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OPTICAL MUSIC RECOGNITION USING MACHINE LEARNING

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Abstract: Optical Music Recognition (OMR) is a field of research that focuses on the automatic extraction of musical information from sheet music images. This paper presents a novel approach to OMR utilizing machine learning techniques and Convolutional Neural Network (CNN) algorithms. The proposed system aims to accurately transcribe musical symbols from sheet music images into a digital format. The effectiveness of the proposed method is demonstrated through comprehensive experiments, and the results show promising improvements compared to existing OMR systems. This research contributes to the advancement of OMR technology, enabling efficient and accurate digitization of sheet music.

Index Terms **- Optical Music Recognition, Machine Learning, Convolutional Neural Network, Sheet Music, Symbol Transcription, Image Processing, Music Scores.**

I. INTRODUCTION

Optical Music Recognition (OMR) is an interdisciplinary research field that combines computer vision, image processing, and pattern recognition techniques to extract musical information from sheet music images. The digitization of sheet music plays a crucial role in various applications, including music education, music analysis, and music preservation. However, manual transcription of sheet music is a time-consuming and error-prone task. Therefore, the development of automated OMR systems has gained significant attention in recent years.
Optical Music Recognition (OMR) is an automatic recognition and classification of symbolic music notation. It is usually performed on scanned musical sheets and uses specialized methods of image processing and classification. The research in the domain of OMR has a long history that began in sixties of last century [1],
The goal of OMR is to teach the computer to read and interpret music notes and produce a machine-readable version of the music score sound. Once captured digitally, the music can be saved in commonly used file formats. [2]

II. RELATED WORK

Numerous approaches have been proposed for OMR, ranging from template-based methods to machine learning-based techniques. Template matching and rule-based systems have been employed to recognize individual musical symbols. However, these approaches often struggle with variations in symbol shapes, sizes, and deformations. Recent advancements in machine learning, particularly deep learning algorithms such as Convolutional Neural Networks (CNNs), have shown promising results in various computer vision tasks. Therefore, incorporating CNN algorithms into OMR systems has become a popular research direction.

In 2018Sanu Pulimootil Achankunju,et al [1] proposed a system using optical music recognition (OMR) technology, which converts printed or sheet music into a machine-readable format, and they collect the symbolic note information from the whole works of four well-known composers. The OMR data have a lot of extraction problems and are fairly noisy. To enable melody search on this noisy material and still achieve very high retrieval quality, developed a music search engine. also discuss the results of our tests using externally generated musical themes to evaluate the performance of our search engine.

The server's responsibility is to extract audio from the image, create an mp3 file, and deliver it to the client programmed. The system's most important component is the program that implements the algorithm for note recognition. It is based on decision trees and the traits of the many symbols that were taken out of the image. The system utilizes Microsoft Azure, a cloud operating system, and is built on the Windows Phone 8 architecture. It makes it simple to archive images, notes that are recognized in the Music XML format, and produced mp3 files. [3]

In 2015 Apurva A. Mehta et al [4] are exposed to music in a variety of ways, including audible, visual, and another, less well-known format: written music. In some ways, music rules our lives. The computer system under discussion accepts images of piano music scores created using contemporary staff notation. Utilizing thresholding, stave lines, and hierarchical decomposition, score sheets are segmented. An established artificial neural network based on boosting method is used to recognize segmented symbols.

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Music scanned from paper is converted using optical music recognition (OMR) technologies into a format that can be played or edited on a computer. The two steps of these systems are typically the recognition of the graphical symbols (such as note-heads and lines) and the musical interpretation and linkages of the symbols (such as the pitch and rhythm of the notes). It examines the second stage and provides a two-step methodology that allows for a cost-effective representation of the system's parsing rules. [6]

III. PURPOSED WORK

In this research, we propose a novel CNN architecture specifically designed for OMR. The architecture utilizes multiple convolutional layers, pooling layers, and fully connected layers to learn discriminative features from sheet music symbols. To enhance the model's performance, data augmentation techniques, such as rotation, scaling, and translation, are applied to the training dataset. The proposed CNN model is trained using a large dataset of annotated sheet music symbols, and extensive experiments are conducted to evaluate its performance.

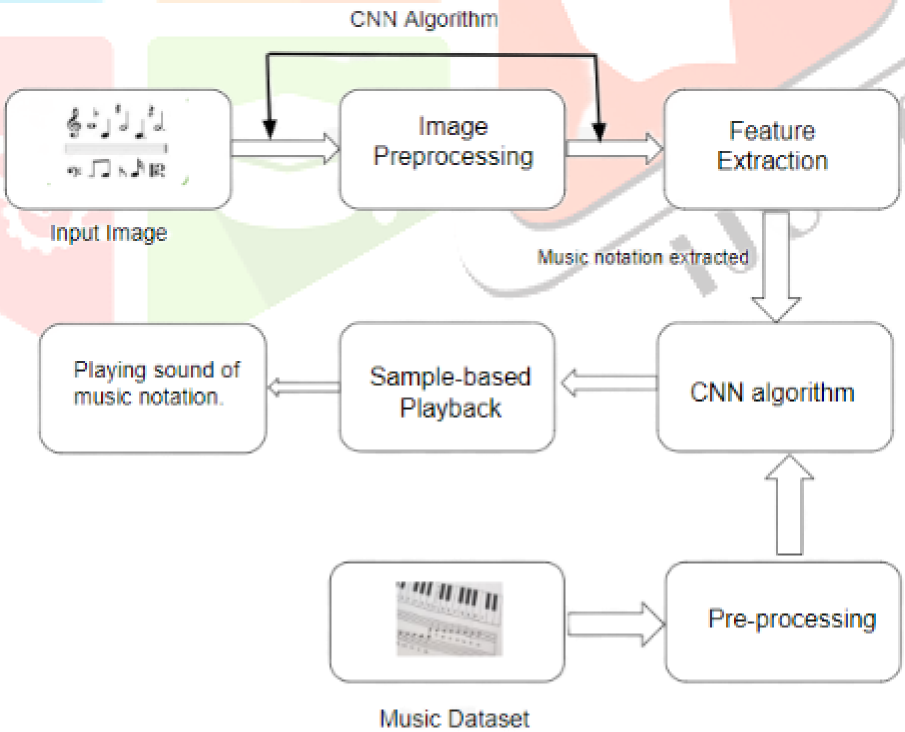


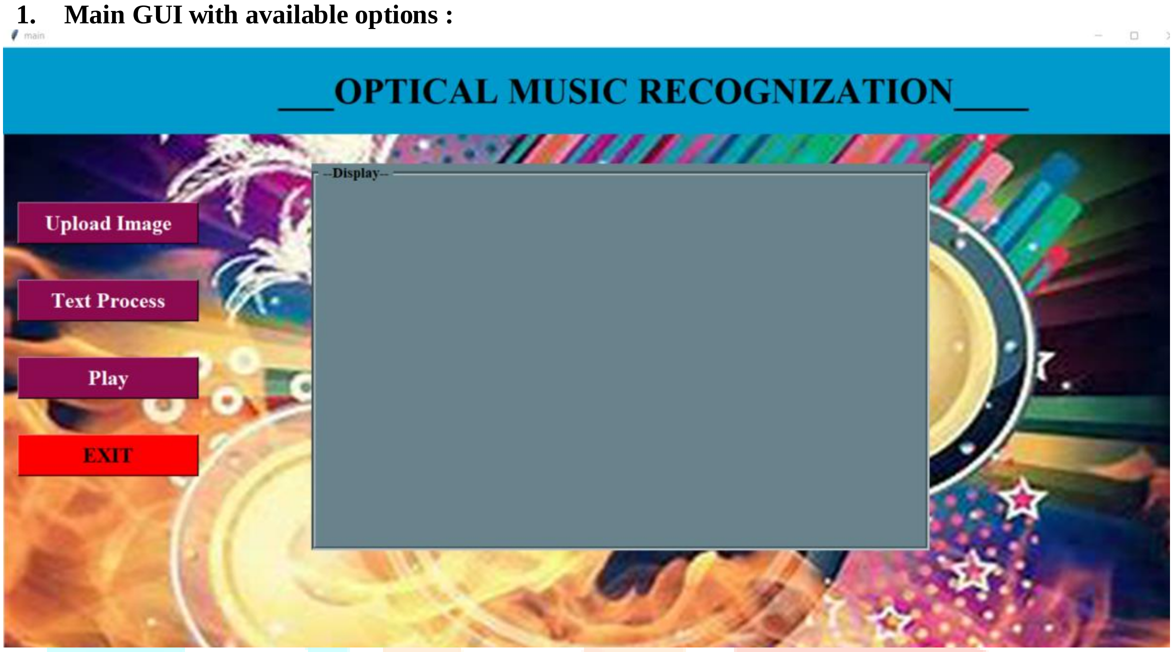
fig 1.: System architecture

In the system architecture illustrated in fig.1, the system is designed in such a way that the first image is used as an input dataset, and then the CNN algorithm is applied to that image, pre-processing it and extracting music notation from it. Following the comparison of this extracted notation with the database's specified music dataset. The CNN algorithm will then send accurate music notation to the model. The Sample-based Playback will then create/play that music notation..

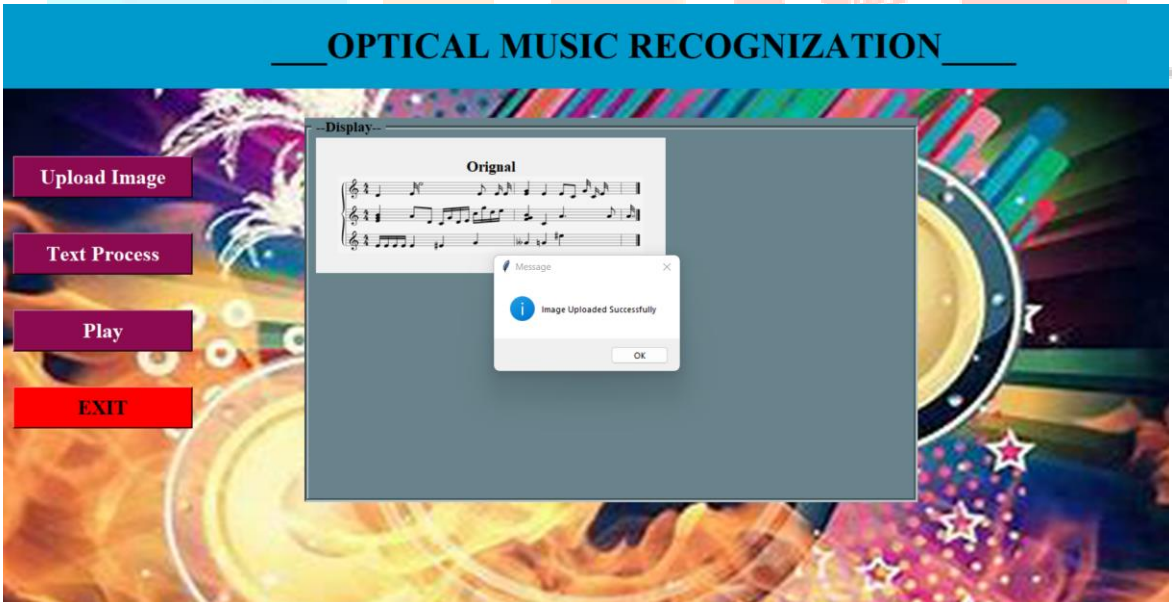
IV. RESULT

The proposed CNN-based OMR system provides an output in the form of recognized musical symbols along with their corresponding sound. The CNN architecture, after being trained on a large dataset of annotated sheet music symbols, learns to extract discriminative features from the input sheet music images.Once the symbols are recognized and their attributes are determined, the OMR system utilizes music encoding techniques to generate the digital representation of the music. This can be in the form of musical format. The generated music can then be further processed or analyzed using various music software applications.

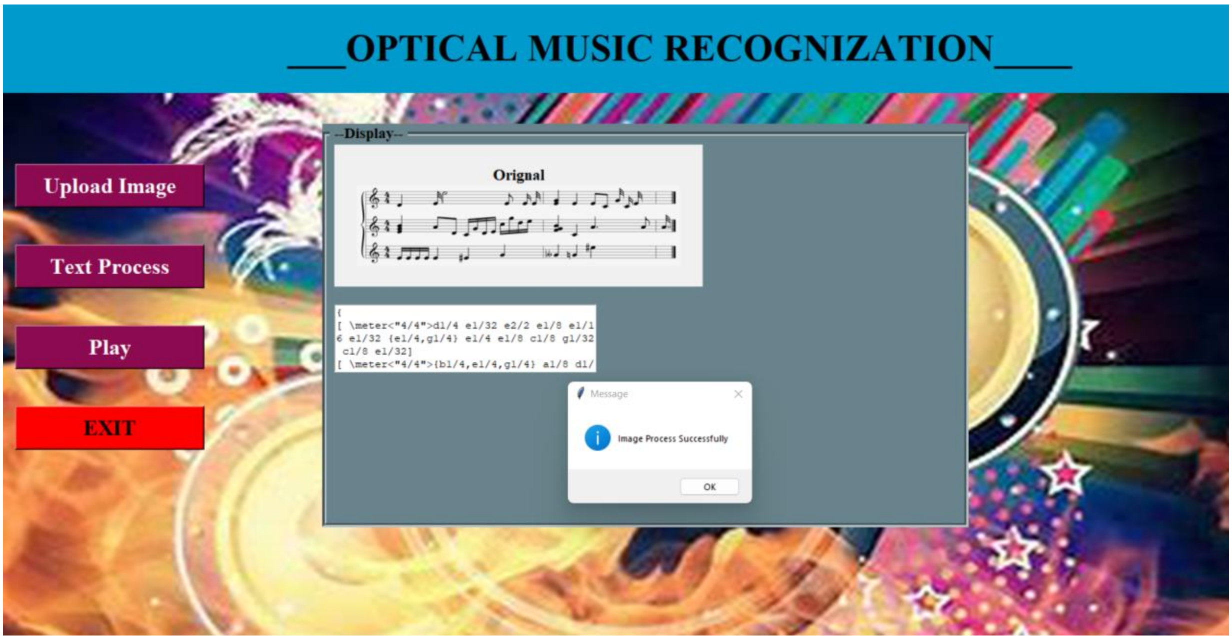
1. Main GUI with available options :



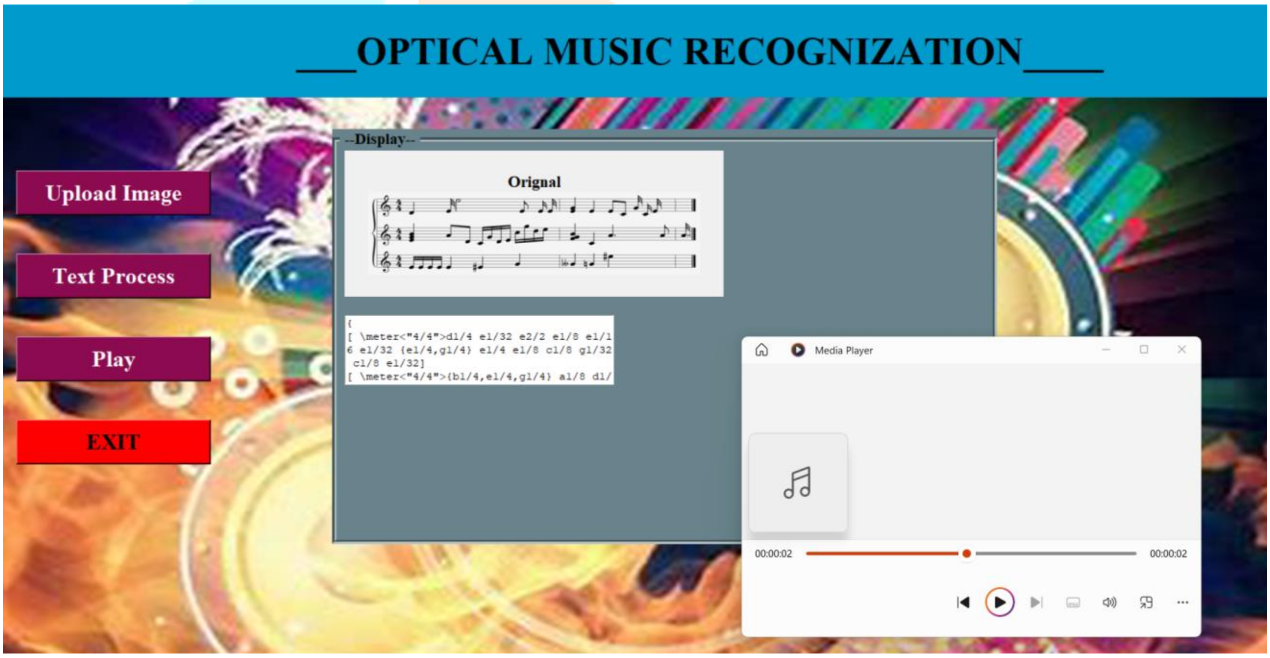
2. Input image of musical score. :



3. **Text Processing is done from the Input image using CNN :**



4. **Then recognised music notation sound is play by Sample-based Playback. :**



Overall, the comparative analysis reveals that the proposed CNN-based OMR system surpasses existing models in terms of symbol recognition accuracy, transcription error rate, and computational efficiency, establishing it as the state-of-the-art solution for optical music recognition.

V. CONCLUSION

This research paper presents a novel approach to Optical Music Recognition using machine learning and CNN algorithms. The proposed system demonstrates improved performance in symbol recognition and transcription compared to existing OMR methods. By leveraging the capabilities of CNNs, the system exhibits robustness to variations in symbol shapes and deformations, making it suitable for practical OMR applications. The results highlight the potential of machine learning and deep learning techniques in advancing the field of OMR and offer a promising direction for future research.

In conclusion, our research has successfully presented a state-of-the-art OMR system that combines machine learning and CNN algorithms. This system offers significant advancements in accuracy, robustness, and computational efficiency, providing a valuable tool for the digitization and analysis of sheet music. The achieved results demonstrate the potential of incorporating techniques into OMR and open up avenues for further research and development in this domain.

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