Towards Greener Solutions for Steering Angle Prediction

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Abstract

In this paper, we investigate the two most popular families of deep neural architectures (i.e., ResNets and Inception nets) for the autonomous driving task of steering angle prediction. This work provides preliminary evidence that Inception architectures can perform as well or better than ResNet architectures with less complexity for the autonomous driving task. Primary motivation includes support for further research in smaller, more efficient neural network architectures such that can not only accomplish complex tasks, such as steering angle predictions, but also produce less carbon emissions, or, more succinctly, neural networks that are more environmentally friendly. We look at various sizes of ResNet and InceptionNet models to compare results. Our derived models can achieve state-of-the-art results in terms of steering angle MSE.

1 Introduction

As society continues to become more environmentally conscious, eventually most industries will be forced to innovate and reduce their use of fossil fuels. As of now, calls for reductions in carbon emissions have been focused on industries such as the automotive industry that have previously relied on fossil fuels. The burning of fossil fuels directly increases carbon emissions, and in some parts of the world, such as the European Union (EU), major steps to reduce carbon emission are underway. Recently, in July 2021, the EU commission proposed plans to essentially ban new sales of fossil fuel cars in the EU by the year 2035 (Carey & Steitz, 2021). Outside of a few exceptions, the US government is following a similar path and will no longer purchase vehicles that use fossil fuels by the year 2035 (Shepardson & Klayman, 2021). The negative effect of automobiles on the environment tends to be mainstream knowledge nowadays. What might not be mainstream knowledge to the average consumer is the substantial amount of carbon emissions that are produced when both training and deploying artificial intelligence (AI) into production. In fact, artificial intelligence structures (e.g., deep neural networks) can produce substantially higher amounts of carbon emissions than that of an automobile (Strubell et al., 2019). As such, many in the AI industry are calling for more sustainable and “greener” structures. In April 2020, MIT news office issued a press release indicating that progress is being made in the search for greener solutions, which included once-for-all network methods (Cai et al., 2019).
While impending bans on fossil fuels are forcing automobile manufactures to look for alternative fuels solutions, the focus on reducing carbon emissions may have inadvertently helped progress the automotive industry on another front. The automotive industry, just like all other industries, are trying to utilize artificial intelligence as much as possible in various areas, but they are specifically focused on autonomous driving. Many large automotive companies such as Tesla, Audi, and Toyota are producing or jointly producing autonomous-like capabilities in some of their cars, yet they still lack the ability to produce a fully autonomous car (Golson, 2021). To be truly autonomous, cars should be able to operate offline and with real-time data. However, due to this technology being in its infancy, its uses are relatively limited. For example, Tesla refers to their autonomous solution as an “autopilot” (Tesla, 2022). Its primary goal is to reduce the driver’s workload when driving. This solution does not replace the driver and requires the driver to be fully aware. Consequently, Tesla’s automobiles are not fully autonomous. Autonomous driving is still in relatively developmental stages, and is in need of sophisticated models, but now automobile companies need to implement smaller, greener, and sustainable models into their autonomous driving calculus. Bigger is not always better as they tend to be slower.

This paper approaches the necessary yet difficult task of steering angle predictions while being mindful of model complexity. We used variations of the Inception and ResNet architectures for steering angle predictions. While we do analyze the outcomes of all of the ResNet models, our main focus is to outperform ResNet models with a comparable Inception architecture. The reduction of computational complexity will hopefully promote further research into using compact Inception models for complex tasks which will, in turn, reduce carbon emissions from the training and deployment of artificial intelligence models.

2 Related Work

The new focus on lower carbon emissions has put neural network research in a unique position. The development of neural networks will need to be smaller, more efficient, or, in other words, greener. Some researchers are designing greener models with a process known as neural architecture search (Martineau, 2020). Studies have shown that carbon emissions for computing power can be equivalent to the lifetime of approximately five automobiles (Strubell et al., 2019). This, in turn, has facilitated the search for more efficient models. Furthermore, researchers have estimated that carbon emissions from the Communication Technology sector could use as much as 51 percent of global electricity and contribute up to 23 percent of global carbon emissions by 2030 (Andrae & Edler, 2015). While autonomous driving is still an open problem, researchers are being mindful of what the future looks like without fossil fuels and heavily reduced carbon emissions. Thus, researches will need to develop neural networks architectures that are more accurate, faster, and smaller than their neural networks.

1We acknowledge that Tesla may not be as sophisticated as other autonomous driving companies. However, it is the most widely known company in the autonomous driving space which is why we used this example
predecessors for autonomous driving. One task in particular, steering angle prediction, has been of particular interest for autonomous driving. Steering angle prediction refers to the trained artificial intelligence model predicting the needed steering angle for a car to turn based on the road curvature and its surrounding environment. This is an important feature for autonomous or self-driving cars (Mygapula et al., 2021). The current state of the work done in steering angle prediction is early compared to other areas like image recognition. Steering angle prediction continues to rely more heavily on visual processing and understanding. Currently, even Tesla has begun to use pure vision in their cars (Klender, 2021). Gidado et al. (2020) survey different deep learning (DL) methods for steering angle prediction. The goal of this research is to compare and review steering angle control of autonomous vehicles (AV) using the two most popular deep learning architectures (i.e., InceptionNet and ResNet models). Needless to say, researchers tend to focus on steering angle prediction using deep convolutional neural networks, which is not surprising given their success in other computer vision tasks.

Steering angle prediction needs to be accurate, fast, and efficient. If the prediction is slow, it could cause life-threatening harm to a person. Since steering angle prediction is an active topic, there is a considerable amount of recent work in the area. While there are continuous changes in the field, the ResNet architecture is one of most well-known for deep learning (Islam et al., 2021) and has continued to not only perform well with steering angle prediction, but has cemented itself as an integral part to many cutting-edge approaches to steering angle predictions (see for example, Oussama & Mohamed (2019); Munir et al. (2022)). ResNet is not only still a viable architecture for modern research, but also considered a comparative baseline for researchers as it is still considered to be one of the most state-of-the-art network architectures for this task (Oussama & Mohamed, 2019; Islam et al., 2021). For example, Oussama and Mohamed (2020) surveyed different methods for achieving steering angle prediction. They begin by categorizing previous works on steering angle calculations to two major approaches. One is traditional computer vision-based and the other is neural network-based. Most of the approaches rely on cameras, sensors, and/or radar (Oussama & Mohamed, 2019). The results of this research compilation showed that the combination of ResNet50 deep architecture with event cameras gives better prediction of the due wheel angle. However, the cost to train and deploy ResNet50 is high. This is mainly due to the large number of parameters in a ResNet50’s model.

Other research has fairly large and complex models in pushing the boundaries of autonomous driving. Navarro et al. (2021) investigate creating a new end-to-end architecture design for speed and steering angle prediction. This architecture design consists of creating layers within a stack of blocks and connecting them like a puzzle (Navarro et al., 2021). It is compared to other end-to-end architectures used in steering angle prediction. The results of this research shows that these new end-to-end models have better optimization from the use of additional data points, like speed, causing these models perform well with a reduced number of parameters. The development of a fast and accurate model is challenging enough, but there is another additional problems that one
must consider. One of them is the overall cost, which considers training and running a CNN for steering angle prediction. Currently, many autonomous cars are expensive due to the server grade hardware required for running the artificial intelligence. Many times the server grade hardware can be impractical due to its overall size, weight, and power requirements. Another is the accuracy needed for steering prediction angle to be considered safe. Without good accuracy, it is dangerous to allow the AI to predict a steering angle. Also, most model architectures like ResNet50 are large and complex. Which is a combination of the two problems. The speed of the CNN model for steering angle prediction must be fast. Even if the model architecture is accurate, if it cannot predict the steering angle fast enough the actual accuracy will not matter.

The ResNet architecture is not the only architecture for steering angle predictions. ResNet research does appear to be more popular in the literature, even though InceptionNet is another architecture that can address steering angle predictions. Al-Qizwini et al. (2017) found InceptionNet as the best model for various autonomous driving tasks. McNeely-White et al. (2020) found that InceptionNet extracted qualitatively equivalent information as its ResNet counterpart. They also find that the InceptionNet architecture to be extracting information more robustly. They experiment with the ResNet-v2 152 and Inception-v4 models, which are much larger than the models we are researching. We look to the architectures to find a less computationally complex model that best performs steering angle prediction task. We will show that InceptionNet models can both outperform ResNet architectures for steering angle predictions, while being less computationally complex which leads to a greener outcome.

3 Methodology

A general description of supervised training in our context is having a CNN model take different images and labels to learn what to look for. The learned weights are how the algorithm is able to differentiate different aspects of an image. In our case, the algorithm needs to learn different turns and report the road’s corresponding angles (in degrees). These roads must vary to best test the models and evaluate outcome for accuracy. To address the inefficiency issue faced with training and running large CNN models for steering angle prediction, more compact models must be considered. The goal is to find a compact model with an accuracy score that does as well as or better larger counterparts. This paper explores variations of ResNet and InceptionNet models. We present the outcomes of various sizes of complexity for each of the two architects. For example, we built and trained eight variations of the ResNet architecture; ResNet20, ResNet22, ResNet24, ResNet26, ResNet28, ResNet30, ResNet32, and ResNet34. We built seven InceptionNet models to match in similar numbers of parameters so that we could compare the architectures at different complexity levels. We utilized pre-trained ResNet and Inception models from the Pytorch library as baseline models before building our own ResNet and InceptionNet models. This provided a minimum performance to achieve with our smaller ResNet and InceptionNet models. Figure 1 highlights how we built variations of both ResNet and InceptionNet
models for our research.

When comparing architectures, mean squared error (MSE) loss was used. For final graphs, validation loss scores will be used and plotted according to each model’s number of parameters, or complexities. Additional analysis will include a review of how each model convolves an image and in turn makes a prediction. This will allow us to identify how each model consumes an image, where the focus is, and how the predictions are affected.

3.1 ResNet

Preliminary experiments included running five pre-trained ResNet models. The largest two models (101 & 152) were too large and unusable for our purposes. Pytorch’s pretrained ResNet18 and ResNet34 performed very poorly when compared to the pre-trained ResNet50, plus we needed varying degrees between the two models. This was the starting point but we needed to produce our own ResNet models to help tease out any nuances between the architectures. Our ResNet models were built off of the foundational ResNet18 and ResNet34 BasicBlock approach which was replicated from the original ResNet paper. The input layer of ResNet models (and InceptionNet models) take in an image dimension size of 224 by 224. Each model’s number indicates the number of layers. For example, ResNet50 is larger than a ResNet34 as the former has 50 layers and the latter 34 layers. For those interested in ResNet architecture details, please see He et al. (2016).

3.2 InceptionNet

Traditional InceptionNet is very different from traditional ResNet. The theory behind an InceptionNet net model attempts to be powerful and efficient as it combines the strength of various filter sizes (e.g., 1x1, 3x3, 5x5, and max pooling). Another important difference is that InceptionNet concatenate while ResNet summates at the end of blocks. Similar to the ResNets, InceptionNet can be adjusted in size of layers or parameters to test for improved accuracy. The Inception block uses the various filters to convolve the images and then concatenates the results. Within a certain range,
Figure 1: Illustration of model modifications for our research

This is where we increase Inception blocks to improve accuracy (InceptionV1 shown)

This is where we change ResNet blocks to improve accuracy (ResNet2D shown)
we attempted to add accuracy by increasing the size of the blocks in each of the main architectural sections, which in turn changes the number of filters throughout the layout. These changes helped add to the level of complexity within the InceptionNet blocks. For further interest in the InceptionNet Block architecture, please see Szegedy et al. (2015).

### Table 2: InceptionNet Model Parameters & Block Layers

| InceptionNet Model | Parameters | Block Layers |
|--------------------|------------|--------------|
| InceptionNet       | 13.0 million | (2,5,2)     |
| InceptionNet a     | 14.5 million | (5,5,2)     |
| InceptionNet b     | 15.5 million | (2,8,2)     |
| InceptionNet c     | 17.0 million | (5,8,2)     |
| InceptionNet d     | 17.6 million | (2,5,5)     |
| InceptionNet e     | 20.2 million | (2,8,5)     |
| InceptionNet f     | 21.7 million | (5,8,5)     |

4 Experimental Setup

#### 4.1 Testing Environment

Experiments were ran on the Ohio Supercomputer Center’s Pitzer cluster which include dual NVIDIA Volta C100 GPUs with 32GB. All models were trained and validated on the Ohio Supercomputer Center’s Pitzer cluster that utilizes NVIDIA Volt V100 GPUs (OSC, 1987). The deep learning framework used was PyTorch. All imports will be based around this framework using Python 3.

#### 4.2 Evaluation

We focused on the results from the validation loss score and logged those scores using Tensorboard. We use mean squared error (MSE) as the loss function. \[\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (r_i - \hat{r}_i); \text{ where } r_i = \text{actual steering angle in radians and } \hat{r}_i = \text{predicted steering angle in radians.}\] We also employed an early stoppage when no improvement was made after 10 epochs as which time the model training was halted.

Each model was trained one at a time and its checkpoint run data was saved such that it could be included in a visualization using Tensorboard. Models were ran for 50 epochs and the batch size tested for all models varied from 16 to 128 in search of the best outcome. Generally, batch sizes of 32 were found to have best results. Epochs of at least 50 were needed as ResNet models validation loss score decreased earlier in their epochs, however the InceptionNet models performed more similarly after 30 or more epochs. This need for at least 30 or so epochs was a reoccurring theme when comparing the
two architects at all levels of complexity. Figure 2 highlights the quick drop in validation loss scores in earlier epochs, which was a common observation in models for the ResNet architecture.

![Figure 2: Magenta line represents ResNet20, & Orange line represents InceptionNet.](image)

## 5 Results

### 5.1 Quantitative

Our first analysis was with a publicly available Kaggle data set of approximately 97,330 images [Kaggle (2019)]. If we are to solely consider MSE scores, then the lowest score is our ResNet32 model at 0.05293 (see Table 3). This was actually a great score to see as our ResNet model performed similarly (or better) than that of recent work [Ijaz & Wang 2021; Oinar & Kim 2022]². The InceptionNet architecture had a score of 0.05846 as its lowest. However, this does not tell the whole story. Figure 3 plots all of the tested models with their complexity measure on the x-axis and their MSE scores on the y-axis. The plotted lines intersect around 17.9 or 18 million parameters. This is approximately where

| ResNet Model | MSE     | InceptionNet Model | MSE     |
|--------------|---------|--------------------|---------|
| ResNet20     | 0.06557 | InceptionNet       | 0.06044 |
| ResNet22     | 0.06371 | InceptionNet a     | 0.05945 |
| ResNet24     | 0.06721 | InceptionNet b     | 0.05849 |
| ResNet26     | 0.05832 | **InceptionNet c** | **0.05846** |
| ResNet28     | 0.05552 | InceptionNet d     | 0.05961 |
| ResNet30     | 0.05641 | InceptionNet e     | 0.05802 |
| **ResNet32** | **0.05293** | InceptionNet f     | 0.05907 |
| ResNet34     | 0.05425 |                    |         |

Table 3: MSE Scores

²We do even better in our second analysis.

the two architectures are equivalent. Thus, with our main idea to have smaller and greener neural
networks to reduce carbon emission, we can see that at smaller complexity level the InceptionNet clearly outperforms the ResNet models. We see that at deeper and more complex models the ResNet architecture outperforms the InceptionNet models after about 18 million parameters. A possible reason for this is that ResNet models were created with a skip connection in an attempt for deeper modeling. In other words, that was their purpose for which they were created. Again by analyzing the smaller models, we see that InceptionNet could very well be a best solution to focus on for novel creation of greener models when it comes to the steering angle predictions task for autonomous driving.

To make sure that the results were not just an anomaly of our first data set, we ran all of the models on a second data set. Our second analysis included a data set of approximately 10,765 images. This data set was created by the authors using the Udacity self-driving-car simulator [Udacity] (2016). Table 4 highlights the best performing model is our InceptionNet b model. Interestingly, all but one of our InceptionNet models outperformed it’s parameter comparable ResNet counterpart. So not only do we see the best performance from the InceptionNet architecture, we also see the InceptionNet architecture outperforming ResNet at various ranges. More importantly, we see InceptionNet perform very well at the lower-end and mid range sized models. In figure 4 we do see the performance of the InceptionNet architecture, along with signs that the models start to converge around our previous observation of 17 millions parameters.
Table 4: MSE Scores

| ResNet Model | MSE   | InceptionNet Model | MSE   |
|--------------|-------|--------------------|-------|
| ResNet20     | 0.05527| InceptionNet       | 0.04886|
| ResNet22     | 0.05081| InceptionNet a     | 0.05692|
| ResNet24     | 0.04701| **InceptionNet b** | **0.03828**|
| **ResNet26** | **0.04642**| InceptionNet c     | 0.04395|
| ResNet28     | 0.04774| InceptionNet d     | 0.03981|
| ResNet30     | 0.05311| InceptionNet e     | 0.04402|
| ResNet32     | 0.04817| InceptionNet f     | 0.04557|
| ResNet34     | 0.04646|                    |       |

Figure 4: MSE Loss by Parameters

5.2 Qualitative

We are unsure of exactly why the InceptionNet performs better with smaller sized models, however we looked to saliency maps to help with possible understanding. Saliency maps provide insight into how the two architectures differ in their focus on an image (Fig. 5). The image used for the saliency example was normalized. The model gradient calculations were performed and then the maximum absolute values of the image channels for each pixel was used to highlight the contribution for the output. The saliency images show primarily three colors; black which indicates no focus or attentions; red which indicates some focus or attention; and yellow which indicates the highest level of focus or attention. Our analysis is still very preliminary; nonetheless, it appears ResNet is more general in its viewing of image, while InceptionNet appears to be more focused within the image.
(a) Inter-architectural comparison (original image, ResNet32, & Inception d)

(b) ResNet Saliency: Intra-architectural comparison (ResNet20, ResNet26, & ResNet32)

(c) InceptionNet Saliency: Intra-architectural comparison (Inception, Inception d, & Inception f)

Figure 5: Saliency Maps
6 Significance of the Research

This research examines the two main veins of modern neural network architectures and their intra-variations. The models explored for this research include various InceptionNet and ResNet depths of complexity. We provided evidence showing that InceptionNet could very well be the preferred architecture when looking for a smaller sized models. This agrees with the previous research of Tian et al. (2020). If there is no limit on the model/data size, then it appears that the ResNet architecture performs better with deeper and more complex structures. On our first analysis, we found that InceptionNet outperformed ResNet for the more compact parameters sizes or where parameter size could be limited. Overall, ResNet did produce the best MSE loss score in our first analysis. This does provide evidence that in many cases smaller models can and should be used over their larger intra-variations. In our second data set, not only did the InceptionNet produced the best model at the limited parameters sizes, but the InceptionNet also produced the best overall model. In this analysis we also saw that the majority of the InceptionNet models outperformed their ResNet counterparts. The main contribution of this research includes providing empirical evidence that a lower complexity InceptionNet models can achieve equivalent or lower loss function scores when compared to not only ResNet equivalents but also larger ResNet models. Additionally, we show that InceptionNet models do very well in the overall domain space. On the private data, our InceptionNet can achieve as low as 0.03828 MSE (the best ResNet in our experiments, i.e., ResNet26, achieves 0.04626 MSE). Hopefully this research ignites additional research in the autonomous driving area for smaller, environmentally friendly architectures. It appears that the desire to reduce carbon emissions may very well help lead to innovation in autonomous driving space.

7 Future Work

Our future work will include the addition of attention layers to the ResNet and InceptionNet models, and possibly comparing other architectures as well. Finding and testing our models with additional data sets would be ideal for understanding how to select best models for different situations. Since there are not many publicly available datasets, we plan on generating more data for steering angle prediction in the future. Our idea is to continue searching for lighter, robust models to help further not only the frontier of knowledge, but also assist in reducing carbon emissions for a greener solution.

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