AANN and KNN based Music Classification using Chromagram

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Abstract: *Automatic music genre classification is very useful in music indexing. Chromagram is one of the feature extraction method uses in classification of musical genre that is based harmonic information in music structure analysis of music signals. Searching and organizing are the main characteristics of the music genre classification system these days. This paper describes a new technique that uses Autoassociative Neural Network (AANN) and K-Nearest Neighbour (KNN) to classify music. The proposed feature extraction and classification models results in better accuracy in music genre classification.*

Keywords: **Music, Feature Extraction, Chromagram, Autoassociative Neural Network (AANN), K-Nearest Neighbour (KNN)**

1. INTRODUCTION

Musical genres have no strict definitions and boundaries as they arise through a complex interaction between the public, promoting, chronicled, and social elements. This perception has driven a few specialists to recommend the meaning of another type grouping plan only for the motivations behind music data recovery [1]. Also, the headway in computerized signal preparing and information mining methods has prompted escalated concentrate on music signal investigation like, content-based music recovery, music kind order, two part harmony examination, Musical record, Musical Information retrieval and musical instrument detection and classification.

The methods for programmed sort characterization would be an important expansion to the advancement of sound data recovery frameworks for music. Advanced music databases are continuously achieving reputation in relations to specialized archives and private sound collections. Due to improvements in internet services and network bandwidth there is also an increase in number of people involving with the audio libraries. Music has additionally been isolated into Genres and sub kinds on the premise on music as well as on the verses too [2]. This makes order more enthusiastically. To cause things more to confound the meaning of music type may have very much changed over the long run [3]. For instance, rock songs that were made fifty years ago are different from the rock songs we have today.

2. CHROMAGRAM

Chroma feature representation is an effective and powerful method to describe harmonic information in music structure analysis [4]. Pitch class is a collection of pitches that share the same chroma. Two dimensions characterize music, tone height and chroma [5]. The dimension of tone height is partitioned into the musical octaves. The range of chroma is usually divided into 12 pitch classes, where each pitch class corresponds to one note of the twelve tone equal temperament. The spectral energy of each of the 12 pitch classes is represented by chromogram. It depends on a logarithmized brief timeframe Fourier range. The chromagram speaks to an octave-invariant (packed) spectrogram that considers properties of melodic discernment [6]. Figure 1. shows the Chromagram Computation.

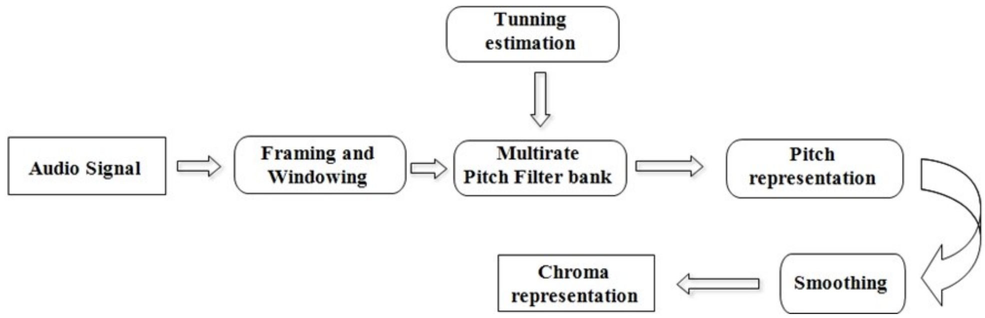

Figure 1. The Chromagram Computation.

3. AUTOASSOCIATIVE NEURAL NETWORK (AANN)

Autoassociative Neural Network (AANN) model comprises of five layer network which catches the dissemination of the component vector as appeared in Figure 2. The information layer in the organization has less number of units than the second and the fourth layers. The first and the fifth layers have more number of units than the third layer [7]. The quantity of preparing units in the subsequent layer can be either straight or non-direct. Yet, the handling units in the first and third layer are non-direct. Back proliferation calculation is utilized to prepare the organization [8].

The shape of the hyper surface is determined by projecting the cluster of feature vectors in the input space onto the lower dimensional space simultaneously, as the error between the actual and the desired output gets minimized.

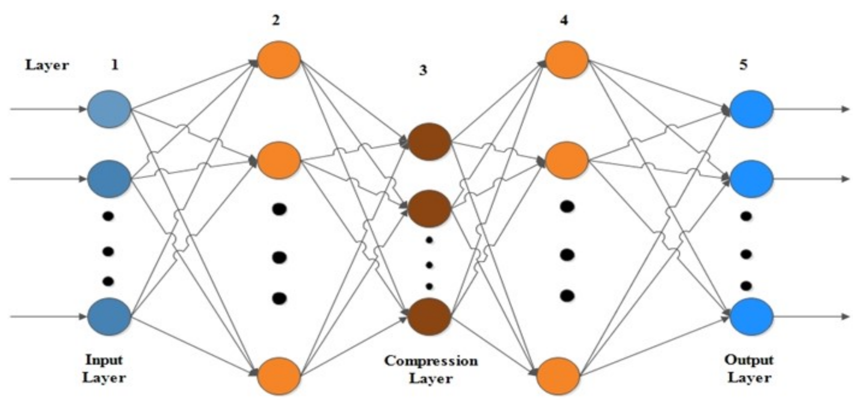

Figure 2. The Five Layer AANN Model.

During testing the acoustic features extracted are given to the trained model of AANN and the average error is obtained. The structure of the AANN model used in our study is 12L 24N 4N 24N 12L for MFCC, for capturing the distribution of the acoustic features.

4. K-Nearest Neighbour (KNN)

KNN is a supervised learning technique where a new instance is classified based on the closest training samples present in the feature space [9]. It does not use any model to fit, and is only based on memory. At the point when a test information is entered, it is alloted to the class that is generally basic among its k closest neighbors. KNN classifier is nonparametric strategy utilized for order. It needn't bother with any earlier information about, the structure of the information in preparing set. On the off chance that the new preparing design is added to existing preparing set. Any ties can be broken indiscriminately.

The K-NN algorithm uses the neighbourhood classification as the prediction value of the new query instance. The KNN algorithm is sensitive to the local structure of the data. The K-Nearest Neighbour is one of those algorithms that are very simple to understand but works incredibly well in practice [10].

5. EXPERIMENTAL RESULTS

5.1 The database

The music data is collected from music channels using a TV tuner card. A total dataset of 100 different songs is recorded, which is sampled at 22 kHz and encoded by 16-bit. In order to make training results statistically significant, training data should be sufficient and cover various genres of music.

5.2 Acoustic feature extraction

In this work fixed length frames with duration of 20 ms and 50 percentages overlap (i.e., 10 ms) are used. The objective of overlapping neighbouring frames is to consider the harmonic information characteristic of audio content. An input wav file is given to the feature extraction techniques. Chromagram 12 dimensional feature values will be calculated for the given wav file. The above process is continued for 100 number of wav files.

5.3 Classification

The training process analyzes music training data to find an optimal way to classify music frames into their respective classes. The feature vectors are given as input and compared with the output to calculate the error. The performance of music classification is studied by varying the number of units in the compression layer as shown in Figure 3.

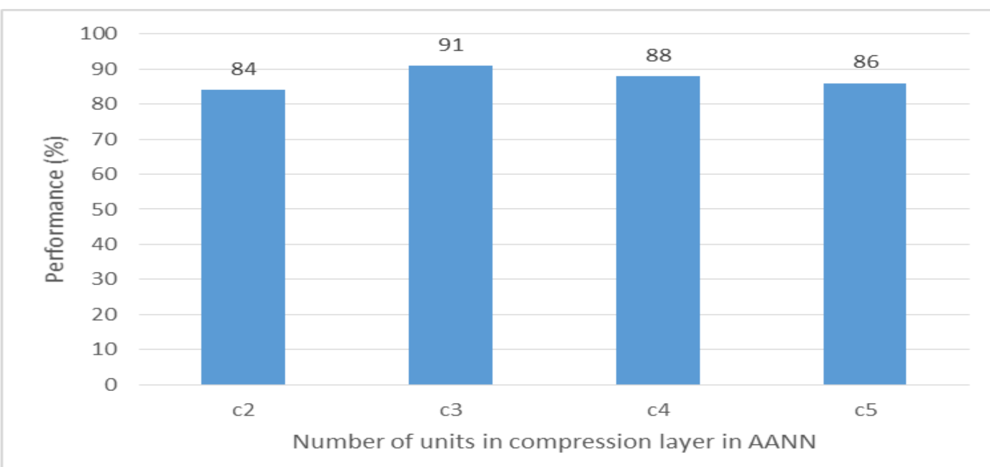

Figure 3. Performance of Music Classification in Terms of Number of Units in the compression Layer

The performance of speech recognition in terms of number of units in the expansion layer is shown in Figure 4. The network structures 12L 24N 4N 24N 12L gives a good performance and this structure is obtained after some trial and error.

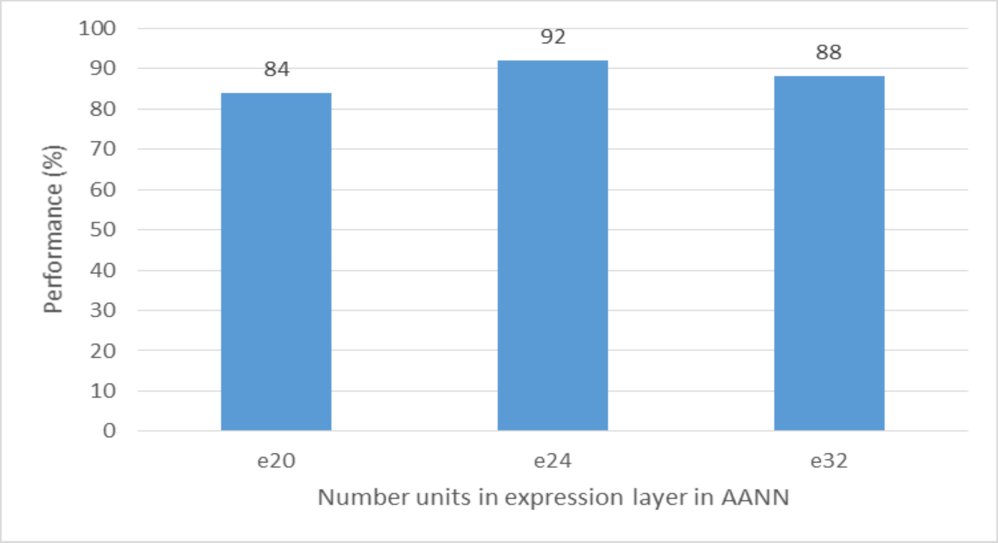

Figure 4. Performance of Speech Recognition in Terms of Number of Units in the Expansion Layer.

Experiments were conducted to test the performance of the system using KNN. Figure 5. shows the performance of music classification using KNN for different duration respectively.

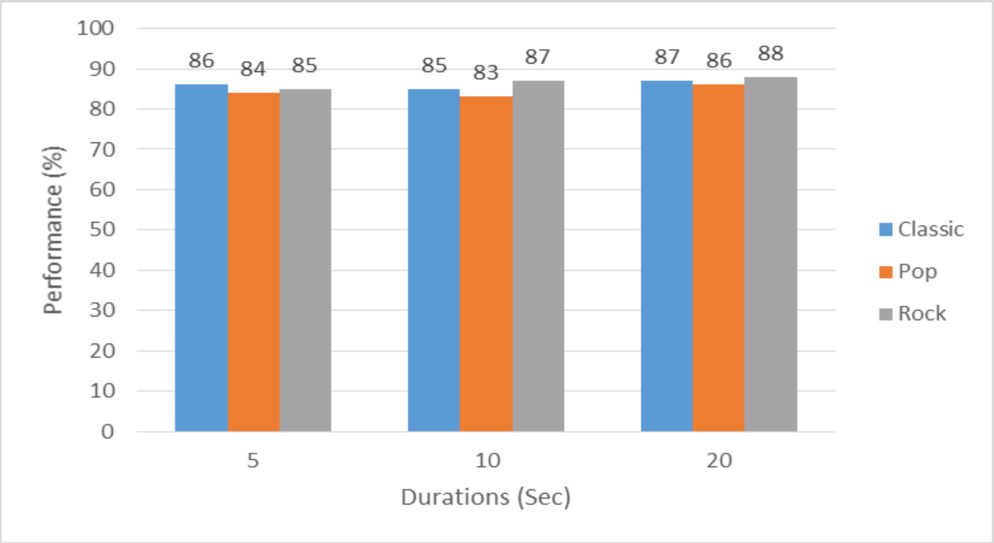

Figure 5. Performance of music classification for different duration of music clips using KNN

6. CONCLUSION

In this paper, we have proposed an automatic music genre classification system using AANN and KNN. Chromagram is calculated as features to characterize music content. It shows that the proposed method can achieve better classification accuracy than other approaches. Experimental results show that the proposed audio AANN method has good performance in musical genre classification scheme is very effective and the accuracy rate is 92% compared with KNN.

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