**CLASSIFICATION OF TRAFFIC SIGNS USING CONVOLUTIONAL NEURAL NETWORK**

by

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# **Abstract**

# **Chapter 1 – Introduction**

## **1.1. Problem Solved:**

The project explores utilising Convolutional Neural Networks (CNN) to classify a collection of different traffic sign classes. Advancements in automatic driving technology   
(SAE J3016 Standard, 2016) has encouraged car manufacturers within the automobile industry to adapt computer vision into driver alert systems. Embedded into such systems often includes traffic sign recognition (TSR) whereby traffic signs are automatically recognised using machine learning technology. Overall these systems would help vehicles better understand the roadway around them to then help aid and protect drivers   
(buy-a-car, 2019). Although the merits of TSR is widely discussed across various academic research, there are many factors that impose challenging problems to traffic detection such as insufficient illumination, partial-occlusion and serious deformation of road sign images which in turn hinders the ability to localise and classify data correctly whilst maintaining high levels of accuracy (TSR Difficulties – Research Gate, 2012).

Recognition of traffic signs is a challenging real-world problem of high industrial relevance. Although commercial systems have reached the market and several studies on this topic have been published, systematic unbiased comparisons of different approaches are missing, and comprehensive benchmark datasets are not freely available.

Traffic sign recognition is a multi-class classification problem with unbalanced class frequencies. Traffic signs can provide a wide range of variations between classes in terms of colour, shape, and the presence of pictograms or text. However, there exist subsets of classes (e. g., speed limit signs) that are very similar to each other.

Humans are capable of recognizing the large variety of existing road signs with close to 100% correctness. This does not only apply to real-world driving, which provides both context and multiple views of a single traffic sign, but also to the recognition from single images.

At present many papers

Existing research and study:  
Many papers discuss ways to automate and

This research aims to develop an efficient TSDR system for Automotive Engineers professionals within the transportation industry. TSDR system would detect and classify a collection of 43 individual traffic-signs taken from real-time environment into different classes for recognition. The project has explored a variety of Convolutional Neural Network (CNN) models to find the best performing one. Each of these models will be trained based on the sample of traffic-sign images derived from the German-Traffic-Sign Dataset. This trained model and

## **1.2. Project Objectives:**

The objectives mentioned in this section are somewhat similar to those highlighted in the project definition document (PDD) which can be found in Appendix (a). Although the main objective has remained consistent, the sub-objectives differed in priority level and it was important to complete these objectives effectively and efficiently given the project timeline hence amendments were made for implementation. For one sub-objective: “Collect at least sufficient training data (minimum of 40 images) that replicates variation of the same image for each individual class of images of the dataset.” The dataset-imposed challenges such as images having low resolution and poor contrast, so to avoid accuracy of the results being hindered the author decided to pre-process each image which would then replicate a whole new dataset for testing. Another objective being to “pre-process 43 traffic-sign images using different filtering techniques (Sobel and RGB filters) to extract as many features as possible.” The author condemned this sub objective as low priority as it did not directly influence the main objective and the convolutional layers will likely extract better and refined features. Thus became voided.

### **1.2.1 Primary Objectives:**

The primary objective of this project is to create a model that can distinguish between 43 different traffic sign classes using their images with an accuracy score of over 90%. The success of this project is underpinned by the accuracy of the classification model, it is measured by calculating how well the model predicts each traffic sign image outlined within the testing set. This objective is only successful only if the following sub-objectives are also achieved:

### **1.2.2 Sub Objectives:**

|  |  |
| --- | --- |
| 1 | Collect at least sufficient training data (minimum of 40 traffic-sign image types) that replicates variation of the same image for each individual class of images of the dataset. |
| 2 | Pre-process the existing image sets of (43 traffic sign classes) to improve image quality that would ensure better accuracy for image detection. This would involve improving the contrast of each traffic sign as well as the resolution. Also ensure each traffic sign accounts for skewed classes. |
| 3 | Pre-process 43 traffic-sign images using different filtering techniques (Sobel and RGB filters) to extract as many features as possible. |
| 4 | Train the processed data using convolutional neural network model taking into account varying activation functions and layers sizes and record the accuracy of using different metrics. |
| 5 | Create a function that outputs all results from training (accuracy metrics). |
| 6 | Implement a script that loads the training model of traffic signs that will help then classify new input images. |
| 7 | Continually increment the images to be processed and test the selected models on it. Compare results and tweak whereby necessary. |

Highlighted within the PDD is also a list of optional objectives such as increasing the number of traffic sign images within training sample, testing on faster R-CNN and support vector machine (SVM) for classification. However not all of these objectives had been adhered to simply because they are not needed to meet the main objective. As a result the author saw no need to increase the number of traffic signs to use within the sample, especially after having created several popular models that reflect a high accuracy of measure it seemed unnecessary to test on further models. On the other hand for research purposes the author decided to use a pre-trained CNN model to then also use to classify traffic sign images, the results from each model can be pinned against one another to determine which model is ideal to derive the highest accuracy. As a result the following set of optional objectives were set and completed.

|  |  |
| --- | --- |
| 8 | Training a faster R-CNN model from scratch to localize and recognize 47 types of traffic signs to the existing 43 types. |

## **1.3. Project Beneficiaries:**

This project aims to help automotive engineers of large-scale firms who specialize in the developing technology closely related to self-driving cars or similarly driver alert systems inside cars will benefit from having a software built specifically for them. This project will enable engineers to significantly improve their image recognition of traffic-signs / road signs for existing systems thus enhancing the safety protocols for road-awareness and overall, the quality of their safety critical systems. However as mentioned above, this project will only construct a small piece of the desired system, which is being able to classify individual traffic sign image from a variation of each images (also skewed). As well as help reinforce other researchers to further improve classifications different variations of traffic signs.

## **1.4. Work Performed:**

All the objectives that had been outlined above have been accomplished. For the dataset relied on for this project the author had carried out in-depth analysis which involved also utilising various pre-processing techniques: shuffling, grey-scaling and normalisation. Filter and feature map plots have also been made to better understand the dataset as well as trained models, which in turn would demonstrate better results. Extensive reading in the subject matter of Convolutional Neural Networks, Image Classification and Computer Vision and its application have been performed, please refer to ‘[**Chapter 3 – Literature Review’**](#_Chapter_3_–).

## **1.5. Assumptions Made:**

The assumption made for this project by the author is that the accuracy of the CNN classification model that parses the images from the dataset are undermined by the fact that dataset classes are skewed, in other words there is no equal distribution of images per traffic sign class. Which would mean those classes (traffic-signs) that have more images within their classes are most likely to be recognised by classifier. Another assumption made by the author that could be a detriment to the CNN classification is that their own current GPU processor (Intel Iris Plus Graphics) may not be sustainable with high performance as required for training the neural network models. Thus a more powerful GPU will be best for improving overall computation of the classifier.

## **1.6. Overview of Upcoming Chapters:**

|  |  |  |
| --- | --- | --- |
| **Chapter** | | **Description** |
| **2** | **Output Summary** | This chapter highlights all the outputs for this project which would also be highlighted within the Appendices. |
| **3** | **Literature Review** | This chapter reviews all the academic research papers that have been studied (Neural Networks, Computer Vision, Deep Learning & Traffic Sign Classification) that aids to further understanding of the project. |
| **4** | **Methodology** | This chapter details the processes of each task of this project undertaken and accomplished. |
| **5** | **Results** | This chapter highlights a detailed analysis of project outputs. |
| **6** | **Conclusion & Discussion** | This chapter summarises the objectives achieved for this project, conclusions from the results and management reflection of the author who conducted this project. |
| **7** | **References** | This chapter reflects all external sources that has been referenced for this report. |
| **8** | **Appendices** | This chapter reflects the project output as well as any additional data that has been referred to for this report. |

# **Chapter 2 – Output Summary**

|  |  |
| --- | --- |
| **2.1 Traffic Sign Dataset** | |
| **Desc & Type:** | Dataset images have been collected by Real-Time Computer Vision Research group and is based on the German Traffic-Sign benchmark. This has been made available on a public domain for academic research purposes and had been popularly used for ***‘International Joint Conference on Neural Networks (IJCNN) 2011’*** (Benchmark, 2010). The dataset contains minimum 40 traffic-sign classes, more than 50,000 images in total for all traffic-sign classes 1.5 GB. For each traffic-sign image / class they are grouped according to their own directory which will be indexed from 0 – 42. Each folder will then contain images of their relevant class. |
| **Recipient:** | Author, other academic researchers exploring machine learning and computer vision. |
| **Use:** | Used for training & testing the models. |
| **Link:** | Traffic-Sign dataset is enclosed within the Dataset folder. |

|  |  |
| --- | --- |
| **2.2 Model Recordings** | |
| **Desc & Type:** | The project has trained and tested using |
| **Recipient:** | Author, other academic researchers exploring machine learning and computer vision. |
| **Use:** | Critical analysis of the results derived from each model will be carried out to evaluate success of classification. Wherever necessary each model will be modified to further improve classification results. |
| **Link:** | Model-Recordings will be enclosed within the Results folder. |

|  |  |
| --- | --- |
| **2.3 Program Files / Utility Files** | |
| **Desc & Type:** | The project has trained and tested using |
| **Recipient:** | Author, other academic researchers exploring machine learning and computer vision. |
| **Use:** | Critical analysis of the results derived from each model will be carried out to evaluate success of classification. Wherever necessary each model will be modified to further improve classification results. |
| **Link:** | Model-Recordings will be enclosed within the Results folder. |

|  |  |
| --- | --- |
| **2.4 Web-Camera Setup** | |
| **Desc & Type:** | The project has trained and tested using |
| **Recipient:** | Author, other academic researchers exploring machine learning and computer vision. |
| **Use:** | Critical analysis of the results derived from each model will be carried out to evaluate success of classification. Wherever necessary each model will be modified to further improve classification results. |
| **Link:** | Model-Recordings will be enclosed within the Results folder. |

# **Chapter 3 – Literature Review**

This project requires familiarity with the topics of Deep Learning and Computer Vision, thus extensive research is required for the project development. Research papers had a large impact on how to undertake the project in terms of collecting, recording, and presenting data. Guides helped understand the libraries used and begin the coding process.

Research forms a major component for the project development.

## **3.1. Deep Learning:**

Deep learning is a subset of machine learning that has made great strides in all the fields that have used it. Whether it is in object detection or classification, speech recognition and in many other domains. Deep learning has been very successful because it can be fed raw data and can extract its own representation of it using different levels of abstraction, unlike in conventional machine learning system where representations are hard coded in, which makes them limited (Lecun et al, 2015). A machine learning model goes through 2 phases, a training phase and a testing phase. The training phase is when the model learns the data and the testing phase is comparing the model’s predictions against the true labels on never seen before data (test data). What are being trained are the model’s weights, which define the input output function.

Deep learning is a subfield of machine learning where

Supervised learning is a form of machine learning that allows us to dynamically correct the model’s predictions while training by providing the correct/desired prediction. Assume the task is to classify between 3 different cat types, during training the model will make a prediction as to what the type is, the prediction produced will be a set of scores for each type of cat (classes). Provided the correct set of score the model will then adjust its weights appropriately using the weight’s gradient and an error function to find which direction to change the weights to have the lowest possible error produced, this is called gradient descent (Goodfellow et al, 2016).

# **Chapter 4 – Method**

# **Chapter 5 – Results**

# **References**

1. **Standards.sae.org. 2021. *SAE International*. [online]**   
   Available at: <http://standards.sae.org/j3016\_201609/>
2. **BuyaCar. 2021. *What is traffic sign recognition, and do you need it?* [online]**

Available at: <https://www.buyacar.co.uk/cars/1138/what-is-traffic-sign-recognition-and-do-you-need it.

1. **ResearchGate. 2012. *(PDF) Difficulties of Traffic Sign Recognition*. [online]**   
   Available at: <https://www.researchgate.net/publication/\_Difficulties\_of\_Traffic\_Sign\_Recognition>
2. **Benchmark.ini.rub.de. 2010. *German Traffic Sign Benchmarks*. [online]**   
   Available at: <https://benchmark.ini.rub.de/gtsrb\_news.html>