

A Machine Learning based Full Duplex System Supporting Multiple Sign Languages for Deaf and Mute

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Abstract: The use of Machine Learning (ML) is increasing and is used extensively to solve various problems. In this manuscript, ML is applied to design a full duplex communication for Deaf and Mute (D-M) people is presented. These individuals are an integral part of our society and their contribution is vital. They face difficulty in communication mainly because others are unable to communicate with them using sign language. This work presents a solution to this problem through a system where D-M and non-deaf and mute (ND-M) individuals can communicate with each other without the need to learn sign language. The system is reliable, easy to use, and based on a commercial-off-the-shelf (COTS) Leap Motion Device device (LMD), to acquire hand gesture data which is then processed using Convolutional Neural Network (CNN). A supervised ML algorithm then performs the rest of the processing and finally converts the hand gesture data into speech. A new dataset for ML-based algorithm is created and presented in this manuscript. The ND-M can communicate by recording speech which is then converted into text and hand gesture images. The system recognizes three sign language datasets i.e., American Sign Language (ASL), Pakistani Sign Language (PSL), and Spanish Sign Language (SSL). The system can be upgraded in the future to support more sign language datasets. The system also provides a training mode that can help D-M individual to improve their hand gestures and also understand how accurately the system is detecting these gestures. The proposed system is validated through a series of experiments and results show hand gesture detection accuracy of more than 95%. Similarities between the three sign languages are also explored and further research can help in creating a new dataset that can be a combination of multiple sign languages.

Keywords: Deaf-Mute person; Hand Gesture Recognition; Leap Motion Device; Machine learning; Multi-language processing; Sign Language Dataset

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1. Introduction

The advancement in technology has a mostly positive impact on society. The focus of this work is the use of information and communication technology (ICT). This area apart from software and hardware also includes using different algorithms to solve some existing problems. This research work is a step towards improving the integration of the Deaf and Mute (D-M) in society. The research work presented in this manuscript provides a common platform for the D-M people using different sign language datasets. The proposed system is based on commercial-off-the-shelf (COTS) hardware integrated with a software application that provides full-duplex communication.

1.1. Importance of Sign Language

There are millions of people who are D-M who rely on sign language to communicate with others. They often find it difficult to establish effective communication with others due to others not being able to use or understand sign language. People with no physical impairment often find it difficult to learn sign language. This creates a scenario where it is very difficult to establish communication. A system is needed to resolve this problem which can provide a platform for D-M and non-deaf and mute (ND-M) to communicate by overcoming the difficulties mentioned in this section.

1.2. Artificial Intelligence and Machine Learning

The impact of artificial intelligence (AI) is positive on society. The use of AI and more specifically machine learning (ML) is increasing and researchers are applying these to solve many problems within different areas. AI and ML are already applied to establish effective communication systems so that D-M and ND-M people communicate. Researchers are using existing algorithms as well as creating new algorithms. ML algorithms are not only being deployed to solve a problem but these algorithms are also reducing the processing time.

1.3. Research Scope

This research work is the continuation of the work published in [1]. In this manuscript a two-way communication system for D-M and ND-M is presented based on American Sign Language (ASL), Pakistani Sign Language (PSL), and Spanish Sign Language (SSL). The scope of this work includes Convolutional Neural Network (CNN) and supervised ML. **Figure 1** shows the scope of this work which includes three main building blocks.



Figure 1. Research scope.

1.4. Manuscript Organization

This section presents a summary of different sections within the manuscript. The next section 2 presents the review of related work to understand the current state of research, novel features, and limitations of existing systems and prototypes. Section 3 presents the research methodology through 4 steps. The next sections i.e. 4 and 5 provide the details of the proposed communication system and its validation through experimental setups. The results of these experiments are presented in section 5. A discussion section is presented in section 6 followed by the last section 7, conclusions and future work.

2. Related Work

This section is a review of recent research work carried out for the development of communication systems involving D-M people. The review includes the novel features presented by the authors as well as the limitations of their proposed systems.

2.1. System Level Review

In [2] authors used a Leap Motion Device (LMD) to acquire hand gesture signals. The D-M people can communicate with others using hand gestures while ND-M people are provided with an android application that converts speech to text. The accuracy of gesture detection is 95%. The authors in [3] presented a system that converts hand gestures from D-M into text. The system also displays a gesture image for the text input. A portable device is designed by authors in [4]. The D-M people can carry this device and their hand gestures are acquired and then converted into speech. In [5] a contactless hand gesture recognition system is presented where the gesture is acquired using an LMD. They used Long Short-Term Memory (LSTM) recurrent neural networks for gesture detection.

The authors used LMD for hand gesture recognition for D-M in [6]. They defined criteria for hand gesture recognition and used different methods like Gaussian Mixture Model (GMM), Hidden Markov Model (HMM), and Dynamic Time Warping (DTW) for image data processing. In [7] the authors acquired sign language gestures using a camera. They compared various neural network algorithms to process the image data and presented the accuracy. The authors in [8] developed a learning system for D-M people. They used Augmented Reality to convert the acquired gesture into a 3D model. They also developed a glove using Flex sensors.

In [9] the authors surveyed to understand different reasons for hearing loss and when the age when this is detected. A prototype of a glove using flex sensors is designed by authors in [10]. The detected hand gesture is converted into text and voice. The researchers reviewed several techniques for hand gesture recognition and highlighted both limitations and advantages of these algorithms and techniques [11]. The survey provides good insight to other researchers. In [12] an automated ASL recognition system is presented. The detected gestures are converted into text. An automated sign language detection system is proposed in [13] where the authors provided a two-way communication. They used the ASL dataset.

The authors used Bangla Sign Language (BSL) dataset in [14] and processed the hand gesture data using Convolutional Neural Network (CNN). They reported an accuracy of more than 98%. In [15] developed a mobile phone application where they can setup a customized interface for individual users. This application provides support for multiple languages. An Arabic Sign language (ArSL) based system is presented by authors in [16]. They have detected ArSL and converted it into voice. The authors also surveyed different techniques.

A CNN-based hand gesture recognition system is presented in [17]. The authors reported a hand gesture recognition accuracy of more than 93%. In [18] the researchers developed a glove that they have used for translating ASL. They reported an accuracy of 95%. A portable hand gesture recognition prototype is presented in [19]. The authors used deep learning to process image data which is then converted to speech. In [20] developed a prototype of a smart glove for detecting sign language and a recorded audio message is played for the recognized gesture. The authors used Indian Sign Language (ISL) dataset. A CNN-based hand gesture detection prototype is presented in [21]. The proposed prototype detects ISL. The authors claim a training accuracy of more than 99%. They have used more than 3000 images for training the model.

In [22] the authors used ASL dataset detection using CNN. They reported an accuracy of more than 95%. The authors in [23] developed a prototype using a glove and flex sensors that interfaced with Arduino. The prototype converts the hand gesture data into text. The authors used K-Nearest Neighbours (KNN) algorithm for image data processing. A PC-based image detection system is presented in [24]. The authors used

Principal Component Analysis (PCA) algorithm. In [25] an automated Sign Language Interpreter (SLI) prototype is presented which is based on a glove connected to Arduino. The authors reported 93% accuracy. A CNN-based prototype for hand gesture detection is presented in [26]. This prototype also provides a training option. There is also support for multiple languages.

The authors developed a mobile application in [27] for D-M people. The application is offline and uses ASL and Filipino Sign Language (FPL) datasets. A PC-based prototype is presented by authors in [28] for detecting hand images. Hand gestures are acquired through sensors. The prototype presented in [29] provides visual feedback. The system is based on an android application. The authors compared different technologies in the manuscript. In [30] the authors surveyed to understand the problems and challenges faced by D-M individuals. They highlighted the impact of hand gesture recognition systems and prototypes in providing a platform to the D-M people.

Table 1 is a summary of the review carried out. The details include hardware, software, features, and limitations of the prototypes and products designed. The last column also includes information related to Sign Language Dataset (SLD).

Table 1. Summary of related work review.

References	Hardware / Software	Summary
[2]	LMD, Android app	D-M to ND-M to D-M, Single SLD
[3]	PC, Harris algorithm	D-M to ND-M to D-M, Single SLD
[4]	Raspberry Pi	D-M to ND-M, Single SLD
[5]	LMD, LSTM Neural networks	D-M to ND-M, Single SLD
[6]	LMD, (GMM, HMM, DTW)	D-M to ND-M, Single SLD
[7]	PC, NN algorithms	D-M to ND-M, Single SLD
[8]	PC, Arduino, Gloves, Flex sensors	Calibration required for the custom made product, D-M to ND-M, Single SLD
[10]	Arduino, Gloves, Sensors	Calibration required for the custom-made product, D-M to ND-M, Single SLD
[12]	PC, TensorFlow	D-M to ND-M, Single SLD
[13]	PC, Various ML algorithms	D-M to ND-M to D-M, Single SLD
[14]	PC, TensorFlow, CNN	D-M to ND-M, Single SLD
[15]	Android	D-M to ND-M, Multi SLD
[16]	Android	D-M to ND-M, Single SLD
[17]	PC, CNN	D-M to ND-M, Single SLD
[18]	Arduino, Gloves, Flex sensors	Calibration required for the custom-made product, D-M to ND-M, Single SLD
[19]	PC NN	D-M to ND-M, Single SLD
[20]	Gloves, Flex sensors, Voice recorder, Matlab	D-M to ND-M, Single SLD
[21]	PC, CNN	D-M to ND-M, Single SLD
[22]	CNN	D-M to ND-M to D-M, Single SLD
[23]	Gloves, Sensors, Arduino, KNN	D-M to ND-M, Single SLD
[24]	PC-based, PCA	D-M to ND-M, Single SLD
[25]	Arduino, Gloves, Sensors, KNN	Calibration required for the custom-made product, D-M to ND-M, Single SLD
[26]	PC-based, CNN	D-M to ND-M, Single SLD

[27]	Android application	D-M to ND-M, Multi SLD
[28]	PC, CNN	D-M to ND-M, Single SLD
[29]	Android	D-M to ND-M to D-M, Single SLD

2.2. Sign Language Dataset Review

In [14] the authors used the BSL dataset to validate their prototype. The dataset includes more than 2500 images. The authors in [16] used a new method to detect ArSL dataset. In [31] authors used a word-level ASL dataset. Their selection of the dataset is based on the number of people who can use this sign language. Argentinian Sign Language (ArgSL) is processed in [32] where they used videos as input. The researchers used Turkish Sign Language (TSL) [33]. They used CNN algorithm to process the dataset.

The Chinese language is spoken by the majority of people around the world. The authors in [34] used Chinese Sign Language (CSL) with hundreds of categories within the dataset. Another word-level ASL dataset is used in [35]. In [36] a large-scale ASL dataset is presented and processed by authors. Russian Sign Language (RSL) is used as input [37]. In [38] the authors processed ArSL. They developed a prototype based on Arduino and a glove with sensors connected.

Table 2 is a summary of the different sign language datasets reviewed. This review is focused on the size of the datasets, how many people can use this dataset, and its complexity.

Table 2. Summary of sign language datasets reviewed.

References	Sign Language Dataset	Dataset size
[14]	Bangladesh Sign Language	2660 images
[16]	Arabic Sign Language	50 signs
[31]	Word-level American Sign Language	More than 2000 words
[32]	Argentinian Sign Language	More than 3200 videos
[33]	Turkish Sign Language	226 signs
[34]	Chinese Sign Language	500 categories
[35]	Word-level American Sign Language	More than 10000 videos
[36]	American Sign Language	10000 signs and 25000 videos
[37]	Russian Sign Language	164 lexical units
[38]	Arabic Sign Language	Not provided

2.3. Machine Learning Algorithm Review

In this section review of some machine learning algorithms is presented. The authors created a new dataset for supervised machine learning in [39] and [40]. The dataset is used to suggest a solution to faults found during electronic product manufacturing. The algorithms are implemented in LabVIEW [41]. The authors in [42] reviewed machine learning algorithms and used it to determine the performance of soldering stations.

In [43] the authors review machine learning algorithms. Their finding includes highlighting the limitations of some algorithms. The authors used Scikit, a Python [44] toolkit to implement machine learning algorithm in [45]

2.4. Related Work Conclusions and Research Gap

In this section, a further summary of the prototypes and systems reviewed is presented. From this conclusion, the research gap is highlighted which forms the basis of the research work carried out in this manuscript.

The majority of the work reviewed here is unidirectional i.e. detection and conversion of hand gestures data into text and or voice. This is a limitation where ND-M people are unable to communicate with D-M. The other limitation is the input sign

language dataset which in most cases is one. This means that those who don't know that particular sign language database are unable to benefit from the system. Some prototypes designed using gloves and sensors require maintenance and calibration and are also difficult to maintain consistency.

The proposed system provides a full-duplex system where both D-M and ND-M people can communicate with each other. This system uses multiple sign language datasets and provides training, which is easy to use and low cost. Systems based on commercial-off-the-shelf (COTS) devices like LMD require a lot less effort to convert the prototype into a product. Affordability is also important so low initial cost and no running cost is an important feature.

3. Research Methodology

In this section, the research methodology is presented. The research is carried out through several steps which are mentioned in this section. Figure 2 shows the block diagram with the steps and relevant details.

3.1. Design Research

In this step, there are two tasks performed. The first task is to list the activities that are within the research topic. This activity is concluded with a clear definition of the scope of this work. It is important to have a clear scope so that the research work can be effective. The scope of this work is to implement a system where a two-way communication system is a setup through sign language interpretation and conversion to audio. After defining the research scope, the next activity is to select certain areas to review the existing work. The details of this are in section 2, literature review.

3.2. Conduct Research

This is the second step where an in-depth review of the selected categories is carried out. The details are presented in section 2. The conclusion of the literature review is necessary to determine which parameters to use for implementing the proposed system. The literature review also highlights the gaps in the existing work and provides a roadmap for further work which is carried out through this research work. This also includes reviewing different algorithms, existing implementations, novel features of the current work, and limitations.

3.3. Design Implementation

In this step the proposed system is implemented. The features of the system are selected after conclusions drawn from the literature review. The design is implemented through five tasks as listed in figure 2. The sign language datasets are selected and information is stored in the database. The rest of the tasks in this step are software development, hardware deployment, and integration.

3.4. Validation and Conclusion

This is the final step where the complete system validation is carried out. The validated system is then tested for performance through different experimental setups and results are presented.

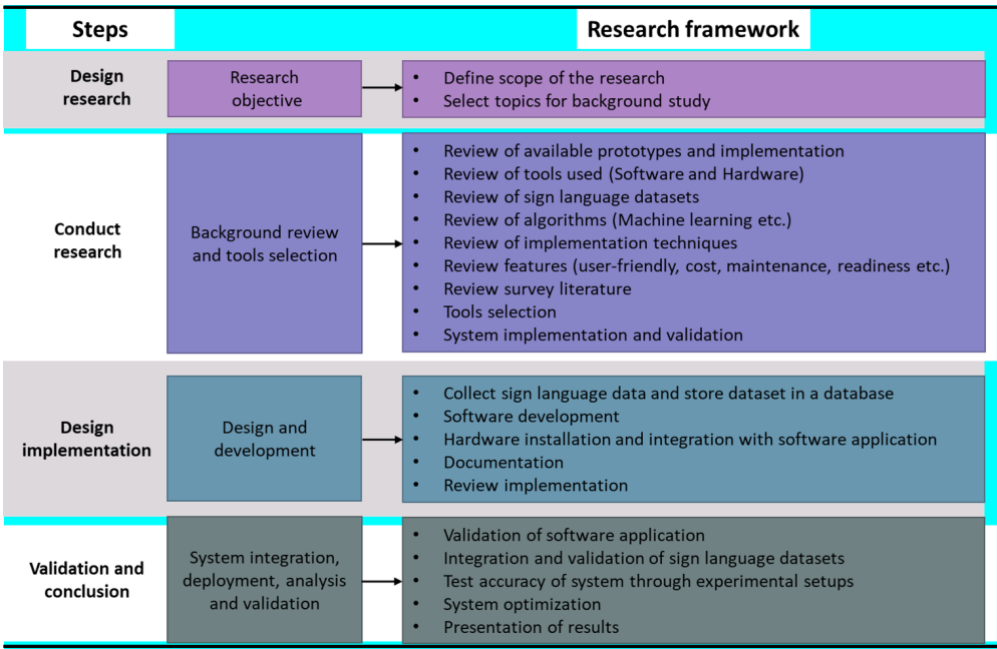


Figure 2. Research Methodology

4. Proposed Communication System for D-M

In this section, the details of the proposed system are presented including some key features of this research work.

4.1. Communication System Novel Features

Figure 3 shows the novel features of the proposed system. The system provides full duplex communication between D-M and ND-M people. This low-cost system is user-friendly and easy to install with no running cost to the end user. The training option is available which allows the features to be customized for individual users. The ML-based algorithm provides a continuous improvement option where a better quality new data i.e. hand gesture image can replace an existing image. The proposed system supports American Sign Language, Pakistan Sign Language, and Spanish Sign Language. More Languages can be added. Hand gestures data is acquired using LMD which is a COTS device and, unlike a glove, does not require maintenance and calibration. The image data is processed using the CNN algorithm.

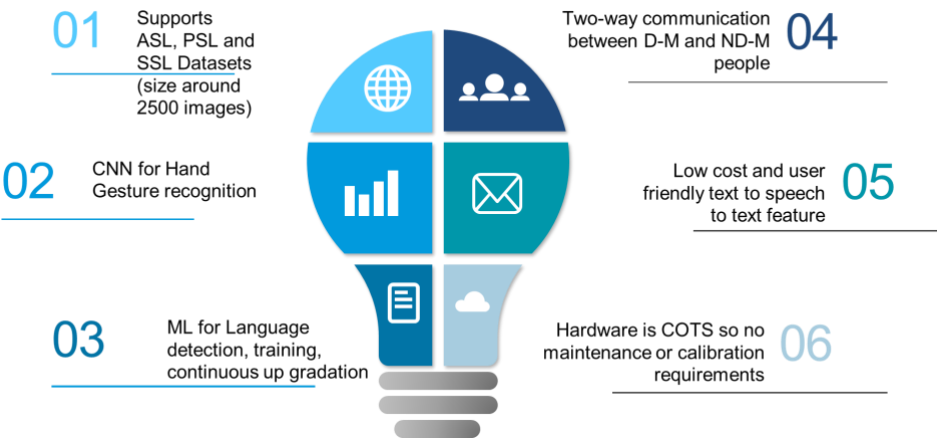


Figure 3. Novel Features of Full Duplex Communication System

4.2. Communication System Block Details

Figure 4 is a full duplex communication system between D-M and ND-M people. The figure shows the implementation of the proposed system. The D-M person is provided with an interface where the hand gestures are acquired using an LMD connected to the PC-based system. The LMD captures hand gestures as an image and forwards them to the PC which is then further processed. The details of the processing are discussed later. The system supports multiple sign language datasets i.e. ASL, PSL, and SSL. The system is reconfigurable and more datasets can be added in the future. The acquired image data goes through multiple processing stages and is then converted into a voice message.

The ND-M person can listen to the voice message. The speech or voice data is generated through the PC sound card output. In response, the ND-M person records a voice message which is acquired by the PC using sound card input. The voice message is then processed by the software application and converted into text as well as in the form of hand gesture images. The D-M person is then able to read the text or see the images. An ND-M person can also initiate a conversation similarly.

The proposed system is low-cost, user-friendly, and does not require any special training. These are the main features that make it easy for more people to be able to use this system. The sign language datasets selected for this system are based on the number of people using these sign language datasets. The selection of ASL, PSL, and SSL is based on the availability and size of datasets and the number of people using these. A small dataset means the size of the training dataset will be small hence the trained system will be less effective or accurate while a large dataset means high accuracy but slow response. Considering this, medium-sized datasets are selected.

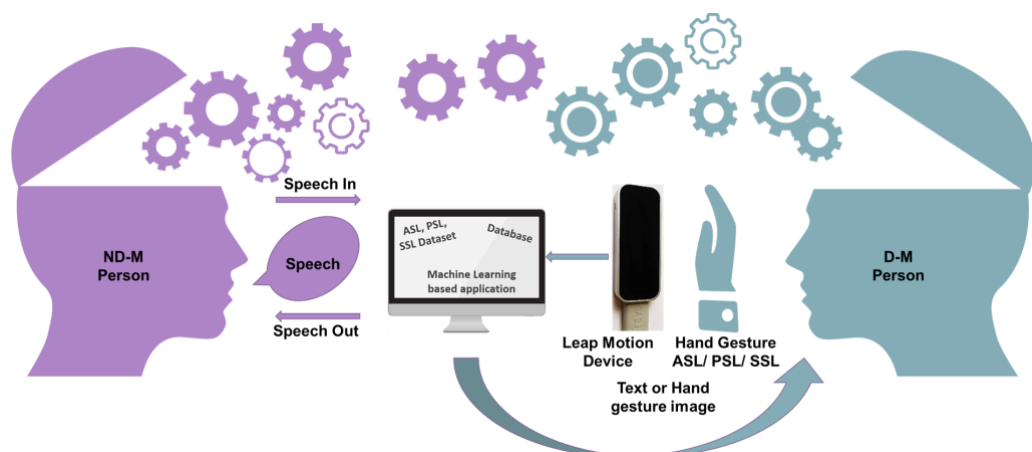


Figure 4. Block Diagram of the Communication System

The system provides a training mode where the user can check the accuracy of the system while undergoing training. In this mode, the hand gestures of the D-M person are processed and the detected results are displayed without going through the text to speech to text conversion. The D-M person can vary hand gestures to check for detection accuracy. In this mode, the system also updates the database by replacing existing images with better-quality ones. The ML-based process compares the new acquired images with the stored images and decide if the existing image can be replaced with the new one or store the new image as well as keeping the existing image or not store the new image at all. Having more image files means an improved dataset which will increase accuracy but this also means the system will need more processing time. It is important to have a balance between these parameters. This decision is taken by the ML-based implementation.

ML algorithm also reviews the user stored data which helps in increasing the processing speed and accuracy. For example if a user profile shows that the user only

understands SSL then the process will bypass the language detection step for this particular user. Similarly, the user can update the profile by adding more sign language datasets and other parameters. The system also maintains a performance record, both for the individual user and the overall system, using the stored user data and new data acquired through the training and normal modes.

Figure 5 shows the ML-based implementation. The block diagram shows the input, output, and hidden layers displaying various activities. The data is fed through the input layer as shown by '1'. The input data includes both the hand gesture image data and the user data which is stored as part of the user profile. In '2' the user profile data is processed. The user can update the profile to reflect any changes. The next step '3' is the training mode. This step is used when the training mode is selected. In normal mode, the ML algorithm can use some options from this step. The language detection is done in step '4'. Currently, there are three datasets but more can be added. The acquired image goes through initialization in step '5'. In step '6' the image goes through initial processing and some features are detected and extracted. CNN algorithm is applied to further process the image data in '7'. The next two steps i.e., '8' and '9' are for data storage. The results are generated through the output layer as marked by step '10'.

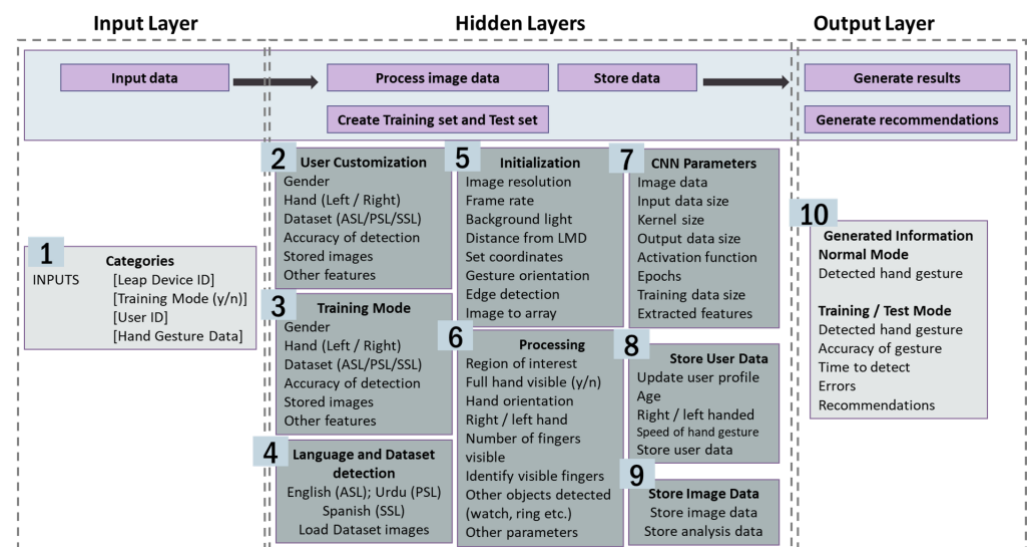


Figure 5. Machine Learning Algorithm

This figure is to be added here to give basic information about how CNN works

Figure 6. CNN Algorithm Processing

5. Experimental Setup and Results

The full duplex communication system is validated using series of experiments which are discussed in this section. A criterion is used for this validation which is presented in the next section.

5.1. System Validation Criteria

The communication system is validated through two stages. The first stage is to select the sign language dataset which in this case are ASL, PSL, and SSL datasets. The second stage is to select a subset of these datasets. It is important to use a known input dataset and a predicted output result. This will help in understanding the system accuracy and limitations of the proposed system. Once the system is validated using these criteria, the full dataset is applied to further determine the performance of the system.

It is important to use a known set of images for initial validation. A study of how sign language datasets are created and also a validation of the datasets is outside the scope of this work.

To validate the proposed communication system, the ASL dataset images are used [46]. These are color images of hand gestures are used. The SSL dataset used for validation is available online [47]. The PSL dataset is created by recording images of letters and numbers. A reference to PSL is also available from [48].

Letters and numbers from the three sign language datasets are used for validating the communication system. For this research work 70% of the hand gesture images from the datasets are used for training while the rest of the 30% are used for testing. The split of 70% and 30% is a good combination for training and testing. A different combination can also be used. As an example, approximately 1800 images of letters and 700 images of numbers from ASL are used which are then split into the ratio as mentioned in this section. Figures 7, 8, and 9 shows subsets of ASL, PSL, and SSL dataset images. Figure 7 shows five numbers and letters from ASL while in figure 8, eight letters from PSL are shown. In figure 9, six letters from SSL are shown.

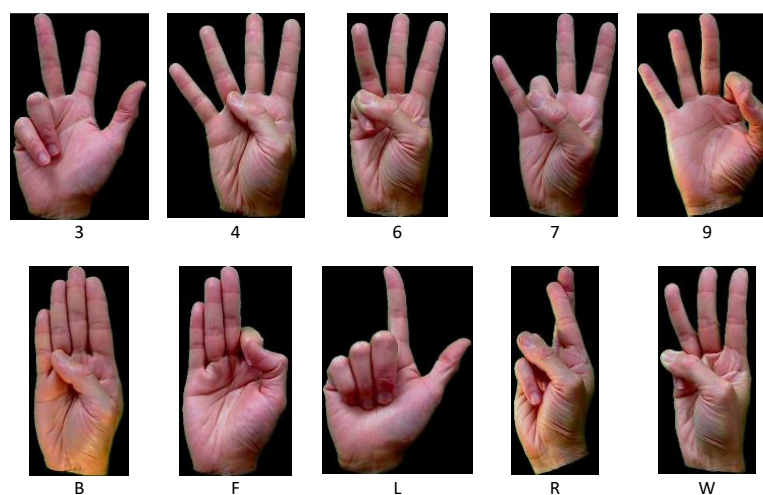


Figure 7. A Subset of American Sign Language Dataset

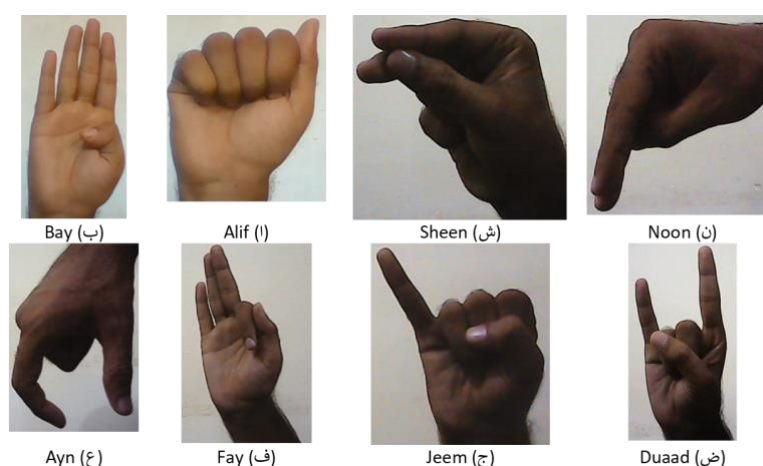


Figure 8. A Subset of Pakistani Sign Language Dataset

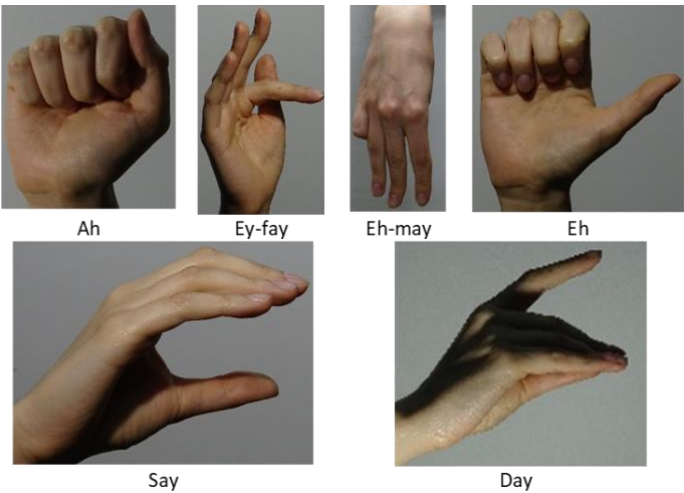


Figure 9. A Subset of Spanish Sign Language Dataset

5.2. Experiment 1—Proposed Communication System Accuracy

In this experiment, the accuracy of detection of hand gestures is presented. The formula for accuracy is presented in equation (1). The accuracy is presented in percentage in table 3. The accuracy values are also used to determine the performance of the algorithm.

Accuracy = $\frac{\text{Correct Detection}}{\text{Total number of tries}}$ (1)

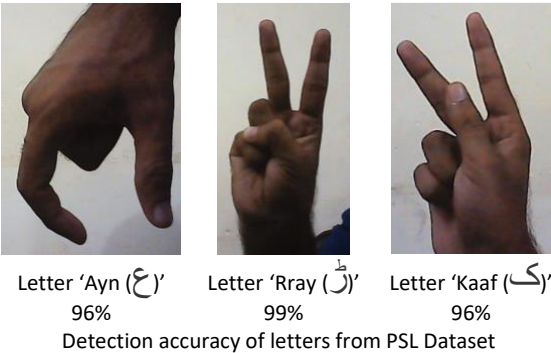
In this experiment, the repeatability of the algorithm is evaluated. The system is validated by processing the gestures of all letters and numbers. For validation, the most accurate gesture is selected and processed. The results are presented in Table 3. The accuracy of the proposed system is also dependent on the accuracy of the hand gestures i.e. how accurately the gesture is made.

Table 3. Accuracy of Detection.

Dataset	Accuracy % (Letters, Numbers)
ASL	98.5%, 98.9%
PSL	93.1%, 92.7%
SSL	94.3%, 93.8%

5.3. Experiment 2—Processing Individual Hand Gestures

In this section hand gesture detection results are presented. In figure 10, three letters from PSL dataset are processed through the proposed system and results show that the detection is 96% or more.



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Figure 10. Processing Hand Gestures (PSL Dataset)

Figure 11 shows the accuracy and loss graphs PSL dataset. The graphs include both actual and test results.

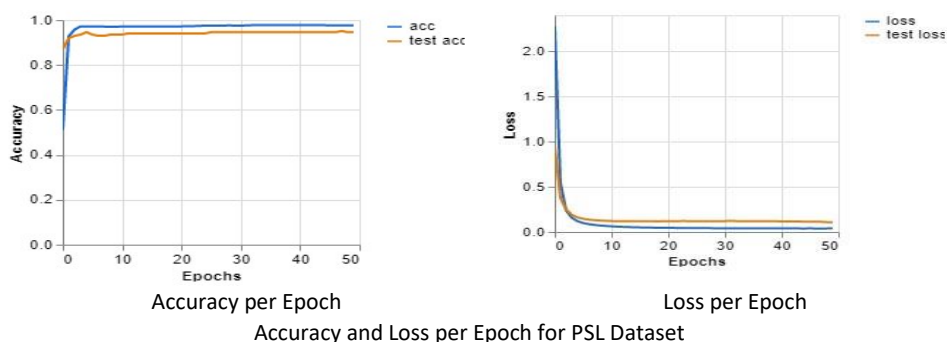
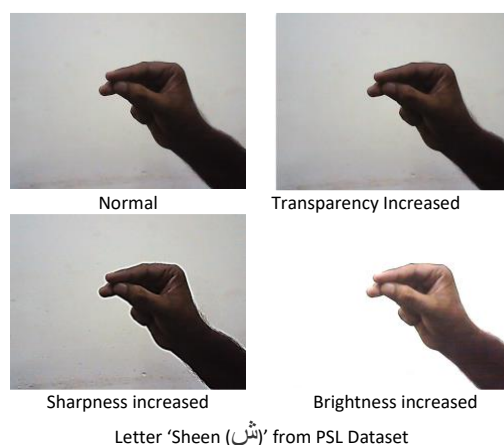
**Figure 11.** Hand Gesture Detection Results for PSL Dataset

Figure 12 shows the hand gesture detection results for SSL dataset. The results are encouraging and showing high accuracy.

**Figure 12.** Processing Hand Gestures (SSL Dataset)

5.4. Experiment 3—Processing Hand Gestures Image Quality

In this section the experiment I carried out by changing the quality of the hand gesture image and then processed through the proposed system. **Figure 13** shows the four variants of a letter from PSL dataset. All the images are correctly detected hence confirming that the proposed system is able to detect the correct gesture for different image quality.

**Figure 13.** Processing Different Image Quality for Same Hand Gesture

5.5. Experiment 4—Processing Variations in Same Hand Gestures

In this section, the variation in hand gestures is processed through the proposed communication system. In figures 14, 15, and 16, two variants of letters from the PSL dataset are processed and the detection accuracy is calculated.

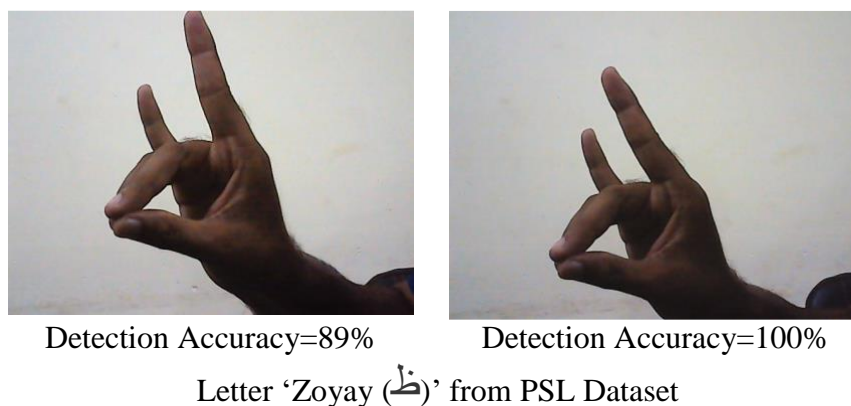


Figure 14. Processing Variation in Same Hand Gesture Scenario 1

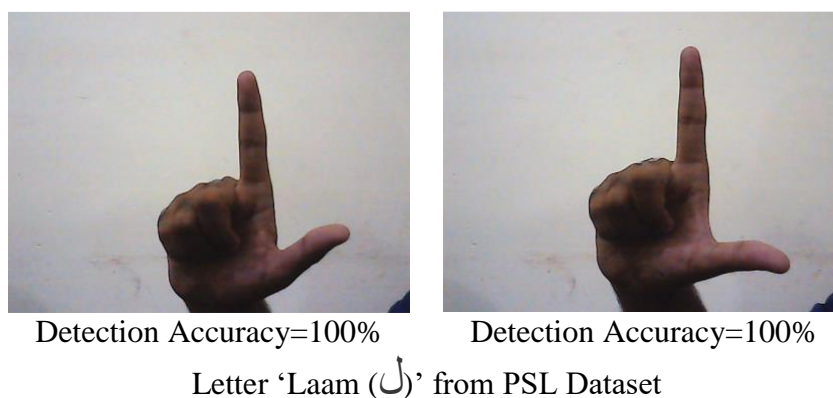


Figure 15. Processing Variation in Same Hand Gesture Scenario 2

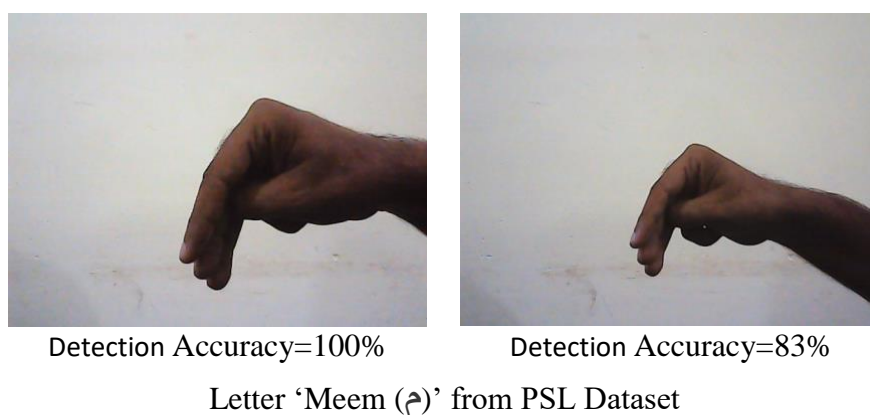
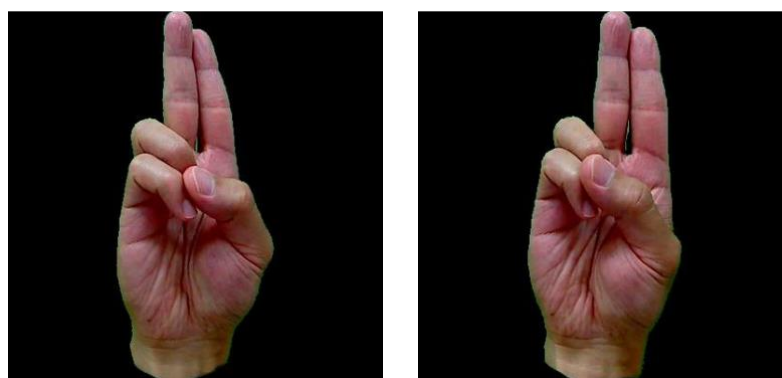


Figure 16. Processing Variation in Same Hand Gesture Scenario 3

In figure 17 a letter from the ASL dataset is shown with the detection accuracy which is more than 90% in this case.



Detection Accuracy=94% Detection Accuracy=98%
Letter 'U' from ASL Dataset

Figure 17. Processing Variation in Same Hand Gesture Scenario 4

5.6. Experiment 5—Processing Similar Hand Gestures

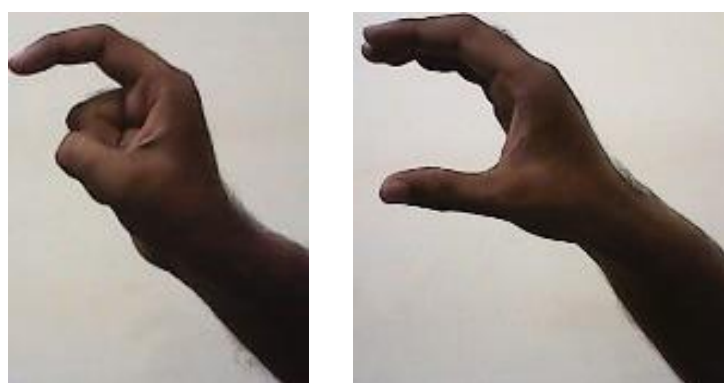
Some hand gestures are similar although not identical and due to this there is a possibility of wrong detection. In this section results of similar hand gesture detection are presented. Figures 18 and 19 show the detection results of two sets of letters from the PSL dataset.



Hey (هـ)

Zay (ز)

Figure 18. Processing Similar Gestures (PSL Dataset) Scenario 1



Daal (د)

Say (ث)

Figure 19. Processing Similar Gestures (PSL Dataset) Scenario 2

5.7. Experiment 6—Detecting Other Objects

This experiment focuses on other objects that can be visible while detecting hand gestures. The proposed system has a unique feature where these objects are also detected and information is removed in some cases so that the correct hand gesture can be detected. Figures 20, 21, and 22 show images with and without other objects. The detection in these examples is correct.



ASL Letter 'A'

Figure 20. Detecting Other Objects – Wrist Watch Scenario 1



ASL Letter 'L'

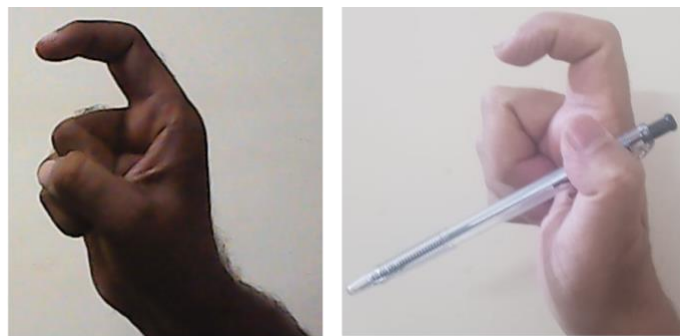
Figure 21. Detecting Other Objects – Wrist Watch Scenario 2



PSL Letter 'Noon (ن)'

Figure 22. Detecting Other Objects – Ring

Figure 23 shows another example of another object captured with the hand gesture. In this instance, the proposed system is unable to correctly detect the hand gesture.



PSL Letter 'Daal (د)'

Figure 23. Detecting Other Objects – Pen

5.8. Experiment 7 – Algorithm Performance

In this section, the performance of the PSL dataset is presented using a confusion matrix. The performance of the system is further evaluated using a confusion matrix. This matrix shows the results for each letter for all other letters. The matrix I use in evaluating the performance of the algorithm and also highlighting any errors. The confusion matrix for letters within the PSL dataset is shown in **figures 24 and 25**.

	Ain	Aliph	aRay	Bariyeh	Bay	Chay	ChotiyeH	Daal	Dall	Dhaal	Dhaad	Djay	Fay	Gaal	GhaIn/Hamza	Hay	Hev	Jeem	Kaaf	Khay	Laam	Meem	Noon	Pay	Qaaf	Ray	Seen	Sheen	Suaad	Tay	Thay	Tocay/n	Vao	Zay	Zocay/n
Ain	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Aliph	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
aRay	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Bariyeh	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Bay	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Chay	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
ChotiyeH	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Daal	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Dall	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Dhaal	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Dhaad	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Djay	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Fay	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Gaal	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
GhaIn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Hamza	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Hay	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Hev	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

Figure 24. Confusion matrix of Letters within PSL Dataset Set 1.

	Ain	Aliph	aRay	Bariyeh	Ray	Chay	Choriyeen	Qaal	Dall	Dhaal	Dhuuad	Dja	Fay	Gaaf	Ghain	Hamez	Hay	Har	Jeem	Kaaf	Khay	Laam	Meem	Noon	Pay	Qaaf	Ray	Seen	Sheen	Susad	Tay	Thay	Toay'n	Vao	Zay	Zay'n
Jeem	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Kaaf	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Khay	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Laam	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Meem	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Noon	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Pay	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Qaaf	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Ray	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Seen	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Sheen	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Susad	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Tay	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Thay	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Toay'n	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
Vao	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Zay	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Zay'n	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Figure 25. Confusion matrix of Letters within PSL Dataset Set 2.

5.9. Experiment 8—Creating a New Dataset

In this experiment, the similarities between the three sign language datasets are presented. In figure 26 three letters, one each from ASL, SSL, and PSL are shown. These symbols are similar and this approach can be used to create a new sign language dataset that can be a combination of multiple sign languages.

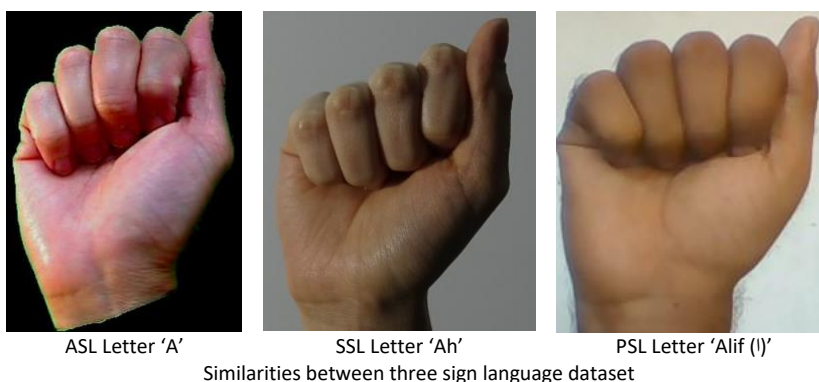


Figure 26. Similarities between different sign languages.

6. Discussion

In this manuscript, a full duplex communication system for D-M and ND-M people is presented. The scope of this work includes ML, CNN, the use of multiple Sign Language datasets, and the use of COTS hardware devices. The proposed system is low-cost and easy to use. The proposed system supports ASL, PSL, and SSL and can be upgraded in the future to support more sign language datasets.

An extensive review is carried out which is discussed in the related work section. This section provides a tabular summary of the review. The review also includes some available datasets of different sign languages which is followed by a review of some machine learning techniques. The section of related work discusses the research gap and conclusions drawn from the review. One conclusion of the review is that most of the available prototypes presented are unidirectional i.e. detection and conversion of hand gestures data into text and or voice only. This is a limitation where ND-M people are unable to respond to D-M individuals. The other conclusion from related work is the use of a single sign language dataset mostly. Some researchers developed prototypes based on gloves and demonstrated the functionality but there is no information related to the maintenance, consistency, repeatability, and reliability of these prototypes.

The proposed system provides a full-duplex system where both D-M and ND-M people can communicate with each other. This system currently uses three sign language datasets. The proposed system does not require any special training, it is easy to use and low-cost. The system is reliable as it uses a COTS device which is the LMD. The system is easier to convert into a product from a prototype. This can be implemented for a low initial cost with no annual running cost.

The proposed communication is a full duplex system providing a link between D-M and ND-M people. The system can be customized for individual users through a training option. The ML-based algorithm provides a continuous improvement option where a better quality new data i.e. hand gesture image can replace an existing image. Hand gestures data is acquired using LMD which is a COTS device and, unlike a glove, does not require maintenance and calibration. The image data is processed using the CNN algorithm.

The system details are discussed in section 4. This section also provides details of the ML algorithm and different options within the algorithm. Finally, the system is validated through a series of experiments which are discussed in section 5. The system can be upgraded by adding more sign language datasets which will also improve the coverage in terms of end users of the proposed system. A training mode is an important option that can help D-M individual to improve hand gestures and also understand how accurately the system is detecting these gestures. Comparison of individual hand gestures is also done as part of this research which can be further explored to create a new sign language dataset that can be a combination of multiple sign languages.

7. Conclusions and Future Work

The system presented in this manuscript provides a communication platform for D-M and ND-M people to communicate with each other without the need to learn sign language. The system is reliable, easy to use, and based on a COTS LMD device, to acquire hand gesture data which is then processed using CNN. Apart from CNN, a supervised ML algorithm is also applied where a new dataset is created and presented in this manuscript. The system provides an audio interface for ND-M and a hand gesture capture interface for D-M individuals. The system recognizes three sign language datasets i.e., ASL, PSL, and SSL, and can be upgraded in the future to support more sign language datasets. A training mode is also available which can help individuals to review how accurately the system is detecting their hand gestures. Having three sign language datasets means the system can treat these as a single dataset of three languages. The proposed system is validated through a series of experiments using ASL, PSL, and SSL datasets and results show an accuracy of more than 95%. The software application is developed in LabVIEW. The database stores the datasets, user profile data, and other data that the ML-based algorithm use.

In the future, more sign language datasets can be processed and added. Dataset size can also be increased based on the recommendations from ML-based algorithm. Datasets can also be improved by adding videos and other data types including word-level hand gestures. More work can be done for doing a comparison between different sign languages to understand and combine datasets of multiple languages to create new datasets.

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511

512

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