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A Review Paper on Image Classification for CIFAR-10 Dataset

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***Abstract*— In recent year, with the speedy development in the digital contents identification, automatic classification of the images became most challenging task in the fields of computer vision. Automatic understanding and analysing of images by system is difficult as compared to human visions. Several research have been done to overcome problem in existing classification system, but the output was narrowed only to low level image primitives. However, those approach lack with accurate classification of images. In this paper, we propose uses deep learning algorithm to achieve the expected results in the area like computer visions. Our system present Convolutional Neural Network (CNN), a machine learning algorithm being used for automatic classification the images. Image classification requires the generation of features capable of detecting image patterns informative of group identity. The objective of this study was to classify images from the public CIFAR10 image dataset by leveraging combinations of disparate image feature sources from deep learning approaches.**

***Keywords*— artificial neural networks; cifar-10; classification; image; convolutional neural networks; machine learning.**

I.INTRODUCTION

The ability to classify things correctly requires many hours of training. People get things wrong many times, until eventually, they get it right. The same structure applies to machine learning. By using a high-quality set of data, deep learning can classify objects comparatively well or even better than humans can. With achieving utterly accurate image classifier, some of the monotonous jobs could be replaced by machines, so that humanity could focus on the most enjoyable activities.

Achieving high classification rate on a set of tiny images tends to be difficult, as some of the features that identify specific class are barely visible even to human eyes. The area of computing vision is under constant development in order to be the most effective in investigating and successfully classifying every kind of object. This type of analysis could advance, for example, the usefulness of autonomous cars, which tend to be ineffective in particular situations of object recognition, leading to significant damages. Most of the traditional neural network algorithms do not achieve as satisfying results to be acceptable for most available jobs. The indicated fact disqualifies machines from replacing the monotonous human activities.

This project implements the structure of CNNs different from traditional, where it performs classification on 10 classes of multiple, evenly distributed images available in the CIFAR- 10 dataset. The improved model replaces the max-pooling and dense function with two-dimensional convolution layers, with the achievement of higher classification rate, basing its structure on the model.

II. LITERATURE REVIEW

According to [1], —The traditional convolutional neural network usually initializes the weights of all network layers at one time before network training, and then updates the weights of the network by back-propagation algorithm to improve the accuracy of the network during network training. However, with the increase of network depth, the computational cost of this method will increase dramatically and the test accuracy will be affected. In order to solve this problem, a method of gradually reinitializing the weights of each layer is proposed, that is, after a certain training period, the weight of the previous layer is determined and remain unchanged, then initialize the weights of all subsequent layers, repeat this step until the weights of all layers are determined. In order to verify the performance of the method, a series of experiments were carried out on the CIFAR10 dataset. The results show that the accuracy of the network is improved by 9% and the training time is reduced by 29%. It shows that the method can improve the accuracy of the network and reduce the training time.

In [2], Training the deep learning models involves learning of the parameters to meet the objective function. Typically the objective is to minimize the loss incurred during the learning process. In a supervised mode of learning, a model is given the data samples and their respective outcomes. When a model generates an output, it compares it with the desired output and then takes the difference of generated and desired outputs and then attempts to bring the generated output close to the desired output. This is achieved through optimization algorithms. An optimization algorithm goes through several cycles until convergence to improve the accuracy of the model. There are several types of optimization methods developed to address the challenges associated with the learning process. Six of these have been taken up to be examined in this study to gain insights about their intricacies. The methods investigated are stochastic gradient descent, nesterov momentum, rmsprop, adam, adagrad, adadelta. Four datasets have been selected to perform the experiments which are mnist, fashionmnist, cifar10 and cifar100. The optimal training results obtained for mnist is 1.00 with RMSProp and adam at epoch 200, fashionmnist is 1.00 with rmsprop and adam at epoch 400, cifar10 is 1.00 with rmsprop at epoch 200, cifar100 is 1.00 with adam at epoch 100. The highest testing results are achieved with adam for mnist, fashionmnist, cifar10 and cifar100 are 0.9826, 0.9853, 0.9855, 0.9842 respectively. The analysis of results shows that adam optimization algorithm performs better than others at testing phase and rmsprop and adam at training phase.

In [3], Training neural networks is a computationally challenging problem that requires significant time efforts. In this paper, we propose two approaches that improve efficiency of this task by actively selecting most relevant points from a training data set. The first approach forms a batch that maximizes the reduction of the estimator’s entropy, while the second approach only trains on datapoints whose predicted probability is below a predetermined threshold. Both techniques rely on data metrics to speed up training while retaining the epochbased neural network training framework. The results demonstrate that the proposed methods enable significant reduction of training time in experiments on the CIFAR10 dataset without compromising the accuracy.

III PROBLEM DEFINITION

Described problem holds significance in the entire area of autonomous devices, which implement a diversified number of classifiers to work independently from human control. The most common autonomous applications can be observed in the automobile and scientific industry, where scientists try to automate the running of vehicles or the analysis of medical scans, which would also output the accurate diagnosis. Both of the mentioned fields are crucial to people as the matter of life depends on a single decision. The goal of automating devices and letting them control the monotonous jobs is to provide the most accurate predictions in the shortest time followed by immediate reaction. With a knowledge of the fastest and most accurate image classification model, multiple industries could advance with the implementation of the most-suited algorithms. However, according to the no free lunch theorem, there is not a single algorithm that will solve every kind of a problem, as each neural network algorithm works differently with different datasets. For example, the CNN model examined in this research should find its usefulness mainly in classifying a low number of classes, made up of tiny images.

The attempt to solve the introduced problem is performed on the widely popular CIFAR-10 dataset, which is commonly used for the evaluation of image classification algorithms. The dataset consists of "60000 32x32 colour images in 10 classes, with 6000 images per class" [3]. The entire set of images is divided into the two sets of 50000 images for the training set and the rest of 10000 images for testing set. The training batch consists of 5000 images from each class, whereas the testing batch has 1000 images representing every class. The CIFAR-10 dataset is a set of the 10 classes divided into six types of animals (bird, cat, deer, dog, frog, horse) and four kinds of vehicles (airplane, automobile, ship, truck). As the publisher informs, the classes are mutually exclusive with no overlaps of similarity, for example, between trucks and automobiles.

The datasets – CIFAR-10 can be downloaded from the official website [5]. The files are available to download in various formats of Python, Matlab and binary version, which is suitable for C programs. After downloading the Python version (cifar-10-python.tar.gz), the data has to be extracted, to reveal the following files:

- batches.meta – consists of a Python dictionary object that defines label names of the 10 included classes.
- data_batch_1, data_batch_2, …, data_batch_5 – training data of 50000 images divided into five files of 30 MB each.
- readme.html – HTML document linking to the official website of the dataset.

- test_batch – testing data of 10000 images in one 30 MB file.

In order to see the actual images and use them, the files have to be decoded with the use of a Python script

VI CONCLUSION

Image classification is one of the most fundamental problems in Machine Learning. It is the core foundation for bigger problems such as Computer Vision, Face Recognition System, or Self-driving car. With the development of deep Convolutional Neural Network (CNN), researchers have achieved good performance on the image recognition task.

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