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# Safety Analysis of Autonomous Vehicle Systems Software

Master's Thesis (30 ECTS)

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# Safety Analysis of Autonomous Vehicle Systems Software

## Abstract:

Machine learning approaches to autonomous driving systems that rely upon computer vision and deep neural networks have demonstrated encouraging results. Some believe that the so-called end-to-end strategy is the only way to deploy self-driving autonomy at scale in vehicles. Safety is a concern as the neural networks are susceptible to adversarial attacks, small perturbations invisible to the human eye but lead to a misclassified output, potentially causing catastrophic consequences such as loss of life or property.

Introduction  
Area of study

The problem  
that I tackle

Literature suggests that there are procedures to defend against such threats. However, there is no understanding of how adversarial defenses can improve the robustness of an end-to-end self-driving model trained in a real-world scenario.

How I tackle  
this problem

This paper aims to create a self-driving model that generalizes better and classifies correctly standard and adversarial input images. First, we select a real-world driving platform and a neural network to drive the model. Then, we designed an experiment, implemented, tested, and evaluated the results.

How I implement  
my solution

In conclusion, adversarial defenses (did/did not) impact the safety and reliability of self-driving end-to-end models. Therefore employing adversarial training (increased/did not increase) the robustness of autonomous vehicles.

The result

## Keywords:

adversarial attacks, adversarial machine learning, autonomous vehicles, driverless cars, self driving cars, open source, OpenCV, TensorFlow, Keras, CNN, deep learning, Raspberry Pi, Google Coral TPU, behavioral cloning

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# 1 Introduction

End-to-end driving is an approach to autonomous driving that has become a growing trend in autonomous vehicle research both in industry and academia[1]. Unlike modular methods that use expensive sensors, end-to-end techniques to autonomous driving rely on computer vision and machine learning to generate models that command steering and acceleration [2]. However, these models are notoriously susceptible and vulnerable to adversarial images[3], which are disturbances imperceptible to the human eye but can cause the model to misbehave.

In the context of end-to-end autonomous vehicles, adversarial attacks can lead to catastrophic consequences such as loss of life and property [4]. Research has been done on the impact of malicious attacks in autonomous-vehicle neural networks but only in simulation environments[5], [5]. To the best of our knowledge, research on strategies to mitigate the issue of adversarial attacks with real-world scaled autonomous cars does not exist.

Fleets of autonomous vehicles that use machine learning are ubiquitous and available to the general public. Creating strategies to defend end-to-end models and add robustness and resilience against adversarial attacks is paramount. Such vulnerabilities must be addressed and mitigated before we can see wider adoption of machine learning models to manipulate the steering and throttle predictions of autonomous cars [6].

This thesis will carry out an experiment to evaluate the effectiveness of defenses strategies against adversarial attacks in real-world scaled autonomous cars.

## 1.1 Motivation

A 2016 study by the National Highway Transportation Safety Administration (NHTSA) found that

Human error accounts for over 90% of all automobile accidents, according to a 2016 study by the National Highway Transportation Safety Administration (NHTSA). Traffic accidents are the leading cause of death among young people aged 5-29, and developing countries have 90% of all road fatalities. Self-driving is a promise to mitigate this issue and make our roads safer.

End-to-end methods to self-driving evolved from being the leading and predominant approach in the DARPA grand and urban challenges to being used in the industry by companies like Wayve and deployed to production models by car manufacturers such as Tesla.

In addition, trends like urban exodus, scarcity of drivers, and a revolution in intelligent transportation systems, including autonomous last-mile delivery systems, pressure the autonomous vehicles industry to act fast and produce safe, reliable, and affordable solutions.

Adversarial attacks to machine learning systems can not be eliminated, but strategies can be deployed to defend the models and make them more robust against such threats. .

## 1.2 Goals

The goal of this thesis is to adopt a Design Science methodology [7] to demonstrate how adversarial machine learning attacks can be used as an artifact to improve the robustness and reliability of a deep learning model of an autonomous driving car.

We investigate the literature to discover methods to train and validate neural networks. Then we implement an experiment to create a self-driving agent and evaluate its capacity to generalize to adversarial images. Finally, to defend against such attacks, we retrain the model and expose it to perturbations while training.

As a result of the defense, the model can generalize better, such as classifying correctly standard input images while becoming immune to the adversarial attack.

The thesis is organized as follows: Section 2 discusses the building blocks to create an autonomous vehicle using neural networks. We then discuss the threats against machine learning and the precautions necessary to deal with adversarial attacks. Finally, we investigate applying those concepts in a real-world scaled autonomous vehicle. Section 3 will illustrate the approach that is taken and the detailed phases necessary to accomplish the experiment. Section 4 supplies the outcomes of each stage described in the prior section. Section 5 discusses lessons learned and the limitations of the project. Finally, Section 6 encloses our evaluation conclusions and gives suggestions for future work.

## **2 Background**

Some text...

### **2.1 Computer Vision in self-driving**

Some text...

### **2.2 Neural Networks**

Some text...

#### **2.2.1 Convolutional Neural Networks**

Some text...

#### **2.2.2 Models**

Some text...

#### **2.2.3 Training**

Some text...

### **2.3 Adversarial Attacks**

Some text...

#### **2.3.1 Fault Injection in Trained Agents**

Some text...

#### **2.3.2 Defence to Adversarial Attacks**

Some text...

### **2.4 Scaled Autonomous Car**

Some text...

### **2.4.1 Donkeycar Platform**

Some text...

**Software**   Some text...

**Open-source Community**   Some text...

**OpenCV**   Some text...

**Keras**   Some text...

**Hardware**   Some text...

**Raspberry Pi**   Some text...

**Google Coral TPU**   Some text...

**Remote Control Car**   Some text...

**IMU**   Some text...

### **2.4.2 Safety**

Some text...

### **2.4.3 Metrics**

Some text...



## **3 Method**

Some text...

### **3.1 Selection of Self-Driving Platform**

Some text...

### **3.2 Selection of Driving Model Architecture**

Some text...

### **3.3 Training Pilot Model**

Some text...

### **3.4 Design and Implementation**

Some text...

#### **3.4.1 Testing 1**

Some text...

**Baseline Metrics**    Some text...

**Adversarial Attack Generator**    Some text...

#### **3.4.2 Testing 2**

Some text...

**Implement Defence Mechanism**    Some text...

#### **3.4.3 Testing 3**

Some text...

**Test Robust Model on Baseline**    Some text...

#### **3.4.4 Testing 4**

Some text...

### **3.5 Evaluation**

Some text...

## **4 Results**

Some text...

### **4.1 Selection of Self-Driving Platform**

Some text...

### **4.2 Selection of Driving Model Architecture**

Some text...

### **4.3 Training Pilot Model**

Some text...

### **4.4 Design and Implementation**

Some text...

#### **4.4.1 Context**

Some text...

#### **4.4.2 Implementation**

Some text...

#### **4.4.3 Baseline Metrics**

Some text...

#### **4.4.4 Testing 1**

Some text...

**Adversarial Attack Generator** Some text...

#### **4.4.5 Testing 2**

Some text...

**Implement Defence Mechanism**   Some text...

#### **4.4.6   Testing 3**

Some text...

**Test Robust Model on Baseline**   Some text...

#### **4.4.7   Testing 4**

Some text...

### **4.5   Evaluation**

## **5 Discussion**

### **5.1 Lessons Learned**

### **5.2 Limitations**

## **6 Conclusion and Future Work**

## **7 Acknowledgement**

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## **Appendix**

### **I. Glossary**

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