

Python-Based Real-Time Sign Language Interpreter Using Computer Vision and Machine Learning

Haritha A¹, Nithisha K², Thulasi R³

¹Assistant Professor, Dept. of CSE, St. Peter's College of Engineering and Technology., Avadi, Chennai, India.

^{2,3}UG Scholar, Dept. of CSE, St. Peter's College of Engineering and Technology., Avadi, Chennai, India.

Emails: haritha@spcet.ac.com¹, nithishak251@gmail.com², ravithulasi47@gmail.com³

Abstract

Humans communicate with one another using body language (gestures), such as hand and head gestures, facial expressions, lip movements, and so forth, or through natural language channels like words and writing. Sign language comprehension is just as crucial as knowing normal language. The primary means of communication for those who are hard of hearing is sign language. Without a translation, speaking with other hearing people can be difficult for those with hearing impairments. Because of this, the social lives of deaf people would be greatly improved by the installation of a system that recognizes sign language. In order to recognize the features of the hand in pictures captured by a webcam, we have presented in this study a marker-free, visual American Sign Language recognition system that makes use of image processing, computer vision, and neural network techniques. This paper deals with full phrase gestures that are used regularly every day and methods used to convert them to text. A number of image processing techniques have been used to identify the hand shape from continuous pictures. The Haar Cascade Classifier is used to determine the interpretation of signs and their associated meaning.

Keywords: Gesture, Haar Cascade, Classifier

1. Introduction

used in place of speech communication and involves body parts, hand shapes, hand positions and motions, arm positions and movements, facial expressions, and lip movements. When communicating, most individuals utilize both words and signs. A sign language is one that communicates through actions or signals rather than sounds. A sign language consists of two main parts, as stated in the definition above [1]. The first crucial element is finger-spelling, which indicates that there is a sign for every letter in the alphabet. Spelling names is the primary application of this kind of communication, while location names are occasionally spelled as well. This can occasionally be used to emphasize or explain a specific phrase or to indicate terms for which there are no indications [2]. Word level sign vocabulary, which indicates that there is a sign in sign language for every word in the vocabulary, is the second essential element of any sign language. When combined with facial expressions, this kind of communication is the most widely used form

between individuals with hearing impairments [3]. In this work we are using American sign language. American Sign Language (ASL) is a visual language used primarily by the Deaf and hard-of-hearing communities in the United States and parts of Canada. It is expressed through a system of hand signs that represent words, letters, and concepts. ASL has its own unique grammar and structure, distinct from English, and often follows a "topic-comment" order. It originated from French Sign Language (LSF) and was influenced by various home sign systems. The language includes fingerspelling, where individual hand signs represent letters to spell out words. ASL is more than just a method of communication; it plays a vital role in Deaf culture, fostering a strong sense of identity and community [4]. Applications like hardware-free remote controls, virtual reality human-computer interaction, gaming, and other human welfare applications can be developed using sign language recognition interfaces, which can also serve as a natural

communication channel between humans and machines [4-5].

1.1.Methods of Sign Language

- **Recording Hand Motions:** In order to ensure high-resolution input for precise recognition, the system records hand motions using either pictures or video. [6]
- **Processing Scenes in Real Time:** Hand movements are continually captured by a camera, and visibility is enhanced by preprocessing methods including noise reduction and background subtraction.
- **Segmentation and Frame Selection:** To reduce computing complexity, a single frame is taken for analysis from the video stream. While noise reduction and contour detection smooth out the image, thresholding and segmentation separate the hand from the backdrop. [7]
- **Gesture Recognition Using CNN:** Accurate gesture classification is achieved via a CNN model that has been trained on an ASL dataset to extract important elements such as hand forms and finger positions.
- **Recognized Motion Output:** In order to facilitate real-time communication for accessibility and intelligent apps, the last step transforms the detected gesture into text output. [8]

The ASL recognition technology accurately and efficiently decodes hand gestures for both common words and alphabets. To ensure resilience, testing took into account a variety of environmental circumstances, such as hand variations and lighting conditions. The system is a trustworthy instrument for sign language interpretation because it operated with few failures in real-time applications. For the hard-of-hearing group, this method greatly improves communication. As indicated below and referenced in the manuscript, tables and figures are presented centrally. Experimental results of Sign Language Interpretation System are shown in Tables. Which clearly shows the success of American Sign Language Interpreter System having average accuracy rate is more than 93.05%. System gives correct output even in the presence of multiple hands

and different lightening situations. This result is satisfactory enough for real time use of this system? (Table 1,2)

Table 1 Success Rate of ASL Alphabets

Alphabet	Success Rate (%)
A	100
B	100
C	100
D	100
E	100
F	100
G	85.00
H	100
I	100
J	100
K	100
L	100
M	85.00
N	85.00
O	100
P	84.00
Q	79.00
R	100
S	100
T	100
U	100
V	89.00
W	87.00
X	89.00
Y	100
Z	99.00

Table 2 Success Rate of ASL Words

Word	Accuracy
Hello	0.62
Thankyou	0.99
Done	0.93

Hand movements are recorded by the system, which then uses a deep learning model to extract important information for precise classification after processing them through segmentation and background removal. Effective communication is ensured by converting

recognized signs into text. Reliability for real-time applications is improved by testing under various circumstances. (Figure 1)

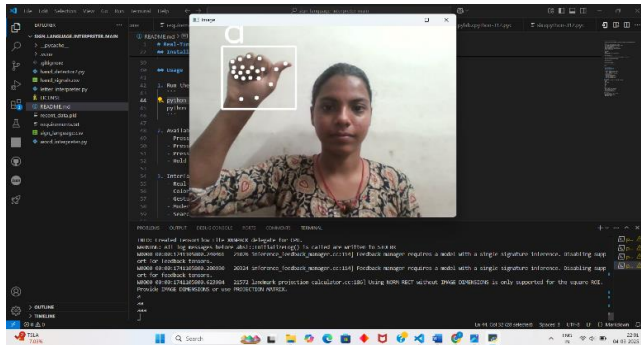


Figure 1 Sign Language Interpreter Interface Recognizing Alphabet Sign "a"

2. Results and Discussion

2.1.Results

The efficiency of the ASL recognition system in correctly recognizing hand movements, including alphabets and common words, is confirmed by test results. It made few mistakes and operated dependably in a variety of scenarios, including hand movements and changes in illumination. The system is a useful tool for the hard-of-hearing community because of its real-time capacity, which guarantees smooth communication. [9]

2.2.Discussion

Real-time applications can benefit from the ASL recognition system's accuracy and efficiency in recognizing hand movements. CNN-based classification guaranteed accurate gesture identification, while image preprocessing approaches enhanced recognition by eliminating noise. The system's dependability was validated through testing in various scenarios, while issues such as incorrect classifications brought on by motion and lighting were noted. Accuracy can be further increased by using motion tracking and improving the dataset. The technology can be extended for usage in smart devices and real-time translation, and it has the potential to overcome communication barriers for the hard-of-hearing community.

Conclusion

The suggested sign language interpretation system helps people with speech and hearing impairments

communicate more easily by efficiently identifying and translating hand gestures into relevant text. Reliability in real-time applications is ensured by the experimental findings, which show great accuracy in identifying both alphabets and common words. The system's resilience is further enhanced by its capacity to adjust to changes in hand positions and lighting. This study's encouraging results pave the door for further advancements in sign language identification, which will eventually help the deaf and mute communities communicate more effectively. [10]

Acknowledgements

Include acknowledgements, together with details on the source of any funding that was obtained for the published work. Include acknowledgements, together with details on the source of any funding that was obtained for the published work. Numerous published papers on neural networks, ensemble learning, sign language recognition, and gesture-based communication make up the references. Real-time gesture detection, machine learning methods, and historical insights are covered in key works. The sources, which support the research with developments in AI, computer vision, and probabilistic modeling, include IEEE papers, journal articles, and conference proceedings. The efficacy of the suggested system in deciphering sign language is confirmed by these references. (Figure 2)

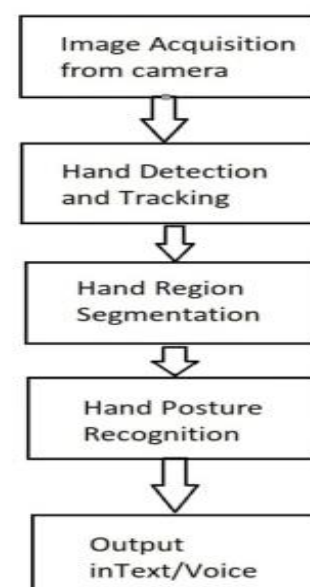


Figure 2 Process of the Dataset [3]

References

- [1]. Brill R. 1986. The Conference of Educational Administrators Serving the Deaf: A History. Washington, DC: Gallaudet University Press.
- [2]. Y. Lecun, L. Bottou, Y. Bengio and P. Haffner, "Gradient-based learning applied to document recognition," in Proceedings of the IEEE, vol. 86, no. 11, pp. 2278- 2324, Nov. 1998.
- [3]. M. Sandler, A. Howard, M. Zhu, A. Zhmoginov and L. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2018, pp. 4510-4520, doi:10.1109/CVPR.2018.00474.
- [4]. L. K. Hansen and P. Salamon, "Neural network ensembles," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 12, no. 10, pp. 993-1001, Oct. 1990, doi: 10.1109/34.58871.
- [5]. Kang, Byeongkeun, Subarna Tripathi, and Truong Q. Nguyen. "Real- time sign language fingerspelling recognition using convolutional neural networks from depth map." arXiv preprint arXiv: 1509.03001 (2015).
- [6]. Suganya, R., and T. Meera devi. "Design of a communication aid for physically challenged." In Electronics and Communication Systems (ICECS), 2015 2nd International Conference on, pp. 818-822. IEEE, 2015.
- [7]. Sruthi Upendran, Thamizharasi. A," American Sign Language Interpreter System for Deaf and Dumb Individuals", 2014 International Conference on Control, Instrumentation, Communication.
- [8]. David H. Wolpert, Stacked generalization, Neural Networks, Volume 5, Issue 2, 1992.
- [9]. Y. Liu, X. Yao, Ensemble learning via negative correlation, Neural Networks, Volume 12, Issue 10, 1999.
- [10]. MacKay D.J.C. (1995) Developments in Probabilistic Modelling with Neural Networks — Ensemble Learning. In: Kappen B., Gielen S. (eds) Neural Networks: Artificial Intelligence and Industrial Applications. Springer, London. https://doi.org/10.1007/978-1-4471-3087-1_37