Indian Sign Language Recognition

CSE4015 Human Computer Interaction

J-Component Report

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1. Chapter 1

1.1 Aim

Communication is one of the major areas where differently abled (deaf and dumb) people face problems on everyday basis. To counter this problem, this project aims at developing an accelerated Indian Sign Language Detector using Deep Learning. The model uses Convolutional Neural Network (CNN) for recognizing signs and converting them to English language. Additionally the proposed model also converts English Speech into Indian Sign Language Signs with help of Google Speech API. An interactive interface is provided to users to use the system

1.2 Objectives

The objectives of the project are:

- To develop Indian Sign Language Detector that can help people with disabilities to communicate better
- To make use of Convolutional Neural Network for creation and development of model which can detect hand signs based on input
- To develop an user friendly user interface for users that will allow them to make best use of the proposed system
- To allow Sign to Text and Speech to Sign Conversion based on the option and input given by the user

1.3 Introduction

Sign Language is used to communication through visual medium by using signs, gestures and facial expression. Deaf and dumb people utilize Sign Language to communicate with others. Different regions and countries have their own versions of Sign Languages. Indian Sign Language (ISL) is used in India and some neighboring countries. However, Sign Language is not understood by most people with normal hearing abilities. This creates a huge communication gap which can lead to lot of misunderstanding.

To solve this problem many Sign Language Recognition models which can detect the hand gestures have been developed. Deep Learning methods inspired by the working of biological neural networks have provided significant breakthroughs in the field of Sign Language Recognition. Recent studies have shown that neural network-based models can have accuracy rate of more than 90%. Majority of these models employ Convolutional Neural Networks (CNNs) for sign recognitions. CNNs have ability to imitate human vision and are highly accurate in image recognition. CNNs create a feature map by applying filters on the given input. The ability to optimize filters makes CNNs reasonably more efficient in image classification and recognition than other machine learning algorithms and methods.

2. Chapter 2

This chapter explains in details about the existing works related to the topic and about existing and proposed system

2.1 RELATED WORKS OR LITERATURE SURVEY

In recent years many approaches for sign language recognition using different technologies and methodologies have been proposed using electronic devices such as smart gloves or using machine learning technologies. Some researchers have utilized traditional machine learning methods while other have used deep learning methods for development of models for recognition of Sign Language. Various Sign Language datasets of different Sign Languages have been used by the researchers.

Following are some of the works done in the field of sign language recognition.

Deep Learning Methods for Indian Sign Language Recognition

In this paper a method to implement real time Indian Sign Language gesture recognition using two methods. First using a depth+RGB based Microsoft Kinect camera and then using a normal RGB camera. For depth+RGB based techniques, the hand segmentation was done using depth perception techniques. For a normal RGB camera semantic segmentation approach was adopted. The usage of semantic segmentation completely removes the necessity of using a depth-based camera and segmentation. For the depth+RGB trained models, techniques like having different lighting conditions and data augmentation helped achieve the generalization in case of static gestures. For dynamic gestures, the procurement of data was done at various fps values so that the model can learn the temporal features [1].

Artificial Neural Network based Indian Sign Language Recognition using hand crafted features

This article presents a methodology to recognize Indian Sign Language (SL) gestures and translate them into English. SL Recognition systems can be useful for facilitating the conversation. There are various systems developed by researchers for implementing a SL recognition system. Being in its developing stage, the grammar rules of Indian Sign Language (ISL) are not documented making the recognition process a challenge. This approach employs hand crafted feature extraction technique and uses Artificial Neural Network for classification of the gestures. The accuracy of model achieved is as high as 98% using this methodology [2].

Recognition of Sign Language Using Leap Motion Controller Data

The paper reviews the state of the art in sign language recognition. The study focuses on data acquisition methods, because they put the major restrictions on a further recognition process. The sign language recognition, using data collected by the Leap Motion Controller, is performed. The device detects user’s hands and transmits it into a three-dimensional model, providing hands and lingers location and posture. This paper presents a system that is capable of recognition and classification of the sign language using deep- convolutional neural network. It highlights the main features of the Leap Motion Controller that improves and simplifies feature extraction [3].

Deep Learning-Based Approach for Sign Language Gesture Recognition With Efficient Hand Gesture Representation

This study proposed a novel system for dynamic hand gesture recognition via a combination of multiple deep learning techniques. The proposed system represented the hand gesture using local hand shape features as well as global body configuration features, which is very efficient for complicated structured hand gestures of the sign language. The openpose framework was used in this study for hand region detection and estimation. A robust face detection algorithm and the body parts ratios theory were utilized for gesture space estimation and normalization. Two 3DCNN instances were used separately for learning the fine-grained features of the hand shape and the coarse-grained features of the global body configuration. MLP and autoencoders were utilized to aggregate and globalize the extracted local features and the SoftMax function was used for the classification. The experimental results showed that the proposed system outperformed state-of-the-art methods in terms of recognition rate, demonstrating its effectiveness [4].

Signet: A Deep Learning based Indian Sign Language Recognition System

The paper presented a vision based deep learning architecture for signer independent Indian sign language recognition system. Here, various existing methods in sign language recognition and implement a Convolutional Neural Network (CNN) architecture for ISL static alphabet recognition from the binary silhouette of signer hand region were reviewed. The system was successfully trained on all 24 ISL static alphabets with a training accuracy of 99.93% and with testing and validation accuracy of 98.64%. The recognition accuracy obtained is better than most of the current state of art methods [5].

Motionlets Matching with Adaptive Kernels for 3-D Indian Sign Language Recognition

This paper proposes characterization of sign language gestures articulated at different body parts as 3-D motionlets, which describe the signs with a subset of joint motions. A two- phase fast algorithm identifies 3-D query signs from an adaptively ranked database of 3-D sign language. A model for recognizing gestures of Indian sign language 3D motion captured data is presented. It is observed that the motionlet based adaptive kernel matching algorithm on 500 class 3D sign language data gives better classification accuracies compared to state–of–the–art action recognition models [6].

Evaluation of CNN Models with Transfer Learning for Recognition of Sign Language Alphabets with Complex Background

A Convolutional Neural Network (CNN) approach with transfer learning to recognize Arabic and American Sign Languages alphabets with complex background is presented. Different techniques to improve the accuracy of the proposed approach such as data augmentation, batch-normalization, and early stopping were adopted. The proposed model is evaluated on three datasets and experiments reveal improved results with high recognition rates. They could have explored more about hand segmentation techniques as it is a very important method for developing a sign language [7].

A Static Hand Gesture Based Sign Language Recognition System using Convolutional Neural Networks

In this paper, an SL interpreter that takes the input sign gesture and gives the output in a display device is developed. They used Convolutional Neural Networks (CNNs) to train the system with a given database. After training we find out the testing accuracy of 99.89% and validation accuracy of 99.85% at 5 epochs. One of the advantages of our model is that it is not dependent on external hardware or device. The limitation is that the background must be light with good lighting conditions. Also, it is applicable only for static gestures [8].

Sign Language Recognition Techniques- A Review

In this paper it is aimed to review various techniques that have been employed in the recent past for SLR that are employed at various stages of recognition. This paper explains the methods of Sign language recognition and describes the steps involved in gesture recognition which include acquisition, segmentation, feature extraction till recognition and classification. But this paper did not discuss or produce a new method to improve the topic [9].

Fine Hand: Learning Hand Shapes for American Sign Language Recognition

In this paper, they present an approach for effective learning of hand shape embedding, which are discriminative for ASL gestures. They demonstrated that higher quality hand shape models can significantly improve the accuracy of final video gesture classification in challenging conditions with variety of speakers, different illumination, and significant motion blur [10].

Alphabetical Gesture Recognition of American Sign Language using E-Voice Smart Glove
In this paper the authors have given the idea of a smart glove that has been designed to be an interpreter between deaf-mute individuals and the normal public. Gesture translation into speech and textural form is carried out through this device. The smart glove is embedded with modern and technologically advanced sensors to make the overall prototype lightweight and easy to carry. Gesture translation is performed by idealizing the standard ASL template. The main problem encountered in this paper is that the idea is not implementable on large scale as the person might not have the means of buying these gloves [11].

Sign Language Recognition with CW Radar and Machine Learning
In another work, the authors have explored the use of low power frequency modulated continuous wave radar for automatic sign language recognition. The proposed system is composed of a radar, a sound cluster, and a computer for transforming signals to spectrograms. Furthermore, as the time-frequency spectrograms are high-dimensional data with redundant information, then dimensionality reduction is performed by extracting the histogram of oriented gradients features from these spectrograms. The features are finally classified by the k-Nearest Neighbor algorithm and a classification result of 95.8% is achieved on the five testing signs. The impact of the k value in the k-Nearest Neighbor is also investigated in this research paper. However, the proposed method is not easy to implement and users can find it hard to use it for daily conversation [12].

Wearable Sensor-Based Sign Language Recognition: A Comprehensive Review
This is a review paper where the authors have prepared a literature review focuses on analyzing studies that use wearable sensor-based systems to classify sign language gestures. A review of 72 studies from 1991 to 2019 was performed to identify trends, best practices, and common challenges. Attributes including sign language variation, sensor configuration, classification method, study design, and performance metrics were analyzed and compared. Many encouraging methods and results related to this field were observed, and common challenges were identified and analyzed. Major challenges of SLR include sign boundary detection, system scalability to larger lexicons, eliminating movement epenthesis, and model convergence. Although attempts have been made to overcome these challenges, techniques are still being developed by researchers [13].

ST-Xception: A Depthwise Separable Convolution Network for Military Sign Language Recognition
In this paper, the authors have collected a new first-person dataset named MSL, which contains 16 classes of 3, 840 tactical gesture samples on battle scenario with more than 11, 0000 video frames performed by 10 subjects. Moreover, they have also presented a novel deep network, called ST-Xception architecture, considering the depth wise separable convolutions to recognize such military sign language. By expanding the convolution filters and pooling kernels into 3D, our network can characterize the inherent spatio-temporal relationship of a certain tactical hand gesture. In particular, they have also further reduced computational cost and relieve overfitting by replacing the fully connected layers with adaptive average pooling. Experimental results show that their model outperforms existing models on their in-house MSL dataset and as well as in two other benchmark datasets. The approach (expansion of convolution filters and pooling of kernels in 3D) applied in this research paper is a very novel one and can considered for further analysis [14].

A Brief Review of the Recent Trends in Sign Language Recognition
In this review paper the author has tried to review both the most commonly used method of sign language recognition. The author talks about two main approaches for sign language recognition that are (I) image based and (II) sensor based. Image based approach involves one or more cameras to capture an image sequence of the signer performing the sign, and then uses image processing to recognize the sign. The sensor-based method uses instrumental gloves assembled with sensors to

track the hand articulates. This paper mainly describes various image or vision-based sign language recognition systems comprising feature extraction and classification. Translation of sign language to speech is also described briefly. Overall, this paper is expected to be a complete introduction to automatic hand gesture recognition and sign language interpretation [15].

Transfer Learning for Videos: From Action Recognition to Sign Language Recognition
In this work researchers have proposed have proposed model for signer-independent sign language recognition. Inflated 3D Convolutional Neural Network has been employed for sign language recognition. The presented method utilizes solely RGB video data. The proposed model can also work on application which do not provide or have access to depth data. The researchers have also demonstrated that transfer of spatiotemporal features to training process for SLR from a large-scale action recognition dataset can be highly beneficial. The presented work was evaluated using the ChaLearn249 Isolated Gesture Recognition dataset and has accuracy of 64.44%. The proposed model performed significantly better than many other rent RGB- based methods [16].

Real-Time Sign Language Recognition Based on Video Stream
A model for real time Chinese Sign Language Recognition has been proposed. The researchers created a dataset for the Chinese Language containing nearly 5000 words along with their demos. RGB video streams are used as the input for model. Optical Flow Calculation has been used for preprocessing the pixels. After preprocessing, the video stream was given as input to 3D Convolutional Neural Network which has the ability to extract both time and space features for extraction of feature vectors. To increase the practicality of the system, motion detection module, hand and head detection module along with an artificial interaction interface was embedded into the system. The proposed model showed highest average accuracy of 90.1% when 3D CNN was used along with Optical flow processing with RGB video stream [17].

Towards Multilingual Sign Language Recognition
Research has also been done to develop models for multilingual sign language recognition. In one such approach hand movement modelling was done with usage of target sign language independent dataset by derivation of subunits of hand movement. The proposed approach was validated against different types of Sign Language. This work demonstrated that sign language recognition models could be developed by utilizing multilingual sign language data. Although considerable performance difference has been observed when hand modelling is done in a language independent manner rather than in language dependent manner [18].

Recognition of Sign Language Symbols using Templates
This work proposes a model for the detection of Sign Language Symbols using facial expression and hand detection. The model uses webcam for image input and works only with static images. The input static images are taken in YCbCr format and skin color detection is performed for development of templates. The developed templates are divided into Quadrants and computation of quad values is carried out. These computed quad values provide threshold values for the purpose of matching and recognition of Sign Language Symbols. The model employs image processing techniques such as feature detection for creation of a template image that can be matched against incoming input and recognize the Sign Language Symbol [19].

Reconstruction of Convolutional Neural Network for Sign Language Recognition
In this approach, Sign Language Recognition model using Convolutional Neural Network (CNN) has been proposed. American Sign Language fingerspelling dataset has been used in the model. Single Shot Multi-Box Detector (SSD) a machine learning model which is highly efficient and precise in object detection has been used for hand capturing and provide input to the Convolutional Neural Network (CNN). The CNN in combination with a fully connected network forms the second module of the model. The second module translates the input signs into text. The proposed model

had an accuracy of 92.21% which was better than many of the existing works that utilized machine learning techniques for sign language recognition. [20]
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2.2 EXISTING AND PROPOSED SYSTEM

While the majority of the works focus on increasing the accuracy for the sign recognition by utilizing various image processing and machine learning techniques. Not much work has been done to reduce the training time of the machine learning models. This is the main objective of our project:
There are two main approaches followed for Sign Language Recognition which are sensor-based approach and machine learning based approach. These approaches have utilized various types of Sign Languages, Preprocessing Techniques and gesture positions. Under various environments, previous works have achieved accuracy ranging from 65 to 90+%.
The key limitations with the current approaches is that sensor devices can be expensive and are vulnerable to wear and tear. Additionally special equipment is need for using the model. For the machine learning models, huge volume of the data is required which can increase the training time for the model. Furthermore, conventional machine learning model cannot handle complexity of image recognition in an efficient manner.
To counter this problem, the proposed model utilizes Convolutional Neural Networks (CNNs). CNNs have ability to imitate human vision and are highly accurate in image recognition. CNNs create a feature map by applying filters on the given input. The ability to optimize filters makes CNNs reasonably more efficient in image classification and recognition than other machine learning algorithms and methods.
Moreover, the proposed model provides an interactive user interface to users to make use of the proposed model rather than providing a statistic system that works on preprocessed images.

3. Chapter 3

This section specifies the proposed system architecture and explains each component in detail along with algorithm used.

3.1 PROPOSED SYSTEM DESIGN ARCHITECTURE

Following is the architecture of the proposed system. The architecture has seven major components which deal with development of machine learning based sign language detection model, creation of user interface for users and prediction of alphabet or sign based on the input given by user. All the components are explained in detail in the architecture explanation section.

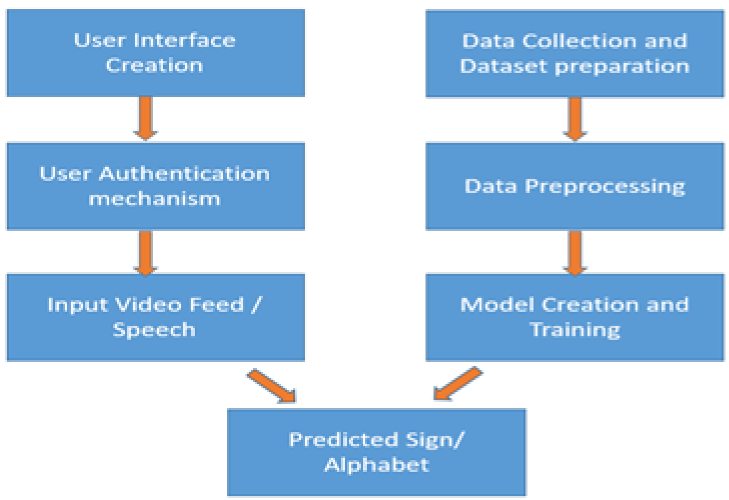

Figure 1: Architecture flowchart of the proposed system

3.2 ARCHITECTURE EXPLANATION

Data Collection and Preparation
In the dataset we have 1200 images of each letter divided into the test and training portion. The size of the dataset is enough for proper training and testing of the model that we are trying to create. After this we have compressed our dataset into zip file for use in the Colab notebook.

Data Preprocessing
The aim of the data preprocessing is to make dataset ready to be input into CNN for training and testing. Two major steps are involved in data preprocessing: Skin detection and segmentation followed by edge detection. OpenCV a well-known library for computer vision and image processing has been used for data preprocessing.
For detection of hand gestures, it is necessary to identify the area of image representing hand and discard other unnecessary features. For skin detection, the unprocessed data (image) is converted to YC_bC_r color space where Y represents the luma component while C_b and C_r represent blue and red difference chroma components respectively. This color space can be formed using RGB values through following equations

$Y=0.299R+0.587G+0.114BY=0.299R+0.587G+0.114B.$ (1)

$Cr=R-YCr=R-Y.$ (2)

$Cb=B-YCb=B-Y$ (3)

After conversion to YC_bC_r color space, image histogram is formed to mark each skin-colored pixel. By this process only the skin-colored pixels representing hand remain all other unnecessary details such as background are removed.

Figure 2: Hand sign image after skin detection has been performed

After skin detection, it is necessary to identify the edges since all the hand signs are identified by the outline or edges of the hand. For this task, Canny Edge Algorithm has been utilized. Canny Edge Algorithm can not only has ability to detect a wide variety of edges but also can reduce noise that occurs during the process. Gaussian filter is used for the noise reduction followed by calculation of intensity gradient. Non- maximum suppression is carried out after gradient calculation. Hysteresis Thresholding is performed at end to remove any false edges.

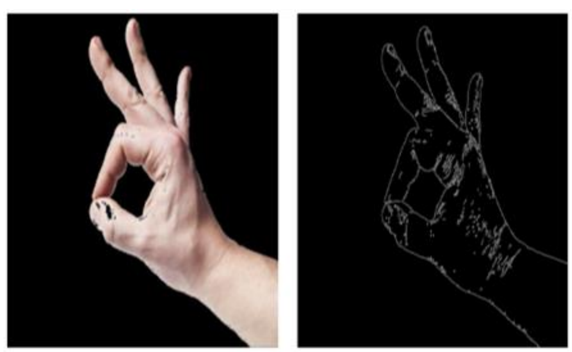

Figure 3: Hand sign image after skin detection has been performed

Model Creation

We created a Convolution Neural Network model here. In our neural network we first added a convolution layer which accepts the image input. After it one more convolution layer was added. A dropout layer was added as it prevents the overfitting. Again, the convolution layers were added and then dropout layer was added and then softmax layer was added which converts the number to vector probabilities. After this optimizer and loss function were added where we used the adam optimizer and categorical cross entropy for loss function. In final step metric was added as accuracy.

After model creation, the model is trained using the preprocessed dataset, to make it ready for Sign Language Detection.

User Interface Creation

In order to facilitate users to utilize the Indian Sign Language Detection system, a Graphical User Interface is developed. The Graphical User Interface is in form of a desktop application developed in Python language with use of Tkinter library. Tkinter is commonly used in Python for development of Graphical User Interfaces. Due to its popularity, it is considered standard GUI library for Python. Combination of Tkinter library with Python gives an efficient and quick method for creation of Graphical User Interface based application due to its vast object-oriented interface.

User Authentication Mechanism

In order to ensure privacy and security of the proposed system, a user authentication mechanism is implemented. The authentication mechanism is implemented using a username and password mechanism which mandates every user to create an account and login using the credentials to use the proposed system. The details of the user are maintained using SQLite library.
SQLite is a serverless, zero-configuration, in-process engine for SQL database. Due to the property of zero-configuration, SQLite does not need prior configuration. Additionally it can be dynamically or statically linked to an application.

Input Video Feed/ Speech

It is essential to give appropriate input to the system to achieve desired output. To give a Sign as input, a webcam of good pixel quality is required. The system using the OpenCV library open the available webcam so that a video feed can be input in the system. The system also provides an appropriate area to put the hand in so that it can be captured more efficiently and processed for detection. From the feed frames are captured and preprocessed so that they can be input into the system.
For speech to Sign conversion, a standard microphone is required. The input speech is processed and converted to words using Speech Recognition library using Google Speech API.

Predict Sign / Alphabet

For Prediction/Detection of Sign, the captured preprocessed frames are feed into the trained model which is stored in form of an .h5 file. This file stores the configuration and model weights that are used to perform prediction. The detected sign is converted into an alphabet and displayed on the screen at top of video feed.
For Speech to Sign conversion, the Google Speech API is utilized for converting the speech into text which is then used for displaying corresponding sign using a python dictionary that is used for displaying the correct sign image.

3.3 ALGORITHMS & PSEUDOCODE

Following the algorithm for the working of the entire system:

1. *Start System*
2. *Login*
3. *If credentials== true then*
4. *display dashboard*
5. *else*
6. *display error message*
7. *Select option from Dashboard*
8. *Display the input instruction*

9. *Take input*
10. *Perform Prediction*
11. *Display Result*
12. *If press(Escape)== true then*
13. *exit*
14. *else goto step 7*
15. *End*

4. Chapter 4

This chapter details with results obtained after implementation of the proposed system. Relevant discussion and future works are also discussed.

4.1 RESULTS & DISCUSSIONS

After development, training and testing of various components of the proposed system, following results were obtained.

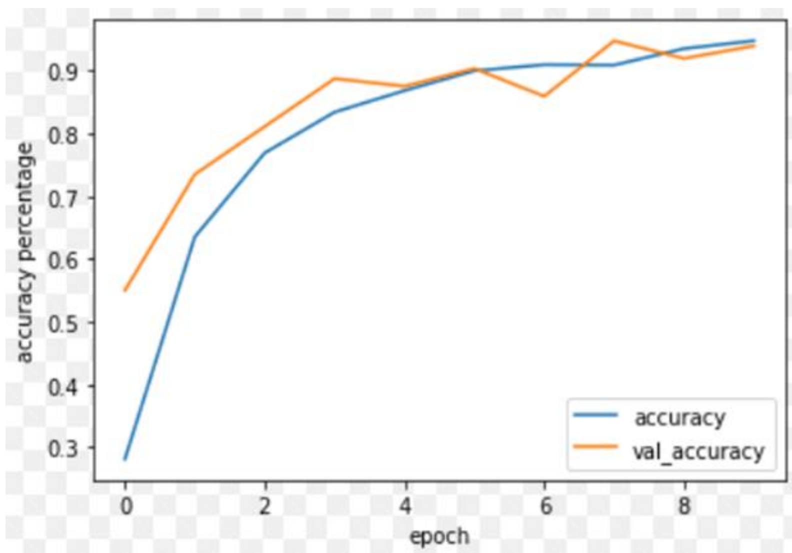

Figure 4: Training accuracy graph for proposed model

The figure 4 shows the training accuracy graph for the proposed system. As can be inferred from the graph the validation and training accuracy both were over 90% for the preprocessed dataset.

Figure 5: Login Panel of the Indian Sign Language Detector

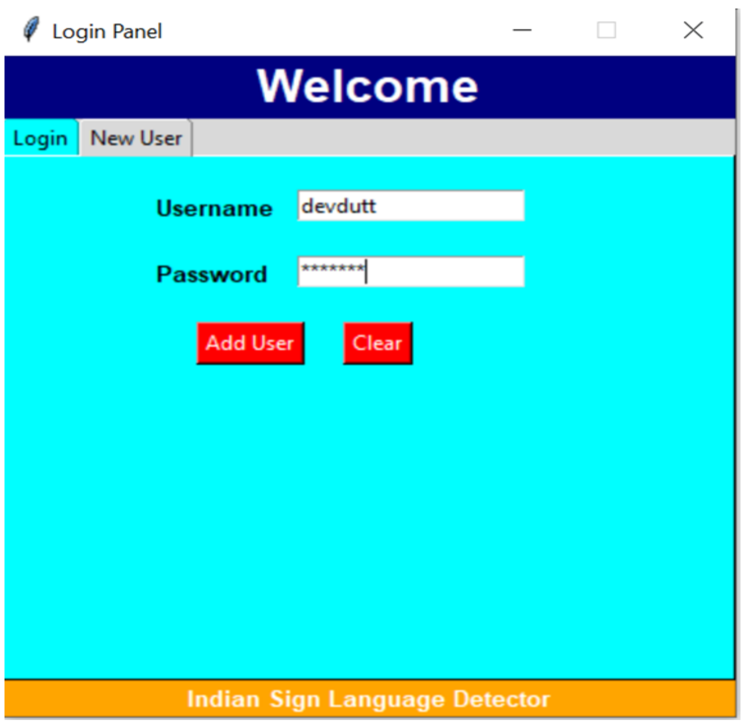

Figure 6: Adding new user to the database of existing users

As can be seen in Figure 5 and Figure 6, the user authentication mechanism was successfully implemented. The authentication scheme allowed only registered users to enter the system. New users could create their account to use the system

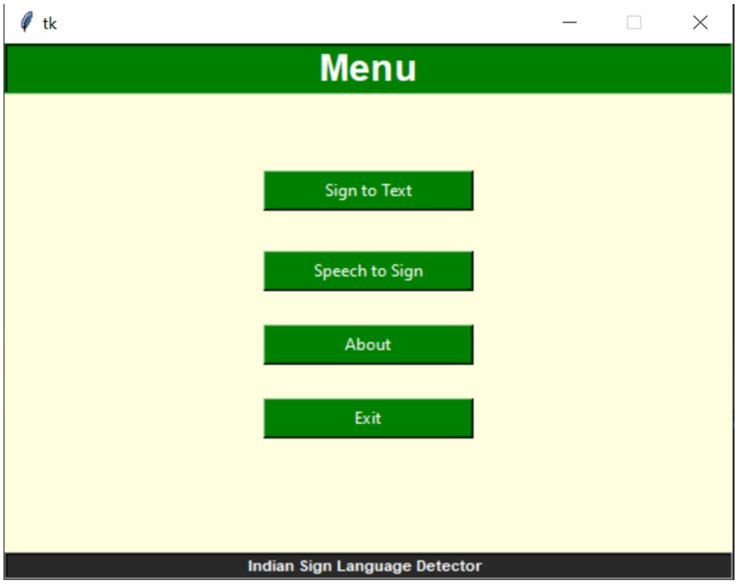

Figure 7: Menu of the proposed system

Figure 7 display the menu of the proposed system that can be accessed after logging in successfully. The menu displays option to convert Sign to Text, Speech to Sign, About the system and option to Exit. User can access the displayed option by clicking on it.

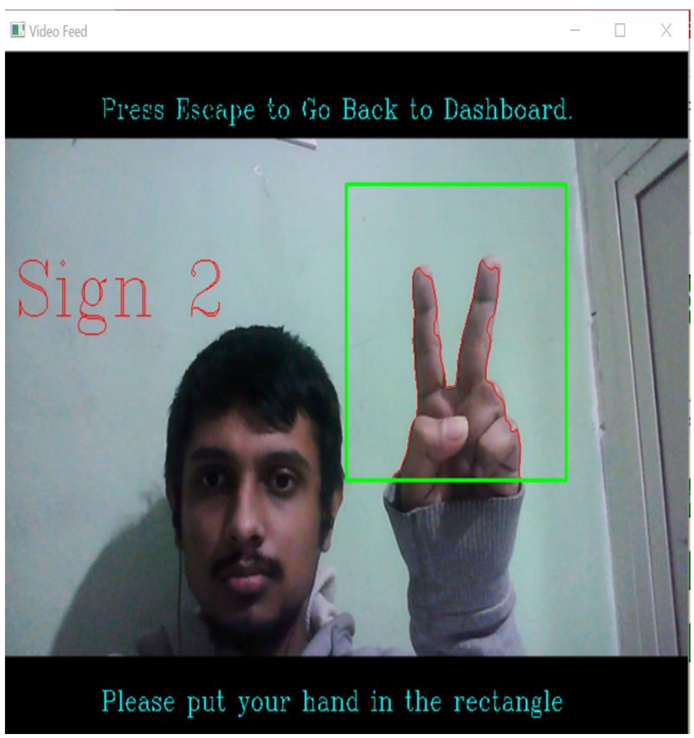

Figure 8: Detection of ISL sign by the system.

After Selection of the Sign to Text option, the system opens the webcam and displays relevant instruction to carry out Indian Sign Language Detection. When the instructions are followed the hand sign is detected and equivalent English Alphabet or number is displayed on screen as can be seen in Figure 8.

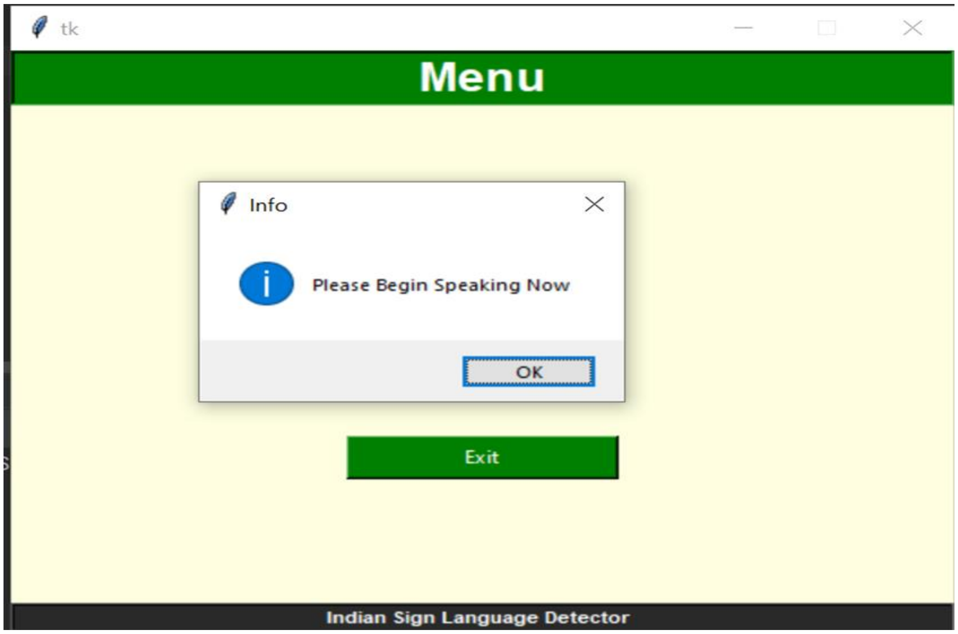

Figure 9: Speech to Sign Conversion message to start speaking

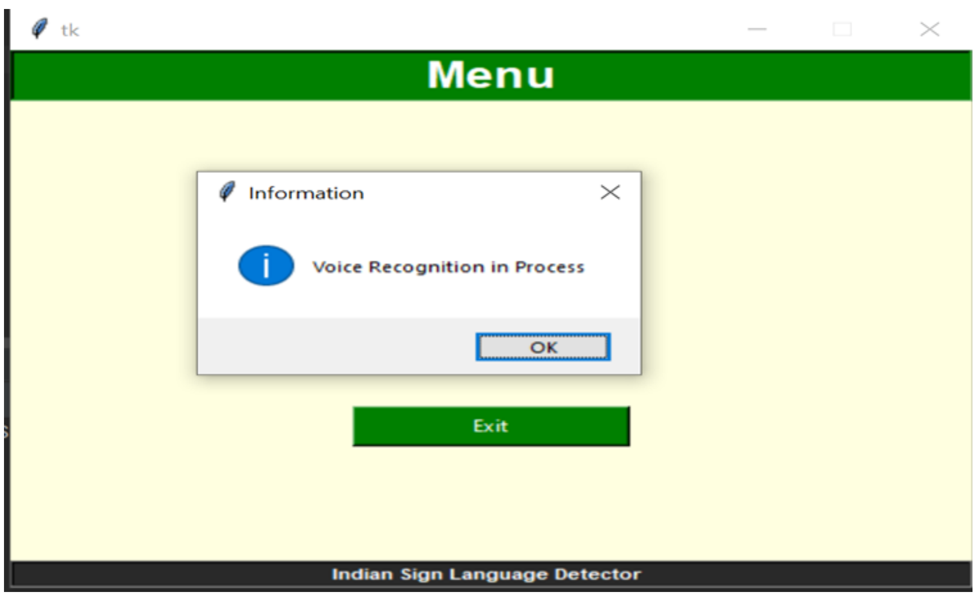

Figure 10: Voice recognition in process.

As can be inferred from Figure 9 and Figure 10, after clicking on Speech to Sign option, a message is displayed to start speaking. After user has spoken, the voice recognition process starts and user is informed about same

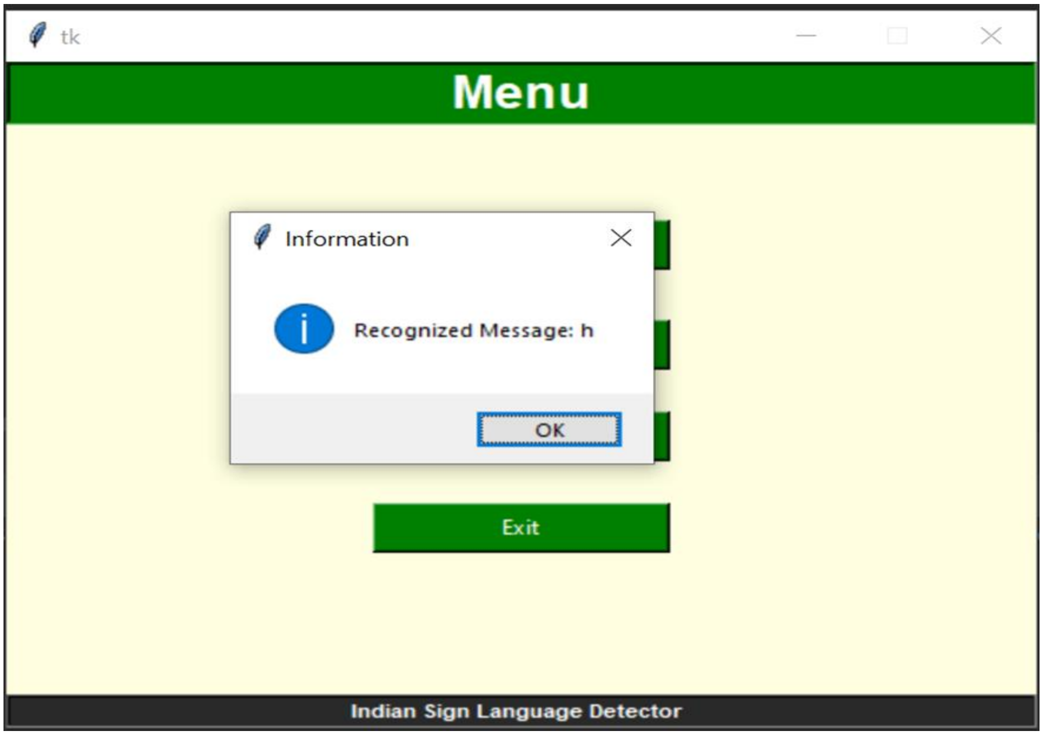

Figure 11: Detection of alphabet from the input voice message.

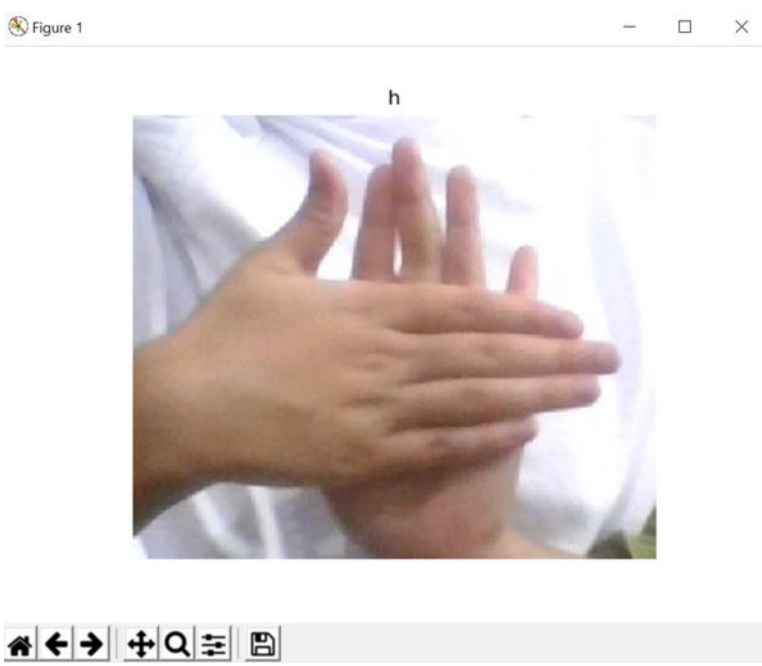

Figure 12: Equivalent ISL sign displayed for the input speech

After the system recognizes the message in the voice, the equivalent message is displayed in text on the screen. Subsequently, equivalent ISL sign is displayed in form of an image on the screen.

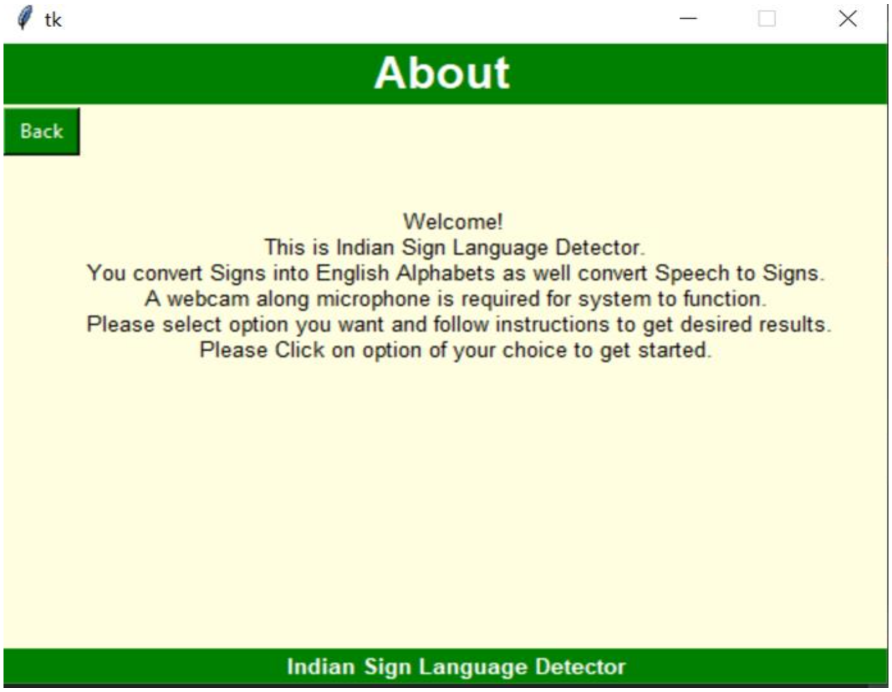

Figure 13: General Information regarding the System

Overall, the proposed system was successfully implemented and achieved all the intended objectives. The User authentication system was successfully implemented. Furthermore, users are able to convert or detect Indian Language Sign into English alphabet or sign. Additionally, the system also converted speech to ISL signs with adequate accuracy and precision.

4.2 CONCLUSION & FUTURE WORK

In this project, an Indian Sign Language Detector was successfully developed and implemented using CNN network. An interactive and user-friendly user interface was developed so that users could use the system and achieve desired results. This project shows the possibility of utilizing machine learning techniques for solving real world problems that have required complex computations.

In future, complexity of the neural network could be increased and a more enriched dataset with variations in background and light could be used to mimic real life scenarios to get further insights into the performance of CNN networks. Additionally model could be trained to form sentences based on given input and user interface could be improved based on user feedback.

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