Object detection using convolutional neural networks to identify automobile characteristics for autonomous vehicles

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Introduction

Artificial intelligence is a growing industry and is becoming a larger part of everyday life. The advancements of autonomous vehicles is a great example of this development. The first fully self-driving vehicle to be put onto a road was in the late 1980's by Mercedes (Organa, 2013) and we have not stopped improving this technology since.

In order for a vehicle to be autonomous it has to use machine vision in order to evaluate the world around it. This allows it to make decisions based on what it sees just like a human would (Srivastava, 2019). There are many forms of machine vision and methods to accomplish them but I have focused on using convolutional neural networks to identify recurring features from a dataset of vehicles, specifically focusing on car lights to tell the vehicle to break.

Detecting colours for information such as tail lights, road signs and general obstacles is a practise not often used due to the nature of reading light information outdoors (D.Buluswar, 2020). I, however, have explored this technique for identifying break light key features in outdoor situations.

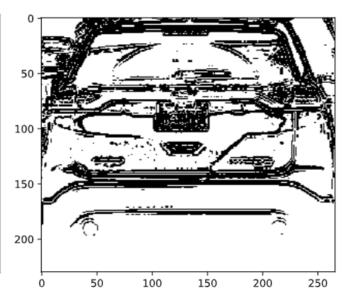
Project Aim

The aim of my project is to train a convolutional neural network to identify tail lights on a car and then present some sort of visual to say something has been detected. Identifying break lights is the priority with the objective to also include the identification of indicators too if possible in the given time frame.

Methods

I will be using the Tensorflow backend through the Keras library in order to train and evaluate my dataset on a CNN. All the programming will be done through the Visual Studio Code IDE as it's my preferred workstation. Using libraries such as NumPy, OpenCV, Pandas and more will grant me the ability to extract data and visualise outputs.





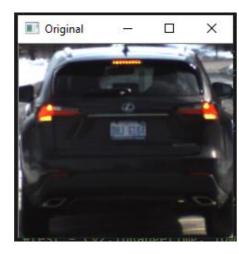
Figures and Results

A CNN takes in only a single image size and it is common practise to use the input value as the size of your smallest image. As my dataset included roughly 60,000 images of various dimensions, I had to make some sacrifices. I evaluated the images and filtered to sizes between 6000 and 300,000 total pixels as that contains the majority of images.

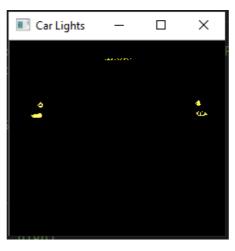
1000 800 400 200 100k 200k 300k 400k 500k 600k

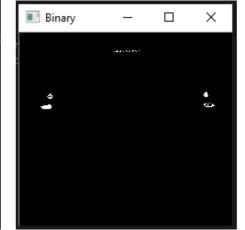
On my first attempt I tried converting each image into an array and also assigned that image a binary value, based on the image tag, to determine what the image contains (break lights, indicators etc). I then continued preprocessing the images and saved them for training.

While the model had around 99% accuracy on the training data, only an average of 65% accuracy was seen on test evaluation data. This drew me to the conclusion that my model was overfitting and to counter this I needed to acquire more specific features of what I needed the model to predict. After some testing I decided to apply a layer mask to separate the break lights based on a colour range as this would help identify the characteristics that are most important.



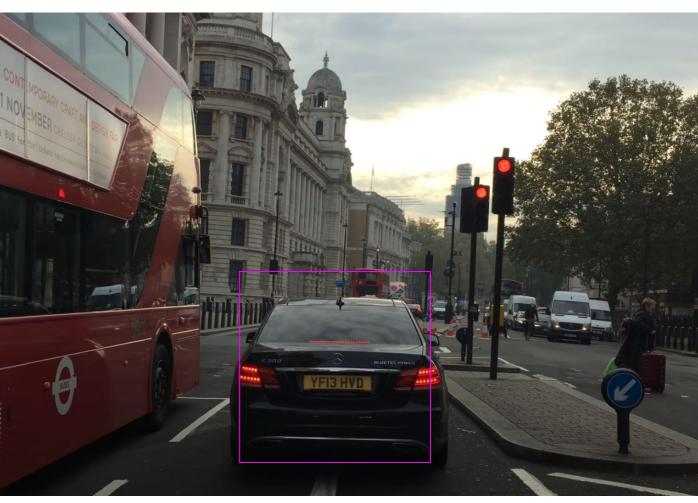
File sizes



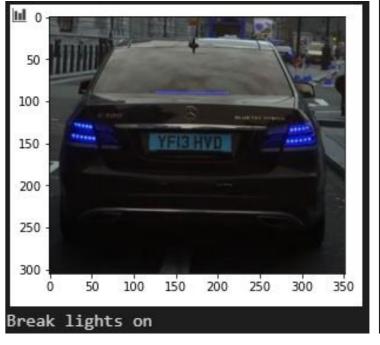


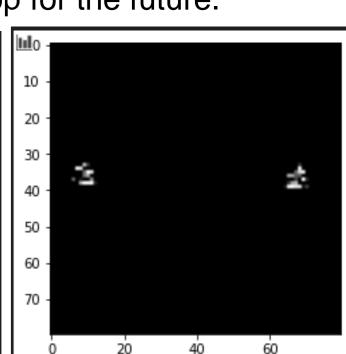
This new model got me around 94% accuracy which I was satisfied with and then moved on to testing both models with a sliding window approach to identify the location of break lights in a given image. The first model proved to be flawed as it would identify positively on almost every single window. The second model however proved to be much more accurate and always gave the rough position of the lights or even sometimes the exact position.

Conclusion



I achieved the most important goal I had set out to do of training a neural network to identify if a car has its break lights on or off. The localisation could use some improvement for different images and giving more time I would include detection of multiple features such as indicators and distance. For identifying lights on a car, applying filters and masks for colour detection proves to be an efficient way of training a CNN to identify the most important features. With the correct amount of training I believe machine vision is a reliable source and an area that should we should continue to develop for the future.





Acknowledgments

I would like to give my gratitude towards my supervisor Kyle Martin for guiding me through this project professionally and enthusiastically. His knowledge and advice on training artificial intelligence was a great help to the completion of this project.

References

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Srivastava, S., 2019.

COMPUTER VISION MAKES AUTONOMOUS VEHICLES INTELLIGENT AND RELIABLE.
[Online]



Honours Project