



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 4, April 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

ijrset@gmail.com

www.ijrset.com

Implementation of Educational Learning-Based Sign Language System Using Machine Learning

Vijay. V. Chakole, Akansha Kadu, Kshitij Meshram, Trishala Mendhe

Students, Department of Electronics & Telecommunication Engineering, KDK college of Engineering, Nandanvan
Nagpur, Maharashtra, India

ABSTRACT: This research proposes an innovative strategy for multicultural education by merging Indian Sign Language (ISL) and American Sign Language (ASL) utilizing Machine Learning (ML) techniques. Through the acquisition and preprocessing of high-quality video data showcasing ISL and ASL, the objective is to develop ML models capable of recognizing and producing signs in both languages. The approach involves bidirectional transfer learning and cross-language representation learning to enhance the learning process and address common obstacles in sign language acquisition. Additionally, personalized learning environments and culturally sensitive design, developed in collaboration with Deaf communities in India and America, aim to ensure inclusivity and accuracy. Evaluation metrics and ethical considerations are integrated into the developmental stages to encourage responsible implementation and continuous enhancement. Ultimately, this initiative aims to establish a foundation for advancing multilingual sign language education on a global scale.

I. INTRODUCTION

In the realm of inclusive education and communication accessibility, a groundbreaking fusion between sign language and advanced technological innovation has emerged—educational learning based on sign language utilizing Machine Learning (ML). This innovative approach harnesses artificial intelligence to revolutionize how we teach, learn, and interact with this unique visual-spatial language. Sign languages, evolving as natural human languages among deaf communities worldwide, convey meaning through intricate hand shapes, body movements, facial expressions, and non-manual signals. Despite their significance as primary modes of communication for millions, traditional methods of teaching sign language often struggle with scalability, consistency, and individualized instruction.

Enter Machine Learning, offering promising solutions by enabling personalized, adaptive, and interactive learning experiences tailored to each learner's needs and abilities. Leveraging ML algorithms, educators can develop intelligent tools and resources that enhance the learning process, making it more engaging, effective, and accessible to students from diverse backgrounds. This convergence of sign language culture with cutting-edge technology not only addresses existing challenges but also paves the way for new possibilities in education, research, and social inclusion.

While research on sign language recognition has predominantly focused on American Sign Language (ASL), there remains a gap in exploring other sign languages, such as Indian Sign Language (ISL). Unlike ASL, ISL presents complexities with signs performed using one or both hands. To bridge this gap, efforts are underway to develop a combined ASL and ISL recognition system. This system holds promise for educational institutes, offering a unified platform for learning both languages and facilitating inclusive education.

II. PROPOSED SYSTEM

Our proposed system leverages machine learning to develop an educational platform for sign language. Through advanced algorithms, we aim to proficiently recognize and generate signs, benefiting both educators and learners. Prioritizing inclusivity and accuracy, we offer personalized environments and cultural sensitivity. Collaboration with Deaf communities enhances the effectiveness of our system in sign language acquisition. Additionally, incorporating evaluation metrics and ethical considerations ensures responsible implementation and continual improvement. Ultimately, our system aims to revolutionize global sign language education.

2.1 Datasets

Creating a sign language recognition dataset involves gathering video recordings of sign language gestures performed by individuals from diverse backgrounds. Each gesture should be clearly captured from multiple angles and under various lighting conditions to ensure robustness. The dataset should also include annotations specifying the corresponding sign language phrase or word for each gesture. Examples include the American Sign Language and Indian Sign Language datasets as illustrated in Figure 2.1.



Fig 2.1 Sign language datasets.

2.2 Existing System

The existing system addresses the fundamental aspects of Sign Language Recognition, starting with a brief introduction to motivation and requirements. This is followed by an overview of sign linguistics and its impact on the field. The types of available data and their relative merits are explored, enabling the examination of extractable features.

Drawbacks:

- Sign language relies on hand gestures, posing challenges for individuals with limited hand mobility due to conditions such as Parkinson's or arthritis.
- ASL has its own distinct grammar and syntax, presenting a learning curve for new users.
- Learning enough signs for basic communication can be time-consuming, taking a year or more.
- Deaf individuals face barriers in accessing health information and services, including interpersonal, cultural, language, and communication barriers.

2.3 Proposed System and Advantages

In our sign language recognition project, we introduce a robust sign detector capable of identifying alphabets from A to Z, with the potential for extension to encompass a wide range of additional signs and hand gestures. By dynamically adjusting the image size based on precise calculations of height and width, we facilitate seamless overlaying and resizing of images or shapes, optimizing the recognition process.

III. ADVANTAGES

- Our proposed system incorporates prediction and testing mechanisms prior to execution, resulting in a significantly high accuracy rate of 95 to 98%. This ensures a robust combat between the executed output and the desired outcome.
- By eliminating the need for bounding boxes and instead executing the predicted value or alphabet within a rectangle, our system achieves more precise execution compared to existing methods.
- We have streamlined the process by simplifying the definition of web camera parameters, hand detection, and gesture verification models. Additionally, employing mathematical calculations like "math.ceil" enhances image capturing accuracy by precisely defining the height and width of hand gestures.

IV. ARCHITECTURE

Efforts are underway to develop sign language recognition systems aimed at facilitating communication between signers and non-signers. One current focus area involves optimizing sign recognition within limited computational resources. To characterize how signs manifest within the signer's space, researchers utilize the five parameters of **sign language**: handshape, palm orientation, movement, place, and non-manual or expressive cues. Research indicates that sign language plays a vital role in enabling young children to express themselves before they can speak. It reduces their frustration levels, strengthens parent-child bonds, and empowers infants to convey essential information such as hunger or discomfort effectively. This highlights the effective utilization of sign language in various contexts.

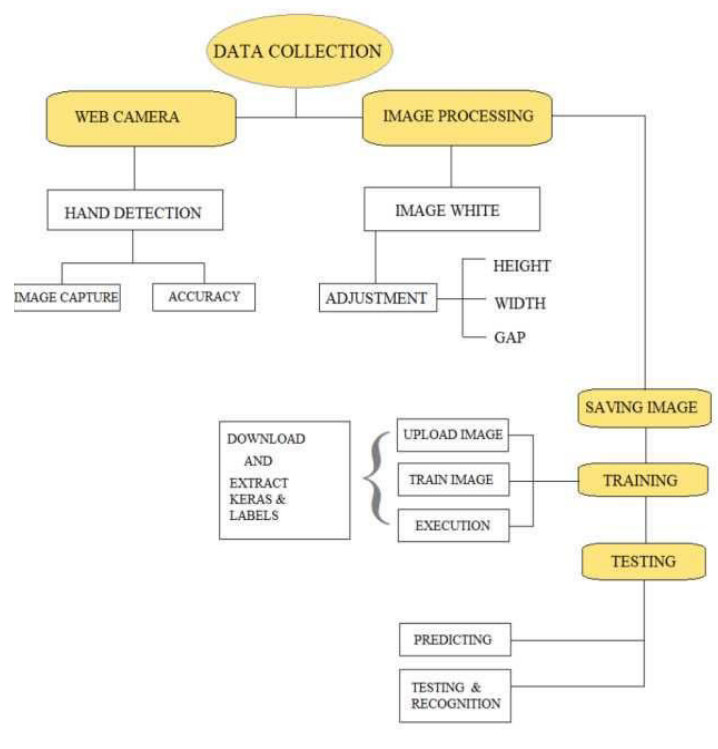


Fig 4.1 System architecture of sign language recognition

System architecture of sign language recognition is as represented in the above fig 4.1 and can be explained in various sections below.

Data Collection

Data collection methods can be categorized into four main types: observational, experimental, situational, and derived. Each method employs specific techniques to gather data, contributing to the overall understanding of a particular phenomenon or research question.

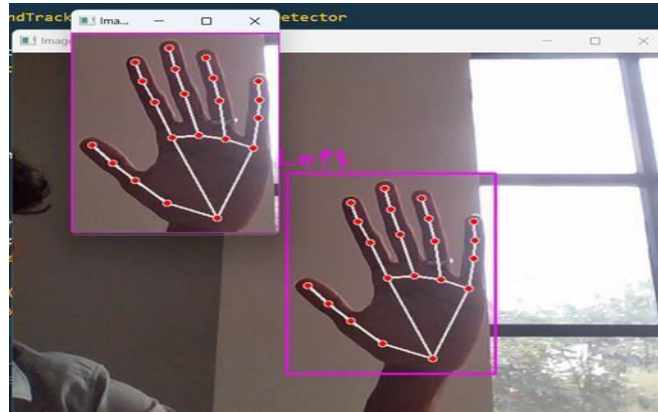


Fig 4.2 Data collection of hand gesture

Integration of Webcam

A webcam, designed to transmit or record video footage to a computer or network, plays a crucial role in various applications, particularly in gesture recognition systems. Web cameras facilitate accurate hand detection, ensuring precise capture of hand gestures. Additionally, they enable the calculation of parameters such as the number of hands present in the frame, providing information on both the maximum and minimum hands detected. Webcam integration also involves processes like hand tracking, enhancing the overall functionality and usability of gesture recognition systems.

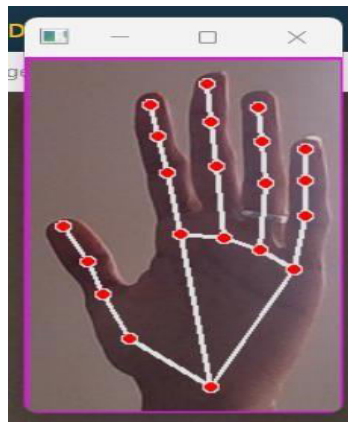


Fig 4.3 Web Cam

Image Processing

After capturing the image, the next step involves creating a white background image where the detected hand gesture will be displayed. This white image must adhere to specific specifications, including an image size of 300 pixels and an offset of 20 pixels. Additionally, it requires a bounding box ("bbox") to ensure precision and adjustability of the gesture, along with a wait key assigned to a specified time limit. The image processing algorithm centers the image and utilizes mathematical functions like "math.ceil" to calculate parameters. A constant "K" is defined to facilitate adjustments, while the image size is dynamically adjusted based on the height and width of the captured hand gesture. This enables seamless image overlaying and resizing, ensuring accurate representation of the detected gesture.

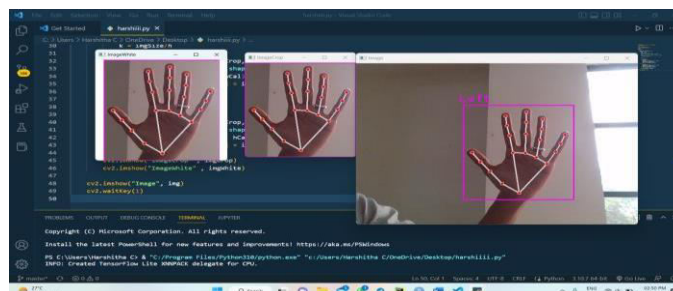


Fig 4.4 Image processing

Saving Image

To save the dataset for hand movement estimation, the process involves specifying the folder path as "Data/relevant name of the file" and setting the counter to 0. When encountering the condition "if key==ord('s')", indicating the user's input to save the image or gesture, the collected data will be stored in the designated folder.

Training

The training process in sign language architecture involves three key classifications: uploading, training, and exporting photographs. Initially, a new project is created in the Teachable Machine platform, requiring the upload of all saved folders containing image gestures. These files or folders are then added to the basic training platform. Subsequently, the image gesture folders are categorized, and the training model is selected in the training area for execution. Training is a critical phase in sign language architecture, as testing cannot be conducted until after completion. Finally, in the export model area, the Keras and label models prompt selection of TensorFlow, enabling the downloading of Keras and models from the Teachable Machine platform.

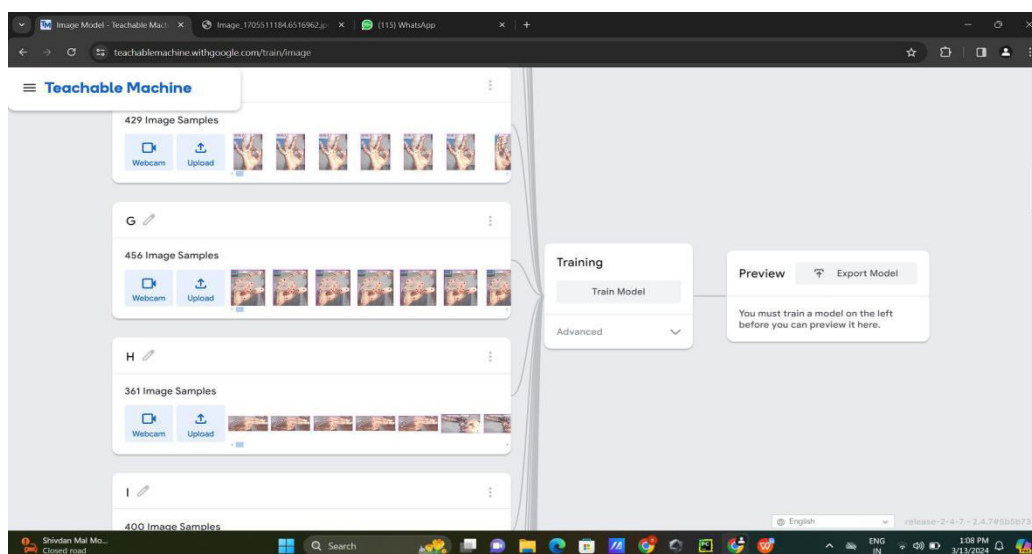


Fig 4.5 Training using Google Machine

The application attempts to categorize and predict the image based on the trained model from the previous training section. By replicating the previous data collection process and omitting the key input, this segment plays a crucial role in executing the detected picture and making predictions. It involves analyzing the image's features confidentially and predicting its value, ultimately detailing the testing and outcome prediction in sign language recognition.

V. RESULT

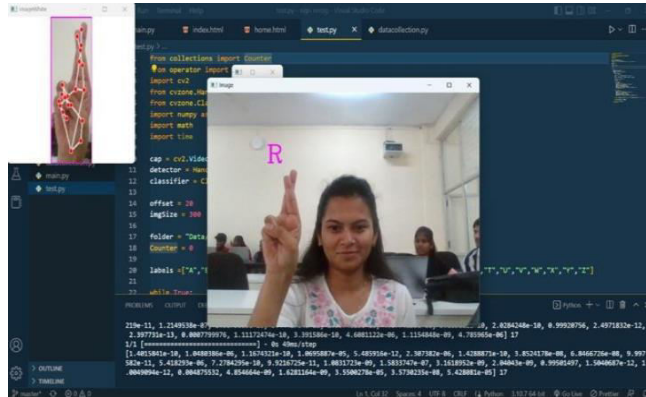


Fig 5.1 Screenshot of predicted alphabet R

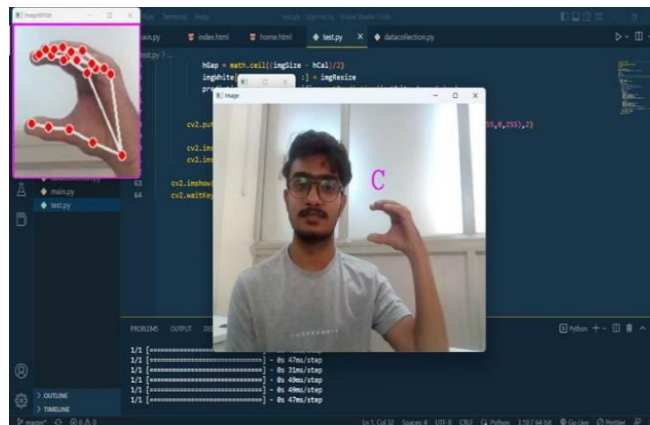


Fig.5.2 Screenshot of predicted alphabet C

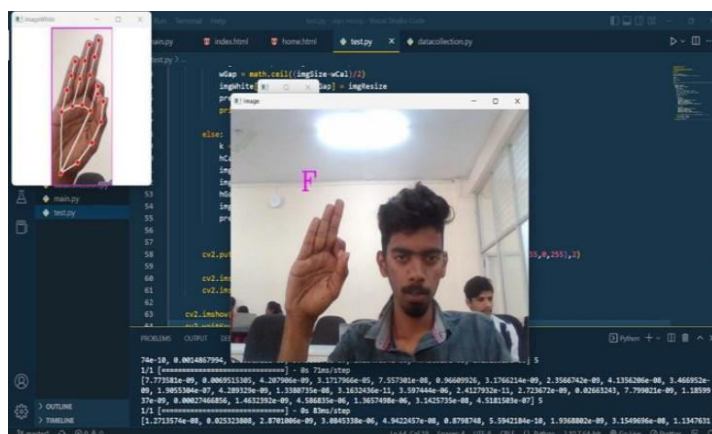


Fig.5.3 Screenshot of predicted alphabet F

The technology developed has the capability to instantly detect Indian Sign Language alphabets. The system was built using TensorFlow's object detection API, employing the pre-trained model SSD MobileNet v2 320x320 obtained from the TensorFlow model repository. For training the algorithm, transfer learning was utilized on a constructed dataset comprising a total of 3173 photos, with each alphabet represented by 100–150 images.



During training, the system's output is determined by the confidence rate, with an average confidence level of 85.45%. This confidence rating is crucial and is summarized in the results for each letter, providing insights into the system's performance. Additionally, the statement emphasizes the potential for enhancing recognition by expanding the dataset, which would consequently elevate the system's confidence level. This suggests a pathway for further improving the accuracy and reliability of the sign language recognition system.

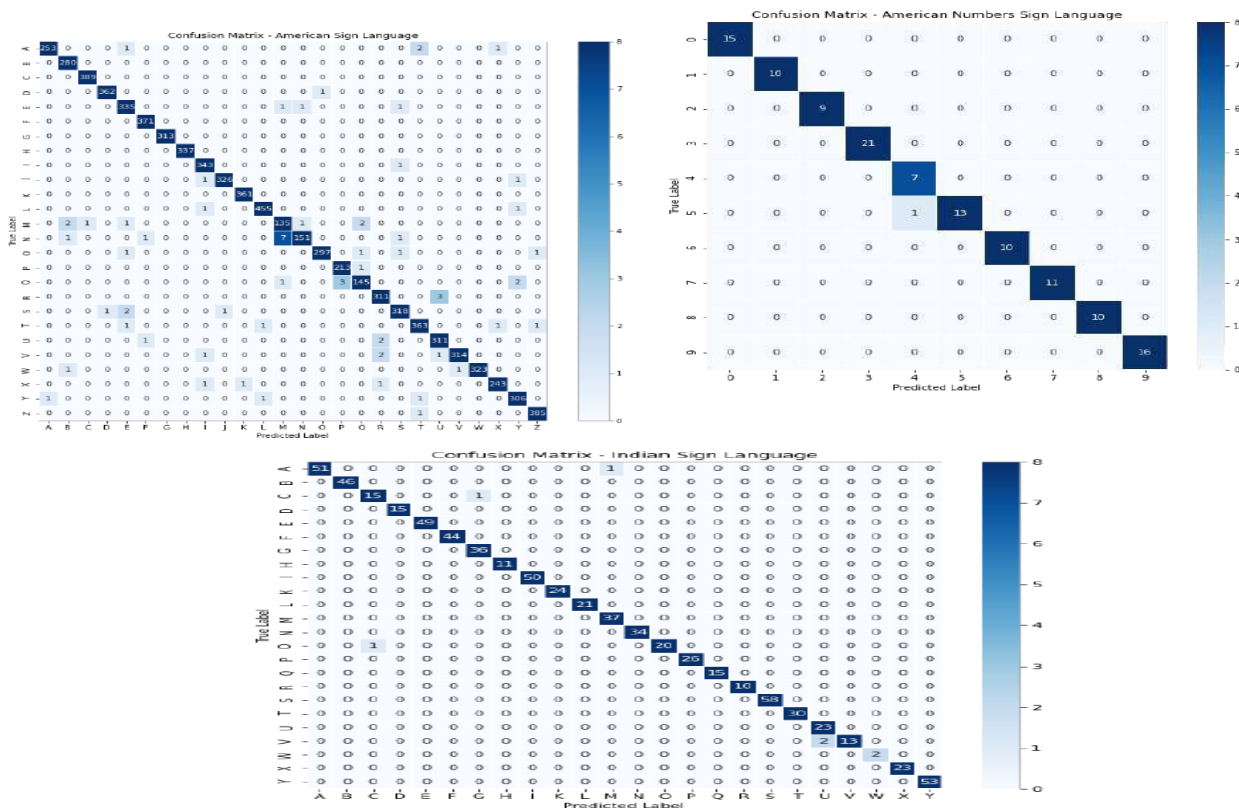


Figure 5.4 Confusion matrix a) American Sign Language (alphabets), b) American Sign Language (numbers), c) Indian Sign Language (alphabets),

A	B	C	D	E	F	G	H	I
94	98	90	90	70	70	73	97	95
J	K	L	M	N	O	P	Q	R
77	87	93	91	55	78	95	95	83
S	T	U	V	W	X	Y	Z	
86	81	87	86	88	90	80	77	

Table. 1 Confidence rate of each alphabet

The system was trained using the alphabet dataset for Indian Sign Language, as referenced in [2]. Leveraging this dataset, the technology exhibits the ability to promptly recognize sign language gestures. Notably, the system's effectiveness is demonstrated through the prediction of various alphabet gestures, including R (fig 5.1), C (fig 5.2), and F (fig 5.3).

VI. CONCLUSIONS AND FUTURE ENHANCEMENT

To acquire data, Python and OpenCV were employed to capture images from a camera, offering a cost-effective solution for data acquisition. Despite achieving a high average confidence rate, it's worth noting that the training dataset utilized in the system is relatively small, thus presenting certain limitations. This acknowledgment highlights the potential for further improvements and optimizations, particularly through the expansion of the training dataset to enhance the system's performance and robustness in recognizing Indian Sign Language gestures.

The primary objective of a sign language detection system is to facilitate communication between deaf and hearing individuals through hand gestures. However, a limitation arises from the fact that not everyone is proficient in sign languages, which can hinder effective communication. To overcome this barrier, Automated Sign Language Recognition systems offer a solution by converting sign language motions into commonly spoken languages, thereby broadening communication possibilities.

The proposed approach can be seamlessly integrated with webcams or other built-in cameras capable of identifying and processing cues for recognition. Our model demonstrates that under controlled lighting conditions, the system yields accurate results. Moreover, the system's flexibility allows for easy addition of new movements and capturing of images from various perspectives.

To further enhance the accuracy of our current models, a more diverse and higher-quality dataset is essential. Additionally, incorporating deep learning techniques or employing more sophisticated models like artificial neural networks to analyze Histogram of Oriented Gradient (HOG) vectors could improve accuracy by extracting richer information.

In our experimentation with hierarchical classification, while increasing the levels of hierarchy may enhance accuracy, conclusive results are yet to be determined. Expanding the dataset would enable the system to recognize additional gestures. Furthermore, the TensorFlow model used in our system can be substituted with alternative models for further exploration and improvement. These avenues for enhancement underscore the ongoing evolution and potential of Automated Sign Language Recognition systems in advancing communication accessibility.

REFERENCES

- [1] Girish L, Harshitha V, J, N, Shreyash, Bhavana C, "Sign Language Recognition using Machine Learning", International Journal of Advanced Scientific Innovation, Volume 5, Issue 1, Feb 2023.
- [2] Prof. Kirti Randhe, Aayush Kapse, Kapil Mankoskar, Aditya Kadam, Prajwal Shankarshetty, "International Journal of Research Publication and reviews, Volume 4, ISSN 2582-7421, June 2023.
- [3] Sakshi Goyal, Ishita Sharma, S. S. Sign Language recognition system for deaf and dumb people. International Journal of engineering Research Technology, Issue 4, April 2013.
- Aashir Hafeez, Suryansh Singh, Ujjwal Singh, Priyanshu Agrawal, Anant Kumar Jayswal, "Sign Language Recognition using Deep-Learning for Deaf and Dumb", Volume 5, Issue 4, April 2023.
- [4] J. L. Raheja, A. Mishra, A. Chaudhary, "Indian Sign Language Recognition Using SVM ISSN 10546618, Volume 26, 2016.
- [5] Arpita Halder, Akshit Tayade, "Real-Time Vernacular Sign Language Recognition Using Mediapipe and Machine Learning" International Journal of Research Publication and Reviews Volume 2, Issue 5, 2021.
- [6] Sakher Ghanem, Christopher Conly, Vassilis Athitsos, "A Survey on Sign Language Recognition using Smartphones", PETRA '17, June 2017.
- [7] Madhuri Sharma, Ranjna pal, Ashok Kumar Sahoo, "Indian Sign Language Recognition Using Neural Networks and KNN Classifiers", ISSN 1819-6608, Volume 9, August 2014.
- [8] Atreya Bain, Shiwam Birajdar, Prof. Manonmani "Sign Language Recognition Using Machine Learning", International Research Journal of Engineering and Technology (IRJET), Volume 8, Issue 8, Aug 2021.



- [9] Prof. Radha S. Shirbhate, Mr. Vedant D. Shinde, Ms. Sanam A. Metkari, Ms. Pooja U.Borkar, Ms. Mayuri A. Khandge, "Sign Language Recognition Using Machine Learning Algorithm", International Research Journal of Engineering and Technology (IRJMET), Volume 7, Issue 3, Mar 2020
- [10] Almasre, Miada A., and Hana Al-Nuaim. "A Real-Time Letter Recognition Model for Arabic Sign Language Using Kinect and Leap Motion Controller v2." IJAEMS Open Access Int. J. Infogain Publ. 2.5 (2016).
- [11] Rumyantsev, Oleg, Matt Merati, and Vasant Ramachandran. "Hand sign recognition through palm gesture and movement." Image Processing (2012).
- [13] Marin, Giulio, Fabio Dominio, and Pietro Zanuttigh. "Hand gesture recognition with leap motion and kinect devices." Image Processing (ICIP), 2014 IEEE International Conference on. IEEE, 2014.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details