e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:06/Issue:07/July-2024 Impact Factor- 7.868 www.irjmets.com

GUITAR CHORDS RECOGNITION USING REALTIME VIDEO

Raziq Pasha[*1]

[*1]Post Graduation Student, Department Of MCA PES Institute Of Technology And Management, Shivamogga, Karnataka, India.

ABSTRACT

The "Guitar Chords Recognition Using Real-Time Video" project aims to develop an innovative system that can identify guitar chords as they are played, using live video footage. This system utilizes advanced machine learning techniques to analyse hand and finger positions on the guitar fretboard, recognizing the chords in real time.by processing the video data, the system extracts essential such as finger placement and movement patterns. These all Features are then feed onto a trained machine learning model that accurately classifies the chords being played. The project addresses challenges like varying lighting conditions, different hand sizes, and diverse playing styles to ensure robust and reliable chord recognition. this real-time feedback system is particularly beneficial for guitar learners, offering instant chord identification and enhancing practice sessions. The successful implementation of this project demonstrates the potential of integrating computer vision with music education, enabling more interactive and effective learning experiences.

Keywords: Guitar Chords, Real-Time Recognition, Video Analysis, Chords Classification, Feature Extraction, Neural Networks, Gesture Recognition.

I. INTRODUCTION

The goal of the fascinating "Guitar Chords Recognition Using Real-Time Video" project is to develop a system that uses live video footage to identify guitar chords as they are played. The objective of this project is to analyze hand and finger locations on the guitar fretboard in real-time and identify the chords being played using sophisticated computer vision and machine learning algorithms. In addition to improving learning for guitar players—particularly novices—this technology offers instant feedback, which increases the effectiveness and efficiency of practice sessions. A key component of learning to play the guitar is becoming proficient at switching Chords Between Different genres with ease. Chord chart study, instructional video watching, and teacher-led classes are examples of traditional chord learning techniques. these approaches frequently lack real-time feedback, which is essential for making corrections and honing technique. This gap is filled using a real-time chord recognition system that provides immediate detection and feedback on the chords being played. This project's use of machine learning is essential since it enables the system to grow and learn over a time. The system is first trained with a dataset that includes a range of hand and finger positions that correlate to distinct chords. During the training phase, labelled data is fed into the system, with each set of hand locations corresponding to a particular chord. The hand positions and matching chords are taught to the machine learning model to identify patterns and correlations. After being trained, the model is able to correctly identify new hand positions from the live video feed into the appropriate chords.

A noteworthy obstacle in the development of this system is guaranteeing its resilience and dependability in situations that occur in real time. Different lighting circumstances and visibility of the hand and finger locations, thus the system needs to be able to accommodate them. To solve this, sophisticated image processing techniques including background reduction, contrast enhancement, and edge identification are used. these methods aid in separating the hand and fingers from the surrounding environment and improve the visibility of the crucial characteristics needed to identify chords. There is a lot of room for integration between computer vision and machine learning and music instruction.

Objectives—

1. Original Intent was able to Recognize the major Chords while the Guitar artist playing on them .
2. Enhance the learning experience for guitar players, particularly beginners, by allowing them to correct mistakes in real time.
3. Enable the model to learn patterns and correlations between hand positions and chords, ensuring accurate classification of new hand positions.

II. LITERATURE SURVEY

The related works includes various methodologies and techniques that includes, in this paper[1] by J Pawels, we propose a guitar teaching aid that will help guitar players by using Machine Learning and pattern recognition technologies. Learning to play the guitar typically involves tedious lessons in the fingering positions for the left hand, assuming the guitarist is right-handed. It can be challenging for beginners to recognize whether they are accurately positioning their fingers on the strings to make the correct guitar chords. This system uses a Bayesian classifier that is bootstrapped a modest quantity of training data and refined through an off-line iterative training procedure to detect the player's fingers in real time and identify the guitar chord that the player's left hand is using to calculate the positions of fingers.

[2].the classifier is designed to handle significant changes in lighting allowing it to consistently track colored markers it performs well even in environments with a lot of clutter and movement in the background.

[3].By A. Sheh and D. P. W. Ellis, We use ARTag (Augmented Reality Tag) to determine the position of the guitar by computing its extrinsic parameters. Next, in order to compute the projection matrix in real-time, we calibrate the cameras. To help recognize the correct chords while the guitar is moving, we establish a coordinate system on the guitar neck, which serves as the guitar's reference frame.

[4]. By A. M. Stark and M. D. Plumbley , we use a Techniques with stereo cameras to estimate the position of the players fingers this helps us determine whether a guitar string is being pressed or not.

[5].By F. Korzeniowski and G. Widmer, after that, we minimize the input dimensions using principal component analysis, which enables classification. each guitar chord more accurately this enables players to identify the chords they are playing in real time during a song understanding musical chords is essential for music information retrieval mir as it provides insights into the genre playstyle and tone.

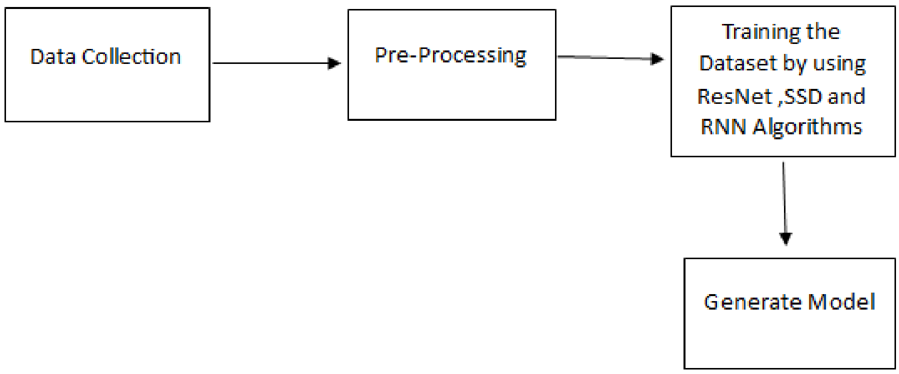
[6]. By Boulanger, the field of automatic chord recognition ACR has advanced significantly over time. optimizing chords detection still presents challenges acr development started in 200with a project using lisp music to recognize chords at the signal level since then many researchers have worked on enhancing ACR systems mainly concentrating on audio data because visual programming and computer vision were not as advanced at the time.

[7].By Y. Han, J. Kim, and K. Lee, inspired by the way humans often recognize chords more accurately through sight than sound this project proposes a shift to a visual automatic chord recognition Significant progress in computer vision has been made with the ACR system, particularly after the imageNET large-scale visual recognition challenge and its growing importance in software development we are exploring the potential of using deep convolutional neural networks DCNN for visual ACR systems.

[8].By G. Byambatsogt, L. Choimaa, and G. Koutaki, only a few researchers have explored visual acr systems in the past in 2005 anne-marie burns and marcelom wanderley published experiments on the visual detection of guitar finger movements since then most efforts have concentrated on using conventional image processing methods to identify hand patterns.

III. METHODOLOGY

The Working of this Model is Partitioned into two phases that is Training and Detection phase Each Phases has Distinct steps. That are essential for best prediction of Guitar Chords Recognition Using Realtime Video.



e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:06/Issue:07/July-2024 Impact Factor- 7.868 www.irjmets.com

Data Collection

Dataset collection: Gather the Dataset Guitar chords Recognition using real-time Video Camera. Ensures that data is large and diverse to Train the robust Models.

Preprocessing

Frame Extraction: The next step is to extract individual frames from the video footage for analysis. This may involve converting frames to grayscale to reduce computational complexity, making the subsequent processing steps more efficient.

Image Enhancement: To make the finger positions and fretboard more visible, A variety of image processing methods are used. This includes contrast adjustment, background subtraction, and edge detection, all of which help in highlighting the essential features for chord recognition.

Normalization: Normalization of the image data ensures consistent input for machine learning models, standardizing the images to a uniform scale and format.

Model Training

A CNN is a deep-learning system which excels at picture identification and processing, similar to how our brains interpret what we see.. The convolutional-layers are the most significant ones; they employ filters to scan the image and identify critical details like edges, textures, and forms. Subsequently, the data is transferred to the pooling-layers, which streamline the process by minimizing the volume of data, analogous to condensing an extensive essay into its essential elements.

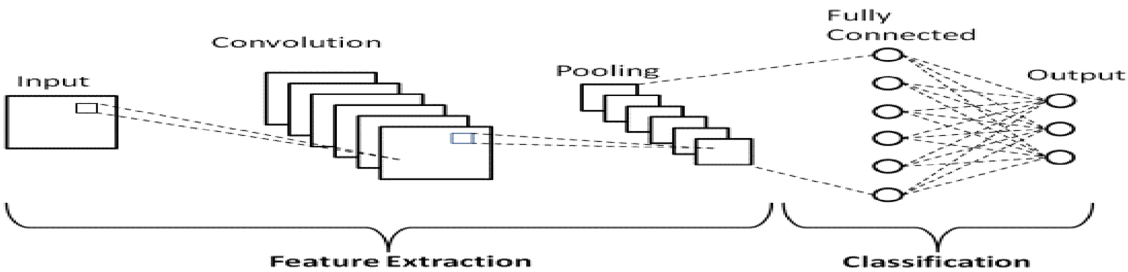
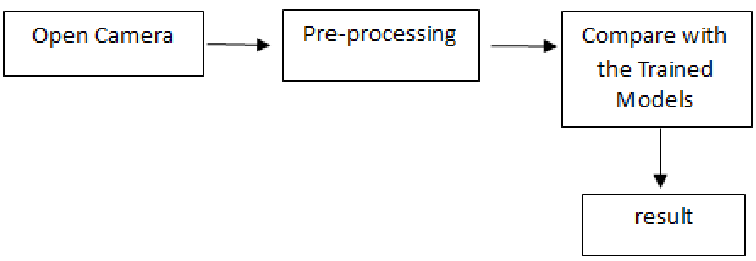


Fig: CNN Architecture

1. Residual Networks: is a deep learning Technology that revolutionized the Machine Learning by introducing residual connections.
2. DenseNet: Train the densely-connected- convolutional-network that connects each layer to every other layer in a feed-forward manner. Use training data to adjust model weights, optimizing for accuracy in osteoarthritis detection.
3. SSD**:** Detects objects in images by generating a fixed set of bounding boxes and scores for the presence of object class instances in those boxes, followed by a non-maximum suppression step to produce the final detections.

Model Generation

- Save Trained Models: Save the trained models to files for use in the detection phase. Each model (ResNet, SSD, DenseNet) will generate a separate model file.



1. Open Camera: Obtain the Video Analysis.
2. Preprocessing: Normalize the test image. Resize the image to match the input dimensions required by the models.

3. Comparison with Model: Load the trained model file (ResNet, SSD, or DenseNet). Feed the pre-processed Video into the model. Perform inference to obtain the prediction result.
4. Result Generation: Interpret the model's output to determine Guitar Chords Recognition . Present the result, indicating whether Chords is detected and its severity level.

IV. RESULTS

Pre-Trained Dataset:

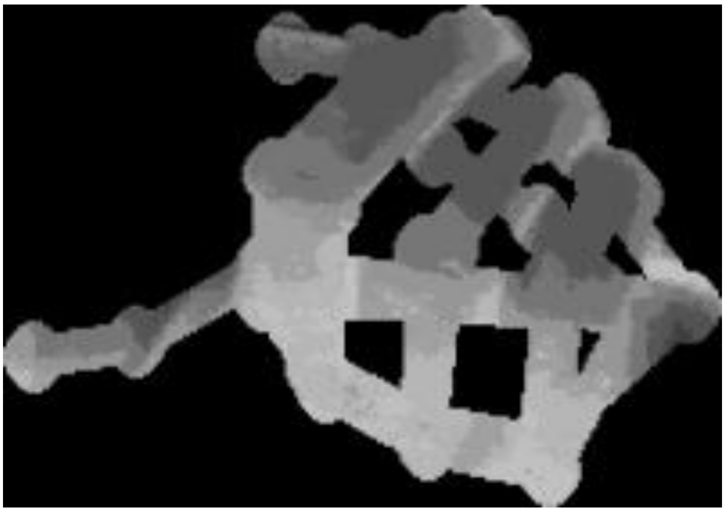


Fig: A Chord Recognition

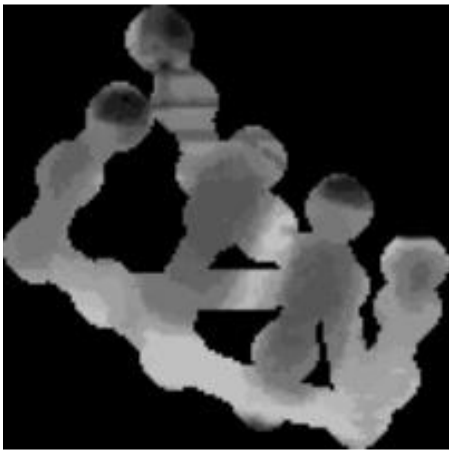


Fig: A Major Chord

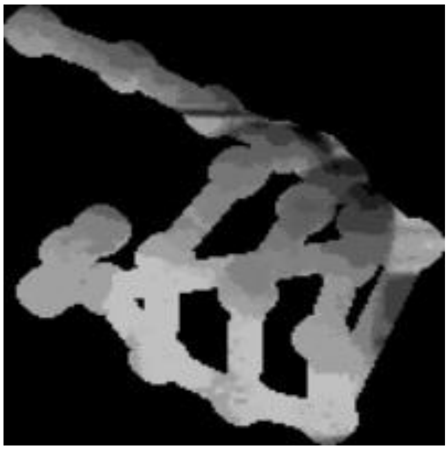


Fig: E Chord

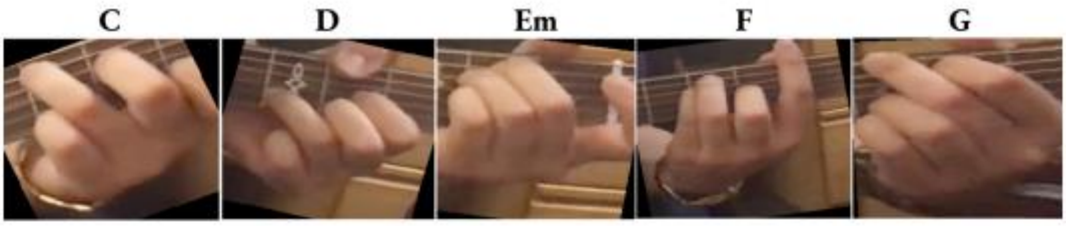


Fig: Post-Trained Output

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:06/Issue:07/July-2024 Impact Factor- 7.868 www.irjmets.com

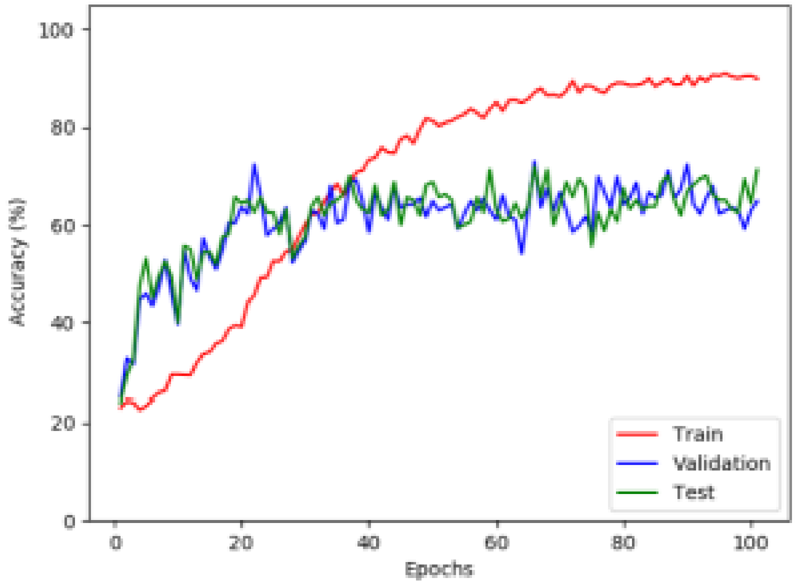


Fig: Accuracy Graph

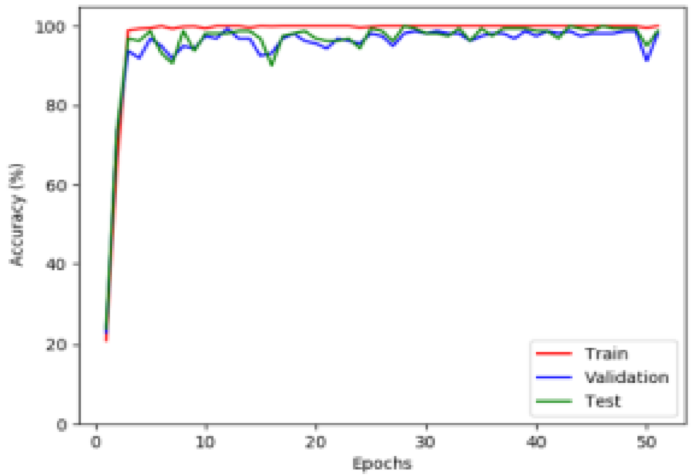


Fig: Loss Graph

V. CONCLUSION

Real-time guitar chord recognition using video is not just a technological marvel but a practical tool with enormous potential. Whether you're a beginner looking for a more engaging way to learn, a performer wanting to enhance your live shows, or a developer creating the next big interactive music app, this technology opens up new possibilities. As it continues to advance, we can look forward to even more innovative and accessible tools for guitarists of all skill levels.

VI. FUTURE ENHANCEMENT

The future of real-time guitar chord recognition using video looks incredibly promising and exciting. We'll see major improvements in accuracy and reliability thanks to advances in computer vision and machine learning. Imagine putting on augmented reality (AR) glasses and seeing chord diagrams overlaid directly on your guitar, guiding you as you play. The technology won't just stop at guitars—it'll recognize chords on other string instruments too. Audio and video data will work together seamlessly to ensure you get precise feedback every time you play. AI will personalize the experience, adapting to your unique style and offering customized tips and practice routines. You'll also be able to jam with friends remotely, share your progress on social media, and learn from interactive lessons built right into the system. Plus, user interfaces will be so intuitive that you can control everything with simple voice commands or gestures. This blend of innovation will make learning and playing music more engaging and accessible than ever before.

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:06/Issue:07/July-2024 Impact Factor- 7.868 www.irjmets.com

VII. REFERENCES

[1] J. Pauwels, K. O'Hanlon, E. G´omez, and M. B. Sandler, "20 Years of Automatic Chord Recognition From Audio," Proceedings of the 20th International Society for Music Information Retrieval Conference, ISMIR 2019, pp. 54–63, 2019.

[2] T. Fujishima, "Real-time Chord Recognition of Musical Sound: A System Using Common Lisp Music," ICMC Proceedings, vol. 9, no. 6. pp. 464–467, 1999.

[3] A. Sheh and D. P. W. Ellis, "Chord segmentation and recognition using EM-trained hidden Markov models," Proc. ISMIR, pp. 185–191, 2003.

[4] A. M. Stark and M. D. Plumbley, "Real-time chord recognition for live performance," Proceedings of the 2009 International Computer Music Conference, ICMC 2009, no. ICMC, pp. 85–88, 2009.

[5] F. Korzeniowski and G. Widmer, "Feature learning for chord recognition: The deep chroma extractor," Proceedings of the 17th International Society for Music Information Retrieval Conference, ISMIR 2016, pp. 37–43, 2016.

[6] N. Boulanger-Lewandowski, Y. Bengio, and P. Vincent, "Audio chord recognition with recurrent neural networks," Proceedings of the 14th International Society for Music Information Retrieval Conference, ISMIR 2013, pp. 335–340, 2013.

[7] Y. Han, J. Kim, and K. Lee, "DCNN for Predominant Guitar Instrument Recognition in Polyphonic Music," vol. 25, no. 1, pp. 208–221, 2017.

[8] G. Byambatsogt, L. Choimaa, and G. Koutaki, "Guitar chord sensing and recognition using multi-task learning and physical data augmentation with robotics," Sensors (Switzerland), vol. 20, no. 21, pp. 1–17, 2020.

[9] L. Nanni, A. Rigo, A. Lumini, and S. Brahnam, "Spectrogram classification using dissimilarity space," Applied Sciences (Switzerland), vol. 10, no. 12, pp. 1–17, 2020.

[10] A. Ghriss, "Deep Automatic Chord Recognition," pp. 1–10, 2017.

[11] J. Witte, "AI-technology behind the chords of Chordify – our algorithm explained," Chordify News, 2021.

[12] O. Russakovsky et al., "ImageNet Large Scale Visual Recognition Challenge," Int J Comput Vis, vol. 115, no. 3, pp. 211–252, 2015.

[13] M. Bajammal, A. Stocco, D. Mazinanian, and A. Mesbah, "A Survey on the Use of Computer Vision to Improve Software Engineering Tasks," IEEE Transactions on Software Engineering, no. October 2020.

[14] A.-M. Burns, "Computer Vision Methods for Guitarist Left-Hand Fingering Recognition," 2007.

[15] C. Kerdvibulvech and H. Saito, "Vision-based guitarist fingering tracking using a Bayesian classifier and particle filters," Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 4872 LNCS, pp. 625–638, 2007.

[16] J. Scarr and R. Green, "Retrieval of guitarist fingering information using computer vision," International Conference Image and Vision Computing New Zealand, pp. 0–6, 2010.

[17] Z. Wang and J. Ohya, "Tracking the guitarist's fingers as well as recognizing pressed chords from a video sequence," I.S. and T International Symposium on Electronic Imaging Science and Technology, pp. 1–6, 2016.

[18] M. H. Purnomo, Y. Kristian, E. Setyati, U. Delfana Rosiani, and E. I. Setiawan, "Limitless possibilities of pervasive biomedical engineering: Directing the implementation of affective computing on automatic health monitoring system," in Proceedings of 2016 8th International Conference on Information Technology and Electrical Engineering: Empowering Technology for Better Future, ICITEE 2016, 2017.