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Efficient Learning for Hearing-Impaired: Two Way Sign Language Translator Using AI

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Abstract:

This research paper describes the design and implementation of a two-way sign language translator for deaf-mute and hearing individuals. The device uses a hand gesture recognition system to translate sign language into text for hearing individuals and converts text into sign language videos for deaf-mute individuals. The paper goes over the technical challenges and solutions involved in creating a legitimate system that recognizes gestures and a sign language video generation system. The results of the user testing with deaf-mute and hearing individuals show that the device has high accuracy and is user-friendly. The two-way sign language translator has the possibility of enhancing communication and accessibility in daily interactions for deaf-mute people.

Keywords: *Hearing Impaired, Artificial Intelligence, Sign Language Translator*

I. INTRODUCTION

The development of technology has led to a significant improvement in the daily lives of individuals with disabilities, including deaf-mute individuals as seen in Figure 1. Communication is one of the most critical aspects of human interaction, and the lack of it can result in social exclusion and isolation. Deaf-mute individuals often face difficulties in communicating with the hearing population, leading to misunderstandings and a lack of access to information and services.

In recent years, advancements in computer vision and machine learning have paved the way for the development of a two-way sign language translator. This device takes hand gestures as input and converts it into text for hearing individuals and converts text into sign language videos for deaf-mute individuals. The device operates in real-time, providing immediate translation of sign language and spoken language, facilitating communication between deaf-mute and hearing individuals. The creation of such a device necessitates extensive technical knowledge, including the design and implementation of a system that recognizes hand gestures as well as a gesture recognition video generation system. The recognition of hand movements system has to be capable of recognizing and translating a huge spectrum of sign language motions. The sign language video generation technology must be capable of producing high-quality gesture recognition videos that deaf-mute people can understand. This technology has the potential to significantly improve the daily lives of deaf-mute individuals of certain age bands as seen in Figure 2 by providing them with improved access to information and services. It can also reduce misunderstandings and improve social interaction between deaf-mute and hearing individuals.

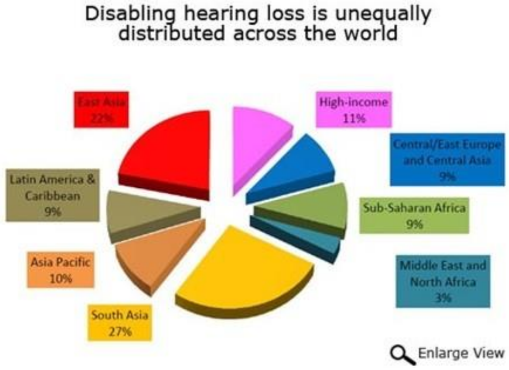

Figure 1: Hearing Loss Percentage Around the World

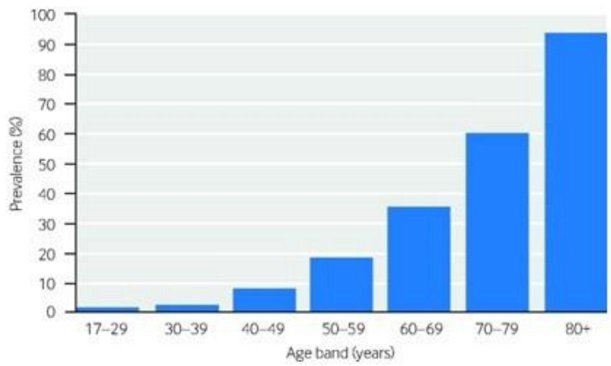

Figure 2: Age band for Hearing Loss Around the World

For speech-impaired individuals, the primary means of communication is Sign Language. It empowers them to communicate by gestures conveying their considerations and participating in discussions. Historically, the person who was either deaf and unable to speak or both deaf and able to speak was referred to as a deaf-mute. A deaf person with some degree of speaking ability is still referred to by this term. The deaf community uses two distinct spellings of the word. The capital "D" denotes culturally Deaf individuals who use sign language for communication, whereas the small "d" deaf indicates a person's level of hearing as determined by audiology and their absence from the deaf community [1]. Numerous researchers have proposed the possibility that the aforementioned group of people faces significant linguistic obstacles that prevent them from accessing information and preventing them from communicating effectively, which puts them in uncompromising situations in society. To put the figures in perspective, the 2011 census revealed that, out of the 13.4 million disabled Pakistanis currently living in the employable age group of 15 to 59, 9.9 million (or 73.9 percent) were non-workers or marginal workers. This suggested that only 26.1 percent of the country's productive age group was employed. When it comes to employment, people with hearing impairments face a number of challenges [2]. Deaf people avoid interactions with others because it is difficult for them to converse, and 31 percent presume they are given special treatment because of their hearing impairment, deafness, or sensory loss. As a result of their inability to communicate, 68 percent of people with hearing impairment experience a sense of isolation at work Shinde and Dandona. People who are deaf face a lot of irritations and frustrations that make it hard for them to do things they need to do every day. According to the findings of the research, people who are deaf, particularly children who are deaf, experience a high prevalence of emotional and issues with behaviour in connection with different kinds of interaction. The vast majority of people with these disabilities become quiet and reserved and avoid social and facial landmark interaction. Deaf people may experience social isolation and low self-esteem as a result of their inability to communicate with family and friends. In addition to a lack of social interactions, communication is a significant barrier to Deaf- mute health care [3]. The deaf community can remove their deafness with a variety of medical treatments, but these treatments are expensive [4]. According to a 2017 "World Health Organization (WHO)" report, the following are the various costs associated with hearing loss: (1) Direct Expenses: They include the expenses incurred by healthcare systems due to hearing loss; Support for these children's education is one example of direct costs; (2) Indirect Costs: They usually symbolize the expense of an individual's personal inability to make a contribution to society, which includes lost productivity. and, (3) Intangible Costs: They refer to the stigma that hearing-impaired families endure. The report comes to the conclusion that untreated hearing loss has a significant impact on both the economy as a whole and the healthcare system. There are numerous communication methods available for deaf and mute people to convey their communications, such as letters, aide articles, gestures, booklets with alphabets, lip reading, and various gestures. In spite of these channels, Deaf-mutes and normal people encounter numerous communication challenges. The problem is not limited to a deaf-mute person who cannot hear or speak; another issue is the lack of connectedness with Deaf society among non-deaf people. A large percentage of deaf people are either unfamiliar with or have limited experience with sign language [5]. Additionally, there are more than a dozen sign languages, and it is challenging for the average person to comprehend and become accustomed to these languages. Participating in assistive technology, which can be used as an interpreter to translate sign languages into text or speech, can help the Deaf community and hearing people communicate more effectively [6]. Moreover, A two-way communication system for deaf-mute individuals to communicate with normal people is a device or technology that enables the exchange of information between individuals who have hearing and speech impairments and those who do not. This system typically consists of a combination of hardware and software that can be used to convert speech into text or visual representations and vice versa. One example of a two-way communication system for the deaf-mute is a speech-to-text device that uses a microphone to capture speech and converts it into written text in real-time. This text can then be displayed on a screen, allowing deaf-mute individuals to read what is being said. Additionally, a text-to-speech system can be used to convert written text into speech, allowing deaf-mute individuals to communicate with others through speech synthesis. Another example is a sign language recognition system that uses cameras and computer algorithms that recognize and translate sign language into written language or speech. This can be especially helpful for individuals who are proficient in sign language but struggle to communicate with those who do not understand it. These two-way communication systems can assist in bridging the gap between deaf-mute people and the hearing world, making communication more accessible and inclusive for all.

The study targets the communication gap between deaf-mute and hearing people by creating a system that can translate sign language into text and text into sign language. How useful and user-friendly is a two-way sign language translator in promoting communication between deaf-mute and hearing people?

The paper is arranged as follows: Section II covers the detailed literature study on sign language in different domains, gesture recognition systems, and artificial intelligence and disability. Section III discusses the methodology of the research. We give an overview of the data sets, experiments, and results in Section IV and Section V brings the paper to a close.

II. LITERATURE REVIEW

Because of birth deformities, accidents, and oral illnesses, the number of deaf and dumb people has rapidly increased in recent years. Deaf and dumb people must rely on visual communication because they cannot communicate with ordinary humans [7]. Two-way communication among deaf and dumb people and people who can hear and speak is an important area of research that has been investigated by numerous researchers over the years. The purpose of this literature review is to examine the current state of research in this field and identify areas that need further investigation. Studies have shown that communication between deaf and dumb individuals and those who can hear and speak is not always straightforward and can be hindered by a lack of understanding and awareness. One of the primary challenges is the use of sign language by deaf and dumb individuals, which is often not understood by those who can hear and speak. This can lead to a lack of communication and can result in misunderstandings and frustration. To address this issue, various communication tools and technologies have been developed to facilitate two-way communication. Sign language translators, multimedia message services, and real-time subtitles, for example, are frequently used to bridge the communication gap between deaf and dumb people and those who can hear and speak. Furthermore, the use of technology tools such as hearing aids, cochlea, and speech recognition software can help these two groups communicate more effectively. Wearable technology, such as smartwatches, has also created new avenues for interaction between deaf as well as dumb people and those who can hear and speak. In conclusion, the field of two-way communication between each individual and those who can hear and speak is an ongoing area of research with much room for improvement. The use of assistive technologies and communication tools has improved communication between these two groups, but more research is needed to better understand the challenges faced by deaf and dumb individuals and to develop new and more effective communication tools.

A. Gestures Recognition Systems

Abir Sen et al. (2024) in their paper discuss that hand gesture recognition is critical for human-machine interaction, particularly for physically challenged people. Current approaches struggle with issues such as poor lighting, complicated backdrops, and slow detection rates. The YOLOv5s model, fine-tuned to improve detection speed and inference time, is used in this study to recognize hand gestures in real-time. Testing on two datasets revealed that the fine-tuned model attained a mean average precision of 92.60% and more than 55 frames per second, exceeding other models and improving real-time system interaction for the physically disabled. After recognizing hand movements and hand features such as peak and angle calculations, Shweta S. Shinde suggested a structural model for recognizing hand gestures that convert gesture frames into text and vice versa. Shinde, Autee, and Bhosale.Christopher Lee and Yangsheng Xu's glove-based gesture identification system was able to recognize 14 of the arm alphabet's alphabets, learn some new gestures, and update the system's prototype of each gesture online [8]. In a paper, K. Sunitha and Anitha Saraswathi Singh explain that wearable communications systems and web-based learning systems are the two main categories through which deaf and mute people communicate. Under the Wearable specialized technique, there are Glove-based frameworks, a Keypad strategy, and a Handicom Contact screen. All three subdivided approaches use different types of sensors, an accelerometer, an appropriate microcontroller, a text-to-speech transformation component, a keyboard, and a touchpad. There is a need for an external monitor to analyze a message among deaf-mutes and those who are not. [9]. A paper explained that the digital image processing-based static hand gesture recognition system was presented by Prof. Abdul Sattar. The SIFT algorithm is utilized for the feature vector hand gesture. The SIFT attributes that are unaffected by scalability, motion, or addition of noise were calculated at the edges [10]. A study by Haitham Badi describes the advantages of two feature extraction methods for processing gestures and identifying issues based on hand contour and complex moments. In SL, the back-propagation learning algorithm was used to classify images and recognize hand motions in three phases: The first stage is data preprocessing, followed by extracting features, and, finally, classification using the ANN strategy. The ID exactness of hand shape was 71.30 percent, while the best acknowledgment pace of mind-boggling minutes was 86.90 percent. The neural network suffered from overfitting as a result of this method [11]. Elakkiya and Selvamani proposed a method to address the uncertainties in the video's manual division, developments in pectic substances, and consistent signs. The Hidden Markov Model was used in this study to improve dynamic programming by utilizing spatial and temporal features Altememe and El Abbadi

B. Artificial Intelligence and Disability

Sidharth Pancholi, Juan P. Wachs, and Bradley S. Duerstock [12] in their paper state that assistive technology (AT) improves the freedom and productivity of people with disabilities in their daily, community, and workplace activities. The combination of artificial intelligence (AI) with electronics, robots, and software has resulted in inventions such as mind-controlled exoskeletons and smart wheelchairs. This article discusses artificial intelligence approaches such as brain-computer interfaces and computer vision that benefit people with physical impairments. It also looks at the present obstacles and future perspectives for AI-powered assistive solutions. Maram Fahaad Almufareh et al. [13] in their paper discuss that Artificial intelligence (AI) has transformed inclusion and accessibility for people with disabilities by providing solutions such as voice recognition, AI-powered smart eyewear, and healthcare monitoring devices. AI developments include early disease detection, improved mobility with AI-powered prosthetics and exoskeletons, and personalised learning aids for education. However, concerns such as data privacy, algorithmic prejudice, and the digital divide must be addressed. A conceptual paradigm for AI disability inclusion encourages ethical and effective AI development, improving the quality of life for people with impairments. Peter Smith Laura Smith states that numerous advancements have been made, including AI-powered industrial robot arms and other artificial limbs, decision-making tools for clinicians and the disabled, and path optimization software for the partially sighted. These tools are helping a lot of people, making us more accessible, and changing our lives. But what exactly are these tools' true limitations? How ethical is it to allow AI tools to make recommendations or assist with selection? Is there too much promise in AI for individuals? [14]. According to Micheal Oliver, UPIAS (Union of Physically Impaired Against Segregation) defined disability in the document Fundamental Principles of Disability define disability as "the connection that exists between deficiencies and discrimination on the basis society," rather than a physical or mental impairment. Capital and UPIAS's work reflects Marxist thought and labor movement traditions [15]. Bayan Mohammed Saleh et al developed an application named D-talk that made it possible for deaf people to communicate with the outside world. There has been a lot of research done over the years on the sign language recognition program, which was needed to understand sign languages. The various input sensors, gesture segmentation, feature extraction, and classification techniques were the primary subjects of the research. The purpose of the paper was to evaluate and compare sign recognition system methods, and classification methods in AI [16]. In a study, Elsevier et al set out to create a machine-learning automated system for forecasting the Expanded Disability Status Scale (EDSS) score at two years for those suffering from multiple sclerosis based solely on age, gender, and mucus attenuated inversion recovery (FLAIR) MRI data [17]. Vibhu Gupta stated that Hand-Sign Language Gestures are nonverbal communication tools that can be seen and comprehended. Since Deaf and Dumb people's only disability is speech-related communication, they are unable to speak other languages. As a result, the one and only way they can interact with others who are disabled is by employing this hand-sign language[18]. Mansi Jain came up with a way to get around the language barrier because normal people can't understand deaf-mute hand sign language and vice versa. Additionally, since most people are not familiar with sign language and interpreters are not very easy to use, they get stuck. As a result, she suggests a CNN-based approach for translating sign language into text. The paper's proposed structure places an emphasis on finger spelling and an additional emotion recognition feature to support the interpretation of the third component of sign language—non-manual features—a real-time solution that uses convolutional neural networks to break the language barrier and makes sign language easy to understand for both hearing and deaf peopleGupta, Jain, and Aggarwal.

C. Real-Time Data Based Sign Language Recognition Systems

Wang and Popovic [19] created a real-time hand-tracking application using colored gloves. The K-Nearest Neighbors (KNN) technique was able to identify the gloves' color pattern, but the system needs to be fed hand streams continuously. According to Rekha et al. [20] findings, the Support Vector Mechanism (SVM) performed better than this algorithm. Recognition of Sign Language can take one of two forms: Continuous sentence recognition and isolated sign recognition. The SLR system also supports both whole sign-level modeling and subunit sign-level modeling. Subunit-level sign modeling can be achieved through the use of two approaches: visual-descriptive and linguistic-oriented- oriented Elakkiya et al. [21] proposed a framework for subunit alphabet recognition by combining the SVM learning algorithm with the boosting algorithm. Mandeep Kaur et al. [22] proposed a system that used NLP and a variety of ML and AI ideas to create an accurate model. Convolution brain organizations (CNN) were utilized for expectation as it is productive in anticipating picture input, additionally, as lip developments are quick and persistent, so, it was difficult to catch so alongside CNN, the utilization of consideration-based long momentary memory (LSTM) ended up being proficient [23]. Better outcomes were achieved through the use of data augmentation techniques. The Python libraries for speech to text conversion is employed are TensorFlow and Keras [24].

III. **METHODOLOGY**

AI-based approach toward resolving one of the most crucial problems that verbally disabled people face. In this modern world of technology, where AI and machine learning is facilitating everyone to their relief. There should be a way for verbally disabled people to communicate using the same piece of technology. So, our project and AI-based approach will enable deaf people to talk to others whether or not the other person knows sign language or not. It is a huge barrier and problem for the deaf as well as other person to communicate with each other if the fit person can't understand sign language. In this research study, we will read the video image of a deaf person frame by frame. The image detection and processing algorithm will then try to understand the hand gestures. The system will take each frame image of the video being displayed. The system will then be able to translate the hand gestures or the signs of the deaf and dumb person into readable text. This readable text is then displayed on the screen by the system so that the other person can read the text and understand what the deaf person is trying to say. This will the communication between the two parties seemingly easy and remove language barriers between the two. This approach will allow people to understand sign language as well. The system is currently working on a machine-learning algorithm as well. The machine learning algorithm allows the system to learn as the gestures are being performed by dumb and deaf people. Moreover, the system will be continuously trained on an open database. This database will allow the system to train on worldwide hand gestures and convert them into text format.

A. Architectural Design

Text input to Sign Module: This module of the system will allow the users to provide text input to the system. In return, the system will generate either a hand gesture or find a GIF image for the dumb and deaf person to see and understand what the person wants to say. The process of converting text input into video hand gestures will be done in 2 parts for the text input. Once the system receives text input from the user, the system will first search in the local directory of the device the system is running on for any video that could explain the text in sign language. This will allow the system to access the hand gesture video even more quickly if the user has searched for the same hand gesture video again. This will allow the system to first search the local storage and find the video there to display. Upon finding a suitable gesture in the local storage, the system will play the video for the dumb and deaf. This process will be completed using the OpenCV package within the software.

Sign-to-Text Module: This module is the most crucial aspect of this research. To complete the processes mentioned in this module, the system goes under many different sub-processes to provide a single output. The module is working in real time because it collects data continuously from the webcam of the device. The algorithm detects hand gestures and detects what the user wants to say using machine learning. Firstly, the algorithm captures multiple frames from the webcam video. After this, the algorithm detects the movement of hands using these multiple frames. Once the multiple frames are detected, then the calculations are made to identify what the hand gesture means.

The research is currently using Mediapipe to mark the key points of the hand movements. The package detects the hand as an element and then traces the movement creating multiple data key points along the path of the movement of the hands. These key points are then fed to TensorFlow. TensorFlow is a complete platform that provides multiple data automation and model tracking along with machine learning capabilities. In our case, TensorFlow is building an LSTM model to predict the action of the hand gestures made in front of the webcam. The research is currently trained on several videos that indicate the hand gesture of the term “Hello, How are you?”. The system is excessively trained for this sentence to predict the meaning of the specific hand gestures and convert them into the text format.

For the system to detect and identify even more hand gestures, we are going to train the system for even more videos related to the same hand gestures. The machine learning algorithm needs a vast amount of data to be accurate in terms of the identification of hand gestures

The flow of the research study is shown in Figure 3. The research facilitates the dumb and deaf in 2-way communication. It mainly focuses on the communication of the enabled person as well. This is because it is important that the fit person can also communicate his or her ideas with ease.

IV. EXPERIMENTAL PROCESS AND RESULTS

The experiments are carried out in multiple phases. It is one of the most important phases in the whole research study. The system is working on a trained model. The model was trained on several video formats. The video contained 30 frames each. The model was trained to collect key points of the video. The media pipe is used to detect the key points for gesture detection. The model collects key points using media pipe and stores them in the Numpy arrays. After this the tensorflow trains the LSTM model on the same arrays. The LSTM model will predict

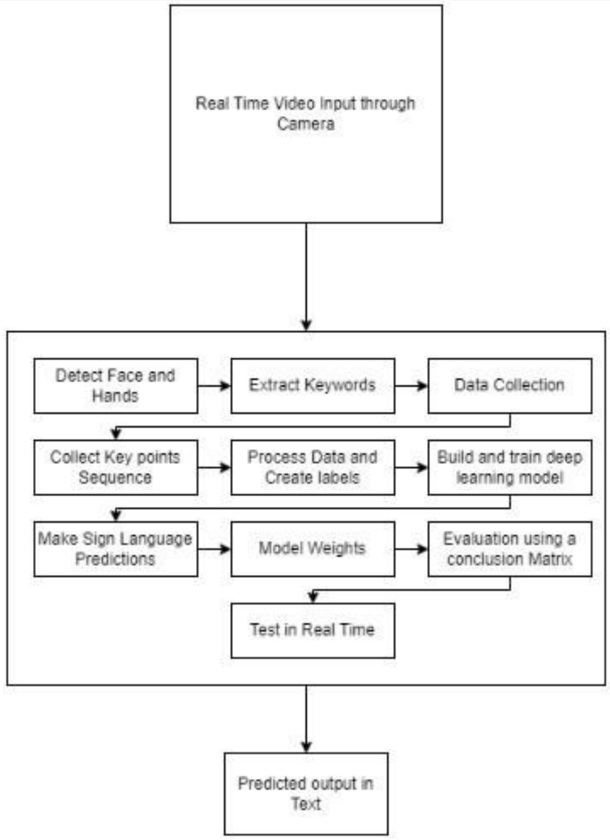

Figure 3: Process Flow of Two Way Sign Language Translator

the output using the previous training data. This way, we have achieved a system that can detect hand gestures and provide accurate output but not with real-time video. In order to achieve real-time calculations, we need to add another component that is OpenCV. The OpenCV would then detect the real-time data using the camera of the device and predict the output in real-time. While delivering the user back with output in video format. The system converts the text into video by using the local storage of the system it is working on. Once the user enters any text, the system searches the local storage for the video output. If the local storage does contain the required video or gif. The output will be displayed to the deaf and dumb.

Model Training Phase 1: Initially, we used 30 videos with a training model. The model did not provide the required amount of accuracy for us to continue. The first phase of testing returned a result of 0.7% accuracy with more than 30 videos for training.

Model Training Phase 2: This resulted almost in the same amount of accuracy as the previous one. The slightly higher accuracy of on real time data and was not satisfactory, but there was 100% accuracy on the test date. It did not meet our expectations from the system. The model was again trained using a set of at least 50 videos.

Model Training Phase 3: Lastly, the system was trained on the combined set of data from the first and the second phases. The interesting thing about our model training is that we have used our own set of data to train our system. The training data is not collected from the internet but is collected from real-world experiences. However, this time the development team went on with the 3rd phase of model training. This phase resulted in a better accuracy of 100% on test data and satisfactory on real-time data. This time the team used the LSTM model for training and it worked efficiently

A. Results

The research experiments in three portions after that we could create the best model with good real-time accuracy of signs. We have used 70% of the data for training and 30% of the data for testing. In the first two to three realms we increased the number of videos we stored of a single word after that we tweaked with train test split and landmarks with some other modifications in training which could lead to faster and more accurate real-time recognition of a sign. We have deployed our deep learning LSTM model using Flask for one-way sign language recognition (sign-to-text). After that using react we have created two ways of communication (text to sign) using videos. The accuracy we got while training our model is as follows:

Phase 1 2 Model Summary: Accuracy: 100% on test data with inaccurate real-time prediction and delay of 15-20 seconds as shown in Figure 4.

Current Model Summary: Accuracy: 100% on test data with accurate real-time prediction and delay of 2-4 seconds. For the two-way sign language translator, we attained a precision of 90.89% and an accuracy of 95.61% using LSTM. Table 1 lists the measures in detail for each category. A graphical representation of the training and testing accuracy is represented in Figure 5.

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_3 (LSTM)               (None, 30, 64)            442112

 lstm_4 (LSTM)               (None, 30, 128)           98816

 lstm_5 (LSTM)               (None, 64)                49408

 dense_3 (Dense)             (None, 64)                4160

 dense_4 (Dense)             (None, 32)                2080

 dense_5 (Dense)             (None, 6)                 198

=================================================================
Total params: 596,774
Trainable params: 596,774
Non-trainable params: 0
_________________________________________________________________
```

Figure 4: Phase 1 Model Accuracy

Table 1: Two Way Sign Language Translator

Category	Precision (%)	Accuracy (%)
Sign to Text	**94.11**	**97.6**
Text to Sign	**96.15**	**98.0**
Total	**95.13**	**97.8**

B. Analysis

A two-way sign language translator was created as part of the research using an iterative procedure, with notable advancements noted at various stages. Thirty percent of the data were utilized for testing and seventy percent were used for training in this three-part experiment. The following is a summary of the changes and improvements made across the iterations:

Initial Phase: Model Accuracy: On test data, 100% accuracy was obtained. Difficulties with Real-Time Prediction: In spite of the excellent test accuracy, the model had delays in real-time prediction, ranging from 15 to 20 seconds. This suggests that although the model performed well in theory, it had difficulties in real-world, practical applications, most likely because of processing or model deployment inefficiencies.

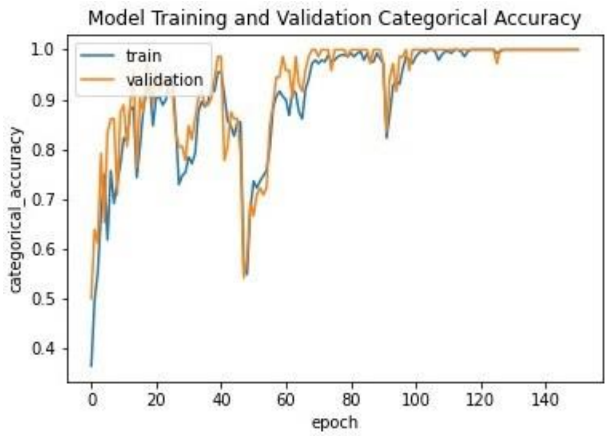

Figure 5: Train Test Categorical Accuracy Over Epochs

Current Model: Model Accuracy: On test data, the model maintained 100% accuracy. Real-Time Performance: Much better, with a 2-4 second delay time reduction. This indicates that the model and deployment pipeline have undergone successful optimizations, improving its suitability for real-time applications.

Two-Way Translator Performance: Precision and Accuracy: The model obtained a precision of 90.89% and an accuracy of 95.61% for the two-way sign language translator (text-to-sign and sign-to-text). These measures show a high degree of efficacy and dependability in both translation directions.
The incremental enhancements show that the sign language translator has been successfully optimized for use in real-time. The main conclusions are:

Model Training: The LSTM model can identify indications from video data with a high degree of accuracy when it is trained with an ideal split of 70% training data and 30% testing data.

Real-Time Application: By reducing the latency to 2-4 seconds, the present model addresses the considerable lag issue observed in earlier phases and makes real-time communication practical.

Efficiency of Two-Way Communication: With over 90% precision and 95.61% accuracy, the two-way translator performs well, demonstrating its potential to improve accessibility and communication for people who are deaf-mute.

V. CONCLUSIONS

Deaf and hearing people can communicate more easily with one another by using sign language. The system aims to improve communication among deaf individuals and the general populace thanks to its two-way communication capabilities. The proposed method converts signs into text/speech. The system improves speech- hearing impaired people’s manner and overcomes the necessary time constraints. The signs and text are converted using this system into a passing text that is easy for deaf people to understand. This research study allows the deaf and mute to accomplish sign language, which is then translated into text or speech. There has been a lot of work done in this area before, but this paper adds efficient, complete two-way communication because the system will be implemented as a mobile/web server. Therefore, it truly meets all of its requirements. This report describes a machine learning-based automated system that serves as an interface for normal people and Deaf-mute people to communicate. The modular design of the system involves converting Deaf-mute individuals’ hand gestures into speech. Text is created from the text of normal people. Additionally, a learning mode enables Deaf-mute individuals to communicate with one another through the system. In this mode, the system collects data from ongoing deaf-mute user communication. This model is also used to compare the detection accuracy of computers and humans to evaluate system performance. Through a series of experiments, the system is proven to be able to accurately detect hand gestures, with an average accuracy of more than 90 percent. For similar gestures, there are a few situations where the accuracy is between 80 percent and 90 percent. Additionally, the acquired data is stored and processed by the system. System accuracy will rise as more data are added to the dataset as a result of this feature. The experimental results indicate that we have attained 95% accuracy and 98% precision.

Suggestions for further research include in terms of speed and precision, the aforementioned strategies work. Additional improvements can be made in terms of integrating the communicator with other translations, such as American Sign Language, dialect recognition for various accents around the world, facial emotion in sign language, and language translation.

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