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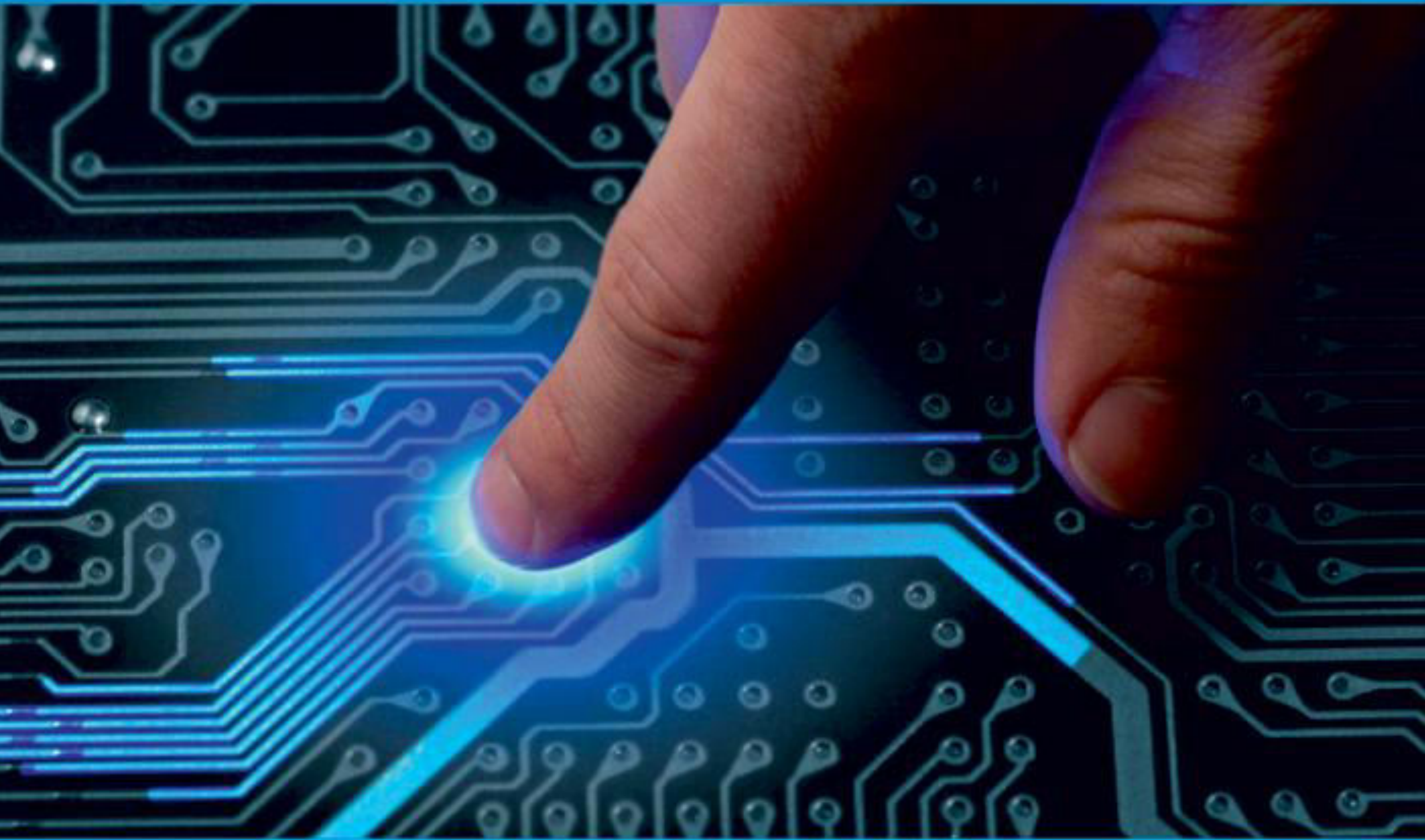

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Five-Layer Convolution Neural Network-based Animal Image Classification and Retrieval System

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ABSTRACT: In various field such as forestry, agriculture, Botany, Ayurveda, medical, etc., image classification is used. It is quite difficult to classify images by human because two or more different images are of similar structure and morphology. Therefore, we require a computerized automatic method to classify these images accurately. This can be done by the help of its different morphological features, like shape, size, color etc. The objective of this paper is to show the working of CNN on animal image classification with the objective of to increase the performance and accuracy for the image classification. In this paper, we suggested a system for theclassification of leaves using a deep learning method called CNN model.There are various successful classification techniques available, out of them some are based on machine learning techniques and supported by image processing methods like SVM, PCA and GLCM. It is quite difficult to select a particular technique out of above given because the reliability of the result of different input data can be inconsistent. The training of the model was done on animal dataset containing 1800 images and an average 91.42% accuracy is successfully achieved using CNN.

KEYWORDS: Image retrieval, CNN, animal classification, image classification

I. INTRODUCTION

Object classification plays a very important role in our ecosystem. For instance, there are various types of animal species on earth, and those species are needed to be classified based upon the images taken in order to know about the extinction of species on earth.Similarly, on earth, there are approximately 1, 00,000 species of plants. It is suspected that there are many undiscovered species, because there has been limited botanical work in this area. Plant leaf classification is important because it is used in many fields such as Botany medicine (Ayurveda), Agriculture, Tea, Cotton and many other industries. We must recognize the dissimilarity of leaf types such as shape, size, texture etc. to identify plants based on their leaves. However, Recognize the plant species on earth is important and difficult task and it results in duplicate identification.

There are many trees in nature which have similar structure and leaves, so it is quite difficult for humans to identify them easily. For instance, they blossom or carry fruits. Significant information is needed to identify these trees, along with the leave's shape, the shape of the branch, the shape of the whole tree, the shape of the leaves mounted directly on the branches, the time of flowering or fruit, the shape of the flowers. It is possible to distinguish plants without time constraints when using biological branches such as phytochemistry, morphological anatomy, molecular biology or cell biology. However, identifying the name of plants or trees using these methods is impractical for the general public when, for example, they are walking in a forest. Plant leaf classifications have been done by many researchers by using Image processing and Machine learning techniques [1].

Digital Image processing is basically to process, communicate and display images by means of a computer. Image processing includes various operations that can be applied on image in order to make it more informative to achieve some specific goal. In our research case our goal is to classify the leaf images which can be done by machine learning techniques. Machine learning is the application to effectively perform image processing task. In machine learning a model is trained for some specific task (e.g. classification) by feeding a set of training data (features of images).

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II. LITERATURE SURVEY

This section discussed various image processing-based techniques for image classification and retrieval that are used by many researcher in last few decades.

AbdolvahabEhsanirad (2010) [2] proposed and performed classification which was based on recognizing leaf images with extracted texture features by using GLCM and PCA algorithms. It was found that GLCM method was more efficient by 96.46% accuracy as compared to PCA method on a dataset of 390 images and with 65 new or deformed images. Prajapati et al. (2016) used image processing and machine learning techniques to classify and detect the cotton leaf. They implemented segmentation and background removal techniques by using RGB to HSV color space conversion for background removal [3].R. Meena Prakash et al. (2017) implemented a method for classification and detection of leaf parts. First, they used K-Mean segmentation for segmentation of leaf part after that they used SVM for classification and extract the GLCM texture features [4].Marki et al. (2017) proposed an algorithm based on hierarchical grid search tuned support vector machine as a classifier and Hu moment and parameters of uniform local binary pattern as features. They checked their proposed algorithm on the regular Flavia dataset benchmark and achieved 94.13% accuracy [18]. ChaowalitKhitthuk et al. (2018), used color imaginary with disease feature analysis to diagnose plant leaf disease. The efficiently salient allows the feature appearance for co-processing of I and H component. To sufficiently classify 4 types of grapes leaf diseases, GLCM and texture features equation was used for simplified fuzzy ARTMAP. To real world plant leaf classification and detection, the desirable result achieved more than 90% accuracy [5].Duong Tan Dat et al. (2019) proposed an efficient image processing method to identifying, detecting and estimating the torn banana leaves, based on contour profiles. For detecting torn leaves contour based method was highly accurate and achieved 94.7% accuracy for identify torn leaves [6].

Deep learning has gained a lot of popularity since the last decade because of its accuracy performance when it is fitted with enormous data. Because of the large number of parameter used, it takes a long time to train using deep learning techniques but it takes less time to test [12], [13]. The traditional machine learning algorithms often take less time to train and more time to test. The convolutional neural network is the basic part of every deep learning model for image processing and machine vision application. Now days convolutional neural network attract the attention of many researchers. We discussed various machine learning based techniques for leaves classification that used by many researcher in last few decades [7].

Hong Zhou et al. (2016), proposed a new approach for the tree species classification using Convolutional Neural Network. In order to make full use of the data they used LeNet architecture and perform 8- cross validation to determine the appropriate parameter for their CNNs model. The achieved accuracy of the model is up to 91.36% with rotation invariance and without rotation invariance the accuracy is 87.57% while testing after 200 times training [8]. Pradip B. Wable et al. (2016) proposed a method which addresses the classification of plant species based on the neural pulse coupled network. Certain characteristics of shape and texture feature are taken as assistant features, while for classification the entropy sequence is taken as the main characteristics obtained by PCNN. Artificial Neural Network is considered to be a classifier. The proposed system achieved 91.98% accuracy [9].

Wang-Su-Jeon et al. (2017) proposed the CNN based new leaf classification approach which used Google Net. They built two models to change the depth of the network and assist the performance. They assessed the work of the each model on deformed and discolored leaf images. The proposed system achieves more than 94% accuracy even if 30% of leaves were impaired [1]. X. Zhang et al. (2018) used Cifar10 and GoogleNet which are the two improved deep Convolutional Neural Network models to identify the nine types of maize leaves. They achieved 98.8% and 98.9% high identification accuracy when the 20% of the whole dataset used for the testing and 80% of the dataset used for the training [10]. Ali Beikmohammadi et al. (2018) combined logistic regression classifier with the MobileNet network architecture for plant leaf classification. In this paper MobileNet used as a feature extractor and logistic regression is perform as a classifier. They achieved 99.6% and 90.54% efficiency on the two botanical datasets, Flavia and Leafsnap [11]. Mercelin Francis et al. (2019) proposed a new approach to identify and recognize the leaf is healthy or disease using Convolutional Neural Network. When compared to other existing models with the minimum number of parameter i.e. 45k, the achieved accuracy was 88.7% [7]. Hang et al. (2019) introduced a deep learning system for recognizing and classifying the diseases of plant leaves. The approach will take advantage of the neural network in order to extract the characteristics of diseased sections, and thus identify target disease area. The traditional convolutional neural network has been strengthened by integrating a starting node structure. A squeeze and excitation (SE) module and a global pooling layer to classify diseases to address the issues of long training convergence time and too large model parameter. Their model delivered better performance compared to some traditional convolutional

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neural network and achieved an accuracy of 91.7% on the test dataset [16]. Sibiya et al. (2019) used neuroph to train a CNN network that recognized and categorized images of maize leaf diseases. Three different types of maize leaf diseases from healthy leaves were recognized by the model developed namely common rust (Puccinia sorghi), gray leaf spot (Cercospora), and northern corn leaf blight (Exserohilum). The proposed method shows average accuracy of 92.85% on dataset taking from online website of plant leaf [17].

It is concluded that machine learning techniques perform better than image processing techniques to classify leaves. Machine learning used SVM, ANN, Fuzzy Logic, Neural Network and Deep Learning etc. Now a day Convolutional neural network that is one of the deep learning techniques attracts more researchers for image classification and gives better result as compare to other techniques. CNN is a deep learning algorithm that can classify and recognize image features. Face recognition, object detection etc. are some of the area where CNN widely used. We used the CNN model to classify and improve the performance and accuracy of our model. A CNN consist an input layer, an output layer and multiple hidden layers. In this paper, we suggested a new approach for classifying leaf types using the Convolutional Neural Network model.

III. PROPOSED MODEL

1.1. Convolutional Neural Network (CNNet)

CNNet applies deep learning to classify the images. A convolutional neural network is a deep learning algorithm that can acquire an input image, attach significance (Learning weights and biases) to different aspects/ objects in the image, and distinguish between them. Recent development in information processing technology and hardware have made deep learning a self-learning approach that makes more feasible use of massive data.

Basic CNN works on the basis of the biological visual cortex. CNN is the variant of the neural network model which implements function closet to the visual structure of humans. In the retina, the parts of an object that have the greatest difference within reflected light intensity are known as the object's edges and the result is sent to the lateral geniculate nucleus (LGN). The whole structure around the object's corner compresses by the LGN neuron and sends to the primary visual cortex (V1). The object's contours, edges, and direction of motion then recognize by the V1 neurons. It also identifies the difference between the images reflected as distances in the left and right eyes' retina, and sends the result to the secondary visual cortex (V2). The V2 neurons perceive the object's overall shape and the difference in color between each component and send it to the tertiary visual cortex (V3). The V3 neurons identify the whole object's color, and the object's overall form and color are recognized at the lateral occipital cortex (LOC). We have taken CNNetin order to perform our proposed method due to its automatic relevant feature extraction capability as we do not need to extract the features manually or using other feature extraction techniques which ease the working of classification task and also reduces the complexity and another reason to use CNNNet is that this deep learning has proven to be efficient in recent studies to accomplish many proposed image classification tasks. A basic CNNet structure is discussed in section 3.2.

1.2. Basic CNNet Structure

Convolutional Neural Network (CNNet) is a deep learning algorithm that can classify and recognize essential image features automatically that contribute to the classification process means that are distinguishable to classify the images. Face recognition, object detection, animal classification and identification, and leaf disease identification, etc. are some of the areas where CNN is widely used. We have used the CNNet model to classify and improve the performance and accuracy of our model. A CNN consist of an input layer, an output layer, and multiple hidden layers to perform different task essential to accomplish the desired task. A basic CNNet structure is shown in figure 1 that has:

The convolution layer as the input layer to take the input and applies the filtering operation on the image by sliding a fixed size kernel to calculate the weighted sum of pixels corresponding to the values of the kernel.
Then, the essential or relevant features are extracted using the max-pooling layer that applies $a * b$ max pool or average pool operation on the digital image that calculates the maximum value of the pixels occurring in a particular pool size and reduces the number of features.
Then, the fully connected layer that is used to classify the input data into different classes based on the softmax function.

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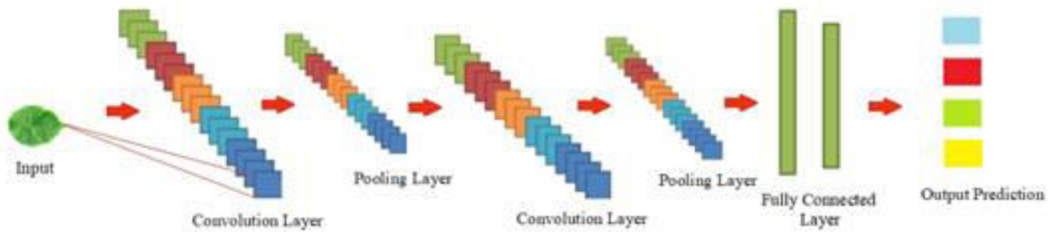

Figure 1. Basic CNNet Structure

1.3. Proposed Model

Table1 shows the proposed structure of CNN, that we have proposed in order to perform image classification based retrieval system. The training images were divided into eight types of 1800 images and 30 images were chosen randomly for testing. Experiments are performed using an HP computer equipped with an AMD A6-7310 APU with AMD Radeon R4 Graphics 2.00GHz Processor, 4 GB RAM. The python colab is used to execute the coded program.

Table 1. Proposed CNN structure

Type of layer	Filter size and Stride	Size of Input
Convolution Layer (CL)	32 9x9x3/1	227x227x32
ReLU Layer (RL)	ReLU	227x227x32
Max Pooling Layer (MPL)	2x2/2	113x113x32
Convolution Layer (CL)	16 6x6x32/1	113x113x16
ReLU Layer (RL)	ReLU	113x113x16
Max Pooling Layer (MPL)	2x2/2	56x56x16
Convolution Layer (CL)	8 3x3x16/1	56x56x8
ReLU Layer (RL)	ReLU	56x56x8
Max Pooling Layer (MPL)	2x2/2	28x28x8
Convolution Layer (CL)	8 3x3x8/1	28x28x8
ReLU Layer (RL)	ReLU	28x28x8
Max Pooling Layer (MPL)	2x2/2	14x14x8
Convolution Layer (CL)	8 3x3x8/1	14x14x8
ReLU Layer (RL)	ReLU	14x14x8
Fully Connected Layer (FCL)	8 Fully Connected layer	1x1x8

2. Results analysis

Following figures shows the result of the implemented model on some images separately, after training while testing. It can be seen from the results that the images are classified and retrieved with 100% accuracy from the dataset, when the proposed model is trained on 80% dataset and tested using the images taken from the remaining 20%dataset. The average accuracy to be found using the following results is 91.42%

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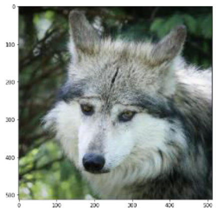
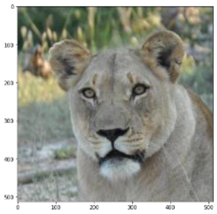
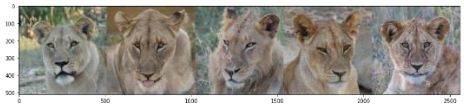
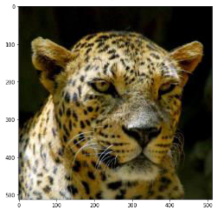


Accuracy: 100%

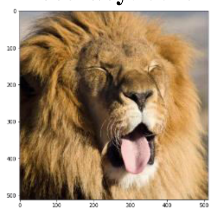




Accuracy: 100%



Accuracy: 80%



Accuracy: 100%

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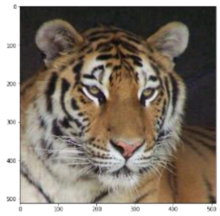
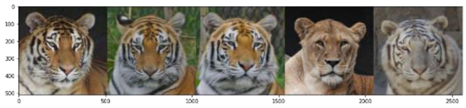
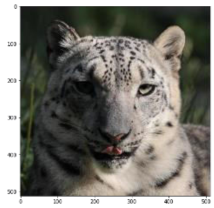
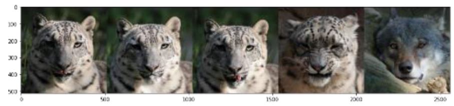


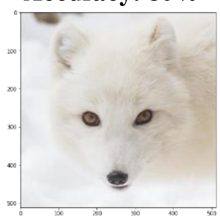


Accuracy: 80%





Accuracy: 80%



Accuracy: 100%

IV. CONCLUSION

In this paper, we suggested a system for theclassification of animals using a deep learning method called CNN model. The state-of-the-art classification techniques are either image processing or machine learning or a combination of both. CNN is a deep learning technique attracts more researchers now-a-days but development of CNN model is a tedious process as compared to other deep learning models to improve accuracy. This paper illustrates the working of Convolution Neural Network for animal classification and retrieval task. The identification rate obtained was higher than 90%. In future, by applying pre-processing using various image processing algorithm and latest architecture of CNN model we can improve the accuracy.

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