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Research article

Gesture generation by the robotic hand for aiding speech and hard of hearing persons based on indian sign language

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ABSTRACT

Speech and hearing impairments are among the most common problems in Indian societies. It can affect anyone, whether children, adults, or more. Many different treatments can help to overcome hearing problems. Different types of hearing aids and cochlear implants help amplify sounds for better hearing. The type of language known as sign language is very scientific and has its grammar and syntax. Still, due to a need for more awareness among hard-of-hearing persons, they need to be made familiar with the institutions where they can learn and equip themselves for communication. This paper describes an approach to aid speech and hard-of-hearing persons so that they are free to communicate with persons who do not have speech and hearing disabilities based on the Indian Sign Language System. To find an appropriate solution, there is a need to develop a system that can act as an interpreter for speech and hard-of-hearing persons. The interpreter system is designed with the help of the Robotic hand model and is programmed using Raspberry Pi 4. Based on the experimental results, it can be observed that the robotic hands generated different signs of the alphabet corresponding to the speech commands uttered by an individual. Several experimental trials were conducted by ten persons who do not have any hearing disabilities. The results of the five experimental trials are shown in this paper. The estimation of performance parameters and statistical analysis are also carried out to analyze better and interpret the experimental results. Based on the experimental results, the proposed robotic hand interpreter system model accurately generates gestures corresponding to different alphabets used in the Indian Sign Language system, yielding an overall accuracy of **94** percent.

1. Introduction

Speech and hearing difficulties are common issues in Indian society. Speech impairment is a disorder that makes it challenging to form sounds. Symptoms of speech impairments include communication problems, feeling stressed, and taking frequent breaks while speaking. Often, there are repetitions of words and sound patterns when communicating. Various techniques, such as hearing aids and lip reading, can address this problem but may not work in all cases. Unfortunately, as India's population grows, so do the problems associated with speech and hearing difficulties, which affect communication between people who are hard of hearing and those who are not.

In India, the most common language for individuals with speech and hearing disabilities is Indian Sign Language. This language facilitates communication between hard-of-hearing and non-hearing-impaired individuals. However, it is not used in schools for deaf

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students or in teacher-training programs. Many parents of hard-of-hearing children need to be aware of sign language and its benefits for communication. There is a critical need for more Indian Sign Language practitioners to facilitate communication between speech and hard-of-hearing individuals. Unfortunately, there are not enough practitioners in India despite the sizeable deaf community. Considering the above effect, the rationale of our study focuses on the need for communication solutions for individuals with hearing impairments in Indian society.

Around the world, efforts have been made to bridge the communication gap between deaf and non-deaf individuals using sign language. One approach is to use computer-based systems to convert speech to sign language using a robotic hand practitioner system. However, sign language varies by region, with each country having its unique grammar and syntax. Sign language relies on bodily movements, facial expressions, and spelling out words alphabetically. Understanding the language and its rudiments is essential to developing an interpreter system for speech and hard-of-hearing individuals. Generating signs for Indian Sign Language is a significant concern for hard-of-hearing individuals seeking to understand speech. However, no perfect or appropriate way to create characters exists, as each country interprets sign language differently.

In 2006, a model was introduced for neural networks aimed at coordinating hand gestures during prehension. The model incorporated a simplified control strategy to shape the entire hand during grasping tasks, facilitating realistic finger coordination. This control scheme is grounded in the growing body of evidence supporting synergistic control of the complete hand during prehension. The model only necessitates two parameters to delineate the evolution of hand shape throughout the task. The proposal entails establishing a Library of Hand Gestures comprising motor primitives for finger pre-shaping in an anthropomorphic dextrous hand. Through computer simulations, the neural dynamics of the model can generate grasping movements with kinematic features resembling those of humans. The model was applied to formulate precise predictions for experimental evaluation at both behavioural and neural levels, as well as for a neural control system for a dextrous robotic hand [1].

In 2010, a research paper discussed a method for gesture recognition in Indian Sign Language to enhance the interaction between the humanoid robot HOAP-2 and humans. In this approach, a classification process was employed using the different aspects of image processing along with the development of the generic algorithm for feature extraction. The classification technique is based on the Euclidean distance metric. The resulting Human-Robot Interaction (HRI) system is designed for machine-based learning. It utilizes the real-time robotics simulation software WEBOTS to simulate Indian Sign Language gestures on the HOAP-2 robot. *A* JAVA-based software was developed to facilitate the entire HRI process. Overall, this innovative approach provides an elegant means for humans to communicate with humanoid robots using Indian Sign Language gestures [2].

In 2012, a research paper introduced the Indian Sign Language Recognition System (INSLR) to enhance communication between deaf and hearing individuals. The system relies on image processing and computational intelligence techniques for recognizing sentences. Specifically, a wavelet-based video segmentation technique is employed to identify hand signs and head movements in videos. Elliptical Fourier descriptions are then utilized to extract the shape features of hand gestures, reducing the feature vectors for each image. Principal component analysis (PCA) minimizes the feature vector for each gesture video, ensuring that the components are not affected by the scaling or rotation of gestures within a video. These techniques generate unique feature vectors for each motion. *A* Sugeno-type fuzzy inference system employs linear output membership functions to recognize gestures from these extracted features. Finally, the INSLR system integrates an audio system to play the recognized gestures and text output. The system was tested using a dataset of 80 words and sentences by ten different signers, and the results demonstrated a recognition rate of 96 % [3].

In 2015, a research paper addressed the significance of continuous Indian sign language (ISL) gesture recognition for hearing-impaired individuals. The study proposed an ISL gesture recognition system utilising both hands, tackling the challenge of interpreting continuous sign language movements. Researchers employed a gradient-based critical frame extraction method to identify keyframes, enabling the segmentation of continuous gestures into meaningful sign sequences by removing irrelevant frames. They further processed and characterised the gestures using an Orientation Histogram (OH) and Principal Component Analysis (PCA) for feature dimension reduction. Experiments were conducted on their custom ISL dataset, captured with a Canon EOS camera in the Robotics and Artificial Intelligence Laboratory (IIIT-*A*). Among various classifiers tested, Correlation and Euclidean distance demonstrated superior accuracy [4].

Early in the year 2016, a representation scheme for illustrating Turkish Sign Language electronically, a machine translation system, was developed, and the basic objective was to translate Turkish primary school educational materials into Turkish Sign Language. Turkish Sign Language needed more electronic language resources to be used in computerized systems. In the proposed scheme, the resource creation was provided by two means, namely, an interactive online dictionary platform for Turkish Sign Language and an ELAN add-on for corpus creation. In the proposed architecture, there were two major layers, namely the translation of the written Turkish material into a machine-readable sign representation and the animation of the produced gesture representation. The proposed technique also used an online dictionary platform consisting of different sets of signs. The different possible variations and the requirement of the layers to feed the ELAN tool were also studied. In the research, no information on the overall accuracy of the proposed technique was provided [5].

In 2017, a research paper outlined the development of a humanoid arm robot that can translate spoken language into sign language. This technology aims to assist individuals with hearing disabilities. The arm's joints were analysed to determine the necessary torque for accurate movements of the servo motors. To aid in processing, an Android app was created for speech recognition testing. An optimal nonlinear controller was designed for finger control, utilising angle, and angular velocity as state variables to manipulate the DC motor's position and ensure proper finger movement. Using conductive pulleys and hydraulic transmission reduced the variables necessary for controlling finger movement, allowing optimal control in opening and closing the fingers. *A* mobile app is set to be used for real-time speech recognition. The team also plans to build a hand-sign language database using motion capture technology for arm movement and manual input in transcription software for hand shapes [6].

Later, in 2018, research based on translating the Arabic text into Arabic sign language was implemented. The translation process was used with the help of machine translation because the Arabic Text and its sign language representation had different structures and grammar. *A* rule-based machine translation system was adopted in the research. The proposed system performed a morphological, syntactic, and semantic analysis of the Arabic sentence to translate it into a sentence based on the grammar and pattern of Arabic Sign Language. *A* gloss system was proposed for the representation of the signs, along with the development of a parallel corpus in the health domain that consisted of 600 sentences. The performance evaluation of the translation system was based on Manual Evaluation, Automated Evaluation, Bilingual Evaluation Understudy (BLEU), Word Error Rate (WER), and Translation Error Rate (TER) metrics. The translation system provided an accuracy of 80 percent during the process of sign translation of the sentence [7].

In a 2020 study, researchers focused on automatically assessing speech impairment in Cantonese-speaking individuals with aphasia, a language disorder often linked to specific brain dysfunction. Standard clinical assessments for aphasia involve analysing spontaneous narrative speech, but they suffer from subjectivity and practical limitations when administered by trained speech-language pathologists. The study introduced a fully automated system to evaluate the speech of individuals with aphasia who speak Cantonese. This system utilized a deep neural network (DNN)-based automatic speech recognition (ASR) system, developed through multi-task training with both in-domain and out-of-domain speech data. The integration of story-level embedding and Siamese networks derived robust text features that, when combined with conventional acoustic features, comprehensively assessed speech and language impairment. Notably, experimental results demonstrated a strong correlation between predicted and subject assessment scores. The best correlation value achieved with ASR-generated transcription was 0.827, compared to 0.844 achieved with manual transcription. The Siamese network significantly outperformed story-level embedding in generating text features for automatic assessment [8].

In this paper, the robotic hand interpreter system was designed to generate the alphabet's signs from *A* to *Z* based on the Indian Sign Language System. The main objective of the study is to develop a robotic hand interpreter system that could generate signs of the alphabet spelled out by hearing individuals to assist speech and hard-of-hearing persons. The persons affected by speech and hearing disabilities cannot understand the voice commands spelled out by hearing individuals. Considering this fact, the objectives of our study are finalized. The robotic hand interpreter system was connected to a computer and was programmed using a Raspberry Pi 4 with other essential hardware devices attached to it. The functioning of the Robotic Hand interpreter system model was tested with ten different persons under five experimental trials, and the results were obtained.

The remaining part of the paper is divided further into five different sections. The Proposed Methodology is discussed in Section 2, which further has two subsections, Section 2.1 and Section 2.2. Section 2.1 introduces the background techniques in the field of sign generation, followed by Section 2.2, which discusses in detail the development of the proposed algorithm for Indian Sign Language generation. The Experimental Setup is discussed in Section 3. The experimental results are further discussed in Section 4, which has seven different subsections, starting from Section 4.1 and continuing to Section 4.7. In Section 4.1, the description of the dataset is presented. In Section 4.2, the robotic hand model for the Indian Sign Language generation for generating different alphabets from *A* to *Z* is discussed. In Section 4.3, the details of the signs of the alphabet that could not be generated by the robotic hand are discussed. Further in Section 4.4, the status of sign generation by the Robotic Hand under different Experimental Trials is discussed. Section 4.5 discusses the estimation of the mean and standard deviation of the data obtained from the experimental results. In Section 4.6, the plots related to the data obtained from the experimental results are discussed. Lastly, in Section 4.7, the experimental results are discussed. The performance evaluation of the robotic hand interpreter system is provided in Section 5, which has two subsections, Section 5.1 and Section 5.2. In Section 5.1, the performance parameters are estimated. In Section 5.2, the analysis of the results of the performance parameters is done. The conclusion of the entire paper, along with the future scope, is provided in Section 6.

2. Proposed methodology

In Section 1, we discussed the problems associated with speech and hearing-impaired persons, followed by the existing research in the field of Sign Language. This section discusses some of the most recent background techniques used in the existing research for gesture generation in Section 2.1, followed by the proposed algorithm for the Indian Sign Language generation in Section 2.2.

2.1. Background

In 2020, a machine-based translation system was developed for sign generation based on Indian Sign Language from English texts. The developed system incorporated human-computer interaction without the requirement of the ISL human interpreter to assist persons with hearing disabilities. The system used a dataset consisting of English words and frequently used sentences. The main components of the system include the ISL parser, the Hamburg Notation System, the Signing Gesture Mark-up Language, and 3D avatar animation for the purpose of carrying out the Indian Sign Language generation. Sign language users conducted many different tests. Based on the experimental results, it was concluded that the developed system was very efficient and achieved an average score of accuracy. The accuracy score was 4.2 for English words and 3.8 for sentences on a scale from 1 to 5. The overall performance was also evaluated using the Bilingual Evaluation Understudy score, which resulted in an overall accuracy of 0.95 [9].

Recently, in the year 2023, a research paper introduced a novel approach for sign language translation using a Convolutional-embedded transformer with an action tokenizer and key point emphasizer. Existing methods faced challenges in translating sign language due to insufficient gloss notation in video frames, the oversight of nonmanual elements, and the need for more effective local context capture in transformer models. To address these issues, the paper proposed an action tokenizer for semantic segmentation, a key point emphasizer, and a Convolutional-embedded Sign Language Transformer (CSLT). When applied to Sign2 (Gloss Text), this resulted in CSLT with an action tokenizer and key point emphasizer (CSLT-AK), offering a streamlined and efficient sign language translation model. Experimental results on the RWTH-PHOENIX-Weather 2014 *T* dataset demonstrated CSLT-AK's superior performance and parameter reduction, showcasing competitive results without requiring regularisation methods compared to other state-of-the-art models [10].

2.2. Proposed Algorithm for Indian Sign Language Generation

In Section 2.1, it was observed that the most recent techniques based on sign generation did not incorporate any robotic technology for assisting individuals with hearing disabilities. Furthermore, the existing research mostly focused on the process of sign recognition. More research is needed in the field of sign generation. The performance evaluation of the developed system involving gesture generation needed to be improved, and there needed to be more information on overall accuracy in some of the existing research. Considering these factors, the proposed methodology for the Indian Sign Language generation for assisting individuals with speech and hearing disabilities was finalized with the help of artificial robotic hands.

The proposed method implemented for the design of the robotic hand interpreter system is discussed in the form of a flowchart, as shown in Fig. 1 below.

The first stage of the algorithm is importing the necessary libraries involved in speech recognition in the Python script used for programming the Raspberry Pi 4. The speech recognition system is an inbuilt system within the Raspberry Pi 4 that consists of a recognizer for the purpose of recognizing the speech commands spelled by different users in front of the external microphone attached to the Raspberry Pi 4. The next stage is the initialization of the recognizer and the microphone function in the Python script. The speech input is in the form of an alphabet based on the Indian Sign Language system and is spelled in front of the external microphone connected to the Raspberry Pi 4. During speech recognition, it involves segmenting and extracting features from speech signals to identify words or phrases. The recognizer function initialized in the Python script recognizes the speech input spelled out by the user. The next stage of the flowchart is the internal speech signal processing done by the processor of Raspberry Pi 4. The primary goals of speech signal processing are to analyze, enhance, and manipulate speech signals to make them suitable for specific applications. The following process involves the transmission of the speech signal from the Raspberry Pi4 to the PCA9685 servo driver using Serial Clock Line (SCL) and Serial Data Line (SDA) pins on the Raspberry Pi 4. In the next stage of the flowchart, the translation system from speech to sign converts the individual alphabets in the form of speech commands to corresponding signs or gestures to be displayed by the dual

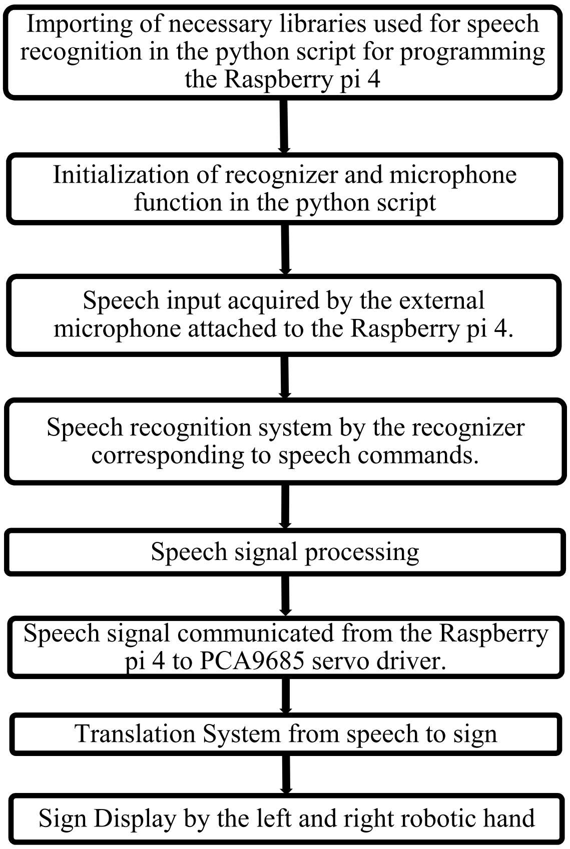


Fig. 1. Algorithm for indian sign language generation by the robotic hand.

robotic hand. In this way, the proposed algorithm for sign generation by the dual robotic hands is implemented.

3. Description of the experimental setup

The description of the experimental setup is shown in Fig. 2 below. We connected the left and right robotic hand to 10 out of 16 pins in the PCA9685 servo driver, a popular 16-channel PWM driver used to control servos, LEDs, and other devices precisely. A Raspberry Pi 4 was used to manage the servos through the PCA9685. The Raspberry Pi 4 was programmed through Python, and it was connected to the servo driver using four pins: 3.3V, *GND*, *SCL*, and *SDA*. An external monitor, keyboard, mouse, and microphone were connected to the Raspberry Pi 4, as shown in Fig. 2 below. The Raspberry Pi 4 was powered using a 5-V, 3 Amp adapter, while the PCA9685 servo driver was powered independently by an external 11.1 V Lithium Polymer Battery and XL-4016 DC-DC Buck Converter. The DC to DC Buck converter decreased the 11.1 V to approximately 5 V for the servos. We used Python programming to generate signs with the left and right robotic hands based on the user's spoken commands. This system model helps hard-of-hearing people interact with others. The experimental results are further discussed in Section 4.

4. Experimental results

4.1. Dataset

The Indian Sign Language dataset selected 26 different English alphabets, each represented by various hand gestures [11]. The images chosen for the dataset were captured in high-definition format and cropped as necessary to display the gestures. These images accurately depict the signs of each alphabet within the Indian Sign Language system.

4.2. Robotic hand model for Indian Sign Language System

Considering the 26 different English alphabets corresponding to Indian Sign Language, the robotic hand was operated based on the alphabets spelled out by a typical user in front of the microphone. The results are presented in Table 1 below. The robotic hand operates in three distinct regions, namely *CLR* (Closed Region), *PLR* (Partial Region), and *OPR* (Open Region). In different regions, namely *OPR*, *PLR*, *and CLR*, the fingers, including the thumb, are fully closed, completely open, and partially open, as illustrated in Table 1 below.

4.3. Details of the signs of the alphabet that could not be generated by the robotic hand

As per Section 4.2 in Tables 1 and it is observed that the signs generated by the robotic hand for alphabet pairs ***'C'*** and ***'U,' alphabet pairs 'H' and 'W,'*** and alphabet pairs ***'T' and 'X'*** are identical after conducting the experiments. These dual robotic hands cannot generate the sign of the letter ***'J'*** due to its dynamic nature.

4.4. Status of sign generation by the robotic hand under different experimental trials

The functioning of the Robotic hand is tested by ten different persons, including five male persons from *P1 to P5* and five female persons from *P6 to P10*. These persons performed multiple experiments and trials to obtain accurate results. The results of the five different experimental trials from *T1 to T5* are shown in Table 2 below. Multiple trials of the experiments are carried out to test the replicability or reproducibility of our methodology. Since the robotic hand fails to distinguish between some of the alphabets stated at the beginning of Section 4.3, the results of these alphabets are excluded. Based on the status of Indian Sign Language generation by the

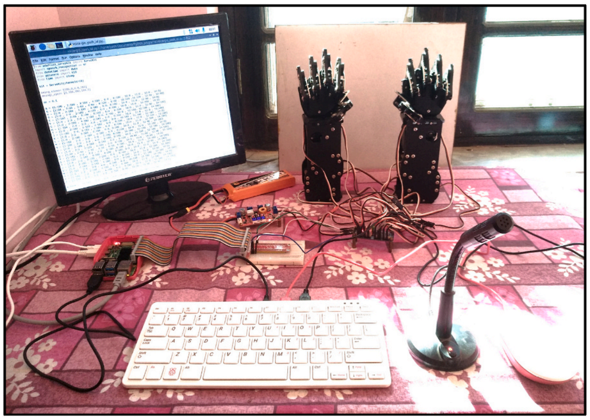
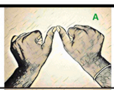
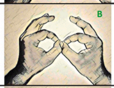
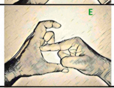
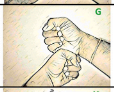
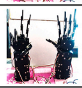
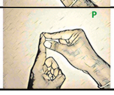
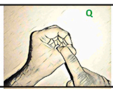
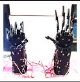
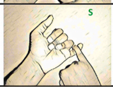
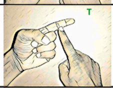
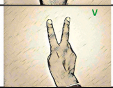
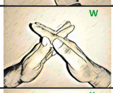
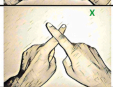
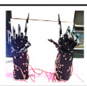


Fig. 2. Experimental Setup of Robotic hand Interpreter system.

Table 1
Details of the sign generated corresponding to different alphabets in the case of Indian Sign Language.

Alphabet	Actual Sign of the Alphabet in the Case of Indian Sign Language	Generated Sign of Alphabet in the case of Indian Sign Language	Orientation of all the fingers, including the thumb, during gesture generation in the case of Indian Sign Language									
			Left Thumb	Left Index Finger	Left Middle Finger	Left Ring Finger	Left Little Finger	Right Little Finger	Right Ring Finger	Right Middle Finger	Right Index Finger	Right Thumb
A			*OPR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*OPR*
B			*PLR*	*PLR*	*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*PLR*	*PLR*
C			*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*PLR*	*OPR*
D			*CLR*	*OPR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*OPR*	*OPR*
E			*OPR*	*PLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*PLR*	*CLR*
F			*CLR*	*OPR*	*OPR*	*CLR*	*CLR*	*CLR*	*CLR*	*OPR*	*OPR*	*CLR*
G			*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*
H			*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*OPR*
I			*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*OPR*	*CLR*
J			*OPR*	*OPR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*OPR*	*CLR*
K			*CLR*	*OPR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*PLR*	*CLR*
L			*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*OPR*	*OPR*
M			*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*CLR*	*OPR*	*OPR*	*OPR*	*CLR*
N			*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*CLR*	*CLR*	*OPR*	*OPR*	*CLR*
O			*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*PLR*	*PLR*	*PLR*	*PLR*	*PLR*
P			*CLR*	*OPR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*PLR*	*OPR*

Q			*PLR*	*PLR*	*PLR*	*PLR*	*PLR*	*CLR*	*CLR*	*CLR*	*OPR*	*CLR*
R			*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*CLR*	*CLR*	*CLR*	*PLR*	*CLR*
S			*CLR*	*CLR*	*CLR*	*CLR*	*OPR*	*OPR*	*CLR*	*CLR*	*CLR*	*CLR*
T			*CLR*	*OPR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*OPR*	*CLR*
U			*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*PLR*	*OPR*
V			*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*OPR*	*OPR*	*CLR*
W			*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*OPR*
X			*CLR*	*OPR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*OPR*	*CLR*
Y			*OPR*	*OPR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*CLR*	*OPR*	*CLR*
Z			*OPR*	*OPR*	*OPR*	*OPR*	*OPR*	*PLR*	*PLR*	*PLR*	*PLR*	*OPR*

Robotic hand correctly by different persons from *P1 to P10*, an entry of *'SS'* or *'FF'* is inserted in Table 2. The entry *'SS'* indicates that the robotic hand generates the sign correctly, whereas the entry *'FF'* means that the robotic hand causes the movement incorrectly.

4.5. Estimation of mean and standard deviation

This section focuses on the calculation of mean and standard deviation for two separate cases under five experimental trials. The first case is based on the estimation of the number of persons with correct sign generation of the alphabet from the **19** total alphabets by the dual robotic hand under different experimental trials. The required results are shown below in Table 3.

As per Table 3, N_{P_T1} corresponds to the number of persons with correct sign generation of the alphabet from the **19** shown alphabets by the dual robotic hand. Similarly, N_{P_T2}, N_{P_T3} , N_{P_T4} and N_{P_T5} to the number of persons with correct sign generation under trials *T2, T3, T4,* and *T5*.

The first entry of **9** corresponding to alphabet *A* in Table 3 is calculated by counting the number of *'SS'* in row *T1* under alphabet *A* of Table 2. Similarly, all the row entries in Table 3 corresponding to other alphabets are computed based on the entries of Table 2 under different alphabets in each of the experimental trials.

In the different column entries from *T1 to T5* and different row entries from alphabet *A* to alphabet *Z*, the corresponding mean and standard deviation are calculated. The results are presented in the last two rows and last two columns of Table 3. $\boldsymbol{\mu_{TA}}$ denotes the average number of persons responsible for the generation of all the ***19*** alphabets by the dual robotic hand. $\boldsymbol{\sigma_{TA}}$ denotes the standard deviation of the data corresponding to different column entries from *T1 to T5*. $\boldsymbol{\mu_{AT}}$ denotes the average number of persons responsible for the generation of a particular alphabet by the dual robotic hand under different experimental trials from *T1 to T5*. $\boldsymbol{\sigma_{AT}}$ denotes the standard deviation of the data of different alphabets in a particular row.

The different equations corresponding to μ_{TA} and σ_{TA} for trials *T1 and T5* are given below in Eqn. (1). to Eqn. (4). μ_{TA_T1} and σ_{TA_T1} corresponds to the estimation of mean and standard deviation concerning trial *T1*. Similarly, μ_{TA_T5} and σ_{TA_T5} corresponds to the estimation of mean and standard deviation concerning trial *T5*. The summation as given below in these equations varies from alphabet *A* to alphabet *Z* based on the data entries as per Table 3. Similarly other equations of mean and standard deviation concerning trials *T2 to T4* can be computed.

Table 2
Performance evaluation of the Robotic hand by different persons during the process of Indian Sign Language Generation under different experimental trials.

Alphabet	Experimental Trial Details	Status of Sign Generation by Robotic hand correctly by different persons in the case of Indian Sign Language										Number of persons with correct sign generation
		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	
A	***T1***	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
	T2	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T4	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
	T5	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
B	***T1***	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
	T2	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	**9**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*FF*	*SS*	**8**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T5	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
D	***T1***	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
	T2	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T5	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
E	***T1***	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*FF*	**8**
	T2	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	**9**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*FF*	**8**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*FF*	**8**
	T5	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
F	***T1***	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
	T2	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T4	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
	T5	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
G	***T1***	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	**8**
	T2	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	**9**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T5	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	**9**
I	***T1***	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	**9**
	T2	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	**9**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*FF*	*SS*	**8**
	T5	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
K	***T1***	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T2	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T5	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
L	***T1***	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T2	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	**9**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T5	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
M	***T1***	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	**9**
	T2	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	**9**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T5	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
N	***T1***	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T2	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T5	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
O	***T1***	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T2	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T5	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
P	***T1***	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	**9**
	T2	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	**9**
	T5	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**

(*continued on next page*)

Table 2 (*continued*)

Alphabet	Experimental Trial Details	Status of Sign Generation by Robotic hand correctly by different persons in the case of Indian Sign Language										Number of persons with correct sign generation
		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	
Q	***T1***	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
	T2	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T5	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
R	***T1***	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	**9**
	T2	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	**9**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T5	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	**9**
S	***T1***	*FF*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	**8**
	T2	*FF*	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	**8**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T5	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
V	***T1***	*SS*	*SS*	*FF*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	**8**
	T2	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
	T3	*SS*	*SS*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
	T4	*SS*	*SS*	*FF*	*SS*	*FF*	*SS*	*SS*	*FF*	*SS*	*SS*	**7**
	T5	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
Y	***T1***	*SS*	*FF*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	**8**
	T2	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
	T3	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T5	*SS*	*FF*	*SS*	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	**8**
Z	***T1***	*SS*	*FF*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**9**
	T2	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T3	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T4	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**
	T5	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	*SS*	**10**

Table 3
Details of persons with correct sign generation of alphabets under different experimental trials.

Alphabets	N_{P_T1}	N_{P_T2}	N_{P_T3}	N_{P_T4}	N_{P_T5}	μ_{AT}	σ_{AT}
A	9	10	10	9	10	**9.6**	**0.49**
B	9	9	8	10	10	**9.2**	**0.75**
D	9	9	10	10	9	**9.4**	**0.49**
E	8	9	8	8	10	**8.6**	**0.8**
F	9	9	10	9	10	**9.4**	**0.49**
G	8	9	10	10	9	**9.2**	**0.75**
I	9	10	9	8	10	**9.2**	**0.75**
K	10	10	10	10	10	**10**	**0**
L	10	10	9	10	10	**9.8**	**0.4**
M	9	9	10	10	10	**9.6**	**0.49**
N	10	10	10	10	10	**10**	**0**
O	10	10	10	10	10	**10**	**0**
P	9	10	10	9	10	**9.6**	**0.49**
Q	9	10	10	10	9	**9.6**	**0.49**
R	9	9	10	10	9	**9.4**	**0.49**
S	8	8	10	10	9	**9**	**0.89**
V	8	9	9	7	9	**8.4**	**0.8**
Y	8	9	9	10	8	**8.8**	**0.75**
Z	9	10	10	10	10	**9.8**	**0.4**
μ_{TA}	**8.95**	**9.42**	**9.58**	**9.47**	**9.58**		
σ_{TA}	**0.69**	**0.59**	**0.67**	**0.88**	**0.59**		

$$\mu_{TA\_T1} = \frac{\sum_{A}^{Z}(N_{P\_T1})}{19} \tag{1}$$

$$\mu_{TA\_T5} = \frac{\sum_{A}^{Z}(N_{P\_T1})}{19} \tag{2}$$

$$\sigma_{TA\_T1} = \sqrt{\frac{\sum_A^Z \left(N_{P\_T1} - \mu_{TA\_T1}\right)^2}{19}} \tag{3}$$

$$\sigma_{TA\_T5} = \sqrt{\frac{\sum_A^Z \left(N_{P\_T5} - \mu_{TA\_T5}\right)^2}{19}} \tag{4}$$

The different equations corresponding to μ_{AT} and σ_{AT} for alphabets *A and Z* are given below in Eqn. (5). to Eqn. (8). μ_{AT_A} and σ_{AT_A} corresponds to the estimation of mean and standard deviation concerning alphabet *A* in each of the trials from *T1 to T5*. Similarly, μ_{AT_Z} and σ_{AT_Z} corresponds to the estimation of mean and standard deviation concerning alphabet *Z* in each of the trials from *T1 to T5.* The summation as given below in these equations varies from N_{P_T1} to N_{P_T5} based on the data entries as per Table 3. Similarly other equations of mean and standard deviation concerning other alphabets can be computed.

$$\mu_{AT\_A} = \frac{\sum_{N_{P\_T1}}^{N_{P\_T5}}(A)}{5} \tag{5}$$

$$\mu_{AT\_Z} = \frac{\sum_{N_{P\_T1}}^{N_{P\_T5}}(Z)}{5} \tag{6}$$

$$\sigma_{AT\_A} = \sqrt{\frac{\sum_{N_{P\_T1}}^{N_{P\_T5}}\left(A - \mu_{AT\_A}\right)^2}{5}} \tag{7}$$

$$\sigma_{AT\_Z} = \sqrt{\frac{\sum_{N_{P\_T1}}^{N_{P\_T5}}\left(Z - \mu_{AT\_Z}\right)^2}{5}} \tag{8}$$

The second case is based on the estimation of the number of correct signs of different alphabets spelled by different persons under different experimental trials by the dual robotic hand. The required results are shown below in Table 4.

As per Table 4, N_{A_T1} corresponds to the number of signs of the alphabets out of **19**, that persons *P1 to P10* are responsible for the correct generation by the dual robotic hand. Similarly, N_{A_T2}, N_{A_T3} N_{A_T4} and N_{A_T5}, corresponds to the number of the signs of the alphabets correctly generated by the dual robotic hand based on the speech commands uttered by different persons from *P1 to P10* under trials *T2, T3, T4*, and *T5*.

The first entry of **16** corresponding to persons *P1* in Table 4 is calculated by counting the number of *'SS'* in column *P1* under *T1* of Table 2. Similarly, all the row entries in Table 4 corresponding to other persons from *P2 to P10* are computed based on the entries of Table 2 under different experimental trials.

In the different column entries from *T1 to T5* and different row entries from persons *P1 to P10*, the corresponding mean and standard deviation are calculated. The results are presented in the last two rows and last two columns of Table 4. $\boldsymbol{\mu_{TP}}$ denotes the average number of alphabets that are correctly generated by **10** persons from *P1 to P10*. $\boldsymbol{\sigma_{TP}}$ denotes the standard deviation of the data corresponding to different column entries from *T1 to T5*. $\boldsymbol{\mu_{PT}}$ denotes the average number of alphabets that are correctly generated by the dual robotic hand based on the speech commands uttered by a particular person under different experimental trials from *T1 to T5*. $\boldsymbol{\sigma_{PT}}$ denotes the standard deviation of the data of different persons in a particular row.

The different equations corresponding to μ_{TP} and σ_{TP} for trials *T1 and T5* are given below in Eqn. (9). to Eqn. (12). μ_{TP_T1} and σ_{TP_T1} corresponds to the estimation of mean and standard deviation concerning trial *T1*. Similarly, μ_{TP_T5} and σ_{TP_T5} corresponds to the estimation of mean and standard deviation concerning trial *T5*. The summation as given below in these equations varies from person *P1* to person *P10* based on the data entries as per Table 4. Similarly other equations of mean and standard deviation concerning trials *T2 to T4* can be computed.

Table 4
Details of the number and percentage of correct signs of 19 alphabets generated by a particular person under different experimental trials.

Persons	N_{A_T1}	N_{A_T2}	N_{A_T3}	N_{A_T4}	N_{A_T5}	μ_{PT}	σ_{PT}
P1	16	17	19	19	18	**17.8**	**1.17**
P2	16	18	18	18	18	**17.6**	**0.8**
P3	16	18	19	18	17	**17.6**	**1.02**
P4	19	19	19	19	19	**19**	**0**
P5	16	18	18	17	17	**17.2**	**0.75**
P6	17	17	18	18	19	**17.8**	**0.75**
P7	16	17	17	18	17	**17**	**0.63**
P8	18	19	18	17	19	**18.2**	**0.75**
P9	19	19	18	18	19	**18.6**	**0.49**
P10	17	18	17	18	19	**17.8**	**0.75**
$\boldsymbol{\mu_{TP}}$	**17**	**18**	**18.1**	**18**	**18.2**		
$\boldsymbol{\sigma_{TP}}$	**1.18**	**0.77**	**0.7**	**0.63**	**0.87**		

$$\mu_{TP\_T1} = \frac{\sum_{P1}^{P10}(N_{A\_T1})}{10} \tag{9}$$

$$\mu_{TP\_T5} = \frac{\sum_{P1}^{P10}(N_{A\_T5})}{10} \tag{10}$$

$$\sigma_{TP\_T1} = \sqrt{\frac{\sum_{P1}^{P10}(N_{A\_T1} - \mu_{TP\_T1})^2}{10}} \tag{11}$$

$$\sigma_{TP\_T5} = \sqrt{\frac{\sum_{P1}^{P10}(N_{A\_T5} - \mu_{TP\_T5})^2}{10}} \tag{12}$$

The different equations corresponding to μ_{PT} and σ_{PT} for trials *T1 and T5* are given below in Eqn. (13). to Eqn. (16). μ_{PT_P1} and σ_{PT_P1} corresponds to the estimation of mean and standard deviation concerning person *P1* in each of the trials from *T1* to *T5*. Similarly, μ_{PT_P10} and σ_{PT_P10} corresponds to the estimation of mean and standard deviation concerning person *P10* in each of the trials from *T1* to *T5*. The summation as given below in these equations varies from N_{A_T1} to N_{A_T5} based on the data entries as per Table 4. Similarly other equations of mean and standard deviation concerning other persons can be computed.

$$\mu_{PT\_P1} = \frac{\sum_{N_{A\_T1}}^{N_{A\_T5}}(P1)}{5} \tag{13}$$

$$\mu_{PT\_P10} = \frac{\sum_{N_{A\_T1}}^{N_{A\_T5}}(P10)}{5} \tag{14}$$

$$\sigma_{PT\_P1} = \sqrt{\frac{\sum_{N_{A\_T1}}^{N_{A\_T5}}(P1 - \mu_{PT\_P1})^2}{5}} \tag{15}$$

$$\sigma_{PT\_P10} = \sqrt{\frac{\sum_{N_{A\_T1}}^{N_{A\_T5}}(P10 - \mu_{PT\_P10})^2}{5}} \tag{16}$$

4.6. Different plots to show the analysis of experimental results

This section presents the pictorial representation of the results of Tables 3 and 4 in the form of different plots for each of the experimental trials from *T1 to T5,* as shown below in Figs. 3 and 4. These plots are constructed in the form of a vertical bar chart for a better understanding of the results. The first plot in Fig. 3 is plotted against the number of persons with correct sign generation of a particular alphabet vs the corresponding alphabet under different experimental trials. The second plot in Fig. 4 is plotted against the number of correct signs of generated alphabets vs the corresponding persons from *P1 to P10* under different experimental trials.

The accuracies of the robotic hand model during the process of sign generation of some of the alphabets are further discussed in the form of plots, as shown in Figs. 5–8. These plots are related to data entries in Table 2. Out of the 19 alphabets, the detailed analysis of the following four alphabets, namely *Y, G, D,* and *A,* are discussed below in detail. In the various plots as shown below, "***NT_Alphabet***" denotes the number of times a sign of the particular alphabet is generated by the robotic hands in all the five experimental trials. Similarly, "***NP_Alphabet***" denotes the number of persons responsible for the generation of the sign of a particular alphabet in each of the five experimental trials.

The first plot in Fig. 5 (a) presents the number of times a particular person from *P1* to *P10* was responsible for the successful generation of the sign of the alphabet *Y* by the robotic hands in five different trials from *T1* to *T5*. It can be observed from the first plot that persons *P1*, *P3*, *P4*, *P6*, *P7*, *P8*, *P9,* and *P10* were 100 percent successful in generating the sign of the alphabet *Y* by the robotic

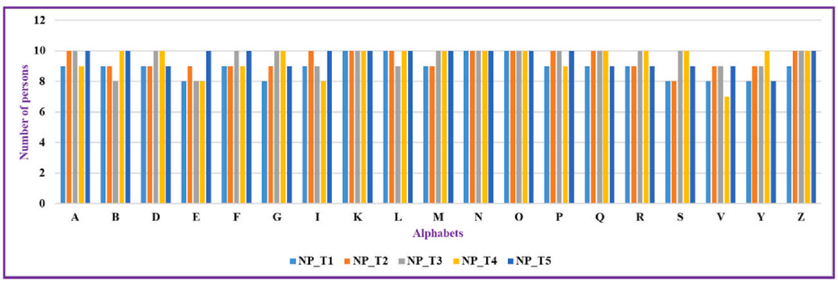


Fig. 3. Plot of the number of persons with correct sign generation of a particular alphabet vs the corresponding alphabet under different experimental trials.

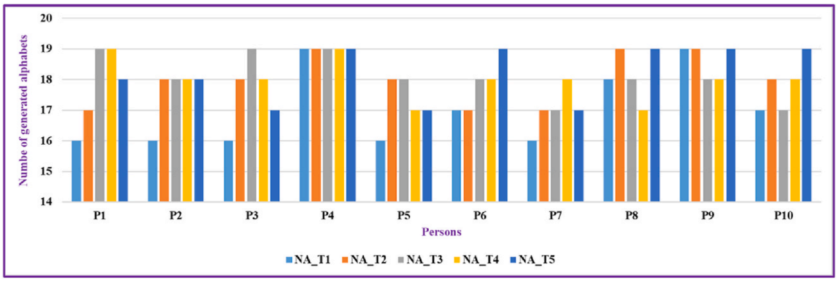
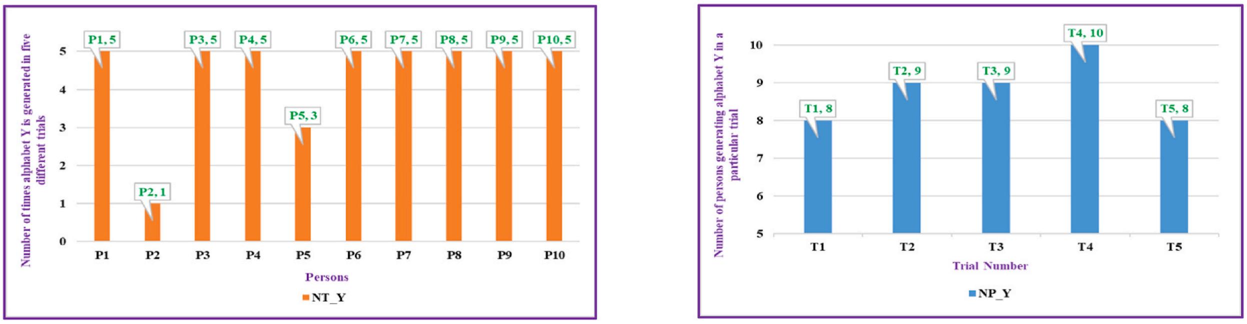
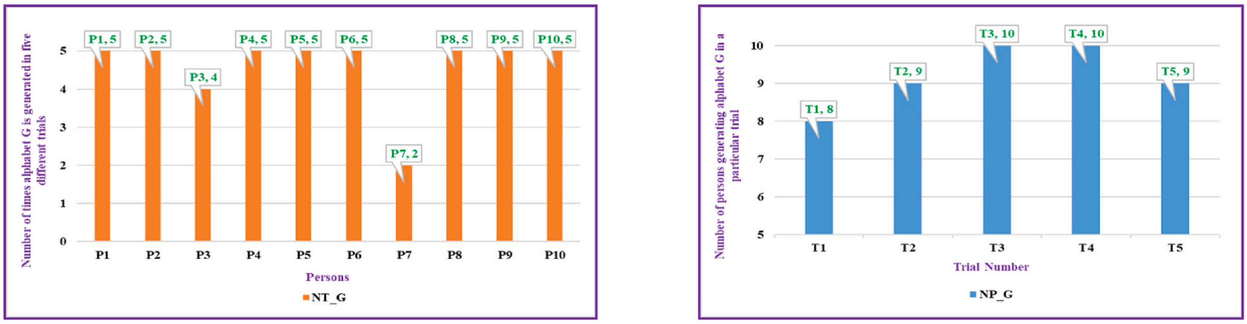


Fig. 4. Plot of the number of correct signs of generated alphabets vs. the corresponding persons from *P1* to *P10* under different experimental trials.



(a) (b)

Fig. 5. (a) Plot of the number of times the sign of alphabet *Y* is generated in different trials vs the corresponding persons. (b) The plot of the number of persons involved in the successful generation of the sign of the alphabet *Y* in a particular trial vs. the corresponding trial number.



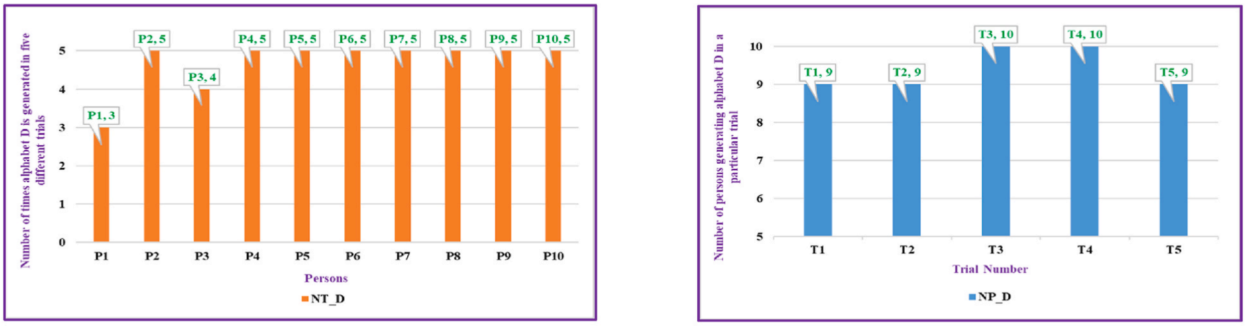
(a) (b)

Fig. 6. (a) Plot of the number of times the sign of the alphabet *G* is generated in different trials vs the corresponding persons. (b) Plot of the number of persons involved in the successful generation of the sign of the alphabet *G* in a particular trial vs the corresponding trial number.

hand. All these eight persons successfully generated the sign of the alphabet *Y* five times out of five. The remaining leftover persons, P2 and P5, could generate one and three times the sign of the alphabet *Y* by the robotic hands, as observed from the plot in Fig. 5 (a). Thus, if we add the number of times the alphabet *Y* was generated in five different trials by ten persons from *P1* to *P10*, the result obtained is 44. This means that out of a total of 50 and 44 times, the sign of the alphabet *Y* was successfully generated by the robotic hand. Based on this fact, it can be concluded that the accuracy of the robotic hand model during the generation of the sign of the alphabet *Y* is 88 %.

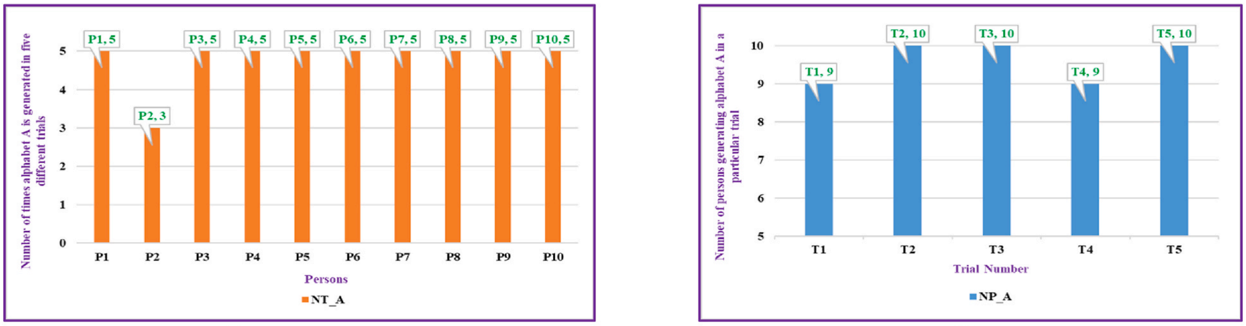
It can also be observed from the plot shown in Fig. 5 (b) that in different trials from *T1* to *T5*, the alphabet Y was generated by 8, 9, 9, 10, and 8 persons. If these observed values from Fig. 5 (b) are added, the result obtained is again 44. Based on the above analysis carried out from Fig. 5 (b), it can again be concluded that the accuracy of the robotic hand model during the generation of the sign of the alphabet *Y* is 88 %.

The first plot in Fig. 6 (a) presents the number of times a particular person from *P1* to *P10* was responsible for the successful generation of the sign of the alphabet *G* by the robotic hands in five different trials from *T1* to *T5*. It can be observed from the first plot that persons *P1*, *P2*, *P4*, *P5*, *P6*, *P8*, *P9,* and *P10* were 100 percent successful in generating the sign of the alphabet *G* by the robotic hand. All these eight persons successfully generated the sign of the alphabet *G* five times out of five. The remaining leftover persons, P3



(a) (b)

Fig. 7. (a) Plot of the number of times the sign of alphabet *D* is generated in different trials vs the corresponding persons. (b) The plot of the number of persons involved in the successful generation of the sign of alphabet *D* in a particular trial vs. the corresponding trial number.



(a) (b)

Fig. 8. (a) Plot of the number of times the sign of alphabet *A* is generated in different trials vs the corresponding persons. (b) The plot of the number of persons involved in the successful generation of the sign of alphabet *A* in a particular trial vs. the corresponding trial number.

and P7, could generate four and two times the sign of the alphabet G by the robotic hands, as observed from the plot in Fig. 6 (a). Thus, if we add the number of times the alphabet *G* was generated in five different trials by ten persons from *P1* to *P10*, the result obtained is 46. This means that out of a total of 50 and 46 times, the sign of the alphabet *G* was successfully generated by the robotic hand. Based on this fact, it can be concluded that the accuracy of the robotic hand model during the generation of the sign of the alphabet *G* is 92 %.

It can also be observed from the plot shown in Fig. 6 (b) that in different trials from *T1* to *T5*, the alphabet G was generated by 8, 9, 10, 10, and 9 persons. If these observed values from Fig. 6 (b) are added, the result obtained is 46. Based on the above analysis carried out from Fig. 6 (b), it can again be concluded that the accuracy of the robotic hand model during the generation of the sign of the alphabet *G* is 92 %.

The first plot in Fig. 7 (a) presents the number of times a particular person from *P1* to *P10* was responsible for the successful generation of the sign of the alphabet *D* by the robotic hands in five different trials from *T1* to *T5*. It can be observed from the first plot that persons *P2*, *P4*, *P5*, *P6*, *P7*, *P8*, *P9,* and *P10* were 100 percent successful in generating the sign of the alphabet *D* by the robotic hand. All these eight persons successfully generated the sign of the alphabet *D* five times out of five. The remaining leftover persons, P1 and P3, could generate three and four times the sign of the alphabet D by the robotic hands, as observed from the plot in Fig. 7 (a). Thus, if we add the number of times the alphabet *D* was generated in five different trials by ten persons from *P1* to *P10*, the result obtained is 47. This means that out of a total of 50 times 47 times, the sign of the alphabet *D* was successfully generated by the robotic hand. Based on this fact, it can be concluded that the accuracy of the robotic hand model during the generation of the sign of the alphabet *D* is 94 %.

It can also be observed from the plot shown in Fig. 7 (b) that in different trials from *T1* to *T5*, the alphabet D was generated by 9, 9, 10, 10, and 9 persons. If these observed values from Fig. 7 (b) are added, the result obtained is again 47. Based on the above analysis carried out from Fig. 7 (b), it can again be concluded that the accuracy of the robotic hand model during the generation of the sign of the alphabet *D* is 94 %.

The first plot in Fig. 8 (a) presents the number of times a particular person from *P1* to *P10* was responsible for the successful generation of the sign of the alphabet *A* by the robotic hands in five different trials from *T1* to *T5*. It can be observed from the first plot that all persons except *P2* were 100 percent successful in generating the sign of the alphabet *A* by the robotic hand. All these nine persons successfully generated the sign of the alphabet *A* five times out of five. The remaining leftover person, *P2*, could generate three times the sign of the alphabet A by the robotic hands, as observed from the plot in Fig. 8 (a). Thus, if we add the number of times the alphabet *A* was generated in five different trials by ten persons from *P1* to *P10*, the result obtained is 48. This means that out of a total of

50 times, 48 times, the sign of alphabet *A* was successfully generated by the robotic hand. Based on this fact, it can be concluded that the accuracy of the robotic hand model during the generation of the alphabet *A* sign is 96 %.

It can also be observed from the plot shown in Fig. 8 (b) that in different trials from *T1* to *T5*, the alphabet A was generated by 9, 10, 10, 9, and 10 persons. If these observed values from Fig. 8 (b) are added, the result obtained is again 48. Based on the above analysis carried out from Fig. 8 (b), it can again be concluded that the accuracy of the robotic hand model during the generation of the sign of alphabet *A* is 96 %.

4.7. Discussion on experimental results

In the experimental results, as discussed in Table 2, under different trials, it is to be noted that the effect of gender type does not have any impact on the results. The inbuilt recognizer of the Raspberry Pi 4, along with the external microphone, functions as a speaker-independent module, which was observed during the experimental results in multiple trials. The results are affected by certain other factors as discussed below.

The first factor that affects the results is the inability of both the robotic hands to carry out the sideways movements of fingers, including the thumb and wrist movements. These robotic hands can perform forward and backward movements. It is to be noted that the backward movements of the robotic hand's fingers only occur once the forward movements of the fingers take place. In other words, the backward movements are completely dependent on the forward movements of the fingers. Furthermore, the movements of the different fingers of the robotic hand cannot overlap. These artificial hands also could not generate dynamic signs. Greater flexibility in robotic hands is needed to perform lateral movements of the fingers, including those of the thumb and wrist, for certain alphabets such as *J* and *X*. The sign for the alphabet *J* is dynamic in nature. To generate the sign for the alphabet *X* in Indian Sign Language, there is a need for overlapping the index fingers of both hands, as observed from the actual sign of the alphabet *X* from Table 1. Additionally, most signs of the different words in Indian Sign Language involve dynamic movements, including forward, backward, sideways, and overlapping movements, along with wrist movement. However, our robotic hands lack the necessary flexibility to carry out overlapping movements of different fingers. To generate signs for different words in Indian Sign Language, robotic hands must also be capable of independent backward movements without relying on forward movements. Currently, our robotic hands can only perform backward movements when a particular finger or thumb is partially or completely closed (i.e., during a forward movement). In cases where a finger or thumb is fully open, backward movements associated with those fingers or thumb cannot occur. Therefore, considering these factors, the need for greater flexibility in robotic hands becomes evident.

The second factor that affects the results is the presence of background noises that includes extreme cases of noisy environments. During experimentation, it was observed that background noises significantly impact speech quality when an individual speaks in front of a microphone. These unwanted sounds—such as air conditioning units, computer fans, and street traffic—interfere with accurate recording. In extreme cases of noise, the microphone fails to capture the intended sound of specific alphabets. When multiple sources of sound, including the individual's voice and background noise, reach the microphone, noise often dominates over the desired input. However, in milder noise conditions, the microphone can accurately capture alphabet patterns. The microphone volume was also kept in the range of 20–30 percent as higher levels of microphone volumes catch the background noises frequently. During the case of lower levels of the microphone volume (less than 20 percent), the microphone failed to catch the sound pattern of the alphabet as spelled by an individual in front of the microphone. The gain of the microphone was adjusted in the range of 10–20 dB during its operation.

The third factor that affects the results is the distance of the individual from the microphone that significantly affects the system's performance. When an individual is closer to the microphone, the signal-to-noise ratio improves, capturing clearer audio with less background noise and thus increases the microphone sensitivity. However, being too close can lead to distortion due to overwhelming sound pressure levels. Conversely, increased distance reduces the direct sound received by the microphone, potentially introducing more ambient noise and decreasing the audio clarity. During the process of experimentation, the distance of the individual from the microphone was in the range of 10–15 cm so that the device could accurately capture the audio input from the individual. There are some other factors as well that affects the system's performance that are discussed in Section 6 of the manuscript.

In Table 2, among the different alphabets, the following alphabets, namely *"K, L, M, N, O, P"*, were recognized by the speech recognizer of the Raspberry Pi 4 along with the externally connected microphone in some of the Experimental Trials from *T1 to T5* during the conduction of the experiments. The recognition of these alphabets varies due to the following most common factors, namely the sensitivity of the microphone, the presence of noisy environments, the way the individual utters the speech commands, and the distance of the individual from the microphone. The recognition of these alphabets is not limited to these factors only; there can be multiple other factors as well. Furthermore, the signs of the following alphabets, namely *"K, L, M, N, O, P,"* can be generated without any fail since these alphabets have distinct signs as per the dataset.

Furthermore, in Table 2, we also excluded the failure results involving the seven alphabets because the signs of these seven alphabets were not distinct. In other words, the robotic hand showed the same sign orientation for some of these alphabet pairs. Also, the sign of the letter *'J'* could not be generated because of its dynamic nature. These artificial hands cannot generate dynamic signs due to their inbuilt hardware design. The various values of accuracies of the robotic hand model for some of the four alphabets, namely *Y, G, D*, and *A*, were also discussed in detail in the forms of different plots. In the same way, the estimation of different values of accuracies of the robotic hands during the process of sign generation of other alphabets can also be visualized through separate plots. The discussion related to the performance evaluation of the robotic hand interpreter system model during the generation of different alphabets is stated in Section 5.

5. Performance evaluation

In the existing research, a system involving a Field Programmable Gate Array-based wearable gesture recognition system was proposed. The main purpose of this system was to assist individuals with speech impairments. In this particular approach, the main attention was based on the lesser number of features for the classification of gestures for the purpose of minimizing the need for computational power. In the proposed system, only one feature, namely the Root Mean Square signal value along with the KNN supervised classification algorithm, was taken into consideration. This algorithm was very simple to implement, with high interpretability and low computational complexity. The performance of the system was assessed in a DE10-Standard Field Programmable Gate Array to demonstrate portability to wearable devices with finite hardware resources. Based on the performance evaluation, the results showed that the subjects required only 3 s per gesture for the purpose of training the system. The main advantage of the technique was to avoid the processing of large amounts of data. The system was observed to reach **95 %** accuracy using only 2 s of data effectively [12].

In the past, research based on electromyography electric signals was carried out to control different devices, and the EMG signals were preprocessed. The approach was based on the design and test of a filter. The designed filter eliminated any non-EMG signal component from the electrical network. For the validation process and interpretation of the preprocessing efficiency, the analysis of different frequency components and the distribution of the filtered EMG signals were implemented. In the next stages, the filtered data was processed using K-means, DBSCAN, and hierarchical clustering algorithms to determine the intention of a subject while carrying out different tasks. Based on the results, the *K*-means clustering algorithm was successful in grouping the nine gestures made by the subjects when compared with the DBSCAN and Hierarchical algorithms. It was also concluded that the *K*-means algorithm obtained a mean success rate near 50 % with all nine clusters taken into account. The algorithms based on *DBSCAN* and *Hierarchical Clustering* presented a low success rate [13].

Based on the above research in Refs. [12,13], it was observed that the research was based on gesture recognition using Machine Learning techniques without incorporating any artificial robotic aids for assisting speech and hearing-impaired individuals. Also, in Ref. [13], the overall accuracy was observed to be near 50 %.

In our study, we adopted the use of robotic hands to generate different gestures based on speech commands in the form of the alphabet uttered by an individual. In this section, we estimated the different performance parameters followed by different plots for better analysis and interpretation of the results. Further, we also calculated the overall accuracy of the robotic hand interpreter system model, as discussed below, based on the estimation of the performance parameters. This section is further divided into two subsections. Section 5.1 discusses the evaluation of the performance parameters along with the estimation of accuracy for the robotic system. Section 5.2 discusses the overall analysis of the experimental results based on the different plots.

5.1. Evaluation of performance parameters

In this section, as shown below in Table 5, the different performance parameters are estimated based on the entries of Tables 3 and 4. All the acronyms used in Table 5 below are already discussed in Section 4.5.

In Table 6 we estmate the minimum, maximum and average values of the different performance parameters as discussed below. All the acronyms used in Table 6 below are already discussed in Section 4.5.

5.2. Analysis of results of the performance parameters

In this section, various plots have been constructed to give a detailed analysis of the results of the performance parameters. The plot of the mean number of generated alphabets by different persons and the plot of the standard deviation of the data of persons vs. the corresponding persons from *P1 to P10* under experimental trials from *T1* to *T5* is shown below in Fig. 9. The plot of the mean number of persons and the plot of the standard deviation of the data of alphabets vs. the corresponding alphabets under experimental trials from *T1* to *T5* is shown below in Fig. 10. The reproducibility accuracy of the individual alphabets can be observed by the plot of $\boldsymbol{\mu_{AT}}$ in Fig. 10. For getting the accuracy in percentage, the observed values can be directly multiplied by 100.

The plot of the mean number of persons responsible for the generation of the different alphabets and the plot of the standard deviation of the data corresponding to different alphabets vs the experimental trials from *T1* to *T5* is shown below in Fig. 11 (a). The plot of the mean number of alphabets generated by different persons from *P1* to *P10* and the plot of the standard deviation of the data corresponding to different persons vs the experimental trials from *T1* to *T5* is shown below in Fig. 11 (b).

Table 5
Different values of performance parameters corresponding to different trials.

Number of persons in different trials	Name of the Parameter		Number of alphabets concerning different trials	Name of the Parameter	
	μ_{TA}	σ_{TA}		μ_{TP}	σ_{TP}
N_{P_T1}	8.95	0.69	N_{A_T1}	17	1.18
N_{P_T2}	9.42	0.59	N_{A_T2}	18	0.77
N_{P_T3}	9.58	0.67	N_{A_T3}	18.1	0.7
N_{P_T4}	9.47	0.88	N_{A_T4}	18	0.63
N_{P_T5}	9.58	0.59	N_{A_T4}	18.2	0.87

Table 6
Estimation of minimum, maximum and average value of the performance parameters.

Parameter Name	Min value	Max value	Average value
μ_{AT}	8.4	10	9.4
σ_{AT}	0	0.89	0.51
μ_{TA}	8.95	9.58	9.4
σ_{TA}	0.59	0.88	0.68
μ_{PT}	17	19	17.86
σ_{PT}	0	1.17	0.71
μ_{TP}	17	18.2	17.86
σ_{TP}	0.63	1.18	0.83

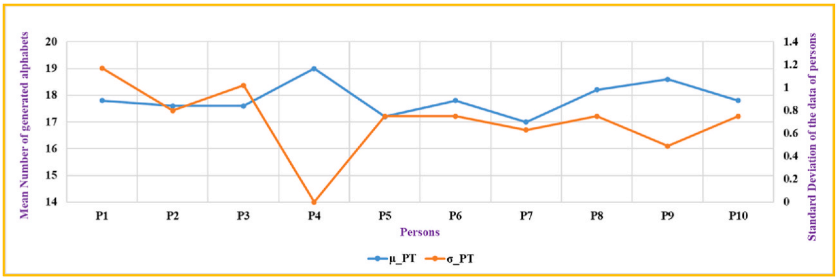


Fig. 9. Plot of the mean number of generated alphabets vs the corresponding persons from *P1 to P10* and the plot of the standard deviation of the data of persons vs the corresponding persons from *P1 to P10* under experimental trials from *T1 to T5*.

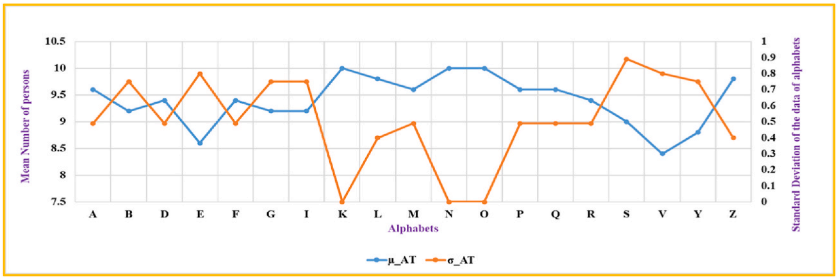
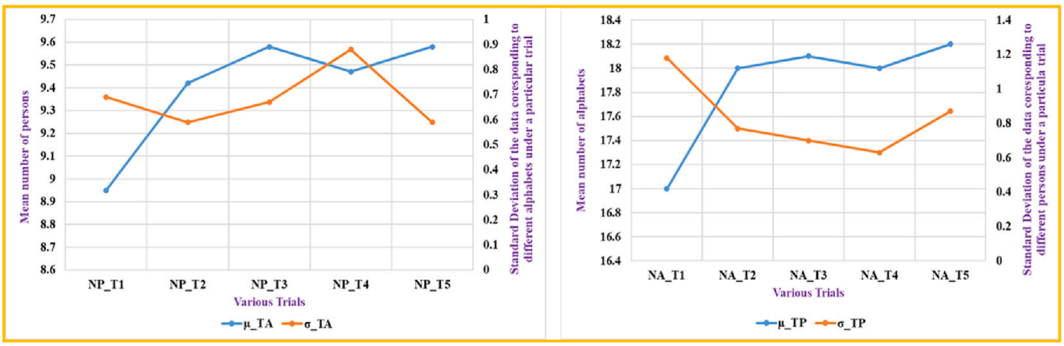


Fig. 10. Plot of the mean number of persons vs. the corresponding alphabets and the plot of the standard deviation of the data of alphabets vs the corresponding alphabets under experimental trials from *T1 to T5*.



(a) (b)

Fig. 11. (a) Plot of the mean number of persons responsible for the generation of the different alphabets and plot of the standard deviation of the data corresponding to different alphabets vs the experimental trials from *T1 to T5*. (b) Plot of the mean number of alphabets generated by different persons from *P1 to P10* and plot of the standard deviation of the data corresponding to different persons vs the experimental trials from *T1 to T5*.

Based on the analysis of results given by Table 4, Table 6 and Fig. 9, the following observations can be made. Among all the persons from *P1 to P7*, the data associated with person ***P7*** has a minimum reproducibility accuracy of **89.47 %** since it has the minimum value of $\boldsymbol{\mu_{PT}}$ based on the different experimental trials from *T1 to T5*. Also, since ***P7***, on average was responsible for the generation of **17** alphabets out of **19** by the dual robotic hand, its reproducibility accuracy comes out to be **89.47 %.** Among all the persons from *P1 to P7*, the data associated with person ***P4*** has a maximum reproducibility accuracy of **100 %** since ***P4***, on an average was responsible for the generation of complete **19** alphabets by the dual robotic hand. The data associated with person ***P4*** also has the greatest reproducibility (least variation in the data) since it has the maximum value of $\boldsymbol{\mu_{PT}}$ and minimum value of $\boldsymbol{\sigma_{PT}}$ based on the different experimental trials from ***T1 to T5***. Among all the persons from *P1 to P7*, the data associated with person ***P1*** has the least reproducibility since it has the maximum value of $\boldsymbol{\sigma_{PT}}$ based on the different experimental trials from *T1 to T5***.**

Based on the analysis of results given in Table 3, Table 6, and Fig. 10, the following observations can be made. The data associated with the generation of alphabet ***V*** by the dual robotic hand based on the speech input uttered by different persons from *P1 to P10* has a minimum reproducibility accuracy of **84 %** since it has the minimum value of $\boldsymbol{\mu_{AT}}$ based on the different experimental trials from *T1 to T5*. The data concerning the generation of alphabets ***K, N, and O*** by the dual robotic hand based on the speech input uttered by different persons from *P1 to P10*, has a maximum reproducibility accuracy of **100 %.** The data associated with these three alphabets has the greatest reproducibility (least variation in the data) since it has the maximum value of $\boldsymbol{\mu_{AT}}$ and minimum value of $\boldsymbol{\sigma_{AT}}$ based on the different experimental trials from *T1 to T5***.** Similarly, the data associated with the generation of the alphabet ***S*** by the dual robotic hand has the least reproducibility (greatest variation in the data) since it has the maximum value of $\boldsymbol{\sigma_{AT}}$ based on the different experimental trials from *T1 to T5*.

Based on the analysis of results given by Table 3, Table 6, and Fig. 11 (a), the following observations can be made. As per Fig. 11 (a), when considering the case of the mean number of persons responsible for the generation of different alphabets by the dual robotic hand, it can be observed that Trial ***T1*** has a minimum accuracy of **89.5 %** during the generation of different alphabets since it has the minimum value of $\boldsymbol{\mu_{TA}}$ which equals **8.95** out of **10**. Trial ***T3*** and ***T5*** have a maximum accuracy of **95.8 %** during the generation of different alphabets by the dual robotic hand, since these have the maximum value of $\boldsymbol{\mu_{TA}}$**,** which equals **9.58**. Trial ***T4*** has the least reproducibility of data due to the maximum value of $\boldsymbol{\sigma_{TA}}$. Trial ***T2* and *T5*** have the greatest reproducibility of data due to the minimum value of $\boldsymbol{\sigma_{TA}}$**.**

Based on the analysis of results given by Table 4, Table 6, and Fig. 11 (b), the following observations can be made. As per Fig. 11 (b), when considering the case of the mean number of alphabets correctly generated, it can be observed that the data associated with Trial ***T1*** has a minimum accuracy of **89.47 %** due to the minimum value of $\boldsymbol{\mu_{TP}}$ which equals **17 out of 19.** Trial ***T5*** has a maximum accuracy of **95.79 %** due to the maximum value of $\boldsymbol{\mu_{TP}}$ which equals **18.2 out of 19.** Trial ***T1*** has the least reproducibility of data due to the maximum value of $\boldsymbol{\sigma_{TP}}$. Trial ***T4*** has the greatest reproducibility of data due to the minimum value of $\boldsymbol{\sigma_{TP}}$**.**

Based on Table 6, the overall accuracy of the robotic hand interpreter system model is **94 %**, considering the average generation of given **19** alphabets from *A* to *Z* under various experimental trials from ***T1 to T5***. The accuracy value is obtained from the average value of $\boldsymbol{\mu_{AT}}$ which is also equal to $\boldsymbol{\mu_{TA}}$ as per Table 6. The overall accuracy of the robotic hand interpreter system model is also **94 %** based on the average number of persons responsible for the generation of different numbers of alphabets by the dual robotic hand under various experimental trials from *T1 to T5*. The accuracy value is obtained from the average value of $\boldsymbol{\mu_{PT}}$ which is also equal to $\boldsymbol{\mu_{TP}}$ as per Table 5. Since the value of $\boldsymbol{\mu_{PT}}$ equals **17.86** out of **19**, therefore converting the value to percentage, it becomes **94.**

In Section 4.6, from Figs. 5–8, we have discussed the accuracies of the robotic hand model during the generation of the signs of some of the alphabets in detail. The different values of accuracies of the robotic hand model during the generation of all **19** alphabets can also be checked graphically in Fig. 10 as well as in the last second column of Table 3. These values can be converted to percentages by directly multiplying them by 100. The details corresponding to the count of the generated alphabets based on the ranges of their reproducibility accuracy are shown below in Table 7. These entries are based on the plots shown in Fig. 10.

From the above Tables 7 and it can be observed that 16 alphabets have reproducibility accuracy of more than **90 %** during the process of sign generation by different persons under different experimental trials. Furthermore, the plots corresponding to the count of generated alphabets vs the different ranges of their reproducibility accuracy are presented below in Fig. 12. Thus, it can be observed that the following three alphabets, namely *V, E*, and *Y*, require slight improvement in their accuracy during the process of sign generation by the robotic hands.

6. Conclusion

The accessible languages for speech and hard-of-hearing individuals include sign languages, which are widely used by speech and hearing-impaired persons in India. Learning sign language is essential for communicating with speech and hard-of-hearing individuals and provides a unique experience. As the need for sign language interpreters grows, it is becoming increasingly important to

Table 7
Details of the 19 alphabets grouped in different ranges of their reproducibility accuracy during sign generation.

Range of μ_{AT} in percentage	Count of generated alphabets	Name of the Alphabets
80–85	1	*V*
85–90	2	*E, Y*
90–95	7	*S, B, G, I, D, F, R*
95–100	9	*A, M, P, Q, L, Z, K, N, O*

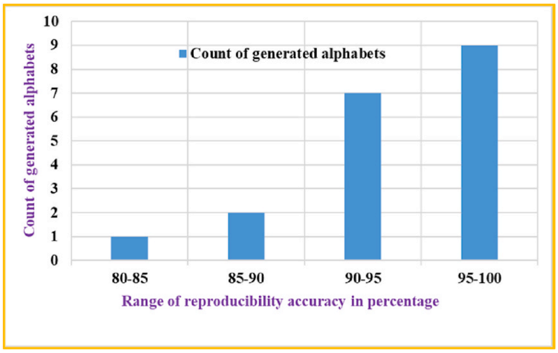


Fig. 12. Plot of the count of generated alphabets vs the range of reproducibility accuracy in percentage.

understand and learn Indian Sign Language. Interpreters are needed in various public places, such as railway stations, police stations, hospitals, and courts, to help hard-of-hearing individuals communicate effectively.

To address this need, a robotic hand interpreter system has been developed to generate signs based on Indian Sign Language. This system helps speech and hard-of-hearing individuals interact with others who do not have hearing disabilities. The performance analysis of the robotic hand during the Indian Sign Generation was tested out by ten different persons under different experimental trials, as discussed in the Experimental Results section.

Considering the signs of the **26** alphabets as per the Indian Sign Language system, **19** alphabets were generated by the robotic hand model due to their distinct sign representation. The remaining seven alphabets could not be generated since the robotic hand generated similar signs corresponding to some of these alphabets, which highlights the limitations of our study. Out of these **19** alphabets the reproducibility accuracy of the **16** alphabets is greater than equal to **90** percent. The remaining three alphabets, namely *V, E,* and *Y,* require slight improvement in their accuracy values, as already discussed previously. Other limitations of our study are also discussed below. Both the left and right robotic hands need to be more flexible to carry out the sideways movements of fingers, including the thumb and wrist movements. These robotic hands must also carry out overlapping movements and can generate dynamic signs. The need for requirements of these above additional features in the robotic hands was already discussed in Section 4.7.

The generation of signs by the robotic hand is also influenced by background noise, extreme noise levels in the environment, the sensitivity of the microphone, the manner in which individuals articulate speech commands, and the distance of individuals from the microphone. Further details on these limitations can also be checked in Section 4.7.

It is due to some of these above-discussed limitations that the accuracy of the gesture generation by the robotic hand is affected. The overall accuracy of the robotic hand interpreter system model based on the experimental results comes out to be approximately **94 percent** and varies in the range of **90 to 95 percent**. The design of the robotic hand interpreter system model is a cost-effective solution with features of improved efficiency and productivity, enhanced precision, and greater flexibility during the process of gesture generation.

The future scope of our study is to overcome the limitations discussed above. Furthermore, an effective approach should be incorporated in future studies to generate all **26** alphabets distinctly to carry out further improvement in accuracy. The generation of dynamic signs, as well as the generation of different words and sentences, should also be incorporated by the application of these artificial robotic hands.

Data availability statement

The input data associated with the study is already available and accessible through the link https://www.mbcnschool.org/tag/indian-sign-language/. It has not been deposited into a publicly available repository. A similar type of dataset related to Indian Sign Language is publicly available in a repository, namely Kaggle.

CRediT authorship contribution statement

Yash Verma: Writing – original draft, Methodology. **R.S. Anand:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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