CSC 481 – FINAL PROJECT REPORT

LEAF SEGMENTATION USING THE CNN

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i. ABSTRACT:

We can learn from this project that it studies the (CNN) Convolutional Neural Networks and how it is affected when we implement CNN on the colored images. We are predicting this for every leaf class on the leaf snap using CNN in the dataset that we gathered from the Kaggle website, which are available publicly. All the leaf images from the dataset were segmented using an automatic mean thresholding technique in order to create binary images, also masking was applied for the color images to separate it from green leaf pixels apart from the background.

The color values that were created has ranges that can be calculated using the 3D grid which in terms gives us the highest quality image in the leaf class. Furthermore, we can see to that by adding 3 color channels to the image, some of the similar images are being misclassified by CNN as it belongs to the same color range. So, it gives us an insight leaf images that belonging to the same color ranges are classified better in comparison to the leaf images with the unique color range that are not properly classified.

ii. INTRODUCTION:

We are able to see that there are various plant species present among us with different kind of shapes, and sizes. However, it would be impossible for an individual to name all of the plant species without having a slight knowledge about the plants, but we can identify some of the common plants.

The goal of the project is to determine if adding the color to the leaf classification problem could prove beneficial. Since, leaf classification are considered to be popular among the computer vision sides, if we are able to make an individual to name the plant species based on the images alone, that could prove beneficial. Under the background section which discuses about the papers that we used in terms for reference tells us that the researches excluded the color of the leaves during the analysis even when some of the plants showed different shades of green in them.

iii. BACKGROUND:

The “**Deep-Plant Identification with Convolutional Neural Network**” **[1]** paper gives us an explanation about the researchers proposing a Convolutional Neural Network in order to identify the leaves and classify them according to the images and featured that we gathered from each image. This kind of approach was used in case of avoiding the black box problem. Based on the Deconvolutional Networks, a visualization was applied to make all the features that the convolutional neural network was working on. According to the paper, the first part was the CNN model to automatically learn the features based on the plant categories. Second step of the project would be to make the DN (Deconvolutional Network) visualize feature that seems to be important. During the classification process of the leaves, we can consider the shape and venation to be the most important features and also the primary focus of the project was to make the CNN to obtain an accuracy of 99.6% by using the shape alone.

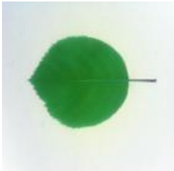
From the “**Leaf snap: A Computer Vision System for Automatic Plant Species Identification**” **[2]** paper which was considered as one of the primary inspirations for this project. The paper illustrated that a mobile application was created and with the help of automatic visual recognition different plant species were able to be identified. So, by using the photographs of the leaves they were able to identify different tree species and also named the Leaf snap as a computer vision system. It was located in North America with the dataset being 184 different tree species. The key techniques used during this project was classifying, extracting, segmenting, and comparing the features within the dataset. They implemented a total of 4 different methods for classification. Furthermore, using the system that they created it was possible to identify the tree species using the mobile picture from the mobile application.

Since, segmentation is considered to be one of the important aspect, this paper "**Leaf Shape Identification Based Plant Biometrics**" **[3]** depicts about it and the goal of this project would be to use the shapes of the leaf in order to identify the different plants using the binary images that got segmented from the backgrounds to visualize the shape of the leaf and apply it to the classification of an image for shape alone. So, from these points we can draw that the leaf can be extracted from its background to provide with the shape of the leaf. Moreover, the binary image process was done manually and mapped out the anchor points for the leaves that performed a successful binary segmentation.

"**Leaf Classification Using Shape, Color, and Texture Features**" **[4]** paper describes about the color being an important aspect. It focused on the leaf classification using the color of the shape and the texture features to identify the different plant species. During the leaf classification process, mostly the color to identify the plants are not that much used because of the color not being that much significant for identification. Moreover, we can learn from this paper that if by adding color, it could prove anything like increasing the performance of the classifier. Probabilistic NN was used instead of the Convolutional NN and additionally feature extraction was also done that allowed the researchers to use shape, venation and texture of different leaves. Furthermore, the final NN was built with an input layer, a summation layer, and an output layer to provide with the results. So, by adding the shape, color, vein, and texture the model attained an accuracy of 93.75%.

iv. METHODS:

As aforementioned, the dataset that we used was taken from the Kaggle which can be used publicly that contains more than 10,000 images of different tree species that contained unsegmented images. We will be implementing methods like Binary and Color since both are considered to be an important aspect towards this leaf snap project.

BINARY SEGMENTATION:

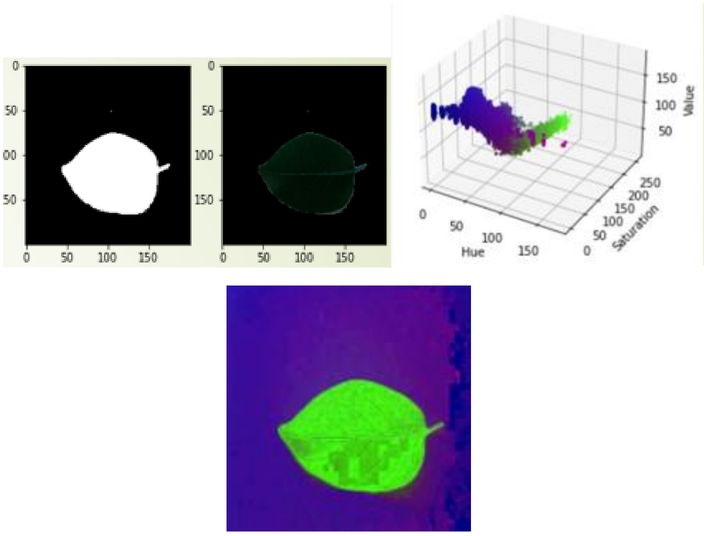
For this method, we first of all we apply the binary segmentation the image for leaves that are present within the dataset. Then afterwards, we apply the grayscale method to all the images in the dataset, so that would make the background to be easily identified from the leaf images. Basically, the white background is considered to have higher pixel values than that of the leaf images. However, the background with the whitest can be applied with the mean thresholding to the image, since the white pixel are having most white due to the high value that are less than the mean.

Since, this thresholding is a form of automatic thresholding, the image is separated into two parts into background, and foreground. This can be done by multiplying the 2 axis of the images and obtaining the mean for the image. Once these steps are done, we can set a loop and can obtain the mean for each of the class leaves where the mean can be computed and the background was segmented from the image itself.

COLOR SEGMENTATION:

Since we can see that the binary segmentation has some problems with the white background present in them, we can use the color segmentation that can be performed on the dataset. Also, here we manually calculate the HSV i.e., Hue, Saturation, and Value space of the class leaves. First step, would be to process the image in order to transform the colored images from the RGB space to the HSV space. Also, a 3D grid was created in order to visualize where the saturation and the hue values are falling down on the scale. The HSV grid charts for these classes proved to be useful since these leaves are to have brighter values and we can also see some the leaves having noises like blue and purple mixed within the leaf ranges. Therefore, these things made it harder to capture the leaf entirely as the background was transformed into blue and purple pixels. The reason why the noises appear is because of the leaves having the same similarity among the colored pixels.

In order to choose the best leaf for the project, we can choose the leaf with the clearest background since those can be used for finding the values that can be used for the thresholding. Once these values are obtained, we can then find the ranges of upper and the lower, from which the masking can be done in order to get the color segmented image.



CONVOLUTION NEURAL NETWORK:

In this project convolution neural network was used as the classifier to check if the neural network could pick up on the image shape itself and identify the leaf species. The model we constructed was about 16 layers with a total number of parameters as 338,790. We constructed four models and this model was the best model in the models we constructed.

Architecture:

The model consists of 8 convolution layers 3 max pooling layer 2 spatial dropout 2D layers 1 flatten layer and 2 dense layers. In the first convolutional layer, there are 64 3x3 filters with padding and second convolution layer with 32 3x3 filters with padding the next is spatial dropout with 0.25 and the next is max pooling layer with 2 strides. This is repeated for another two times with an additional convolution layer but every convolution layers in the rest are 32 3x3 filters with padding.

Activation function: Rectified Linear Unit

Optimizer: Adam

Layer (type)	Output Shape	Param #
conv2d_16 (Conv2D)	(None, 150, 150, 64)	1792
conv2d_17 (Conv2D)	(None, 150, 150, 32)	18464
spatial_dropout2d (SpatialDr	(None, 150, 150, 32)	0
max_pooling2d_11 (MaxPooling	(None, 75, 75, 32)	0
conv2d_18 (Conv2D)	(None, 75, 75, 32)	9248
conv2d_19 (Conv2D)	(None, 75, 75, 32)	9248
conv2d_20 (Conv2D)	(None, 75, 75, 32)	9248
spatial_dropout2d_1 (Spatial	(None, 75, 75, 32)	0
max_pooling2d_12 (MaxPooling	(None, 25, 25, 32)	0
conv2d_21 (Conv2D)	(None, 25, 25, 32)	9248
conv2d_22 (Conv2D)	(None, 25, 25, 32)	9248
conv2d_23 (Conv2D)	(None, 25, 25, 32)	9248
max_pooling2d_13 (MaxPooling	(None, 8, 8, 32)	0
flatten_4 (Flatten)	(None, 2048)	0
dense_10 (Dense)	(None, 128)	262272
dense_11 (Dense)	(None, 6)	774

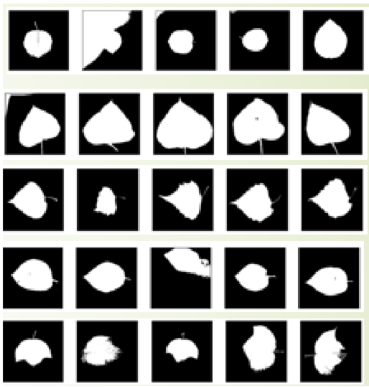
Total params: 338,790
Trainable params: 338,790
Non-trainable params: 0

v. RESULTS:

BINARY SEGMENTATION:

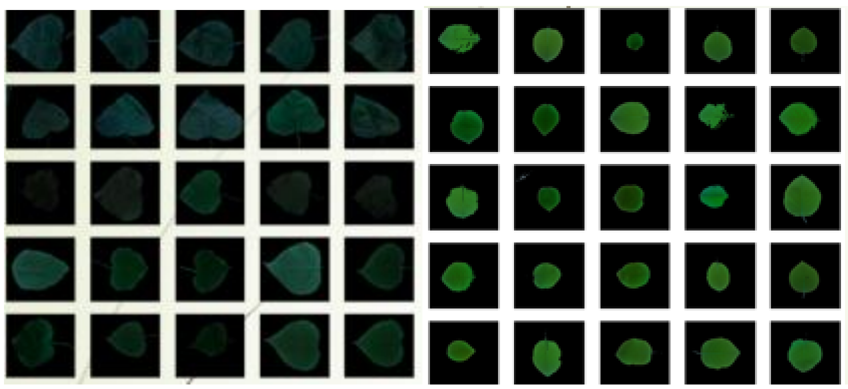
Once, we got the results for both the methods the images were properly segmented using the automatic mean thresholding technique. Mostly all leaf images were captured within the segmentation technique and the background was slightly identified to have the highest value. We can further notice that some of the leaves within the dataset have white pixels present around the corner but however the entire leaf was captured in an acceptable segmentation.

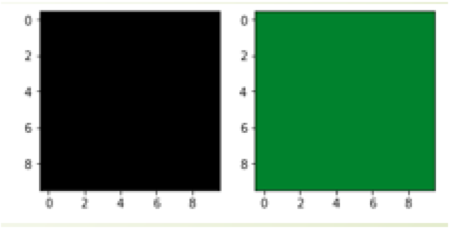
There was no error in segmenting the leaf images that had brighter colors but for the leaf with darker colored images were identified as the background for the leaf. But avoiding these problems we were able to get good results. There few classes that got impacted the most as it was taken in a darker lighting and few classes turned out to be good as it had better lighting.



COLOR SEGMENTATION:

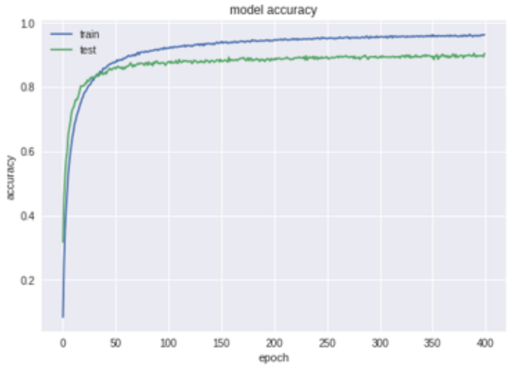
During the result process the color segmentation turned out to be good as using the HSV grid chard estimation method. The classes of all the leaves within the dataset were segmented using different shades of green that were present within the leaf image. Some of the pixels within the dataset the classes were not captured correctly as there were black pixels located within the leaf itself. Also, at the same time some of the class even showed noise that were detected on some of the corners.

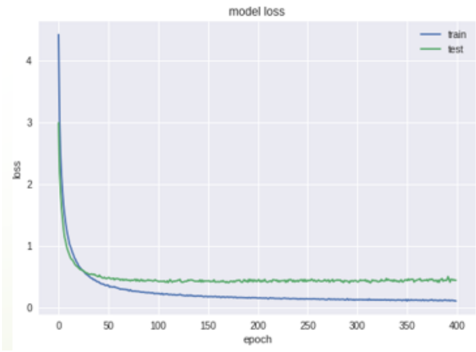




CONVOLUTION NEURAL NETWORK:

The test picture's classes are predicted using our model and creating a data frame which holds these predictions together with all the relevant information's. Basically, the use of CNN increased the performance of our model by 89% that was trained on an average of 133 examples per each of the 185 classes of the plant species. Furthermore, this shows us how promising the approach of CNN's are for the image classification.





Most of the plant species were predicted with the color using the Convolutional Neural Network. Abies Concolor, Abies Nordamanniana, Acer Campestre, Acer griseum, and Acer palmatum, etc., are example classes that has no errors while predicting. However, we faced an error (12) for the class of Ulmus glabra with 118 examples.

	errors	examples	error_amount
Abies concolor	0.0	186	0.0
Abies nordmanniana	0.0	128	0.0
Acer campestre	0.0	122	0.0
Acer griseum	0.0	106	0.0
Acer palmatum	0.0	172	0.0
Acer saccharum	0.0	149	0.0
Aesculus hippocastamon	0.0	128	0.0
Albizia julibrissin	0.0	118	0.0
Amelanchier laevis	0.0	121	0.0
Betula alleghaniensis	0.0	117	0.0
Betula populifolia	0.0	120	0.0
Carya cordiformis	0.0	170	0.0
Carya ovata	0.0	123	0.0
Carya tomentosa	0.0	152	0.0
Cedrus libani	0.0	134	0.0
Cercidiphyllum japonicum	0.0	112	0.0
Chamaecyparis pisifera	0.0	149	0.0
Chamaecyparis thyoides	0.0	125	0.0
Corylus colurna	0.0	68	0.0
Fraxinus americana	0.0	78	0.0
Gymnocladus dioicus	0.0	121	0.0
Larix decidua	0.0	112	0.0
Liquidambar styraciflua	0.0	129	0.0
Maclura pomifera	0.0	382	0.0
Malus hupehensis	0.0	127	0.0
Morus alba	0.0	119	0.0
Morus rubra	0.0	108	0.0
Oxydendrum arboreum	0.0	129	0.0
Picea abies	0.0	139	0.0
Pinus peuce	0.0	124	0.0
Pinus resinosa	0.0	136	0.0
Pinus sylvestris	0.0	121	0.0
Populus deltoides	0.0	135	0.0
Populus grandidentata	0.0	133	0.0
Prunus pensylvanica	0.0	121	0.0
Quercus acutissima	0.0	135	0.0
Quercus coccinea	0.0	120	0.0
Quercus macrocarpa	0.0	132	0.0
Quercus palustris	0.0	112	0.0
Quercus phellos	0.0	110	0.0
Quercus robur	0.0	118	0.0
Quercus shumardii	0.0	121	0.0
Salix babylonica	0.0	143	0.0
Styrax obassia	0.0	87	0.0
Syringa reticulata	0.0	77	0.0
Taxodium distichum	0.0	139	0.0
Tilia tomentosa	0.0	112	0.0
Tsuga canadensis	0.0	152	0.0

	errors	examples	error_amount
Ulmus glabra	12.0	118	0.101695

vi. CONCLUSION:

Using a bigger dataset with better balanced and containing different species might be useful for the predictions. Since, the picture versions have a higher resolution of 64x64 pixels that can be passed as input to the CNN in order to boost up the performance.

In the future work, when we rely on the leaf images that is showing no background should be trained with a Convolutional Neural Network. Furthermore, we were able to increase the performance for the point species that were relatively smaller in size which were available to benefit from this approach.

vii. RESEARCH REFERENCES:

1. Lee Huan Sue, Chan Seng Chee, Paul Wilkin, Remagnino Paolo. (2015). *Deep-Plant: Plant Identification with convolution neural networks*. INTERNATIONAL CONFERENCE ON IMAPE PROCESSING (ICIP). https://ieeexplore.ieee.org/document/7350839

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4. Kadir Abdul, Nugroho Edi Lukito, SusantoAdhi, Santosa Insap Paulus. (2011). *Leaf Classification Using Shape, Color, and Texture.* INTERNATIONAL JOURNAL OF COMPUTER TRENDS AND TECHNOLOGY. *https://arxiv.org/ftp/arxiv/papers/1401/1401.4447.pdf*