ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

Vol 10, Issue 10, October 2023

Kathak Dancing Accompanying Audios Identification and Grouping

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Abstract— *Using an innovative methodology, the audio recordings utilized in the Indian Classical Dance (ICD) version of Kathak have been identified and categorized. This footwork for the Kathak Ladi was created from an audio dataset. This audio dataset was examined for classification purposes, and feature extraction was performed. To identify the beginning of the beats, beat detection is used. Beat tracking is then applied to the audio signals. Then, based on rhythms and mfccs, Ladi audios are identified and categorized into seven classes—L2, L3, L4, L5, L6, L7, and L8—using a machine learning-based approach. The Convolution Neural Network (CNN), which is now in its experimental stage, can produce results that are more accurate. Our study recommends more subclassification of each class based on the underlying variations in the quantity of bols and taals in the related audios of Kathak dance.*
1)

Index Terms— *kathak, ladi audios, Indian classical dance, beat.*

I. INTRODUCTION

Here, a technique for automatically classifying and identifying the auxiliary audio files used for Kathak Dance footwork (Ladi) has been developed. This was achieved using the Ladi dataset. The mono audio signals that were captured while a Kathak dance performance was taking place are included in this Ladi audio dataset. There are at least one millisecond between each audio train. Each audio train is then subjected to a main pre-processing procedure in order to remove the unwanted noise. Beat detection is then conducted using this repeated dataset. The accuracy of the onset determination approach is the foundation of our beat detection system. Using measurements and mfccs, the K Nearest Neighbor's method is also utilized to locate and classify Ladi audios into 7 categories, namely L2, L3, L4, L5, L6, L7, and L8.

II. RELATED WORK

Indranil Sarkar, Saptami Ghosh, Anirban Saha, and Partha Pratim Das, 2021.

A new algorithm has been employed in their study, To recognize and classify the additional audios used in the Indian classical dance (ICD) variation of Kathak. The result was obtained using an audio dataset of Kathak Ladi footwork. On this audio dataset, feature extraction and classification have both been performed. The beat onsets are located via beat detection. The audio streams are then subjected to beat tracking. Additionally, based on measurements and mfccs, Ladi audios are connected and divided into seven classes using a machine learning approach: L2, L3, L4, L5, L6, L7, and L8.

Dr. Suvarna Nandyal, 2020 [2], Bhavana.R The Indian Classical Dance Video Database (ICD Database), a shared database featuring original dance videos set to popular music genres, is detailed in their study. There are 100 dancing videos in it, each featuring a different action. While considerable effort has gone into compiling vast video databases of Kathak and Kuchipudi dance videos from India that feature various facial, hand, and leg movements. Only one female dancer wearing a costume is featured in the video. Currently available activity identification databases have ten odd activity classifications that have been amassed on ideal circumstances.

Laura Garcia-Hernandez, Vedika Gupta, Nikita Jain, Vibhuti Bansal, Lorenzo Salas-Morera, and Deepali Virmani[3] are among the authors. Indian classical dance (ICD) classification is a fascinating topic because of its complex body posture. It acts as a testing ground for several computer vision and deep learning techniques. The transition from traditional to online platforms has necessitated automated teaching solutions due to changes in learning processes. A rich cultural and intangible legacy must be conserved and enhanced at all costs, and ICD is an essential part of that heritage. In their study, they attempted a thorough taxonomy of dance genres into eight groups. Using ResNet50, they developed a deep convolutional neural network (DCNN) model for classification that performs better than various cutting-edge methods. The pre-processed samples are then put through a shortened DCNN based on ResNet50. The accuracy score for the suggested model is 0.911 points.

The Indian classical dance style of Bharatanatyam, according to Mallick, Tanwi, and Partha Pratim Das[4], is a representation of the country's storied past. To maintain cultural history, such dance forms need to be examined and acknowledged. A Bharatanatyam dancer performs in time to Sollukattu, an organized kind of rhythmic music that fuses vocalized utterances (bols) with instrumental rhythms to create a rhythmic music framework. As a result, in order to analyze Bharatanatyam using computers, a structural analysis of Sollukattus is required. To identify bols in this study, voice processing techniques are used. The preset Sollukattus structures and the newly discovered bols are used to identify the Sollukattu. We use two techniques to estimate the tempo period. Finally, they use beat tracking to fully annotate the audio signal. For this, they also make use of the beat data gleaned from the onset envelope of a Sollukattu signal. Their accuracy rates for bol recognition are 85%, Sollukattu recognition is 95%, tempo period estimation is 96%, and beat marking is around 90%.

III. PROPOSED SYSTEM

On beat tracking and beat recognition, the suggested strategy is grounded. Each audio data file's spectral-grounded novelty function was determined. Also, peak selecting and peak counting were performed using the spectral-grounded novelty function. Occasionally the original energy rise isn't followed by peak. The original beginning of the musical note has been determined by going backward from each peak to the former original optimum — in this case, the original minimum. After that, we perform onset discovery and tempo estimation. The peak count and MFCCs are finally used as features by our K-Nearest Neighbors approach to categorize and identify the auxiliary audios in Kathak dance. Since spoken words and bottom striking sounds are included in the audio data, we computed MFCCs from each sampled batch of audio data. The mean and covariance for the first 20 MFCCs have been calculated. The point vector was created by also combining the MFCC's mean and covariance matrix. The distance function metric used by KNN to determine the distance between two point vectors is why it was selected. This separation from point vectors is used to calculate its closest neighbors. In the beginning, we separated the task into training and testing. On the training set, we also performed K-fold cross confirmation with K set to 10. The system we propose allows for further subclassification of each class because of the initial shift in the quantity of bols and taals in the related audios of Kathak dance. The convolution neural network (CNN), which is still in the experimental stage, can produce more eeetrustworthy results.

IV. METHODOLOGY

The **dataset** used in the proposed study contains a total of 200 photographs that were gathered from publically accessible sources and by taking screenshots of YouTube movies. It is made sure that the eight classes receive an equal distribution of the data. Despite being tiny, the dataset presents difficulties for classification tasks because the backdrops and the quantity of dancers in the photographs vary.

Feature Extraction: Features such as spectral centroid, spectral round-off, spectral bandwidth, zero crossing rate, Mel-frequency Cepstral coefficients (MFCCs), value feature, etc. have all been extracted using a variety of popular techniques. The Kathak dance accompaniment audios will be categorized and identified using some of these traits.

Beat detection is the method of identifying and locating the beat in a musical composition utilizing computer hardware or computer software. There are numerous different beat detection methods, yet accuracy and speed are always trade-offs. It employs a variety of statistical model techniques, including those that apply comb filters, are based on the energy of sound, or employ other techniques. They may be slow and limited to brief music snippets or lengths, or they may be quick enough to operate in real time. fb = range2beat(r , slope) translates a linear FMCW signal that has been dechirped into the corresponding beat frequency. slope is the FMCW sweep's gradient.

fb = range2beat(r , slope , c) describes the speed of the signal propagation.

Novelty Function Sudden changes in the audio stream that signal the beginning of transient regions must be located in order to carry out note onset detection. The majority of the time, an increase in the signal's amplitude envelope signals the presence of an onset candidate. However, there are situations when such is not the case because, for instance, when a guitar is being played with slurred notes, the note onset may shift from one specific pitch to another without altering the amplitude. Novelty functions show local variations in signal characteristics like spectral richness or energy. We employ a spectral-based novelty function in this case because the sole percussion instrument we used to create the beat was the tabla.

Spectral Novelty Function Following these methods, we generated a novelty function based on spectral data. The log amplitude spectrogram should be computed and calculated. Calculate the energy-based novelty function for each frequency bin denoted by 'k' by looking at (i) the first-order difference and (ii) half-wave rectification. 3. Sum each frequency bin, indicated by the letter "k." Spectral flux and the Onset strength function were used to compute the novelty-based function.

Peak picking is the technique of recognizing peaks in an audio stream, as the name implies. Consider the following scenario: we want to locate and identify peaks in a novelty function while doing onset detection. The start of the music would correspond to these peaks.

The first detection The automatic recognition and identification of musical events in an audio stream is one of the most difficult and critical issues that a musical information retrieval system encounters. In this example, a transitory component of an audio signal is identified, detected, and targeted in audio recordings of Kathak dance.

Detection of Onset Algorithm The actions are:

1. Construct a novel function using spectral data.
2. Look for the peaks in the novelty function based on spectral data.

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ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

Vol 10, Issue 10, October 2023

3. The previous local optimum, in this case the local minimum, is reached by going backwards from each peak.

Onset Based Segmentation: By use of the Onset, section For backtracking, we used onset-based segmentation. To find the peaks in a novelty function based on a spectral representation, we applied the onset detection method previously discussed. The initial energy rise may not always be followed by these peaks, though. To comprehend the origin of a musical note, one must work backwards from each peak to a previous local optimum (minimum). It is frequently important to go back and discover the segmentation points so that the onset follows the segment's start promptly.Bugs were avoided by working backward from the detected onsets.

Beat Tracking: It entails obtaining a musical auditory input and separating it into numerous beat instants, which may correlate to when a listener taps his foot, for example.

Timing Evaluation The tempo of a musical beat specifies how swiftly it is played. It conveys the musical piece's tempo. The reciprocal of the beat period determines it. It is measured in BPM (beats per minute).

The tempo of a single piece might vary greatly. The tempogram is used as a feature matrix to display the frequency of any certain tempi at each time sequence.

The novelty function's magnitude spectrogram can be compared to a Fourier tempograph. Wherever there is a strong candidate for the beat time and a high auto-correlation, the auto-correlation tempogram is applied. When analyzing a signal, the auto-correlation helps to identify repeated patterns. For instance, the automatic correlation can reveal information on the fundamental frequency of the signal at short latencies. A musical signal with significant lags may be described in depth using the auto-correlation. Using the autocorrelation concept, the tempo at each section of the novelty function has been computed. One such example is the (spectral) novelty function's short-time autocorrelation.

Rhythm Detection Any regular movement, sound, or symmetry that is characterized by a precisely timed succession of powerful and delicate elements occurring under dissimilar or opposing circumstances is said to have rhythm. With periodicities ranging from a few microseconds on the low side to many seconds on the high side, a variety of naturally occurring cycles can be described by this broad definition of a regular pattern or recurrence in time.

V. SYSTEM ARCHITECTURE

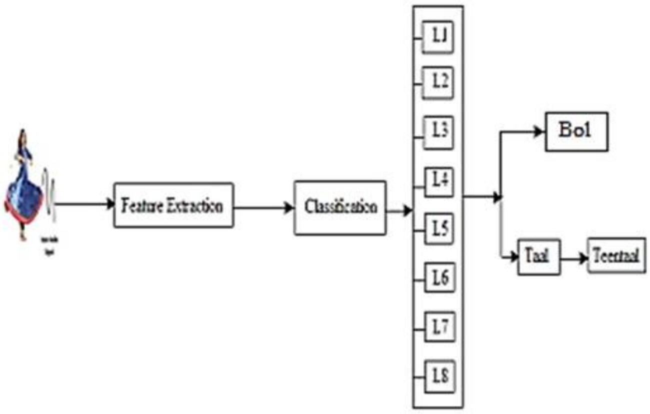


Figure 1: System Architecture

VI. RESULTS

When choosing the Ladi audio of the kathak dance in the current system. The system recognizes the ladi type and its bol.

Figure 3: Menu

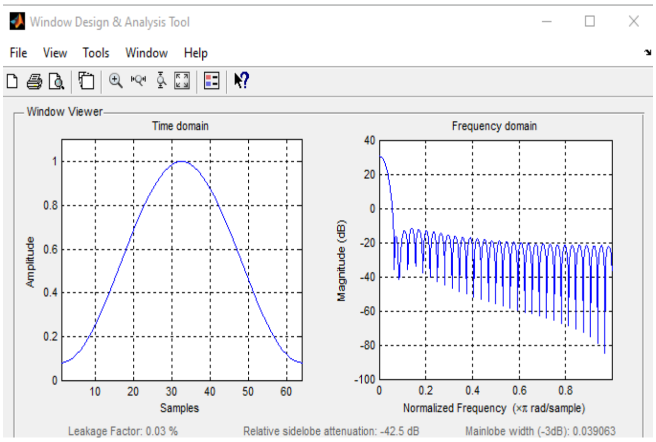


Figure 4: Preprocessing

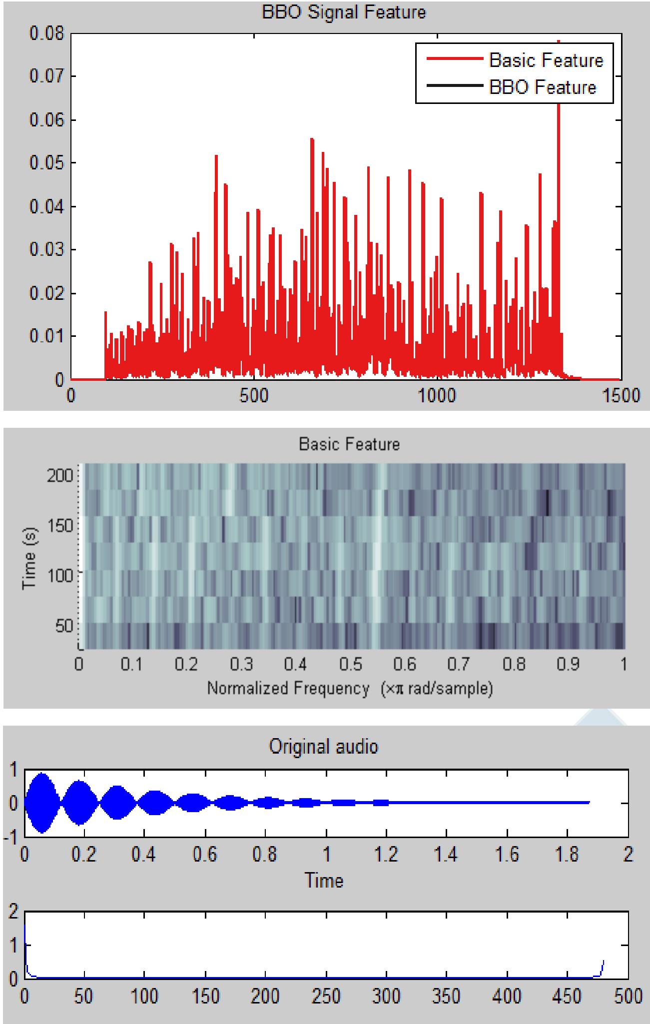


Figure 5: Feature Extraction

To distinguish the qualities of the audio signal. By using the mean and standard deviation, standardize the features.

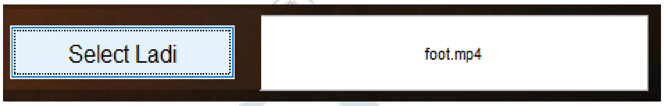
features = extract(aFE,audioIn);

features = (features - mean(features,1))./std(features,[],1);

Figure 6: Ladi Detection

In this figure it displays the detected ladi with Bol and step image based on foot step audio file.

Optimization To extract audio signal properties based on biogeography, use the BBO evolutionary technique. The system uses the "Energy Entropy" feature from the spatial domain and the "Spectral Centroid" feature from the frequency domain as inputs to construct the "Short Time Energy" feature from the time domain. The BBO method returns an evolutionary signal feature based on the nature of the final feature vector. Due to its great speed for numerous signal feature extraction tasks, BBO is appropriate for this use.



Ladi Foot Image:

Ladi : TeenTaal

Bol:Takit Dhikit Ghin

Figure 7: Ladi Detection

This module selects the ladi sound file and recognizes the ladi, and bol and displays the corresponding foot image

VII. CONCLUSION

Here, we present a powerful technique for accurately classifying and identifying Kathak dance audios, which is usually quite difficult to do. This is due to the complexity of the various taals, which necessitate correct categorization into 10 classes, including L2, L3, L4, L5, L6, L7, and L8. We do this using the K-Nearest Neighbors supervised learning method and the Ladi dataset.

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ISSN (Online) 2394-2320

International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

Vol 10, Issue 10, October 2023

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