Distinguishing Violinists and Pianists based on their Brain Signals

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Abstract. Many studies in neuropsychology have highlighted that expert musicians, who started learning music in childhood, present structural differences in their brains with respect to non-musicians. This indicates that early music learning affects the development of the brain. Also, musicians' neuronal activity is different depending on the played instrument and on the expertise. This difference can be analysed by processing electroencephalographic (EEG) signals through Artificial Intelligence models. This paper explores the feasibility to build an automatic model that distinguishes violinists from pianists based only on their brain signals. To this aim, EEG signals of violinists and pianists are recorded while they play classical music pieces and an Artificial Neural Network is trained through a cloud computing platform to build a binary classifier of segments of these signals. Our model has the best classification performance on 20 seconds EEG segments, but this performance depends on the involved musicians' expertise. Also, the brain signals of a cellist are demonstrated to be more similar to violinists' signals than to pianists' signals. In summary, this paper demonstrates that distinctive information is present in the two types of musicians' brain signals, and that this information can be detected even by an automatic model working with a basic EEG equipment.

Keywords: Artificial Neural Networks · Brain Signals · Music

1 Introduction

Music influences the development of the brain from childhood to adulthood [11]. The pattern of brain architecture, brain's plasticity, and behaviour development are affected by early music learning, and music-specific neural networks have been also hypothesised [43]. Further, structural differences have been highlighted between the brains of adult musicians and non-musicians [55,24]. Nevertheless, the development and the nature of these structural differences are not clear, but generally they affect complex motor, auditory, and multi-modal skills

[48]. Indeed, musicians' neural activity changes depending on the played instrument because playing music with different instruments usually involves different sensory-motor activities, different components of the nervous system, and hierarchically organized gross and fine movements [58]. Moreover, during a musical performance the sound is also processed by the musician's auditory circuitry, and the brain adjusts the movements based on the processed information. Also, the brain visually processes and interprets symbols if the musician is reading music [17].

These aspects can be studied by processing electrical brain activity, especially through computational models. To this aim, biosensors can be used to record brain signals that allow direct communication between neural activity and an external device [57]. The human brain contains billions of inter-connected neurons across different areas of the brain and the interactions between neurons create very small electrical discharges. Although each of these currents is very difficult to measure from outside the skull, the overall current created by thousands of neurons can be measured by external detectors and reported as electroencephalographic (EEG) signals [40]. Emotional states, thoughts, and music-related brain activity are somehow related to the signals produced by different concurrent neuronal aggregations from several areas of the brain. Using arrays of sensors on the skull, the signals of these aggregative regions can be recorded. Processing these signals through computational models helps finding patterns correlated to the thoughts, the actions, and the emotional states produced by a certain situation [50].

EEG signals have been used in research on human cognitive and sensory-motor functions [26,23], and applications to music have recently focussed on music perception and composition [22,34]. For example, music has been deduced from brain signals in neurotherapy [54], stress control [52], brain activity monitoring [4], and music generation [45]. Several studies have modelled the correlation between music and brain waves patterns to understand brain changes due to long-term music training using neurophysiological analytical frameworks [41,39,51]. The drawbacks of these approaches are that (i) they require complex and expensive equipment, (ii) aim at explicitly modelling very complex and unknown phenomena, and (iii) typically their answers are generic. For example, they can distinguish a musician from a non-musician but they cannot identify the type of musician.

In this paper, EEG signals and Artificial Neural Networks (ANNs) are used to automatically distinguish between piano and violin players based on their brain signals recorded while playing different classical music pieces. Results are presented based on a 40 minutes collection of recordings, and show that a high-performance automatic classifier can be built even using one biosensor placed at the frontal-pole position of the cerebral cortex (Fp1 in the International 10-20 electroencephalogram system [28]). Cloud computing is used to identify the highest accuracy ANN among a huge set of possible parametrisations. Overall, the aim of this paper is to demonstrate that it is possible to automatically detect the presence of similarities in the brain signals of professional musicians without using either complex equipment or neurophysiological analytical models.

Expert musicians who learned music in childhood (5-8 years old) were involved in the experiment, in order to include factors related to early modifications of the brain besides the played instrument. Also, a good (non-expert) violin player who started playing at adult age (18 years old) and a basic piano player were involved to test the model's performance when basic expertise is introduced in the training set. Finally, an expert cello player was introduced to test if his brain signals were better classified as belonging to a violinist or a pianist.

2 Equipment and Method

2.1 EEG device

Electroencephalography (EEG) has applications in several domains, including health, education, and entertainment [9,27]. Although complex EEG systems may cost thousands of dollars, cheaper solutions exist that use biosensors collecting electrical signals from the surface of the scalp that originate from sources in the cerebral cortex. These systems can be quite accurate, portable, and may come with embedded noise filtering and signal processing functions [25,2].

For the experiment presented in this paper, the NeuroSky EEG biosensor embedded in the NeuroSky MindWave toolkit was used. This toolkit is a wearable headphone-like tool that uses one dry NeuroSky biosensor to be placed at the frontal-pole (Fp1) position of the cerebral cortex. This biosensor digitizes and amplifies raw analog brain signals, with a 512 Hz sampling frequency, and produces a one-dimensional signal. The NeuroSky product has been used as a development platform in other scientific experiments as well as in professional and entertainment products due to its fair precision and low cost [37,36]. The biosensor embedded in the NeuroSky products has been evaluated to be at 96% as accurate as state-of-the art EEG sensors [32,56,38].

The NeuroSky MindWave toolkit includes a built-in noise reduction filter and a signal processing module that calculates the power spectrum of the signal every 1s. The signal spectrum was band-pass filtered (between 0.5Hz and 100Hz) and classified according to common subdivision ranges of brain signals frequency bands [19]: Gamma (40-100 Hz), Beta (12-40 Hz), Alpha (8-12 Hz), Theta (4-8 Hz), and Delta (0.5-4 Hz) waves. Usually, these frequency bands are correlated with different brain states, for example Beta waves are correlated with logical-rational processing, whereas Alpha waves are associated with intuitive processes involving internal focus of attention and with top-down sensory inhibition [21]. The power spectrum of these five bands was used as numeric vector of features in our model.

One advantage of the NeuroSky MindWave toolkit is that it is sufficiently lightweight and portable to not obstruct musicians' movements. However, one problem in our recording sessions was that the biosensor was subject to shifts and disconnections. Thus, the collected signals included noise and gaps that our model had to manage. Generally, motion artefacts are a common source of noise when using dry sensors, although most of the artefact energy is concentrated in the frequencies under 5Hz [42]. These artefacts can be reduced by using a high-pass filter (over 0.5Hz) and a filter based on contact impedance variations [6]. In our experiment, the band-pass and the built-in noise reduction filters were used for this purpose.

One criticism in using the NeuroSky toolkit is that it uses one channel only at the Fp1 position, whose activity is correlated also to other movements (e.g. eyes' ones) and only indirectly to music [33,7]. However, one of the aims of this paper is to demonstrate that a machine learning approach can manage a musicians' classification task even using this equipment, because it can recognize the indirect effects of playing different instruments on the EEG signals in Fp1.

2.2 Classification Model

An Artificial Neural Network (ANN) can be used to build an automatic classifier that associates an input vector to one category among several [8]. In particular, a multi-layer Feed-Forward ANN was the best suited model for the dichotomic classification problem managed in this paper, i.e. classifying a segment of brain signal as belonging either to a violinist or a pianist (Section 3). Indeed, Feed-Forward ANNs are suited for classification tasks where a numeric vector represents a mono-dimensional time series spectrum like it was a picture, and have proven to gain comparable or higher performance than other techniques (e.g. Support Vector Machines and Naive Bayes classifiers) in several domains [16,18]. Further, our purpose was to assess the possibility to use brain signals for musicians classification more than reaching the highest possible classification performance, thus deep-learning convolution steps were not necessary [49].

Although ANNs are powerful models, the main disadvantage of using them is that it is not possible to reconstruct the analytical form of the simulated function. In fact, despite the model can recognize that similarities exist in vectors belonging to the same class, the related patterns remain unknown. Nevertheless, learning quality measurements can reveal if the model has been able to detect the presence of distinctive information in the training set [5].

2.3 Cloud Computing Platform

Our method required testing a large number of ANNs in order to find the length of the EEG signal portion and the best topology that optimised the classification. These tests were performed using a cloud computing platform that trained alternative ANNs concurrently and allowed exploring a large space of parameters in a reasonable amount of time. In particular, an open-source computational system was used (DataMiner [14,15]) that is part of a distributed e-Infrastructure for Open Science (D4Science [10]).

The ANN implementation used for this paper, is open-source and part of the DataMiner framework and is published as a free to use Web service [13,12] under the Web Processing Service standard (WPS [1]). WPS standardises the representation of the input and output and makes the service usable by a number of clients and by external software. DataMiner saves the history of all trained and tested models using a standard and exportable format [30]. Every executed process can be re-executed and parametrised multiple times by other users, thanks to collaborative experimentation spaces [35]. In this view, this platform allowed making the presented experiment compliant with Open Science directives of repeatability, reproducibility and re-usability of data and processes.

DataMiner is made up of 15 machines with Ubuntu 16.04.4 LTS x86 64 operating system, 16 virtual cores, 32 GB of RAM and 100 GB of disk space. As for our experiment, each machine concurrently trained and tested different ANN topologies.

3 Experiment and Results

3.1 Experimental Setup and Model Training

Using the technology presented in the previous section, an automatic classifier of nine male musicians was built (schematised in Figure 2), which distinguished pianists from violinists based on the power spectra of their brain signals. The characteristics of these players are reported in Table 1 and a visual comparison of brain signals is displayed in Figure 1. The musicians were all volunteers, and all expert musicians started their music training during childhood.

Table 1. Characteristics of the musicians involved in the presented experiment.

ID	Instrument	Age	Begin Age	Expertise
Pianist 1	Piano	16	7	Expert
Pianist 2	Piano	19	5	Expert-Professional
Pianist 3	Piano	50	6	Expert
Violinist 1	Violin	16	6	Expert-Professional
Violinist 2	Violin	53	7	Expert
Violinist 3	Violin	19	7	Expert-Professional
Cellist	Cello	19	8	Expert-Professional
Non-expert 1	Violin	29	18	Good
Non-expert 2	Piano	30	18	Basic

Each player was asked to play two pieces without reading a score: the first was a piece the player knew well and that was not demanding (*easy-familiar* piece); the second was a more difficult piece requiring higher concentration (*challenging-unfamiliar* piece). All pieces were different from each other, because this maximised the players' comfort and allowed for better concentration on the music. The musicians played one after the other, and wore the NeuroSky MindWave toolkit while playing. The recording sessions were done in the Montecastelli Music Hall, a chamber concert hall that hosts both scientific venues and concerts [3].

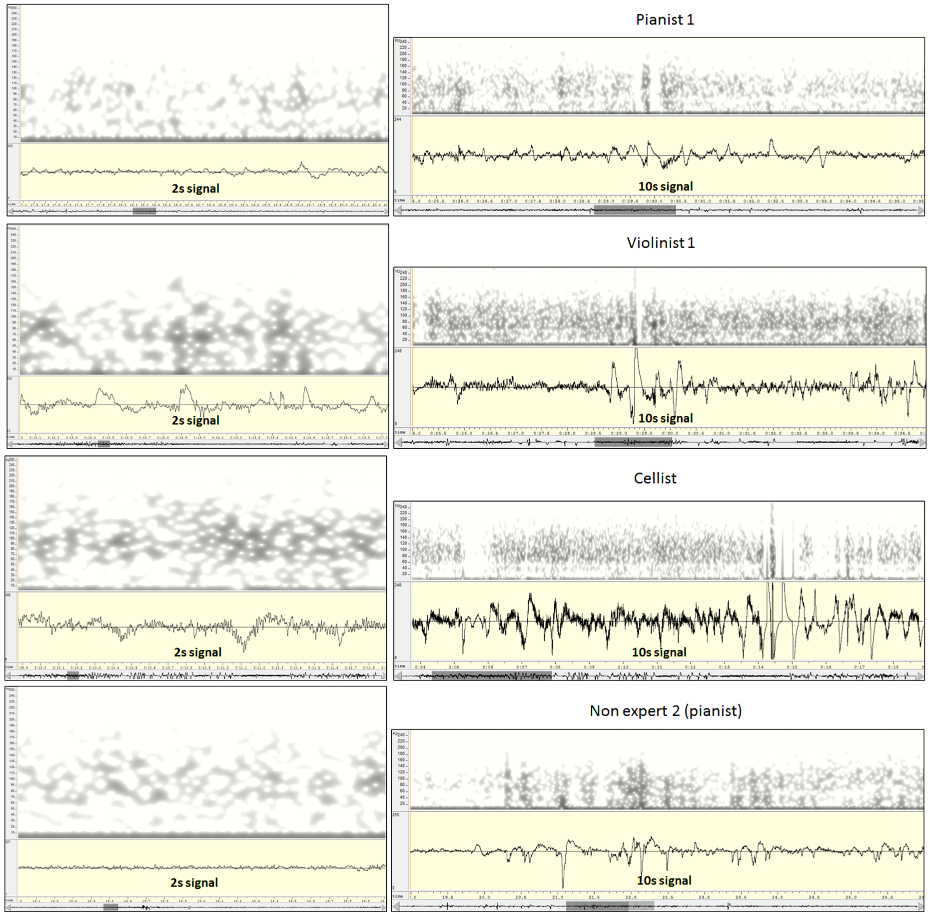

Fig. 1. Visual comparison of brain signals of the involved musicians. For each musician, signals of 2s and 10s are reported, which were selected from high-concentration moments in the execution of a piece.

The music hall was reserved for this experiment and the musicians were isolated from distractions. At the end of the recording sessions, 40 minutes of audio and brain signals had been recorded in total, with equal distribution of time per musician. The power spectra in the Gamma-Delta bands were extracted (5 features at 1s rate). Although the number of musicians was not high, a large number of brain signals and spectral features were collected.

Segments of EEG signals with several lengths were cut and treated as different signals for models training and testing. Training and test sets involved also signals belonging to the same musician, i.e. they included a potential intra-subject correlation. However, a time series cross-correlation analysis revealed an average 0.2 correlation score (with maximum 0.4 and minimum 0.008) across all training sets. This means that there was poor intra-subject correlation, possibly because the played pieces were articulated and did not contain repeated musical sequences. To further decrease this effect, completely disjoint training and test sets were also prepared though a *leave-one-out* procedure, where the tested musician's signals were not involved in the training set, i.e. for every musician, an ANN was tested for the classification of the EEG segments of the musician, after being trained on the EEG segments of the other musicians.

An Artificial Neural Network classifier was built to automatically classify a musician's signal segment as belonging to either a piano or a violin player (Figure 2). The segment length containing the maximum discriminant information was one parameter to identify, other than the ANN topology maximising the classification performance. Segment lengths between 1s and 30s were explored (which maintained the size of the training and test sets statistically significant), and the optimal ANN topology was searched between 2 and 5 layers. The ANN used a logistic sigmoid activation function in the neurons and a standard backpropagation algorithm implementation for network training [47], with 1000 maximum iterations, 0.9 learning rate, and a 0.001 threshold on the mean squared error. A total number of $\sim$700,000 combinations of segment lengths and topologies were tested, which explains the necessity of using a cloud computing platform. For each fixed-length segment, DataMiner used a *growing* strategy to search for the best (i) number of layers, (ii) number of neurons in each layer, and (iii) a dichotomic classification threshold on the output. This strategy basically consists in adding neurons and layers as far as the error with respect to the training set decreases down to a certain threshold [8].

As input to the ANN, power spectrum features vectors from the brain signal segments were used. Features associated to a segment larger than 1s were built by concatenating the 1s power spectrum vectors completely included in the segment. For example, a 20s segment was represented as the concatenation of 5 spectral features (one for each second), i.e. as a 100 features vector ($= 20 \cdot 5$). Features in all bands were used because the EEG reported instrument-specific activity in all of them, sometimes with long time span. The ANNs were trained to output 0 for pianists and 1 for violinists and a 10-fold cross-validation test (using each EEG segment as one instance) was used to assess the performance of each step of the growing process, i.e. the EEG segments were assigned to

10 clusters and one cluster was used to test the model trained with all the other clusters. For each cluster, the accuracy of the classification was calculated as $\frac{n.\ of\ test\ segments\ correctly\ classified}{overall\ n.\ of\ test\ segments}$ and an overall accuracy on all clusters was calculated as the average of the single-cluster accuracies. In order to reduce overfitting issues and dependency between the training vectors, consecutive signal segments were never assigned to the same cluster.

The schematic flow of our method for model building can be summarised as follows:

```
For each musician m ∈ [1,9]:
    Record brain signals while playing an easy-familiar piece
    Record brain signals while playing a challenging-unfamiliar piece

For each musician's brain signal:
    Prepare sets of segments containing signals from length 1s to 30s:
       {S_1}_m ··· {S_30}_m

For each union of all the sets of segments of length k seconds (with
   k ∈ [1,30]), i.e G_k = {S_k}_1 ∪ {S_k}_2 ∪ ... ∪ {S_k}_9:
    Distribute all G_k segments onto 10 groups, with the constraint
       that one group should not contain consecutive segments from one
       brain signal
    Find the ANN topology with the highest performance, using a growing
       strategy while performing a 10-fold cross-validation test using
       the previously defined 10 groups
    Use the best found ANN topology to perform a cross-validation test
       based on the nine {S_k}_m sets constituting G_k (leave-out-out
       process)

Record the ANN topology with the highest performance in the 10-fold
   cross-validation test, which thus identifies the optimal segment
   length k*
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By using this flow, the optimal segment length k^* was found to be 20s (i.e. the ANN had 120 input neurons). The best topology was made up of 2 hidden layers with 100 neurons in the first hidden layer and 20 neurons in the second, and one output neuron (Figure 2). Further, our flow reported an optimal classification threshold of 0.7 for this topology in the 10-fold cross-validation test.

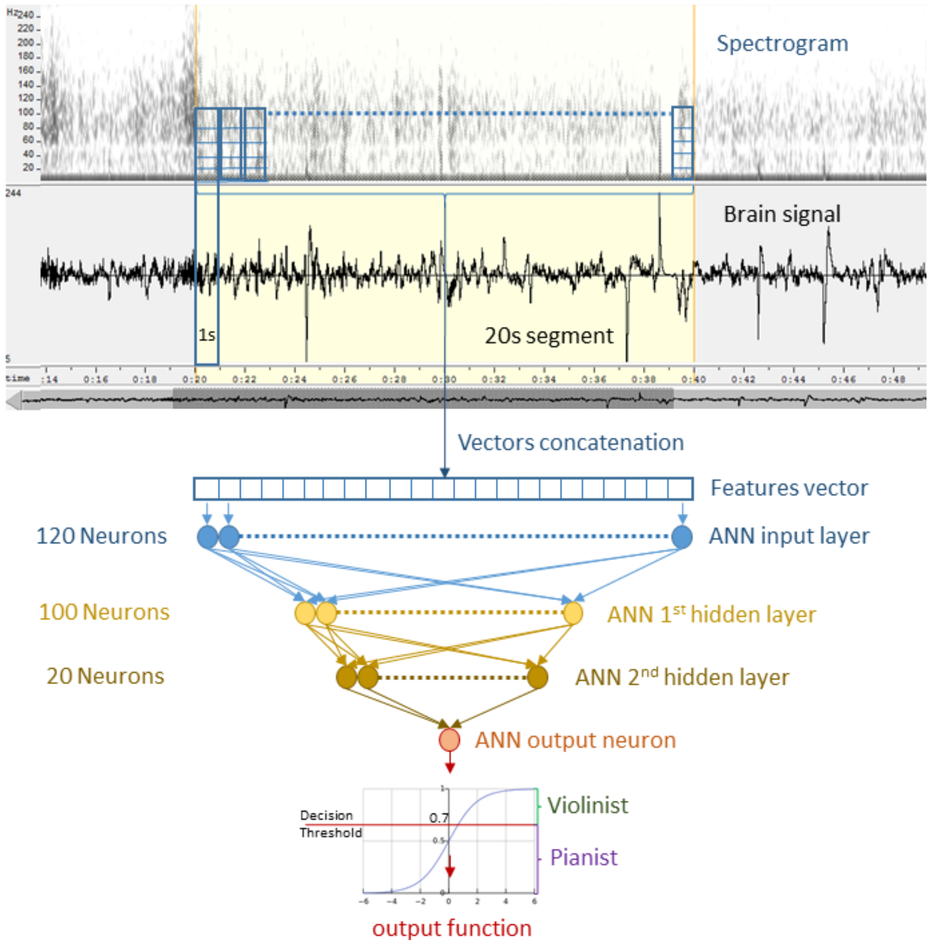

Fig. 2. Schema of our automatic classifier. The power spectrum is extracted from the spectrogram at 1s rate as a vector of numeric features; the vectors in a 20s signal segment are concatenated and used as input to a multi-layer Artificial Neural Network; the output of the model is a continuous function on which a threshold is used to classify the input vector as either belonging to a violinist or a pianist.

3.2 Performance

Table 2. Performance of our automatic classifier at the variation of the pieces, of the involved musicians, and of their expertise.

Average Accuracy	Max. Accuracy	Min. Accuracy
***Easy-familiar* pieces only - expert musicians only - no cellist**		
65%	70%	50%
***Challenging-unfamiliar* pieces only - expert musicians only - no cellist**		
65%	75%	50%
All pieces - expert musicians only - no cellist		
72.5%	87.5%	50%
All pieces - expert musicians + cellist (as violinist)		
80%	90%	70%
All pieces - expert and good musicians + cellist (as violinist)		
81.6%	**91.7%**	**75%**
All pieces - expert and good musicians + cellist (as pianist)		
59.9%	75%	50%
All pieces - expert, good, and basic musicians + cellist (as violinist)		
74.3%	85.7%	64.3%

The variation of the performance of our model was calculated at the variation of the musicians and of the pieces involved in the training process (Table 2). In particular, involving the cellist increased the performance when he was classified as a violinist in the training set (from 72.5% to 80%). On the contrary, indicating his brain signals as pianists' signals decreased the overall model's performance to 59.9%. This scenario indicates that the cellist's signals resemble more the violinists' ones. This observation may seem intuitive, but is not trivial because playing a cello involves completely different movements with respect to playing a violin, although these are both arc instruments. However, other studies have reported this same scenario from a neurophysiological perspective by observing that cellists and violinists have larger and similar cortical activation patterns in the right hemisphere, whereas pianists have larger activity in the left hemisphere [20,29].

Including a non-expert player in the model's training, improved the performance (from 80% to 81.6%) only if he had some experience. In fact, including a player with basic expertise strongly decreased the performance (down to 74.3%), i.e. the ANN was confounded by his brain signals. Overall, the model with the highest performance was the one involving both expert and good players and all pieces (81.6% with a peak of 91.7%). With these pieces and musicians, an average accuracy of 79.5% was calculated by using a *leave-one-out* approach, where all the signals of the tested musician were excluded from the training set and were used only for testing the performance. This low decrease of performance indicates that the model is poorly affected by intra-subject correlation.

The performance of our model likely depends on other factors than motion artefacts, because these mostly affect only one of the involved features (the Delta) and were partially mitigated by the used filters. Thus, our model is indeed capturing distinctive information that exists in the brain signals recorder by the Fp1 EEG sensor.

4 Conclusions

In this paper, an automatic classifier of violinists and pianists has been presented, based on features extracted from EEG signals in the Fp1 cortex position. Existence of distinctive information, probably related to common patterns in the brain signal spectra of the players, has been identified especially in 20s signal segments by a four-layer Artificial Neural Network. This model was built after testing a large parameters space through a cloud computing platform, which was able to overcome the use of a non-optimal equipment and the absence of neurophysiological *a priori* assumptions.

Our study is a preliminary investigation and enforcement of the very complex hypothesis that musicians' brain signals similarities depend on the played instrument and on musical expertise. The main drawback of our model is that it does not report explicit patterns, because it is not possible to extract an analytical form of the classification function associated to the ANN. Nevertheless, it reveals that distinctive information exists and should be further explored, e.g. with more powerful equipment or by embedding neurophysiological information in the model or by using deep-learning techniques. Also, our results suggest to investigate musicians' brain signals similarities in terms of their correlation with the way sound is produced [44]. For example, the highlighted similarity between the cellist and the violinists may be due to their constant interaction with a continuous sound, whereas pianists interact with digital-like sounds. This difference could be explored starting from the evaluation of how music reading and listening would change the performance of our classifier. Indeed, the effect of music on EEG activity has been already highlighted by other studies [53], some of which have also classified and categorized musicians based on their EEG response to music listening [31,46]. Our computational approach is suited for these further explorations especially because of its Open Science compliance, since it allows (i) repeating the experiment with a larger corpus, (ii) involving other musicians and instruments, and (iii) reusing the ANN model thanks to its publication a standardized Web service.

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Compliance with Ethical Standards

The authors declare no conflict of interest. This research has been conducted in compliance with the Helsinki Declaration for Ethical Principles for Medical Research Involving Human Subjects, under the responsibility of the authors and of the Auditorium della Compagnia Montecastelli association. Consent was provided by the participants and, in the case of minors, by their parents who were present during the experiments. Since this is not a medical research and it is not an invasive experiment, we did not ask an official ethics committee to formally approve the experiment.

Supplementary Material

A sample of the collected corpus is downloadable through the D4Science e-Infrastructure at
https://data.d4science.org/shub/E_dE9JVUw4Z1dFeWtIUG9xMnk0R09PVlNzU28rdnlvYTBEMDlnNkczNWlxdXRtNjA4YWl3b2RPZHNxdTlVN3BxZg==

The services used for this research are freely usable after registration on the D4Science cloud computing platform at the following links:

https://services.d4science.org/group/scalabledatamining/data-miner?OperatorId=org.gcube.dataanalysis.wps.statisticalmanager.synchserver.mappedclasses.transducerers.FEED_FORWARD_NEURAL_NETWORK_REGRESSOR

https://services.d4science.org/group/scalabledatamining/data-miner?OperatorId=org.gcube.dataanalysis.wps.statisticalmanager.synchserver.mappedclasses.transducerers.FEED_FORWARD_NEURAL_NETWORK_TRAINER

The source code is available at http://svn.research-infrastructures.eu/public/d4science/gcube/trunk/data-analysis/EcologicalEngine/src/main/java/org/gcube/dataanalysis/ecoengine/models/

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