

COMPARATIVE ANALYSIS AND STUDY OF DIFFERENT CONVOLUTIONAL NEURAL NETWORK STRUCTURES FOR IMAGE CLASSIFICATION

By Pooja Mudgil, Nikunj Gupta, Vidisha Dahiya, Priya Agrawal,

Abstract: Deep learning technologies are becoming the major approaches for natural signal and information processing, like image classification and speech recognition. Deep learning is a technology that is inspired by the functioning of human brain. In deep learning, networks of artificial neurons analyze large dataset to automatically discover underlying patterns, without human intervention, deep learning identify patterns in unstructured data such as, images, sound, videos and text. Convolutional neural networks (CNN) become very popular for image classification in deep learning; CNN's perform better than human subjects on many of the image classification datasets. In this paper, a deep learning convolutional neural network based on keras is deployed using python for multiclass image classification. In the study, a large number of different images, which contains ten species of monkey, are used for image classification. The structures of CNN are compared on CPU system, with two different combinations of classifiers and activation functions. It is shown that, for Multi-class image classification combination of softmax classifier and Relu activation function gives higher classification accuracy than any other combination of classifier and activation function.

I. INTRODUCTION

Deep learning technology is inspired by the functioning of human brain. In deep learning, networks of artificial neurons analyze large dataset to automatically discover underlying patterns, without human intervention. In deep learning, a computer learns to classify images, text, video and sound. The computer is trained with large image datasets and then it changes the pixel value of the picture to an internal representation, where the classifier can detect patterns on the input image. Deep learning for image classification has become essential in use of machine learning method to increase performance of the application of neural networks to learning tasks that contains more than one hidden layers. Deep learning is part of a broader family of machine learning methods based on learning data representation, as opposed to hard code machine algorithms. One of the most frequently used deep learning method for image classification is the

convolutional neural network (CNN). CNN learns directly from the image dataset, thus eliminating manual feature extraction. Common problem with image classification using deep learning is low performance because of over fitting. To increase the performance and prevent over fitting large dataset and models used. CNN have fewer connections and hyper parameters that make CNN models easy to train and perform slightly worse than other models. In this paper, a deep learning convolutional neural network based on keras is deployed using python for multi-class image classification. In this study, approximate 1400 different images, which contain ten species of monkey, namely as follows are used for classification:

aloutta_palliata(mantledhowler),erythrocebus_patas (patas_monkey), cacajao_calvus (bald_uakari),macaca_fuscata(Japanese_macaque), cebuella_pygmea (pygmy marmoset),

cebus_capucinus (white_headed_capuchin),
mico_argentatus (silvery marmoset),
saimiri_sciureus (common_squirrel_monkey),
aotus_nigriceps (black_headed_night_monkey),
trachypithecusjohnii (nilgiri_langur).

In this paper, two different structures of CNN are compared on a CPU system, with combination of different classifiers and activation functions, namely softmax classifiers, Relu and Tanh activation functions. For computation and processing we are using Tensorflow and Keras framework. Tensorflow is one of the libraries used for image classification in deep learning. Tensorflow is an open source software library developed by the google in 2015 for numerical computations. Keras is an open source neural network library written in python, it is capable of running on top of MxNet, Deep learning, Tensorflow, and Theano. It is designed to enable fast experimentation with deep neural networks. The first section of this paper contains general introduction about deep learning, Tensorflow, keras and dataset. Second section contains basic theory about CNN, classifiers and activation functions. Third section of this paper contains literature review, research methodology, and final section contains experimental setup and results.

II. BASIC THEORY

A. Neural Network: Neural Network receives an input and passes it through a number of hidden layers. Each hidden layer has set of neurons, where each neuron is fully connected to all other neurons in the previous layer. Each layer in a single layer functions independently. The last layer in neural network is called “output layer”, which represents the class to which input belongs.

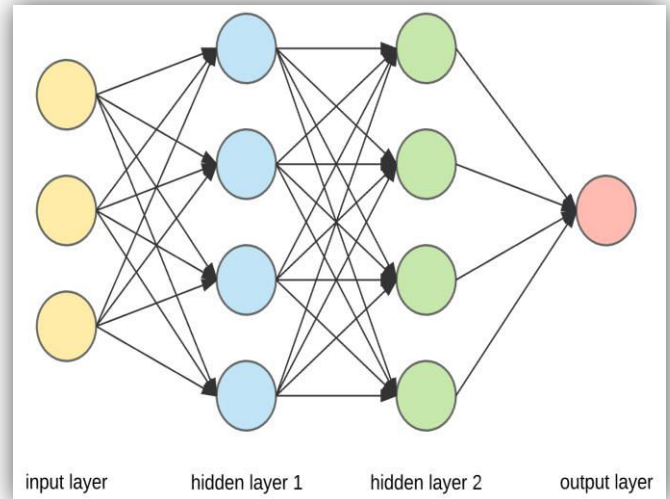


Fig. 2.1 Neural Network Architecture

B. Convolutional Neural Network (CNN): Convolutional Neural Network is a special type of feed-forward artificial neural network, which is inspired by visual cortex. In CNN, the neuron in a layer is only connected to a small region of the layer before it, instead of all the neurons in a fully connected manner, so CNN handles fewer amounts of weights and also less number of neurons.

C. Relu Activation Function: Relu function $F(x) = \max(x, 0)$, is mostly used deep learning activation function. A rectified linear unit has output “0” if the input is less than “0”, and raw output ‘otherwise’. Relu is the simplest non-linear activation function. Researches have shown that Relu result is much faster for large networks training. Most frameworks like Tensorflow make it simple to use Relu on hidden layers.

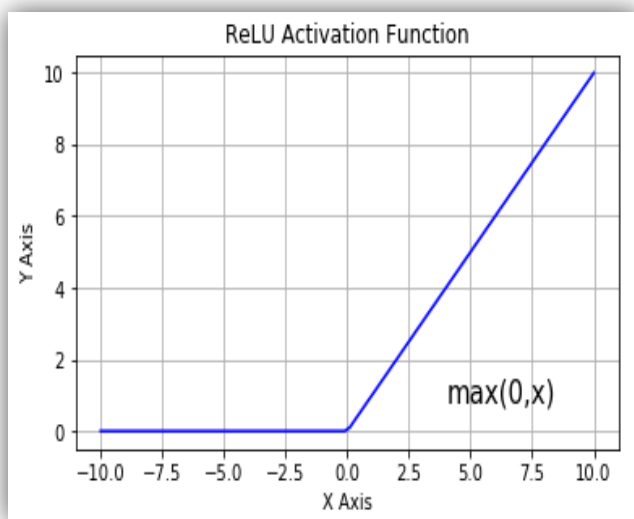


Fig. 2.2 ReLU Activation Function

D. Tanh activation function: Tanh activation function $[\tanh(x) = (e^x - e^{-x}) / (e^x + e^{-x})]$ produces output range of -1 to +1. It is a continuous function, which produces output for every 'x' value.

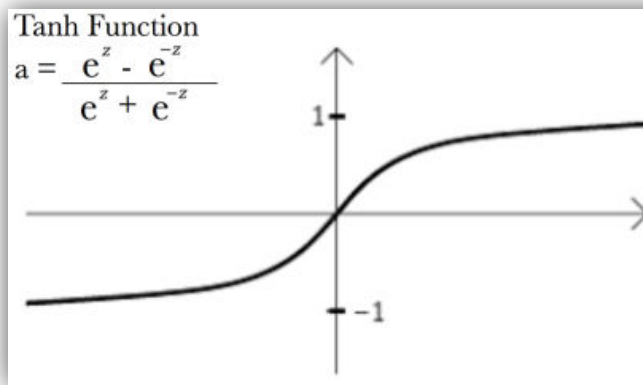


Fig. 2.3 Tanh Activation Function

E. Softmax classifier: The softmax classifier $[F(x) = e^{x^{(i)}} / \sum_{j=0}^k e^{x_k^j}]$ squashes the outputs of each unit to be between 0 and 1, just like a sigmoid classifier. But it also divides each output such that the total sum of the outputs is equal to 1. The output of the softmax classifier is

equivalent to a categorical probability distribution, it tells you the probability that any of the classes are true. Softmax classifier is used for multiple data classification.

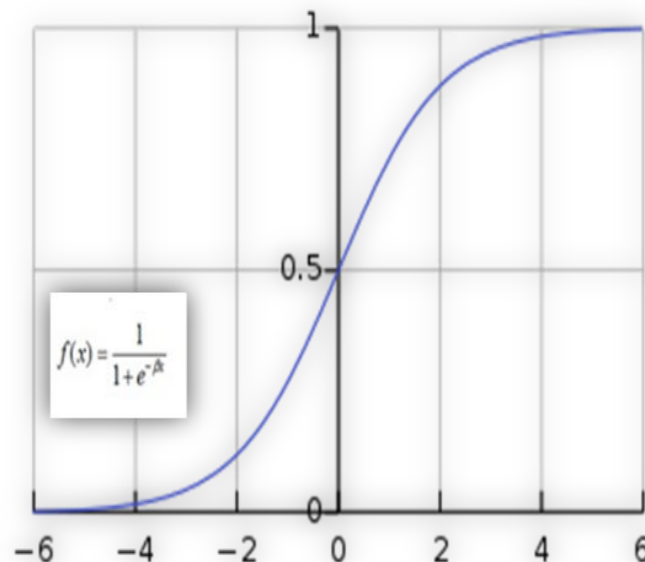


Fig. 2.4 Softmax Classifier

III. LITERATURE REVIEW

Deepika Jaswal, Sowmya V, K P Soman "Image Classification Using Convolutional Neural Network". In the study of this paper we observed that the main objective is to apply the concept of a Deep Learning Algorithm namely, Convolutional Neural Network (CNN) in image classification. The algorithm was tested on various standard datasets, like remote sensing data of aerial images (UC Merced Land Use Dataset) and scene images from SUN database. The performance of the algorithm was evaluated on the basis of the quality metric known as Mean Squared error (MSE) and the classification accuracy.

Chen Wang yang Xi "Convolutional Neural Network for Image3 Classification". From the study of this paper we observed that the theory of behind back-propagation was deduced and

then applied to the neural network classifier to solve a tough image classification problem CIFAR-10.

Hasbi Ash Shiddieqy, Farkhad Ihsan Hariadi, Trio Adiono “Implementation of Deep-Learning based Image Classification on Single Board Computer”. In the study of this paper we observed that a deep-learning algorithm based on convolutional neural-network is implemented using python and tflearn for image classification, in which two different structures of Convolutional Neural Networks (CNNs) are used, namely with two and five layers and it was concluded that the CNN with higher layer performs classification process with much higher accuracy.

Sameer Khan and Suet-Peng Yong “A Deep Learning Architecture for Classifying Medical Image of Anatomy Object”. From the study of this paper we observed a modified CNN architecture that combines multiple convolution and pooling layers for higher level feature learning is proposed. In this study, medical image anatomy classification has been carried out and it showed that the proposed CNN feature representation outperforms the three baseline architectures for classifying medical image anatomies.

IV. RESEARCH METHODOLOGY

The flow diagram of proposed methodology is shown in following figure. Each block of proposed flow diagram is clearly labeled and represents processing steps. Using this methodology, we compared two different structures of CNN with two different combinations of classifiers and activation functions. In the first step, image dataset is prepared, there are two files in dataset, which contains 1400 images of monkeys belonging to 10 different species, where 1100images are used for training and 300 images are used for testing purpose. In the second step, we define parameters for image classification to python. In the third step, we create CNN with two

convolutional layers then we select different combination of activation functions and classifiers for comparison purpose. In the next step, we fit the created CNN to image dataset and train, test the system with training and test datasets respectively. Finally, we obtain the accuracy for different CNN structures and compare these accuracies for performance measurement, and then get the resultant CNN structure.

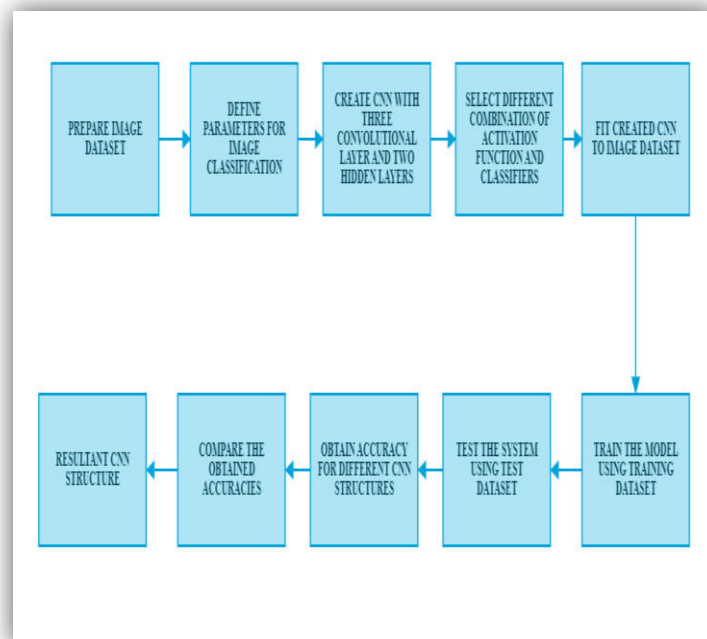


Fig. 4.1 Proposed Methodology

V. EXPERIMENTAL SETUP

In this paper, we performed the experiment on Windows 10 in python 3.6 on CPU System and create the CNN model based on keras and Tensorflow libraries. The CNN model used for the experiments is shown in following figure. This model mainly consists of four layers including convolutional, pooling, flattening and fully connected layers.

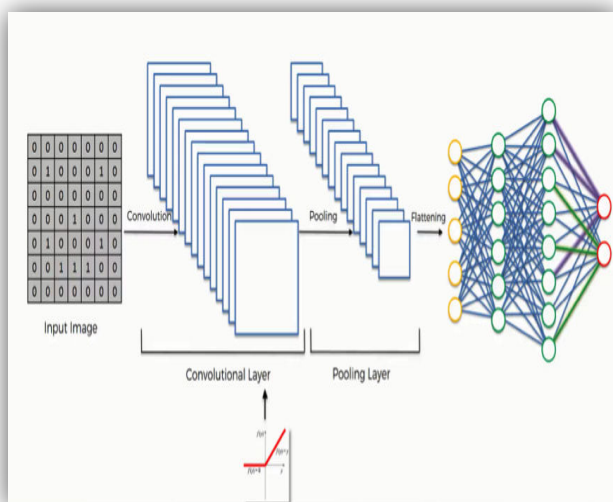


Fig. 5.1 Convolutional Neural Network

For convolutional layer, the size of input image is set to 150*150 pixels with 3 channels (RGB). To extract the features from the image we use 32 filters of size 3*3 pixels. For pooling layer, we use a window of size 2*2 pixels, which is used to compress the original image size for further processing. For performance measurement we use two activation functions namely, Relu (Rectified Linear Unit), Tanh (Hyperbolic tangent), and classifiers namely Softmax.

In the experiment, we use combination of these activation functions and classifiers, and analyze that which combination gives better classification accuracy for multi-class image classification.

Table 5.1 Combination of Activation Function and Classifier

| S.No. | Activation Function | Classifier |
|-------|---------------------|------------|
| 1. | ReLU | Softmax |
| 2. | Tanh | Softmax |

After implementing all the 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. RESULT

Table 6.1 Obtained accuracies with different combinations of activation function and classifier

| S.No. | Activation Function | Classifier | Accuracy |
|-------|---------------------|------------|----------|
| 1. | ReLU | Softmax | 85.29% |
| 2. | Tanh | Softmax | 84.19% |

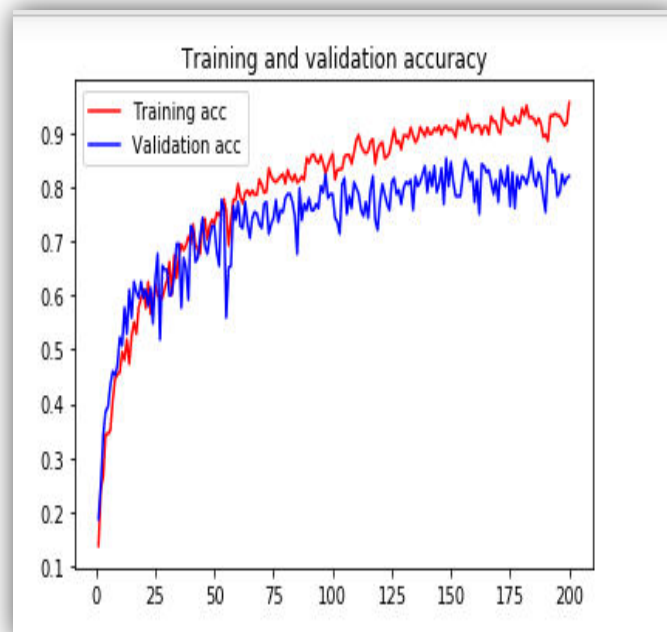


Fig. 6.1(a) Accuracy with ReLU and Softmax

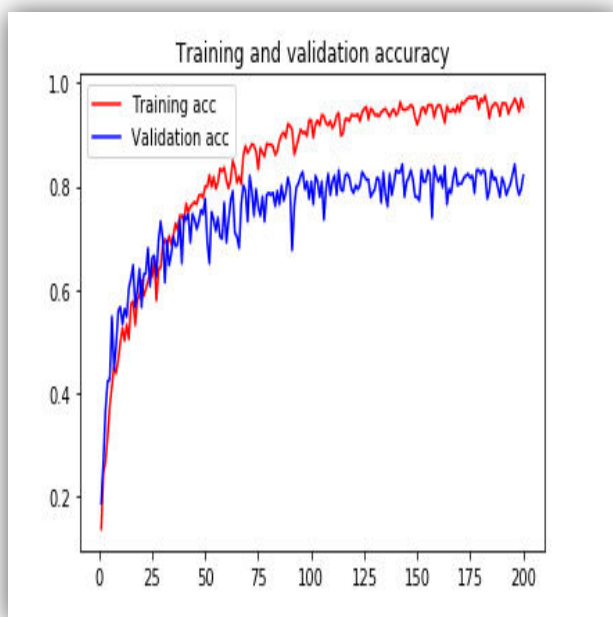


Fig. 6.1(b) Accuracy with Tanh and Softmax

We compare accuracies of graph 6.1(a) and 6.2(b) and we found out that CNN with combination of ReLU activation function and softmax classifier – graph (a) gives better accuracy.

VII. CONCLUSION

Deep learning is a learning method for data analysis and predictions, now-a-days it also has become very popular for image classification problems. In this paper, a deep learning convolutional neural network based on keras and Tensorflow is deployed using python for multi-class image classification. In this study, we compared two different structures of CNN on CPU system, with different combinations of classifier and activation function. With this experiment, we obtained results for ReLU and sigmoid combination and observed that for multi-class image classification, ReLU activation function and Softmax classifier combination gives classification accuracy of 85.29% which is

better than the other combination of activation function and classifier.

So, we conclude that on the stated CPU system, ReLU activation function and Softmax classifier gives better classification accuracy for multi-class image classification.

ACKNOWLEDGMENT

We would like to thank Ms. Pooja Mudgil, Assistant Professor, IT Department, Bhagwan Parshuram Institute of Technology, Delhi for her motivation without which we would not be able to write this paper. We are also grateful to our family and friends for their support.

REFERENCES

- [1] Deepika Jaswal, Sowmya.V, K.P.Soman "Image Classification Using Convolutional Neural Network", International Journal of Advancements in Research & Technology, Volume 3, Issue 6, June-2014 1661 ISSN 2278-7763.
- [2] Samer Hijazi, Rishi Kumar, and Chris Rowen, IP Group, Cadence "Using Convolutional Neural Networks for Image Recognition".
- [3] Chen Wang, Yang Xi "Convolutional Neural Network for Image Classification".
- [4] Muthukrishnan Ramprasath, M. Vijay Anand, Shanimugasundaram Hariharan "Image Classification using Convolutional Neural Network", International Journal of Pure and Applied Mathematics Volume 119 No. 17 2018, 1307-1319 ISSN: 1314-3395.
- [5] Hasbi Ash Shiddieqy, Farkhad Ihsan Hariadi, Trio Adiono "Implementation of Deep-Learning based Image Classification on Single Board Computer", International Symposium on Electronics and Smart Devices (ISESD), ISBN 978-1-5386-2779-2, pp. 133-137, 2017.

- [6] Sameer Khan and Suet-Peng Yong “A Deep Learning Architecture for Classifying Medical Image of Anatomy Object”, Annual Summit and Conference, ISBN 978-1-5386-1543-0, pp. 1661-1668, 2017.
- [7] Rui Wang, Wei Li, Runnan Qin and JinZhong Wu “Blur Image Classification based on Deep Learning”, IEEE, ISBN 978-1-5386-1621-5 pp. 1-6, 2017.