Shallow Convolutional Neural Network Architectures for Music Genre Classification

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***Abstract*—In this paper I implement and evaluate the shallow convolutional neural network architecture proposed by Schindler et al. [1] for the task of music genre categorisation.**

***Index Terms*—Music Information Retrieval, Music Genre Classification, Convolutional Neural Networks**

I. Introduction

The explosive growth of digital music platforms has sparked significant advancements in the field of music information retrieval (MIR), a rapidly evolving discipline that focuses on developing computational techniques to extract valuable insights from music and audio signals. As MIR technologies continue to advance, they are becoming increasingly crucial for the music industry, enabling the creation of more effective tools such as recommender systems, which can provide a competitive edge in a crowded market.

One of the key challenges in MIR is genre classification, which involves identifying the musical genre of a given audio signal. Accurate genre classification can help music providers organise and categorise their catalogs, and enable users to search and discover new music in a more efficient and effective way. Early efforts to solve this problem, such as that proposed by Tzanetakis and Cook [2], employed statistical classifiers that were trained on vector summaries of features such as timbral texture, rhythmic content and pitch content. However, these summaries fail to capture the temporal structure of the underlying audio. In recent years, researchers have turned to audio spectrograms, which represent frequency data over time, to train state-of-the-art deep-learning models that can effectively classify audio signals based on genre.

Convolutional neural networks (CNNs) are one type of network that have been widely employed, following their successes in the field of computer vision. In this paper, we explore the use of CNNs for genre classification, and specifically investigate the shallow CNN architecture proposed by Schindler et al. [1], which was shown to achieve modest performance on this task.

II. Related Work

Liu et al. [3] recently proposed a novel architecture named a Bottom-up Broadcast Neural Network (BBNN) to deal with some of the problems traditionally associated with genre classification. They identified that many previously developed architectures had focused on abstracting high-level semantic features layer-by-layer; as a result, these architectures suffer from a huge loss of lower-level features which are critical to the task of genre classification. Thus, the BBNN architecture was specifically designed to simultaneously abstract high-level information while preserving the lower-level features.

Large datasets are frequently required to train powerful deep neural networks. However, in the MIR domain, there is often a lack of large training datasets. Hung et al. [4] published some very recent work that successfully dealt with this problem. They introduced a novel method called input-dependent neural model reprogramming—a transfer learning training scheme—that leverages pre-trained models for music classification. They successfully applied this method to reprogram two published models that were pre-trained on speech and audio data.

III. Dataset

I used the GTZAN dataset, compiled by Tzanetakis and Cook [2], to train and evaluate my models. The dataset contains a total of 1000 WAV audio tracks, each 30 seconds in length. GTZAN is a balanced dataset, containing 100 tracks for each of the 10 genres labelled in the dataset: blues, classical, country, disco, hip-hop, jazz, metal, pop, reggae and rock.

I utilised a stratified-by-genre split to produce a training and test set: the training set consisted of 750 tracks (75 tracks from each genre), while the test set contained the remaining 250 tracks of audio tracks.

IV. CNN Architecture

I recreated the shallow CNN architecture described by Schindler et al. in [1]. Figure 1 displays a schematic representation of the architecture. The network takes log-mel spectrograms of shape 80×80 as input, of which the dimensions corresponding to frequency and time. To effectively process the temporal and spectral characteristics of the input spectrograms, the architecture employs a parallel design. The upper pipeline captures frequency relations in the input, while the lower pipeline captures temporal relations.

The upper pipeline includes a convolutional layer with 16 kernels of shape 10×23 (with padding), which produces 16 sqaure feature maps of shape 80×80. These feature maps are then downsampled using a max pooling layer with a window

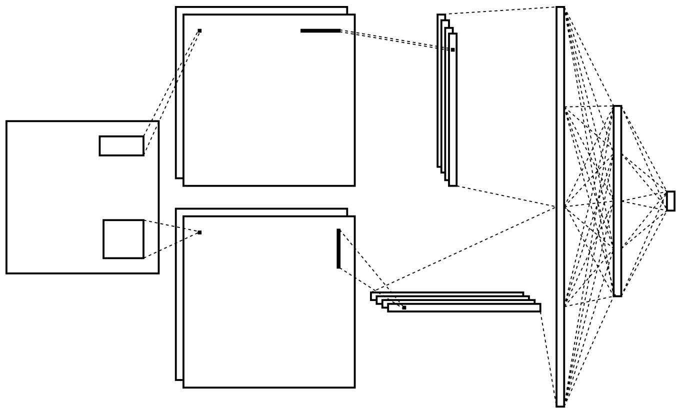


Fig. 1: Schematic representation of the shallow CNN architecture as described by Schindler et al. in [1].

of shape 1×20, resulting in 16 vertical rectangular feature maps of shape 80×4.

The lower pipeline also includes a convolutional layer with 16 kernels (with padding), but these are approximately square of shape 21×20. The resulting 16 square feature maps of shape 80×80 are downsampled using a max pooling layer with a window of shape 20×1, resulting in 16 horizontal rectangular feature maps of shape 4×80.

The 16 feature maps from each piepline are flattened and concatenated to a shape of 1×10240, which is mapped to a 200 neuron fully-connected layer. These final 200 neurons are then mapped to 10 output neurons, with 10% dropout utilised to mitigate overfitting. The softmax function is applied to these 10 output neurons to produce a pseudo-probability distribution that indicates the probability that a given input belongs to each of the 10 genres.

Except for the final layer, each convolutional and fully-connected layer is passed through a Leaky ReLU activation function with $\alpha = 0.3$. Leaky ReLU is an extension to the ReLU activation function that outputs a small non-zero value $f(x) = \alpha x$ for negative inputs.

V. Implementation Details

A. Preprocessing

The network was trained and evaluated using a total of 15000 log-mel spectrograms. To create these spectrograms, each audio track in the GTZAN dataset was first split into chunks of approximately 0.93 seconds, using a step size of 50%. 15 randomly selected chunks from each track were then transformed into log-mel spectrograms of shape 80×80 using a fast Fourier transform with a window size of 1024, and a step size of 50%. To avoid data leakage, the tracks were split into training and test sets before the spectrograms were created. This ensured the model would not have access to any information about the test set during training, allowing for a fair and accurate evaluation of its performance.

B. Training Details

I constructed and trained the CNN using Python and the PyTorch [5] machine learning framework. The training process was implemented according to the method described by Schindler et al. in [1]. I used cross-entropy loss to evaluate the performance of the network, and employed L1 regularisation with a penalty value of 0.0001 to mitigate overfitting. I used the Adam optimiser [6]—an extension of stochastic gradient descent—to optimise the network, using a learning rate of 5×10^{-5}, $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\epsilon = 1 \times 10^{-8}$ for numerical stability. I trained the network on a BlueCrystal Phase 4 GPU node, which contains two NVIDIA Tesla P100 GPUs [7].

C. Weight initialisation

Weight initialisation is a crucial design choice, as it determines the starting point of the optimisation procedure. In the shallow CNN architecture proposed by Schindler et al. in [1], the authors did not specify the weight initialisation procedure they used. However, there are modern heuristics for weight initialisation that depend on the activation function used in the network. In this case, since the network uses the Leaky ReLU activation function throughout, I implemented He Gaussian initialisation, which is well-suited for networks with Leaky ReLU activations.

D. Batch size

Batch size is an important hyperparameter to consider when training deep learning models. Smaller batches give rise to longer epochs and introduce extra noise to the weight updates; however, this noise can prove beneficial if the error manifold has many deep local optima. Conversely, larger batches give rise to shorter epochs, but networks trained with large batches often struggle to generalise. Schindler et al. did not identify the batch size they used for training in [1]. Therefore, I experimented with multiple batch sizes in preliminary experiments and found that a batch size of 64 yielded the best results.

VI. Replicating Quantitative Results

Table I displays the mean accuracy my implementation achieved on the test set over five runs; the accuracy achieved by Schindler et al. [1] is also displayed for comparison. I trained my network for a total of 500 epochs, but there was negligable difference in accuracy after 200 epochs because the network had already overfit—achieving a test accuracy of near 100%—so training the network for additional epochs did not improve the network's ability to generalise. In this respect, if the network were trained for longer, it is likely the test accuracy would decrease.

TABLE I
Accuracy achieved on the test set

Model	Epoch	Accuracy
My CNN	100	62.96
	200	64.01
Schindler et al.	100	66.56
	200	67.49

Our results differed by approximately 3% from those reported in the original paper [1], likely due to differences in the experimental setup and assumptions made between the two studies.

Figure 2 is a confusion matrix displaying the the performance of my implementation after 200 epochs. Notably, there is a large inconsistency in the per-class accuracy of different genres. For example, the network achieved a high per class accuracy of over 80% on the blues, classical and metal genres. While conversely, it achieved less than a 40% per-class accuracy on the reggae and rock genres; in particular, it misclassified 21% of rock songs as blues.

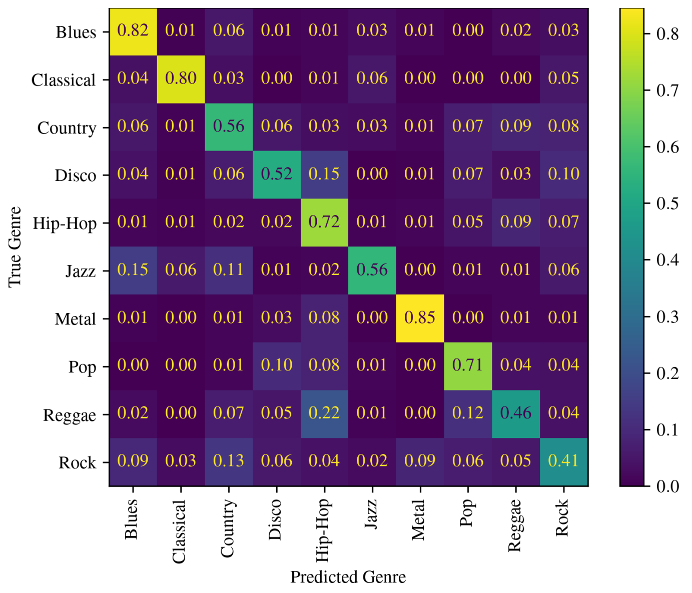


Fig. 2: Confusion matrix displaying the performance of my network on the test set after 200 epochs for a single training run. The value in a given cell represents the proportion of samples from the true genre categorised as the predicted genre.

VII. Training Curves

Overfitting occurs when a network learns the noise in the data as if it represents the structure of the underlying model. To detect overfitting, I monitored the loss and accuracy my network achieved on both the training and test set throughout the training process. Figure 3 and Figure 4 display the accuracy and loss curves for my network, respectively.

After 200 epochs, there was a discrepency of approximately 35% in the accuracy of the model on the training and test sets—this strongly indicates that the shallow CNN architecture overfit. Despite using L1 regularisation and dropout, the model had memorised almost every sample in the training set, and therefore struggled to generalise to unseen data.

VIII. Qualitative Results

Deep neural networks are frequently described as black-box models, because it can be exceptionally difficult to reason about the features they extract to produce their outputs. Figure 5 displays three log-mel spectrograms produced from samples from the audio tracks in the GTZAN dataset. An analysis of these spectrograms, as well as listening to the audio files

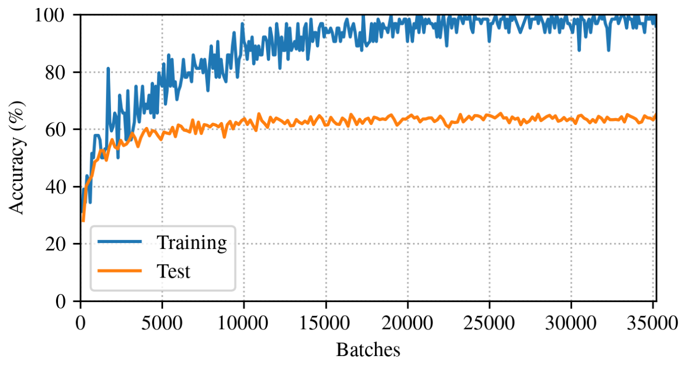


Fig. 3: Plot of accuracy data from the same training run as Figure 2. The line labelled ‘training’ is the accuracy achieved on the training set, calculated every 100 batches; the line labelled ‘test’ is the accuracy achieved on the test set, calculated every epoch.

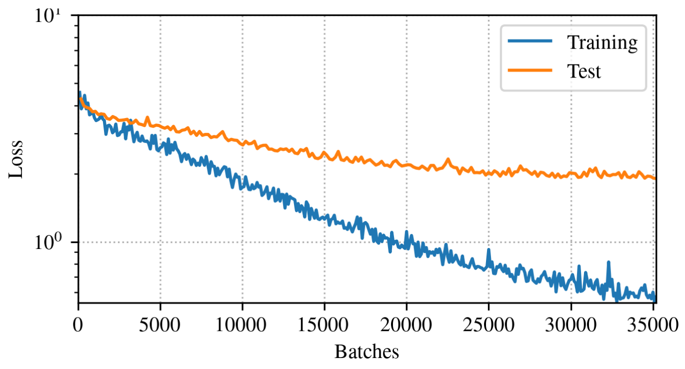


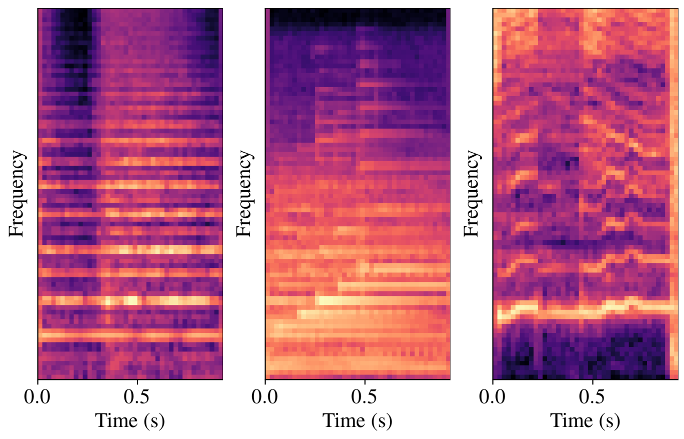
Fig. 4: Plot of loss data from the same training run as Figure 2. The line labelled ‘training’ is the loss achieved on the training set, calculated every 100 batches; the line labelled ‘test’ is the loss achieved on the test set, calculated every epoch.

from which they were derived, yields some clues as to the discrepencies in per-class accuracy that the network achieved.

The spectrogram in Figure 5a was correctly classified as belonging to the classical genre, and as were the other 14 log-mel spectrograms extracted from ‘classical.00070.wav’. The audio within the file is very characteristic of classical music, with long notes played from a violin. Harmonics produced by the violin are represented by the long parallel lines that stretch across the entirety of the file. An analysis of other spectrograms produced from classical music appear very similar. One can see how a neural network could relatively easily learn that extended parallel lines such as these indicate classical music.

Conversely, the network incorrectly predicetd the class for all spectrograms produced from ‘jazz.00003.wav’. A spectrogram produced from a segment of the audio file is shown in Figure 5b, in which there are long parallel lines characteristic of classical music. In fact, nine of the spectrograms derived from the file were classified as being classical. This lends credence to the idea that the network classifies spectrograms with long parallel lines as being classical music.

The spectrogram in Figure ‘pop.00064.wav’ was also incorrectly classifed, as were 13 of the other spectrograms



(a) classical.00070 (b) jazz.00003 (c) Correct

Fig. 5: Log-mel spectrograms produced from three of the samples in the test dataset.

derived from the same file. In fact, 11 of the spectrograms were incorrectly classified as being disco music. This arguably highlights a fundamental problem with using genre as a way of classifying music: its subjective nature. Genres are often not defined objectively. It is highly unlikely even a human would agree with all of the genre classiciations in the dataset, which makes it understandable that a machine too would incorrectly classify so many samples.

IX. Improvements

A. Maximum Probability and Majority Voting

Thus far, I have computed the 'raw' accuracy of my model, by predicting the genre for each sample in my dataset independently. However, this is not the optimal method since it ignores all file dependencies—there are 15 spectrograms for each WAV audio track in the GTZAN dataset. Schindler et al. recognised this, and achieved a substantial improvement in accuracy by introducing two new methods of classification: maximum probability and majority vote, both of which take file dependencies into account. To classify an inputted audio file by maximum probability, the probabilities output by the final softmax layer for each segment are first summed; then, the predicted class is determined by the largest value amongst the summed probabilities. To classify an inputted audio file by majority vote, a class is determined for each segment by the largest value output by the final layer; then, a majority vote is conducted over the predicted classes for each of the segments.

Table II displays the accuracy achieved using each of the raw, maximum probability and majority vote approaches. The relative improvement in accuracy provided by the two new approaches are consistent with the findings of Schindler et al. The increase in accuracy is due to to there being some level of independence in the predictions of samples from a given file. This independence can be attributed to the 0.93 second samples often being too short to be representative, as well as the model overfitting the training data. The majority vote and maximum probability classification methods essentially cancel out many of the individual errors to produce more accurate predictions for entire files.

TABLE II
Improved accuracy achieved on the test set

		Accuracy		
Model	**Epoch**	**Raw**	**Max**	**Maj**
My CNN	100	62.96	75.80	73.53
	200	64.01	77.60	76.60
My CNN + Batch Norm	100	66.30	77.30	77.56
	200	**66.55**	**78.68**	**77.64**

B. Batch Normalisation

Batch normalisation [8] is a technique frequently employed to increase the speed and stability of the training process. This is achieved via a normalisation step that fixes the means and variances of each layer's input. When applied to the output from a convolutional layer, this is implemented as follows:

$$\hat{x}_{i,c,x,y} = \gamma_c \frac{x_{i,c,x,y} - \mu_c}{\sqrt{\sigma_c^2 + \epsilon}} + \beta_c$$

where x is the output from the previous layer; $\hat{x}$ is the input to the subsequent layer; i, c, x and y are the batch, channel, width and height indices; γ_c and β_c are parameters learned during the optimisation process to restore the representative power of the network; and γ is a small constant for numerical stability.

I implemented a two-dimensional batch normalisation layer following each of the two convolutional layers in my network using $PyTorch$'s `nn.BatchNorm2d` class. Table II displays the accuracy of my network with the inclusion of the batch normalisation layers. Not only did batch normalisation provide a reasonabe improvement in accuracy after 200 epochs—especially in the case of raw accuracy—but, it also reduced the number of epochs required for convergence to a small degree. Unlike in the case of the CNN trained without batch normalisation, the difference in accuracy between 100 and 200 epochs is very minimal. The precise reasons for the improved performance are unclear: Batch normalisation has strong empirical performance, but there is some disagreement as to the theory behind its effectiveness. Santukar et al. [9] proposed that batch normalisation significantly smoothes the optimisation landscape, which induces a more predictive and stable behaviour of the gradients, thus facilitating faster training.

Figure 6 displays the raw accuracy the network achieved on the training and test set during the training process. It is evident that the degree to which the network is overfitting has been reduced. This is because batch normalisation also works as a regulariser, due to the fact that the mean and standard deviation is computed from each mini-batch, rather than the entire dataset.

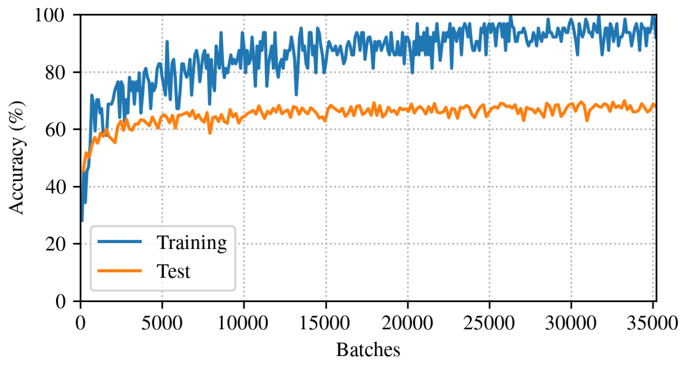


Fig. 6: Plot of accuracy data for my improved network from a single training run. Format is the same as for Figure 3.

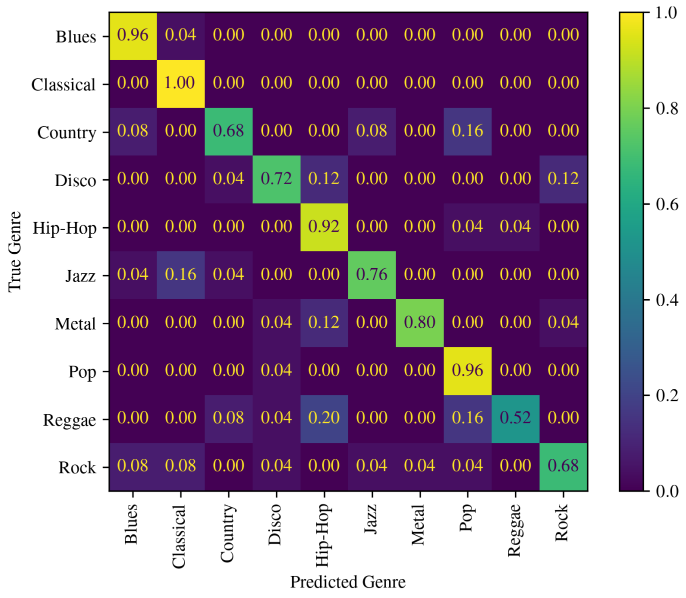


Fig. 7: Confusion matrix displaying the performance of my improved network with batch normalisation on the test set after 200 epochs for a single training run. Classification was performed using the maximum probability method. Format is the same as for Figure 2.

X. Conclusion and Future Work

In this paper I have reimplemented the shallow CNN architecture as originally described by Schindler et al. [1]. While I was unable to reproduce the results published in the original paper, I have exposed a significant discrepency in the per-class accuracy when the the network is trained using the GTZAN dataset. Moreso, I have conducted an extensive qualitative analysis to gain an insight into potential reasons for this discrepency.

In the latter part of this paper, I have also proposed an extension to the architecture with the inclusion of two batch normalisation layers. I found that the inclusion of these layers offered an advantage over the original architecture by reducing the time required for convergence, as well as providing a modest improvement to accuracy.

Future work should focus on eliminating the stark discrepency in per-class accuracy. Further extensions should also be considered with the aim of reducing the degree to which the network overfits. Data augmentation provides a potential avenue to explore in this respect.

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