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Techniques for Identification and Classification of Flowers using Image Processing and Computer Vision: A Survey

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Abstract— Recognition is one of the essential tasks of pattern recognition which deals with the classification of objects into various categories. Image recognition is one of the fundamental steps in image processing useful for the development of various computer vision applications. In this paper, a comprehensive survey of various flower species recognition methods using image processing is presented. The existing techniques use color, texture, and shape features. The classifiers such as neural networks (NN), Fuzzyy Logic, support vector machines (SVM), K-Nearest Neighbor (KNN) model, Decision trees, etc. are employed. When compared to statistical features, it was observed that texture features gave optimal results.

Keywords- Flowers classification, Image Processing, Feature Extraction, Machine Learning, TensorFlow.

Introduction

People use flowers daily as they have significant cultural, environmental, and economical value in our life. The flowers vary in size, shape, color, texture, and hence there is a great difficulty in identifying flowers. The computer vision systems need to be automated for the identification and classification of flowers. Such systems help the flower export business.

The flower classification systems require technological solutions for various tasks such as feature extraction, machine learning, and classification. The feature extraction methods use characteristics like color, shape, and texture; these features are more complicated and confusing. Because flower characters vary based on time and environment and most of the flowers have similar characteristics. If the selected features cannot sufficiently characterize the target, then recognition accuracy will be reduced. Machine Learning models learn the characteristics of flowers and create a knowledge base useful for classification. The classifiers use learned information to classify the lowers into various categories. In recent years, many significant contributions are made in developing various techniques for flower classification. The essential techniques are summarized in the ensuing section.

The further part of the paper is structured into various sections. Section 2 presents a description of existing methods. The challenges are reported in section 3. Section 4 contains a comparative study of existing methods. Section 5 describes the methodology, and Section 6 gives conclusions of the work.

Image Processing & Machine Learning Technologies for Flower Identification and Classification

Some of the essential contributions in the field of flower identification and classification are as below.

(D. S. Guru et al., 2019) The proposed method uses cluster-based approaches to extract keyframes in flower videos. The textural and scale-invariant features suchlike local feature [rotation, scaling, and translation], are extracted from keyframes of the video. The Gray-Level Co-occurrence Matrix method is used to extract texture features (GLCM). The clustering techniques such as GMM and K-means clustering techniques are used to group similar frames. Multi-class SVM is used to retrieve similar videos from the database. The author created his dataset for testing, and it contains 1919 videos for the experimentation. The F-measure, recall, precision, and accuracy parameters are used to evaluate the system performance. The proposed system yields 90% accuracy when combine LBP, GLCM, and SIFT features. The accuracy of the system can be enhanced by combining different features.

(D. S. Guru et al., 2018) The proposed algorithm selects keyframes from a flower video. In pre-processing step, the size of each frame is reduced to 250X250. The Algorithm extracts color (HSV, Red, and Blue), entropy, Modified Histogram of Oriented Gradient (MHOG), and texture features. The block size, a number of bins, and cell size parameters are used to extract HOG features. The proposed algorithm uses a k-means clustering algorithm to select keyframes and extract features such as color, GLCM, MHOG, and entropy. For the experiment, the author developed his dataset, and it contains 225 videos. For a given flower video, the proposed algorithm is capable of generating all possible keyframes.

(Ping Lin et al., 2018) The system proposes detection of strawberry flower. The framework uses faster region convolutional neural network [R-CNN], Fast R-CNN, and R-CNN methods to detect an object. The details, such as location and object class, are manually hand annotated. The developed framework is trained and tested on 400 and 100 strawberry flower images, respectively. It has been observed that the detection rate of the Faster R-CNN is higher compare to R-CNN and Fast R-CNN. Future work demands the usage of different techniques such as tracking, association, and feature matching.

(Jyoti V. K. et al., 2018) The proposed framework facilitates to retrieve similar videos. The Gaussian gradient filter is used to extract the flower gradient. The framework uses clustering techniques such as k-means and Gaussian mixture models to group similar frames. The algorithmic model extracts color, texture, gradient, and entropy features. The SVM classifier is used to differentiate two classes. The performance of the proposed system is measured by considering F-measure, recall, precision, and accuracy parameters. The results of DATASET-1 with segmentation are 97.79, 97.08, 97.26 & 97.08, without segmentation - 97.72, 97.95, 96.59 & 96.72 and with Gradient of flowers 95.27, 94.93, 94.62 & 94.30 respectively. By considering same parameters analyzed result of DATASET-2 without segmentation are 94.37, 95.00, 94.67 & 94.69, with segmentation - 97.09, 97.08, 96.72 & 96.76 and with Gradient of flowers 91.84, 92.70, 91.27 & 91.44 respectively.

(M. Thilagavathi et al., 2018) The proposed method automatically recognizes plant species from given flower images. In the preprocessing step, the noise can be effectively removed using a median filter algorithm. The color and texture features are extracted. 609 individuals of 25 species are found in the tested dataset. The Cascade-Forward Neural Network (CFNN) classifier is used to categorize the species. The developed method yields an accuracy of 96.8%. In future work, the precision of the recognition process can be improved by scrutinizing various training techniques.

(M. V. D. Prasad et al., 2018) The developed algorithm exercise convolutional neural networks (CNN) to categorize flower images. In preprocessing stage size of the flower is reduced to 128X128X3. The edges, lines, corners and high level features are extracted in the proposed technique. The author prepared various datasets by considering parameters such as a number of flowers [Single or Multiple], lighting [Right or Poor], and leaves. A gradient-descent algorithm is used at two stages to train CNN. In the first stage, the feed-forward pass handles the multi-class classification problem, and next stage handles the back-propagation pass. The author created his dataset for experimentation, and it has 9500 images of 132 classes. The proposed model achieved an accuracy of 97.78 % and is highest compared with the other classifiers, namely Adaboost, ANN, and Deep ANN.

(Buzhen Huang et al., 2018) The proposed framework classifies flowers. In the preprocessing step, for the input flower, V space is removed and converts to HSV color space. The proposed technique extracts texture, Histogram of Oriented Gradient [HOG], and local features. The AlexNet method extracts various features, namely saturation, directional gradient, hue, color, local features, and scale-invariant feature information. The algorithm extracts gradient direction and amplitude information from Sobel and Laplacian gradient operators. The framework uses the multi-response linear regression method as a secondary learning algorithm. The oxford 102 dataset is used for testing. The proposed framework achieves an accuracy of 85.66%. The system performance can be improved using deep learning methods.

(Hazem Hiary et al., 2018) The proposed technique classifies an extensive range of flowers. The framework uses developed segmentation approach as a binary classifier. The developed dynamic CNN classifier categorizes the dissimilar types of flowers. The color, shape, edges, and blobs features are extracted from the flower. Testing is carried out on Oxford 102, Oxford 17, and Zou–Nagy datasets. The proposed classifier method is tested on various datasets namely Oxford 17 & 102 and, Zou–Nagy and accomplishes a classification accuracy of 98.5%, 99.0%, and 97.1%, respectively. Some of the test cases are failed due to incorrect manual annotation.

From the above-detailed survey, it is being observed that most of the techniques provide either the best performance or best accuracy. But none of the methods/techniques provide both. It's been observed that none of the author trained or tested the developed system for heterogeneous flowers in a single digital image. Most of the researchers used Zou–Nagy and Oxford 17 &102 datasets for training and testing. But none of the dataset contains heterogeneous flower types in an image. Existing techniques works only for images which contain similar types of flowers in a digital image. Hence there is a huge scope to work on flower species identification and classification for heterogeneous flowers in a single digital image. The segmentation of heterogeneous flowers in a single digital image is a challenging work. The future work is carried out on heterogeneous images in a single digital image.

Challenges and Issues in Flower Identification and Classification

Based on our detailed survey, the identification and classification of flower species with the bare eye are very difficult due to the various features such as shape, structural patterns, size, color, and many more characteristics. There is also a wide range of flower species are available. Hence, researchers are facing the following challenges to identify, classify, and grade the species of flowers from a given data set.

1) *Dealing with size and color variables.*
2) *The flower recognition is difficult due to extensive features and large species of available flowers.*
3) *Classification of the flower is difficult due to slight variations in shape and texture features.*
4) *The segmentation of heterogeneous flowers in a single digital image.*
5) *Identification of disease in flowers.*
6) *Grading of flowers.*

Methodology

As shown in figure 1 a black box that takes a video stream as input, segment the flowers, identify and detect the flowers, and give out the required information as output. In figure 2 the video stream can be feed by a camera device or a file in various video formats. However, the initial version of the implementation uses an AVI video file format as the source. A flower detector is a black box that has to be implemented. It will house a deep neural network to detect and identify the flowers. The output is the relevant information of the flowers detected in the video stream. Just like input, the output format, ideally, should configure to one of the standard data formats - JSON, CSV, XML, XLS. But in the initial version, the output is only available in JSON format. The flower detector mainly works in 2 modes - Detection mode & Training Mode. As shown in figure 3 Video stream processing mainly involves parsing, normalizing, and splitting the input video stream from the camera device or video files of various encoding formats (AVI, H.264, Matroska, etc.) into individual image frames in a standardized format which can be understood by the neural network to detect the flowers. The neural network can be considered as the brain of the Flower detector. The main task of the neural network is to detect flowers in the image frame (image frame - consider a video stream to be a sequence of images, and we pass each of these images to the neural network), which can be put into the computer vision domain of object detection. The figure 4 describes the training mode. Train the neural network to detect flowers by feeding it a labeled flower dataset — most of the deep neural networks trained similarly. Let's look at each step in detail. Labeled Flower Dataset in the initial implementation of the application is a hand-curated set of images of the flowers. The labeled flower dataset can be as granular as required; for example, if we want to detect jasmine flowers and jasmine buds separately then, we can create them as two separate categories and have images for each of them. The neural network should learn to detect the two flower categories separately. Image augmentation is mainly done to prevent over-fitting of the neural network to the training dataset. A neural network mainly trains via the process of transfer learning. After training the neural network with the labeled dataset, we arrive at a set of Neural Network Weights, which we can compare for most accuracy over a sampled set of test images and choose the best one accordingly.

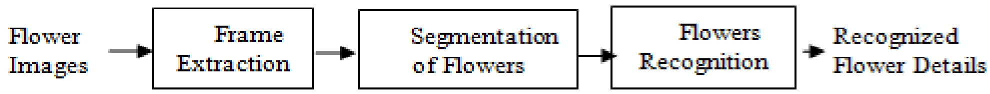

Figure 1: Block Diagram of the proposed methodology

Figure 2: Overview

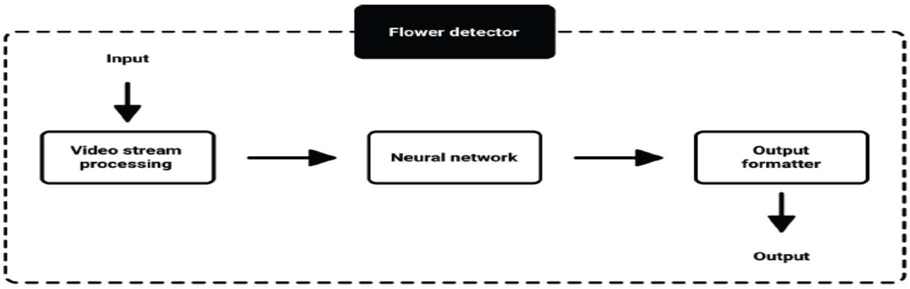

Figure 3: Flower Detector in Detection Mode

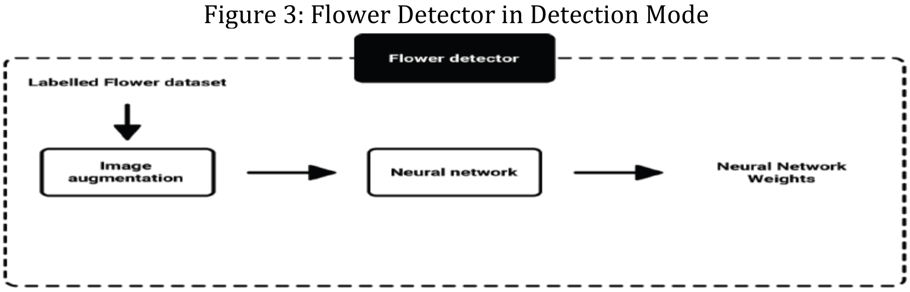

Figure 4: Flower Detector in Training Mode

Conclusion

The agriculture, environmental science, and ecology use widely for flower recognition approach. The flower recognition bit difficult due to extensive features available across the world based on environmental conditions and abundant species of available flowers. The methods available used to recognize, and the classification of flowers are not up to the mark and follow the traditional way. The computer vision approaches towards flower recognition and classification proliferates because of numerous applications. As a part of the discussion on available techniques, will concluding survey by adopting machine-learning approaches for flower classification and recognition.

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