Autonomous Vehicle Steering Wheel Estimation from a Video using Multichannel Convolutional Neural Networks

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Abstract: The navigation technology in autonomous vehicles is an artificial intelligence application which remains unsolved and has been significantly explored by the automotive and technological industries. Many image processing and computer vision techniques allow significant improvements on such recent technologies. Using this motivation as a basis, this work proposes a novel methodology based on Multichannel Convolutional Neural Networks (M-CNN) capable of estimating the steering angle of an autonomous vehicle, having as only input images captured by a camera attached to the vehicle's frontal area. We propose five Convolutional Neural Network architectures: 1-channel, 2-channel and 3-channel in the convolution step. Based on the performed tests using a public video dataset, it is presented a quantitative comparison between the proposed models.

1 INTRODUCTION

Nowadays, autonomous driving and navigation technology in autonomous vehicles is an artificial intelligence application that has drawn great attention with the popularity of intelligent vehicles. In these application areas, unsolved issues still remain and have been significantly explored by the automotive and technological industries, due to the potential impact that such innovation will bring in the near future (Pomerleau, 1989; Thrun et al., 2006; Thorpe et al., 1988).

Over the last decades, many works have approached this theme: In 1989, (Pomerleau, 1989) described the construction of an autonomous vehicle based on artificial neural networks. The proposed network is responsible for providing guidance to the vehicle and the architecture of the network consists of a classical artificial neural network (ANN) with a single intermediate layer, containing 29 neurons fully connected to the input units.

Many works involving ANN in autonomous vehicle applications can be found in the vast literature available. However, a lot has changed since the advent of new network architectures. With the rise of deep learning, Convolutional Neural Networks (CNN) have improved the image comprehension tasks by learning more discriminative features, allowing an useful development on several systems, including autonomous vehicles (Wang et al., 2018). We will describe a small sample of the numerous applications of these networks architectures as follows: in (Chen et al., 2015) it is proposed an autonomous navigation system called *DeepDriving* based on CNN. The speed, acceleration, brake and steering angle are computed from the CNN output values, which are then used as input to an algorithm that describes the control logic of the vehicle.

The works of (Bojarski et al., 2016) and (Bojarski et al., 2017) propose a CNN called *PilotNet* capable of estimating the steering angle of a vehicle. In order to observe the features extracted by *PilotNet*, a deconvolution-based algorithm (Zeiler et al., 2011) is used. It finds regions of the image that have the highest levels of activation in the maps produced by the convolution layers of the network. The *PilotNet* network was tested in a car and was able to carry out a 15 minute journey in urban area without human intervention by 98% of the time.

Finally, in this work we propose a novel approach to construct new models based on Multichannel Convolutional Neural Networks (M-CNN) that are capable of estimating the steering angle of a vehicle given only a set of images from its frontal view, which is a task that many autonomous vehicle systems must solve.

To reach this main objective, the sections of this work are divided as follows: Section 2 describes in

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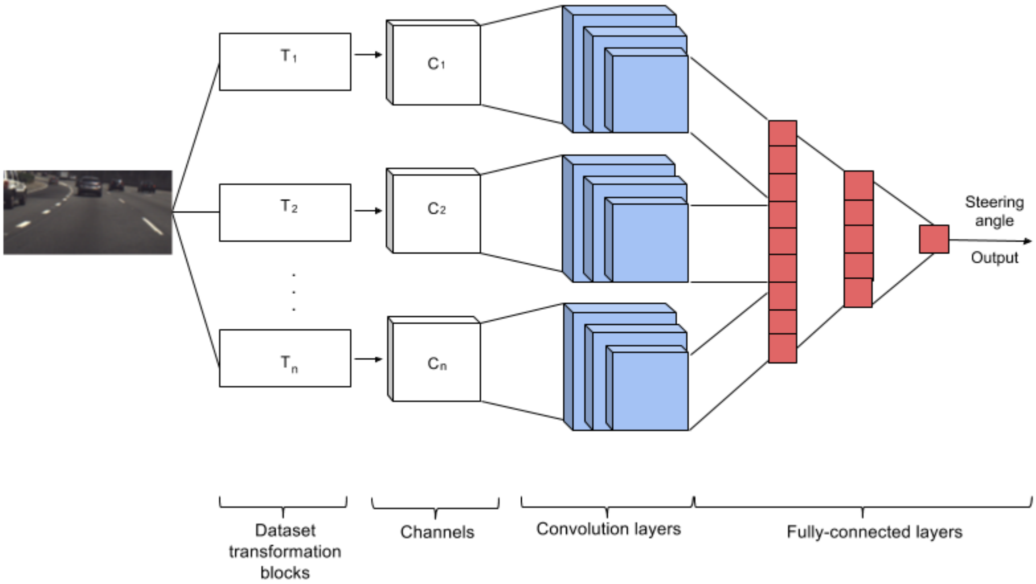
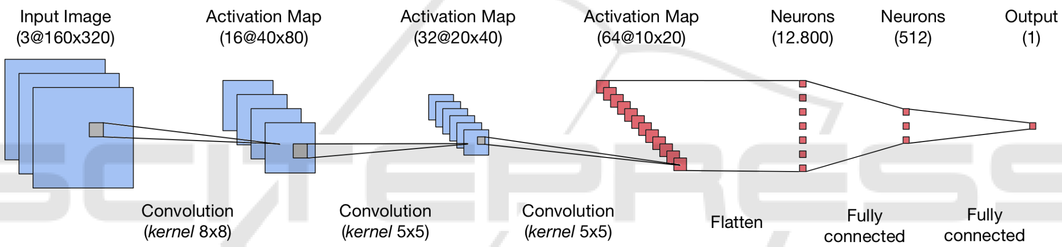


(a) Proposed M-CNN architecture.



(b) Base CNN architecture diagram.

Figure 1: Details of the proposed M-CNN architecture.

details the proposed methodology. In Section 3 the results are shown and discussed. Section 4 is dedicated to conclusions and further works.

2 PROPOSED METHODOLOGY

As seen in the related works presented in Section 1, artificial neural networks have presented promising results in the construction of many parts of autonomous vehicles systems. Hence, in this work we propose a novel method based on multichannel convolutional neural networks capable of estimating a vehicle's steering angle using only information from real traffic video scenes. In this specific case, the developed system receives as input a collection of RGB images captured using a dash cam placed inside the vehicle and outputs the estimated steering angle at the given instant, meeting the requirements of autonomous vehicles.

2.1 Dataset

Based on the proposed methodology, illustrated on Figure 1-(a), a dataset provided by the *comma.ai* organization[1] is used. The dataset is composed of 11 videos with a 320x160 pixels resolution, variable duration and captured in a 20Hz frequency using a dash cam installed inside the vehicle (i.e. Acura ILX 2016), capturing frames of its frontal vision while driving during day and night periods, usually on a highway. In total, the dataset is composed of 522,434 frames, resulting in approximately 7 hours of recording time. For the purposes of this work, the only information that was taken into account was the video frames (in RGB format) and the steering angle values. The steering angle is given in degrees and corresponds to the rotation angle of the vehicle's steering wheel. Every angle value present in the dataset belongs to the interval $[-502.3, 512.6]$.

[1]The dataset is made available on the CC BY-NC-SA 3.0 license.

2.2 CNN Architecture

According to (Goodfellow et al., 2016), CNNs are specialized artificial neural networks that process input data with some kind of spatial topology, such as images, videos, audio and text. Also in (Goodfellow et al., 2016), an artificial neural network is considered convolutional when it has at least one convolution layer and receives a multidimensional input (also referred as a tensor) and applies a series of convolutions using a set of filters. In addition to convolution layers, CNNs are usually composed of other types of layers.

2.2.1 Multichannel CNNs

Multichannel CNNs (M-CNNs) are commonly adopted when some sort of parallel processing of the input data is desired. Such streams can eventually merge into one in the latter layers of the network.

In recent works (Baccouche et al., 2011; Ji et al., 2013), it is common for the point of concatenation to be present before the first fully connected layer of the network, that is, the parallel processing is concentrated between the convolution layers. Action recognition, for example, is a problem that has been explored with M-CNNs due to the difficulty of traditional CNN in handling temporal information from input videos.

It is proposed in (Karpathy et al., 2014) a multichannel methodology capable of generating labels of the main action in a video. In (Karpathy et al., 2014), a 2-channel CNN is proposed, each channel receiving two frames of the input video. Another advantage of using M-CNNs is also highlighted by (Karpathy et al., 2014) and it consists in reducing the dimensionality of the network input, which helps to decrease the processing time.

2.2.2 Architecture

The objective of the proposed approach is to basically solve a regression problem: estimate the steering angle given a set of images. Therefore, this work uses as base a preexisting single channel CNN architecture proposed by the *comma.ai* organization, described by:

Figure 1-(b) presents the diagram of the base CNN. In more details, the network contains 13 layers and has 6,621,809 parameters to be learned. In topological order, the layers are described by:

1. **Normalization:** an image in the RGB format is given as input to the CNN, such that the value of every pixel belongs to the interval $[0,255]$. The first layer of the network is responsible for normalizing the pixel values to range $[-1,1]$. Thus, the following operation is executed:

$$w' = \frac{w}{127.5} - 1 \quad (1)$$

Output dimension: $3 \times 160 \times 320$

2. **Convolution Layer (CONV):** the parameters of the first convolution layer are present in Table 1.

Table 1: Parameters of the first convolution layer.

N^o of kernels	Kernel dimension	Stride	0-padding
16	8×8	4×4	2

Output dimension: $16 \times 40 \times 80$

3. **ELU**
Output dimension: $16 \times 40 \times 80$

4. **Convolution Layer (CONV):** the parameters of the second convolution layer are present in Table 2.

Table 2: Parameters of the second convolution layer.

N^o of kernels	Kernel dimension	Stride	0-padding
32	5×5	2×2	2

Output dimension: $32 \times 20 \times 40$

5. **ELU**
Output dimension: $32 \times 20 \times 40$

6. **Convolution Layer (CONV):** the parameters of the third convolution layer are present in Table 3.

Table 3: Parameters of the third convolution layer.

N^o of kernels	Kernel dimension	Stride	0-padding
64	5×5	2×2	2

Output dimension: $64 \times 10 \times 20$

7. **Flatten:** flattens the input data. For example, if the input has a 100x42 dimension, the output will be a $\mathbb{R}^{4200}$ vector. This step is done so that the spatial information learned through the convolution steps can be transferred to fully-connected layers.
Output dimension: $1 \times 12,800$

8. **Dropout:** the *dropout* layer was originally proposed by Srivastava et al. (Srivastava et al., 2014), and it is used as a form of regularization to prevent the occurrence of overfitting. This layer is used just in the training phase, and its operation consists in setting a value of 0 for each unity with a probability of p.
Dropout probability: 20%
Output dimension: $1 \times 12,800$

9. **ELU**
   Output dimension: $1 \times 12,800$

10. **Fully-connected layer (FC)**
   Output dimension: 1×512

11. **Dropout:** as in the previous dropout layer, it is used only in the training step.
   Dropout probability: 50%
   Output dimension: 1×512

12. **ELU**
   Output dimension: 1×512

13. **Fully-connected Layer (FC):** the last layer of the CNN is fully connected with the 512 units from the previous layer. It outputs $h \in \mathbb{R}$, which consists in the vehicle's steering angle at the moment the input image was captured.
   Output dimension: 1×1

2.3 Proposed Architectures

From the base architecture presented in Subsection 2.2.2, this work proposes the construction of two CNNs composed of multiple input channels, as shown in Figure 1-(a). The motivation behind the idea is to observe the impact that M-CNNs have in solving the supervised problem of estimating a vehicle's steering angle, incorporating temporal and spatial information obtained by the camera.

Following the original CNN architecture described in Figure 1-(b), we propose a multichannel model that processes the inputs in different channels until the last ELU layer. In other words, the outputs of the last ELU layers from each channel are concatenated and are passed as input to the first fully connected layer.

2.4 Developed Models

After defining the dataset and the CNN architectures, we now propose a framework used to generate all models trained from scratch that are able to receive a set of input images captured in a given instant by a vehicle's dash cam and output an estimation of the steering angle in such moment.

The proposed framework primarily consists in modifying the original dataset to allow the multichannel networks to be trained. Afterwards, 5 distinct types of models are trained. Lastly, the trained models can be tested and evaluated. More details about these models are described in Section 2.4.2.

2.4.1 Dataset Preparation

The base CNN proposed by *comma.ai* has a single input channel. Given that the methodology of this work proposes the usage of M-CNNs (`C1` for channel 1, `C2` for channel 2 and `C3` for channel 3), the original dataset (for future references, we will denote the original dataset as `BASE_1`) had to be adapted, generating four more versions of datasets. All these generated datasets were inspired in the work developed by (Karpathy et al., 2014) and are described as follows:

- `BASE_2`: original frame (`C1`) + frame subsampled in 50% (`C2`).
- `BASE_3`: original frame (`C1`) + central region of the image in original scale (`C2`).
- `BASE_4`: original frame (`C1`) + frame subsampled in 50% (`C2`) + central region of the image in original scale (`C3`).
- `BASE_5`: frame subsampled in 50% (`C1`) + central region of the image in original scale (`C2`).

Notice that the central region takes a 50% portion of the original frame.

2.4.2 Training Models

Five different models were trained, each one used one of the dataset versions presented in Section 2.4.1 and are described as follows:
Model 1 (trained with `BASE_1`): In this model, the original single channel CNN is used. This is done for comparison with the other proposed models as a reference model.
Model 2 (trained with `BASE_2`): The second model uses the two-channel CNN architecture. In one channel it receives the original image and in the other one it receives the same frame subsampled in 50%. Hereby, we can observe how the CNN behaves with the input given in different scales.
Model 3 (trained with `BASE_3`): The third model uses the two-channel CNN architecture. In the first channel it receives the original image and in the second channel it receives the original image's central ROI. Based on this model, we can observe how the neural network can react when receiving a region of the frame that probably contains objects closer to the vehicle and that are present in the same road lane.
Model 4 (trained with `BASE_4`): The fourth model uses the three-channel CNN architecture. The objective behind this model is to observe whether the neural network can produce better results if the additional information provided in models 2 and 3 are

given as input at the same time, combined with the original frame.

Model 5 (trained with BASE_5): The fifth model uses the two-channel CNN architecture and it was based on the idea of multi-resolution CNNs proposed by Karpathy et al. (Karpathy et al., 2014), which introduces two input channels: fovea and context. The fovea channel receives the central ROI of the input frame in original resolution (resulting in a 160x80 ROI in our dataset). The context channel receives the image subsampled in 50% (also containing a 160x80 resolution in our dataset). Thereby, the dimensionality of the CNN input is halved, which can present a better performance in terms of training time. Therefore, the fifth model is proposed to observe the impact on how M-CNNs can cause when receiving input with information loss.

3 EXPERIMENTAL RESULTS

This section presents the results obtained based on the datasets and CNN architectures detailed in the methodology. The GPU used for training the proposed models was an NVIDIA GeForce GTX 1070 and all models were developed using the TensorFlow (Abadi et al., 2015) and Keras (Chollet et al., 2015) frameworks.

The performed experiments correspond to the tests of the five models presented in the previous section. Each model was trained in 200, 350 and 500 epochs, such that the epoch size is 10,000 examples. Each training session with N epochs was repeated 3 times and each time the dataset was randomly partitioned in training/validation/test subsets, following the 70/15/15 proportion schema.

Given that the proposed CNNs output the steering angle using raw image data as input, it is crucial that the model's accuracy is correctly evaluated. All values presented in this section correspond to the error that each trained model had for their corresponding test set. The error is calculated between the estimated vehicle's steering angle and the ground truth angle obtained with an internal sensor, which is provided by the database.

The error measurement generally used to evaluate the prediction of numerical values is the root of the mean squared error (RMSE), which is described by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y'_i)^2} \qquad (2)$$

where n corresponds to the number of predictions, y_i equals to the ground truth angle of the i-th example and y'_i is the predicted steering angle given by the CNN's output. Thus, the lower the RMSE is, the greater is the model's generalization capacity. In order to enable the comparison between models trained under different combinations of subsets, the normalized form of the RMSE (NRMSE) was chosen. It is evaluated in Equation 3:

$$NRMSE = \frac{RMSE}{y_{max} - y_{min}} \qquad (3)$$

where y_{min} and y_{max} correspond to the lowest and greatest angle values observed in the test set, respectively.

The values described in Table 4 shows the average of the obtained NRMSE errors and the lowest values for each epoch are highlighted. The graph presented in Figure 2 shows the average of the obtained NRMSE errors.

Table 4: Average test errors of all trained models.

	200	350	500
Model 1	0.057548	0.047214	0.048096
Model 2	**0.040906**	0.046397	0.047917
Model 3	0.048535	**0.038011**	**0.047673**
Model 4	0.047513	0.046985	0.051179
Model 5	0.048974	0.051207	0.052770

3.1 Discussion

Based on the results obtained for each model present in Figure 2, it is observed that the NRMSE values for the multichannel models are similar between each other. However, it can be observed that the proposed models have better performance when compared to the reference model (i.e. Model 1). It is possible to notice that the Model 3 trained for 350 epochs presented an average NRMSE of **0.038010**, 7.07% less than the second best model (i.e. Model 2 trained for 200 epochs).

Figures 3-(a) up to (e) show how the estimated angles compare to the ground truth on some test videos. It can be seen that the predicted angles are likely to match the direction from the ground truth. Additionally, it is observed that the models output subtle variations in the steering wheel. Through the test charts, it is also noted that the error is more expressive at the beginning and end of the tests. This is due to the fact that in the used database, the ends of the videos correspond to the moment of entry and exit of the vehicle inside a garage, an event that implies a great variation in the steering angle.

On average, the models trained for 500 epochs did not bring improvements in the results. Thus, it is ex-

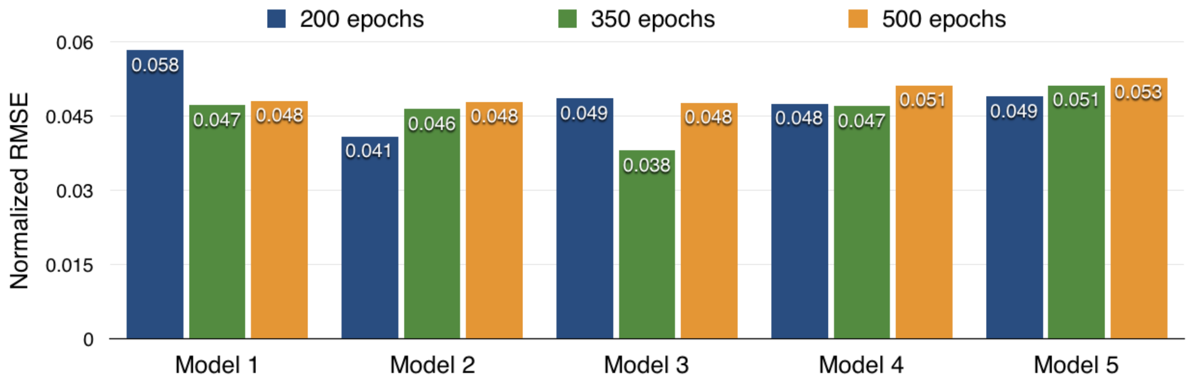


Figure 2: Average test errors of all trained models.

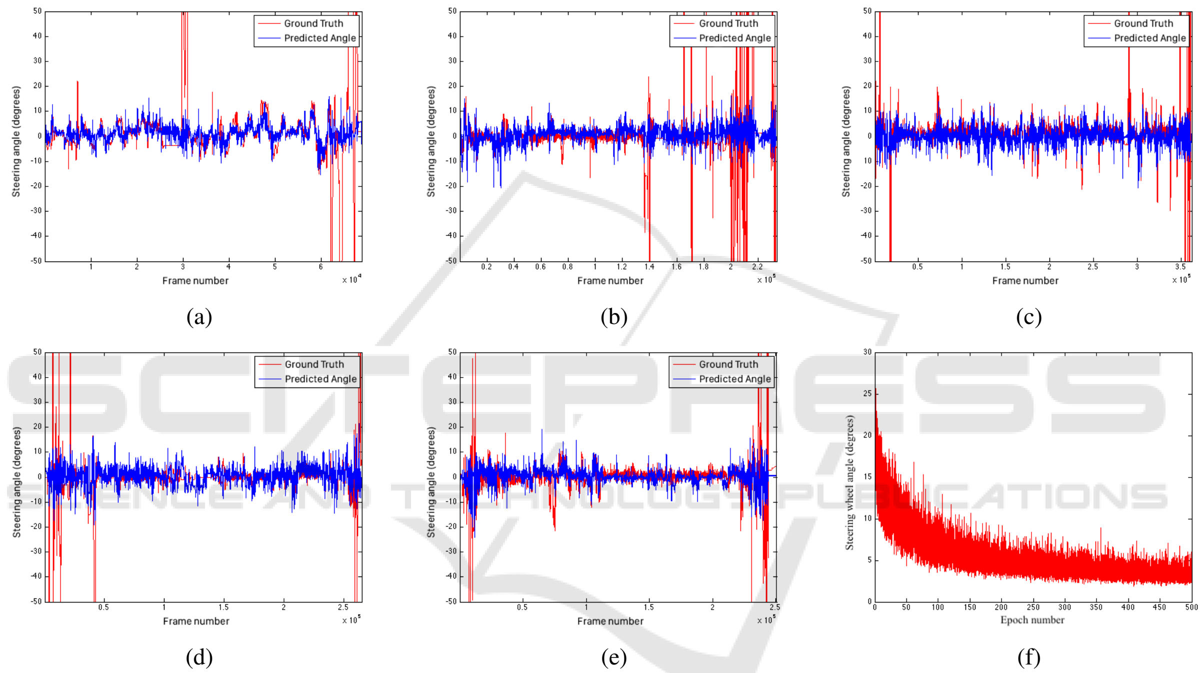


Figure 3: Figures (a) up to (e) show predicted outputs for models 1 up to 5 respectively trained for 200 epochs. In (f) it is shown the training error variation of Model 5 trained for 500 epochs.

pected that the model should suffer from overfitting when trained with more epochs, losing its capacity for generalization. For example, notice in Figure 3-(f) the training error of Model 5 trained for 500 epochs. It can be seen that the error does not significantly decrease after 200 epochs.

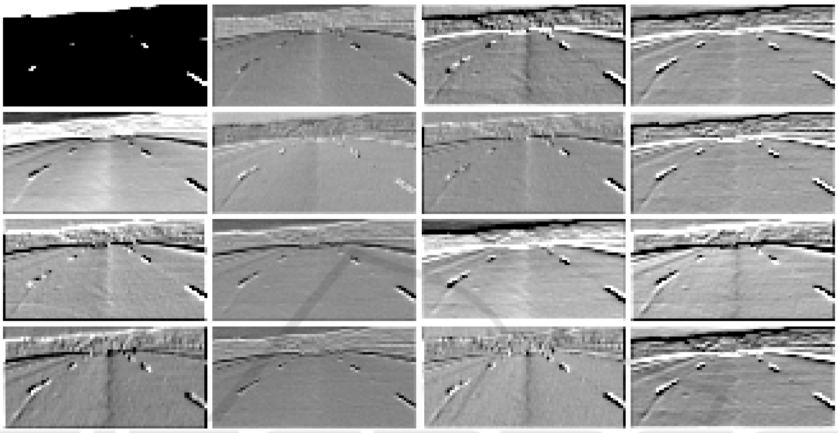
Finally, it is possible to perform a qualitative evaluation of the proposed models, following the idea described in (Karpathy et al., 2014), by visualizing the activation maps given as output by one of the convolution layers. Hence, Figure 4-(b) shows 16 activation maps produced by the first convolution layer from Model 1 trained for 200 epochs, given the frame on Figure 4-(a) as input to the network.

With the activation maps in Figure 4-(b), it is observed that the filters from the first convolution layer highlight the lane marks. In other words, the CNN was able to detect the presence of visual elements in the scene without being previously programmed to perform such task. By finding the lane marks (Figure 4-(b)), it is possible that the network was able to learn that the vehicle should keep itself between them while estimating the steering angles.

4 CONCLUSIONS AND FURTHER WORKS

This work proposes a methodology based on M-CNN that is able to estimate the steering angle of a vehicle

(a) Frame corresponding to the activation maps.



(b) Activation maps produced by the first convolution layer.

Figure 4: Activation maps from Model 1 trained for 200 epochs.

using only videos as input. As seen in Section 3, it is possible to observe that the third proposed model trained with 350 epochs obtained a lower NRMSE when compared to the others, including the single channel as reference model. Specifically in this model, it can be seen that M-CNNs provide significant improvements in their use in autonomous vehicle applications. The performance of the best model was approximately 7% better than the reference model.

Furthermore, the fifth model presents results similar to the others, showing that it was capable of maintaining robustness even when receiving an input with reduced dimensionality.

Future works may include the addition of explicit space-time information during the training stage, creating new versions of datasets and training models, exploring how M-CNNs architecture respond to this information. Also, new datasets and more complex situations must be tested to validate the approach.

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