An Empirical Analysis of the Performance of Convolutional Neural Network for Object Identification

Binita Roshima Hinz[1], Dr. Biswarup Samanta[2]
[1]Research Scholar, Department of CSE, Sarala Birla University, Ranchi, India
Email – hinzroshima.bb@gmail.com
[2]Associate Professor, Department of CSE, Sarala Birla University, Ranchi, India
Email – biswarup.samanta@sbu.ac.in

ABSTRACT- This abstract provide concept of a Deep Learning algorithm, viz.; Convolutional neural networks (CNN) in image classification. The algorithm is 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 is evaluated based on the quality metric known as Mean Squared Error (MSE) and classification accuracy. The experimental result analysis based on the quality metrics and the graphical representation proves that the algorithm (CNN) gives fairly good classification accuracy for all the tested datasets. This paper presents an empirical analysis of the performance of popular convolutional neural networks (CNNs) for identifying objects. The most popular convolution neural networks for object detection and object category classification from images are Alex Nets, GoogLeNet, and ResNet50. A variety of image data sets are available to test the performance of different types of CNN's. The commonly found benchmark datasets for evaluating the performance of a convolutional neural network are an ImageNet dataset, and CIFAR10, CIFAR100, and MNIST image data sets. This study focuses on analyzing the performance of three popular networks: Alex Net, GoogLeNet, and ResNet50. We have taken three most popular data sets ImageNet, CIFAR10, and CIFAR100 for our study, since, testing the performance of a network on a single data set does not reveal its true capability and limitations. It must be noted that videos are not used as a training dataset; they are used as testing datasets. Our analysis shows that GoogLeNet and ResNet50 are able to recognize objects with better precision compared to Alex Net. Moreover, the performance of trained CNN's vary substantially across different categories of objects and we, therefore, will discuss the possible reasons for this.

Key words - Deep Learning, CNN, Object detection, Object classification, Neural network.

1.INTRODUCTION

Now a day's internet is filled with an abundance of images and videos, which is encouraging the development of

search applications and algorithms that can examine the semantic analysis of image and videos for presenting the
user with better search content and their summarization. There have been major breakthrough in image labeling, object detection, scene classification, areas reported by different researchers across the world. This leads to making it possible to formulate approaches concerning object detection and scene classification problems. Since artificial neural networks have shown a performance breakthrough in the area of object detection and scene classification, specially convolutional neural networks (CNN), this work focuses on identifying the best network for this purpose. Feature extraction is a key step of such algorithms. Feature extraction from images involves extracting a minimal set of features containing a high amount of object or scene information from low - level image pixel values, therefore, capturing the difference among the object categories involved.

Some of the traditional feature extraction techniques used on images are Scale-invariant feature transform (SIFT) , histogram of oriented gradients (HOG) , Local binary patterns (LBP) , Content-Based Image Retrieval (CBIR) , etc. Once features are extracted their classification is done based on objects present in an image. A few examples of classifiers are Support vector machine (SVM), Logistic Regression, Random Forest, decision trees etc.

A few key points to understand about CNNs for classification:
CNNs can learn to recognize patterns and features in images through the use of convolutional layers, which apply a set of filters to the input data to detect specific patterns.
CNNs are able to automatically learn spatial hierarchies of features, starting with simple patterns such as edges and moving on to more complex patterns as the layers get deeper. This hierarchical feature learning is particularly well-suited to image classification, where the visual features of an image can vary widely.
Some CNN architectures are able to process images in real-time, making them suitable for applications where quick classification is important, such as in self-driving cars or security systems.
CNNs have achieved state-of-the-art performance on many image classification benchmarks and are widely used in industry and research.

2.PROPOSED METHODOLOGY

CNN Image Classification with Keras and CIFAR-10
Step 1: The first step is to choose a dataset for the image classification task. There are many publicly available datasets, such as CIFAR-10, CIFAR-100, and MNIST, that can be used for training and testing the CNN. For this will be using the CIFAR-10 dataset, which consists of 60,000 32×32 color images across ten classes, with 6,000 images in each class.

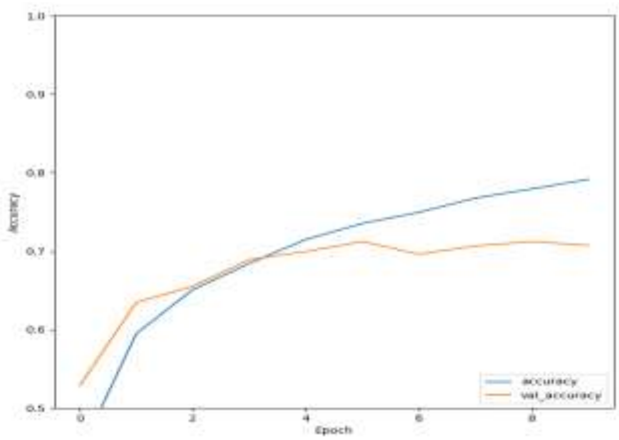
Step 2: Prepare the Dataset for Training
Next, will load the CIFAR-10 dataset and prepare it for training. This involves splitting the dataset into training and test sets, and then normalizing the pixel values of the images to the range of 0 to 1.

Step 3: Create Training Data and Assign Labels use the training set of images and labels to train the CNN. The flow_from_directory() method from the keras.preprocessing.image module to create a generator that will read the images from the directory and apply data augmentation.Assign labels to the data by converting the categorical class labels to one-hot encoded vectors.

Step 4: Define and Train the CNN ModelDefine the CNN architecture using the Keras library. The model will consist of several convolutional layers followed by max pooling layers, and a fully connected layer with a softmax activation function. Then train the model using the *fit()* method.

Step 5: Test the Model's Accuracy
Finally, evaluate the trained model on the test set using the evaluate() method and calculate the accuracy of the model.

charts



CNN Image Classification in TensorFlow :-
step 1: Upload Dataset

The MNIST dataset is available with scikit

Create a train/test set- split the dataset with train_test_split

Scale the features-Finally, scale the feature with MinMaxScaler as shown in the below image classification using TensorFlow CNN example.

Step 2: Input layer
This step reshapes the data. The shape is equal to the square root of the number of pixels. For instance, if a picture has 156 pixels, then the shape is 26×26. You

need to specify if the picture has colour or not. If yes, then you had 3 to the shape- 3 for RGB-, otherwise 1

Step 3: Convolutional layer
.Next, you need to create the convolutional layers. You apply different filters to allow the network to learn important feature. You specify the size of the kernel and the amount of filters.

Step 4: **Pooling layer**
In the third step, you add a pooling layer. This layer decreases the size of the input. It does so by taking the maximum value of the a sub-matrix. For instance, if the sub-matrix is [3,1,3,2], the pooling will return the maximum, which is 3.

Step 5: Add Convolutional Layer and Pooling Layer
In this step, you can add as much as you want conv layers and pooling layers. Google uses architecture with more than 20 conv layers.

Step 6: Dense layer
The step 6 flatten the previous to create a fully connected layers. In this step, you can use different activation function and add a dropout effect.

Step 7: Logit Layer
The final step is the prediction.

Comparison of Various Image Classification Methods

Common Data Sets for Image Classification
The following are several commonly used classification data sets, with increasing difficulty in classification.

1. MNIST [**262**]: The image resolution of this dataset is a 28 × 28 grayscale image. Each picture has 784-pixel grayscales with an integer value of [0, 255]. It contains a training set of 60,000 examples and a test set of 10,000 examples. And it is composed of handwritten numbers (0–9) from 250 different people, see Figure(a).
2. CIFAR-10 [**263**]: The image resolution of this dataset is 32 × 32 RGB images, including 60,000 images, which are divided into 10 categories and independent of each other. Each category contains 6000 images, including 5000 training images and 1000 test images, see Figure (b).
3. CIFAR-100 [**263**]: The dataset image resolution is 32 × 32 RGB images, including 60,000 images, divided into 100 categories and independent of each other. Each category includes 500 training images and 100 test images. Compared with the data set CIFAR-10, this dataset divides 100 classes into 20 super classes, see Figure(c).
4. ImageNet [**101**]: The dataset has approximately 1.5 million annotated images, at least 1 million images provide border annotations, and contain more than 20,000 categories, and each category has no less than 500 images. Beginning in 2010, the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) held every year will end after 2017. Competition items include image classification, target positioning, target detection, video target detection, scene classification, and scene analysis. The data used in ILSVRC is only a part of the ImageNet dataset, in Figure(d).

Figure 1-: Image classification

3.Conclusions
In this survey, here not limited to a systematic summary of mainstream CNN models (such as architecture and characteristics), but also related introductions to non-pure CNN methods, mixed models, and training strategies. These methods are shining points in the development of image classification field.
CNN image classification has revolutionized the field of computer vision, enabling accurate recognition of objects within images. With its ability to

automatically learn and extract complex features, CNNs have become a powerful tool for various applications.

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