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Classifying soil texture images using transfer learning

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Abstract. Transfer learning is a machine learning technique which makes use of a pre-trained neural network to classify new objects. This study was conducted to evaluate the performance of Inception-v3 in classifying Soil texture images on different conditions. Specifically it achieved the following objectives 1) Identified the features of Inception-v3 and 2) Classified Soil Texture images using Inception-v3. The study used literature review to identify the features of Inception-v3. The study found that Transfer Learning comprises of two portions: a) feature mining and b) classification. Moreover, Inception-v3 highest prediction rating of a Soil texture image is 98% and 86% as the lowest. The study concludes that Transfer Learning method through the use of Inception-v3 can be used to classify Soil texture images.

1. Introduction

Today's image recognition models have millions of factors. Training models from scratch requires a lot of computing power and labeling them could be tedious. Transfer Learning (TL) is a method that cut short the processes by learning from a model that was previously trained on one task and apply the same on a new task [1]. It is a machine learning technique which makes use of a pre-trained neural network. It is a procedure where a model trains on a set of task and re-configured on another set of task [2]. Moreover, it allows a rapid performance when applying on a related task [3].

The purpose of Transfer Learning is to improve learning by maximizing information from the source task. Transfer might improve learning with the following measures: a) Use of transferred knowledge before any further learning; b) Amount of time spent on the transferred knowledge versus the time spent in learning knowledge from scratch and c; Final performance level attainable in the target task versus the final level from scratch [4].

Today, "TL" is common in predictive modeling problems using image data as input.

The said image could either be a photograph or video. For these types of problems, a deep learning model pre-trained for ImageNet Large Scale Visual Recognition Challenge (ILSVRC) can be used. ILSVRC is a classification and detection on hundreds of object categories and millions of images standard [5].

Oftentimes, the research organizations releases for reuse the final model of the ILSVRC under a permissive license. There are three models of this type that can be downloaded namely: Oxford VGG Model, Google Inception Model, and Microsoft ResNet Model.

The common version released by Google is the Inception-v3 model. The said model is an image classifier [6]. It is said to be trained for the ILSVRC using the data from 2012. It is a standard job in computer vision [1]. It is a widely-used image recognition model because of its 78.1% accuracy in prediction [6].

This study was conducted to evaluate the performance of Inception-v3 in classifying Soil texture images on different conditions. Specifically it achieved the following objectives:

1) Identified the features of Inception-v3
2) Classified Soil Texture using Inception-v3

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2. Methodology

To identify the features of Inception-v3, the author conducted a literature review by of twenty (20) Transfer Learning articles written by enthusiasts, data scientist and the tutorial developed by TensorFlow.

To classify Soil texture images, the directories were labeled as Clay, Sand and Silt. Next, images which were highly recognizable and intentionally blurred using Gaussian and Motion were placed into the directories manually as shown in figure 1, 2 and 3. 70% of data were used for training while 30% percent of the data were used for testing. Testing data were blurred using Gaussian, Pixel and Motion.

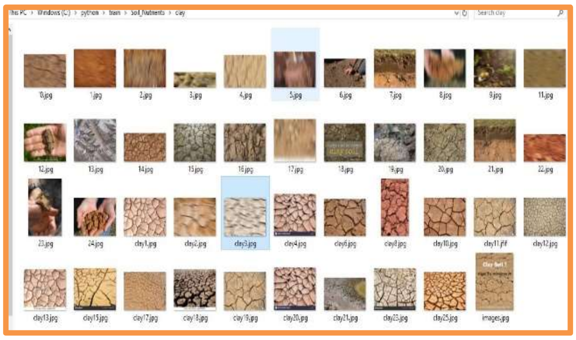

Figure 1. Clay images

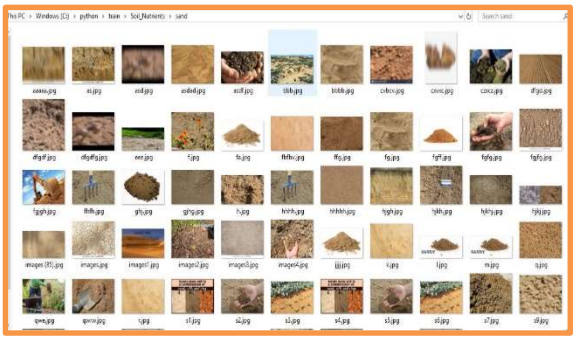

Figure 2. Sand images

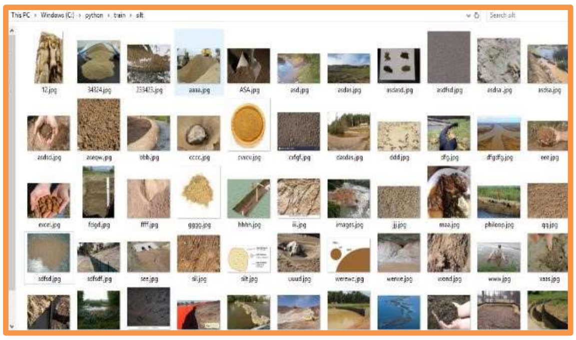

Figure 3. Silt images

3. Results and Discussions

3.1 Features of Ineception-v3

The Inception-v3 is a deep convolutional network intended for classification responsibilities on ImageNet. It has a dataset comprising of 1.2 million Red, Green, and Blue images from 1000 classes [7]. The Inception-v3 model comprises of two portions: a) feature mining layer. It is a portion where a convolutional neural network is located; and b) Classification layer. The said layer is portion where the fully-connected and softmax layers are located. The model extracts general features from input images in the first part and classifies them based on those features in the second part.

3.2 Classifying Soil Texture using Inception-v3

Firstly, to demonstrate that Inception-v3 is capable of classifying images, figure 4, 5, and 6 are hereby presented.

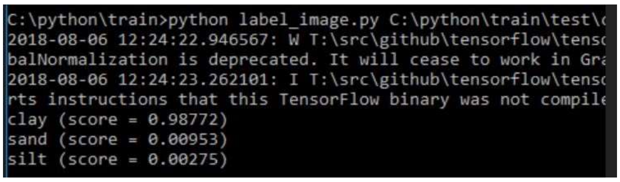

Figure 4. Clay prediction result

It can be gleaned on Fig 6 the prediction result of the classifier to a Clay image. Clay has a score of .98772, sand has a score of .00953, and silt has a score of .00275. If the values are to be converted in percentile, .98772 means 98 percent, .00953 means 0 percent, and lastly, .00275 is also 0 percent. Therefore, the classifier is 98 percent sure that the image is a clay, 0 percent sure that the image is sand and silt. This means that 98 being the highest in terms of percentile rating in the classifier prediction, the image fed is classified to be Clay.

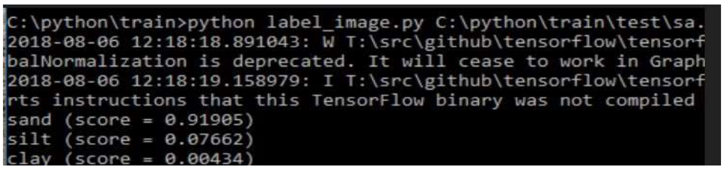

Figure 5. Sand prediction result

It can be seen on Fig 7 the prediction result of the classifier to a Sand image. Sand has a score of .91905, Silt has a score of .07662, and clay has a score of .00434. If the values are to be converted in percentile, .91905 means 92 percent, .07662 means 8 percent, and lastly, .00434 is 0 percent. Therefore, the classifier is 92 percent sure that the image is a sand, 8 percent sure that the image is silt, and 0 percent sure that the image is clay. This means that 92 percent being the highest in terms of percentile rating in the classifier, the image fed is classified to be Sand.

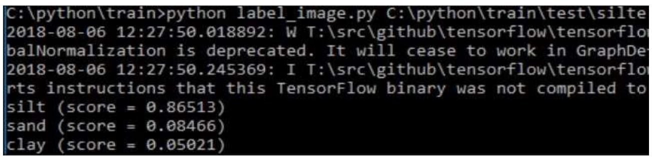

Figure 6. Silt prediction result

Fig 8 shows the prediction result to a Silt image. Silt has a score of .86513, Sand has a score of .08466, and clay has a score of .05021. If the values are to be converted in percentile, .86513 means 87 percent, .08466 means 8 percent, and lastly, .05021 is 5 percent. Therefore, the classifier is 87 percent sure that the image is Silt, 8 percent sure that the image is sand, and 5 percent sure that the image is clay. This means that 87 percent being the highest in terms of percentile rating in the classifier, the image fed is classified to be Silt.

To demonstrate the performance of Inception-v3 to images which were blurred, figure 7, 8 and 9 are hereby presented.

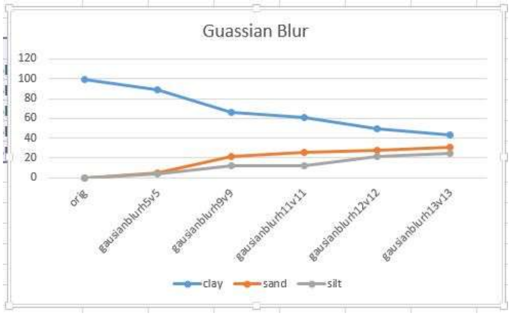

Figure 7. Gaussian Blur

Figure 7 shows the prediction pattern of model when tested with images applied with Gaussian blur. It can be seen that as the horizontal and vertical value of Gaussian blur increases, the percentile prediction rating of the Inception-v3 model of the image to be a clay decreases while its percentile prediction rating on sand and silt increases. Of the five tests, the average prediction rating of the model of the image to be clay is 61.6 percent.

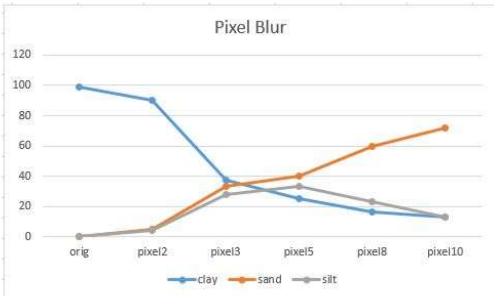

Figure 8. Pixel Blur

Figure 8 displays the prediction pattern of model when tested with images applied with Pixel blur. It can be seen that as Pixel value increases, the percentile prediction rating of the Inception-v3 model of the image to be a clay decreases while its percentile prediction rating on sand increases. Of the five tests, the average prediction rating of the model of the image to be clay is 36.2 percent.

Figure 9. Motion Blur

Figure 9 shows the prediction pattern of model when tested with images applied with Motion blur. It can be seen that as the length and angle values increases, the percentile prediction rating of the Inception-v3 model of the image to be a clay decreases while its percentile prediction rating on sand and silt increases. Of the five tests, the average prediction rating of the model of the image to be clay is 46.6 percent.

The predictions of Inception-v3 is impressive when images are clear and recognizable. In this evaluation, it has an average percentile rating of 98% prediction accuracy to images that were not altered. However, when the image is blurred with Gaussian, Pixel and Motion blurs, Inception-v3 percentile prediction decreases as shown in figure 7, 8, 9. It can hardly recognizes objects that are altered.

4. Conclusions

Transfer Learning comprises of two portions: a) feature mining and b) classification. Transfer learning using Inception-v3 is effective in classifying soil texture images. Soil Texture images are just but an example of what could be impressively done with Transfer Learning. Definitely it could be used to classify other interesting objects.

The predictions of Inception-v3 is impressive when images are clear and recognizable. However, when the image is blurred with Gaussian, Pixel and Motion blurs, Inception-v3 percentile prediction decreases. It can hardly recognizes objects that are altered.

5. References

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