Image Classification Using Deep Learning Methodologies

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Abstract- Deep learning techniques are becoming the main approaches to natural signal processing and information processing, such as classification of images, recognition of voice. Deep learning is a technology that is influenced by human brain activity. Throughout deep learning, artificial neural networks analyze large datasets to automatically discover underlying patterns throughout unstructured data such as images, sound, video, and text without human intervention. Convolution neural networks (CNN) are becoming very common for deep learning image classification; on many of the image classification datasets, CNN performs better than human subjects. This paper uses python for binary image classification to deploy a deep learning convolution network based on keras and tensor flow. In this analysis, a large number of different images are used for image classification, which includes two types of animals, cat and dog. On the CPU system, four different CNN structures are contrasted with four different classifier and activation functions combinations.

Keywords- Deep Learning, Convolution Neural Network, Keras, Tensor flow, Classification.

I. INTRODUCTION

Deep learning is a technology that is influenced by human brain activity. Artificial neuron networks examine large data set in deep learning to automatically detect underlying patterns without human intervention. 9] The machine learns how to identify pictures, text and sound in deep learning. The machine is equipped with large image datasets and then the pixel value of the image is changed to an internal representation where patterns on the input image can be identified by the classifier. [4] The use of machine learning methods is central to deep learning for image classification.

CNN have fewer connection and hyper parameter that make CNN model easy to train and perform slightly worse than other models. [7] In this paper, a deep learning convolution neural network based on keras and tensor flow is deployed using python for binary image classification. In this study, 10000 different images, which contains two types of animals, namely cat and dog are used for classification. Fig. 1.1 shows the example of dataset. In this study, 10000 different images, which contains two types of animals, namely cat and dog are used for classification. Fig. 1.1 shows the example of dataset.

Fig.1: Dataset Sample

Four different CNN structures with different classification schemes and activation features, namely softmax, sigmoid and Relu functionality, Tanh activation are being compared on CPU device. We use the Tensor flow and Keras software for computing and processing. Tensor flow is one of the libraries used in deep learning to identify pictures. Tensor flow is an open source software library for numerical computing created by Google in 2015. Keras is a python-written open source neural network library that can run on top of MxNet, Deep Learning, Tensor flow, and Theano.It was designed to allow quick testing of deep neural networks. A general introduction to deep learning, tensor flow, keras and data sets can be found in the first section of this article. The second section includes basic CNN theory, classifications and functions for activation. The third section of this article includes a literature review,

methodologies for study and the final section contains experimental arrangements and performance.

II. RELATED DATA

Neural Network: Neural Network receives an input and transmits it through several layers. Each secret layer has neurons, in which every neuron in the previous layer is completely connected with the neurons. Each layer operates independently in one layer. The final layer in the neural network, which represents the class to which the input belongs is called "output layer."

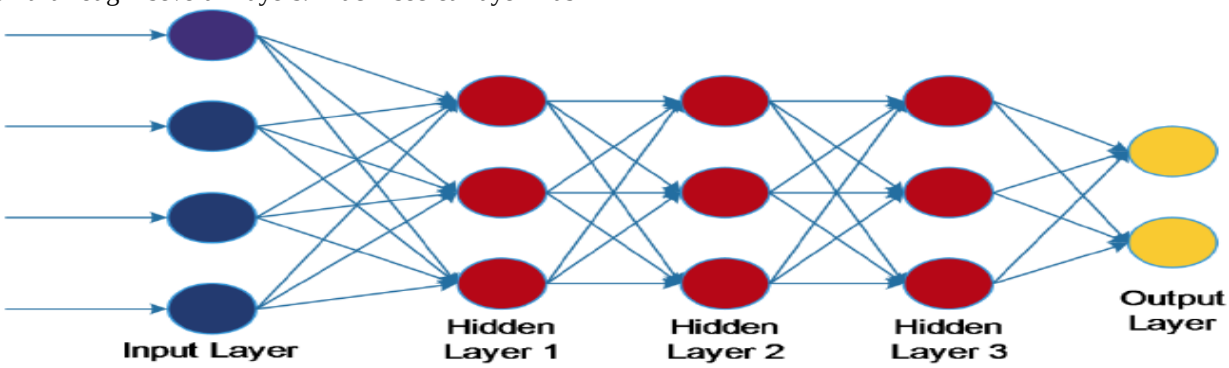

Fig.2: Neural Network Architecture

CNN: The CNN is a special feeding artificial neural network inspired by visual neurotic cortex. CNN is a special feeding network. In CNN, only a small layer before the neuron is connected to the neuron, instead of all of the neurons, so that CNN carries fewer weights and also less neuron.

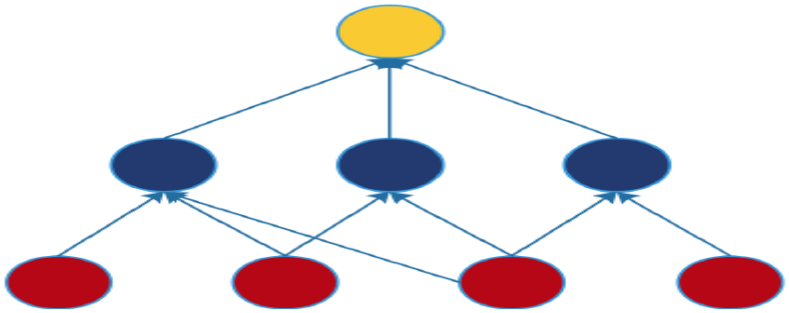

Fig.3: Convolutional Neural Network

Relu Activation Function: The deep learning feature Relu F(x) = max (x, 0), mostly used for hidden layers. A modified linear unit generates "0" when the input is below "0," while "otherwise" is the actual output. Relu is the easiest non-linear function to trigger. Work has shown that Relu tests for large network testing are much quicker. Some frameworks such as tensor flow make Relu on cloaked layers easy to use.

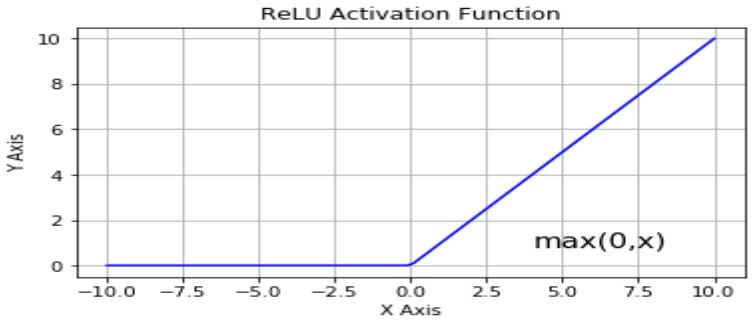

Fig.4: Relu activation function

Tanh activation function: Tanh function [tanh(x) = (ex - e-x) / (ex + e-x)] produces output in range of -1 to +1. It is continuous function, which produces output for every „x" value.

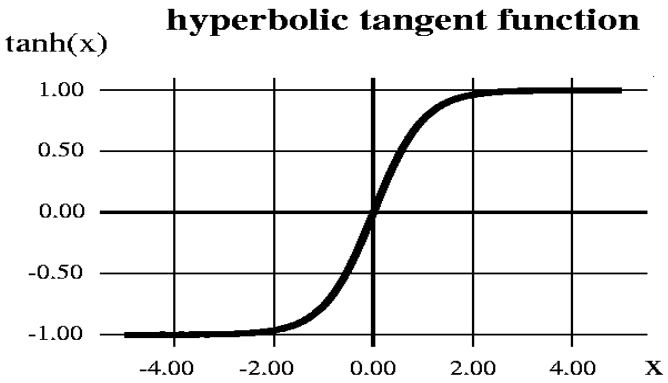

Fig.5: Tanh activation function

III. LITERATURE REVIEW

In this paper, the Deep-Learning Algorithm is implemented using the Python and tflearn for the image classification, in which two different structures of the CNN are used-two and five layers-and it concludes that the CNN is used for the CNN classification and is based on the convolutions of the neural network. Hasbi Ash Shiddieqy, Farkhad Ihsan Hariadi, Trio Adiono "Blur Image Classification based on Deep Learning," Rui Wang, Wei Li, Runnan Qin, JinZhong Wu,The experimental results show that SFA's performance in classification accuracy is equivalent to Alexnet and superior to other classification methods, which is 96.99percent for a simulated blur dataset and 92.75percent for a natural blur dataset. In this papers a modified CNN architecture, that combines multiple convergence and pool layers, is proposed by Sameer Khan and Suet-Peng Yong as a deeper learning structure to classify a medical imaging of anatomy object.It has shown that the proposed CNN function representation is above the three basic architectures for the classification of medical image anatomies. The anatomy classification has been done. This paper proposes a deep learning algorithm to distinguish photovoltaic events from others and shows that a deep convolutionary neural network can achieve a higher classification accuracy compared to a fully connected model. This paper proposes a deeper learning algorithm to differentiate photovoltaic events from other grid events.

IV. PROPOSED METHODOLOGY

The proposed methodology flow diagram is illustrated in fig. The 4th of June. Each block is clearly marked and represents steps of processing. We compare four different CNN structures using that methodology, with four different classification and activation combinations.

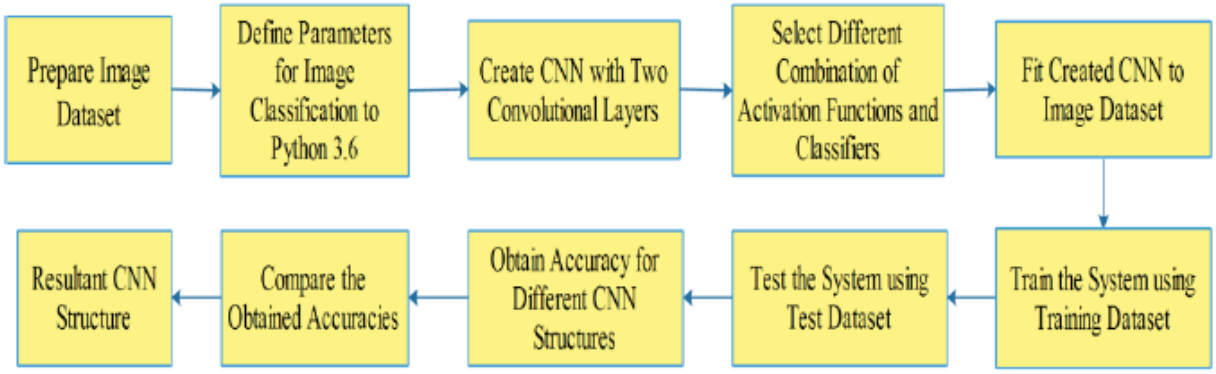

Fig.6: Proposed Methodology

In the first phase image dataset is created, there are four files in the dataset containing 10,000 images of dogs and cats in which 8,000 images are used for training and 2,000 images are used for research. Defines parameters for python image classification in the second step. In the third step, we build CNN with two convolutionary layers that we select for comparison purposes different combinations of activation functions and classifiers. We fit the generated CNN into the

image dataset and Train in the next steps, respectively testing the system with training and test datasets.Finally, we obtain the accuracy for different CNN structures and compare these accuracies for performance measurement, and then get the resultant CNN structure.

V. RESULTS OBSERVED

In this paper, in python 3.6 on the CPU framework, we perform experiments on windows 10 and build the CNN model based on keras and tensor flow libraries. Figure 5.1 displays the CNN model used for experiments. This model consists mainly of four layers including layers that are convolutionary, pooling, flattening, and completely connected.

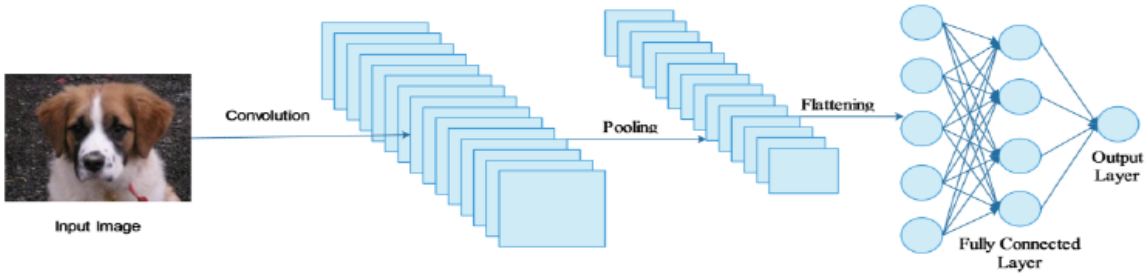

Fig.7: Convolutional neural network model

The size of the input image is set at 64* 64 pixels with 3 channels (RGB) for convolution layer. We use 32 3* 3 pixel size filters to extract the features from the image. We use a 2* 2 pixel size window to compress the original image size for further processing for pooling layer. Two activation functions are used for output assessment, namely Relu (Rectified linear unit), Tanh (Hyperbolic tangent) and two Softmax, Sigmoid, classifiers. In experiment, we use the combination of these activation functions and classifiers and evaluate what combination provides better accuracy for the classification of binary images.

Table 5.1 Combinations of activation function and classifier

Serial number	Activation Function	Classifier
1.	Softmax	Relu
2.	Sigmoid	Relu
3.	Softmax	Tanh
4.	Sigmoid	Tanh

After implementing all above parameters in python, we train and test CNN model using training and test datasets, and then obtain accuracy for different CNN structures. After then we compare the obtained accuracies and find a CNN structure with higher accuracy.

VI. CONCLUSION

Deep learning is a method of learning for data analysis and predictions, and nowadays it is also becoming very common for problems with image classification. In this paper, using python for binary image classification, a deep learning neural network based on keras and tensor flow is deployed. In this study, we compare on CPU system four different CNN structures with different classifier and activation function combinations. With experiments, we obtained results for each combination and observed that Relu activation function and Sigmoid classifier combination for binary image classification provide better classification accuracy than any other combination of activation function andSigmoid classifier gives better classification accuracy for binary image classification.

VII. REFERENCES

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