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Tune detect: Musical Mastermind for Musician

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Abstract: This paper presents a system that embodies the essence of sonic detective work. Like a musician, it first extracts certain features from the sound, identifies individual instruments, checks the notes or sounds they play, and then synchronizes the notes with the music. The end result is like a beautiful piece of music that takes the messy sounds and organizes them into something pleasant. It could be a new music mix or music score. People can listen to it and have a great time enjoying the music. This project is designed for listening to polyphonic music played by a variety of instruments together, and it does a lot of things well. For the purpose to advance the musical field we are developing the system that is capable of identifying instruments from polyphonic instrument sound from the feature extracted using Kernel PCA (Probabilistic Component Analysis) ,the classification is performed using SVM (Support Vector Machine).This allows system to efficiently identify the instruments. Then the pitch is detected from the instruments identified using Cepstrum method which is capable of detecting pitches from detected instruments. The detected pitches are then synchronized to provide a synthesized audio file as output using HMM (Hidden Markov Model) and DTW (Dynamic Time Wrapping).

I. INTRODUCTION

In the fascinating world of music and sound exploration, there is a fascinating project that plays the role of musical alchemist. The project explores the world of polyphonic sound, where various instruments work together to create a symphony of different tones and melodies. Its task is to eliminate the complexity of this musical work and transform it into a harmonious and complete simple task. The present project is an attempt for the identification of the Musical Instruments for a given polyphonic audio signal. Monophonic signal, often referred to as a "mono" signal, consists of a single audio source or a single line of music. In other words, it carries only one audio channel, typically representing a single instrument or voice. A polyphonic signal, on the other hand, is one that contains multiple independent audio sources or lines of music playing simultaneously. These signals contain multiple audio channels, and each channel may represent a different instrument or voice. Despite the research done in Musical Instrument identification over the last years, no one has seen a much significant work done on musical instruments. The paper presents a simple and dependable method to recognize musical instruments in polyphonic audio signals that can overcome some of the main restrictions faced in the past. A system is capable of detecting the pitches of a instruments in polyphonic music is useful in many areas. The pitched component supports multiple-instrument polyphonic music, as well as tuning changes and frequency modulations .In addition to pitched sounds, the system also incorporates an "unpitched component"This unpitched component allows the model to recognize various drum kit instruments, which are typically characterized by non-pitched, percussive sounds. This process can be challenging, as it requires handling issues like onset detection, note tracking, and temporal alignment. Developing synchronization algorithms that can handle various musical nuances and complexities is a critical step in advancing the field . While much work has been done in the domain of polyphonic pitch detection and transcription, the implementation of synchronization is a relatively less explored area. The system is capable of producing new audio file with different frequencies which can be useful for music production . This can be also very helpful for music education in order to learn different instruments pitches and tones.

II. PROBLEM STATEMENT

There are many obstacles to overcome in the development of an automated system for pitch detection, synchronization, and instrument identification. Polyphonic audio processing, which is typified by overlapping sounds from several instruments, requires advanced algorithms that can separate and isolate individual components due to its intrinsic complexity. Pitch detection algorithms must be resilient since different musical genres have different pitch characteristics and playing styles, which makes instrument recognition less accurate The requirement for real-time processing in live performances imposes limitations on computational efficiency and latency, necessitating a careful balancing act between responsiveness and accuracy. Furthermore, the system needs to be able to work with a wide range of musical genres and handle a subjective harmonizing difficulty. The development hurdles are further compounded by constraints in the dataset, the need to adapt to atypical instruments, and the necessity to provide a user-friendly interface. These factorshighlight the need for a complete and nuanced strategy to advance the state-of-the-art in automated polyphonic instrument processing.

III. OBJECTIVES

To create an application which performs the following functionalities:

- Provide an intuitive user interface so that people can communicate with the system without difficulty.
- Create algorithms that will automatically recognize and categorize different instruments in recordings of polyphonic music
- Using sophisticated pitch identification techniques to precisely determine the pitch of every note played by instruments that have been identified.
- To get immediate feedback on synchronization, pitch accuracy, and instrument recognition, enable real-time processing capabilities.
- Make that the system is resilient to changes in recording conditions, musical complexity, and input quality.
- Techniques for designing systems that handle polyphonic audio signals and extract pertinent data from several instruments performing at once.

IV. *EX*PECTED OUTCOMES

It is expected that the AI yoga pose detection system would give. The automated polyphonic instrument recognition, pitch detection, and synchronization system is expected to provide an audio file that is a synthesis of recognized instruments with precisely detected and synchronized pitch.

V. LITERATURE SURVEY

1. "Music Instrument Identification using MFCC"

"Music Instrument Identification Using MFCC " by Weng, Lin, and Jang (2003) [1] discusses the use of MFCC (Mel-Scale frequency cepstral coefficients) for music instrument identification, specifically focusing on the erhu. When detecting distinct erhu instruments, the study examines the efficacy of power spectrum and MFCC; the results show that MFCC is more effective in this regard. In addition to highlighting the application of FFT, LDA, and GMM for feature extraction, dimensionality reduction, and model creation in the context of ETR, the study offers a thorough literature review in the topic of music timbre recognition. Future research directions were also addressed, including the potential of MFCC and the investigation of other audio aspects for music instrument assessment..

2. "Music Instrument Identification using MFCC"

"Music Instrument Identification Using MFCC " by Monica S. Nagawade and Varsha R. Ratnaparkhe [2] presents a method for identifying musical instruments from solo recordings using Mel Frequency Cepstral Coefficients (MFCC). With regard to the cello, piano, and trumpet, the accuracy of the system is 91.66%; for the flute and violin, it is 83.33%. The suggested technique makes use of K-Nearest Neighbour (K-NN) classification and feature extraction. The outcomes demonstrate that the MFCC strategy works well for feature extraction; nevertheless, the accuracy of the system could be increased by utilising additional feature extraction techniques and classifiers. The difficulties that arise when using musical instrument identification in real-world settings are also covered in the article. These difficulties include handling background noise, adjusting to different playing styles, and handling many instruments in group recordings. To tackle these obstacles, advanced signal processing algorithms must be created, and extensive annotated datasets must be used for training and assessment.

3. "Musical Instrument Classification using Support Vector Machine"

"Musical Instrument Classification using Support Vector Machine, Multi Layer Perceptron, and AdaBoost Classifiers", 2021 by Swati D. Patil and Priti S. Sanjekar [3]. The automatic classification of musical instruments using Support Vector Machine (SVM), Multi Layer Perceptron (MLP), and AdaBoost classifiers is covered in this study. The system's goal isto simplify classification and reduce reliance on human oversight. A dataset of musical instruments and their characteristics is used to train and evaluate the classifiers. The findings indicate that AdaBoost outperforms SVM and MLP in terms of accuracy. The system's goal is to enhance how musical instruments are categorised for music information retrieval systems. The study covers the application of Formal Concept Analysis (FCA) to illustrate the connection between musical instruments and their characteristics in addition to categorization strategies. Using various techniques, the system—which is meant for binary classification—is expanded to multi-class classification. The system's methodology focuses on automatic music classification, which has drawn a lot of attention because it can be challenging to classify music according to its attributes. The system's objective is to automatically classify musical instruments using AdaBoost, Multi Layer Perceptron, and Support Vector Machine classifiers. Each classifier's performance is assessed. The use of various classifiers and the examination of heterogeneity and constraints in current instrument classification schemes are some recent developments in the field of musical instrument classification that are also covered. The usage of ensemble learners like AdaBoost for music classification and the construction of instrument taxonomies based on the H-S system in OWL are highlighted in this work.

4. "Indian Instrument Identification from Polyphonic Audio using KNN Classifier"

"Indian Instrument Identification from Polyphonic Audio using KNN Classifier" by S.V. Chandan, Mohan R. Naik, Ashwini, and A. Vijay Krishna [4] presents a method for identifying Indian musical instruments from polyphonic audio using a KNN classifier. The paper discusses K Nearest Neighbours (KNN) classification, feature extraction, and feature selection. The results show high accuracy in spotting instruments with selected features. In addition to MFCC coefficients and Chroma vectors, the study covers the extraction of 34 features from the audio signal, including standard deviation, mean, skewness, and autocorrelation. For instrument classification, the KNN classifier is employed, and feature selection is carried out to lower dimensions and boost accuracy. Accord ing to the findings, the KNN's overall F1 measure for 34 features is 97.3%; the F1 value drops to 95.3% when features from the excellent and mediocre categories are excluded. The importance of this discovery is also highlighted in the report, since little research has been done on Indian musical instruments in polyphonic audio signals.

5. "Instrument Recognition in Polyphonic Music"

"Instrument Recognition In Polyphonic Music" by Slim ESSID, Gael RICHARD, and Bertrand DAVID [5] proposes a new approach to machine recognition of musical instruments in a polyphonic context. The system is capable of segmenting audio signals based on the number of sources it detects. The paper also describes an approach for identifying musical instruments in commercial recordings of polyphonic music. Gaussian Mixture Models, feature selection, and a hierarchical classification tree are used in its classification process. For brief periods of time, the system is successful at identifying up to four instruments playing simultaneously, allowing segmentation. The method employs a taxonomy of instrument combinations that are influenced by the musical genre and is predicated on prior knowledge of the musical environment. A jazz piano quart et ensemble is used to carry out the experimental validation. High recognition accuracy is attained by the method for up to four simultaneous instruments.

6. "Pitch Detection In Polyphonic Music Using Instrument Tone Models"

"Pitch Detection In Polyphonic Music Using Instrument Tone Models" by Yipeng Li and DeLiang Wang [6] introduces a system for detecting the pitch of a particular instrument in polyphonic music using Hidden Markov Models (HMM). Different instruments, levels of polyphony, and signal-to-noise ratio (SNR) scenarios all yield good performance from the system. The difficulties of identifying instrument presence in music audio processing are also covered, along with a comparison of several instrument modelling approaches. The NSF and AFOSR provided money for the project. References to relevant studies and study instruments are included in the publication. Additionally, a pitch hypothesis selection technique to lower octave-higher mistakes in instrument modelling is presented in the research. It investigates the use of kernel density estimation to model an instrument and defines the pitch hypothesis's likelihood using a probabilistic framework. Western classical music pieces are used to evaluate the system, and it demonstrates good detection accuracies for various instruments at varied signal-to-noise ratios.

7. "Automatic Transcription of Real-world Music Using Probavilistic Note Event Modeling"

"Automatic Transcription of Real-World Music Using Probabilistic Note Event Modeling" by Matti P. Ryynanen and Anssi Klapuri [7] presents a method for automatic transcription of real-world music signals, focusing on pitched musical instruments. The technique transcribes notes from stereo input files using probabilistic note event modelling using hidden Markov models and a musicological model. A realistic music database was used to evaluate the approach, and it produced recall and precision scores of 39% and 41%, respectively. The system's architecture allows it to transcribe a wide range of musical genres without restricting the number of instruments or polyphony levels. The study also reviews prior research in the area of music transcription and addresses t he evaluation criteria that were employed, such as recall rate, precision rate, and mean overlap ratio.

8. "Pitch Detection Algorithm :Autocorrelation Method and AMDF"

"Pitch Detection Algorithm: Autocorrelation Method and AMDF" by Li Tan and Montri Karnjanadecha [8] describes the implementation and testing of two pitch detection algorithms, autocorrelation and AMDF, for speech signal processing. The study discusses feature extraction, preprocessing, classification testing, and algorithmic principles. The precision of the results is acceptable, and the autocorrelation approach clearly shows the impacts of preprocessing. However, more analysis in practical tone-classification systems is required. The background information on the methodologies, feature extraction, post - processing approaches, and preprocessing methods is also included in the study. Additionally, the implementation of a modified autocorrelation method is discussed. The autocorrelation method clearly illustrates the impacts of preprocessing, and the findings demonstrate an adequate level of accuracy. Nonetheless, additional assessment in practical tone-classification systems is required. Along with background information on the methodologies, post-processing techniques, preprocessing strategies, feature extraction, and the application of a modified autocorrelation method, the study also includes feature extraction.

9. "Robust Feature Extraction Using Kernel PCA"

"Robust Feature Extraction Using Kernel PCA" by Tetsuya Takiguchi and Yasuo Ariki [9] investigates a robust speech feature extraction method using kernel PCA. The technique is suggested as a substitute for the widely used Mel Frequency Cepstral Coefficient (MFCC) for speech detection in environments with a lot of reverberation and noise. Experiments on reverberant speech using word recognition demonstrate the efficacy of the suggested approach. The findings indicate that for reverberant speech, kernel PCA performs better than DCT (Discrete Cosine Transform). The presentation of the experimental setup and findings shows how using kernel PCA can increase recognition rates. The limitations of current noise- removal methods and the difficulties in totally eliminating non-stationary noise or reverberation are also covered in the study. It suggests using kernel PCA for robust feature extraction rather than DCT, projecting the main speech element onto low-order features and noise or reverberant elements onto high-order features. Additionally, the paper offers a thorough explanation of the kernel PCA feature extraction procedure, including how polynomial kernel functions are applied and the kernel matrix is computed.

10. "Automatic Transcription of pitched and unpitched sound from polyphonic Music"

"Automatic Transcription Of Pitched And Unpitched Sounds From Polyphonic Music" by Emmanouil Benetos, Sebastian Ewert, and Tillman Weyde[10] presents a method for automatically transcribing both pitched and unpitched sounds from polyphonic music recordings. The model allows for the recognition of both unpitched sounds from drum kit components and pitched sounds from other instruments, extending the probabilistic latent component analysis algorithm. In tasks such as drum transcription and multi-pitch identification the suggested approach demonstrates encouraging outcomes. The model parameter estimation, and experimental findings are presented in the study. Multiple overlapping notes and sounds from various drum kit components could be detected by the system. The trials yielded encouraging outcomes for the drum transcription and multi-pitch identification tasks. In order to enhance drum transcription performance, the authors intend to expand the system further and add varying-Q time-frequency representations for better temporal resolution.

11. "Implementation of Pitch Detection Algorithm for Pathological Voices"

"Implementation of Pitch Detection Algorithms for Pathological Voices" by Karishma Kolhatkar, Mahesh Kolte, and Jyoti Lele [11] discusses the implementation of pitch detection algorithms for pathological voices. Pitch is determined and voice samples are divided into normal and disordered voices using a variety of algorithms used in the study. The Cepstrum method has the highest accuracy, according to the results, followed by the Autocorrelation algorithm. The study also contrasts how quickly the various algorithms perform. The significance of reliable pitch detection for voice classification is emphasised in the conclusion. The research also outlines the possible uses of pitch detection algorithms in vocoder systems, speech training for the hard of hearing, speaker recognition, and differentiating between normal and abnormal voices. The study advances the fields of speech processing and voice pathology research by offering insightful information on the application of pitch detection algorithms for voice analysis and categorization. Additionally, a thorough comparison of various pitch recognition algorithms is provided by the research, illuminating the precision and efficiency of each approach.

12 . "Proposed combination of PCA and MFCC feature extraction in speech recognition system"

"Proposed combination of PCA and MFCC feature extraction in speech recognition system" by Hoang Trang, Tran Hoang Loc, and Huynh Bui Hoang Nam [12] presents a novel approach to feature extraction in speech recognition systems. The study compares the effectiveness of two modified variants of MFCC feature extraction that combine PCA and MFCC with the standard method, showing possible gains in recognition accuracy and decreased processing time complexity. The study highlights the superior performance of the PCA and MFCC combination by comparing the recognition accuracies and time complexities of several MFCC algorithms. The Ministry of Science and Technology funded the study, which recommends investigating other dimensions reduction techniques in the future. The authors also go into how PCA approaches can be used to change the data matrix and how that affects training, with a focus on how this can lead to better recognition accuracy and less time complexity. In addition, the paper sheds light on the technical components of the suggested method by offering insights into the pre-emphasis, frame blocking, windowing, FFT transform, Mel frequency filter bank, and cepstrum techniques employed in the feature extraction process. The authors also go into how computing delta coefficients and adding time derivatives to get stable parameters can improve speech recognition.

13 "A Novel Approach for MFCC Feature Extraction"

"A Novel Approach for MFCC Feature Extraction" by Md. Afzal Hossan, Sheeraz Memon, and Mark A Gregory [13] introduces a novel approach for speaker verification using distributed Discrete Cosine Transform (DCT-II) based Mel-Frequency Cepstral Coefficients (MFCC). The usage of the Gaussian Mixture Model (GMM) for classification is highlighted in the study's comparison of this approach with Delta-Delta MFCC and traditional MFCC. The study assesses the effectiveness of several feature extraction techniques and highlights the possibility of integrating DDMFCC and DCT-II to enhance speaker verification systems even more. The experiment setup and results are also presented in the study, showing that the suggested strategy raises identification accuracy to 96.72%. Additionally, the study emphasises how the novel feature extraction method may improve speaker verification system performance. In order to increase the precision and effectiveness of speaker verification systems, the research offers a thorough examination of earlier speaker recognition systems and suggests a novel feature extraction strategy.

14. "Detecting Pitch Of Singing Voice In Polyphonic Audio"

"Detecting Pitch Of Singing Voice In Polyphonic Audio" by Yipeng Li and DeLiang Wang [14] presents a new algorithm for detecting the pitch of singing voice in monaural polyphonic music. The approach has potential uses in sound separation and performs better than other popular pitch detection algorithms. NSF and AFOSR funding helped to fund the research. The programme makes use of statistical integration of periodicity information using HMM, as well as the prominence of the singing voice and the thumping phenomenon in high frequency channels. For sound separation, the pitch of a singing voice can be recognised. The performance of the suggested algorithm is also contrasted with that of other well-known pitch recognition algorithms in the paper. The method is divided into five steps, beginning with a 128-channel gammatone filterbank and the auditory peripheral. Each high frequency channel's output envelope is recovered once the channels are divided into low and high frequency categories. Next, a normalised autocorrelation is used to retrieve the periodicity information in each channel. Rock, pop, and country music are among the test samples taken from commercial CD recordings to assess the suggested algorithm. When compared to previous algorithms, the system performs better in rock and country music, exhibiting noticeably higher overall pitch identification accuracy.

VI. REQUIREMENT SPECIFICATION

Hardware requirements

This application is designed to run on the minimum possible configuration of hardware.

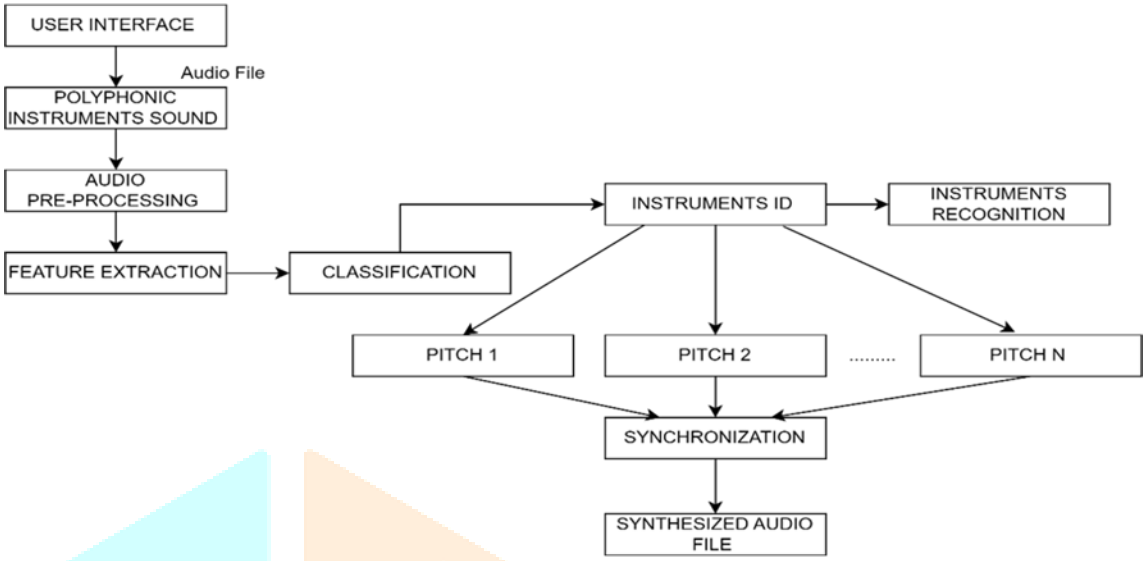
- Processor: Intel i7
- RAM: 8 GB
- Hard disk space: 1TB or More SSD storage
- Operating System: compatibility with operating system (e.g., Windows, macOS Linux)

Software requirements

- Tool: PyCharm
- Programming Languages: Python
- Integrated Development Environment :PyCharm
- Machine Learning Libraries: PyTorch for deep learning
- Package Management: Pip package managerFramework: Django
- Libraries: LibROSA, Essentia, or MARSYAS
- Computer Vision Libraries: OpenCV Audio

VII. SYSTEM DESIGN

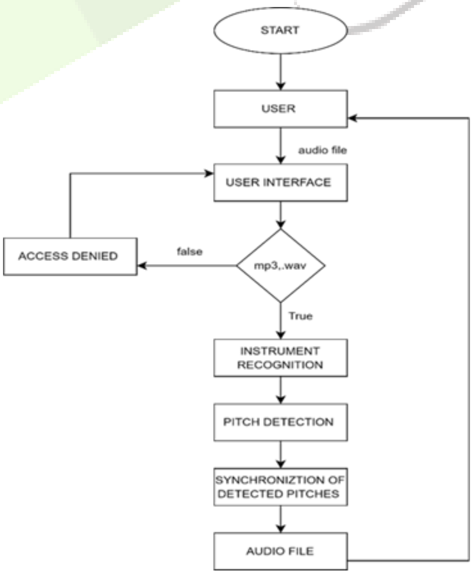
Initially Polyphonic Instrument audio file is provided to the system through User Interface. The audio signal is preprocessed which involves segmentation, removal of noisy data, conversion of low dimensional space input into high dimensional space into order to extract more features from the audio signals.The audio signals consists of many features which is required for classification .The features includes temporal,chroma,spectrum features etc. These features are required for classification and extracted using feature extraction methods. The classification tends to recognition of different instruments from polyphonic instrument sound. The pitch is detected from each recognized instrument ids .The detected pitches are synchronized into single pitch thus synthesized audio is produced.



Architecture of the system

Dataflow diagram

Initially the audio file is provided from the user to the system. The audio file should be of format .mp3 or .wav. The other format is not supported. The message is sent back to user as access denied. From the audio file provided the instrument is detected by applying feature extraction algorithms and classifiers. The pitch is detected from detected instruments by using pitch detection algorithm. The detected pitches are synchronized and thenew audio file is generated and provided to user through user interface. By using the feature extraction method and classifier the instrument is detected first from the polyphonic audio sound provided by the user to through user interface. The pitch is detected from each instrument's id by using pitch detection algorithms.The pitches that are detected synchronized into single pitch inorder to give new audio file.The audio file provided by user varies from the audio file given as output by the system.The synchronization is not a single process.It requires combination of methods.It is complex task as it requires synchronizing of overlapping and different pitches into single pitch.



Dataflow diagram of system

VIII. RESEARCH METHODOLOGY

The research approach for Tune Detect: Musical mastermind for musicians starts with a clear definition of the project goals and the synthesized audio file in output as target. The extensive literature review that follows examines the most recent methods and developments in monophonic and polyphonic instrument assessment. As Audio contains many features like temporal,spectral,timbre etc, preprocessing techniques are applied to convert low dimensional space into high dimensional space to extract more signal features. We may use MFCC,DCT MFCC,PCA ,Kernel Pca for extracting feature from features from audio signals.For classification SVM(Support vector machine),KNN K-Nearest neighbor can be effective classifiers. Autocorrelation method,cepstrum method, Data reduction method, Simplified Inverse Filtering method can be used for effective pitch detection .
The synchronsing the pitches is not still implemented so far.Since we are dealing with polyhonic sound it is complex task to synchronize it. Some algorithms like HMM(Hidden Markov Model),DTW(Dynamic Timw Wrapping) can be used. From above research there is separate implementation of each modules like instrument identification, feature extraction methods, pitch detection, pitch detection method, classification methods etc.In this project we are integrating all the modules by dealing with polyphonic instrument sound,and adding the extra feature called synchronizing the detected pitch into single pitch.Also above research we observed there is no direct output of any audio file ,either it is MIDI data or transcripted data.In this project the targeted output is new audio file .

IX. CONCLUSION

In conclusion “Tune Detect: Music Mastermind for musicians , the proposed project involves creating a complete system that combines pitch detection, pitch synchronization, feature extraction, and classification for instrument identification from polyphonic audio input. The system seeks to precisely identify individual instruments within intricate audio mixtures, extract pertinent attributes, classify instruments, detect pitch information, and synchronize the recognized pitches by utilizing cutting-edge algorithms and real-time processing capabilities. The incorporation of an interface that is easy to use improves accessibility by enabling users to effortlessly contribute audio recordings. In addition to its contribution to the field of audio processing, this system has potential uses in interactive music systems, music transcription, and other areas where accurate analysis of polyphonic instrument sounds is crucial. Focusing on accuracy, flexibility, and usefulness, the proposed solution is in line with the changing requirements of the audio processing industry, providing a useful resource for scholars, artists, and fans in equal measure.

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