International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 /doi:10.14445/22315381/IJETT-V69I3P234

Volume 69 Issue 3, 229-232, March 2021
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Performance evaluation of Googlenet, Squeezenet, and Resnet50 in the classification of Herbal images

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Abstract - *Computer-aided classification of medicinal herbs is of major concern in medicinal research. The real challenge lies in the complexity and variability of plants belonging to the same species. Conventional approaches involve feature extraction and classification. Feature extraction is not that effective due to the shift variance of plots. Hence an exhaustive research technique is needed to perform the classification of medical herbs. Convolutional Neural Networks are the recently accepted paradigm for classification with the help of pre-trained neural networks. In this paper feasibility of GoogleNet, SqueezeNet, Resnet 50 for the classification of medicinal herbs is studied. Its is found that Resnet 50 provides high sensitivity for both trained and test dataset.*

Keywords: *GoogleNet, SqueezeNet, Resnet 50, Herbs, Classification, Sensitivity, Specificity*

I. INTRODUCTION

India is a country noted for its rich cultural heritage and medicinal values. Right from ancient days, medicinal herbs have become an integral part of every household. Even today, diseases like the common cold, asthma, and body pain are cured with herbs and herbal medicines, A wide variety of herbs with medicinal values are still prevalent in various parts of India, especially in hills and mountains. It has attracted a large number of researchers to pursue their research work. Also, when these varieties of herbs when categorized and digitized, they would be of great support to the field of medicine. In recent days, multiple researchers are working to bridge the gap between modern medicine and herbal medicine.

Considerable research has been carried out in this area for automated characterization of anomaly/abnormality/flowers/herbs. [5] used Euclidean-based color image segmentation for the extraction of abnormal features. Conventionally features are extracted, and these features are fed to the classifiers. Conventional classification techniques involve the following steps: Features are extracted from the input images, exemplars are created with the features as input parameters and the type of the herb as the output parameter, exemplars are divided into two sets, one for training and the other for testing, the neural network is trained and tested, trained neural network and its weights are stored. Having done this, any input image of the herb (to be classified) is considered. Features are extracted, and these features are fed to the already trained neural network, and the output is obtained. The output indicates the type of herb.

In the above case, the performance of the classifiers is strongly dependent on the extracted features. Hence an efficient feature extraction technique has to be identified. Though various image segmentation techniques are available in the literature, these techniques do not work well for real-time images[6]. Computational complexity is more as the features are extracted with an image segmentation technique followed by feature representation. Hence it is necessary to develop a classifier that does not involve feature extraction but performs automated classification. Recently deep learning neural networks have changed the paradigm of classification by accepting images as inputs. [4] used faster Region-based CNN (R-CNN) for fruit detection to aid automated fruit harvesting. Near InfraRed and RGB images are used as inputs to R-CNN for the detection of fruits. The performance of the proposed network can be improved by fusing NIR and RGB images. [3] studied the feasibility of GoogleNet and AlexNet for the categorization of 102 classes of flowers. From the heuristic analysis, it is evident that GoogleNet outperformed AlexNet in the categorization of flowers. Hence in this research work, the performance of three different Convolution Neural Network (CNN) in classifying the herb images is evaluated. CNN, Alexnet, and GoogleNet are used for the detection of 9 sets of fruits. Though all three networks provide 100% detection, CNN is computationally less complex.

This paper is organized as follows. Section 2 describes the research database, section 3 deals with the proposed algorithm, results are discussed in section 4, conclusion, and future directions are described in section 5.

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II. Research Database

In this work, an exhaustive database of Chinese herbs is considered for the research work. It had 61 groups with at least 4 images in groups. The number of herbal images in each of the 61 categories is shown in Figure 1. A sample image in each category is shown in Table 1

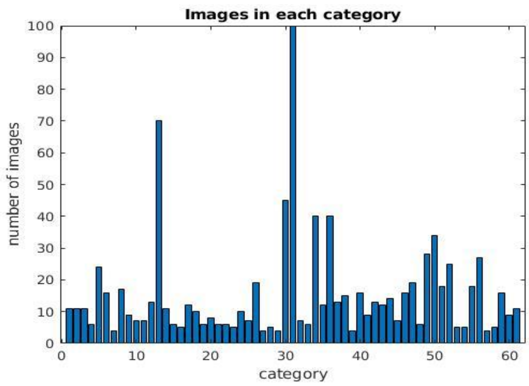

Figure 1 Number of images in each category

Table 1: One sample image in each class 1-15 (courtesy:http://libproject.hkbu.edu.hk/was40/search?lang=en&channelid=1288)

III. PROPOSED WORK

In recent years, convolutional neural networks are used for the classification of images. The advantage of such classifiers is that they consider the images as inputs rather than features. Hence the performance of the proposed network is better than the conventional neural networks. CNN performs both feature extraction and classification through a series of layers, namely convolution layer, subsampling layer, and Rectified Linear unit (ReLu) (for feature extraction), and softmax function (classification)[2]. Features are extracted from the input image by the convolution layer. The number of features is reduced by the subsampling layer. Negative co-efficient are converted into absolute values by Rectified Linear layer. Various CNN architectures include AlexNet, Resnet, GoogleNet, SqueezeNet, etc.

GoogleNet, a CNN architecture proposed by Google, consists of an inception module. Fully connected layers are replaced with average pooling. Also, the number of features is reduced by optimizing the weights through a newly introduced convolution layer at the beginning [1]. Steps involved in training GoogleNet are as follows: Providing the input images: 60 groups of images and at least four images in each group are loaded. These are true color images. Training and testing the pretraining GoogleNet. In this step, the pretrained GoogleNet architecture is loaded and is trained and tested with two different sets of images. Then the architecture is finalized, and the network is ready for use for the given image database.

Having understood the feasibility of Convolutional Neural Networks, the next step is to develop FPGA for the pretrained networks. In such a case, the smaller the size, the easier its implementation is. Such a smaller CNN is SqueezeNet, where major modifications are performed. A major number of 3x3 filters in the convolution layer are replaced with 1x1 filters without affecting the accuracy of operation. The number of inputs to each filter is also reduced. A module called the fire module is developed, which has a convolution layer (1x1 filter) and an expand layer (that has both 1x1 and 3x3 filters). Also, Squeezenet uses the max-pooling technique.

Any function can be represented with a single layer in a feedforward network. But it involves a large number of neurons in that layer, and hence it may result in overfitting the data. Hence more and more layers are used in CNN. However, the weight gradient becomes smaller due to the backpropagation of the error and hence repeated multiplication. It results in saturation of the results. Hence in resnet, in order to increase the performance, one or more layers are also skipped. Residual mapping is fitted instead of fitting the desired mapping.

IV. RESULTS & DISCUSSION

Initially, GoogleNet was chosen for categorizing the herbal images. 50% of images are used for training, and 50% of images are used for testing. Then the network is used for determining the class of the key image. Of a total of 697 images, only 115 images were classified correctly. The overall accuracy of GoogleNet is 16.5%. The performance of GoogleNet in terms of sensitivity for each category is shown in Figure 2.

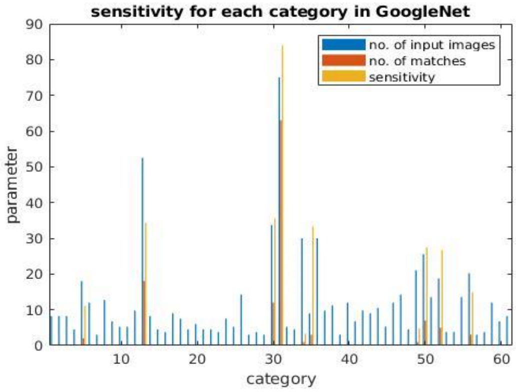

Figure 2: Performance of GoogleNet in terms of sensitivity

From Figure 2, it is evident that GoogleNet has not classified images in most of the categories. It has classified images belonging to the following 10 groups, namely A5, A13, A30, A31, A34, A35, A49, A50, A52, and A56. Hence in order to improve the performance, a squeeze net is used for classifying the images. In Squeezenet also, 50% of the images are used for training, and 50% are used for testing. Then the network is used for determining the class of the key image. Of a total of 697 images, only 128 images were classified correctly. The overall accuracy of Squeezenet is 18.3%. The performance of Squeezenet in terms of sensitivity for each category is shown in Figure 3.

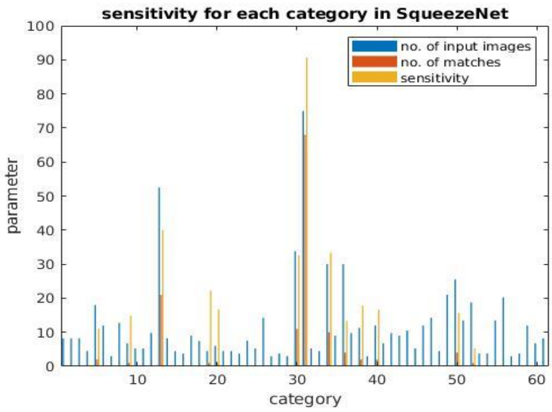

Figure 3: Performance of SqueezeNet in terms of sensitivity

From Figure 3, it is evident that SqueezeNet has not classified images in most of the categories. It has classified images belonging to the following 13 groups, namely A5, A9, A13, A19, A20, A30, A31, A34, A36, A38, A40, A50, and A52. Hence in order to improve the performance, resnet50 is used for classifying the images. In resnet50 also, 50% of the images are used for training, and 50% are used for testing. Then the network is used for determining the class of the key image. Of a total of 697 images, only 328 images were classified correctly. The overall accuracy of resnet50 is 47.1%. The performance of resnet50 in terms of sensitivity for each category is shown in Figure 4.

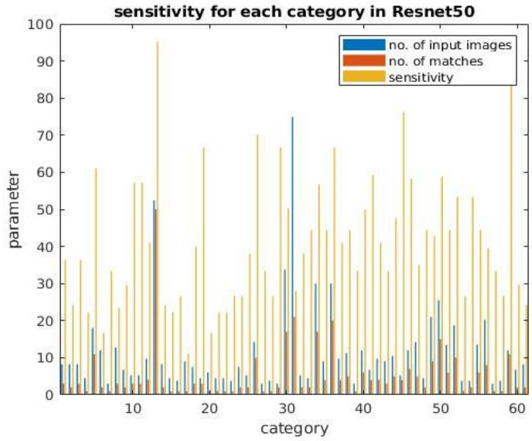

Figure 4: Performance of Resnet50 in terms of sensitivity

From Figure 4, it is evident that reesnet50 has classified images in all the 61 categories. Also, the sensitivity for each category is better than the other two networks. Performance evaluation of GoogleNet, squeeze net, and Resnet50 in terms of successfully classified groups and overall accuracy is shown in Table 2.

Table 2: Performance evaluation of GoogleNet, squeeze net and Resnet50

Network	No. of successfully classified categories	Successfully classified categories	Overall accuracy
GoogleNet	10	A5, A13, A30, A31, A34, A35, A49, A50, A52 and A56	16.5%
SqueezeNet	13	A5, A9, A13, A19, A20, A30, A31, A34, A36, A38, A40, A50 and A52	18.3%
Resnet50	61	A1 to A61	47.1%

From Table 2, it is found that Resnet50 outperforms both Googlenet and Squeezenet. Though the overall accuracy of resnet50 is 47.1%, and sensitivity of resnet50 for individual categories is shown in Table 3. It implies that for 44 categories, less than or equal to 50% of the images are correctly classified. For 18 categories, more than 50% of the images are classified correctly.

Table 3: Sensitivity Analysis of Resnet 50

Sensitivity	No. of categories
<=50	44
>50 and <=65	9
>65	7

Performance evaluation of GoogleNet, Squeezenet, and resnet50 for each category in terms of percentage sensitivity is shown in Figure 5.

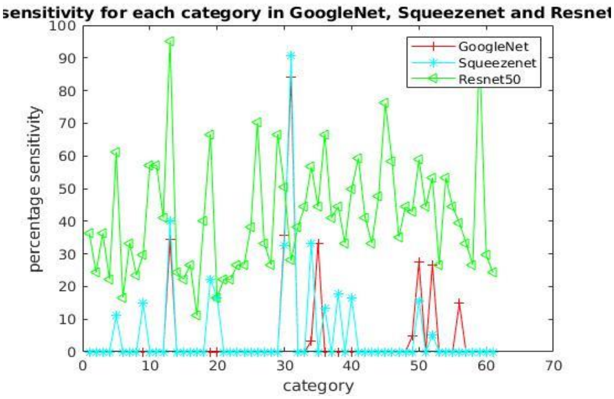

Figure 5: Performance evaluation of GoogleNet, Squeezenet, and resnet50

From Figure 5, it is visible that the sensitivity of Resnet50 for each category is better than GoogleNet and Squeezenet. It gives a maximum sensitivity of 95% for the A13 category. Indeed, all three networks had higher sensitivity for A13. It is because the images in that category are similar to each other and are different from the other categories (shown in Figure 7).

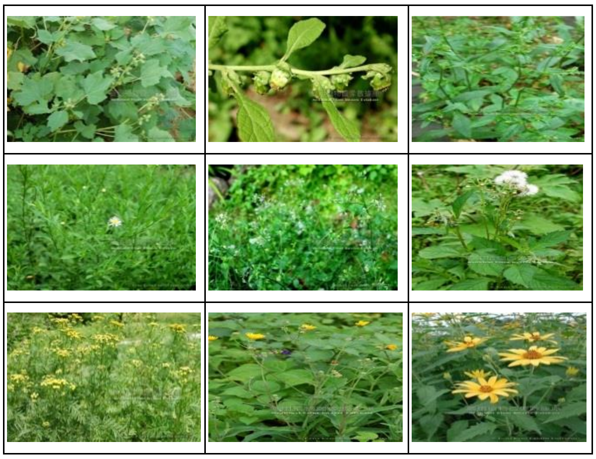

Figure 7 Sample images from A13 (courtesy: http://libproject.hkbu.edu.hk/was40/search?lang=en&channelid=1288)

V. CONCLUSION AND FUTURE WORK

In this paper, the feasibility of GoogleNet, Squeezenet, and Resnet50 for the classification of herbal images. These neural networks are fed with the images as inputs rather than features as inputs. Hence in these networks, the limitation in performance due to feature extraction is avoided. It is found that GoogleNet works well only for herbal images that have high intraclass variance and less interclass variance. Squeezenet works well for a large number of groups. On the other hand, Resnet50 works well for all groups. It is evident from the high sensitivity and accuracy of Resnet50 for all the groups of herbal images. The impact of layers on the performance of classification is yet to be studied, and sensitivity can further be increased. Also, the feasibility of other Convolutional Neural Networks for the classification of herbal images is yet to be studied.

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