SNR classes project - birds species recognition using deep neural networks - second stage report

Michał Sypetkowski, Marcin Lew

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1 General information

Git repository:
`https://github.com/msypetkowski/SNR-proj.git`.
Previous stage report:
`https://github.com/msypetkowski/SNR-proj/blob/master/doc/main.pdf`.

In all experiments we use Adam optimizer and we expoenentially decrease learning rate by 50% for 1000 iterations. We use batch size of 128.

The whole document is a sequence of sections corresponding to various experiments that modify model, that turned out to give the best results in the previous experiment (an exception is chapter 2, because it hasn't a preceding experiment).

2 Establishing Layers count

First, we experiment with layers count. We trained 3 different models (they have respectively 11, 8 and 6 layers). Detailed layers descriptions for each model are shown in tables respectively 1, 2 and 3. Rounded total trainable parameters count is respectively: 2.0M, 1.7M and 1.5M.

Batch normalization with relu activation layers are used in all these models, where the horizontal lines occur in the tables.

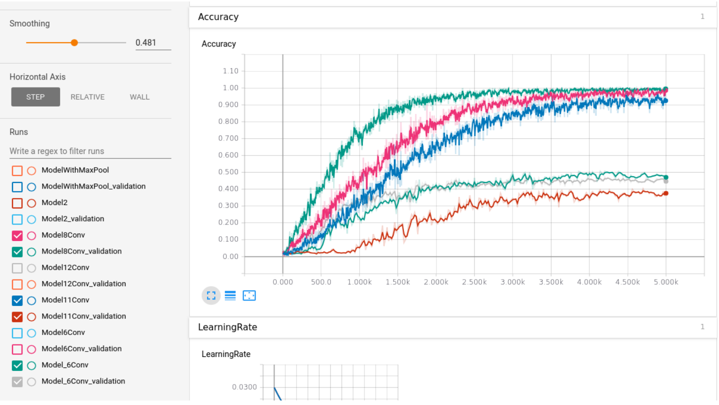
Table 1: 11 layer convolutional NN architecture

Layer	kernel/window	strides	output shape
Conv1	(5, 5)	(1, 1)	224x224x64
MaxPool1	(2, 2)	(2, 2)	112x112x64
Conv2	(5, 5)	(1, 1)	112x112x64
MaxPool2	(2, 2)	(2, 2)	56x56x64
Conv3	(5, 5)	(1, 1)	56x56x64
MaxPool3	(2, 2)	(2, 2)	28x28x64
Conv4	(5, 5)	(1, 1)	28x28x64
MaxPool4	(2, 2)	(2, 2)	14x14x64
Conv5	(5, 5)	(1, 1)	14x14x64
MaxPool5	(2, 2)	(1, 1)	14x14x64
Conv6	(5, 5)	(1, 1)	14x14x64
MaxPool6	(2, 2)	(2, 2)	7x7x64
Conv7	(5, 5)	(1, 1)	7x7x64
MaxPool7	(2, 2)	(1, 1)	7x7x64
Conv8	(3, 3)	(1, 1)	7x7x128
MaxPool8	(2, 2)	(2, 2)	4x4x128
Conv9	(2, 2)	(1, 1)	4x4x128)
MaxPool9	(2, 2)	(1, 1)	4x4x128
Conv10	(2, 2)	(1, 1)	4x4x128)
MaxPool10	(2, 2)	(1, 1)	4x4x128
Conv11	(3, 2)	(1, 1)	4x4x128)
MaxPool11	(2, 2)	(1, 1)	4x4x128
Flatten	-	-	2048
Dense1	-	-	512
Output	-	-	50
Softmax	-	-	50

2.1 Results

We use cross entropy as a loss function. We train each model for 5K iterations with initial learning rate of 0.03. Accuracy curves are shown in figure 1.

Training accuracy increases faster for models with fewer layers. Smaller networks naturally learn faster, but they have fewer degrees of freedom and may get worse results in the end. 11-layer network architecture shown to be too complicated for our dataset and/or training method. Best accuracy was achieved by medium – 8-layer network. We use this architecture for further experiments.



Smoothing 0.481

Horizontal Axis: STEP RELATIVE WALL

Runs

Write a regex to filter runs

- ☐ ModelWithMaxPool
- ☐ ModelWithMaxPool_validation
- ☐ Model2
- ☐ Model2_validation
- ☑ Model8Conv
- ☑ Model8Conv_validation
- ☐ Model12Conv
- ☐ Model12Conv_validation
- ☑ Model11Conv
- ☑ Model11Conv_validation
- ☐ Model6Conv
- ☐ Model6Conv_validation
- ☑ Model_6Conv
- ☑ Model_6Conv_validation

Figure 1: Accuracy curves for models with different layers count

3 Experiments with last convolutional layer size

Our 8-layer network from section 2, outputs feature vectors of size 2048 from the last (see Conv11 in table 2) convolutional layer (after flattening). We tried models with 1024 and 4096 sizes of these vectors. The results are shown are shown in figure 2. These dimensions significantly affect total trainable parameters count (around 1.1M in case of 1024 dimensions and around 2.8M in case of 4096 dimensions). Decreasing or increasing this parameter caused only loss in accuracy (models have in the end not enough or too many parameters for our dataset).

Table 2: 8 layer convolutional NN architecture (layer names correspond to some layers names in 11 layer architecture 1)

Layer	kernel/window	strides	output shape
Conv1	(5, 5)	(1, 1)	224x224x64
MaxPool1	(2, 2)	(2, 2)	112x112x64
Conv2	(5, 5)	(1, 1)	112x112x64
MaxPool2	(2, 2)	(2, 2)	56x56x64
Conv3	(5, 5)	(1, 1)	56x56x64
MaxPool3	(2, 2)	(2, 2)	28x28x64
Conv4	(5, 5)	(1, 1)	28x28x64
MaxPool4	(2, 2)	(2, 2)	14x14x64
Conv6	(5, 5)	(1, 1)	14x14x64
MaxPool6	(2, 2)	(2, 2)	7x7x64
Conv8	(3, 3)	(1, 1)	7x7x128
MaxPool8	(2, 2)	(2, 2)	4x4x128
Conv9	(2, 2)	(1, 1)	4x4x128)
MaxPool9	(2, 2)	(1, 1)	4x4x128
Conv11	(3, 2)	(1, 1)	4x4x128)
MaxPool11	(2, 2)	(1, 1)	4x4x128
Flatten	-	-	2048
Dense1	-	-	512
Output	-	-	50
Softmax	-	-	50

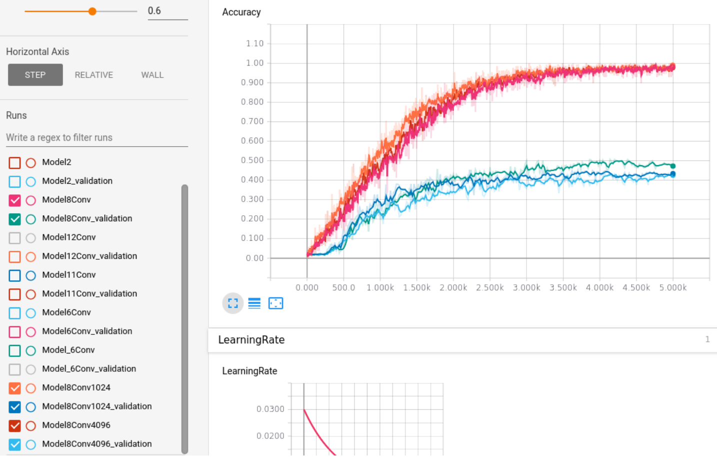
Table 3: 6 layer convolutional NN architecture (layer names correspond to some layers names in 11 layer architecture 1)

Layer	kernel/window	strides	output shape
Conv1	(5, 5)	(1, 1)	224x224x64
MaxPool1	(2, 2)	(2, 2)	112x112x64
Conv2	(5, 5)	(1, 1)	112x112x64
MaxPool2	(2, 2)	(2, 2)	56x56x64
Conv3	(5, 5)	(1, 1)	56x56x64
MaxPool3	(4, 4)	(4, 4)	28x28x64
Conv6	(5, 5)	(1, 1)	14x14x64
MaxPool6	(2, 2)	(2, 2)	7x7x64
Conv8	(3, 3)	(1, 1)	7x7x128
MaxPool8	(2, 2)	(2, 2)	4x4x128
Conv11	(3, 2)	(1, 1)	4x4x128)
MaxPool11	(2, 2)	(1, 1)	4x4x128
Flatten	-	-	2048
Dense1	-	-	512
Output	-	-	50
Softmax	-	-	50

4 Experiments with activation function

We tested using sigmoid activation function in 8-layer network from section 2. We trained the sigmoid model variant for 5000 iterations longer. As we can see in figure 3, experimental model learns significantly slower, but achieves only slightly worse result in the end.

Training accuracy grows relatively fast – test accuracy starts giving better answers than random choice (above 2%), when the training accuracy is above 90%. Experimental model learns more memory-like rules for first 3k iterations. When this strategy achieves its limit, the generic rules emerge. In the end, validation accuracy have sigmoid-like shape.



0.6

Horizontal Axis

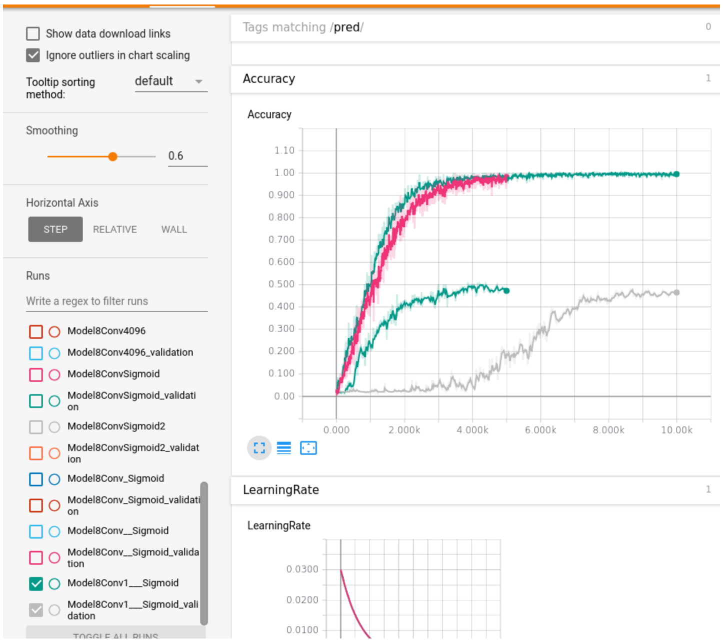
STEP RELATIVE WALL

Runs

Write a regex to filter runs

☐ ○ Model2
☐ ○ Model2_validation
☑ ○ Model8Conv
☑ ○ Model8Conv_validation
☐ ○ Model12Conv
☐ ○ Model12Conv_validation
☐ ○ Model11Conv
☐ ○ Model11Conv_validation
☐ ○ Model6Conv
☐ ○ Model6Conv_validation
☐ ○ Model_6Conv
☐ ○ Model_6Conv_validation
☑ ○ Model8Conv1024
☑ ○ Model8Conv1024_validation
☑ ○ Model8Conv4096
☑ ○ Model8Conv4096_validation

Figure 2: Accuracy curves for models with different last convolutional layer size



☐ Show data download links
☑ Ignore outliers in chart scaling

Tooltip sorting method: default

Smoothing

0.6

Horizontal Axis

STEP RELATIVE WALL

Runs

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☐ ○ Model8Conv4096
☐ ○ Model8Conv4096_validation
☐ ○ Model8ConvSigmoid
☐ ○ Model8ConvSigmoid_validation
☐ ○ Model8ConvSigmoid2
☐ ○ Model8ConvSigmoid2_validation
☐ ○ Model8Conv_Sigmoid
☐ ○ Model8Conv_Sigmoid_validation
☐ ○ Model8Conv__Sigmoid
☐ ○ Model8Conv__Sigmoid_validation
☑ ○ Model8Conv1__Sigmoid
☑ ○ Model8Conv1__Sigmoid_validation

Figure 3: Accuracy curves for model with sigmoid activation function

5 Experiments with loss function

We tested MSE (Mean Squared Error) as activation function instead of cross entropy. Nowadays, it is a common knowledge that using cross entropy instead of MSE in classification models works better. In our experiment, MSE works generally worse during the whole training. Accuracy and training curves are shown in figure 4.

6 Experiments with SVMs

We experimented with using features from batch normalization layer after last dense layer and last convolutional layer (to be exact – from flattening layer). For training each SVM, we use 20k feature vectors. We use various kernels in this experiment. Last dense layer has 512 output features and last convolutional layer has 2048. Results of this experiments are shown in table 4.

Most surprising fact is that linear kernel after last convolutional gives better results than variant without SVM. In the cases, where we train SVMs after last convolutional layers we use in fact a model with significantly fewer parameters (we

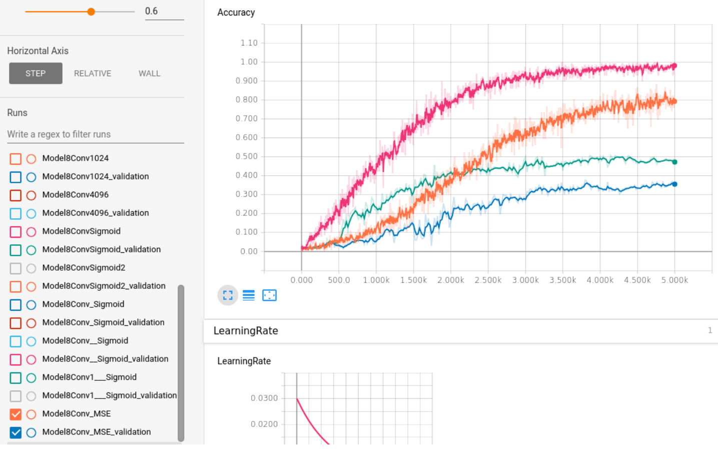

Figure 4: Accuracy curves for model with MSE loss function

have around 0.7M instead of 1.7M). Inspired by this observation we did experiment described in section 7.

Table 4: Accuracy for various SVMs usages

method	accuracy
noSVM	46.3%
RBF after last dense	49.3%
RBF after last convolutional	49.6%
linear after last dense	47.6%
linear after last convolutional	48.0%
polynomial (degree=3) after last dense	49.6%
polynomial (degree=3) after last convolutional	51.3%
sigmoid after last dense	46.0%
sigmoid after last convolutional	37.0%

7 Experiment with removing dense layer

Inspired by results achieved previous section, we trained model without last dense layer. New model have 0.7M trainable parameters instead of 1.7M. Accuracy curves are shown in figure 5, and SVM experiments results – in table 5.

As we can see, training SVMs after flattened last convolutional layer output gives only worse results in this case.

This experiment shows that sometimes training model with a certain amount of trainable parameters, then removing more than a half of them (in our case decreasing from 1.7M to 0.7M) and adding SVM, may actually give better results than training model with lower parameters count from the beginning and then adding SVM.

Table 5: Accuracy for various SVMs usages (on model without last dense layer)

method	accuracy
noSVM	40.0%
RBF after last convolutional	39.6%
polynomial (degree=3) after last convolutional	6%

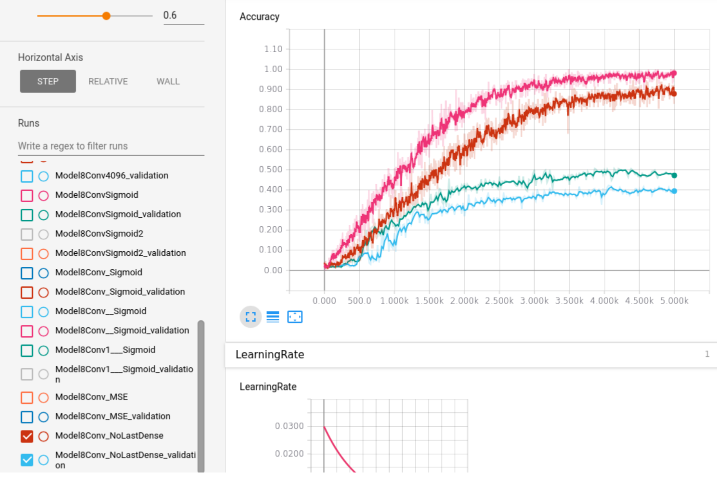

Figure 5: Accuracy curves for 8-convolutional-layer model without dense layer