

A Review on Hand Gesture Recognition Using Image Processing

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Abstract

Sign language, an important nonverbal communication strategy, is mostly used by people who are deaf or have speech difficulties to engage with those who have similar obstacles. Many existing sign language systems, on the other hand, are characterized by a lack of flexibility and cost, presenting challenges for end-users. In response to these obstacles, a prototype system for automatically detecting sign language has been created, providing a more efficient way of communication for the deaf and speech challenged. Deaf people typically struggle to communicate with the hearing community because sign language is often misinterpreted. Interpreters may not always be available, and visual communication can be challenging to comprehend. Within the speech and deaf impaired community, sign languages serve the primary mode of communication, uniting individual with similar conditions and their families. The intricate syntax and nuanced meanings conveyed through a myriad of sign language gestures make it an indispensable means of bridging the communication gap in this community. This novel method has the capacity to improve communication accessibility and inclusion for anyone.

Keywords: Computer Vision, Sign Language Recognition, CNN, Image Recognition, SVM.

1. Introduction

Individuals who are deaf or mute face significant communication challenges, making effective interaction with society a crucial necessity. Sign language serves as a bridge to overcome these barriers, enabling those with hearing and speech impairments to express themselves. Sign Language Recognition (SLR) involves deciphering sequences of hand gestures, facial expressions, and movements to convey meaning. However, despite advancements in this field, there remains a substantial gap in research focusing on region-specific sign languages.

In a linguistically diverse country like India, where multiple languages are spoken across states, each region also has its corresponding sign language. Maharashtra, for instance, is home to millions of individuals who rely on Marathi Sign Language (MSL) for communication. [1] Despite its widespread use by over 900,000 deaf and mute individuals, research on MSL remains underdeveloped, particularly in terms of technological advancements for automated recognition. Most existing studies focus on American Sign Language (ASL) or Indian Sign Language (ISL), leaving a pressing need for localized solutions.

Globally, an estimated 466 million people experience hearing disabilities, and this number is expected to rise to 900 million by 2050. Given this increasing demand, technological solutions leveraging computer vision, artificial intelligence (AI), and deep learning are becoming essential in bridging the communication gap. These approaches enable real-time interpretation of sign languages, making education, employment, and daily interactions more accessible for the deaf and mute community.

This study explores sign language recognition with a specific focus on gesture-based communication and advanced computational techniques that facilitate accurate interpretation. By analyzing existing methods such as image processing, machine learning, and sensor-based tracking, this paper highlights the current state of research, identifies gaps, and suggests directions for future improvements. The ultimate goal is to develop automated, region-specific, and scalable solutions that enhance accessibility and foster the social inclusion of individuals with hearing impairments.

2. Sign Language

Non-verbal communication in sign language primarily relies on hand gestures and is a lifeline for individuals

who are deaf or mute, as they face challenges in speaking and hearing. A vital component of human contact is effective communication, but in recent years, there has been a steady increase in the number of people who are deaf or mute because of congenital abnormalities, accidents, or dental disorders [2]. These individuals, unable to engage in conventional verbal conversations, must resort to visual forms of communication. Across the globe, a multitude of languages cater to this purpose. According to the World Health Organization's 2019 data, an estimated 466 million people worldwide grapple with disabling hearing loss. Alarmingly, this figure is projected to exceed 900 million by 2050 [3]. Throughout history, individuals with disabilities have relied on intermediaries and written text to bridge the communication divide with the non-disabled population.

Sign language, Visual sign language, which is mostly used by people with speech and hearing impairments, and tactile sign language, which is used by people with both visual and hearing impairments, can be broadly classified into two primary forms as a communication medium. Our focus is on addressing the communication needs of the deaf and mute through Visual Sign Language [4].

It is crucial to recognize that sign language exhibits significant regional variations influenced by cultural factors. Unlike universal sign language, sign languages have naturally evolved within specific communities, resulting in a plethora of distinct variants. Presently, there exist approximately 138 to 300 different sign languages worldwide [5]. For example, Indian Sign Language (ISL), for example, is widely used in India, whereas American Sign Language, or ASL, is used in the United States and Chinese Sign Language (CSL) is used in China. Sign language is a comprehensive communication system that conveys message through hand types, body posture, and facial expressions. Each gesture has its own importance.



Fig. 1. American Sign Language

The journey of learning sign language often begins with mastering the manual alphabet, commonly referred to as "fingerspelling." This enables signers to manually spell out the names of persons, places, and things for whom no standardized signs exist. It is crucial to remember that not all sign languages use the Latin alphabet, resulting in sign language alphabet variances. Some manual alphabets, such as ASL and French Sign Language, are one-handed, whereas others, such as British Sign Language (BSL), are two-handed [6]. Although several manual alphabets have similarities, each sign language has its own style, modifications, and distinguishing features.

Sign Languages (SL) rely on visual cues and physical motions to communicate meaning. It is the primary mode of communication for the deaf or hearing-impaired while engaging with the hearing population, allowing them to express their thoughts and emotions. SL has a wide range of gestures, hand motions, facial expressions, and head movements to indicate letters or symbols, with a sign for each letter of the alphabet. Diverse groups of people engaging develop the rich fabric of SL, resulting in between 138 and 300 distinct sign languages used globally today. American Sign Language (ASL), British Sign Language (BSL), Arabic Sign Language (ArSL), and many others are examples [7].

It is critical to distinguish Sign Language from "body language," which is a distinct type of nonverbal communication. Manual signs in SL can be broken down into four components: Handshape, Location, Movement, and Orientation. Researchers often employ various methods, such as data gloves to capture finger

configurations and hand orientations, or cameras to record signers' movements for SL recognition datasets. In the Arab world, deaf individuals utilize Arabic Sign Language, although it's noteworthy that each country typically has its own unique Sign Language. The World Federation of the Deaf (WFD) has also created an international and unified Arabic Sign Language (ArSL) to serve the worldwide deaf population [7], [8].

3. Study Review

This study focuses on reputable academic articles related to specific keywords found either in the title or content, as suggested by Prof. Sonali Rokade. These keywords include 'computer vision,' 'sign language recognition,' 'CNN,' 'HMM,' 'image recognition,' and 'SVM.' The primary objective is to analyze these selected papers and extract essential information, addressing the following research questions to streamline data gathering and analysis:

RQ1: What methods are employed for data acquisition in Sign Language Recognition (SLR)?

RQ2: What processes are utilized in the SLR pipeline?

RQ3: Which machine learning techniques are used for classification?

Table I. Selection criteria based on the following constraints.

Selection Criteria	Constraints
The paper must be an internationally recognized academic publication.	Papers published prior to the year 2020 will be excluded from consideration.
The paper should comprehensively cover stages related to Sign Language Recognition.	-
The paper should be directly relevant to the current research paper's objectives.	Web documents or non-academic sources will not be included in the review process.

The study draws upon various electronic databases, all of which exclusively host internationally recognized academic documents. These databases include AAI, BMVC (British Machine Vision Conference), Springer, IEEE Xplore, Ijsret, Semantics Scholar, ACM Digital Library, and Elsevier. To ensure the inclusion of eligible works, the study applies three selection and exclusion criteria rigorously.

This strategy allows for a thorough review of the relevant literature, revealing insight on the methodologies, procedures, and algorithms at the heart of Sign Language Recognition research.

After collecting the relevant papers, we conducted an analysis based on the research questions to gain insights into the methods used in Sign Language Recognition (SLR) research. Here are our findings:

RQ1: What methods are employed for data acquisition in Sign Language Recognition (SLR)?

The classification problem in SLR falls under the supervised learning category, necessitating the acquisition of labeled image data for training and testing. Data consistency is crucial since classifiers require images in specific formats. Various methods are employed to obtain data for SLR, and we have compared and analyzed them. The most common data acquisition method involves using standard video cameras, which produce 2-dimensional images. Because of the ubiquitous availability of smartphones with built-in cameras, this strategy is popular. However, image quality varies depending on the camera, and preprocessing is frequently required. Low-quality cameras can inject noise into collected pictures, which might interfere with feature extraction. Furthermore, resolution differences across cameras may demand preprocessing to standardize picture formats. Some researchers use Kinect, which uses sensors and cameras to gather colorful visuals as well as depth data. This method yields more comprehensive data, which can help in categorization.

Depth characteristics are very important for segmentation, as they differentiate between background and foreground objects. Abdelnasser presented a novel technology, WiGes, that uses Wi-Fi signal intensity to detect in-air hand motions surrounding the device. Input is provided by changes in the returning signal. While this method provides multi-directional sensing without the requirement for an object, it is difficult to implement. Another source of data is existing datasets available on the internet, which are ready to use and usually come in big volumes with high quality. For instance, Bhavesh employed the Kaggle dataset, comprising around 27,000 sign language images.

Leveraging high-quality existing datasets allows researchers to focus on other aspects of SLR. In cases where the collected data is insufficient, Data

Augmentation techniques can be employed to generate additional data. Data Augmentation involves creating new data by manipulating existing data. This saves time and enhances classifier accuracy by preventing overfitting to specific sign language instances while introducing data variations. For SLR using image inputs, hand images are captured from different angles and distances, resulting in scale and rotation invariance. A common Data Augmentation technique involves slight image rotations.

RQ2: What processes are utilized in the SLR pipeline?

Among the reviewed papers, several processing stages were identified after data acquisition to enhance classifier performance. Pre-processing, Segmentation, and Feature Extraction are among these processes.

Pre-processing: Involves altering the acquired data to improve classifier performance and remove inaccuracies. Common pre-processing techniques include Gaussian Filters and Median Filters, which reduce noise in 2-dimensional images, enhancing edge detection during segmentation. Additionally, image resizing or cropping may be applied to standardize data formats and reduce computational complexity for the classifier.

Segmentation: In Sign Language Recognition (SLR), the most crucial element is the interpretation of hand gestures, primarily conveyed through the intricate movements of the signer's hands. Image segmentation is crucial in facilitating correct recognition of these motions. This process involves the isolation of the Region of Interest (ROI), typically the signer's hand, while removing any unwanted data such as backgrounds or extraneous objects from the input image. The effectiveness of SLR depends significantly on how well this segmentation is executed, making it a critical component of the overall recognition pipeline.

Gray Scaling: One of the fundamental segmentation techniques is gray scaling, which is employed to convert RGB or colored images into grayscale. In the context of SLR, the color of the signer's skin is often irrelevant, and removing color information simplifies subsequent processing steps. Additionally, gray scaling aids in distinguishing between the background and foreground, facilitating cleaner segmentation results.

Thresholding: Thresholding is typically used after grayscale conversion to provide a binary representation of the image. This procedure draws a clean line between the background and the foreground, with

black representing the background and white representing the foreground. To designate these zones, researchers choose a suitable threshold value, with some using automated methods to speed up the process.

Skin Segmentation: Skin segmentation is a popular choice due to its simplicity and effectiveness. It involves specifying a predefined color range or color histogram corresponding to human skin tones. By doing so, the image is filtered to display only the selected skin color, effectively removing any background or objects that do not fall within this range. However, researchers must carefully choose the color space to use, and this method may sometimes inadvertently detect objects with colors resembling skin tones.

Morphological Filters: Morphological filters or operations are often applied to binary images generated through segmentation. These operations help reduce errors in both foreground and background regions, effectively expanding the Region of Interest to ensure it accurately encapsulates the signer's hand gesture.

Canny Edge Detection: Canny edge detection is a useful method for extracting picture edges. This method is very beneficial for accentuating the curves of the signer's hand, making it easier to identify the Region of Interest.

Background Subtraction: When video input is available, background subtraction becomes a viable segmentation method. This approach entails removing static objects like backgrounds from the video feed. It simplifies the segmentation process, especially when the signer's hand is in motion. However, challenges may arise when there are multiple moving objects, such as cars or televisions, as they may also be classified as foreground objects.

In summary, segmentation methods in SLR are diverse and tailored to the specific requirements of the task. These strategies are critical for separating the signer's hand motion, which is the foundation of sign language recognition. Effective segmentation guarantees that the recognition system can correctly identify and interpret these movements, hence improving communication accessibility for those who use sign language as their major form of expression. In conclusion, our analysis of the reviewed SLR papers reveals the diversity of methods used for data acquisition and the importance of data processing

stages such as pre-processing in improving classifier accuracy and robustness.

Feature Extraction: Feature extraction is an important stage in Sign Language Recognition (SLR) since it isolates and improves significant information for the classification process. It involves selecting essential features from the Region of Interest (ROI) while discarding redundant data. In SLR, the choice of feature extraction methods varies based on the researcher's goals. Here, we explore the diverse techniques commonly used in SLR: CNNs are a popular choice for feature extraction due to their ability to capture crucial image details. CNN convolution layers excel at extracting crucial information, while MaxPooling layers improve this process even further. CNNs are well-known for their resilience, which has led to their widespread use in SLR research. PCA is used to reduce feature dimensionality, resulting in uncorrelated variables. This improvement improves classification performance and reduces overfitting. To compress pictures more efficiently, researchers frequently use the Discrete Cosine Transform (DCT) before PCA. The Principal Component Analysis Network, or PCANet, is well-known for its computational efficiency in feature extraction. It effectively extracts critical patterns from photos, making it an excellent choice for SLR. SURF excels in detecting local features and interest spots in data and is inspired by the Scale-Invariant Feature Transform (SIFT).

It is computationally efficient and resistant to changes like as scale, rotation, occlusion, and others. SURF is particularly suited for image classification tasks that involve different sign rotations. The feature extraction approach used in SLR is determined by the unique study requirements and robustness levels needed. CNNs are recommended for their thorough feature capture, whilst PCA and PCANet provide dimensionality reduction and computational efficiency. SURF, which is based on SIFT principles, is very good at recognizing local features, making it a good choice for image classification jobs with changing sign rotations. The proper feature extraction approach must be chosen for accurate and efficient sign language identification, which benefits those who rely on sign language for communication.

RQ3: In SLR, which machine learning techniques are used for classification? [10] Various classification methods are employed in the Sign Language Recognition (SLR) process, each with its own set of

advantages and drawbacks. Here is an analysis of the different classification methods utilized in SLR research:

Convolutional Neural Network (CNN): CNNs are the most prevalent choice due to their exceptional accuracy, often exceeding 99.39%. Unlike Artificial Neural Networks (ANN), CNNs incorporate additional convolutional layers for feature extraction. They determine the category to which data belongs and continually improve based on training outcomes. Increasing the number of layers enhances accuracy but also escalates computational demands. Many previous CNN models require extensive experimentation to optimize layer configurations. Some researchers apply Transfer Learning with CNNs, simplifying the architecture selection and focusing on training and prediction tasks.

Support Vector Machine (SVM): SVM is a well-established method known for solving margin maximization optimization problems. It constructs a Decision Boundary to improve generalization in linear classifiers. SVM outperforms some linear and non-linear classifiers, making it a robust choice for SLR [11].

Hidden Markov Model (HMM): HMMs maximize the posterior probability of data categorization while minimizing prior probability errors. GMM-HMM, which combines HMM with Gaussian Mixture Models, demonstrates enhanced accuracy compared to standard models. Cross-Correlation Coefficient: This method measures the similarity between two signals at different time-shifted functions. It proves effective for dynamic gestures, a critical aspect of sign language. Moreover, it is computationally efficient and suitable for implementation on standard hardware.

Minimum Distance Classifier: Some researchers employ the Minimum Distance Classifier, often combined with Mahalanobis Distance, for efficient classification. While less adept at accommodating varying hand shapes and sizes, it is a cost-effective option suitable for implementation on a wide range of hardware.

In conclusion, SLR research explores various classification methods, each offering unique benefits. CNNs are favored for their high accuracy, while SVMs, HMMs, Cross-Correlation Coefficients, and Minimum Distance Classifiers provide alternative solutions catering to different needs and hardware constraints. The classification method used is determined by the unique needs and limits of the SLR job at hand [12].

4. Discussion Result Overview

This section offers an overview of prior research’ methodology and results in the subject of Sign Language Hand Gesture Recognition (SLR). As shown in Figure, these studies highlight five critical phases in the SLR process: data collecting, pre-processing, segmentation, feature extraction, and classification. Each of these steps has a substantial impact on the overall performance of SLR systems [13]. To summarize the techniques utilized in these five stages and the corresponding accuracy results, we present them in Table.

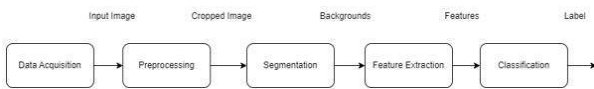


Fig. 2. Steps of Sign Language Recognition

When it comes to data acquisition, the most prevalent method involves the use of cameras, while others have explored alternatives such as Kinect or leveraging existing datasets from diverse sources. Some researchers employ preprocessing techniques, including cropping, grayscale conversion, and Gaussian smoothing, while others opt for a more direct approach without preprocessing. Remarkably, all the studies demonstrate commendable performance in their respective SLR tasks. Although this research include different forms of gesture detection, such as static and dynamic gestures, we have combined them into a single table, concentrating on the approaches used. In the realm of feature extraction and classification, Convolutional Neural Networks (CNNs) stand out as the most popular choice, with some studies even incorporating hybrid methods like CNN-HMM. Other classification algorithms, such as ANN (Artificial Neural Networks) and hidden Markov models (HMM), have also been investigated [13]. Aside from CNNs, other academics have experimented with approaches such as Speeded-Up Robust Features (SURF) for feature extraction and Principal Component Analysis (PCA)[14]. In conclusion, this overview provides insights into the diverse methodologies used in previous SLR studies, highlighting the pivotal role of each stage in the SLR process. These works, taken together, help to advance the area of sign language recognition and communication accessibility [15].

5. Conclusion

In this comprehensive review, over research publications concentrating on Sign Language Hand

Gesture Recognition (SLR) were analyzed. According to our findings, the SLR process generally consists of five major stages: data collecting, pre-processing, division, extraction of characteristics, and classification. The primary method of data collecting includes the use of conventional video cameras, which allow the capturing of hand photos from a variety of persons, angles, lighting situations, backdrops, and hand sizes.

Table II. Accuracy analysis of different research papers

Data Acquisition	Feature Extraction	Accuracy
Standard Video Camera [1]	Enhanced Grasshopper Optimization Algorithm (EGOA)	99.05%
Standard Video Camera [2]	support vector machine (SVM)	94.1%.
Standard Video Camera [3]	3D reconstruction	95%
cameras, infra-red sensors, ultrasonic sensors, and radar sensors [4]	3SVM and k-NN	93.33%
x and y coordinates [5]	CNN.	99%
nvGesture dataset [6]	3DCNN, ResNet	77.5%
Standard Video Camera [7]	Histogram of Oriented Gradient (HOG), Convolutional Neural Network (CNN), Principal Component Analysis (PCA)	88%
Xethru-x4 model IR-UWB radar [8]	SVM	96%
Ultra-wideband impulse radar [9]	CNN, k-NN, SVM	93.33%
Pen positions sampled [10]	-	97.40%
Standard Video Camera [11]	Mel-frequency cepstral coefficients (MFCC), cochlear frequency cepstral coefficients (CFCC)	93.2%

Data Acquisition	Feature Extraction	Accuracy
Millimeter wave frequency modulated continuous wave (FMCW) [12]	CNN	93.1%
NinaPro, CapgMyo, cslhdemg [13]	sEMG	99%
Standard Video Camera [14]	K-NN, SVM	90%
Standard Video Camera [15]	ANN	92.5%
Standard Video Camera [16]	AFuzzy logic, DBN	89.33%
Standard Video Camera [17]	WiGeR, WiG, Short-Time Energy (STE)	97.28%
Standard Video Camera [18]	VECAR	70.11%

Some researchers, however, opt to leverage publicly available datasets from the internet [16]. Additionally, alternative techniques such as Kinect, WiGest, and data augmentation have been explored to enhance data collection. Among the classification algorithms employed in SLR, Convolutional Neural Networks (CNNs) emerge as the dominant choice, featured in 8 out of the 18 studies. The preference for CNNs is attributed to their remarkable accuracy, often exceeding 90% in SLR tasks. Notably, while many models exhibit impressive static image recognition capabilities, some limitations become evident when dealing with sign languages like American Sign Language (ASL), which involve dynamic hand movements. Real-time, live translation is essential for conveying the nuances of ASL, especially for alphabets that necessitate hand movement. In summary, our examination of these research projects gives insight on the various procedures and approaches used in the field of sign language translation. These findings contribute significantly to continuing efforts to improve communication accessibility for people with hearing impairments.

References

[1] Khan, F. S., Mohd, M. N. H., Soomro, D. M., Bagchi, S., & Khan, M. D. (2021). 3D hand gestures segmentation and optimized classification using deep learning. *IEEE Access*, 9, 131614-131624.

[2] Hsieh, C. C., Liou, D. H., & Lee, D. (2010, July). A real-time hand gesture recognition system using motion history image. In *2010 2nd International Conference on Signal Processing Systems* (Vol. 2, pp. V2394). IEEE.

[3] Zeng, B., Wang, G., & Lin, X. (2012). A hand gesture-based interactive presentation system utilizing heterogeneous cameras. *Tsinghua Science and Technology*, 17(3), 329-336.

[4] Skaria, S., Al-Hourani, A., & Evans, R. J. (2020). Deep-learning methods for hand-gesture recognition using ultra-wideband radar. *IEEE Access*, 8, 203580-203590.

[5] Suarez, J., & Murphy, R. R. (2012, September). Hand gesture recognition with depth images: A review. In *2012 IEEE RO-MAN: The 21st IEEE International Symposium on Robot and Human Interactive Communication* (pp. 411-417). IEEE.

[6] Al-Hammadi, M., Muhammad, G., Abdul, W., Alsulaiman, M., Bencherif, M. A., & Mekhtiche, M. A. (2020). Hand gesture recognition for sign language using 3DCNN. *IEEE Access*, 8, 79491-79509.

[7] Mohamed, N., Mustafa, M. B., & Jomhari, N. (2021). A review of the hand gesture recognition system: Current progress and future directions. *IEEE Access*, 9, 157422-157436. doi:10.1109/ACCESS.2021.3129650.

[8] Ghaffar, A., Khan, F., & Cho, S. H. (2019). Hand pointing gesturesbased digital menu board implementation using IR-UWB transceivers. *IEEE Access*, 7, 58148-58157. doi:10.1109/ACCESS.2019.2914410.

[9] Skaria, S., Al-Hourani, A., & Evans, R. J. (2020). Deep-learning methods for hand-gesture recognition using ultra-wideband radar. *IEEE Access*, 8, 203580-203590. doi:10.1109/ACCESS.2020.3037062.

[10] Tokuno, J., Inami, N., Matsuda, S., Nakai, M., Shimodaira, H., & Sagayama, S. (2002, August). Context-dependent substroke model for HMM-based online handwriting recognition. In *Proceedings Eighth International Workshop on Frontiers in Handwriting Recognition* (pp. 78-83). IEEE.

[11] Luo, G., Yang, P., Chen, M., & Li, P. (2020). HCI on the table: Robust gesture recognition using acoustic sensing in your hand. *IEEE Access*, 8, 31481-31498. doi:10.1109/ACCESS.2020.2973305.

- [12] Smith, J. W., Thiagarajan, S., Willis, R., Makris, Y., & Torlak, M. (2021). Improved static hand gesture classification on deep convolutional neural networks using novel sterile training technique. *IEEE Access*, 9, 1089310902.
- [13] Hu, Y., Wong, Y., Dai, Q., Kankanhalli, M., Geng, W., & Li, X. (2019). sEMG-based gesture recognition with embedded virtual hand poses and adversarial learning. *IEEE Access*, 7, 104108-104120. doi:10.1109/ACCESS.2019.2930005.
- [14] Choi, J. W., Ryu, S. J., & Kim, J. H. (2019). Short-range radar-based real-time hand gesture recognition using LSTM encoder. *IEEE Access*, 7, 33610-33618. doi:10.1109/ACCESS.2019.2903586.
- [15] Liu, C., Li, Y., Ao, D., & Tian, H. (2019). Spectrum-based hand gesture recognition using millimeter-wave radar parameter measurements. *IEEE Access*, 7, 79147-79158. doi:10.1109/ACCESS.2019.2923122.
- [16] Alonazi, M., Ansar, H., Al Mudawi, N., Alotaibi, S. S., Almujally, N. A., Alazeb, A., ... & Min, M. (2023). Smart healthcare hand gesture recognition using CNN-based detector and deep belief network. *IEEE Access*.
- [17] Al-Qaness, M. A. A., & Li, F. (2016). WiGeR: WiFi-based gesture recognition system. *ISPRS International Journal of Geo-Information*, 5(6), 92.
- [18] Yang, M. T., & Liao, W. C. (2014). Computer-assisted culture learning in an online augmented reality environment based on free-hand gesture interaction. *IEEE Transactions on Learning Technologies*, 7(2), 107-117. doi:10.1109/TLT.2014.2307297.
- [19] Praja Patil, R., Pandey, V., Jamindar, N., Yadav, N., & Phadnis, N. (2018). Hand gesture recognition and voice conversion for deaf and dumb. *International Research Journal of Engineering and Technology (IRJET)*.
- [20] Shingate, D. S., Bajaj, R., Singh, A., Walzade, G., & Bhavar, Y. (2019). Sign language interpretation. *International Journal of Scientific Development and Research (IJS DR)*.
- [21] Fryza, T., & Bravenec, T. (n.d.). Multiplatform system for hand gesture recognition. *Department of Radio Electronics, Brno University of Technology*.
- [22] Priya, S. A., Nair, A., Madhavan, S., & Issac, K. (2023). Sign language recognition by image processing. *International Journal of Creative Research Thoughts (IJCRT)*, 11(6). ISSN: 2320-2882.
- [23] Kumar, A. R. V., Darshan, U. R., Venkatesh, B., Vinodh, R., & Prakash. (2024). Hand gesture recognition system for dumb and deaf people. *International Journal of Creative Research Thoughts (IJCRT)*, 12(1). ISSN: 2320-2882.