**Is 3 Seconds Enough? A Methodology for Music Genre Classification Based on Spectrogram Analysis**

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**ABSTRACT**

In this paper, we introduce a methodology for the classification of audio data that leverages the many classification tools that currently exist for non-audio data. The classification of images and text data is well-established in the field of machine learning and many libraries and frameworks have been developed for such analysis. Audio classification, on the other hand, has lagged behind its atemporal counterparts, largely due to inherent difficulties in working with audio data. Our methodology allows researchers to apply an image classification tool to audio data by analyzing spectrograms, opening up many avenues in audio analysis and, we hope, accelerating progress in the development of tools for audio classification and analysis.

**Keywords**

Keywords are your own designated keywords separated by semicolons (“;”).

# INTRODUCTION

Music in today’s world is ubiquitous. It can remind us of specific products and brands, thoughts and ideas, and past and imagined events, and can affect our mood significantly. When we hear a piece of music, we almost unconsciously categorize it in our minds – a pop song on the radio, electronic dance music in a nightclub, classical masterpieces at the symphony – and most of the time, we accomplish this labeling within the first 30 seconds of hearing the music. Therefore, there must be certain recognizable characteristics of different musical styles or genres themselves that allow us to classify what we hear so quickly, rather than through analysis of the complete musical work after hearing it in its entirety.

Machine learning offers a way of giving us some insight into the problem. If a model can predict the genre of a piece of music with only data from the first 30 seconds, it will have achieved the same feat – and in an automatable way. The automation of music genre classification has become a busy area of research in recent years due to the demands of the music entertainment industry. To expand, a music service/business must amass a growing collection of musical works, and the manual annotation and organization of these ever larger and larger music collections has quickly become a wholly unscalable process. The search for efficient ways of automating the classification of music by genre (and many other labels) is thus quickly becoming an essential task in the music industry.

Unfortunately, in the field of machine learning, audio analysis has reached what some researchers call the “bottleneck of music genre classification” [Li, *et. al.*]. This is partially due to the lack of established conventions surrounding the format of audio data. Currently available audio datasets sometimes consist of raw audio files in varying formats, but more frequently researchers have chosen to reduce the size of the problem by training their models on a data set of derived features or annotations of the raw data rather than the raw audio itself. This has achieved some success – for example, Tzanetakis, *et. al.*, was able to reach a ~60% accuracy rate using standard classifiers and feature sets based on timbre (musical texture), rhythm, and pitch – but many of these feature sets are determined based on previous research in speech recognition, which does not necessarily translate well to the much more complex feature space of musical data. Primarily, these feature sets fail to capture *musical intent*, that is, the inherent patterns underlying the composition of the music, rather than qualities of a particular recording or sample. Musical intent is a key characteristic of music that is not found in speech (the closest example might be spoken word performances), and which is not capturable by investigating pitch, rhythm, or timbre alone.

While much of the research on music genre classification has gone in the direction of feature set analysis, some intrepid researchers have set forth to do battle with raw audio data. Li, *et. al.*, showed promising results when applying CNN methodology directly to audio data (84% accuracy) using a fascinating modification to the image-based CNN in which they took windows of adjacent, overlapping audio clips along the duration of the full piece (paralleling the windows and stride parameters in image analysis). However, they only achieved 30% accuracy on their test dataset, which they acknowledge is due to overfitting. They additionally note that their method is highly sensitive to variations in musical timbre and other features, and performs less well when trained on data containing more than 4 labels and/or containing genres that might be considered as being similar to each other.

Thus a major problem remains of reliably classifying large music datasets that contain several labels of varying degrees of similarity. Due to the size of the datasets, it is not possible for manual classification to annotate each track.

# METHODS

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# RESULTS

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# CONCLUSIONS

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# SUMMARY & FUTURE WORK

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# ACKNOWLEDGMENTS

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