Voice of Hearing and Speech Impaired People

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***Abstract*— Sign language serves as a vital medium of communication for individuals who are hearing and speech impaired, yet the communication gap between this community and the general public persists due to limited understanding of sign language. In response, this research introduces a comprehensive application aimed at fostering inclusive communication. The proposed application leverages advanced technologies, including deep learning and computer vision, to translate sign language gestures into written text and spoken language, and vice versa. Key objectives encompass accurate translation, user-friendly interface design, and promotion of inclusivity. Drawing from a review of related literature, methodologies integrate data collection, preprocessing, feature extraction, and classification, utilizing Convolutional Neural Networks (CNNs) and natural language processing techniques. Notably, a significant aspect of this project lies in the collection of extensive datasets for American Sign Language (ASL) and Pakistan Sign Language (PSL), contributing to higher accuracy and reliability. The application facilitates cross-modal communication, enabling real-time translation of sign language to text/voice and vice versa for both ASL and PSL. An Android application is developed using React Native to extend accessibility to mobile platforms. Applications span educational accessibility, customer support enhancement, medical communication facilitation, governmental accessibility, and broader societal inclusivity. Future enhancements include incorporating additional sign languages, improving context comprehension, integrating assistive technologies, enhancing learning experiences, and expanding social integration. Ultimately, this project contributes to bridging the communication gap between hearing and non-hearing individuals, promoting inclusivity and accessibility in diverse contexts.. The uniqueness of this study revolutionizes communication for hearing and speech impaired people, enabling them to engage with the world more comprehensively and efficiently.**

Keywords—CVZone, OpenCV, Keras, Tkinter, NumPy, colab, MediaPipe, HandDetector, React-Native.

I. Introduction

Sign language serves as the primary means of communication for individuals who are hearing and speech impaired, allowing them to convey their thoughts and ideas through hand and body gestures [1]. However, communication between the hearing and speech impaired community and the general public often faces challenges due to a lack of understanding of sign language by many individuals. This results in communication barriers, social isolation, and limited opportunities for interaction between these two groups.[2] To bridge this communication gap [3] and promote inclusivity, the project aims to develop a comprehensive and user-friendly application that facilitates two-way communication. [4] The developed application has the capability to translate sign language gestures into both written text and spoken language, as well as translate written text and spoken language back into sign language. By doing so, the application enables effective communication between the hearing and speech impaired community and the general public[5].

The key objectives of the project include:

A. Accurate Translation

The application should accurately translate sign language gestures into written text and spoken language and vice versa to ensure that the intended messages are conveyed in a correct way.

B. User-Friendly Interface

The application will be designed with a user-friendly interface that is intuitive and easy to use, catering to the needs of both the hearing and speech impaired community and the general public.

C. Promoting Inclusivity

By facilitating effective communication between the two communities, the application aims to break down communication barriers, reduce social isolation, and create more opportunities.

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II. Related Works

The program "Recognizing Sign Languages Using Pattern Recognition" was created by Ismunandar in 2010. He employed a 3D-CNN model in this study to recognize the hand motions and translate them into text. Using OpenCV, he recorded the frames of the photos and used them to train the CNN model [6].

Working on "American Sign Language alphabet recognition using Convolutional Neural Networks with Multiview augmentation and inference fusion" in 2018, Tao, W., Leu, M. C., & Yin, Z. Using the CNN model and the data augmentation technique, an interface was developed to translate sign language into text. Microsoft Kinect was used to record the photographs. To prevent overfitting, the photos were enhanced to produce more perspective views [7].

In 2019, the "Sign Language Recognition System Based on Weighted Hidden Markov Model" project was created by Wenwen Yang, Jinxu Tao, Changfeng Xi, and Zhongfu Ye. In order to handle the variation, a weighted hidden Markov model (HMM) [8] is put forth in this study. Additionally, they produced strong sign features using the Kinect sensor to increase recognition rates. On a dataset of 156 isolated sign words in Chinese sign language, their system is assessed. The experimental results demonstrate that the suggested method performs better than previous methods with a high recognition rate of 94.74%.

Neural sign language translation based on human key point estimation was the focus of Ko, S. K., Kim, C. J., Jung, H., and Cho's work in the same year. They proposed "RGB" and "RGB-D" in this work. These static gesture detection techniques employ the "VGG19" model, which has been fine-tuned, and use a feature concatenate layer of those photos to boost accuracy. When they used the model to a dataset for recognizing American Sign Language, they obtained 94.8% accuracy.

Kinect devices [9] have been utilized by many previous projects for sign language recognition, which involves hardware expense. Moreover, the earlier proposed software based or hybrid i..e both software and hardware based sign language recognition systems have relatively less accuracy, less effective in terms of functionality, poor real-time performance then our proposed software based sign language recognition system which eliminates hardware needs and offers promising accuracy rates.

III. Datasets

We sought to work with raw images, at first. The dataset was initially acquired from Kaggle, which led to low accuracy and resulted in inaccurate results each time because dataset [10] is not diverse, i.e. not taken from different annotations. Hence, for our project, we made the decision to create our own dataset and the technology used is python cvzone hand tracking python module. Creating our own dataset aided in improving the model's accuracy and produced accurate predictions. 11,200 images were taken for American Sign Language (ASL) dataset and

16,000 images were taken for Pakistan Sign Language (PSL), and this resulted in high accuracy rate and correct predictions. All images are in JPEG format and of pixel size 300x300. The images are palm images representing various alphabets or fingerspells / handshapes of ASL
and PSL.

TABLE I. COMPARISON OF ACCURACIES ON KAGGLE AND COLLECTED DATASET

Dataset	Accuracy
Kaggle dataset	96 %
Collected dataset	98 %

We collected the American Sign Language (ASL) and Pakistani Sign Language (PSL) datasets ourselves using Python OpenCV cvzone module and captured 400 images for each handshape fingerspell by capturing the hand movements of individuals signing different words and phrases of ASL and PSL sign languages using the laptop's built-in webcam. In American Sign Language (ASL), the individual letters are called "handshapes" and the entire set of letters is referred to as the "ASL manual alphabet". In Pakistani Sign Language (PSL), the individual letters are called "fingerspelling" and the entire set of letters is referred to as the "PSL fingerspelling alphabet" or simply "PSL alphabet".

The ASL [11] dataset consists of 11,200 images that are labeled in 28 classes A-Z [26], del and nothing.

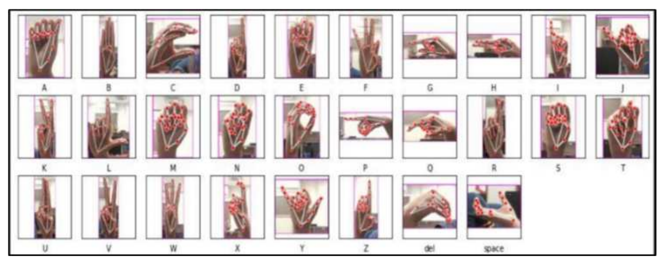

Fig. 1. Data Visualization of American Sign Language (ASL)

The PSL [12] dataset consists of 16,000 images that are labeled in 40 classes. The final dataset is an image dataset. The below images specifies various sign gestures.

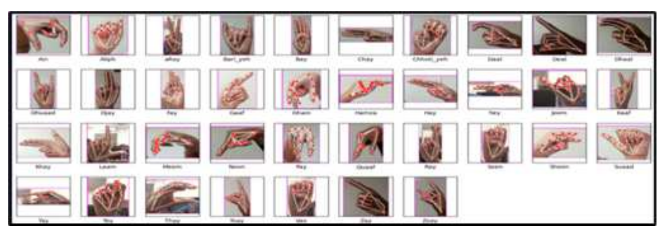

Fig. 2. Data Visualization of Pakistan Sign Language (PSL)

To guarantee correctness, the dataset was labeled and standardized. The CNN model that was employed in this experiment was created especially for the recognition of sign language and had demonstrated promising results in the precise classification of sign language motions.

By comparing the previous datasets with the dataset used in this research, it is clear that the larger, standardized dataset used in this project contributed to the higher accuracy achieved in this study.

IV. TRAINING CONVOLUTIONAL NEURAL NETWORK MODEL

Convolutional Neural Network (CNN) is employed for text/speech recognition to sign language and vice versa. CNNs [13] are deep learning models well-suited for image processing tasks, including object detection, classification, and segmentation. The CNN model is trained on images categorized into 28 classes of American Sign Language (A-Z, space, delete) and 40 classes of Pakistan Sign Language. The model architecture consists of 12 layers, comprising convolutional, maxpooling, flatten, fully connected, and output layers. Rectified Linear Unit (ReLU) activation function is utilized in each layer to introduce nonlinearity and mitigate the vanishing gradient problem. As the optimizer, Adam optimizer is chosen for updating the model based on the loss function output, amalgamating advantages from stochastic gradient descent algorithms. The CNN [14] model is specifically tailored for sign language gesture classification, utilizing a dataset encompassing American and Pakistani Sign Languages. During training, the Adam optimizer with default learning rate is utilized, employing a batch size of 315 and training for 5 epochs to achieve optimal accuracy and loss convergence.

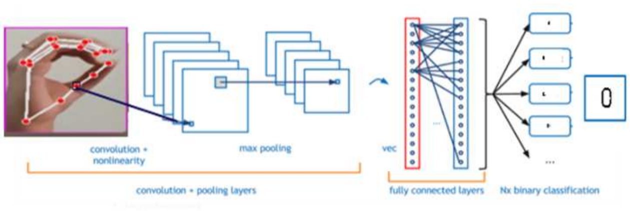

Fig. 3. F Convolutional Neural Network (CNN) Model Architecture

The accuracy of our model, which is higher than that of the majority of related recent studies on American Sign Language and Pakistan Sign Language, was 85.82% in the first epoch, 99.14% in the second, 99.64% in the third, 99.59% in the fourth, and 100% in the fifth.

V. METHODOLOGY

Data collection and visualization, preprocessing, feature extraction, and classification are the processes that make up the technique for this project. Video recordings of sign language users were used to record the data; the recordings were then preprocessed to reduce background noise and extract pertinent information. The collected features were then used to train a Convolutional Neural Network model, a type of machine learning model, to recognize sign language.

Finally, using natural language processing techniques [15] , the recognized sign language was translated into written text or audible speech and vice versa.

The sign to text/speech module of American Sign Language (ASL) and Pakistan Sign Language (PSL) begins with raw data in the form of images captured from video recordings of sign language gestures. These images undergo preprocessing to enhance quality and extract relevant features. Subsequently, a Convolutional Neural Network (CNN) classifier is trained and tested using the preprocessed data to recognize sign language gestures. Upon successful training, the trained model is utilized to predict signs from input images. The predicted signs are then sent via a POST request to a Flask server. The server captures the image and processes it further to display the corresponding letter and speak the word associated with the sign, providing real-time translation from sign language to text and speech. The flow chart below resembles the sequential process of sign to text/speech module.

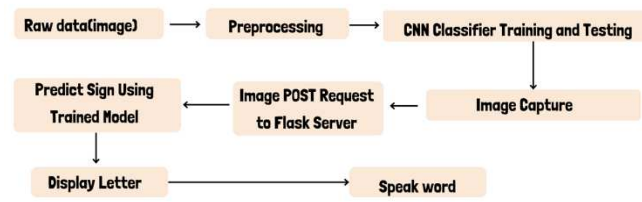

Fig. 4. Flow Diagram of Sign to Text/Speech Module

The text/speech to sign module begins by reading user input in the form of voice or text. The input is then processed to convert words into individual letters. Subsequently, the module searches for corresponding images based on the filenames of the letters. Once a match is found, the module displays the image of the letter, providing a visual representation of the input text or speech in sign language.

The flow chart below resembles the sequential process of text/speech to sign module.

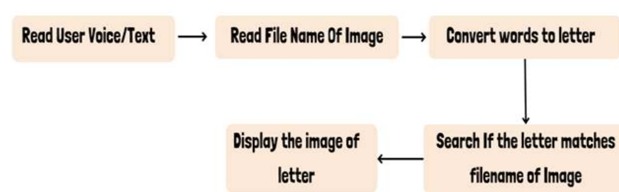

Fig. 5. Flow Diagram of Text/Speech to Sign Module

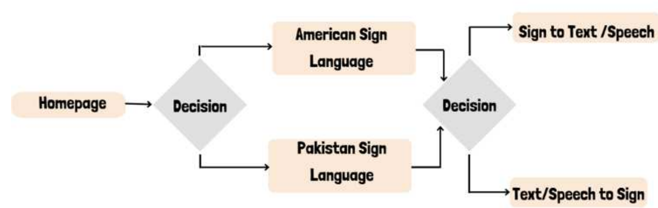

Fig. 6. Sign Language Application Flow Diagram

Upon launching the application, the initial interface displayed is the home screen, serving as a gateway to distinct sign language translation functionalities. This screen showcases two prominent buttons: "American Sign Language (ASL)" and "Pakistan Sign Language (PSL). The application flow is represented by the flowchart below.

Upon selecting the "ASL" option, user is directed to the American Sign Language module. Here, they are presented with two choices: "Voice/Text to Sign" and "Sign to Voice/Text." Upon opting for "Sign to Voice/Text," user is navigated to an advanced interface where the device's camera is seamlessly activated. This camera interface captures user-generated sign gestures and subsequently translates them into textual form, offering an immersive experience that bridges the gap between visual and auditory communication realms. Conversely, the "Voice to Sign/Text" pathway prompts users to input either spoken or written communication. The system then transforms this input into corresponding sign gestures, enhancing inclusivity and communication potential.

Equally compelling, upon selecting "Pakistan Sign Language (PSL)" from the home screen, users are transitioned to the Pakistan Sign Language module. This section mirrors the ASL counterpart, offering a similar dichotomy of choices: "Voice/Text to Sign" and "Sign to Voice/Text." By choosing the "Sign to Voice/Text" option, the camera interface once emerges, capturing sign gestures and converting them into intelligible textual representations. On the other hand, the "Voice to Sign/Text" alternative empowers users to contribute spoken or written prompts, subsequently translating these inputs into coherent sign gestures, thereby fostering meaningful interaction, and understanding.

VI. WORKING

The tools and techniques used in the implementation of this project include Python TKinter for the frontend, Adam optimizer for efficient gradient descent in deep learning, CVZone [16] Hand Tracking Module for data collection, OpenCV for sign language image processing, Keras for

deep learning, Python for interface implementation, Visual Studio Code for project development, and Google Colab for model creation. Data preprocessing involved utilizing Python libraries like NumPy, OpenCV, Tensor Flow, Keras, and PIL for image manipulation, scaling, and transformation.

The project involved hand tracking using two Python [17] libraries, MediaPipe and OpenCV. The hand tracking process consists of two stages: palm detection, which provides a cropped image of the hand, and hand landmarks identification, where MediaPipe identifies 21 hand landmarks on the cropped hand image. These hand landmarks were essential for recognizing gestures and understanding hand positions.

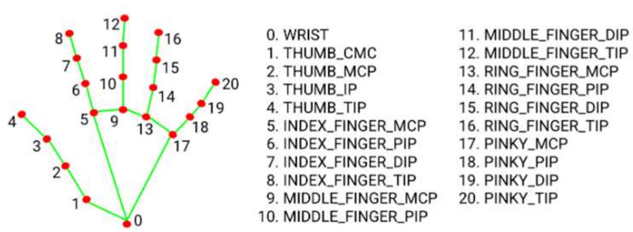

Fig. 7. Hand Landmarks of Media Pipe Hands

We used the 'cvzone' library, including the 'HandDetector' for hand tracking and the 'Classifier' for image classification tasks [18]. The 'HandDetector' object was configured to detect a single hand using the 'maxHands' parameter. The 'Classifier' object was initialized with the paths to a trained classification model and a text file containing class labels.

The implementation captured image input from the webcam, converted the image to RGB format (required by MediaPipe) [19] , identified hands in the image, retrieved hand landmark information (x, y coordinates, and id of each point), determined image dimensions, calculated central positions of identified hand points, and created a blank white image for image masking.

Image masking involved creating a blank white image using the NumPy library, cropping a region of interest (ROI) based on hand detection bounding box coordinates, and storing the cropped hand region for further processing. Aspect ratio calculations can help distinguish different hand shapes.

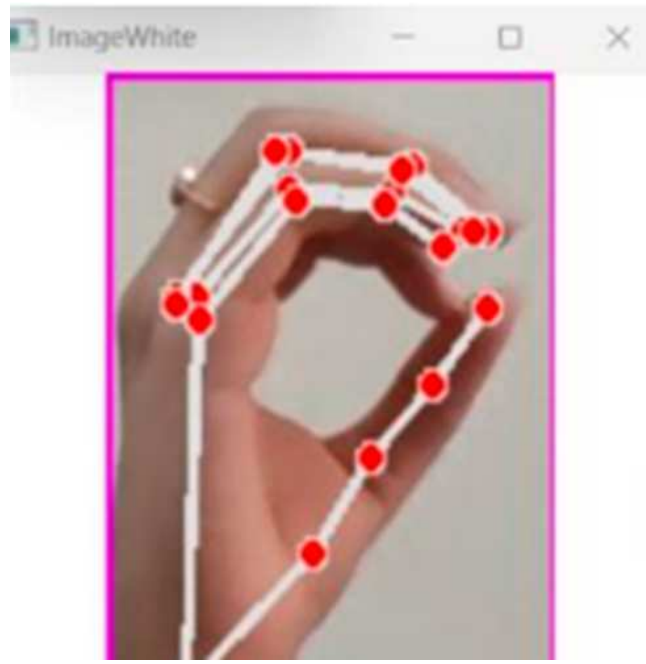

Fig. 8. Image Masking Using Python CVZone

Drawing hand landmarks and connections on the hand image was done by circling specific hand points, such as the tip of the pinky finger (point 20), and connecting hand landmarks based on their ids.

The final output was a real-time video [20] displaying the user's hands with tracked hand landmarks and connections drawn on the hands. This comprehensive process aims to recognize hand gestures, identify hand positions, and facilitate effective sign language recognition, which can be used to bridge the communication gap between the hearing and speech impaired community and the general public. The use of computer vision techniques, image processing, and deep learning contributes to the development of an accurate and efficient system for hand gesture recognition.

VII. CROSS-MODAL COMMUNICATION

The Pakistan Sign Language (PSL) sign to voice/text conversion focuses on camera usage, sign recognition and text to speech synthesis to enable real time translation of PSL signs into spoken text. Users [21] can interact with the camera feed, record signs, receive recognized text and even hear the spoken representation of the signs they've recorded.

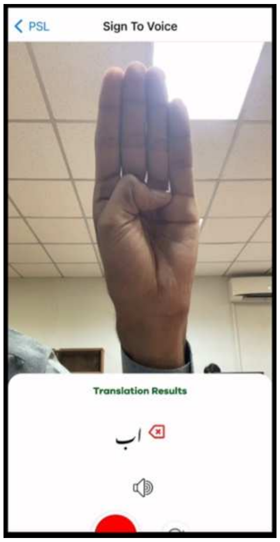

Fig. 9. PSL sign to text/voice detection

The PSL voice/text to sign conversion facilitates users input text through voice or text, triggering speech recognition and translation processes.The integration of an external translation API [22] is used for converting text/voice to PSL.

Fig. 10. PSL text/voice to sign conversion

The American Sign Language (ASL) voice/text to sign conversion uses react native components and react-native-voice library for voice recognition. Users [23] can speak into the app and their speech is converted to text. The text is then visually represented using images associated with each letter of the recognized text.

Fig. 11. ASL voice/text to sign conversion

The ASL sign to text/voice conversion uses the device's camera. It allows users to input sign language which gets recognized and translated into voice or speech and text as an output.

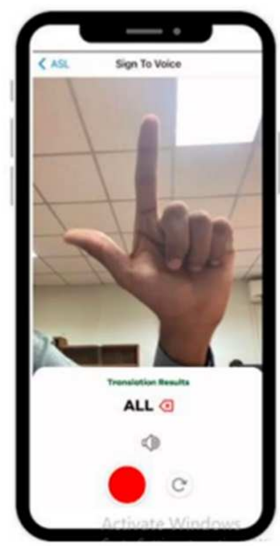

Fig. 12. ASL sign to text/voice detection

VIII. Applications

The proposed technology offers a wide range of applications aimed at enhancing accessibility and inclusivity for individuals who use sign language [24].

Firstly, it can revolutionize education by making educational content more accessible to students who rely on sign language as their primary mode of communication. Moreover, organizations providing customer support, helplines, and other communication services can utilize this technology to improve accessibility for customers with hearing impairments.

In the healthcare sector [25], it can facilitate effective communication between medical professionals and patients who are deaf or hard of hearing, ensuring comprehensive and accurate healthcare delivery. Government agencies can leverage this technology to enhance accessibility and communication with citizens, fostering a more inclusive society.

In public spaces, events, and online platforms, it ensures that infomation is readily accessible to everyone, regardless of their hearing abilities. Lastly, integration into language learning apps and platforms can promote cross-cultural [26] understanding and inclusivity by teaching sign language to a broader audience.

IX. Future Enhancements

In considering the potential for future development, several avenues emerge to enhance the utility and functionality of the system [27]. Firstly, the application's versatility renders it applicable across various domains, including medical and educational fields. Future iterations could incorporate additional features such as language translation options, enabling users to convert text into different languages based on their preferences, thereby expanding accessibility and usability.

There is potential to transition from a single sign recognition approach to supporting sequences of signs, allowing for the interpretation of phrases or sentences rather than individual signs alone. Additionally, the application currently supports finger spelling techniques predominantly used in ASL and PSL; however, future enhancements could broaden its scope to encompass other forms of sign languages [28].

Integration with live streaming platforms, assistive devices, and social media channels presents an opportunity to extend the application's reach and impact, facilitating seamless communication across diverse contexts. Lastly, the introduction of interactive learning tools such as exercises, quizzes, and learning games could enrich the user experience, promoting engagement and proficiency in sign language acquisition.

X. Conclusion

This research is useful for differently abled, speech impaired and for people who cannot listen properly. This research focuses on sign language recognition and communication, involving data collection, preprocessing, feature extraction, and classification. Video recordings of sign language users were used to extract features and trained using a Convolutional Neural Network (CNN) [29] model for gesture recognition. The recognized sign language was then translated into text using natural language processing techniques. The 'CVzone' library facilitated hand tracking and image classification tasks. This way communication between both hearing and non-hearing individuals can be easily done [30].

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