Recognising German traffic signs using Neural Networks with Transfer Learning

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Abstract

Demonstrate how transfer learning can be applied to previous trained  Convolutional  Neural Network to accurately recognise German traffic signs.

**Keywords:** Convolutional  Neural Network, Transfer Learning

# 1 Introduction

Traffic sign recognition is essential for autonomous vehicles if they are to obey the rules of the road. Traffic signs are simple in their design with simple shapes and colours to inform all road users of various hazards or changes to road use like speed limits in all weather and/or lighting conditions both during the day and at night.

However, autonomous vehicles use cameras to detect traffic signs. These devices are subject to obstructions, poor lighting, motion blur, bad exposures, and other impediments to clear images of traffic signs. [Arcos-García, Álvarez-García and Soria-Morillo, 2018]

There is a need to classify the images of the traffic sign correctly under various and numerous conditions. Convolutional  Neural Network (CNN) offer a mechanism to classify images into appropriate classes however they require significant amounts of data and computing resources to train [Simonyan & Zisserman, 2014]. Trained CNNs have knowledge about images and their classification like cars. That knowledge gained from training a neural network on a different but related problem and can be used to classify images, say of trucks, where one or more of the pre-trained layers from an existing model are used in a new model to classify images. This process is called transfer learning and it will applied in this paper to an existing model to classify images of German traffic signs.

# 2 State of the Art

Currently there are three popular models for transfer learning, they are: [Brownlee, 2021]:

* VGG (e.g. VGG16 or VGG19).
* GoogLeNet (e.g. InceptionV3).
* Residual Network (e.g. ResNet50).

The current best preforming CNN for German road traffic signs is DeepKnowledge Seville who used a CNN with 3 spatial transformers with an accuracy of 99.71% [GTSRB - German Traffic Sign Recognition Benchmark, 2018].

# 2 State of the Art

## 2.1 Dataset

For this experiment the dataset of the German Traffic Sign Recognition Benchmark was used [Stallkamp et al., 2011]. This dataset contains 39209 training images and 12630 test images split into 43 classes of road signs. A sample of these images are displayed in Figure 1. The images are not balanced amongst all 43 classes as shown in Figure 2. The training images were further split into 2 datasets, a training dataset of 31368 images and a validation training set of 7841 images.

The images have various dimensions ranging from 32 x 32 pixels up to 224 x 201 pixels.



Figure 1: Sample traffic signs from German Traffic Sign Recognition Benchmark dataset

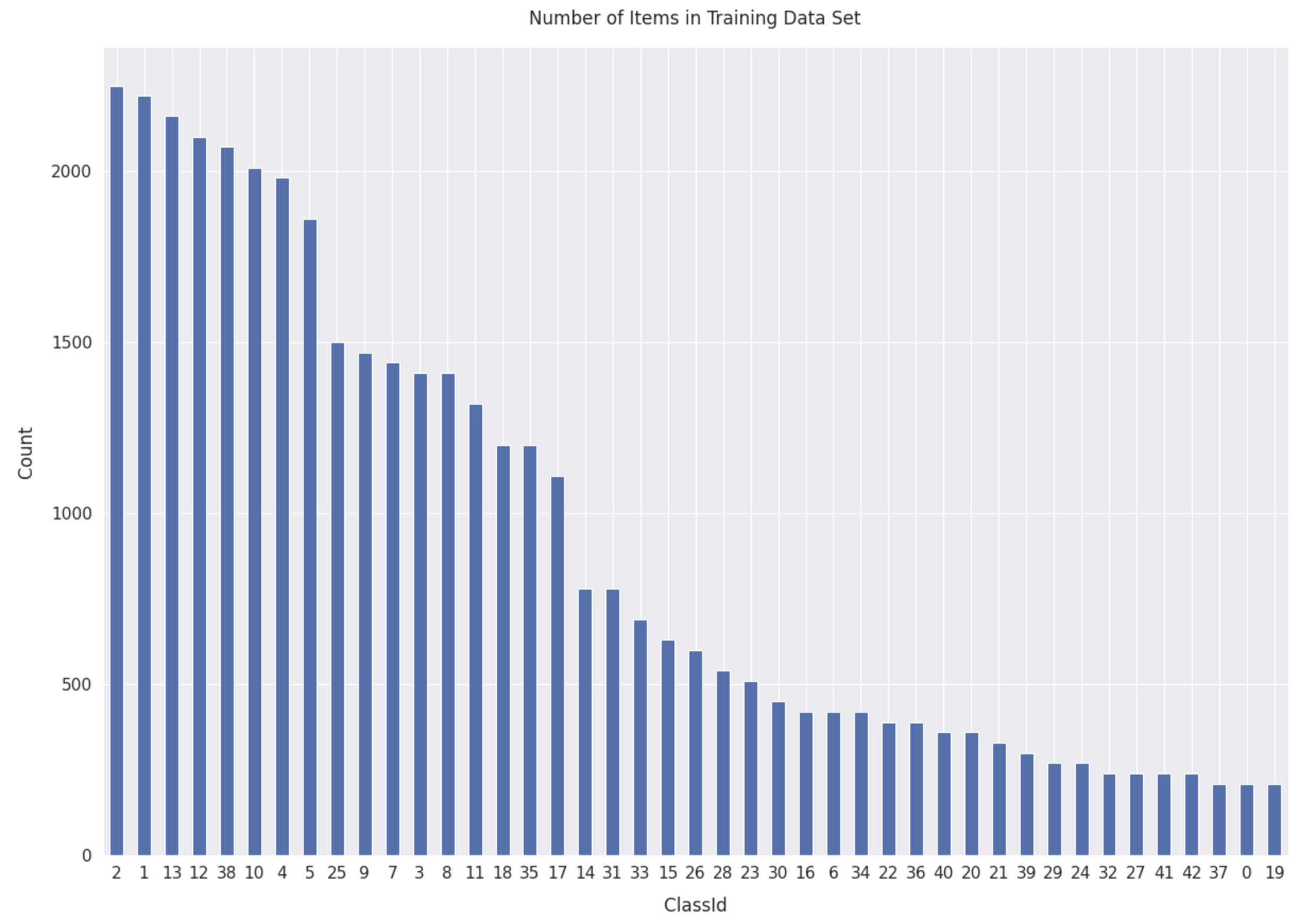


Figure 2: A figure

### 2.1.2 Subsubsection

quam nihil molestiae consequatur, vel illum, qui dolorem eum fugiat, quo voluptas nulla pariatur?

# 3 My Work

, quam nihil molestiae consequatur, vel illum, qui dolorem eum fugiat, quo voluptas nulla pariatur?

**My Paragraph:** All execution was performed on a Google Cloud virtual machine with four vCPUs, 26GB of Ram and one Nvidia Tesla T4 GPU.

An example table is shown in Table 1.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Model | Pre-processed Input | Trainable Layers | Epochs | Execution Time | Training Accuracy | Training Loss | Validation Accuracy | Validation Loss | Testing Accuracy |
| 1 | No | 0 | 14 | 41:55 | 97% | 0.293 | 76.2% | 13.103 | 73.71% |
| 2 | No | 5 | 17 | 57:20 | 100% | 0.001 | 96.5% | 0.583 | 95.86% |
| 3 | Yes | 5 | 21 | 1:11:15 | 99.9% | 0.009 | 95.7% | 0.612 | 96.17% |
| 4 | Yes | 10 | 23 | 1:41:59 | 99.9% | 0.002 | 98.5% | 0.078 | 97.38% |

Table 1: Results of model training.

Sed

# 7 Conclusions

Sed ut perspiciatis , unde omnis iste natus error sit voluptatem accusantium doloremque laudantium, totam rem

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