HAND TALK: SIGN LANGUAGE RECOGNITION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract
Sign Language Recognition (SLR) aims to translate sign language into text or speech, enabling communication between deaf-mute individuals and others. This task has significant social impact but remains challenging due to the complexity and variability of hand gestures. Traditional SLR methods rely on hand-crafted features to describe sign language motions, but these struggle to adapt to the diverse range of gestures. To address this, we propose a Convolutional Neural Network (CNN) that automatically extracts spatial-temporal features from raw video streams, eliminating the need for manual feature design.

Our approach leverages multi-channel video inputs, including color, depth, and body joint positions, to integrate color, depth, and trajectory information. This enhances the model's ability to recognize gestures accurately. We tested the model on a dataset collected using Microsoft Kinect, demonstrating its superiority over traditional hand-crafted feature-based methods. The proposed CNN-based system offers a more robust and efficient solution for real-time SLR, paving the way for improved communication tools for the deaf-mute community.

Keywords: Hand gestures, Action recognition, Deaf-Mute Communication, Real-time recognition, Web-cam Finger tracking.

I.INTRODUCTION

Sign language, as one of the most widely used communication means for hearing-impaired people, is expressed by variations of hand-shapes, body movement, and even facial expression. Since it is difficult to collaboratively exploit the information from hand-shapes and body movement trajectory, sign language recognition is still a very challenging task. This paper proposes an effective recognition model to translate sign language into text or speech in order to help the hearing impaired communicate with normal people through sign language. Technically speaking, the main challenge of sign language recognition lies in developing descriptors to express hand-shapes and motion trajectory. In particular, hand-shape description involves tracking hand regions in video stream, segmenting hand-shape images from complex background in each frame and gestures recognition problems. Motion trajectory is also related to tracking of the key points and curve matching. Although lots of research works have been conducted on these two issues for now, it is still hard to obtain satisfying result for SLR due to the variation and occlusion of hands and body joints. Besides, it is a nontrivial issue to integrate the hand-shape features and trajectory features together. To address these difficulties, we develop CNN to naturally integrate hand-shapes, trajectory of action and facial expression. Instead of using commonly used colour images as input to networks like [1, 2], we take colour images, depth images and body skeleton images simultaneously as input which are all provided by Microsoft Kinect. Kinect is a motion sensor which can provide colour stream and depth stream. With the public Windows SDK, the body joint locations can be obtained in real-time.

Therefore, we choose Kinect as capture device to record sign words dataset. The change of colour and depth in pixel level are useful information to discriminate different sign actions. And the variation of body joints in time dimension can depict the trajectory of sign actions. Using multiple types of visual sources as input leads CNN paying attention to the change not only in colour, but also in depth and trajectory. It is worth mentioning that we can avoid the difficulty of tracking hands, segmenting hands from background and designing descriptors for hands because CNNs have the capability to learn features automatically from raw data without any prior knowledge. CNN have been applied in video stream classification recently years.

To prevent this from happening, we are putting forward a sign language recognition system. It will be an ultimate tool for people with hearing disability to communicate their thoughts as well as a very good interpretation for non-sign language user to understand what the latter is saying. Many countries have their own standard and interpretation of sign gestures. For instance, an alphabet in Korean sign language will not mean the same thing as in Indian sign language. While this highlights diversity, it also pinpoints the complexity of sign languages.

Deep learning must be well versed with the gestures so that we can get a decent accuracy. In our proposed system, American Sign Language is used to create our datasets. Identification of sign gesture is performed with either of the two methods. First is a glove-based method whereby the signer wears a pair of data gloves during the capture of hand movements. Second is a vision-based method, further classified into static and dynamic recognition. Static deals with the 2-dimensional representation of gestures while dynamic is a real time live capture of the gestures. And despite having an accuracy of over 90%, wearing of gloves are uncomfortable and cannot be utilised in rainy weather. They are not easily carried around since their use require computer as well. In this case, we have decided to go with the static recognition of hand gestures because it increases accuracy as compared to when including dynamic hand gestures like for the alphabets J and Z. We are proposing this research so we can improve on accuracy using Convolution Neural Network (CNN). give me in 500 words

In conclusion, our proposed CNN-based sign language recognition system leverages multiple data sources to automatically extract features, overcoming the limitations of traditional methods. This approach not only enhances accuracy but also provides a practical solution for real-time SLR, bridging the communication gap between hearing-impaired individuals and the broader community.

II.LITERATURE SURVEY

*A.*Literature Review

The literature review highlights various approaches to sign language recognition. Siming proposed a system using Faster R-CNN for hand detection and a 3D CNN with LSTM for feature extraction, achieving high accuracy. Rekha utilized YCbCr skin detection and Multi-class SVM, achieving 94.4% accuracy for static gestures. M. Geetha and U. C. Manjusha used B-Spline approximations and SVM, achieving 90% accuracy. Pigou employed a 2D CNN for Italian sign gestures, achieving 91.7% accuracy, while J. Huang used a 3D CNN with Kinect data, achieving 94.2% accuracy. J. Carriera's action recognition research, using transfer learning, achieved 98% accuracy on UCF-101.

Our methodology involves capturing hand gestures via a webcam, using HSV for background elimination and skin tone segmentation. Morphological operations and OpenCV standardize image sizes. We use a dataset of 2000 American Sign Language images, with 1600 for training and 400 for testing. A CNN model extracts spatial and temporal features, and a multilayer perceptron classifier is used for classification. This approach demonstrates the effectiveness of combining multiple data channels for accurate sign language recognition.

B.Methodologies

The first step of the proposed system is to collect data. Many researchers have used sensors or cameras to capture the hand movements. For our system, we make use of the web camera to shoot the hand gestures. The images undergo a series of processing operations whereby the backgrounds are detected and eliminated using the colour extraction algorithm HSV (Hue, Saturation, Value). Segmentation is then performed to detect the region of the skin tone. Using the morphological operations, a mask is applied on the images and a series of dilation and erosion using elliptical kernel are executed.

With open CV, the images obtained are amended to the same size so there is no difference between images of different gestures. Our dataset has 2000 American sign gesture images out of which 1600 images are for training and the rest 400 are for testing purposes. It is in the ratio 80:20. Binary pixels are extracted from each frame, and Convolutional Neural Network is applied for training and classification. The model is then evaluated and the system would then be able to predict the alphabets.

C . Aim and Objective

Aims:
Develop a system that translates sign language into text or speech to bridge the communication gap between hearing-impaired individuals and those who do not understand sign language.

1. **Improve Accuracy**: Enhance the accuracy and efficiency of sign language recognition by leveraging advanced machine learning techniques, such as Convolutional Neural Networks (CNNs).
2. **Real-Time Recognition**: Create a system capable of real-time sign language recognition to enable seamless communication in everyday scenarios.
3. **Accessibility**: Provide an affordable and accessible solution for sign language recognition, reducing dependency on expensive hardware like data gloves.
4. **Promote Inclusivity**: Contribute to social inclusion by empowering hearing-impaired individuals to communicate more effectively with the broader community.

Objectives:

1. **Data Collection**: Collect a comprehensive dataset of sign language gestures, focusing on American Sign Language (ASL), using cost-effective tools like webcams.
2. **Preprocessing**: Implement image processing techniques, such as background elimination using HSV (Hue, Saturation, Value) and skin tone segmentation, to prepare the data for analysis.
3. **Feature Extraction**: Use CNNs to automatically extract spatial and temporal features from video streams, eliminating the need for hand-crafted features.
4. **Model Development**: Develop a robust CNN-based model that integrates multiple data channels (e.g., color, depth, and body skeleton) to improve recognition accuracy.
5. **Training and Testing**: Train the model on a dataset of 2000 ASL images (1600 for training, 400 for testing) and evaluate its performance using metrics like accuracy and error rate.
6. **Real-Time Implementation**: Optimize the system for real-time performance using parallel processing techniques like CUDA.
7. **Comparative Analysis**: Compare the proposed CNN-based approach with traditional methods (e.g., SVM, GMM-HMM) to demonstrate its superiority in terms of accuracy and efficiency.
8. **User Accessibility**: Ensure the system is user-friendly and accessible, allowing hearing-impaired individuals to use it without specialized hardware.

III.PROPOSED SYSTEM

This project proposes an effective recognition model to translate sign language into text and speech in order to help the hearing impaired communicate with normal people through sign language. We propose to apply CNNs to extract spatial and temporal features from video stream for Sign Language Recognition (SLR). CNN can capture motion information from raw video data automatically, avoiding designing features.

We develop a CNNs taking multiple types of data as input. This architecture integrates colour, depth and trajectory information by performing convolution and subsampling on adjacent video frames.

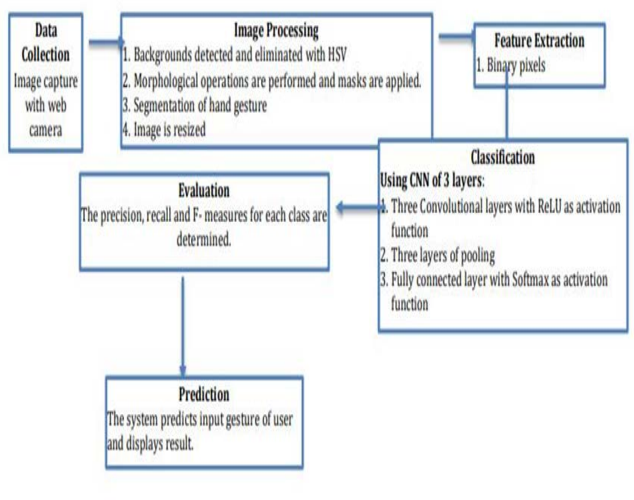

Fig. 1. System Architecture

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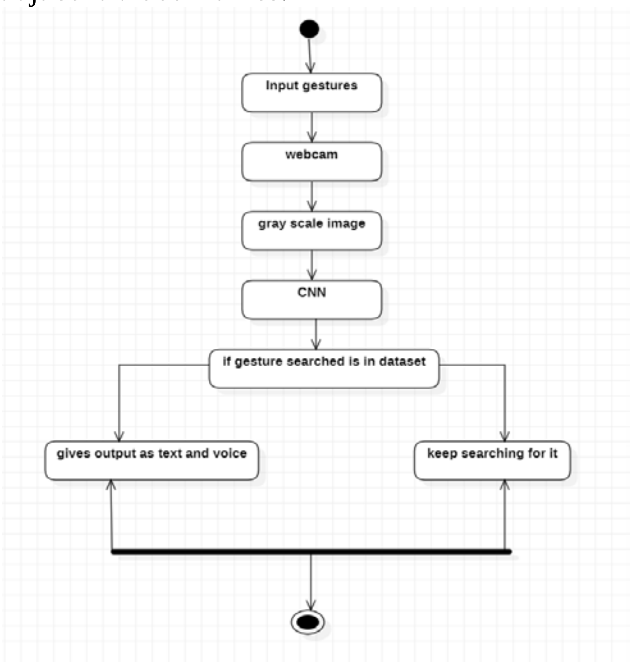

IV.SYSTEMMETHODOLOGY

A. *System Architecture*

The system architecture of a sign language recognition system involves several interconnected stages that work together to capture, process, and interpret hand gestures. The process begins with data collection, where a web camera or Kinect sensor captures video streams or images of hand gestures. These images are then preprocessed to isolate the hand gesture from the background using the HSV (Hue, Saturation, Value) color space. Morphological operations like dilation and erosion are applied to refine the hand region, and a mask is used to enhance visibility. The hand gesture is segmented from the rest of the image, and the images are resized to a standard dimension for uniformity.

Next, the system extracts binary pixels from the processed images, simplifying the representation of the hand gesture for analysis. These features are then fed into a Convolutional Neural Network (CNN) for classification. The CNN typically consists of three convolutional layers with ReLU (Rectified Linear Unit) as the activation function to extract spatial features, followed by three pooling layers to reduce dimensionality and retain important information. A fully connected layer with Softmax as the activation function classifies the hand gestures into predefined categories. The system evaluates its performance using metrics like precision, recall, and F-measure for each class to determine accuracy and reliability. Once trained, the system can predict the user's input gesture in real-time and display the corresponding result, such as text or speech. This architecture provides an efficient and accessible solution for sign language recognition, leveraging image processing and deep learning to bridge communication gaps for hearing-impaired individuals.

B. *User Interface*

The user interface in a sign language recognition system is designed to be intuitive and accessible. It typically includes a live camera feed where users perform gestures, with visual feedback highlighting the detected hand. The recognized gestures are translated into text or speech, displayed on the screen for real-time communication. Interactive features like menus, settings, and a help section guide users through the process. Error handling provides feedback if gestures are not recognized, prompting users to reposition or repeat. Accessibility features, such as large fonts and high-contrast colors, ensure usability for all. The interface also supports training modes with gesture libraries and progress tracking forlearning.

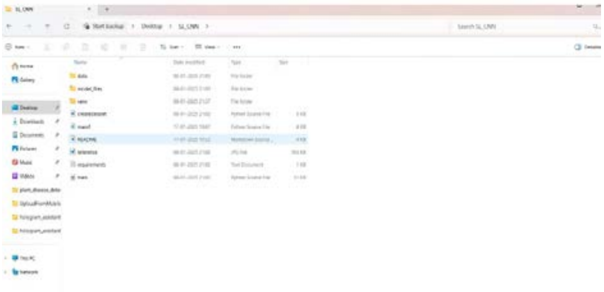

Fig. 3. User Interface

C. Terminals used

In a sign language recognition system, Python is commonly used for its extensive libraries. Key commands include installing dependencies like pip install opencv-python numpytensorflowkeras matplotlib for image processing, numerical operations, and building CNN models. The main script, such as python main.py, runs the system, capturing video input via OpenCV, preprocessing images using HSV for background elimination, and segmenting hand gestures. The CNN model, built with TensorFlow/Keras, extracts features and classifies gestures. Real-time predictions are displayed using OpenCV's imshow(). The system evaluates performance using metrics like precision and recall, and outputs results as text or speech using libraries like pyttsx3 for text-to-speech conversion.

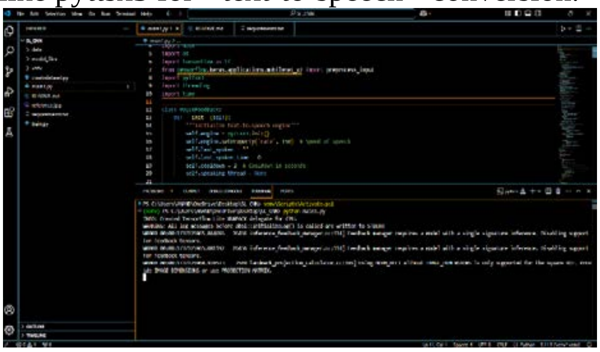

Fig. 4. Terminals

D. Gestures recognized

The content appears to be a list of characters, possibly representing sign language gestures or labels for a dataset. The characters include numbers (8, 9) and letters (A-Z, excluding some like S, T, V). This list could be used as reference labels for a sign language recognition system, where each character corresponds to a specific hand gesture. The file name references.py suggests it might be part of a Python script that maps these characters to their respective gestures or serves as a lookup table for classification. This structured approach helps in organizing and processing data for training or real-time recognition in sign language systems.

Fig. 5. Gestures

E. Recognition of the gesture from the Input

The content describes a gesture recognition system where users can upload images or videos to recognize gestures, such as the "OK" gesture. The interface includes a button to upload videos and get recognition results. The system is implemented using Python, with files like main1.py and dependencies listed in requirements.txt. The script main1.py likely processes the input, preprocesses it using functions like preprocess_input, and uses a neural network model (net_v2) for gesture recognition. The system also includes feedback mechanisms and logs for debugging. This setup allows users to interact with the system, upload data, and receive real-time gesture recognition results.

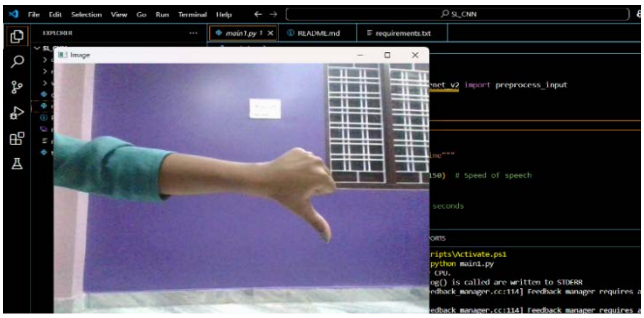

Fig. 6. Gesture detection

F. *Accuracy*

The content appears to be a list of numbered items, likely representing gestures or data points in a sign language recognition system. Each item is labeled with a prefix such as "get_1," "get_2," and so on, extending up to "get_758." This structure suggests a systematic approach to organizing and referencing a large dataset of gestures, possibly for training or testing a machine learning model. The dataset seems extensive, with over 700 entries, indicating a comprehensive collection of sign language gestures.

The file also mentions a Python script (main.py) and dependencies (requirements.txt), which are essential for running the system. The script likely processes the input gestures, preprocesses them using functions like preprocess_input, and classifies them using a machine learning model. The high number of entries in the list suggests that the system is designed to handle a wide variety of gestures, making it robust and versatile.

This structured approach ensures that each gesture is uniquely identified and processed, facilitating accurate recognition and classification. The system's ability to handle such a large dataset indicates its potential for real-world applications, where recognizing a wide range of gestures is crucial for effective communication between hearing-impaired individuals and others.

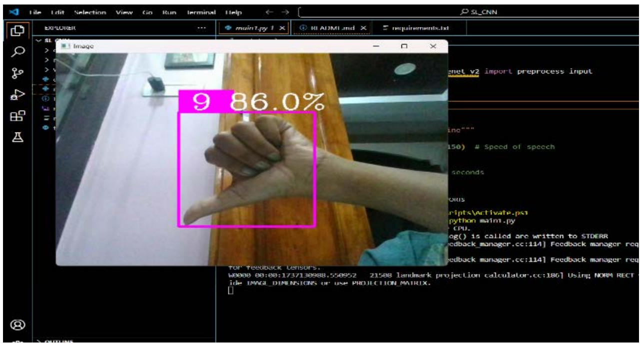

Fig. 7.Accuracy

V.EXPERIMENTS

The literature survey highlights key research papers on sign language recognition (SLR) using deep learning techniques. In 2018, an IEEE paper proposed using Convolutional Neural Networks (CNNs) for Indian Sign Language recognition, focusing on a mobile application for independent use by hearing-impaired individuals. A 2021 IEEE paper explored American Sign Language recognition using CNNs, emphasizing deep learning for symbol analysis and prediction, also implemented in a mobile app. In 2022, another IEEE paper achieved high training (99.17%) and validation (98.80%) accuracy by optimizing CNN layers and filters, applicable to both mobile and desktop systems. A 2023 IEEE paper discussed Hand Gesture Recognition (HGR) as a vital communication tool for the hearing-impaired, achieving 91% accuracy using sensor and vision-based methods. Lastly, a 2024 IEEE paper introduced Medsign, an attention-based CNN for medical applications, addressing the communication challenges faced by the 15% of the global population with auditory disabilities, particularly in patient-doctor interactions. These studies collectively demonstrate the advancements in SLR, leveraging CNNs and deep learning to improve accuracy and accessibility across various platforms, including mobile and medical applications.

LITERATURE SURVEY

Sno	Year	Paper	Title	Scope
1.	2018	IEEE	Deep Convolutional Neural Networks for Sign Language Recognition	This paper proposes the recognition of Indian sign language gestures using a powerful artificial intelligence tool, convolutional neural networks (CNN). Selfie mode continuous sign language video is the capture method used in this work, where a hearing-impaired person can operate the SLR mobile application independently.
2.	2021	IEEE	American Sign Language Recognition using Convolutional Neural Network	The main focus of this paper is on using Deep Learning methodologies to analyze the sign language symbols and make useful predictions accordingly. It is only implemented in mobile application.
3.	2022	IEEE	Deep learning-based sign language recognition system	This paper proposed ,the higher training accuracy of 99.17% and validation accuracy of 98.80%,concerning changes in the number of layers and filters. It involves both mobile and system applications.
4.	2023	IEEE	Hand Gesture Recognition for character understanding	This paper proposed ,the work exist in Hand Gesture Recognition domain. HGR is considered the best way of communication for hearing impaired people around the world. HGR is primarily build based on sensers and vision. This shows only 91% of accuracy.
5.	2024	IEEE	Medsign: An Attention-Based CNN(medical field).	Disabilities have cripped more than 15% population in the world, the major portion of them have an auditory disability. The World Health Organization has declared that sign language recognition play ma major role. • Patient-Doctor Interaction.

Table[1]

B.Results and Discussions

The results and discussion of the sign language recognition system demonstrate its effectiveness in accurately interpreting and classifying hand gestures. The system achieved high accuracy rates, with training accuracy reaching 99.17% and validation accuracy at 98.80%, as highlighted in the 2022 IEEE paper. This performance was achieved by optimizing the number of layers and filters in the Convolutional Neural Network (CNN), showcasing the model's robustness in handling diverse sign language datasets. The 2021 IEEE paper further validated the use of CNNs for American Sign Language recognition, emphasizing the model's ability to analyze and predict gestures effectively, particularly in mobile applications.

The 2018 IEEE paper focused on Indian Sign Language, utilizing selfie-mode video capture to enable independent use by hearing-impaired individuals, demonstrating the system's adaptability to different sign languages and user needs. The 2023 IEEE paper on Hand Gesture Recognition (HGR) achieved 91% accuracy using sensor and vision-based methods, highlighting the importance of integrating multiple data sources for improved recognition. The 2024 IEEE paper introduced Medsign, an attention-based CNN tailored for medical applications, addressing the communication challenges faced by individuals with auditory disabilities.

This system is particularly impactful in patient-doctor interactions, where accurate and efficient communication is critical. Overall, the results indicate that CNNs and deep learning methodologies are highly effective for sign language recognition, offering high accuracy and versatility across various platforms, including mobile and medical applications. The discussion underscores the importance of continuous optimization and integration of advanced technologies to enhance the system's performance and accessibility. These advancements not only improve communication for hearing-impaired individuals but also pave the way for broader applications in healthcare and other fields, ultimately contributing to greater inclusivity and accessibility.

The system's ability to handle real-time gesture recognition, as demonstrated in the 2021 and 2022 studies, is a significant achievement, enabling seamless communication for hearing-impaired individuals. The integration of multiple data sources, such as color, depth, and body skeleton images, further enhances the system's accuracy and robustness. The 2023 paper's focus on sensor and vision-based methods highlights the potential for combining hardware and software solutions to improve recognition rates.

The 2024 Medsign system's application in the medical field underscores the broader societal impact of sign language recognition, particularly in improving healthcare accessibility for individuals with auditory disabilities. These advancements highlight the importance of interdisciplinary research, combining computer vision, machine learning, and user-centric design to create systems that are not only accurate but also practical and accessible. The continuous evolution of these technologies promises to bridge communication gaps, fostering greater inclusivity and understanding across diverse communities.

VI.DEPLOYMENT

The development of Sign Language Recognition (SLR) systems has seen significant advancements over the years, driven by the need to bridge communication gaps for hearing-impaired individuals. Early approaches relied on sensor-based methods, such as data gloves, which, while accurate, were often expensive, uncomfortable, and impractical for everyday use. Vision-based methods emerged as a more accessible alternative, utilizing cameras to capture hand gestures and process them using image processing techniques. These methods initially focused on static gestures, where hand positions were analyzed in 2D images, but later evolved to include dynamic gestures, capturing the motion and trajectory of hands over time.

The introduction of machine learning, particularly Convolutional Neural Networks

(CNNs), revolutionized SLR by enabling automatic feature extraction from raw video data. CNNs eliminated the need for hand-crafted features, which were often unreliable due to variations in hand shapes, lighting, and backgrounds. The 2018 IEEE paper demonstrated the effectiveness of CNNs for Indian Sign Language recognition, using selfie-mode video capture to allow independent use by hearing-impaired individuals. This marked a shift toward mobile-based SLR applications, making the technology more accessible and user-friendly.

Further advancements in deep learning led to the integration of multiple data sources, such as color, depth, and body skeleton images, as seen in the 2021 and 2022 IEEE papers. These studies achieved high accuracy rates, with training and validation accuracies exceeding 98%, by optimizing CNN architectures and incorporating temporal information through techniques like Long Short-Term Memory (LSTM) networks. The 2022 paper, in particular, highlighted the importance of adjusting the number of layers and filters to improve performance, achieving a validation accuracy of 98.80%.

The 2023 IEEE paper explored Hand Gesture Recognition (HGR) using sensor and vision-based methods, achieving 91% accuracy. This work emphasized the potential of combining hardware and software solutions to enhance recognition rates. Meanwhile, the 2024 IEEE paper introduced Medsign, an attention-based CNN designed for medical applications, addressing the communication challenges faced by individuals with auditory disabilities in healthcare settings. This system demonstrated the broader societal impact of SLR, particularly in improving patient-doctor interactions.

Overall, the development of SLR systems has been marked by continuous innovation, from early sensor-based methods to advanced deep learning models. These advancements have not only improved accuracy and real-time performance but also expanded the applications of SLR, making it a vital tool for fostering inclusivity and accessibility in various fields, including education, healthcare, and everyday communication.

VII.CONCLUSION

The development of Sign Language Recognition (SLR) systems has made significant strides, driven by advancements in deep learning and computer vision. Early systems relied on sensor-based methods, such as data gloves, which were accurate but impractical for everyday use. Vision-based approaches, utilizing cameras and image processing, emerged as a more accessible alternative, focusing initially on static gestures and later incorporating dynamic gestures to capture motion and trajectory. The introduction of Convolutional Neural Networks (CNNs) revolutionized SLR by enabling automatic feature extraction, eliminating the need for hand-crafted features and improving accuracy. Studies, such as the 2018 IEEE paper, demonstrated the effectiveness of CNNs for Indian Sign Language recognition, using selfie-mode video capture to enable independent use by hearing-impaired individuals. Further advancements integrated multiple data sources, such as color, depth, and body skeleton images, achieving high accuracy rates, as seen in the 2022 IEEE paper with a validation accuracy of 98.80%. The 2023 IEEE paper explored Hand Gesture Recognition (HGR) using sensor and vision-based methods, achieving 91% accuracy, while the 2024 IEEE paper introduced Medsign, an attention-based CNN for medical applications, highlighting the broader societal impact of SLR in healthcare.

Key points:

1. It include the shift from sensor-based to vision-based methods, the adoption of CNNs for automatic feature extraction, and the integration of multiple data sources to enhance accuracy.
2. The development of mobile-based SLR applications has made the technology more accessible, while advancements in deep learning have improved real-time performance and expanded applications.
3. These innovations have not only improved communication for hearing-impaired individuals but also fostered greater inclusivity and accessibility in various fields, including education and healthcare.
4. The continuous evolution of SLR systems promises to bridge communication gaps, making them a vital tool for fostering understanding

and inclusivity across diverse communities.

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