iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IV Month of publication: April 2026

DOI: https://doi.org/10.22214/ijraset.2026.79931

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

Hand Gesture Recognition for Sign Language Using ML

Arjun Vinod Shinde[1], Aditya Jajoo[2], Aditya Jha[3], Ayush Kumar Shrivastava[4], Yugal Kishor[5]
[1]*Assistant Professor in Computer Science and Engineering Department, Shri Shankaracharya Technical Campus, Bhilai, India*
[2,3,4,5]*UG – Computer Science and Engineering, Shri Shankaracharya Technical Campus, Bhilai, India*

Abstract: Sign language is a main mean of communication among the people who are hearing and speech impaired. In spite of its significance, there is communication void between users of sign language and the general population. The study is aimed at creating a solution, which will automatically identify the sign language gestures based on the artificial intelligence approach. The suggested system is based on the image processing and deep learning models to identify hand gestures and translate them into the readable text. MobileNetV2 is a pre-trained deep learning model that is used with Teachable Machine to enhance the accuracy and allow real-time gesture recognition. The system is designed to offer a convenient, effective and easily accessible communication solution.
Keywords: Sign Language Recognition, Deep Learning, CNN, MobileNetV2, Teachable Machine, Computer Vision, Gesture Recognition.

I. INTRODUCTION

Communication is a significant aspect of life. Deaf and mute people use sign language to convey their ideas and thoughts. Sign language is, however, unknown to most people thus posing a barrier to communication. Sign Language Recognition (SLR) systems are designed to bridge this divide and translate hand gestures into text or speech. It is now possible to create systems capable of identifying gestures with very high accuracy in real time with the development of artificial intelligence, and in particular, computer vision. This research aims to create an efficient and accurate machine learning-based system that can recognize and categorize sign language gestures.

II. LITERATURE REVIEW

Previous studies in sign language recognition primarily focused on rule-based systems and traditional machine learning techniques. These methods involved hand feature extraction hence less efficient and less precise. Recent advances have brought about deep learning algorithms, especially convolutional neural networks (CNNs), automatically identifying features in images. These models are very effective in enhancing recognition and minimizing human input.

Two systems: There are two systems:

Camera-based systems, which involve taking of gestures through the use of cameras.

Sensor-based systems that use wearable devices such as gloves

Despite the effectiveness of deep learning models, there are still problems like light variability, complicated backgrounds, and movement gestures.

III. METHODOLOGY

A. Data Collection

In this step, pictures of hand gestures that portray various signs including alphabets and numbers are gathered. All pictures are identified by their respective gestures.

It contains a total of 35 gesture classes (digits, 1-9, and alphabets, A-Z). Per class, there are about 500-600 pictures, which were gathered with the help of a webcam with Teachable Machine. The dataset has been diversified in terms of lighting conditions, backgrounds, and orientations of hands to enhance the generalization capacity of the model.

B. Data Preprocessing

Raw pictures are manipulated and are then utilized in the model:

Resizing: All pictures are resized to a standard size.

Normalization: The pixel values are normalized between 0 and 1.

Noise Removal: The background noise has been eliminated to concentrate on the hand gesture.

This measure guarantees regular and tidy data, enhancing the functionality of the models.

©IJRASET: All Rights are Reserved

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

C. Model Development

A Convolutional Neural Network (CNN) is used for gesture recognition. CNNs are effective in image processing tasks as they automatically detect important features such as edges, shapes, and patterns.

This study uses a pre-trained deep learning model, MobileNetV2, via Teachable Machine. MobileNetV2 is a lightweight network that is to be used in real-time applications.

Transfer learning is used to train the model where the initially trained model is fine-tuned with custom gesture data. This saves time on training and enhances accuracy.

D. Training and Testing

The data set is separated into training and testing sets.

Training Set: This is used to train the model.

Testing Set: This is used to test performance.

The model parameters are adjusted during the training process to reduce errors. This model is trained with the help of transfer learning on MobileNetV2, and Teachable Machine automatically splits the dataset.

E. Prediction

After the training, the model is applicable in real time.

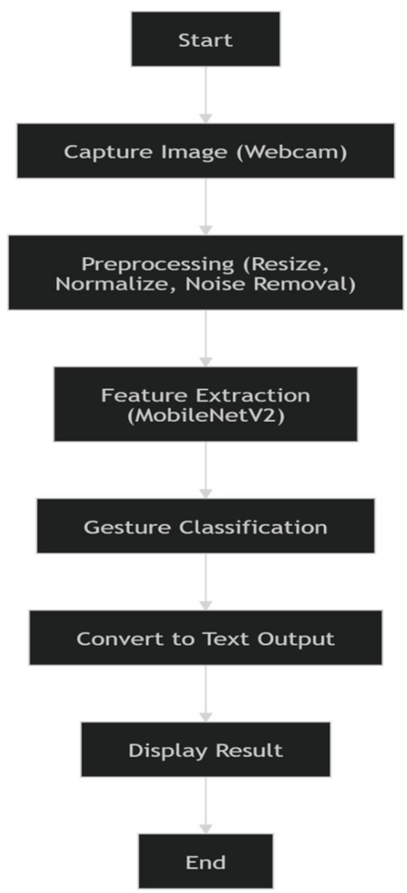
An image is captured in the system.

The image is preprocessed

The gesture is predicted by the model.

The gesture predicted is then translated to readable text.

F. Flow Diagram of Proposed System



©IJRASET: All Rights are Reserved | SJ Impact Factor 7.538 | ISRA Journal Impact Factor 7.894 |

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

IV. SYSTEM ARCHITECTURE

The system records hand gestures with the help of a webcam. The acquired image undergoes preprocessing to eliminate noises and normalize input size. The image is processed by a CNN model (MobileNetV2) to extract features and classify the features according to a set of categories of gestures. The resultant output is shown on the screen in the form of text.

V. RESULTS AND DISCUSSION

The system was very accurate when it detected the hand gestures at rest. The model was trained using about 17,500-21,000 images of 35 classes.

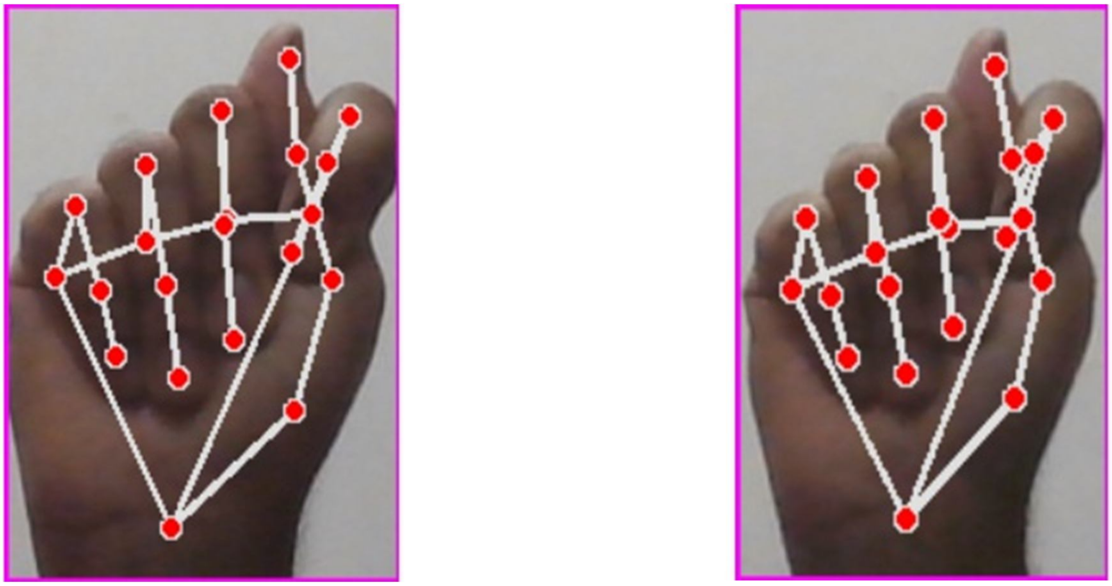


Figure .5.1and 5.2 taking input

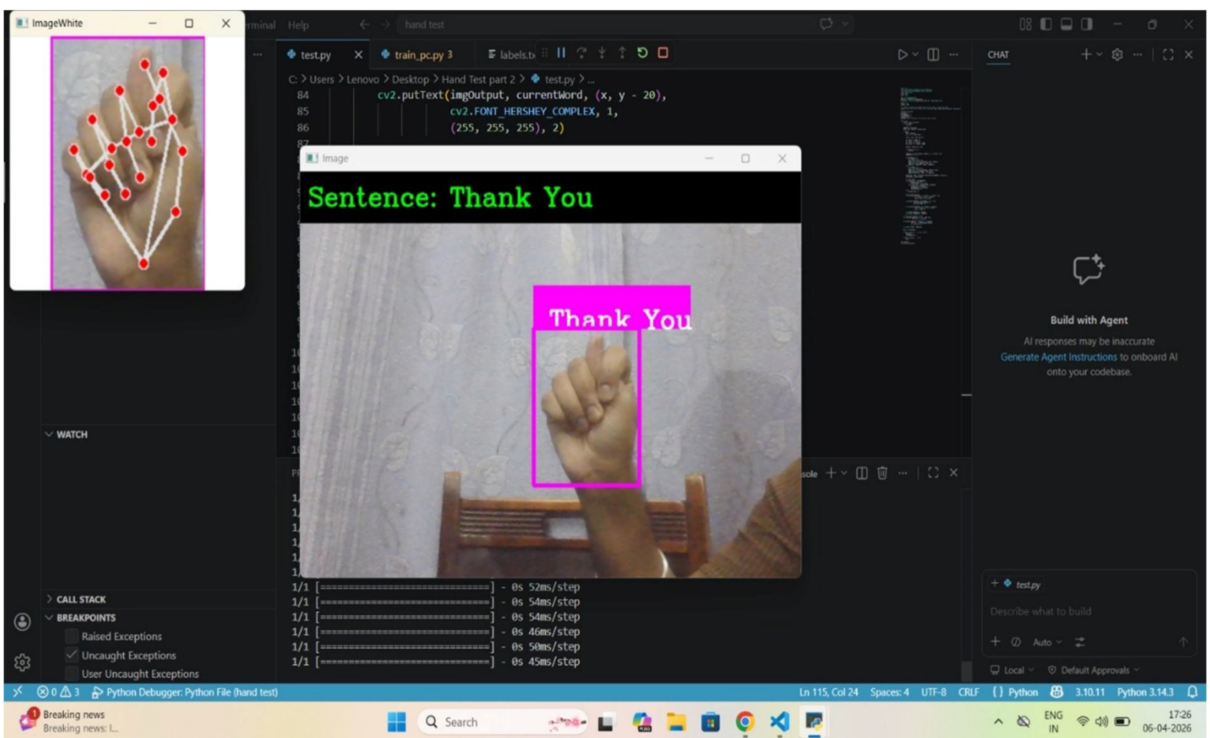


Figure.5.3 checking the image with dataset and giving input

The system with an accuracy of about 90-95 is an indication that MobileNetV2 is effective in extracting and classifying features.
But certain limitations were noted:
Problem with the recognition of dynamic gestures.
Light sensitivity and background sensitivity.
Mandatory a huge amount of data.
Evaluation Metrics
The model performance is measured with:
Accuracy
Loss
Confusion Matrix

VI. APPLICATIONS

Human-computer Interaction: Instead of using a keyboard or mouse, these systems let people use hand gestures to talk to computers. For instance, a person can tell the computer what to do by making gestures, and the computer will understand and do what the person wants. This makes technology easier to use and more natural, especially for people with disabilities.
Educational Tools: You can use sign language recognition in learning apps to help students learn sign language. It can give feedback in real time, which can help learners figure out if they are making the right gestures. It helps both deaf students and people who want to learn how to sign.
Smart assistive Devices: You can use this technology in smart devices like smart glasses, mobile apps, and wearable gadgets. These gadgets can instantly turn gestures into speech or text, making it easier for people to talk to each other anytime and anywhere. It makes life better and gives people with hearing or speech problems more freedom.

VII. IMPLEMENTATION DETAILS

Tool: Teachable Machine.
Model: MobileNetV2
Input Device: Webcam
Output: Text
Platform: Web-based

VIII. LIMITATIONS

Trouble with dynamic gesture recognition.
Sensitivity to environmental conditions
Reliance on the size of datasets.

IX. FUTURE SCOPE

It can also be improved in the future with real-time sentence recognition, integration of mobile applications, multi-language support and the use of better models like transformers.
Contribution
This work introduces an easy to use, effective and inexpensive sign language recognition system based on transfer learning so that it can be applied in real-time and in low-resource settings.

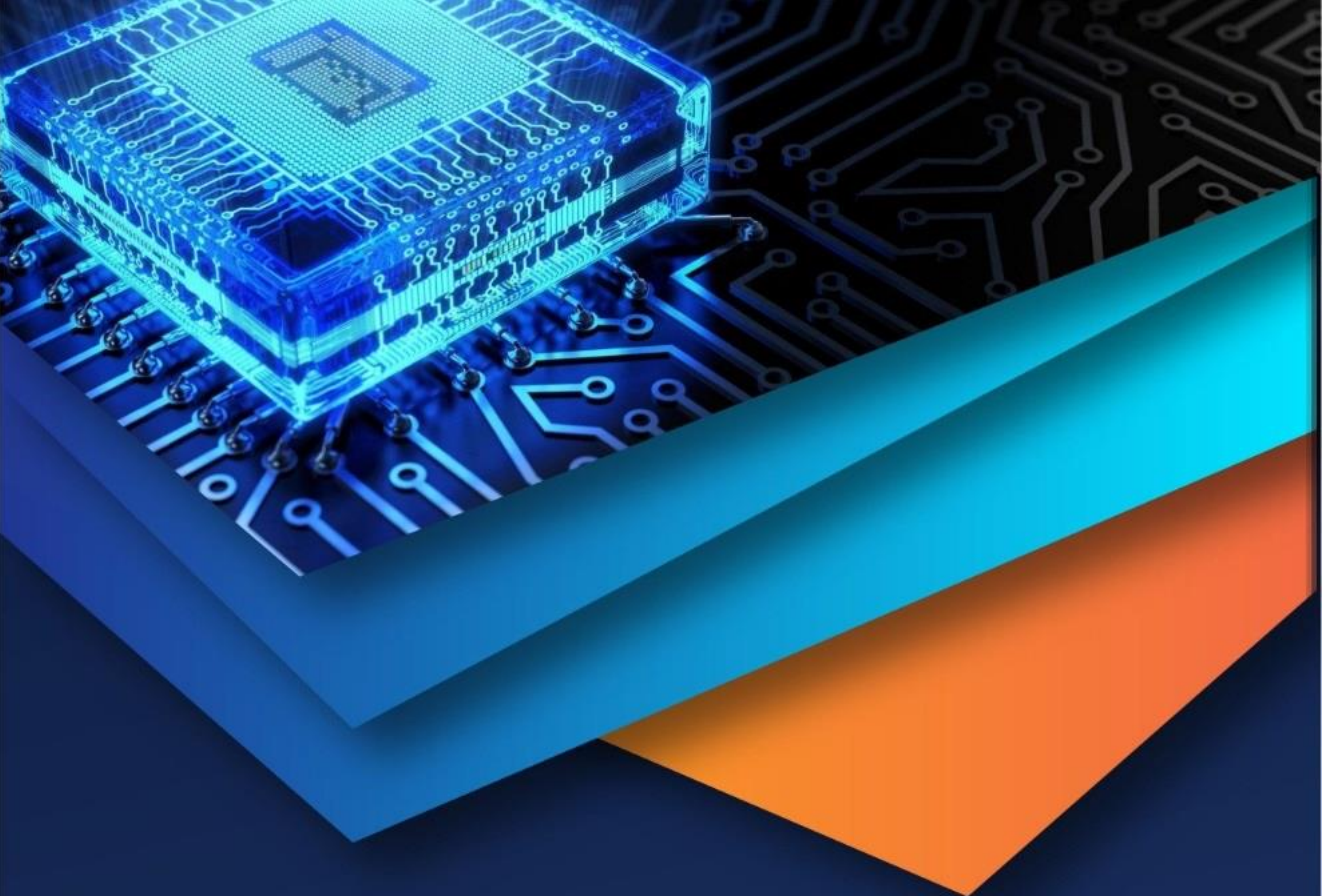
X. CONCLUSION

Sign Language Recognition systems are a great way of enhancing communication among the hearing and speech impaired individuals. Gesture recognition can be accomplished with high accuracy and in real-time because of the incorporation of deep learning techniques.
Teachable machine + MobileNetV2 is a practical and efficient solution to gesture recognition systems.

REFERENCES

[1] arons, D. (1994). Aspects of the Syntax of American Sign Language. PhD dissertation, Boston University.Google Scholar
[2] Aarons, D., Bahan, B., Kegl, J. & Neidle, C. (1992). Clausal structure and a tier for grammatical marking in American Sign Language. Nordic Journal of Linguistics, 15, 103–142.CrossRefGoogle Scholar

[3] Aarons, D., Bahan, B., Kegl, J. & Neidle, C. (1995). Lexical tense markers in American Sign Language. In Emmorey, K. & Reilly, J. S. (eds.), Language, Gesture and Space (pp. 225–253). Hillsdale, NJ: Lawrence Erlbaum Associates.Google Scholar
[4] Abdel-Fattah, M. (2005). Arabic Sign Language: A perspective. Journal of Deaf Studies and Deaf Education, 10, 212–221.CrossRefGoogle ScholarPubMed
[5] Abercrombie, D. (1967). Elements of General Phonetics. Edinburgh: Edinburgh University Press.Google Scholar
[6] Aboh, E. O., Pfau, R. & Zeshan, U. (2005). When a wh-word is not a wh-word: The case of Indian Sign Language. In Bhattacharya, T. (ed.), The Yearbook of South Asian Languages and Linguistics 2005 (pp. 11–43). Berlin: Mouton de Gruyter.Google Scholar
[7] Adams, M. (2003). Historia de la Educación de los Sordos en México y Lenguaje por Señas Mexicano. Spring Valley, CA: Fundación de Sordos Hispanos de San Diego.Google Scholar
[8] Aitchison, J. (1991). Language Change: Progress or Decay? Cambridge: Cambridge Unversity Press.Google Scholar
[9] Ajavon, P. A. (2003). The Incorporation of Nigerian Signs in Deaf Education in Nigeria: A Pilot Study. Frankfurt am Main. Brussels: Peter Lang.Google Scholar
[10] Ajello, R., Mazzoni, L. & Nicolai, F. (2001). Linguistic gestures: Mouthing in Italian Sign Language (LIS). In Braem, P. Boyes & Sutton-Spence, R. (eds.), The Hands Are the Head of the Mouth: The Mouth as an Articulator in Sign Languages (pp. 231–246). Hamburg: Signum.Google Scholar
[11] Akach, A. O. (1993). Squibbles barriers. Sign Post, 6(1), 2–4.Google Scholar
[12] Aldersson, R. & McEntee-Atalinanis, L. J. (2007). A lexical comparison of Icelandic and Danish Sign Language. Birkbeck Studies in Applied Linguistics, 2, 41–67.Google Scholar
[13] Aldrete, G. S. (1999). Gestures and Acclamations in Ancient Rome (Ancient Society and History). Baltimore, MD/London: Johns Hopkins University Press.Google Scholar
[14] Allen, G. D., Wilbur, R. B. & Schick, B. S. (1991). Aspects of rhythm in ASL. Sign Language Studies, 72, 297–320.CrossRefGoogle Scholar
[15] Allott, R. (2000). Brain, Lexicon, Syntax. Rutgers, NJ: Language Origins Society.Google Scholar
[16] ,American School for the Deaf (1818). Second Report of the Directors of the Connecticut Asylum for the Education and Instruction of Deaf and Dumb Persons. 5. Hartford: American School for the Deaf.Google Scholar
[17] Anderson, J. M. (1971). The Grammar of Case: Towards a Localist Theory. London: Cambridge University Press.Google Scholar
[18] Ann, J. (1993). A linguistic investigation of the relationship between physiology and handshape. PhD dissertation. University of Arizona, Tucson.
[19] Ann, J. (1998). Contact between a sign language and a written language: Character signs in Taiwan Sign Langauge. In Lucas, C. (ed.), Pinky Extension and Eye Gaze: Language Use in Deaf Communities (pp. 59–99). Washington, DC: Gallaudet University Press.Google Scholar
[20] Ann, J. (2006). Frequency of Occurrence and Ease of Articulation of Sign Language Handshapes: The Taiwanese example. Washington, DC: Gallaudet University Press.Google Scholar
[21] Aramburo, A. (1989). Sociolinguistic aspects of the Black Deaf community. In Lucas, C. (ed.), The Sociolinguistics of the Deaf Community (pp. 103–119). San Diego, CA: Academic Press.CrossRefGoogle Scholar



doi crossref

10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

ISI

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)