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A NOVEL APPROACH FOR CLASSIFICATION OF PLANT SPECIES USING CONVOLUTION NEURAL NETWORK

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Abstract

Farmers and botanists need application to classify the plant species. In the forest areas large plant species are available. There is lots of plant species used for medical application. Then we understand the biodiversity of plant species. Our objective is to identify the vascular plant species from the long tailed collection. That vascular land plants contain lycophytes, ferns, gymnosperms and flowering plants. Image analysis helps to classify the plant species. Plant species classification is implemented with the help of deep convolutional neural networks. There are lots of plant species parameters available. Family, Species and genus is used for the plant classification model. The accuracy achieved from this model is94.8%.

Keywords: Convolution Neural Network (CNN), Comma Separated Values (CSV), Machine Learning (ML), WeedControl.

1. INTRODUCTION

Weed control is an important usage of crop scouting. Segregating the plant species with small differences is a challenging task. Vascular land plants contain lycophytes, ferns, gymnosperms and flowering plants. Lycophytes are the major component of coal deposits, ferns. A fern indicates ecosystem health and gymnosperms help to find the major habitats of animals. Flower plants help to find crops, vegetables and fruits. 40000 leaves images used are used for training and 10000 used for testing. These image details are converted into the train.json and test.json. For the training model use json input format. In that json input file it contains annotations, category, images, information, licenses and regions. In that category there are various features available. The features are namely id, name, family and genus. Then training should be for family not for genus and category. Then the training will be repeated until it reaches the certain level. Deep convolutional neural networks are used for the image analysis.

2. RELATEDWORKS

2.1 Plant Species Classification Using a 3D LIDAR Sensor and MachineLearning

U Weiss et al [1] proposed work in the agricultural robotics field the farmers need major application is crop scouting. Weed control is an important usage of crop scouting. For drastic detection of plant and species weed control is a key enabler. Segregating the plant species with small differences is a challenging task. The challenge is changing the symbolic level description of the appearance and distinguishing between the humans, into machine level language. Identify the 97% of plants correctly.

2.2 Plant Species Classification Using Leaf Shape andTexture

Hang Zhang et al [2] proposed work shows importance of the plant Species classification on

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the earth is helpful to human beings for classification of plant species. Thus it would be useful to develop automatic image classification methods in an effective manner. The solution is a problem: They propose a new approach to design a convenient method to generate the feature space that combines co-occurrence matrix statistics and local texture features using wavelet decomposition and global shape features to describe the collected plant leaves. Then the accuracy of using SVM the methods with 1900 leaves from 30 different species is93%.

2.3 Plant species classification using flowerimages

Marco Seeland et al [3] proposed work that improves the image analysis methods and introduces an interesting image analysis related plant species classification. Lots of methods proposed for object detection and classification. Evaluation of classification pipeline the datasets are evaluated and compared to baseline methods. Then their proposed work is to develop an image classification on the flower based datasets. They work about span from detection, extraction of the images, fusion, max-pooling, and padding, decoding and encoding the local features for extracting the shape and color information from the flower images. They use the flower image datasets Oxford flower 17 and Oxford flower 102 also Jena Flower 30 for their implementation.

2.4 Plant species classification using deep convolutional neuralnetwork

Mads Dyrmann et al proposed work shows weed species are present in agriculture fields in weed management. The network is developed containing 10 thousand images and 22 types of crop and weed species in early stages. The images from six different datasets that have resolution, variations respect to lighting and soil type. This taken images controlled conditions with regard to camera stabilization and illumination with hand held mobile phones in fields with changing lighting conditions and various soil types. In these 22 species, the deep convolutional network achieves a classification accuracy of 86.2%.

2.5 Leaf Species Classification Based on a Botanical Shape Sub-classifierStrategy

H.Liu et al proposed work is smartphone based application framework helps human beings to identify the plant species in the forest. A sub classifier strategy is used for this framework. The scope of recognizing the botanical properties of leaves in different global and local shape criteria used in flora books. After that decision function is applied to classify the shape categories and it gives the final decision of leaf species. Fusion Strategy and corresponding Random forest classifier algorithms are used. These algorithms help botanical leaf shape recognition demonstration for classification.

2.6 Mobile plant species classification: A low computationalapproach

S Prasad et al proposed work is about mobile device based plant classification systems using reduced shape and color feature extraction. This classification system helps botanists, farmers, scientists and other plant identification. After getting the original image it is reduced to a similar aspect ratio and it doesn't affect shape. It reduces the computational cost compared to total cost. The algorithm calculates geometric features and fourier transforms. Next it trained using the K Nearest Neighbor classifier. Then two nearest classes are selected on the basics of smallest distance using a decision tree. The algorithm proves to be better in performance compared to other already existingalgorithms.

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3. PROPOSEDWORK

3.1 CONVOLUTION NEURALNETWORK

Convolution neural networks solve the image classification problem. Research work shows best performance of image dataset. It is very useful for global and local pattern structures. The conventional neural network solves text classification and human face recognition. In the past it classified the shapes and curves. Now we implement image processing in leaves. Different the published studies we observe are used for lung image patches. Deep layers do not perform well in the distinct structures. The training network is large and contains a large number of parameters. Leaf images also consist of a large network. So we want to overcome the overfitting problem. In this research paper we proposed a Conventional neural network for classifying the multi class image and avoid the overfitting problem.

Conventional neural network consists of three layers:

- Inputlayer
- Hiddenlayer
- Output layer

Hidden layersare:

- Convolutionallayer
- Stride
- Padding
- ReLUlayer
- Max poolinglayer
- Fully Connectedlayer
- Dropoutlayer

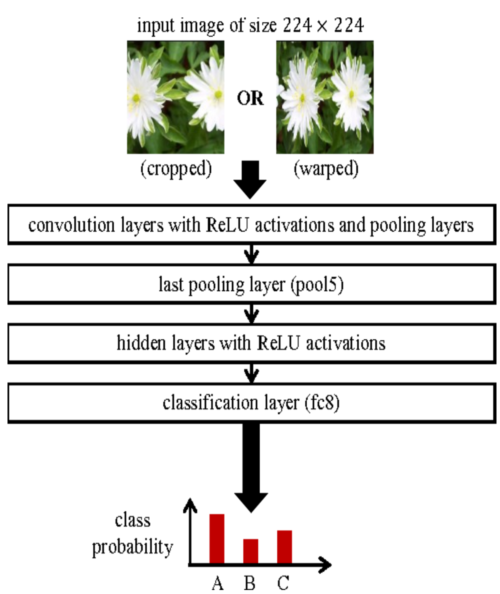

Figure 1: The CNN Layer model

3.1.1 Input Layer

Convolutional neural networks consist of the input layer. The input layer contains the image data. In the input layer we fed the input images. The image data can be represented as three dimensional matrixes.

3.1.2HIDDEN LAYER

- **Convolutionallayer**

The convolution layer is an important feature used in Convolution Neural Network. In the convolutional layer we feed the three dimensional image into the network. The weight of the image is 32 X 32 X 3. It is used to connect the input layer and the next layer with neurons. The convolution which is a linear operation performs multiplication with input and set of weights. Multiplication is often performed between an array of input and array of weights which are two-dimensional which are called as kernel or filter. The size of the filter is small compared to input data and type of multiplication applied between filter sized patch of input and filter is a dotproduct.

The output from multiplying the filter with the input array one time is a single value. As the filter is applied n of times to the input array, the result is a two-dimensional array of output values that represent a filtering of the input. As such, the two-dimensional output array from this operation is called a "feature map".

Once a feature map is created, we can pass each value in the feature map through nonlinearity, such as a ReLU, much like we do for the outputs of a fully connected layer.

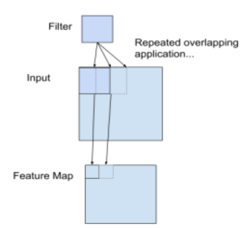

Figure 2: Filter applied to a 2D input to create a feature Map

- **Stride**

Conventional neural networks decrease the parameters and want to reduce the side effects. Stride is the number of pixels shifts over the input matrix. When the stride is 1 then we move the filters to 1 pixel at a time. When the stride is 2 then we move the filters to 2 pixels at a time and soon.

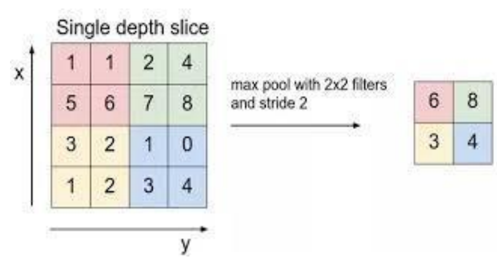

Figure 3: Example of stride in CNN

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- **Padding**

Padding is a process of adding layers of zeros to our input images. One of the drawbacks in convolution network is loss of the information in the border image. To solve this problem we use zero padding. Benefit of the zero padding is managing the output size.

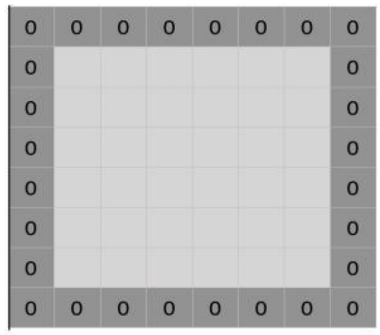

Figure 4: Zero padding added to an image

- **ReLUlayer**

The rectified linear activation is the default activation when developing multilayer Perceptron and convolutional neural networks. RELU is just a non-linearity and it‟s useful alike to neural networks. The ReLU layer gives output g as a function of its input f is with g(f) = tanh(f).

- **Max PoolingLayer**

It is one of the pooling methods. It segments the images into sub-region and it returns the maximum value of the sub-region. Common size used in max-pooling is 2x2. Pooling is used for non-equal filters and wants to improve the strideefficiency.

- **Fully connectedlayer**

Fully connected is a traditional neural network. Then every node is connected to another node directly. It includes lots of parameters. Fig 6.8 shows the fully connected layer.

- **DropoutLayer**

It is implemented in all hidden layers. To prevent the over fitting we use the dropout layer. It is an approach to regularization of neural networks.

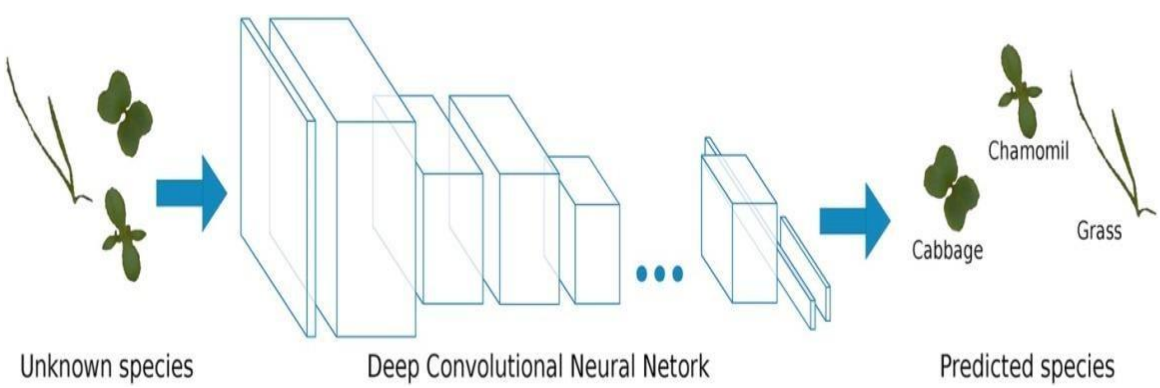

Figure 5: Plant species classification using CNN

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3.2 Proof of ConceptArchitecture:

Plant Species Classification:

In this classification we use plant species leaf as input images. Lots of input images used for classification. We use json file for training. It uses as alternate way of data frame. Vascular land plants contain lycophytes, ferns, gymnosperms and flowering plants. For the training model use json input format. In that json input file it contains annotations, category, images, information, licenses and regions. In that category there are various features available. The features are namely id, name, family and genus. Then training should be for family not for genus and category. Then the training will be repeated until it reaches the certain level. 32 X 32 X 3 image use as input.

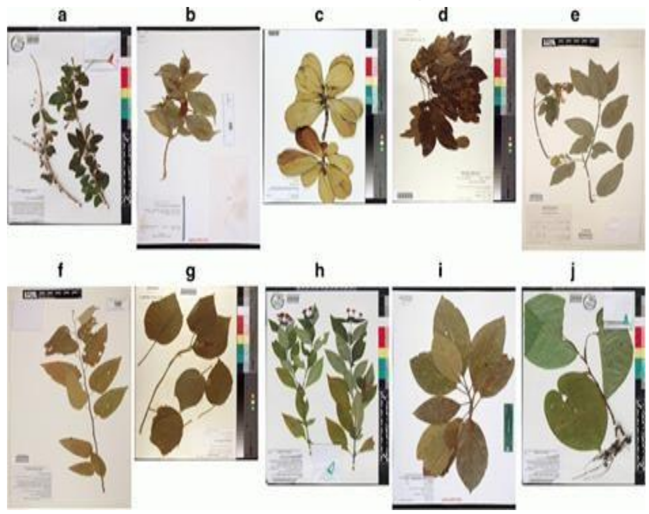

Figure 6: Sample input images

Deep Convolutional neural network uses for the plant species classification. It consist convolutional layer, max pooling layer, fully connected layer, drop out layer, and the output layer. After that model training we use test the model with the help of test.json. The Output in the form of CSV file. The three different CSV files are generated namely family, genus and category. The output csv files are image name and category id.

3.3 FilterCapacity:

The ability of filters to measure the complexity of the images is known as filter capacity. If the filter capacity is small, then it depicts that only local features of the image are mapped to the next layer. If the capacity is large, it states that filter is able to identify the complex structures of elements that are not neighbors in the input image. The filter capacity can be calculated as follows:

$$\text{Capacity}=\frac{\text{Real filter size}}{\text{receptive field}}$$

Where the real filter size is size of the kernel for which padding or striding is done. For example if the input layer with kernel size n x n is down sampled by the factor „a‟, the real filter size would be an x an. In CNN there are three 2x2 pooling layers. The real size filter after first max pooling layer would be 2nx2n, 2^2n x 2^2n for the second max pooling layer and goes on. The portion of the original image that the filter can "see" when following one path back through the network is known as receptivefield.

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3.4 Coverage:

The ratio of receptive field to input image size is known as coverage. As with capacity, the coverage of the network is calculated from the maximum available receptive field, i.e. the main branch of the network. For this network, the convolutional filters covered 66.4% of the input image and thus never covered more than the size of theimage.

$$\text{Capacity}=\frac{\text{Real filter size}}{\text{receptive field}}$$

ExperimentalResults:

The network architecture is given below and the confusion matrix is predicted for 21 species. (Sherpherd's-Purse, Chamomile, knotweed family, Cranesbill, Chickweed, Veronica, Fat-Hen, Narrow-leaved grasses, Broad-leaved grasses, Field Pancy, Black Nightshade, Annual Nettle, Cabbage, Tobacco, Thale Cress, Cleavers, Common Poppy, Cornflower, Wheat, Maize, Sugar Beet, Barley).

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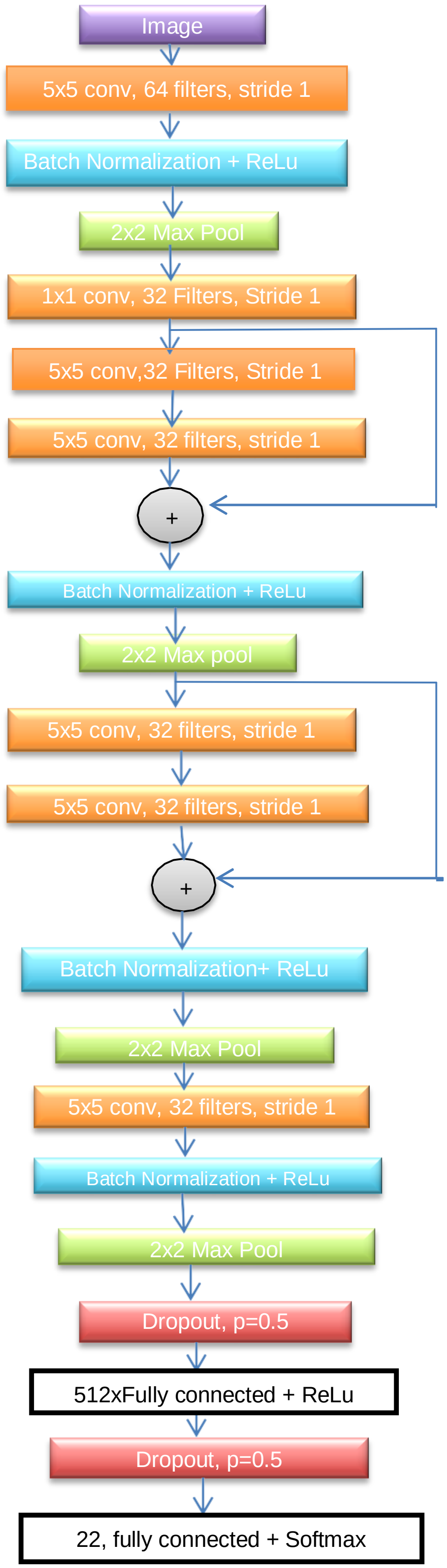

Output Size	Coverage (%)	Capacity (%)
3x128x128		
64x128x128	3.91	100
64x128x128		
64x64x64		
32x64x64	3.91	40
32x64x64	10.16	76.92
32x64x64	16.41	47.62
32x64x64		
32x32x32		
32x32x32	28.91	54.05
32x32x32	41.41	37.74
32x32x32		
32x32x32	41.41	37.74
32x16x16	66.41	47.06
32x16x16		
32x8x8		
32x8x8		
512		
512		
22		

Figure 7: Network Architecture

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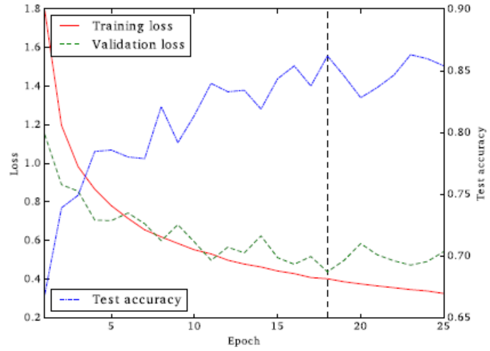

Figure 8: Cross entropy loss and classification accuracy.

The above figure 8 shows the loss and accuracy for each epoch of the training. In order to achieve the highest accuracy possible without over-fitting the network, the training was stopped after 18 epochs. At this point the classification accuracy of the test set was 86.20%. After the 18th epoch, the validation loss starts to flatten and the gap between the training and validation loss increases. From the confusion matrix given below in figure 9, the fraction of misclassifications for each of the 22 species isshown.

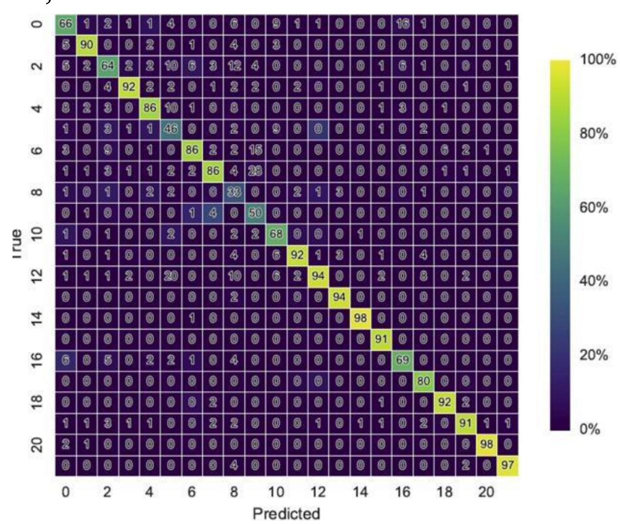

Figure 9: Confusion matrix for the 21 species.

4. Results and Discussion:

The proposed model uses Deep Convolutional Neural Network to categorize the plant in the forest. There are four kinds of layers used in the neural networks namely Pooling layer, ReLULayer, Max Pooling layer, fully connected layers and dropout layer. The result is finally obtained as a CSV file which contains the plant species id and predicted id of family. The proposed model achieves an accuracy of 94.8% while classifying the plant species in the forest. This helps the botanist to classify the plant species and also monitor biodiversity. In future, a greater number of images with different colors of leaves will be trained to improve the accuracy.

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