Artist Recognition with Convolutional Recurrent Neural Networks

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1. Introduction

Deep convolutional neural networks have been successfully applied to many tasks. Chiefly among those have been image and video classification or recognition related tasks. But convolutional neural networks have also been successfully applied for speech recognition and even music classification [1].

For audio related tasks, the raw audio is usually converted to a time-frequency representation such as Mel-spectograms. This is then supplied as input for some neural network. Choosing and creating the correct representation however, requires the right domain knowledge. Therefore, it would be helpful if this could be skipped, and audio could be directly fed into a convolutional network. This way less domain knowledge would be required to create an effective neural network.

[2] proposes deep convolutional models that performs convolutions on a small number of samples in the range of 2 to 5 samples at a time. These networks were used for music auto-tagging. For this project these models have been extended with a recurrent layer. These models are then used for artist recognition instead of auto-tagging.

In this paper these convolutional recurrent neural networks are described in detail. Experiments with this network have been performed on the MagnaTagATune dataset for different parameters. The question is how well do these recurrent convolutional models perform on their own and when compared against the original convolutional models for the task of artist recognition. The impact on musical on prediction accuracy is also evaluated.

2. Model

The models used are based on the ones that worked best in [2]. In this paper, the models were build out of standard building blocks that consist of a convolutional layer with a filter size of *n* followed by a max-pooling layer with a pool-size of *n*. The convolutional layer in these block is padded so the output has the same size as the input. Therefore, after each of these blocks, the input size is reduced by a factor of *n*.

The input layer is also a convolutional layer. This layer performs directly on the raw audio samples. This is a strided convolutional layer with the stride equal to the filter size. So, this first layer reduces the input by a factor equal to the filter size. The best results are obtained when this layer works on a small number of sample. Therefore, the filter size of this layer should be small.

These blocks are than combined in such a way that after all the standard building blocks the input has been reduced to size 1. For this project, the best configuration found by [2] is used. This configuration is *n* = 3, and a filter size and stride of 3 for the initial convolutional layer. This means the input needs to be a power of 3. This configuration is shown schematically in table 1.

Table 1. Original model, m is # standard blocks		
Input Size = 3^{m+1}		
Layer	Configuration	Output
Convolutional layer	Size = 3, Stride = 3	3^m * number of filters
Repeat m times the standard building block		
Convolutional layer Max-Pooling layer	Size = 3, Stride = 1 Pool size = 3	3^{m-1}
After m repetitions		3^0 = 1 * number of filters last building block
Fully Connected layer	-	Number of nodes
Output layer	-	Number of classes

A concrete example of a possible model is shown in table 2. This model takes 729 samples as input. The first strided convolutional layer cuts this input by a factor of 3 to 243 samples. Each Max-pooling layer of the standard blocks reduces the input by a factor of 3 again. To get an output size of 1 at the end, $^{3}\log(243)$ = 5 building blocks are necessary. Following the final block is a fully connected layer. The last layer is the output layer. In this example there would be 64 different classes.

Table 2. Example original model		
Input Size = 729		
Layer	Configuration	Output
Convolutional layer	Size = 3, Stride = 3, Filters = 64	243*64
Convolutional Layer Max-Pooling Layer	Size = 3, Stride = 1, Filters = 64 Pool size = 3	243*64 (padded) 81 * 64
Convolutional Layer Max-Pooling Layer	Size = 3, Stride = 1, Filters = 64 Pool size = 3	81*64 (padded) 27 * 64
Convolutional Layer Max-Pooling Layer	Size = 3, Stride = 1, Filters = 128 Pool size = 3	27*128 (padded) 9 * 128
Convolutional Layer Max-Pooling Layer	Size = 3, Stride = 1, Filters = 128 Pool size = 3	9*128 (padded) 3*128
Convolutional Layer Max-Pooling Layer	Size = 3, Stride = 1, Filters = 128 Pool size = 3	3*64 (padded) 1*128
Fully Connected Layer	Size = 128	128
Output Layer	Size = 64	64

The best results obtained in [2] are with an input size of 3^{10} = 59049 samples and 9 building blocks. A music clip is likely to be longer than 59049 samples. In that case, it needs to be divided into segments and each segment is then classified separately. There might however, be dependencies between these different segments that these models are then unable to learn as it sees each segment individually.

Therefore, for this project the fully connected layer in the models described above is replaced with a recurrent layer. This way the convolutions can be performed on each segment individually and inputted one by one into a recurrent layer as a sequence. A recurrent layer retains a memory of previously seen elements of the sequence. If a new element is inputted into the recurrent layer, it is combined with this memory and the memory is updated. After the final element of the sequence has been inputted, a final output is generated that has considered all elements of the sequence. This way, the network may learn information about the dependencies between segments that is useful for the classification tasks, which in our case is artist recognition.

The new recurrent version is shown schematically in table 3. LSTM stands for long short-term memory and is a type of recurrent layer.

Table 3. Recurrent model, m is # standard blocks, s is # segments

Input Size = s * 3^{m+1}		
Layer	Configuration	Output
Convolutional layer	Size = 3, Stride = 3	s * 3^{m} * number of filters
Repeat m times the standard building block		
Convolutional layer Max-Pooling layer	Size = 3, Stride = 1 Pool size = 3	s * 3^{m-1}
After m repetitions		s * 1 * number of filters last building block
LSTM layer	-	Number of nodes
Output layer	-	Number of classes

A concrete example of the recurrent model can be found in table 4. In this example there are 7 segments of 729 samples. Convolutions are performed on each segment separately. These are all inputted into the LSTM layer as a sequence, after which the combined output of all segments in inputted into the output classification layer.

Table 4. Example recurrent model

Input Size = 7 * 729		
Layer	Configuration	Output
Convolutional layer	Size = 3, Stride = 3, Filters = 64	7 * 243*64
Convolutional Layer Max-Pooling Layer	Size = 3, Stride = 1, Filters = 64 Pool size = 3	7 * 243*64 (padded) 7 * 81 * 64
Convolutional Layer Max-Pooling Layer	Size = 3, Stride = 1, Filters = 64 Pool size = 3	7 * 81*64 (padded) 7 * 27 * 64
Convolutional Layer Max-Pooling Layer	Size = 3, Stride = 1, Filters = 128 Pool size = 3	7 * 27*128 (padded) 7 * 9 * 128
Convolutional Layer Max-Pooling Layer	Size = 3, Stride = 1, Filters = 128 Pool size = 3	7 * 9*128 (padded) 7 * 3*128
Convolutional Layer Max-Pooling Layer	Size = 3, Stride = 1, Filters = 128 Pool size = 3	7 * 3*64 (padded) 7 * 1*128
LSTM	Size = 128	128
Output Layer	Size = 64	64

Activation functions in each for this project have been changed for this project from the proposed version from [2]. Both the recurrent and original model use the same activation functions. For the convolutional layers this is ReLu. For the LSTM layer and fully connected layer this is Tahn and for the output layer this is softmax.

3. Experiments and Results

This section describes the dataset used, the training procedure, the experiments performed on the trained models and the results.

3.1 Dataset

Because the models have been designed to work on raw samples, a dataset with for which the actual audio is available is necessary. Therefore, the dataset chosen is the MagnaTagATune dataset for which most audio is available. This audio however is only available in mp3 format. This audio is therefore first converted to wav format.

Following this some clips are removed from the dataset. Firstly, there are some clips with no audio available, and therefore not usable for these experiments. Secondly, some clips are from songs from compilation albums. These are for example tagged with artists names like *various artists* and not the actual original artist. This makes them also unsuitable for these experiments and all clips identified as coming from compilation albums are removed.

This leaves 24847 clips from 222 different artists. Each clip is around 30 seconds long and contains 465984 at a sample rate of 16 kHz. This means there is around 207 hours of audio in the dataset. This data is split in two different ways in a test set and training set. The 30 second clips result from longer songs that are cut up into pieces. For the first train and test set the clips are divided in such a way that the percentage of clips from a given artist roughly corresponds in both the train and test set. This means that clips from the same song are in both test and training set. The second dataset divides the clips in such a way that the percentage of clips per artist still roughly corresponds between both training and test set, but also ensures that clips from the same song only occur in either the test or training set.

3.2 Training Procedure

All models are implemented with the Keras python library with the tensorflow backend and trained on a single GTX 1080 Ti GPU for 50 epochs. This can take between 12 to 24 hours, depending mainly on the number of segments each clip is divided into.

During training batch normalization is used before each activation function as in [2]. The Adam optimizer is used, and the loss function is set to categorical cross entropy for all models. All models are trained three different times and results reported are the average of these three runs.

3.3 Performance for different splitting of the data

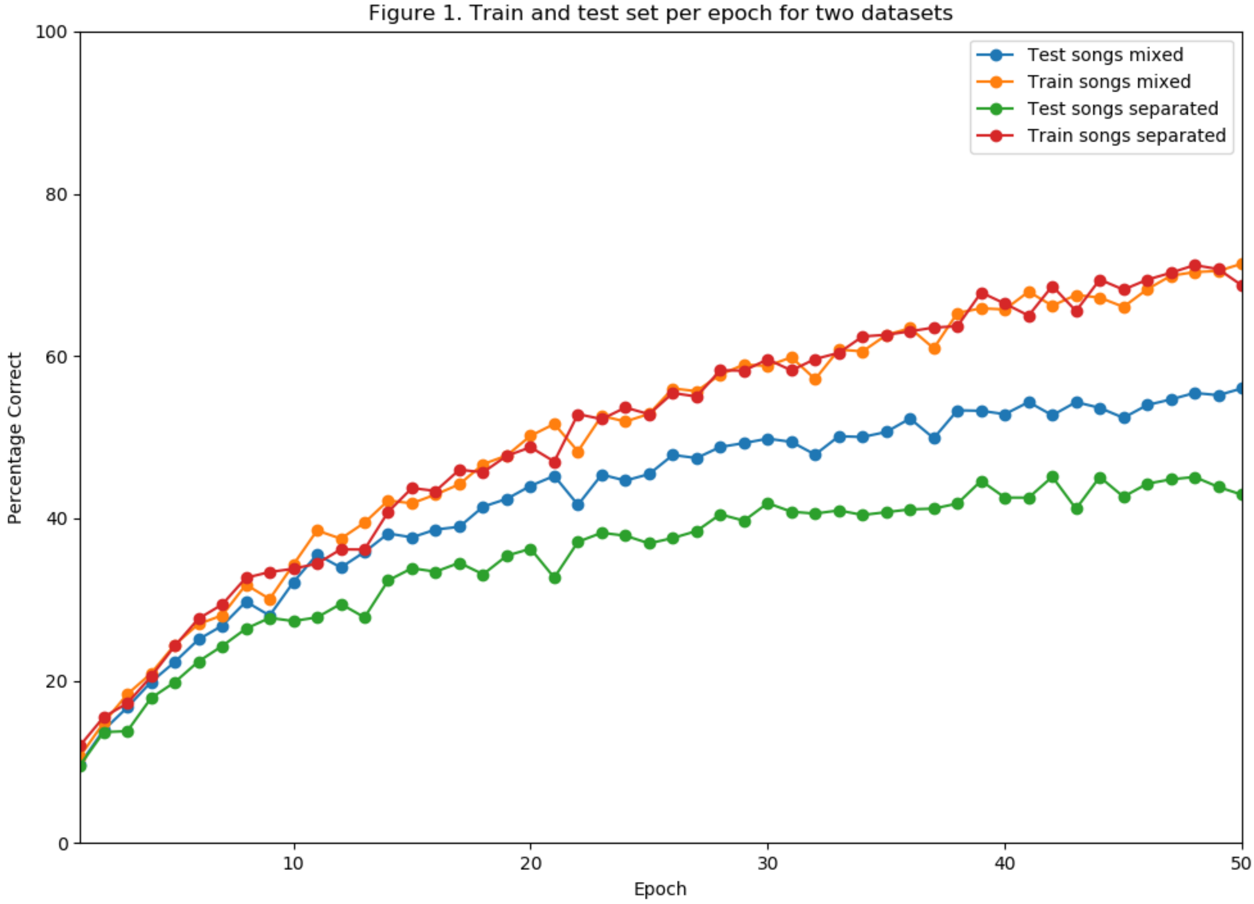
The first experiment tries to measure the difference of performance of the same model between the two different ways of splitting the data as described in section 3.1. In case different sections of the same song are in both the training and test set, the performance measured may be the ability of the network to recognize a song instead of an artist. This way good results could be reported, while the model may fail to recognize the artist when it sees a completely unknown song.

The model used in this experiment is the recurrent version. Clips are cut into 7 segments of 59049 samples. Any leftover samples are discarded. Using 59049 samples mean that there are 10 convolutional layers: the first strided one, and 9 layers each followed by a max-pooling layer. The exact number of filters and nodes used in each layer can be found in table A.1 for model number 1.

The accuracy in percentage is plotted in figure 1 for both training sets and test sets. It shows that while the accuracy on both training sets is similar, recognizing artists is more difficult when it is done on completely unknown songs. The accuracy on the test set after 50 epochs on the first dataset is around 56% on average, but around 42% for the second dataset. But while there is a noticeable reduction in accuracy, it does also not completely fail. This indicates that it is indeed the artist that is being recognized instead of the song.

The graph also shows that for at least the second dataset the peak accuracy is reached at epoch 42. After that the accuracy starts fluctuating. A dropping and then rising accuracy can also be observed at other place for both datasets. The first dataset however, reaches peak accuracy at epoch 50. It may therefore be possible that better results could still be achieved with further training. A good stopping point may therefore be found by creating another validation set and stopping the training when the accuracy on the validation set stops increasing for some amount of epoch.

Figure 1. Train and test set per epoch for two datasets



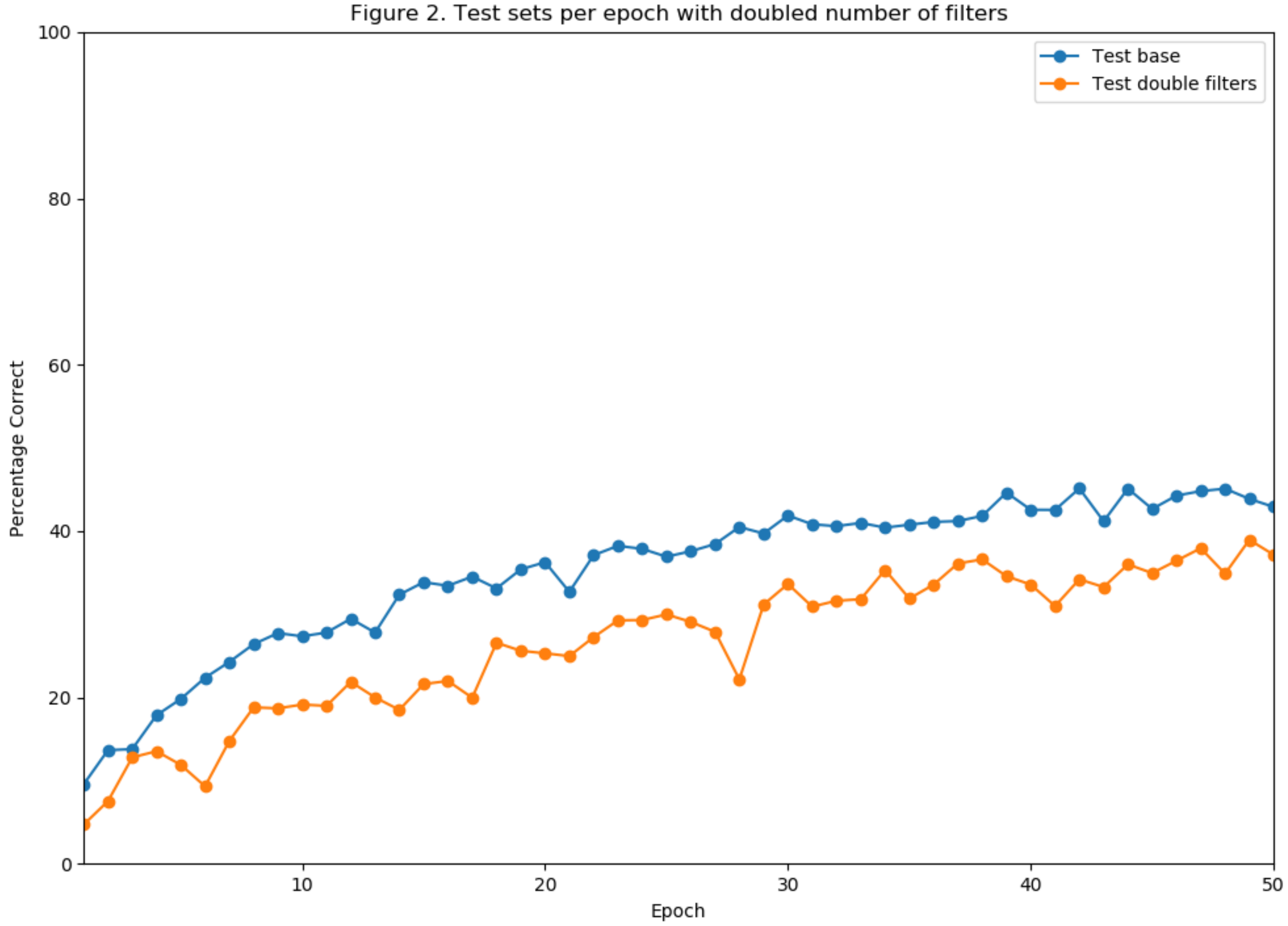
As the results show that the second dataset is the harder problem, all other experiments are performed on this dataset.

3.4 Number of filters

The second experiment measures the effect of the number of filters used. Figure 2 plots the result of two different models for the test set against the number of epochs. The first is the same one used in section 3.4. The second one is identical, except for the number of filters which have been doubled. The exact number of filters can be found in table A.1. for model 1 and 2.

The figure shows that the model with the lower number of filters consistently outperforms the other model. It is therefore important to choose this correctly to get a well performing model.

Figure 2. Test sets per epoch with doubled number of filters



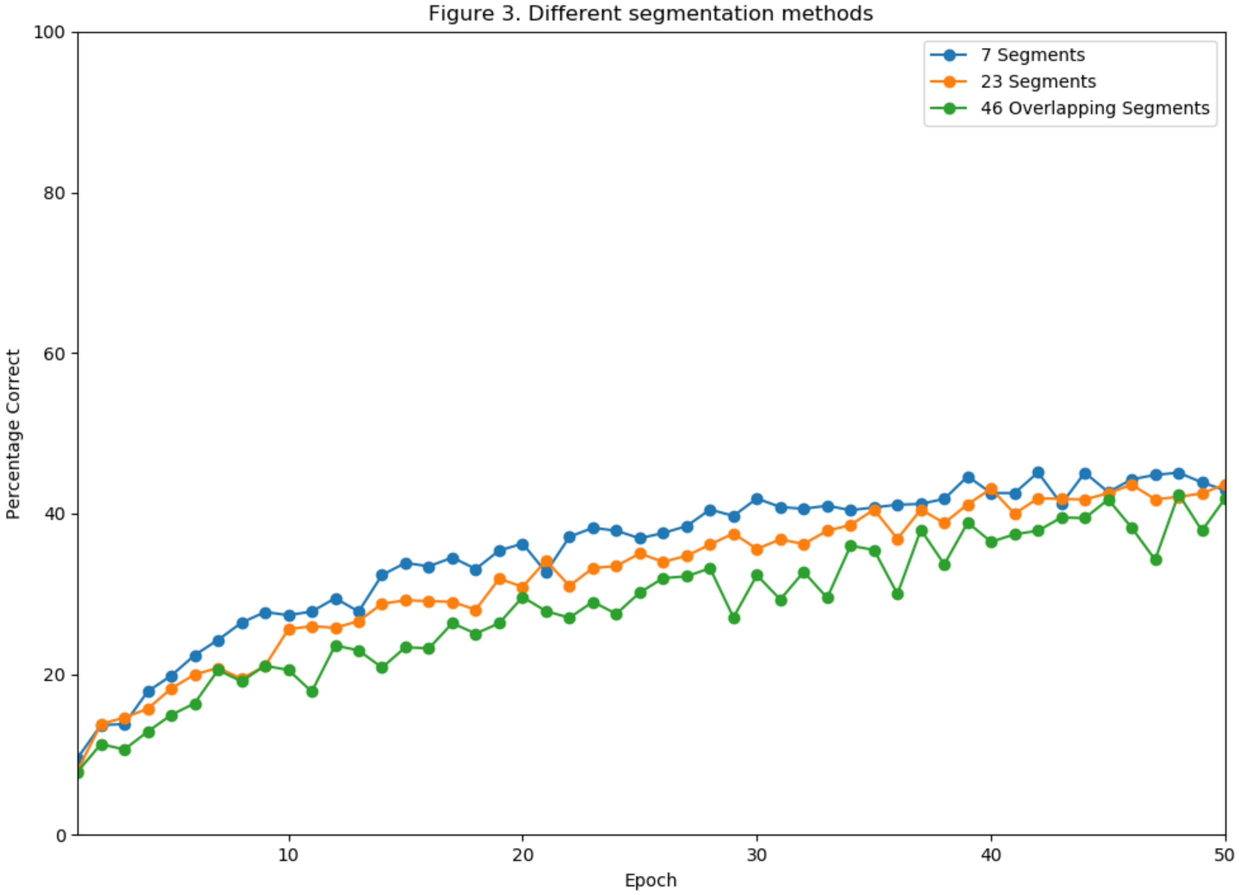
3.5 Different Segmentation Methods

The third experiment measures the impact on performance by different segmentation methods. Three segmentation methods are used:

- 7 segments of 59049 samples. This is the same as in section 3.3 and 3.4
- 23 segments of 19683 samples. This means there are 9 convolutional layers instead of 10, but a longer sequence is inputted into the convolutional layer.
- 46 segments of 19683 samples. For clips have been cut into segments with a window of 19683 samples, but with a stride of 9841 samples. This means the last half of each segment is equal to the first half of the next segment.

Any leftover frames are discarded. The exact number of filters can be found in table A.1. for model 1, 3 and 4 respectively.

The performance on the test set is plotted per epoch in figure 3. It shows that using more overlapping segments is not useful for the artist recognition, as it performs the worst. Using 7 larger segments also tends to give better performance than using smaller but more segments. This is similar to the results found by [2], where larger segments give somewhat better results.



3.6. Recurrent vs Non-Recurrent model

The fourth experiment is used to measure the effectiveness of the recurrent convolutional network against just a convolutional network. For the convolutional network, the recurrent layer is replaced with a dense layer as described in section 2. During training this model is trained on each segment of a clip individually. Two evaluation methods are used for this model. The first is simply predicting each segment individually. The second is averaging the predictions of all segments of a clip and using this for the final prediction. For both the recurrent and non-recurrent model, the clips are cut into 7 segments. The exact numbers of filters and nodes in the LSTM or dense layer used can be found in table A.1. for model 1. The results on the test set are plotted in figure 4.

The figure shows that the non-recurrent version works better than the recurrent version for both methods of evaluation. The point of the recurrent layer is to try and learn dependencies between segments useful for classification. It results show however, that this does not help, but only complicates the learning process. The original non-recurrent model as proposed by [2] works better for the artist recognition task.

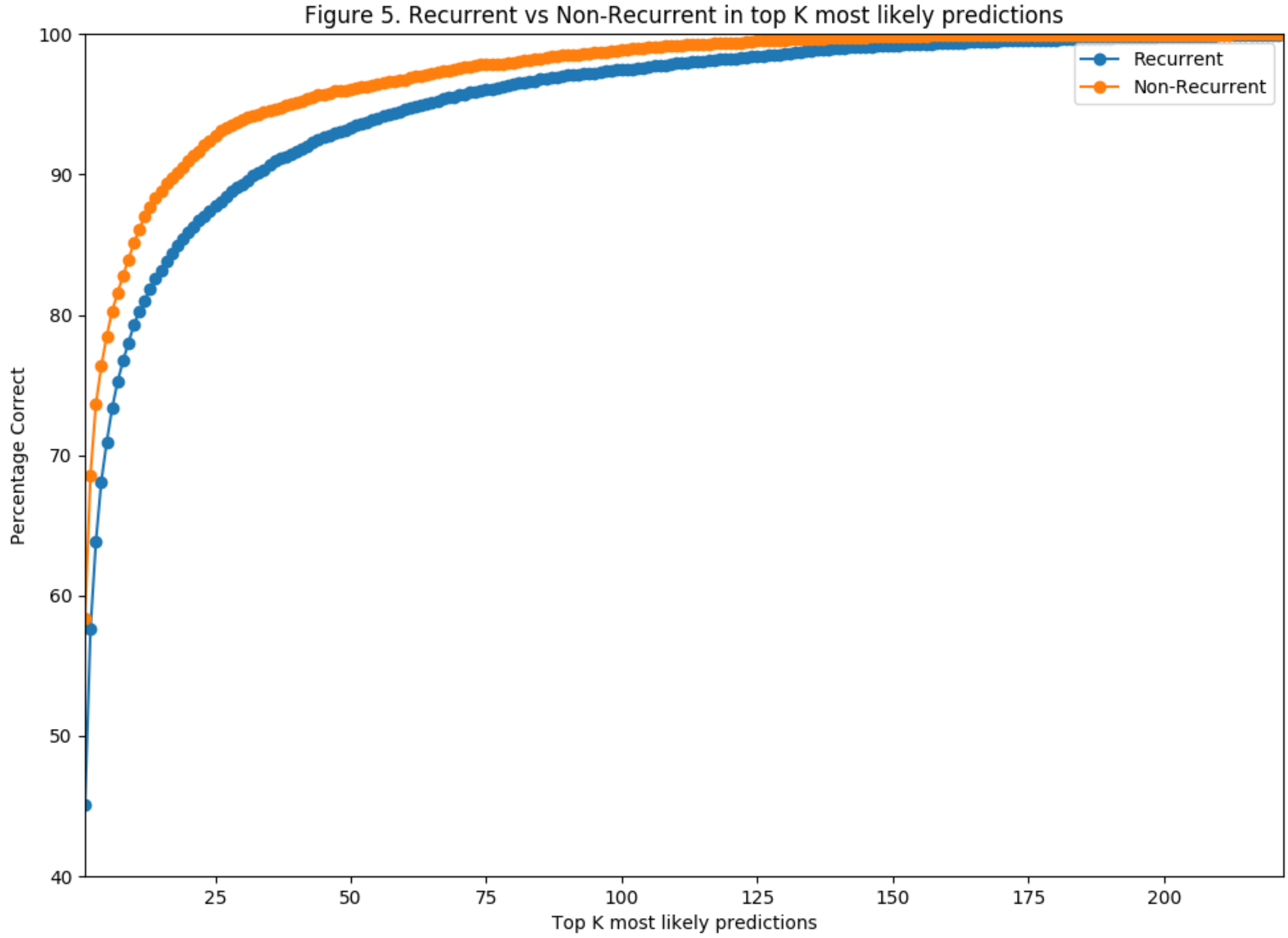
The figure does show that there is a clear benefit in considering all segments of a clip together instead of individually. This is however better done by the simpler procedure of averaging the results afterwards, instead of trying to incorporate it into the learning process.

3.7. Top K results

All the above results are obtained by looking at only the most likely artist predicted by the networks. It can also be useful to look at the top 2 or more predictions instead to see if the correct artist is among those. For instance, in the used dataset there are several artists that appear on their own, or in collaboration with another artist. Some results do show that the predicted artist is sometimes the artist on its own while the collaboration is the second most likely and correct prediction or vice versa. Therefore, the percentage predicted correctly on the test set when looking at the top K predictions for K = [1,222] has been plotted in figure 5. This has been done for both the recurrent and non-recurrent version of the network. The same configurations for the models are used as in section 3.6

Initially it shows the accuracy increasing quickly when K is increased. The non-recurrent version scores around 80% for K=6. The improvements each time K is increased slow down later however. The non-recurrent version only reaches 100% for K=221 and the recurrent version only when K=222. So, the correct artist is for some clip predicted as least likely, indicating that there some clips that are very hard to predict.

Figure 5. Recurrent vs Non-Recurrent in top K most likely predictions



3.8. Impact of Musical Genre

Finally, the impact of genre is examined. The albums in the MagnaTagATune dataset are tagged with up to three different genres from ten different possibilities. This data however, is not complete, so we have tried to complete this. As the albums are tagged and not the songs itself, the clips are assigned the genres of the album it is from. The artists are also tagged with the union of the genres of all their albums.

Table 5 shows the percentage of clips predicted incorrectly of each genre on the test set by both the recurrent and non-recurrent model. While the table shows Electronic Rock to be very difficult to predict the artist for, there are very few clips with this genre in the dataset, so this result may not be reliable. The same is true for Hip Hop. Otherwise the table shows that Jazz and Classical are the easiest to predict the correct artist for while Electro Rock is the most difficult.

Table 5. Percentage of clips with genre predicted incorrectly

Genre	% Incorrect Recurrent	% Incorrect Non-Recurrent
Alt Rock	73.38	50.85
Electro Rock	90.14	71.12
Classical	29.66	21.36
Electronica	65.87	58.05
Electronic Rock	100	61.5
Jazz	14.10	3.84
New Age	46.83	45.6
Hip Hop	66.67	50
Ambient	47.97	49.42
World	60.58	43.31
Hard Rock	56.52	33.54

It may be a reasonable idea that the predicted artist for a clip is wrong, because that artist works within the same genre. Table 6 shows the percentage of errors for which at least a single genre of the wrongly predicted clip is among the genres of the predicted artist. For both models this lies around 60%. This indicates that the genre may be a decent indicator for why the wrong artist is predicted.

Table 6. Percentage of wrong predictions where at least one genre of the clip was in the genre of the predicted artist

% Recurrent Version	% Non-Recurrent
59.80 %	60.63 %

4. Conclusion and Future Work

In this paper a recurrent convolutional model is described based on the convolutional model proposed by [2]. Both the original convolutional and recurrent convolutional model work directly on raw samples, so that no further transformation of the audio is necessary. Both have been used for the task of artist recognition on the MagnaTagATune dataset. While the recurrent convolutional model works relatively well when configured correctly, the experiments also show the original convolutional model works better for this task. Experiments also show that the musical genre appears to be a factor when it comes to the correct prediction of an artist.

All experiments have been done on the relatively small MagnaTagATune dataset. Future experiments could be done to verify how well these models scale to larger datasets such as the million-song dataset. The actual audio would need to be obtained however, no just a set of extracted features. Further analysis could also be done on what exactly the learned filters learn and react to.

A copy of this paper, together with the scripts and data to reproduce all experiments can be found here: http://liacs.leidenuniv.nl/~s1253727/API/

References

1. Hershey, Shawn, et al. "CNN architectures for large-scale audio classification." *Acoustics, Speech and Signal Processing (ICASSP), 2017 IEEE International Conference on*. IEEE, 2017.
2. Lee, Jongpil, et al. "Sample-level Deep Convolutional Neural Networks for Music Auto-tagging Using Raw Waveforms." *arXiv preprint arXiv:1703.01789* (2017).

Appendix

Table A.1. Input size and number of filters / nodes all models

Model	Input size	1st # filters	Following # filters	LSTM/Dense # nodes	Output # nodes
1	7 * 59049	64	- 1*64 - 6*128 - 2*256	512	222
2	7 * 59049	128	- 1*128 - 6*256 - 2*512	1024	222
3	23 * 19683	64	- 1*64 - 5*128 - 2*256	512	222
4	46 * 19683	64	- 1*64 - 5*128 - 2*256	512	222