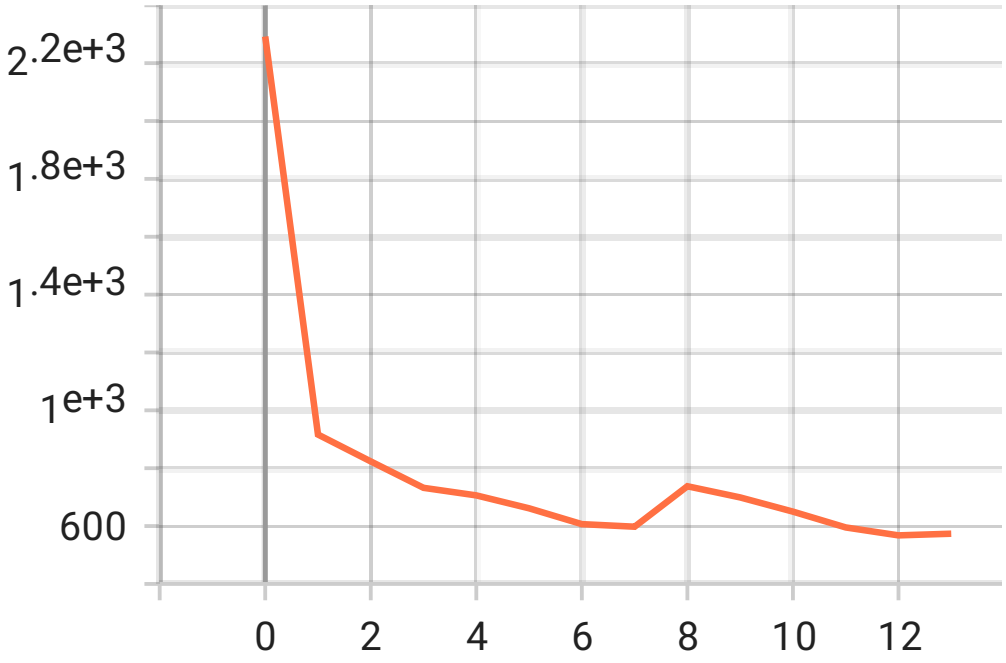
Results analysis

In this file we will analyse the performance of the models. We have decided to run the models with augmentated data on default parameters. Let's analyse the results.

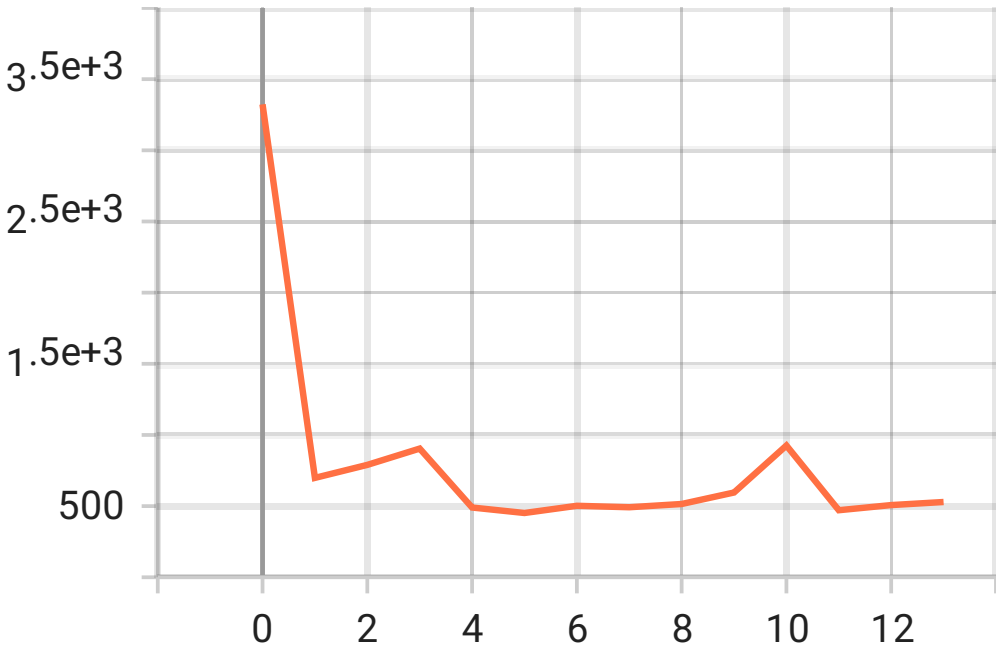
1. **Quick mention about training without augmentated data**

Before we analyse the models let's take a quick look on how the models behave when data isn't augmentated.

Regression model



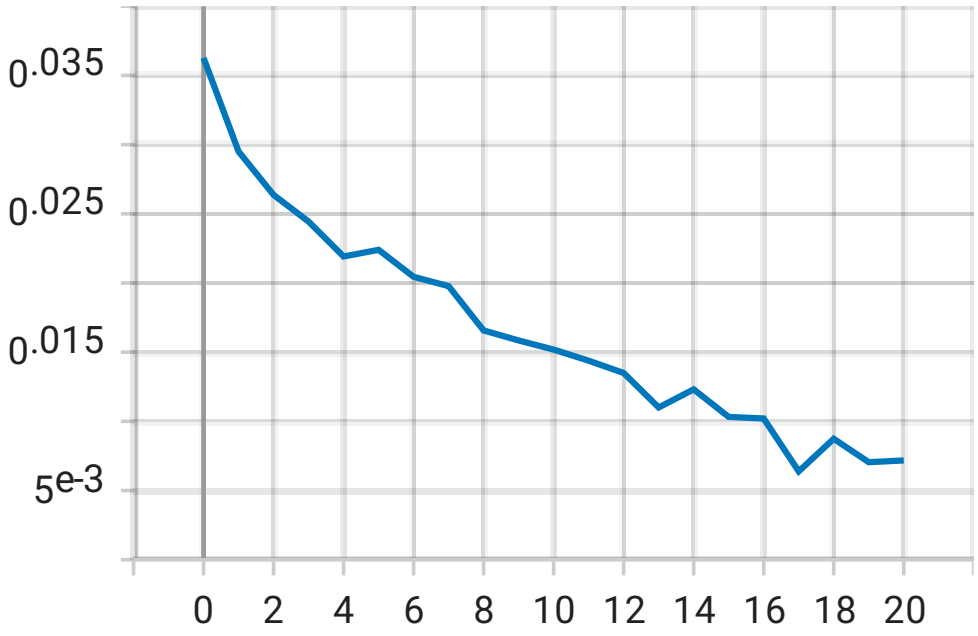
Train loss



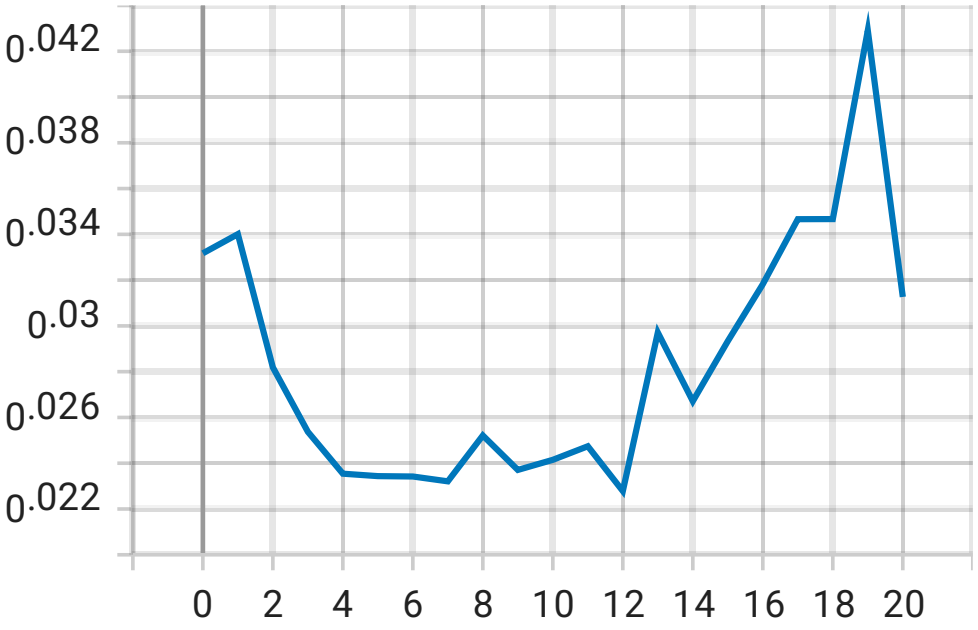
Validation loss

Test loss - 506,68

Classification model



Train loss



Validation loss

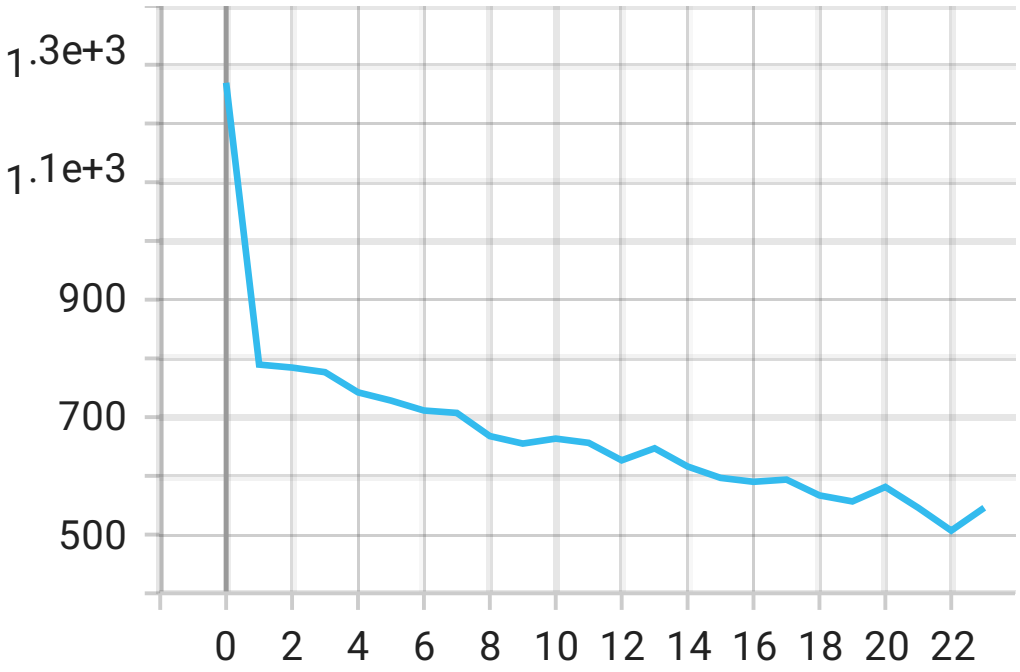
Test loss - 0.0329 (accuracy 0.8058)

We can see that without augmentated data models have very hard time generalising. It may be due to a low number of training images.

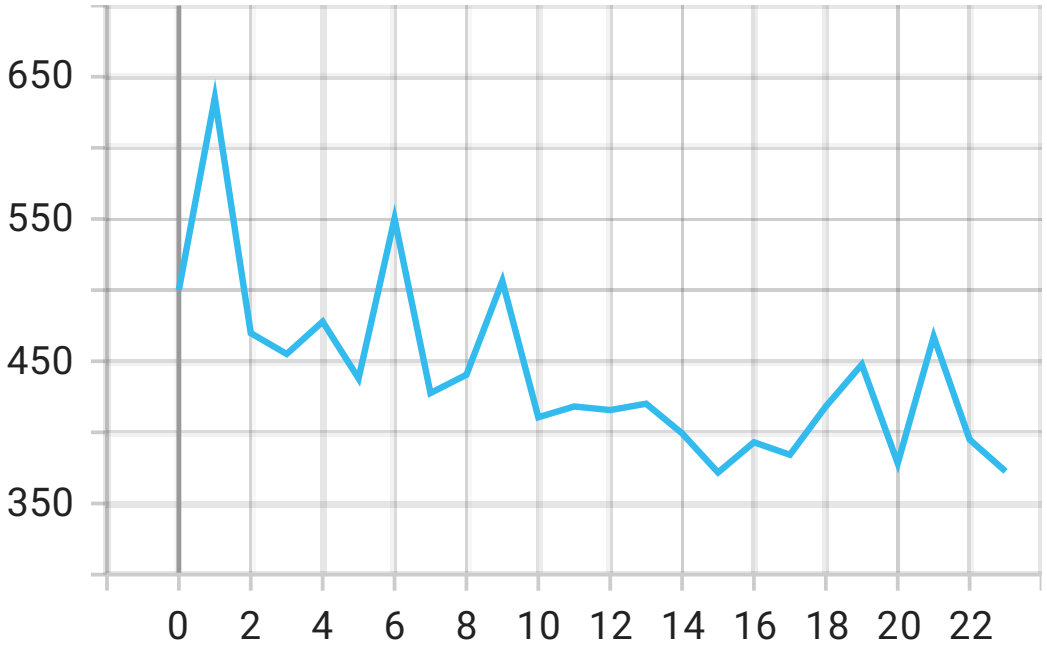
2. **Training with augmentated data**

Let's take a look at the losses and the images showing correct vs predicted gate location (seed was set to 1 to show what the models have learned and what was hard for them to learn)

Regression model



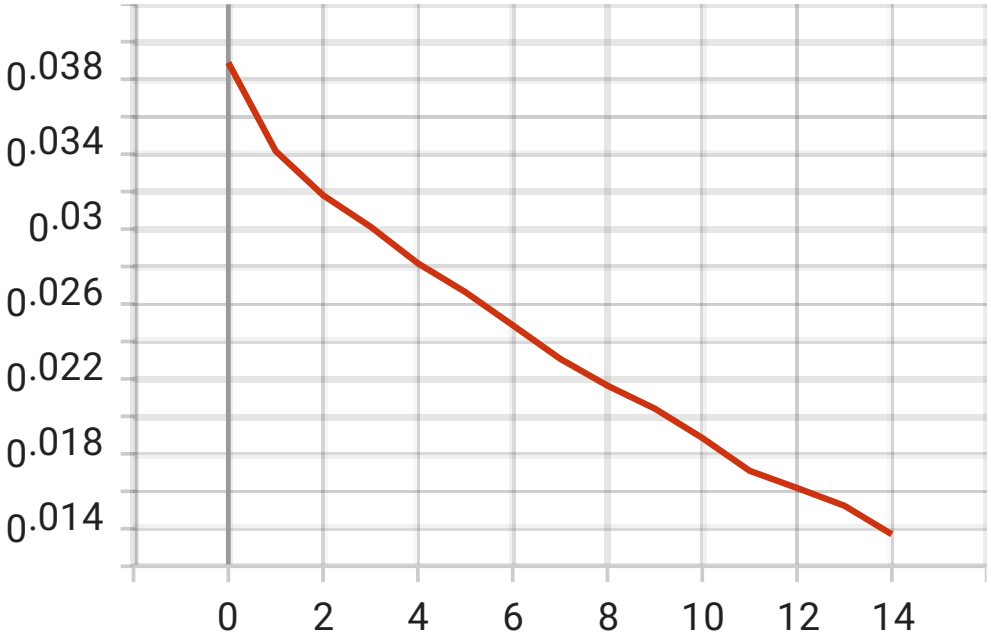
Train loss



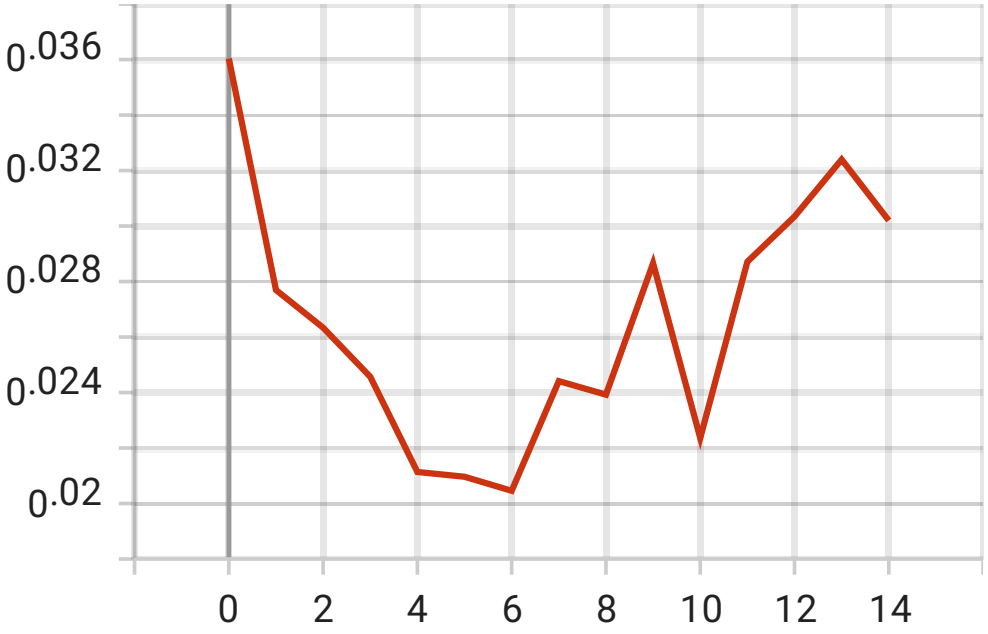
Validation loss

Test loss - 463.97

Classification model



Train loss



Validation loss

Test loss - 0.0279 (accuracy 0.7961)

8 images (seed - 1, it is advised to run python show_results.py -seed 1 to see pictures in larger dimension)

Image 1

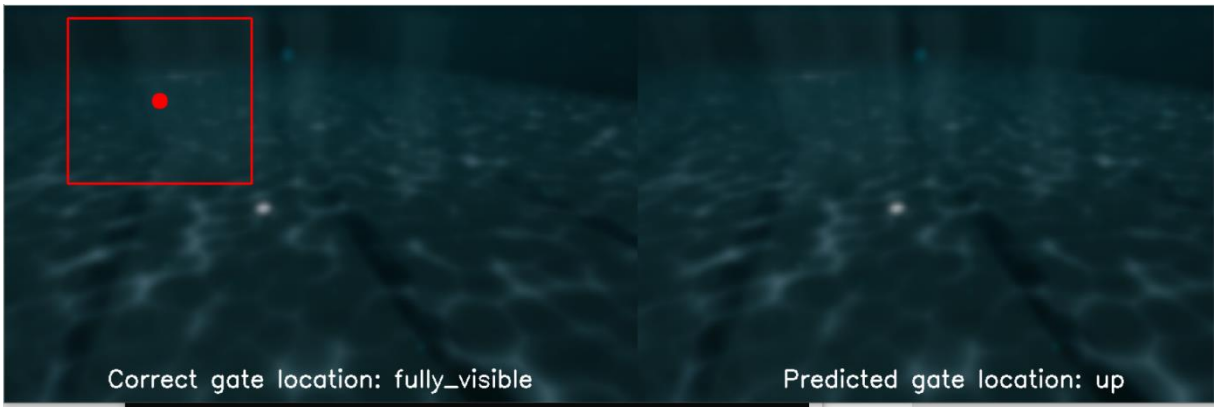


Image 2

Image 3

Image 4

Image 5

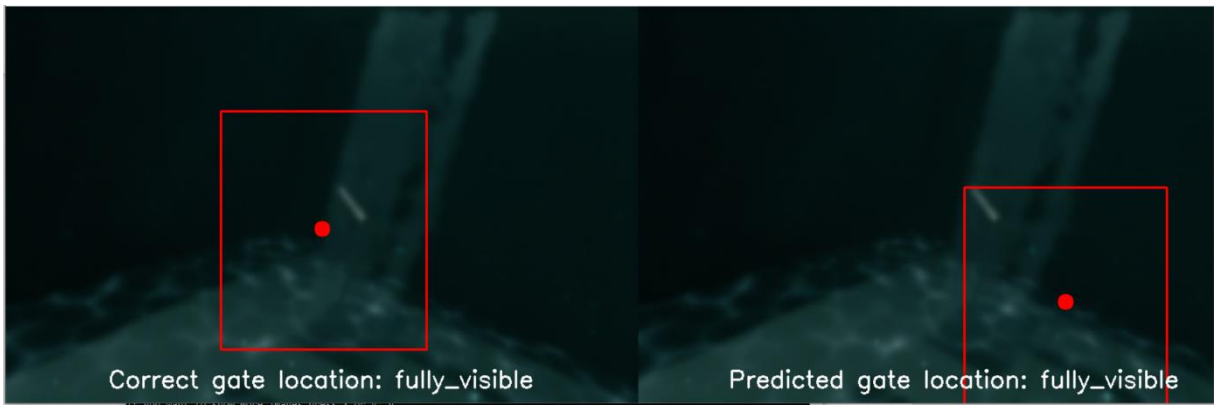


Image 6

Image 7

Image 8

From the analysis of the losses we can see that the learning was more stable and we achieved better results compared to training without augmentated data. Although it's important to notice that we didn't achieve the best losses and models still had hard time generalising.

From the images we can see the following things:

1. Classification model is usually able to predict gate location correctly. It sometimes mistakes the fully visible location with up location. The model didn't predict left, right, down locations because there are not to many gates in the dataset that are located in any of those ways.
2. Regression model managed to learn the shape of the gates. If the gate is located in front of the robot (or under a small angle) then the model is usually able to predict the coordinates of the gate pretty well (it may fail slightly when it comes to location to shape but overall it's quite good) although they may be exceptions to this rule (image 5). The problem starts when gates are under high angles (image 4 or image 6). The model fails there to locate the center of the gate.

3. Conclusion – what to do next

From the analysis of losses and performance of the models we can deduce the following things:

1. Data augmentation improved the quality of the learning
2. Our models performed well. They could be better but the results are satisfactory.
3. We may try these things to improve the learning process even more:
    a. Add more diversified data
    b. Implement more data augmentation techniques to make the training set more diversified
    c. Try to analyse the images that we have. We could for instance delete images that are too blurry or those on which human cannot see the gate. We could also think if we could deduce some important info from the data that we could use in the learning process