proposed. Such modules usually include multiple convolutional layers with different filter sizes and these layers are combined together by stack or concatenation. In a GoogLeNet architecture, such as, (1, 1, C)-size, (3, 3, C)-size and (5, 5, C)-size are usually combined together to form an" Inception" module and even with filter size of (1, 3, C) or (3, 1, C).

In addition to modularizing the network, communication and connections across multiple layers also improve the performance of the network. This seems to be a similar idea with Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) architecture in Recurrent Neural Network (RNN). Residual Network (ResNet) and Highway Network adopted such ideas to allow connections to skip multiple layers. Without any blocking in a backward propagation pass, these "bypass" connections can effectively send back the gradients across multiple layers if necessary.

2. CNN for Object Detection

With the advancement of accuracy in image recognition, object detection research has also grown at a rapid rate.
Before 2013, the high precision of the PASCAL data set could be achieved by feature extraction techniques such as the combined application of HoG and SVM. In 2013, the introduction of Region based Convolutionary Neural Networks (RCNN), proposed by Girshick and Ross, caused a fundamental revolution in this field.

First, RCNN suggests possible regions for resident objects, and then uses CNN to classify objects in those regions. These two separate operations, however, require elevated computation and make it time consuming. Girshick and Ross are making a modification to R-CNN, which is called fast R-CNN.

The two independent tasks are integrated into one multitask loss function by this architecture, which accelerates the computation and classification of proposals. Later, Ren et al. suggested a more integrated version of RCNN, namely a faster version of RCNN, which is more than 10x faster than the original RCNN. RFCN with a completely convolutionary layer as the final parameterized layer, a recent proposal, further shortens the computation time used for regional proposals.

R-CNN can be regarded as a cornerstone for the development of CNN for object detection. A large amount of work is based on this architecture and achieves great accuracy. However, a recent work shows that CNN based object detection can be even faster. YOLO (You Only Look Once) is such an architecture integrating region proposition and object classification into one single stage, which significantly contributes to simplification of the pipeline of object detection, as well as reduction of the total computation time.

3. Toward Smaller Models

With CNN going deeper, it is necessary to store more parameters, which makes the model larger and larger. Usually, deeper CNN and larger modules achieve higher accuracy, but people wonder if a small model can achieve an accuracy similar to a large model. This paper talks about several popular model compression techniques in this subsection that aim to reduce the size of CNN models. To decrease matrix dimensionality, singular value decomposition (SVD) is widely used. To decrease model size, it is also added to pretrained CNN models. Network Pruning, proposed by Han et al., which prunes the parameters below a certain threshold to construct a sparse CNN, is another reported approach. Han et al. have recently further improved their approach and proposed a new approach, Deep Compression, to accelerate the computation of CNN models, together with their hardware design.

A recent study called SqueezeNet even shows that the accuracy of AlexNet can be compressed to smaller than a complex CNN model. One can anticipate that there is much room left for compressing these CNN models, to better fit them to portable devices.

III. Literature Survey

1. Plant Recognition System based on Leaf Image

A system is developed which recognizes plants automatically based on leaf structure using image processing. Moreover, evolutionary changes are also taking place in plants and it has impact on identification and classification. Image data base and related information is stored on cloud. So an attempt is made to develop an automatic identification system where in an image of leaf is captured by any smart phone, uploaded on cloud, where image available and complete data base is trained. Captured image is processed features will be extracted and gives to classifies the plant classification result will be transmitted back to smart phone and related information. [2]

In this paper the module is implemented in Android, using Cloud ML Model.

2. A Leaf Recognition Approach to Plant Classification Using Machine Learning

The identification of plants is a very important component of workflows in plant ecological research. This paper presents an automated leaf recognition method for plant identification. It is based on a combination of two types of texture features, named Bag-of-features (BOF) and Local Binary Pattern (LBP). These features are utilized as inputs to a decision-making model that is based on a multiclass Support Vector Machine (SVM) classifier. The introduced method is evaluated on a publicly available leaf image database.

Their approach has two main stages, the two stages are:

1) Feature extraction
2) Classification.

The feature extraction strategy uses a combination of two different texture techniques, bag-of-features (BOF) and local binary pattern (LBP). The motivation for combining BOF and LBP is that this combination inherits the advantages of BOF, which are aggregates local components to form a global histogram characterization. In addition, it inherits the computational efficiency of LBP and avoids the limitations of LBP as well. [3]

In this paper the module is completely implemented only for non-portable devices like PCs, laptop, etc. It is not portable for Mobile Systems.

3. Leaves Classification Using Neural Network Based on Ensemble Features

An automated plant identification is necessary to identify plants, especially rarely seen ones. In this paper a framework to identify plant species based on leaf's characteristics is introduced. First, 31 features of leaves from 13 species are extracted that represents colour, shape and texture of the leaves. Then, the features are selected according to their correlation to the class label. The data with 25.8% pruned features are then used to train a feed forward neural network. The network is trained and tested using 975 images by implementing 10-fold mechanism yields 95.54% accuracy.

System in which it is implemented is not specified. [4]

4. Survey on Leaf Recognization and Classification

Classification procedure is carried out through number of sub procedures. An identification or Classification issue is managed by mapping an input data with one of the unique classes. In this procedure, at first, database of a leaf images is created, that comprises of images of test leaf with their equivalent plant information. Essential features are extracted using image processing techniques. The features have to be stable in order to make the identification system robust. Subsequently the plant/leaf is recognized using machine learning techniques. In this paper a survey is presented on the various types of leaf identification process.

Categorization of plants has a wide usage forthcoming in horticulture and medication, and is particularly critical to the science assorted qualities explore. Leaf image Classification method is the most preferred choice when compared to methods like Cell biology or Molecule Biology methods for leaf plant classification.

Feature extraction is a critical stage because the ability of a system to discriminate various types of leaves depends on the features extracted. The features have to be stable in order to make the identification system robust. Subsequently the plant leaf is recognized using techniques of machine learning.

This paper is grouped into four sections as mentioned below: Section I represents introductory part of leaf identification and classification techniques. Section II describes general framework of leaf identification system. Various leaf identification techniques are discussed in section III and section IV describes classification techniques followed by conclusion and future enhancement.[5]

IV. Existing Systems and Its Drawbacks:

LEAFSNAP-Plant Identification	PLANTNET-Plant Identification	PLANTSNAP-Plant Identification
Cloud ML / AI.	Cloud ML / AI.	Cloud ML / AI.
UI is too heavy for some budget phones.	UI is too heavy for some budget phones.	Required High Network Connection.
Required High Network Connection.	Required High Network Connection.	In poor Network Connections time latency is High.
Advertisement /In App Purchase.	In poor Network Connections time latency is High.	It Allows only 10 Sample Scan per Day.

Table 4.1: Systems and Drawbacks

V. Conclusions:

This paper compares various types of image classification for leaf species identification processes.

This paper focuses on various existing automated systems for plant classification and recognition. Recognition is a method designed for the assignment of every individual leaf image to its respective plants with regard to their regular traits. The manual procedure is very tedious and it has been mostly done by botanists. This is the reason to drive the researchers to develop a computer-aided plant recognition system.

In computer vision, computer-aided plant recognition is still a testing errand because of deficiency of appropriate procedures or representation plans. An efficient feature extraction algorithm along with a robust classifier is required for achieving a good recognition rate.

Hence, good combinations of algorithms are to be used in order to develop an efficient leaf recognition system.

VI. Future Scope:

The Android application can be further improved on its stability and functionality. Also, apps which are based on old and less efficient interface, which is called "InferenceInterface". The detection latency and stability can be improved by switching the interface to" Tensorflow Lite".

The leaf identification process makes this application useful to amateur stakeholders as well as experts.

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