Report of Iterative Development

Machine Learning Project

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Minor AI

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1. Milestone I: First Model

1.1 Introduction

Sheltered cats and dogs display specific characteristics which can be considered determinants of adoption[1]. Since animals that are not adopted can be subject to suffering in different forms[2], it seems logical for shelters to attempt to focus their resources on determinants with an increasing effect on the likelihood that a given animal will be adopted[1]. Petfinder.my, a Malaysian platform regarding animal welfare, operates using a similar concept[3]. The organization uses artificial intelligence to determine a score for a Cuteness Meter, which corresponds to the attractiveness of pictures of cats and dogs. A higher score correlates to a more attractive picture. This score can be used to improve photo-quality in order to optimize the chances of adoption. The current algorithm does not consistently function adequately as it is still under development[4]. The model described in this report seeks to provide an improved version of this algorithm. The aim of this report is to elucidate the process of formation of said model.

The first version of the model in question is a convolutional neural network which takes images of animals and designated attractiveness scores as inputs and performs a number of computations to estimate the score of attractiveness for another given image.The rationale behind this approach is that deep learning is known to be successful in tasks that require image recognition[5]. The goal regarding the performance of this model, is to achieve a model that shows a decrease in its loss over a number of epochs. This shows the designed model has the capacity to be trained.

1.2 Data Analysis and Preprocessing

The data provided for every sample is composed of the images of a set of pets and additional tabular data regarding every given image. The tabular data states whether the following composition parameters were present or absent in a given image: "*Focus (Pet stands out against uncluttered background, not too close / far), Eyes (Both eyes are facing front or near-front, with at least 1 eye / pupil decently clear), Face (Decently clear face, facing front or near-front), Near (Single pet taking up significant portion of photo (roughly over 50% of photo width or height), Action (Pet in the middle of an action (e.g., jumping)), Accessory (Accompanying physical or digital accessory / prop (i.e. toy, digital sticker), excluding collar and leash), Group (More than 1 pet in the photo), Collage (Digitally-retouched photo (i.e. with digital photo frame, combination of multiple photos), Human (Human in the photo), Occlusion (Specific undesirable objects blocking part of the pet (i.e. human, cage or fence). Note that not all blocking objects are considered occlusion), Info (Custom-added text or labels (i.e. pet name, description)), Blur (Noticeably out of focus or noisy, especially for the pet's eyes and face. For Blur entries, "Eyes" column is always set to 0)*"[6]. Additionally, the tabular data also includes the "*Pawpularity*", which reflects each pet profile's page view statistics[6]. It was noted that this dataset only contains 9912 samples, which is a relatively small amount for training.

The tabular data was analyzed using the *Normal Equation*. It was established that the relation between the features and the outcome "*Pawpularity*" was not linear. Furthermore, it was established that the tabular data does not contain any missing values.

The data used for this version of the model comprises two parts: the "*Pawpularity*" within the tabular data and the images of pets. Figure X shows that the used dataset is imbalanced, as most images have a "*Pawpularity*" score of approximately 30. The mean "*Pawpularity*" score is 38.

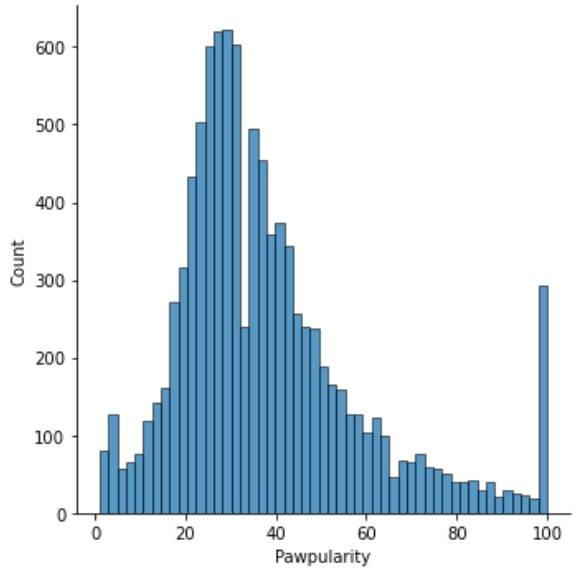


Figure 1: This figure is a histogram that presents the number of images for every "Pawpularity" score. It shows the dataset is imbalanced.

Regarding the images, every image was resized to a shape of 128x128x3.All provided testing data had this specific shape, whereas there the shapes of the samples in the training data differed. Therefore, it was decided to resize all training data to the same shape as testing data. Additionally, these relatively large images allow training with a large amount of information.
Furthermore, the data was split into training and testing data, corresponding with 67% and 33% of all data respectively.

No further preprocessing or augmentation was applied to the images.

1.3 Model Pipeline and Training

The current predictive model is a convolutional neural network. The input of a given sample is the image of a pet, whereas the output is the "*Pawpularity*" score.
The architecture of the convolutional neural network consists of an input layer, three hidden layers and an output layer.

With the exception of the last layer, a ReLu activation function was used in every layer. The output layer provides one output. No activation function was applied in this layer. Given that the task at hand is a regression problem, no non-linear activation function should be necessary in the last layer.
Further details regarding the model pipeline are presented in Figure 2.

Model: Mile stone I

Layer (type)	Output Shape	Params
Convolution (2D)	(128, 128, 3)	1792
Max pooling (2D)	(64, 64, 64)	0
Flatten	(262144)	0
Dense 1	(512)	134218240
Dropout (0.1)	(512)	0
Dense 2	(256)	131328
Dense 3	(128)	32869
Dense 4	(1)	129

Total params: 134,384,385
Trainable params: 134,384,385
Non-trainable params: 0

Figure 2: Details regarding the model pipeline

Concerning the training of the model, the Mean Squared Error was used as the loss function for optimization. Additionally, the Root Mean Squared Error was used as a metric to judge the performance of the model, since this is customary in regression problems such as the one at hand. The optimizer Adam was applied. The model was trained using 20 epochs.

1.4 Evaluation and Conclusions

Regarding the model loss, there is a clear decrease for the training data (Figure 3). Although this decrease seems to stagnate after the first epoch in Figure 3, it is actually consistent over the course of 20 epochs. The loss for the validation loss also consistently decreases through 20 epochs.
A similar trend was observed in the root mean squared error; the error decreases over the course of 20 epochs in both the training and the validation data, though this is not clearly visible in the graph of the learning curve (Figure 3).
The decreases in both the model loss as well as the root mean squared error are a manifestation of the trainability of the model, thus the goal of forming a model with the capacity to be trained was obtained.

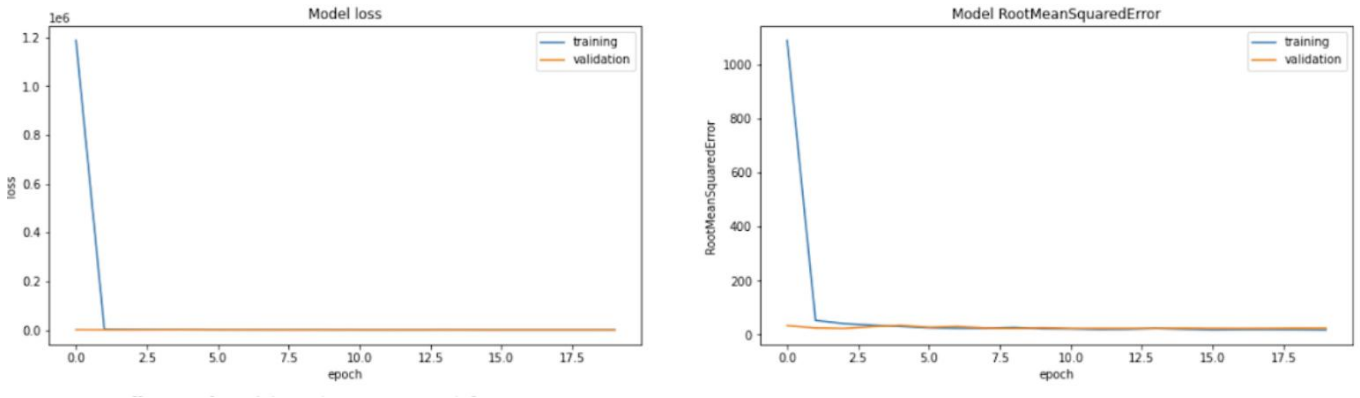


Figure 3: This figure shows the graphs of convergence of the model over 20 epochs.

Figure 3 shows that the model loss and root mean squared error were relatively high after the first epoch. Because of this the relatively small nuances between the training and the validation values are not visible in the learning curves. In order to clarify this image, the y-axis for the model loss was limited to a value of 10000 and the y-axis for the root mean squared error was limited to 100 for the model loss and root mean squared error respectively. The outcome is illustrated in Figure 4.

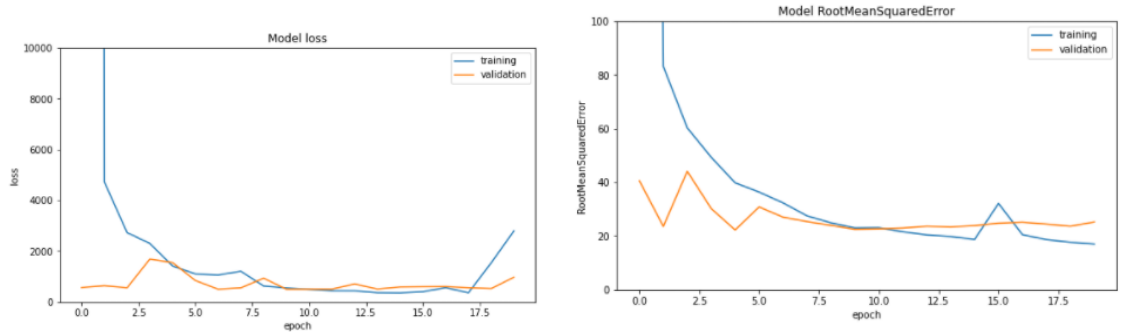


Figure 4: This figure shows the graphs of convergence of the model over 20 epochs with limited y-axes.

In Figure 4, the graph of the model loss shows that after approximately 17 epochs, the model loss and root mean square error both start to increase for the training data. This is a manifestation of divergence rather than convergence in gradient descent. This could be caused by a learning rate that is too high.

Given the small amount of available data,the application of k-fold cross validation and data augmentation could improve the training process of the model in future versions. Additionally, the use of preprocessing and augmentation methods in the images could derive better results. In addition, the increasing difference between the training loss and the validation loss during the last epochs seems to imply overfitting. Lastly, the problem of divergence should be solved.

2. Milestone II: Early stopping

2.1 Introduction

In the previous version of the predictive model, the learning curves appeared to be quite similar for the training and validation data up until epoch 16. After this epoch, the model loss steeply moves upwards (see Figure 4). This problem will be addressed in this version of the model by applying the method of early stopping. Early stopping is traditionally used to prevent overfitting[7]. However, it seems that it could also be a way to improve the current learning curves.

2.2 Data Analysis and Preprocessing

No adaptations regarding data analysis or preprocessing were made in the current version of the model. See section 1.2 for a description of the current situation.

2.3 Model Pipeline and Training

In this version of the model, only 16 epochs were used to train the model. No further improvements were made with regard to the model pipeline.

2.4 Evaluation and Conclusions

In this version of the model,the model loss no longer shows a lift towards the last epochs. Both the model loss as well as the model root mean squared error now seem to be on a similar trend downwards. 16 epochs seems to be the optimal number of epochs for the model in its current state.

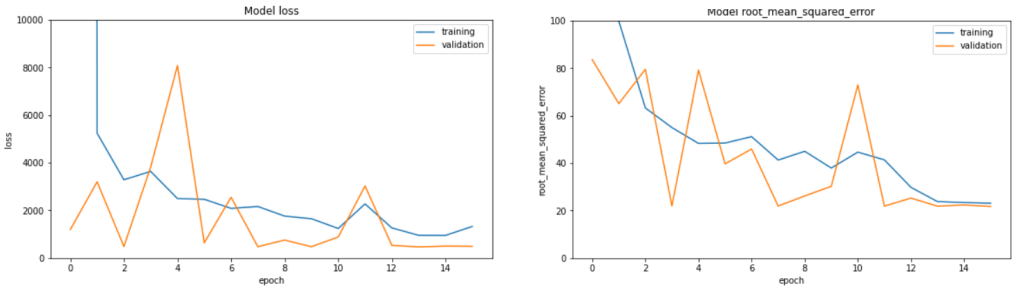


Figure 5: This figure shows the graphs of convergence of the model over 16 epochs with limited y-axes.

The learning curves both seem to show a stagnation at the last epochs rather than a decrease in the model loss or the model root mean squared error. It seems as if the model lacks complexity to fit the data better.

3. Milestone II: A Deeper Convolutional Neural Network

3.1 Introduction

The previous version of the convolutional neural network consisted of a single Conv2D layer. Adding more of such layers should correspond to adding complexity to the predictive model. This could enable the predictive model to learn more high level features. Which illustrates the rationale for making a deeper neural network for the current version of the model. This could enhance the performance of the model, which should manifest itself in a decreased loss and mean squared error in the learning curves at the last epochs, compared to the previous version of the model.

3.2 Data Analysis and Preprocessing

In this version of the model, no modifications were made concerning data analysis or preprocessing. See section 1.2 for the most recent updates regarding this matter.

3.3 Model Pipeline and Training

The convolutional model was expanded with three additional Conv2D layers. Numbers of four, five and six additional Conv2D layers were put to the test as well. However, as the model seemed to behave very similarly after adding these layers, a number of three additional Conv2D layers was chosen for the optimal model at this stage in the development of the model. Figure 6 provides additional details regarding this optimal model pipeline.

Model: Mile stone II

Layer (type)	Output Shape	Params
Convolution 1 (2D)	(128, 128, 3)	1792
Max pooling 1 (2D)	(64, 64, 64)	0
Convolution 2 (2D)	(64, 64, 128)	73856
Max pooling 2 (2D)	(32, 32, 128)	0
Convolution 3 (2D)	(32, 32, 256)	295168
Max pooling 3 (2D)	(16, 16, 256)	0
Convolution 4 (2D)	(16, 16, 512)	1180160
Max pooling 4 (2D)	(8, 8, 512)	0
Flatten	(32768)	0
Dense 1	(512)	16777728
Dropout (0.1)	(512)	0
Dense 2	(256)	131328
Dense 3	(128)	32869
Dense 4	(1)	129

Total params: 18,493,057
Trainable params: 18,493,057
Non-trainable params: 0

Figure 6: Details regarding the model pipeline

3.4 Evaluation and Conclusions

In this version of the model, the training loss around the last epoch is approximately 200. In the earlier version this value used to be approximately 2000. There is a clear decrease in model loss between the respective models, thus the model seems to be trained better in its more complex form. The trade-off is that the model now appears to be overfitting, given that the training loss still seems to follow a decreasing trend, whereas the validation loss has stagnated, starting at approximately 6 epochs.
The situation is quite similar concerning the model mean squared error; the error for this version is lower compared to earlier versions, but the increasing difference between the values for the training data and the validation data imply overfitting (see Figure 7).

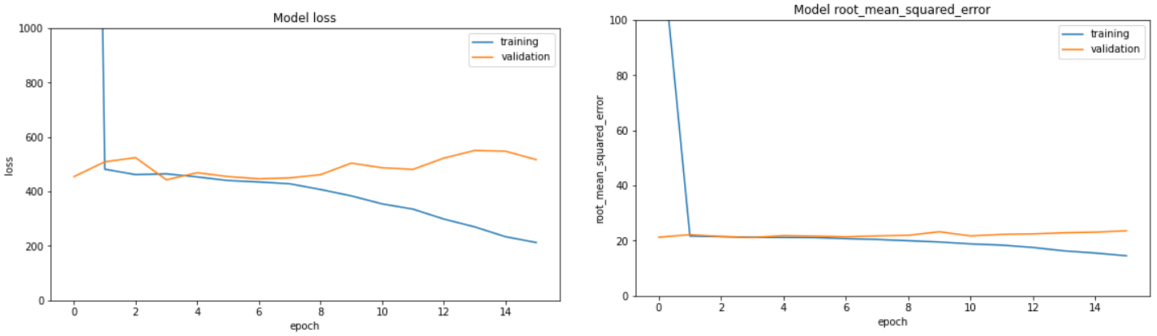


Figure 7: This figure shows the graphs of convergence of the model over 16 epochs with limited y-axes.

4. Milestone II: Normalization

4.1 Introduction

The ReLu activation function was chosen for the hidden layers of the predictive model to avoid problems such as vanishing gradient during backpropagation in training[8]. As the ReLu function is only non-linear around the coordinate (0,0) and non-linearity is a necessity for a model to learn complex decision boundaries[9], the input of the model should be normalized to have a mean of zero and standard deviation of one. In this version of the model, normalization will be applied to the input samples. More efficient training should expectedly manifest itself in earlier conversion to a local optimum during gradient descent, by showing that learning curves stagnate earlier compared to earlier versions of the model.

4.2 Data Analysis and Preprocessing

Referring back to section 1.2, the only update with regard to the data is the application of normalization to the image features. The pixels were normalized to have a mean value of zero and a standard deviation of one. In this way, the pixels of every sample (i.e. image) were normalized towards zero.

4.3 Model Pipeline and Training

In this version, the model pipeline remains unchanged to the pipeline described in section 3.3.

4.4 Evaluation and Conclusions

Normalization was applied under the assumption that it would make training more efficient. In the prior version of the model, the learning curves stagnated after approximately 8 epochs. In this version, this event occurs after approximately 1 epoch (Figure 8). It seems that the training process of the model has indeed become more efficient.

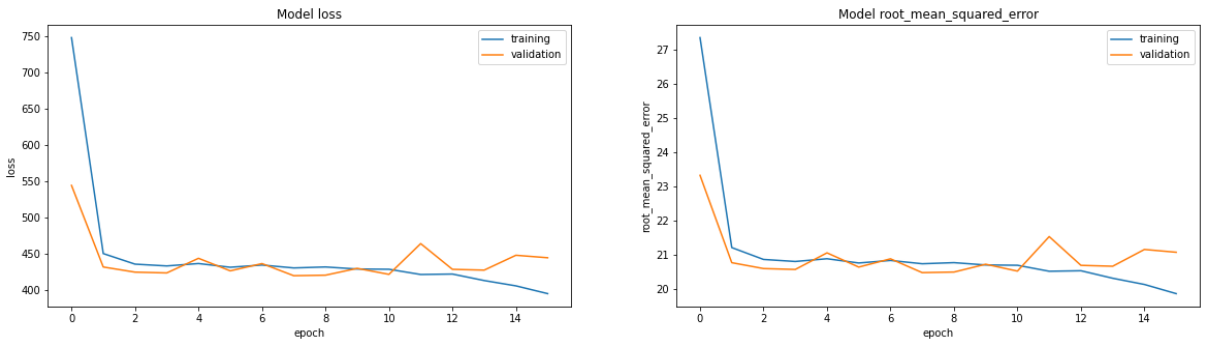


Figure 8: This figure illustrates the model loss and model root mean squared error after the input of the model was normalized.

5. Milestone II: Batch Normalization

5.1 Introduction

In the previous versions of the model the input nodes of the model were normalized to have a mean and standard deviation of zero and one respectively. Considering the depth of the convolutional neural network. it seems appropriate to additionally normalize the values of all hidden layers. This will be done by applying batch normalization[10]. Batch normalization reduces the problem of input values changing in between layers and makes the training process of a neural network more efficient[11].

5.2 Data Analysis and Preprocessing

No further improvements regarding data analysis or preprocessing were made in this version of the model.

5.3 Model Pipeline and Training

In the current version of the model, a batch normalization layer was added after every maxpool layer consecutively. This resulted in three different models which were compared to select the optimal model regarding batch normalization For details regarding the model pipeline. see Figure 9.

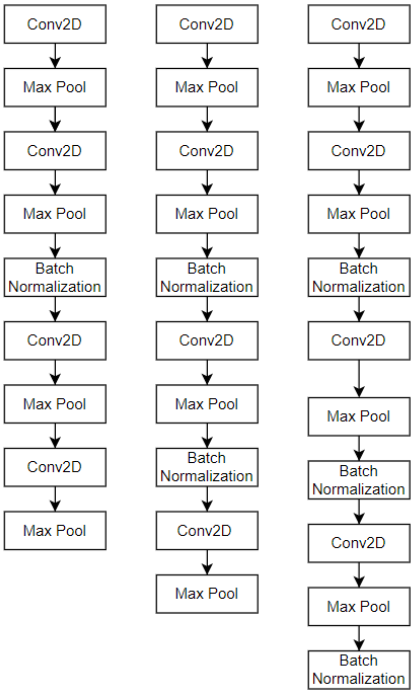
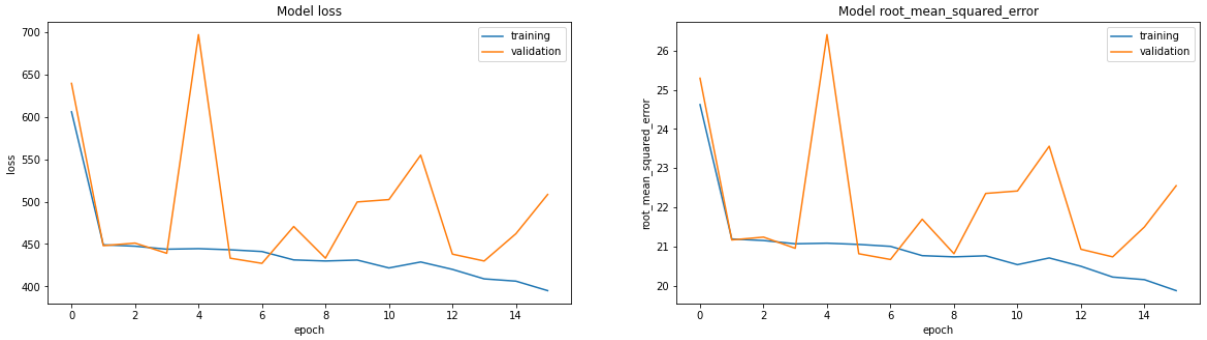


Figure 9:This figure shows the part of the model pipeline that was used for experiments in this version of the model, which is everything up until the flatten layer. A batch normalization layer was added after every experiment.

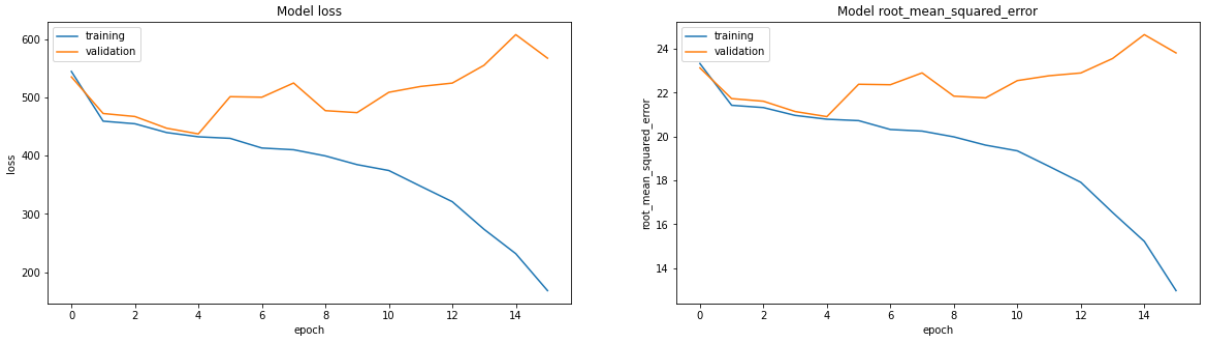
5.4 Evaluation and Conclusions

Figure 10 shows that the course of the validation cost is most smooth after the application of three batch normalization layers, compared to both prior versions as well as versions with additional batch normalization. Additionally, overfitting hsa become clear in this model, as both the model loss continues to decrease for the training data, whereas it stagnates for the validation data, starting after approximately 4 epochs. The model with three batch normalization layers will be maintained for the development of future versions of the model.

A single layer of batch normalization



Two layers of batch normalization



Three layers of batch normalization

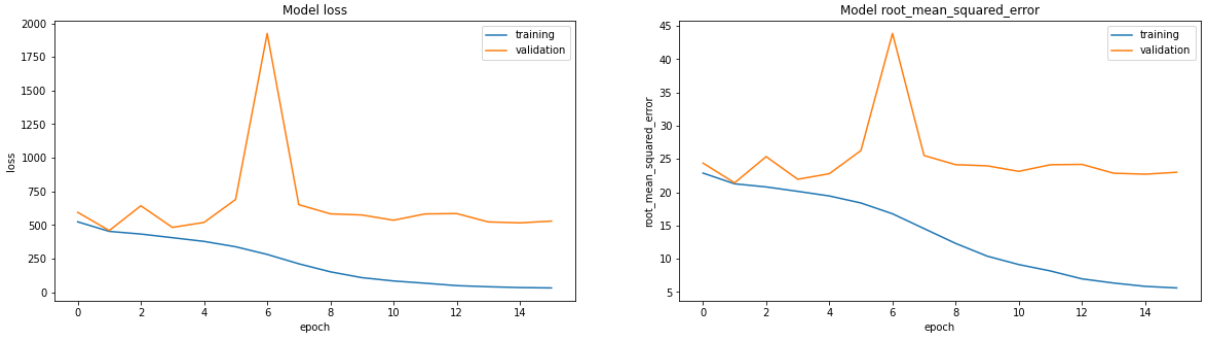


Figure 10: This figure illustrates the model loss and model root mean squared error after the consecutive application of batch normalization layers.

6. Milestone II: Dropout

6.1 Introduction

A problem regarding the earlier versions of the model is overfitting. In order to address this problem, in this version, dropout will be applied to the model. Dropout is a regularization method that prevents a neural network relies too heavily on specific nodes by randomly selecting nodes and setting them to zero during training. Because of this, the neural network becomes less likely to rely on specific nodes or weights in training[10].

6.2 Data Analysis and Preprocessing

In this version of the model, no adjustments were applied in data analysis or preprocessing. See section 2.2 for the most recent modifications regarding this matter.

6.3 Model Pipeline and Training

Several experiments regarding dropout were conducted for this version of the model.
Firstly, before every dense layer, a dropout layer was added with a dropout rate of 0.4, which means approximately 40% of the inputs in these layers will be randomly set to zero.
Secondly, dropout was added before the two last Conv2D layers, with a dropout rate of 0.2. This dropout layer has a lower dropout rate compared to the dropout layers before the dense layers in order to preserve the information regarding high-level image features earlier in the convolutional neural network.
Figure 11 presents a summary of the pipeline concerning the current model.

Model: Mile stone II, dropout

Layer (type)	Output Shape	Params
Convolution 1 (2D)	(128, 128, 3)	1792
Max pooling 1 (2D)	(64, 64, 64)	0
Convolution 2 (2D)	(64, 64, 128)	73856
Max pooling 2 (2D)	(32, 32, 128)	0
Convolution 3 (2D)	(32, 32, 256)	295168
Max pooling 3 (2D)	(16, 16, 256)	0
Dropout 1 (0.1)	(16, 16, 256)	0
Convolution 4 (2D)	(16, 16, 512)	1180160
Max pooling 4 (2D)	(8, 8, 512)	0
Flatten	(32768)	0
Dropout 2 (0.4)	(512)	0
Dense 1	(512)	16777728
Dropout 3 (0.4)	(512)	0
Dense 2	(256)	131328
Dropout 4 (0.4)	(512)	0
Dense 3	(128)	32869
Dropout 5 (0.4)	(512)	0
Dense 4	(1)	129

Total params: 18,493,057
Trainable params: 18,493,057
Non-trainable params: 0

Figure 11: Details regarding the model pipeline

6.4 Evaluation and Conclusions

Figure 12 shows that there is a much smaller difference between the training and validation in both model loss as well as model root mean squared error, compared to prior versions of this convolutional neural network. This implies the model is still overfitting. However, the loss is no longer decreasing either. The next step should be to explore alternative methods against overfitting.

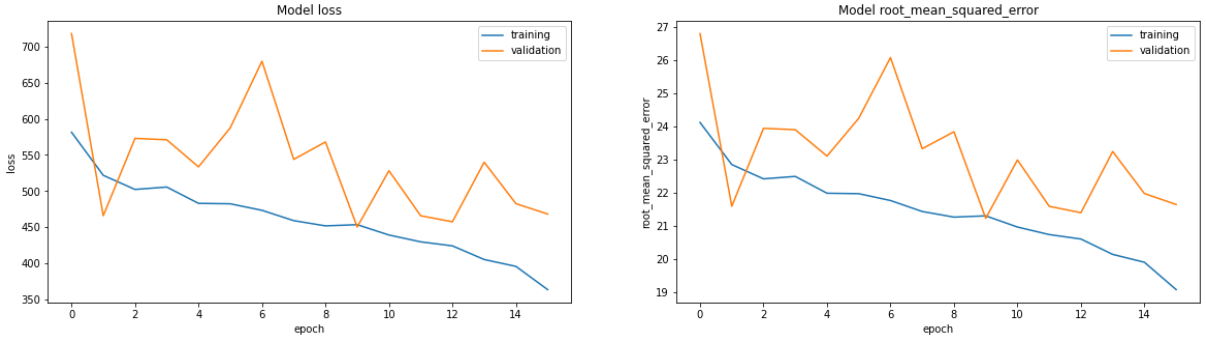


Figure 12: This figure illustrates the model loss and model root mean squared error after the application of dropout.

7. Milestone III: Additional Regularization techniques

7.1 Introduction

Given that the previous version of the model seemed to suffer from an overfitting problem that cannot be solved with dropout only, it makes sense to apply additional regularization methods at this stage of the model. For this reason, L2 regularization will be applied next[13]. This chapter will explore the interaction between dropout and L2 regularization. The reason for applying L2 regularization instead of L1 regularization is that L2 works by forcing weights to be smaller, but not 0, which should help against overfitting. Furthermore we also chose to use an activity regularization in favor of a bias or kernel regularization, since this regularization should work best against overfitting by reducing the layer's output[13].

7.2 Data Analysis and Preprocessing

No additional improvements regarding data analysis or processing were made in this version of the model.

7.3 Model Pipeline and Training

In this version, L2 and regularization were applied at various places in the model. See Figure 13 for a schematic overview of the model that was eventually selected.

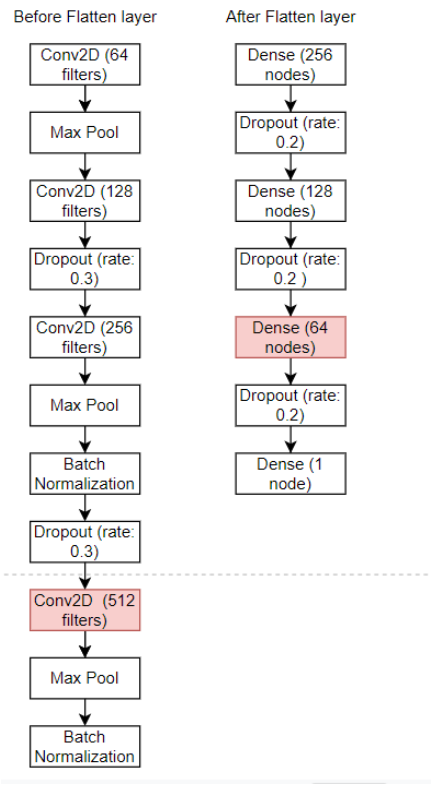


Figure 13: Details regarding the model pipeline. L2 regularization was applied in the layers highlighted in red.

7.4 Evaluation and Conclusions

Figure 14 shows that the validation root mean squared error does not improve beyond a value of approximately 20. The training root mean squared error even drops beneath the validation values after approximately 10 epochs. After this point the model seems to overfit the validation data. Before this point, the training loss decreases as the trend in the validation loss stays stable. This, in contrast, looks like a problem of underfitting. It seems that the performance of the model in its current form cannot be enhanced through regularization techniques. Perhaps artificially augmenting the data might improve the validation performance in the section of the model where it seems to underfit.

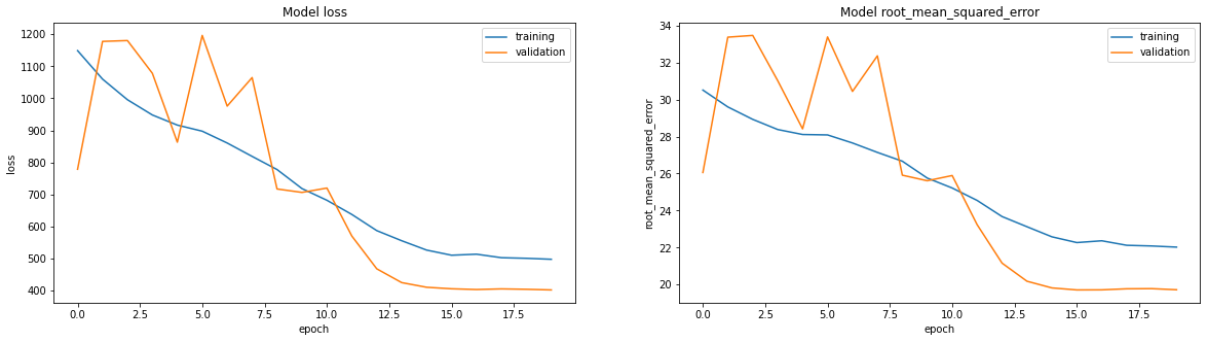


Figure 14: This figure illustrates the model loss and model root mean squared error after applying additional regularization.

8. Milestone III: Tabular Data

8.1 Introduction

Though it has not been used in any version of the model thus far, a set of tabular data was provided in addition to the image data. Adding this data to the model is a potential way of enhancing the performance of the model. For this reason, this chapter describes the development of the prior model into a convolutional neural network with added tabular data.

8.2 Data Analysis and Preprocessing

For this version of the model, all tabular data was taken into consideration, in addition to the image data which was included in previous versions of the model. No further analysis was conducted on the data and no further improvements were made.

8.3 Model Pipeline and Training

To add the tabular data, a second model was created and concatenated with the original model. We experimented with different layers to find the most optimal model for the tabular data to add to our original model. We tried a single layer to just use the tabular data as it is and we also tried to make it more complex by adding more layers to see whether the performance of the model would improve.

8.3.1 Tabular Model 1

For tabular model 1, only the raw tabular data was used. We did not make the model more complex.

8.3.2 Tabular Model 2

For tabular model 2 we added 4 extra layers before we concatenated it to the main model. This will enable the model to learn more complex ideas for combinations with the tabular data. The layers for this model evolve as follows (12*, 30, 50, 30, 10). After, the models combine.

8.3.2 Tabular Model 3

For tabular model 3 the impact of more layers on the loss was explored. This would mean it will make the data more complex. We implemented the following layers (12*, 30, 90, 270, 810, 270, 90, 30, 12).

8.4 Evaluation and Conclusions

No tabular data:

We can see that with no tabular data training curves of the model start stagnating at around 15 epochs for both the training and validation.

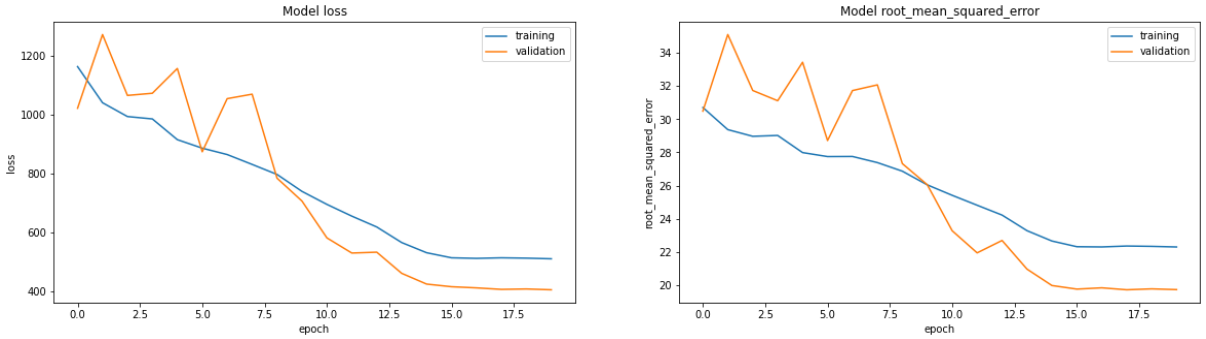


Figure 14: The model without tabular data

Model 1:
When adding one layer without any complexity we can see that by just adding the tabular data the model becomes less accurate compared to having no tabular data at all. But only by a small margin. It does seem like the data starts stagnating around its minimum faster.

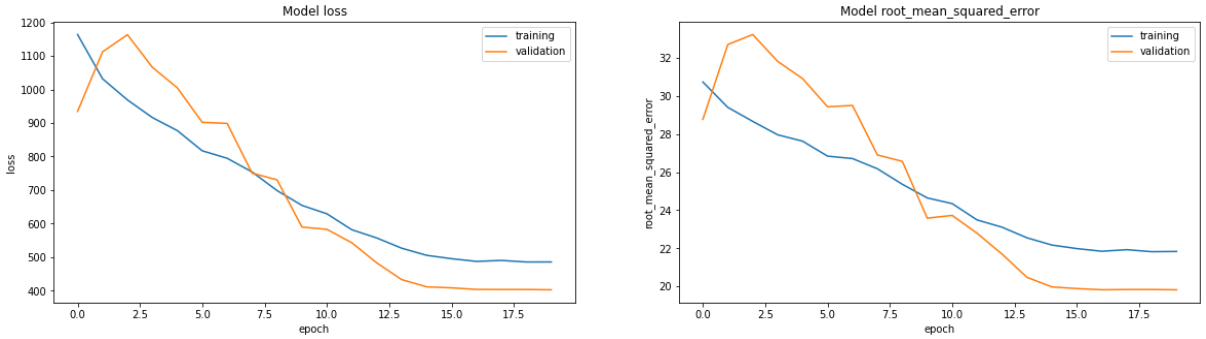


Figure 15 : The model with tabular data without added complexity

Model 2:
When using 4 layers the model learned a lot faster. As it already starts stagnating around its minimum after only 3 epochs. The validation costs are also lower than not using tabular data at all.

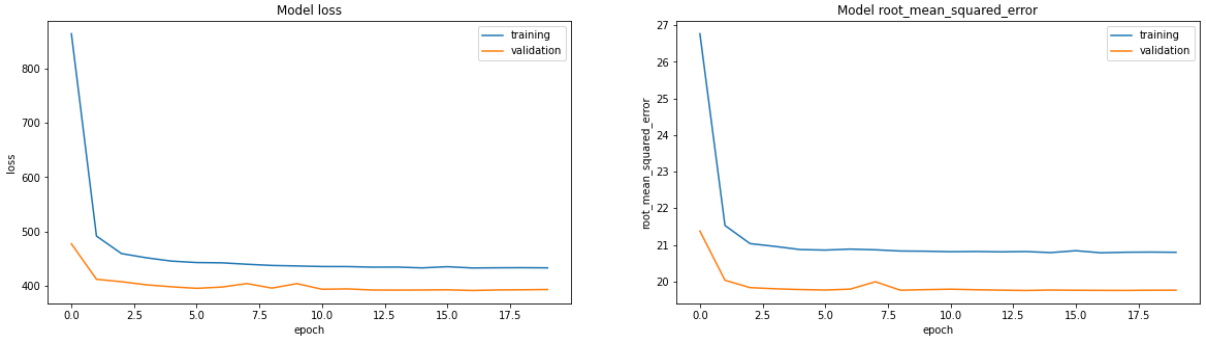


Figure 16: The model with tabular data with added complexity

model 3:

For model 3 we added more complexity to the model. From the image below we can see that this increased the average rmse and made the model less consistent. The model has a higher rmse and does not seem to be the best fit. The model does start stagnating at its minimum even faster as it is already close to its minimum after only 2 epochs.

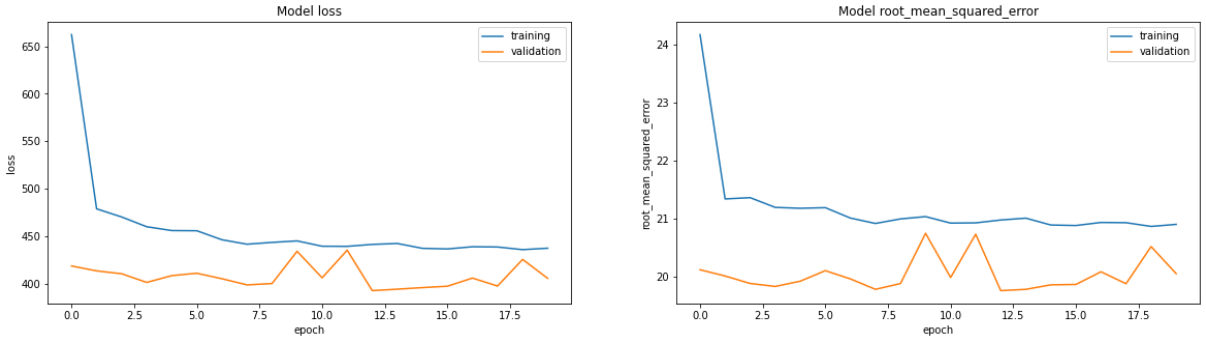


Figure 17: The model with tabular data with additional added complexity

From the images above we can conclude that model 2 seems to be the best model to continue using. It reaches the lowest RMSE value. Additionally, the course of the RMSE is the most consistent compared to not using the tabular data and using more and less complexity for the tabular data.

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