Deeper Networks for Image Classification

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***Abstract*—This paper represents a comparison between different Convolutional Neural Networks. In particular, the models GoogLeNet, VGG-16 and ResNet are compared on different datasets, such as MNIST and Cifar10.**

***Index Terms*—GoogLeNet, ResNet, VGG-16, MNIST, Image Classification, Deep Learning**

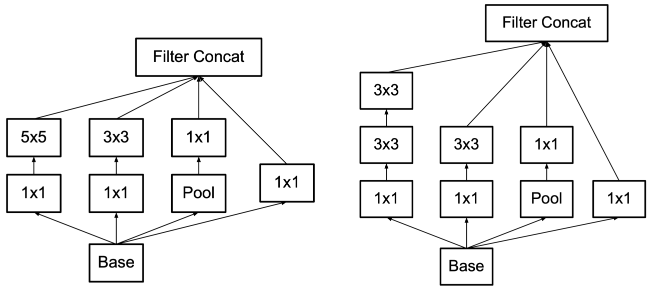
I. Introduction

This paper represents a comparison between different Convolutional Neural Networks. In particular, the models GoogLeNet, VGG-16 and ResNet. These three models are compared on the datasets MNIST and Cifar10. This document is split in 6 chapters. The I. Chapter represents a short introduction to the topic and serves as and overview of the document. The II. Chapter presented a Literature Review containing a short overview and history of the models and the datasets. Chapter III describes the implementation of the models, the conducted experiment and the dataset usage. In Chapter IV the Finding of the experiments are presented, which are then discussed in Chapter V. Followed by a conclusion in Chapter VI

II. Literature Review

A. Neural Network models

1) GoogLeNet: GoogLeNet was initially developed as a submission for the ImageNet Large-Scale Visual Recognition Challenge 2014, which it won. The main hallmark of this model is the improved utilization of the computing resources inside the network. It has 12 times fewer parameters than the winner of 2012 (AlexNet) but performs significantly better. [8] This model first introduced the idea of an inception module, which can be seen in Figure 1a. A second version of the model was published a year later, which then introduced an improved inception module, which can be seen in Figure 1b. This new version reduced computational costs, as bigger convolutions are disproportionately more expensive. Using two 3x3 convolutions instead of 5x5 is computationally less expensive while improving the performance. Although there are is also a V3 and V4 of GoogLeNet, for this paper, the V2 Inception has been used. In total the model has 22 layers.



(a) Original Inception module [8]

(b) V2 Inception module [9]

Fig. 1: Three simple graphs

2) VGG-16: VGG-16, is the biggest of the models used in this paper (Figure 2). It also has been developed as a submission for the ImageNet Challenge, in which it won first and second place for the localization and classification tracks, respectively. It consists out of 16 layers and uses only 3x3 convolutions. Although it has fewer layers than GoogLeNet, each layer is computationally more complex. Ultimately, this model resulted in better scores then the GoogLeNet V1 [7].

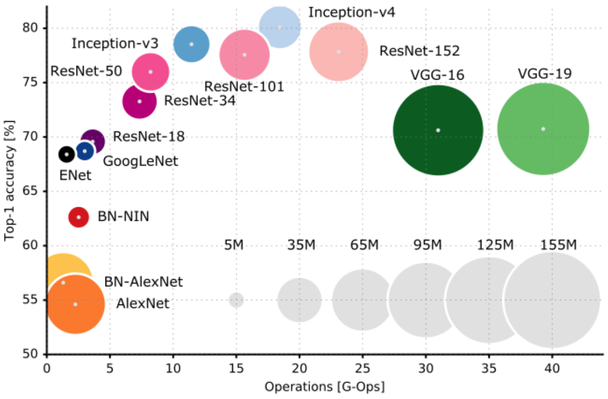
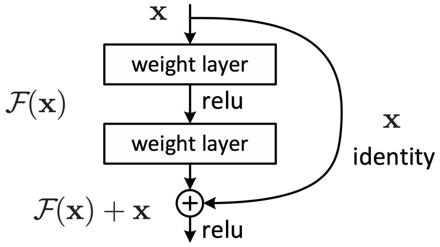


Fig. 2: top-1 one-crop accuracy versus amount of operations required (circle size represents the amount of parameters)

3) ResNet: ResNet, has the highest amount of layers. While there are multiple versions, for this paper a 50 layer version has been chosen. In Figure 2, it can be observed that the model



x
weight layer
$\mathcal{F}(\mathbf{x})$
relu
weight layer
x
identity
$\mathcal{F}(\mathbf{x}) + \mathbf{x}$
relu

Fig. 3: Residual learning: a building block [6]

size is in between GoogLeNet and VGG-16, yet the best result can be expected according to this comparison. ResNet has been built with the goal of easing the training of deep networks. The network design is based on chaining multiple residual learning blocks on a row. One residual learning block can be seen in Figure 3. [6]

B. Image datasets

1) MNIST: The MNIST database contains 70,000 28x28 black and white images. 60,000 images are for training and 10,000 images for testing. The images' portrait handwritten numbers from 0 to 9. [10] Examples of the classes can be seen in Figure 4.

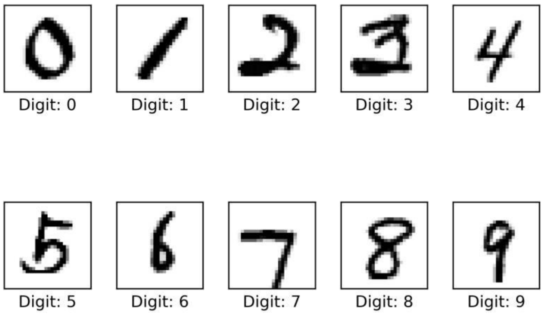


Fig. 4: Cifar10 image samples [2]

2) Cifar10: The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images. The classes are mutually exclusive.[1] Examples of the classes can be seen in Figure 5.

Fig. 5: Cifar10 image samples [3]

III. Methodology

In the first subsection III-A the implementation of the models using the framework Keras will be explained. In the subsection III-B it will be explained how the datasets have been made compatible with the models.

A. Model implementation

1) GoogLeNet: GoogLeNet considering only the parameters, is the most lightweight model of the three. Nevertheless, it has 108 operational layers ordered in 22 layers, which can be logically segmented into five stages, excluding input and output. The first two stages of the model consist of multiple 2D convolutions, followed by a `BatchNormalization` layer and a `MaxPooling2D` layer. Using the `BatchNormalization` layer is a unique attribute of the second version of GoogLeNet. Stage 3 consists of two V2 inceptions, as seen in Figure 1b, followed by a `MaxPooling2D` layer. Stage 4 has five inceptions and two auxiliary modules, followed by a `MaxPooling2D` layer. In Stage 5, we have two inception modules followed by a `GobalAveragePooling2D` layer, equivalent to the 7x7 convolution found in other versions of this network. The model then finishes with a Dropout of 0.4 and a fully connected layer using `softmax` as its activation function. [9]

2) ResNet: For this paper, the ResNet-50 Model has been chosen. The number 50 meaning, that the model consist out of 50 layers of residual blocks (Figure 3) stacked on top of each other. As mentioned before, there are different versions of ResNet, which all hold a different amount of layers. Based on the original paper results, ResNet-50 has the second best results, behind ResNet-110. [6]. For this paper, the ResNet version designed for the ImageNet dataset has been used. There is a version in the original paper, that has been adapter to use (32,32,3). In an effort to keep results between the networks comparable, the version accepting smaller images has not been used. The main final network architecture consists out of 4 blocks, each starting with a convolutional block, followed by a varying number of identity blocks (2,3,5,2).

3) VGG-16: VGG-16 is the biggest model of the three regarding the parameters. Based on layers, this model is the smallest, as it only consists of 16 layers, which are segmented into 5 blocks. Each block is structured in the same manner: two or three 2D convolutions, followed by one 2D MaxPolling layer. The five blocks are then followed by three dense layers, one dropout of 0.5 and a final fully connected layer using `softmax` as its activation function. The full network architecture can be seen in Figure 6. [7]

Unfortunately, this model was too complex for the Google Colab environment, even using Colab Pro. Therefore, the model was modified using suggestions made in the Stack Overflow forum. [5] The alterations were as follows: each block with three convolutions has been reduced to two, each block with two has been reduced to one convolutional layer, and the final three dense layers have been reduced to only one dense layer. Furthermore, the batch size has been reduced to 32. The rest of the model was not modified. This led to horrible results. Due to a lack of other options for training the model, except for Google Colab, this model results will not be further discussed and the original VGG-16 architecture will be part of the project folder.

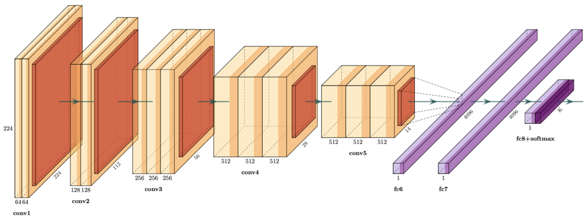


Fig. 6: VGG-16 architecture [4]

B. The Datasets

The dataset used in this paper both have a resolution of 28x28 pixels. On top, the Cifar10 dataset has three colour channels, while the MNIST dataset only has one grey channel. This represents an issue, as the Neural Networks has initially been designed to work with the Microsoft ImageNet dataset. This dataset has 3 colour channels and a resolution of 224x224 pixels. The goal was not to change the input of the models, as this would have significant implications for the layers following, resulting in a significant change in the model design. Therefore, the datasets have been altered as follows to fit the input dimensions of the models.

1) MNIST dataset alterations: The MNIST dataset has the shape (28,28,1), while our models required an input shape of (224,224,3). In order to change the dimensionality, the OpenCV library has been used. Using OpenCV, the image has been interpolated to fit the 224x224 image size. Afterwards, the image was stacked three times to obtain our three-channel input. Although, there is the OpenCV function `cv2.cvtColor(src, cv2.COLOR_GRAY2RGB)`, which can convert from greyscale to RGB. The results are not different from our stacked layers. This is due to the unique properties the MNIST dataset has. Using the stacked layers is computational lightweight.

2) Cifar10 dataset alterations: The Cifar10 dataset is already in RGB. Therefore, we do not need to convert it into a different colour space. Therefore, this dataset has been interpolated from the shape (28,28,3) to (224,224,3) using the OpenCV library.

C. Project structure

This project aims to create a GitHub repository that is fully documented and allows for easy replication of the results presented in this paper. In Figure 7, the file structure of this project can be seen. All project files, are public on GitHub. The Checkpoints can be downloaded from Google Drive.

The project has 3 entry points, which are each a Jupiter Notebook file. Each Notebook is dedicated to one Neural Network. At the top of the Notebooks, the Hyperparameters of the network can be adjusted as well as runtime environment variables. The notebooks have two modes, one for a Google Colab execution and one for a local execution. In case of a Google Colab execution, the notebook will use Google Drive for Checkpoints rather than the Checkpoint folder within the project. In order to minimize the code within the notebooks and create a clean and easing readable code, code has been outsourced into dedicated python files. The `helper.py` file, takes care of Hyperparameters as well as evaluating the model. The `dataset.py` handles the dataset download and the alterations described in Section III-B. The three other python files define the neural networks, corresponding to their names. Every function within the python files is documented, and the notebooks are divided into descriptive sections.

```
/
|__Checkpoints
|  |__GoogLeNet
|  |__ResNet
|  |__VGG
|__GoogleNet.ipynb
|__VGG.ipynb
|__ResNet.ipynb
|__py
|  |__ResNet.py
|  |__googLeNet.py
|  |__VGG.py
|  |__helper.py
|  |__datasets.py
|__Latex
   |__Report.tex
   |__Report.pdf
   |__img
```

Fig. 7: Project file structure

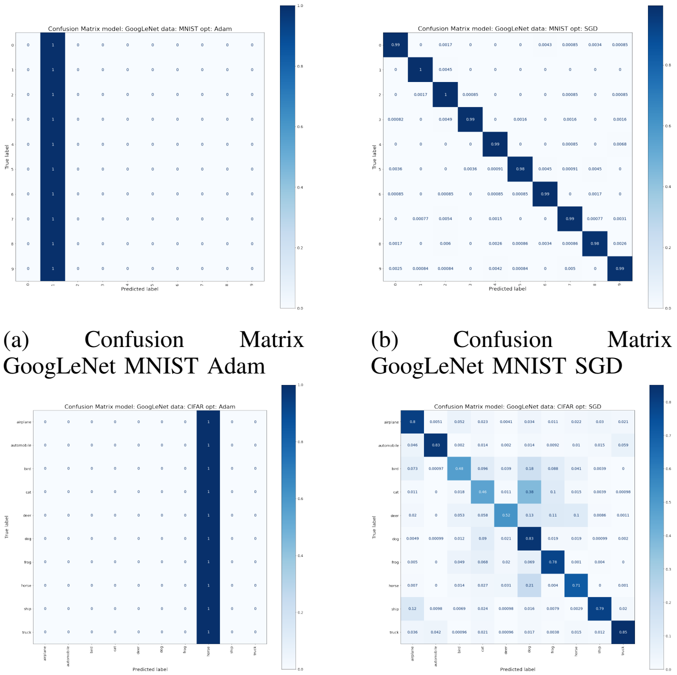
IV. Results

Each model has been trained over 20 epochs twice for each dataset, once using the Adam optimizer and once using the SGD optimizer. The overall accuracy and the confusion Matrix have been recorded. In the following chapter, the results will be presented.

A. GoogLeNet

Using the SGD optimizer, the model performed very well on the MNIST dataset but was suboptimal on the CIFAR-10 dataset. If we look at the confusion matrix of the model using the SGD optimizer on the CIFAR-10 dataset, we can see that the low accuracy comes from a localized inadequate recognition of the labels bird, cat & deer, which even as a human are very difficult to distinguish from each other.

We can see a significant reduction in accuracy and a double in training speed with the Adam optimizer. In Figure 8a & 8c we can clearly see, that using the Adam optimizer in both cases led to no training at all.



(a) Confusion Matrix GoogLeNet MNIST Adam

(b) Confusion Matrix GoogLeNet MNIST SGD

(c) Confusion Matrix GoogLeNet Cifar10 Adam

(d) Confusion Matrix GoogLeNet Cifar10 SGD

Fig. 8: GoogLeNet Confusion Matrices

TABLE I: GoogLeNet model Results

Model accuracy			time/step	
	Adam	*SGD*	*Adam*	*SGD*
MNIST	11.02%	98.96%	133s 354ms	258s 688ms
CIFAR-10	10.17%	66.34%	110s 351ms	109s 349ms

B. VGG-16

As mentioned previously, this model is too big to be execution using Google Colab Pro and the only results that could be obtained, are from a heavily simplified version of the model, which expectedly performs very bed. As this poor performance become evident very quickly, the model has only been trained on the CIFAR dataset using the SGD optimizer. The results can be seen in Tbale II

TABLE II: VGG-16 model Results

Model accuracy		time/step
	SGD	*SGD*
CIFAR-10	9.33%	152s 121ms

C. ResNet-50

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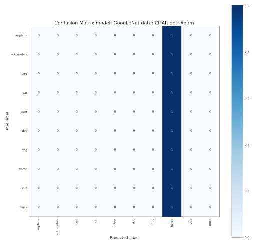
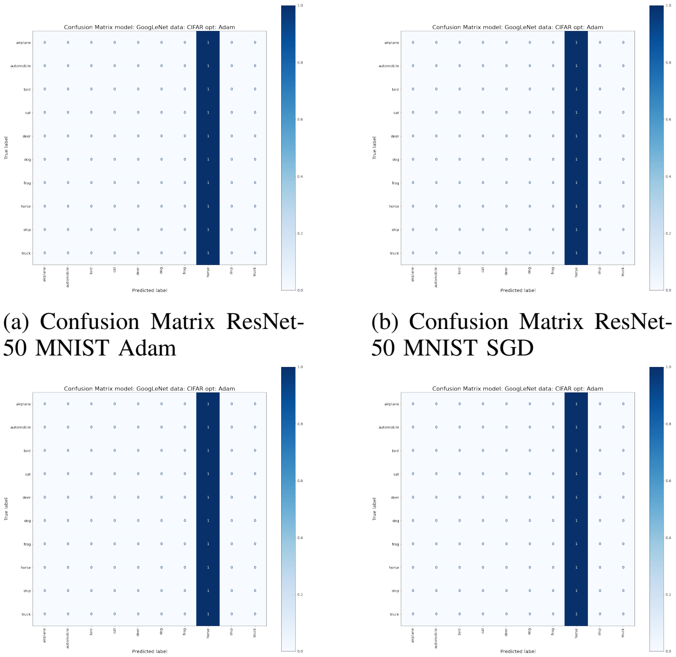


Fig. 9: Confusion Matrix simplified VGG-16 Cifar10 SGD

TABLE III: ResNet-50 model Results

Model accuracy			time/step	
	Adam	*SGD*	*Adam*	*SGD*
MNIST	%	%		
CIFAR-10	%	%		



(a) Confusion Matrix ResNet-50 MNIST Adam

(b) Confusion Matrix ResNet-50 MNIST SGD

(c) Confusion Matrix ResNet-50 Cifar10 Adam

(d) Confusion Matrix ResNet-50 Cifar10 SGD

Fig. 10: ResNet-50 Confusion Matrices

V. Discussion

VI. Conclusion

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