

DEPARTMENT OF INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Bachelor's Thesis in Informatics

**Android-based camera-based traffic sign  
detection in driving simulator data with  
OpenCV**

Tobias Bauer

DEPARTMENT OF INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Bachelor's Thesis in Informatics

**Android-based camera-based traffic sign  
detection in driving simulator data with  
OpenCV**

**Android-basierte Kamera-gestützte  
Verkehrsschilder-Erkennung in  
Fahr simulator-Daten mit OpenCV**

Author:	Tobias Bauer
Supervisor:	Prof. Dr. Uwe Baumgarten
Advisor:	Sebastian Eckl, M.Sc.
Submission Date:	15.02.2018

I confirm that this bachelor's thesis in informatics is my own work and I have documented all sources and material used.

Munich, 15.02.2018

Tobias Bauer

## Acknowledgments

# Abstract

# Contents

<b>Acknowledgments</b>	<b>iii</b>
<b>Abstract</b>	<b>iv</b>
<b>1 Introduction</b>	<b>1</b>
1.1 Section . . . . .	1
1.1.1 Subsection . . . . .	1
<b>2 Motivation</b>	<b>2</b>
2.1 Section . . . . .	2
2.1.1 Subsection . . . . .	2
<b>3 Related Work</b>	<b>3</b>
3.1 Section . . . . .	3
3.1.1 Subsection . . . . .	3
<b>4 Artificial Neural Networks</b>	<b>4</b>
4.1 Fundamentals . . . . .	4
4.1.1 Neurons . . . . .	4
4.1.2 From Neurons To Networks . . . . .	5
4.2 Common Types . . . . .	6
<b>5 Concept</b>	<b>7</b>
5.1 Feature Extraction . . . . .	7
5.1.1 Circle Hough Transform . . . . .	8
5.2 Classification . . . . .	9
<b>6 Integration into existing App</b>	<b>10</b>
<b>7 Implementation</b>	<b>11</b>
7.1 Android Studio . . . . .	11
7.2 Native Development Kit . . . . .	11
7.3 Image processing (Opencv) . . . . .	11

## *Contents*

---

7.4	Neural Net Classification . . . . .	11
7.4.1	Building Neural Network . . . . .	11
<b>8</b>	<b>Evaluation</b>	<b>12</b>
8.1	Section . . . . .	12
8.1.1	Subsection . . . . .	12
	<b>List of Figures</b>	<b>13</b>
	<b>List of Tables</b>	<b>14</b>

# 1 Introduction

## 1.1 Section

### 1.1.1 Subsection



## 2 Motivation

### 2.1 Section

Citation test [**latex**].

#### 2.1.1 Subsection

**SubSub**

## 3 Related Work

### 3.1 Section

Citation test [latex].

#### 3.1.1 Subsection

## 4 Artificial Neural Networks

Artificial Neural Networks, or simply Neural Networks, are certain kind of computing systems that are inspired by the functionality of Biological Neural Networks, for Example the brains of mammals'. ANNs are import representatives or techniques for modern Artificial Intelligence, although the idea of NNs is not as new as the recent hype over them, seen in the last couple years. Actually, the beginning of ANNs point back to the 1940s. These networks are basically trained by feeding data and telling them what the corresponding output should look like. So what has changed over the last couple of years, is the massive amount of new data and a general increase in computing power, these two major advantages over earlier years, may have been contributed to the new success of Artificial Neural Networks.

### 4.1 Fundamentals

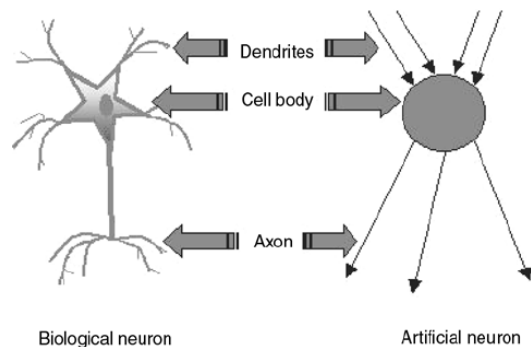


Figure 4.1: Biological and Artificial Neuron

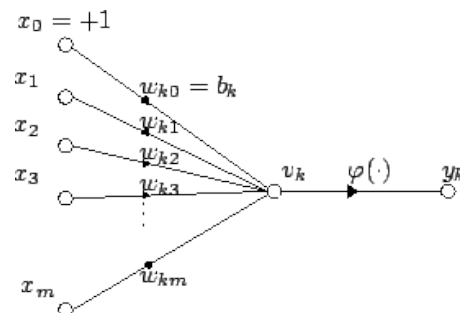


Figure 4.2: Single Artificial Neuron

#### 4.1.1 Neurons

As already mentioned, ANNs have several things in common with Biological Neural Networks, in this Analogy, an Artificial Neuron is a simplified abstraction of a Biological Neuron, both have a cell body and incoming respectively outgoing connections, called Dendrites and Axons (Figure: 4.1). Every arriving signal over the Dendrite is first

multiplied with it's corresponding weight, then added together. Be noted that  $x_0$  is no input signal from a different Neuron, but rather is always set to 1 and is called the bias input.

After totalizing the input values, our signal is channeled through an activation- or transfer function (Figure 4.2). There are several possibilities for the transformation function to choose from, which aims to handle when the Neuron produces output and when it remains silent. Another reason would be to keep the values between certain boundaries, usually it is desirable to stay in range  $[0;1]$ . Common transfer functions would be the Sigmoid- (4.3) and the Heaviside Step Function (4.4). Coming back to previous analogy, the Sum-Operator in series connection to the Activation function form the artificial cell body.

After forming an output signal  $y_k$  (4.2), the Axon can fork into one or multiple branches, serving one or multiple Neurons as it's or their input dendrites, after they have been weighted by their corresponding new weights.

$$v_k = \sum_{i=0}^m x_i w_{ki} \quad (4.1)$$

$$y_k = \varphi(v_k) = \varphi\left(\sum_{i=0}^m x_i w_{ki}\right) \quad (4.2)$$

$$S(x) = \frac{e^x}{e^x + 1} = \frac{1}{1 + e^{-x}} \quad (4.3)$$

$$H(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (4.4)$$

#### 4.1.2 From Neurons To Networks

Feeding a signal or data through a Neuron and transporting resulting output further to the next Neurons basically forms a Network. Now as the major purpose of Artificial Neural Networks are to process any sort of data given to the ANN and produce some sort of output. Consequently a model needs to have two different kinds of Interfaces for importing and exporting data.

The input part comprises a so called Input Layer, containing several Neurons that can be fed with data from outside of the network. Respectively there is the other end of the ANN, that produces a result after the calculation, performed by our net. Every Neurons outputting data outside of the net is called output Neuron, these Neurons together form the Output Layer. The remaining Neurons between input and output are hidden Neurons, they can be grouped in one or more hidden layers, depending on the

architecture, normally each Neuron of a layer  $l_n$  has a connection to every Neuron of it's subsequent layer  $l_{n+1}$ .

## 4.2 Common Types

There are a lot of different types of Neural Networks, but digging deeper into the matter would definitely go beyond the scope of this discussion, so i am going to limit this section to describe more or less shallowly only the two main types of ANNs.

The type of architecture, which I used in my project is called Feed Forward Neural Network, in this approach data is only fed in one direction, meaning from the Input Layer successively to the Hidden Layer(s) and at some point to the Output Layer, forming no cycles or loops.

In contrast to this Recurrent Neural Networks are slightly more complex than FFNNs, because they add the directed cycles component, therefor these networks have internal memory to a certain extent, that is capable of forming dynamic temporal behavior.

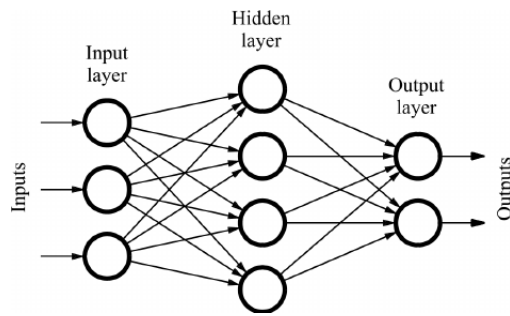


Figure 4.3: Feed Forward Neural Network

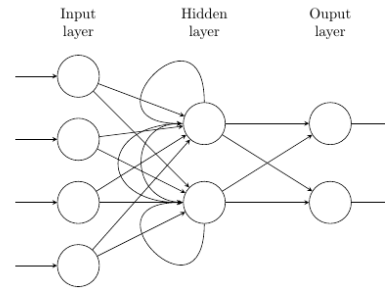


Figure 4.4: Recurrent Neural Network

## 5 Concept

The task of looking at a picture and telling what is in it, is quite trivial to humans and would usually not pose a challenging task to perform, whereas it is not that simple to Computers. In order to Classify images, or more exactly the objects comprised, machines ordinarily need a certain amount of Preprocessing to extract characteristic Features. As described in chapter 4 it is common practice to partition the many small steps of the process in two bigger, more generalized, steps of Feature Extraction and Classification. Our targeted devices are going to be any smartphones running Android as operating system, basically the App on the device should be able to handle live input from the Camera, detecting and classifying in real time. In the following subsections I am going to break down in detail, what methods are used and how they work.

Komponentendiagramm

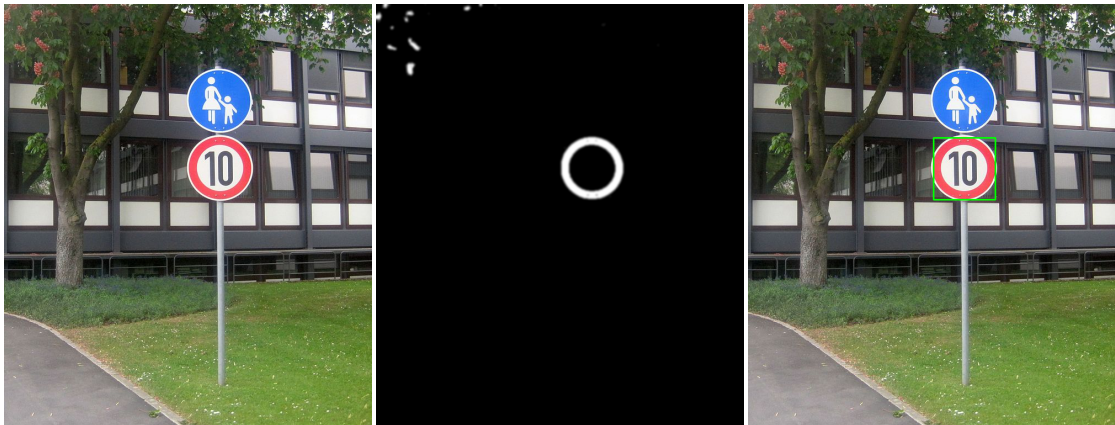


Figure 5.1: Original image    Figure 5.2: Filtered Image    Figure 5.3: Detected image

### 5.1 Feature Extraction

Before we pass data through to the Classification phase, it is a reasonable step in our Program, to specify a Region Of Interest, with regard to saving some processing power. In order to specify ROIs, I took advantage of the red circle around European Speed

signs, the main steps of this part are to filter every red pixel out of the original image (Figure: 5.2), subsequently an algorithm checks the filtered image for circles (Figure: 5.3). Filtering red pixels from a picture is not that big of a sorcery, so i am going to skip that part for now and come back later to this in the implementation section. The real magic happens when you try to search an image for circles, therefore a common method is the Circle Hough Transform.

### 5.1.1 Circle Hough Transform

The Circle Hough Transform is a special case of the Hough transform, which determines lines in an image through Edge Detection Algorithms. There are two slightly different Circle Hough Transforms, the first is only able to find circles of fixed radial size, the second is generally capable of finding Circles of any size. At first I am just going to start with the fixed radius form of the algorithm, subsequently we are going to extend that approach to a more universal algorithm.

#### Fixed Radius

First of all our image is being Converted to a binary image (Figure: 5.4), further it is being processed via edge detection to determine every visible edge contained in the photo (Figure: 5.5). After this, the actual core of the Algorithm is being executed. Therefore an Accumulator Matrix is initialized with zeros. As the radius of the circle is considered constant, every ring in the picture can solely be described by two variables (x and y coordinate), therefore the helping Accumulator Matrix is 2-Dimensional. Above-mentioned Matrix can be pictured as a grid over the original image, where single pixels can be combined to bigger baskets. Now every basket or pixel of a detected edge (Figure: 5.5) becomes the center of a new circle, with given fixed radius. Now each pixel that got "cut" by the circle gets incremented or up-voted in corresponding Accumulator Matrix (Figure 5.6). The baskets or pixels with the highest votes can be considered centers of circles.

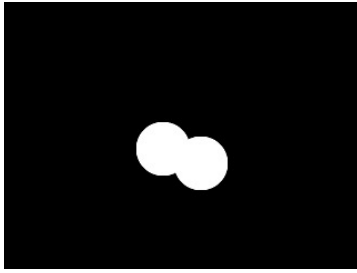


Figure 5.4: Binary image

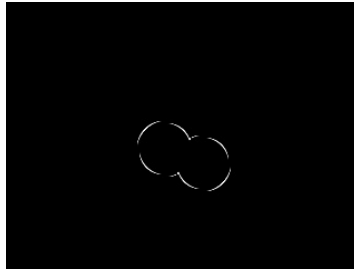


Figure 5.5: Edge detected

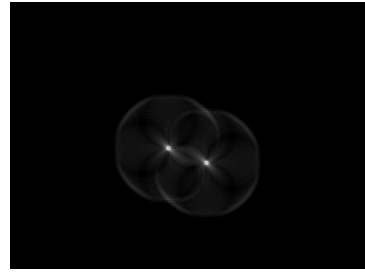


Figure 5.6: Voted image

### Variable Radius

A circle on a two-dimensional plane can be described by following formula:

$$(x - a)^2 + (y - b)^2 = r^2$$

, meaning the circle can be represented by the parameters (a, b, r), where "a" and "b" are the 2-Dimensional coordinate values representing the center of the circle, whereas the variable "r" provides the radius of given ring.

The preprocessing (Figure: 5.4 and Figure: 5.5) is identical to the fixed-radius Circle Hough Transform, but what makes the difference now is, our Accumulation Matrix gains another Dimension, from having variable radii, therefore it is 3-Dimensional now. Usually you specify a range for the radiuses to make things a little easier. Now the voting happens exactly as it would with algorithm described before, but the difference now is that it has to be done with every radius in the before determined range. The center of the potential circles are now the ones with the most voted radii in all radius-dimensions. The desired radius of a point is the radius with the highest vote.

## 5.2 Classification

Preceding stage delivers an image of fixed size, that needs to be categorized into one out of 10 groups, these are Speed limits "10km/h", "20km/h", ..., "90km/h" and "no sign". To gain these information about the sub-image of the original image, I decided to apply a Feed Forward Deep Neural Network. Said Neural Network is fed each individual pixel, provided by the ROI to its input neurons, the trained Model then outputs a prediction on what class the input picture might belong to.

wieso nur bis 90?

Neuronales netz model



## 6 Integration into existing App

The App I had to build upon, already had some features related to the open source car driving simulator "Speed Dreams", but before we go deeper into these functionalities, I am going to start with the present structure and Appearance. First of all, a dark theme has been chosen for the design of the App. As can be seen in Figure 6.1, the main screen contains different tiles for each task. It is possible to choose the source of intended input, therefore the user decides between loading an existing image (Figure 6.2), or hitting the camera icon to call a live-video feed of the back-facing camera. Depending on which input source has been chosen, the functionalities are applied either one single time or multiple times per second, both ways the outputs are printed onto the original images. Both features, that are named "Vehicle Detection" and "Lane Detection" are pretty much self explaining, but it should be mentioned that both methods are very likely trained by "Speed Dreams" data, meaning that the Lane detection is good for detecting lanes in the game, but might not be that brilliant in detecting real lanes, furthermore the vehicle detection recognizes only the back of the red car in the virtual rally course.

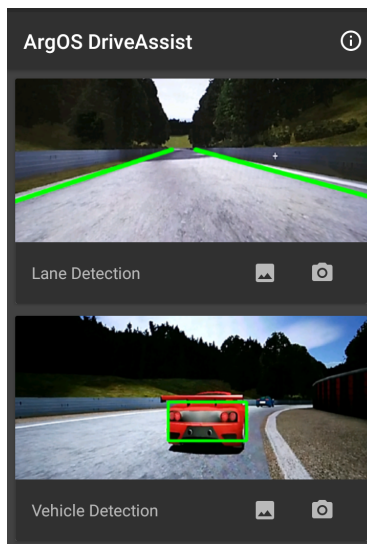


Figure 6.1: Main screen

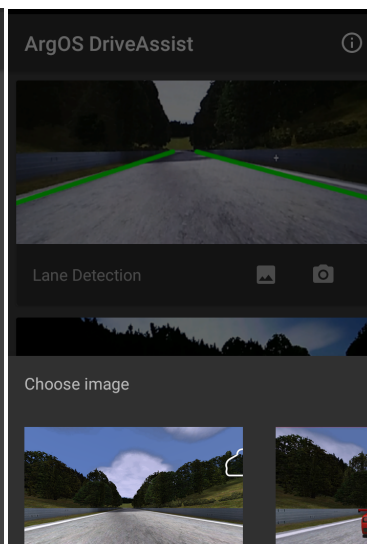


Figure 6.2: Load Image

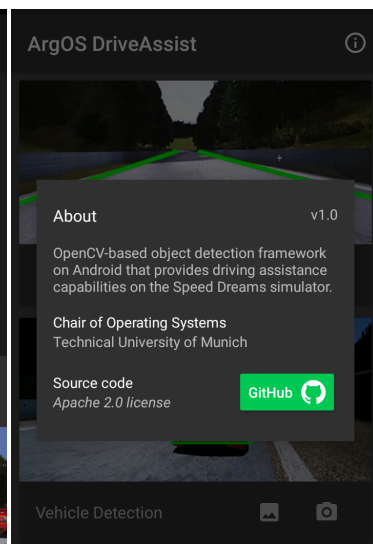


Figure 6.3: About

## **7 Implementation**

### **7.1 Android Studio**

### **7.2 Native Development Kit**

### **7.3 Image processing (Opencv)**

### **7.4 Neural Net Classification**

#### **7.4.1 Building Neural Network**

# 8 Evaluation

## 8.1 Section

Citation test [latex]. [meinkampf]

### 8.1.1 Subsection

## List of Figures

4.1	Biological and Artificial Neuron . . . . .	4
4.2	Single Artificial Neuron . . . . .	4
4.3	Feed Forward Neural Network . . . . .	6
4.4	Recurrent Neural Network . . . . .	6
5.1	Original image . . . . .	7
5.2	Filtered Image . . . . .	7
5.3	Detected image . . . . .	7
5.4	Binary image . . . . .	9
5.5	Edge detected . . . . .	9
5.6	Voted image . . . . .	9
6.1	Main screen . . . . .	10
6.2	Load Image . . . . .	10
6.3	About . . . . .	10

## List of Tables