Machine Learning Homework 2

Alex Parri - 2140961 - Master’s Degree in Cybersecurity

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Abstract

This is the report for the **second homework** of the Machine Learning course directed by Luca Iocchi for the Academic Year 24/25 for the Master's Degree in **Artificial Intelligence and Robotics** at Sapienza University of Rome.

In this homework, the goal was to devise a model that would learn how to drive a car on a track in a **2D top-view**, more specifically taken from gymnasium's "car racing" environment. All models and their variations have been tested with the same simulation seed, thus on the same exact race track, meaning that results **may vary** for different ones.

It was decided to keep that specific track as it is a rather **insidious** one, thus performing well on it would most likely correspond to a better outcome in more general cases.

More specifically it is an **image classification** problem whose objective was to learn the following

$$f : X = \{\underbrace{(96 \times 96 \times 3)}_{\text{colored images}}\} \to Y = \{0, 1, 2, 3, 4\}$$

The (supervised) dataset for the problem is composed of colored screenshots each of size (96×96) pixels and has been provided by the **professor itself**, already split between training and test set as shown in the following table

Class label	Training samples	Test samples
do nothing	1000	133
steer left	1500	275
steer right	1500	406
gas	2000	1896
brake	369	39
TOTAL	6369 (69.9%)	2749 (30.1%)

There were no attempts at trying to balance the dataset due to the **low amount** of samples for each class. Of the above training samples, $\frac{1}{5}$ where used for validation and the remaining $\frac{4}{5}$ for actual training. Multiple **random states** of these splits have been tested for variability.

Moreover, it is important to state that the dataset is somewhat **noisy** due to the presence of misclassified images, which is a recurring trait in real world image classification problems. Anyhow, it is a crucial factor to consider when evaluating the models' **accuracy**.

Two main approaches based on **Convolutional Neural Networks - CNNs** have been trained to try and learn the problem:

- **Model 1** prioritizing feature elaboration through manual hyperparameter searching
- **Model 2** more focused on feature extraction through automatic hyperparameter searching

Both abovementioned models are equipped with **Sparse Categorical Cross-Entropy - SCCE** loss function, one of the best to consider when we have classification problems with **integer encoded** labels as we have

$$\text{SCCE} = -\frac{1}{N}\sum_{i=1}^{N} \log \hat{P}_i(y_i)$$

Where $\hat{P}_i(y_i)$ is the predicted probability for the true class y_i of sample i.

The above works well in conjunction with the **softmax** function in the output layer, normally the one chosen for multiclass classification

$$\sigma(\mathbf{x}) = \frac{e^{x_i}}{\sum_{j=1}^{K} e^{x_j}}$$

The results that will be shown are **not guaranteed** to be the best achievable ones. Testing as many configurations as possible was the priority, as the homework's main objective was to enchance the student's knowledge about image classification and CNNs.

Note: Generative AI has been utilized in this project solely as inspiration for the code. The project in its entirety has been developed **individually** without any other external collaborators, including this report.

The **hardware** utilized to train the models is Nvidia RTX 3070 GPU (8GB VRAM) with driver version 560.35.03 and CUDA version 12.6 on Ubuntu 24.04.01 LTS x86_64 and 16GB of RAM.

Preprocessing and data augmentation

Preprocessing is performed in machine learning to transform data in a **more suitable format** for model training, it has a relevant role in improving result quality and model efficiency: in this case, it has been applied to inputs given to both proposed models both in the training and prediction phase by **normalizing** the data contained in each pixel between **0 and 1 included**.

Data augmentation is an important approach towards improving model generalization, thus **reducing overfitting**. In our problem the decision was to apply the following augmentations on all samples (values are in % compared to the original)

Augmentation	Minimum	Maximum
random gamma	90%	110%
random constrast	90%	110%
random quality	75%	95%

Not all kinds of data augmentation make sense depending on the specific problem: for this case in fact **flipping** images horizontally or vertically would confuse the model leading to misclassification of left with right and viceversa more often. In practice, that would translate to a significantly worse model.

Preprocessing and augmenting all the data takes around **16.7 seconds**.

Model 1

The first model is focused on feature elaboration more than extraction. It is composed of three convolutional layers with exponentially increasing units and two dense layers, which in one of its best form, after **manual hyperparameter searching**, seems to be the following

Layer	Units	Activation	Padding	Kernel size	Out Shape	Parameters
Conv2D	32	ReLU	valid	(2, 2)	(95, 95, 32)	416
MaxPooling2D	-	-	valid	(2, 2)	(47, 47, 32)	-
Conv2D	64	ReLU	valid	(2, 2)	(46, 46, 64)	8,256
MaxPooling2D	-	-	valid	(2, 2)	(23, 23, 64)	-
Conv2D	128	ReLU	valid	(2, 2)	(22, 22, 128)	32,896
MaxPooling2D	-	-	valid	(2, 2)	(11, 11, 128)	-
Flatten	-	-	-	-	15488	-
Dense	256	ReLU	-	-	256	3,965,184
Dropout 0.5	-	-	-	-	256	-
Dense	64	ReLU	-	-	64	16,448
Output	5	softmax	-	-	5	325

The total number of trainable parameters is **4,023,525** of which 98.96% are from the dense layer.

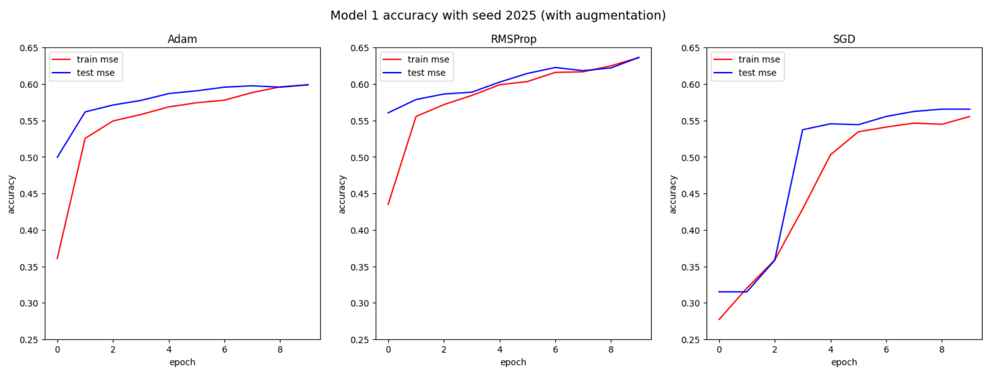
Note: despite the hardware capabilities, performing automatic hyperparameter searching on the models themselves would take a **significant amount** of time as there are many possible configurations to try. For practical reasons, it was automatically performed only on the second model's **optimizers' hyperparameters**. It will be shown that despite this, this decision leads to good results in both cases.

Choosing the optimizer

The optimizers with manually searched hyperparameters are the following

Optimizer	Hyperparameters	Training time	Batch size
Adam	$\begin{cases} \eta = 0.0001 \\ \beta_1 = 0.6 \\ \beta_2 = 0.8 \end{cases}$	114.65s	64
RMSProp	$\begin{cases} \eta = 0.0001 \\ \mu = 0.8 \\ \rho = 0.8 \end{cases}$	115.86s	64
SGD	$\begin{cases} \eta = 0.001 \\ \mu = 0.9 \end{cases}$	105.63s	64

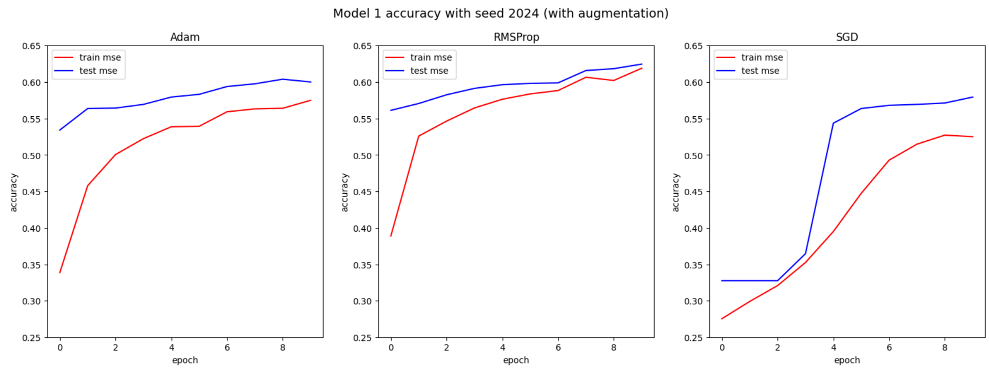
By training three identical copies of first model for only **10 epochs** reveals the following result



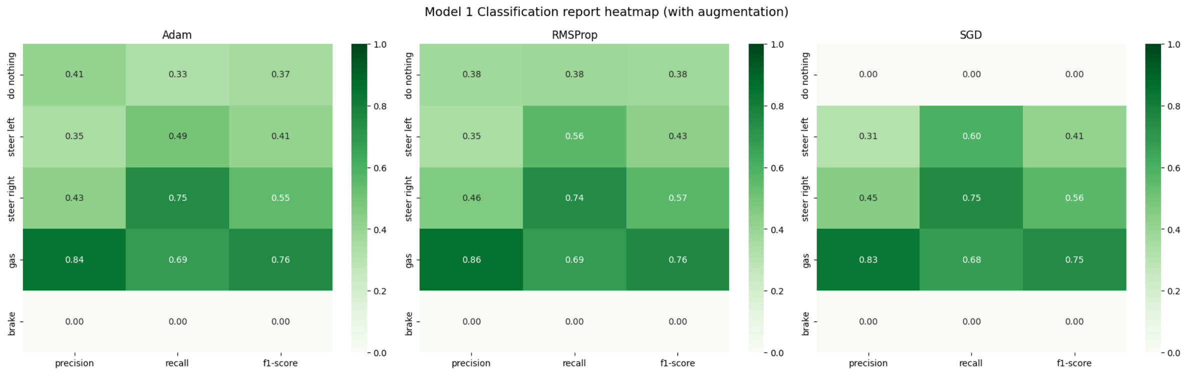
In terms of **validation set accuracy**, RMSProp seems to be the most performant with 62.77, with Adam slightly behind at 58.63 and SGD in last place with just 56.06. These seem like already good results, considering that predicting images at **random** would result in an accuracy of $\frac{1}{|classes|} = \frac{1}{5} = 0.20$.

These numbers are subject to change depending on the random weights with which the models are initialized with.

By testing a different validation split seed, the result shows slightly more overfitting, but overall is more or less **the same** for all three optimizers, likely due to the small size of the dataset itself

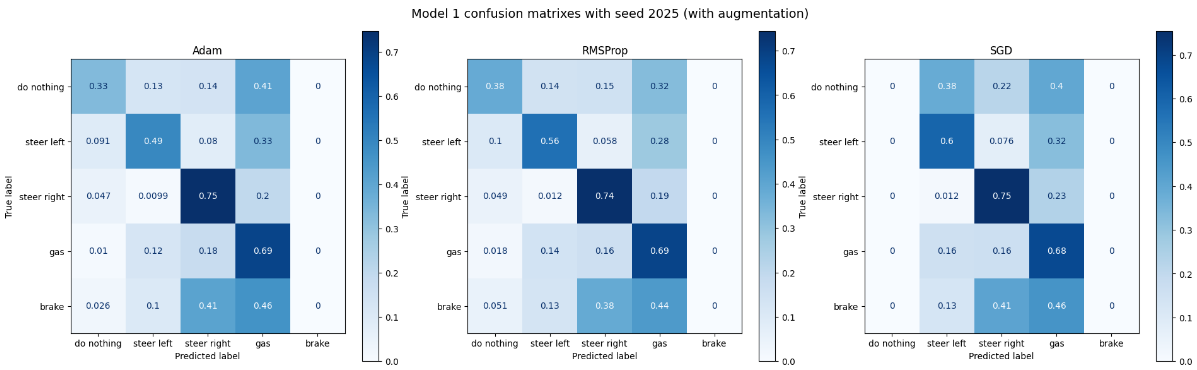


From the **classification report** below it is possible to see decent results across the board



Adam and RMSProp present very similar results, with the *gas* class having most precision and f1-score likely due to its **large support**. The other classes do not perform that well, especially the *brake* class with score zero across all optimizers, very probably due its low amount of support.

All things considered the models have learned the problem quite well, as the following normalized **confusion matrixes** are showing



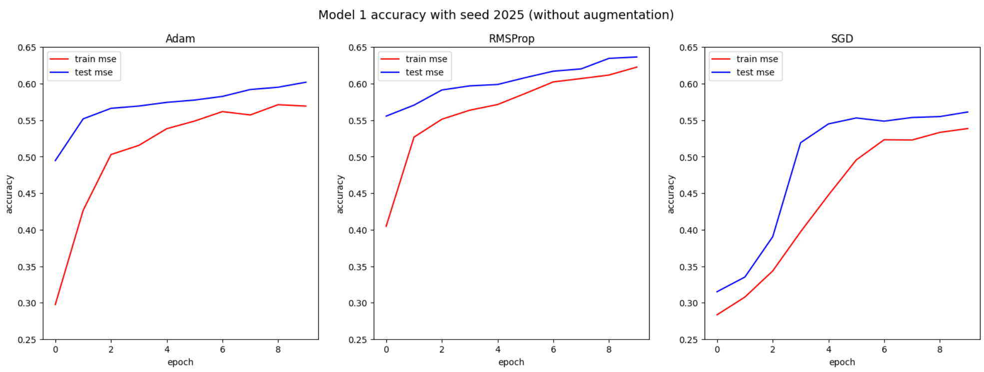
Anyhow, it is possible to notice the **same pattern** repeated throughout all optimizers

- *steer right* and *gas* classes are well recognized
- *brake* is practically never predicted and sometimes misclassified as *steer right* or *gas*
- almost all classes are usually misclassified as *gas*

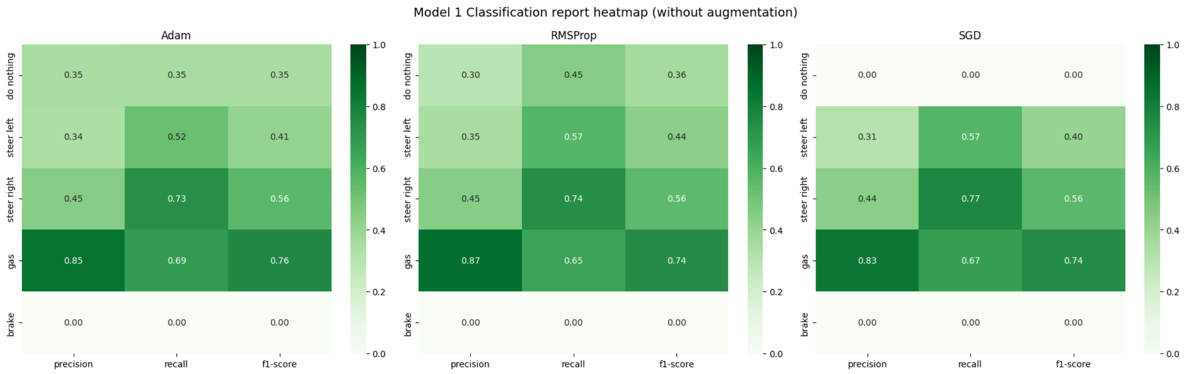
The latter are factors contributing to bringing the prediction accuracy down. However, if the end goal is just driving the car on the track and not **how gracefully** this driving is performed then it makes little difference: the above numbers **do not** tell the full story, in fact by utilizing the above on the simulation we obtain the following scores

Optimizer	Simulation Score	Remarks
Adam	729.91	Consistently and precisely on road
RMSProp	736.64	Offroads for a short period then saves itself
SGD	662.58	Takes many useless turns and drives too fast

Despite what the simulation scores say, Adam performs best when it comes to the **time spent** on the road and how many corners were cut. If we **did not use** augmentation with same hyperparameter values and split seed as before, training presents **more overfitting**, as expected



A different seed shows the same result. Classification report also shows **practically identical numbers** as before, some parameters are better some are worse but the average is the more of the same across all optimizers.



These values would **hint** at a simulation score that is exactly the same, however this is not the case at all as it is possible to see in the table below

Optimizer	Simulation Score	Remarks
Adam	303.55 (new worst)	Goes compltely offroad almost right away
RMSProp	659.21	Offroads for a short period then saves itself
SGD	780.42 (new best)	Cuts many corners

It is rather curious to notice that SGD seems to perform best when no data augmentation was performed, but from a **stability point of view** it would be fair to say that Adam with augmentation performs best for the provided seed, although the simulation score isn't representative of that.

Model 2

This second model is taylored towards more towards extracting features, therefore an additional convolutional layer was added (for a total of four) and one dense layer removed (thus only one remaning). The result is a **latent space** twice as deep as before: (6, 6, 256) vs (11, 11, 128).

Layer	Units	Activation	Padding	Kernel size	Out Shape	Parameters
Conv2D	32	tanh	valid	(2, 2)	(96, 96, 32)	416
MaxPooling2D	-	-	valid	(2, 2)	(48, 48, 32)	-
Conv2D	64	tanh	valid	(2, 2)	(48, 48, 64)	8,256
MaxPooling2D	-	-	valid	(2, 2)	(24, 24, 64)	-
Conv2D	128	tanh	valid	(2, 2)	(24, 24, 128)	32,896
MaxPooling2D	-	-	valid	(2, 2)	(12, 12, 128)	-
Conv2D	256	tanh	valid	(2, 2)	(12, 12, 256)	131,328
MaxPooling2D	-	-	valid	(2, 2)	(6, 6, 256)	-
Flatten	-	-	-	-	9216	-
Dense	512	tanh	-	-	512	4,719,104
Dropout 0.7	-	-	-	-	512	-
Output	5	softmax	-	-	5	2,565

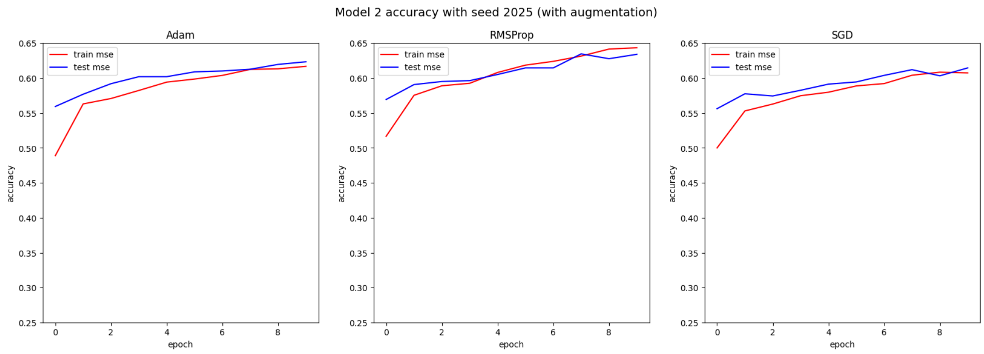
The number of trainable parameters amounts to **4,894,565** of which 96.46% are from the dense layer.

Choosing the optimizer

The same optimizers were tested but this time their hyperparameters were automatically searched with the Hyperband tuner, which resulted in the following

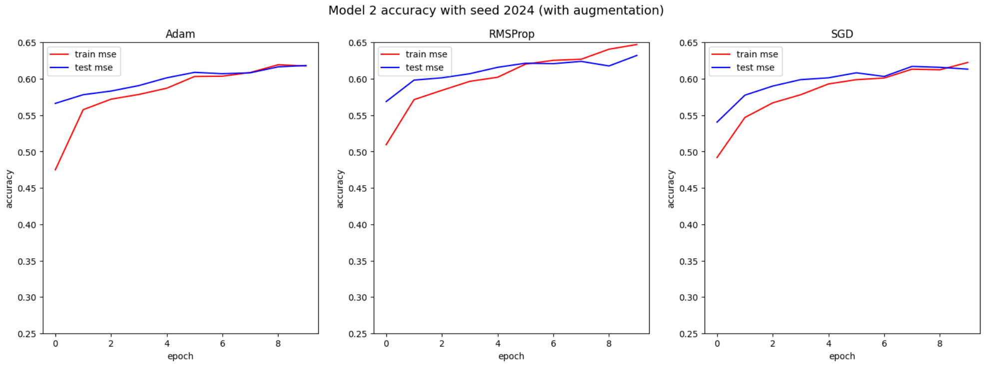
Optimizer	Hyperparameters	Training time	Batch size	Search Time
Adam	$\begin{cases} \eta = 0.0000929 \\ \beta_1 = 0.7247 \\ \beta_2 = 0.4154 \end{cases}$	148.56s	64	30m 25s
RMSProp	$\begin{cases} \eta = 0.0000909 \\ \mu = 0.6831 \\ \rho = 0.8475 \end{cases}$	150.20s	64	30m 58s
SGD	$\begin{cases} \eta = 0.0497819 \\ \mu = 0.6927 \end{cases}$	137.60s	64	28m 41s

The above model was trained with the same weights as Model 1, same validation split speed and **10 epochs**, showing the following output

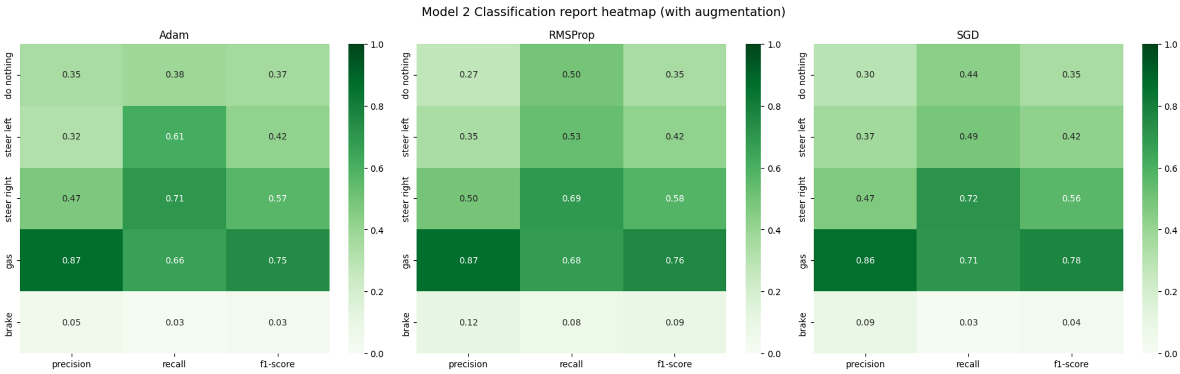


Immediately on the **validation set accuracy** it is possible to notice an improvement with respect to Model 1 in almost all optimizers: RMSProp is still the best as with 63.67 (vs 62.77 of before), Adam has improved to 63.28 (vs 58.63 of before) and SGD has reached a much better 60.77 (vs 56.06 of before). May be an improvement, but we will need to verify that there actually has been one.

By testing a different validation split seed, the result differs on average by **less than** 0.20 for all three

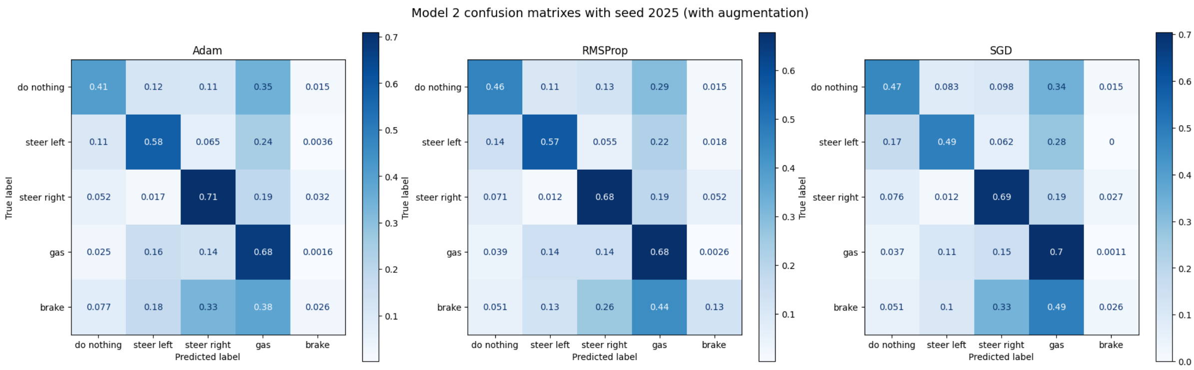


From the **classification report** below it is possible to see better results with respect to before



In particular the *do nothing* and *brake* classes have marginally improved across all metrics for RMSProp and SGD, especially for **recall**, meaning that more true positives are getting classified. The low amount of support for both is still felt, but the model was able to somewhat work around it.

The normalized **confusion matrixes** show noticeable improvement with respect to Model 1

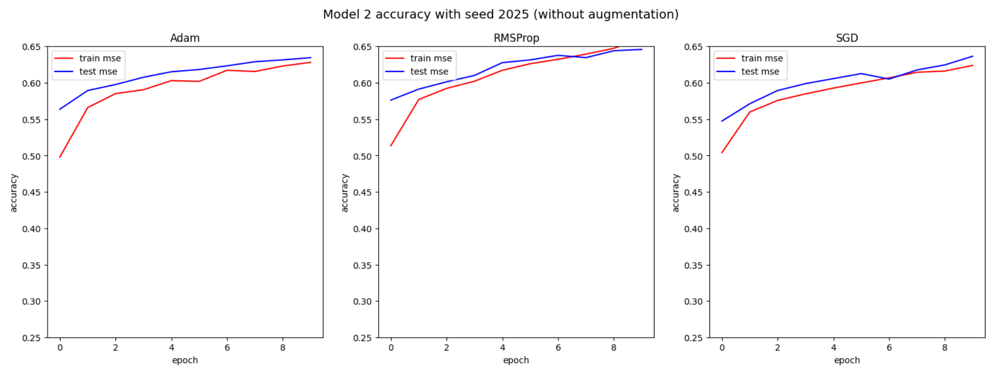


In particular the *brake* class started getting predicted, although not much, there is definitely **less confusion** with the *gas* class and the *do nothing* class is much better classified, especially in SGD.

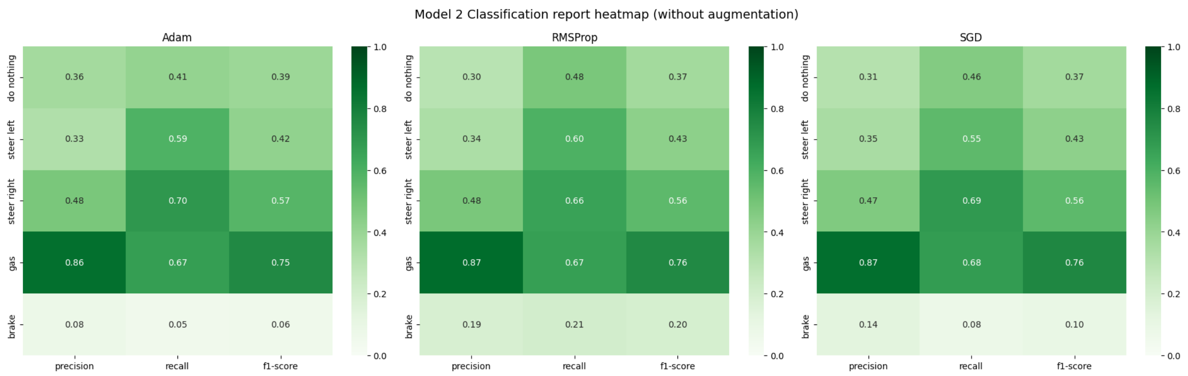
By running the models on the track a rather interesting result was obtained

Optimizer	Simulation Score	Remarks
Adam	871.33 (new best)	Really good handling
RMSProp	665.94	Offroads most of the time
SGD	575.03	Very good until it offroads completely

Not only in terms of simulation score but also in terms of overall driving **Adam performs best**, even better than Model 1, while the others have drastically worsened. If we refrained from using augmentation, the output would be the following



Classification report again shows **practically identical numbers**, with the class *brake* improving only in RMSProp.



Meaning that again the simulation should look similar to the case with augmentation, however again this is really not the case

Optimizer	Simulation Score	Remarks
Adam	426.86	Drifts at a turn and starts diving in reverse
RMSProp	900.07 (new best)	Almost flawless driving
SGD	430.25	Exactly like Adam

Every optimizer has worsened, except for RMSProp which shows the best result so far across both models. This is probably due to it **overadapting** to the noise produced by the augmentation, although every other optimizer seems to **disagree** on that.

Conclusions

Image classification is a **difficult** task, as higher validation accuracy does not necessarily correspond to an overall better model. Better performance is closely related to the **context** and to the specific definition of "accuracy" when it comes to using the model to predict.

In this specific context it could be:

- driving stability
- driving speed
- simulation score
- …
- a mix of the above

The problem's difficulty was additionally **exacerbated** by noise and unbalance of the dataset, considering the low amount of samples it is not that trivial to obtain a high accuracy.

Plots are not enough if considered **independently**, to get a better idea of how a model is performing it is necessary to have all metrics written down and shown. Despite all of that, it may still not be enough to figure out its **actual performance** and it may only be possible to figure that out only when the model is actually used in the field.

Augmentation may **not always** improve the result, in fact in this report it was shown that, interestingly, it was possible to obtain the best result without it. We may never know if doing it improves performance unless we actually try it and compare results.

In conclusion, both homeworks were very **useful and insightful** for practicing machine learning concepts hands-on. There is so much power at our (literal) fingertips, and it is only going to get better in the future. **Exciting times** are coming up soon for this field.