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Comparison for Image Prediction with Different Sample Count and Different Number of Epoch

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Abstract: Image classification is a complex process that may be affected by many factors. There are supervised and unsupervised classification techniques. The emphasis is placed on the deep neural network classification approach and how this technique is used for improving classification accuracy. Neuropie (CNN) signs have been developed for implementing the process and relating to extensive development and events. CNN looks at the number one or more in establishing the nonlinear line and / or any of these actions. CNN is a major feature of the transparency of all intermediate and geographic areas. We provide portraits to interfaces and telephones for applications. CNN is working to fight against family members and robbers. The file size in 64x64 in all cases is a lineage at all points. The designers were 4, 4, 4 in the series that were hidden from product conversion. Applications can be used by 48x48 with 3600 pixels. Here we have detected the samples of cat and dogs with 2000 samples, 100 samples and 500 samples. Similarly for 2000 training samples we use two different optimizers ADAM and ADAGRAD and evaluate the performance of both filters.

Keywords: Convolution neural networks, dataset, training, testing, validation error

I. Introduction

Image classification is a complex process that may be affected by many factors. There are supervised and unsupervised classification techniques. The emphasis is placed on the deep neural network classification [2] approach and how this technique is used for improving classification accuracy.

Cabral et al (2011) [1] described classification of remote sensing data is used to assign corresponding labels with respect to homogeneous characteristics of groups. The main aim of classification is to discriminate multiple objects from each other within the image. It can be said that classification divides the feature space into several classes based on a decision rule. Figure 1 shows the concept of classification of data. He learning algorithms are broadly classified into supervised and unsupervised learning techniques. The distinction is drawn from how the learner classifies data. In supervised learning, the classes are predetermined. These classes can be conceived of as a finite set, previously arrived at by a human. In practice, a certain classes of data will be labeled with these classifications. M. M. Cisse (2013) [3] reviewed the classes are then evaluated based on their predictive capacity in relation to measures of variance in the data itself. Some of the examples of supervised classification techniques are Back Propagation Network (BPN)[4], Learning Vector Quantization (LVQ)[5], Self Organizing Map (SOM)[6,7], Support Vector Machine (SVM)[8,9], etc., Here we will use the convolution neural network technique for classification.

The design of the actual experience, and it is unlikely that a computer program will be analyzed by certain features of a subdivision or computer, we will encourage third parties to call this type of action. Why cannot he teach? Therefore, a person uses the use of P by a user.

At present, in order to fix this task, we have a unique E, which is in view of many images. So, many of my favorite images, business contacts, and lots of times, as well as more and more time. At this time, for this topic T and E, we use a P-called P and this measurement that we use today, and there is something we deserve. So it's the function we use here, we now find that our experience has increased, which corresponds to the number of times we translate and the number of images we were discussing here. Sin cometh down; We know that we can recognize our work and emphasize the magnitude of this work. So, as the performance increases, they become more and more accurately and, consequently, our error continues to decrease, well. Therefore, the speaker of this activity in the area T about the program challenged by this P service will be helpful and timely in this case if we are trying "for the In this regard, there is no difference in this idea in the context of the student's education. In fact, human learning is also quite similar: as human beings, when we say we learn something, the whole task of learning is to get better results and to get more and more 'knowledge. What does a person do, so with him? We get more experience and then our degree is becoming more and more high compared with a certain class of tasks. Therefore, it is the source of the general formula.

II. Methodology and Work Objectives

In our real life applications sometimes we have some images which are blurred or noisy and they are not recognizable. By choosing the appropriate deep learning tool we can predict the lost information of the image and classify it that the image belongs to which category? CNN use the following methodology to solve the problem of deep learning.. (i) Dense connections (ii) Parameter allotment equivariant, and Representations. Moreover, convolution provides a means for working with inputs of variable size. We have seen the working procedure of convolution neural network. Now we are applying the CNN for the detection of Cat vs Dog. Here we have a data set of 2000 cats and dogs (1000 images of cats and 1000 images of dogs). This data set has downloaded from “Kaggle”. We have collect validation set of 200 samples a test samples are also of 200 size. In test dataset 100 images of cats and 100 images of dogs are there. Test criteria for image detection are average loss and accuracy. Here we are also calculating the validation loss and validation accuracy. we have detected the samples of cat and dogs with 2000 samples, 100 samples and 500 samples. Similarly for 2000 training samples we use two different optimizers ADAM and ADAGRAD and evaluate the performance of both filters. .

III. Convolution neural networks frame work for image detection

We're use convolutional neural networks (CNNs) to perform our task of image detection using deep learning. We're going to try to create a deep learning CNN model for an old Kaggle completion called Dogs vs Cats. There are more than 25000 images of cats and dogs are available for training purpose and 12,500 in the test set that we have to try to label for this dissertation work. Out of which we are using a data set of 2000 samples for training purpose and choose 200 images (100 of each) for testing purpose and finally checked that how our network is performing. Design the 2D convolution neural networks having the input shape of size 64 x64 x 3 and the activation function is Relu. Choose the pooling size of 2x2 and taking the max pooling. Add a second convolution neural network of size 32x3x3. In the second layer of network the activation function is Relu and the pooling sixe is 2x2 remain same. Flattening is the process to flatten the CNN architecture. The output dimension of the fully connected network is the 128 and activation function is relu. Finally we take the single output and output activation function is 'sigmoid'. For the compilation of the network we have ‘adam’ is the optimization algorithm and the loss function is 'binary cross entropy'. We have choose the target size is (64, 64), batch size is 32 and Class mode is 'binary'. Target size and test size parameters are keeping same.

IV. Python libraries and setup for deep learning program

Here we are using the following python libraries.

- KERAS
- TENSORFLOW
- THEANO

Libraries of KERAS used in program

- Sequential
- Convolution2D
- MaxPooling2D

- Flatten
- Dense
- PlotLossesKeras

V. Output Result and discussions

To run the program we have choose the 2000 samples per epoch and there are total 15 epoch in our program. For the above parameter the executed results are as follows.

After completing the execution of the program the conclusive results are shown in table5.1

By above table our conclusion is as follows

- We choose a sample size of 2000 images
- We choose 200 images for testing and also for validation
- We choose 15 epoch and choose 6000 iteration in each epochs.
- We got the validation accuracy is 72%
- We got the Test accuracy is 99.88%
- As we have reduce the sample size we found that training of the model is degraded and the testing accuracy reduced as the sample size is reduced.
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Here test accuracy is much higher than the validation accuracy. Test accuracy is 99.88 % which reflect the higher degree of precision of network. It may be because of the over fitting of the network. But finally we our designed network is giving the 99.88% prediction result and it clearly classify the difference between.

VI. Conclusion

Test criteria for image detection are average loss and accuracy. Here we are also calculating the validation loss and validation accuracy. For input layers we choose the activation function RELU and for output layer we choose the SIGMOID as activation function. We have ‘ADAM’ is the optimization algorithm and the loss function is 'binary cross entropy. After completing the execution of the program we found that test accuracy of the network is 99.88% and the validation accuracy is 72%. The output result is approximately 100% correct, which implies that our network is over fitted. But if we choose the same network for same application it will work with same accuracy. Adam is better than the ADAGRAD

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