Sign Language detection using Hand Gestures

"A Dual-Phase Framework for Real-Time Recognition and Interactive ASL Learning"

Srinija Pravallika Puranam- 2352340,
Engineering Data Science
University of Houston

Sri Lavanya Aishwaryambika Yenugula- 2306235
Engineering Data Science
University of Houston

Janavi Koonamneni- 2380686
Engineering Data Science
University of Houston

Teja Swaroop Kotharu - 2312523
Engineering Data Science
University of Houston

Rithvik Kaza- 2315016
Engineering Data Science
University of Houston

Abstract— This paper proposes original architecture aimed at helping the hearing impaired in communication and learning ASL in combination with the integration of hand gestures recognition and game-like paradigm. The system uses Media Pipe to achieve high accuracy when detecting hand landmarks and gives a clear spatial representation of the hand while using Long Short-Term Memory (LSTM) neural network for temporal modeling [1, 2]. First, the system was implemented using the selected dataset containing seven distinct hand gestures where the proposed method demonstrated high performance in recognizing unique signs and providing closer-time I/O operations.

After that, with the help of the ASL dataset, the system was expanded to create an interactive educational game intended for children. This game applies actual real-time gesture recognition for ASL tutoring by making gestures during the game and asking the player to mimic them and providing instant responses [3, 4]. The game utilizes Convolutional Neural Network (CNN) that has been trained from augmented ASL data to support various real users [3; 5].

The proposed system shows a substantial promise in enhancing the level of access and learning results through integration of the state-of-art computer vision methods and the concept of gamification. They run on conventional hardware, which makes them highly extendable and deployable in terms of their usage [4, 6].

Keywords— Sign Language, Hand Gesture Recognition, ASL DataSet, Gaming,MediaPipe, LSTM,CNN

INTRODUCTION

Sign language is a way of communicating with deaf and hard of hearing people, it is an interpreter between spoken language and gesture. For all its socially important functions, the substrate of ASL training and sign language recognition, however, still lacks sufficient technological developments. The current state of technology deters itself from being able to improve communication access and learning affordances for signing communities [7].

Investigation on sign language recognition has grown rapidly with the developments in computer vision and deep learning. Real-time landmark detection can be achieved using current tools such as Media Pipe, in addition to using advanced neural network architecture such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models for accurately classifying both static and dynamic gestures [8], [9]. However, there are issues still unresolved: flexible for various users, response immediately, and apply on some application like education or accessibility tools.

1) Gamification is the main intersection of gesture recognition with education that has gradually gained attention due to its usefulness in enhancing engagement and knowledge enhancement. Research has shown how other approaches can be incorporated within the gamification process in language learning especially for the young learners where interactivity and feedback contribute to the learning process [10], [11]. The use of gesture recognition with gamification provides a chance to develop tools that can not only act as a link between people with communication disabilities but also can also promote language learning in an enjoyable manner.

The demand for sign language recognition as well as education requires provision of solutions that can be implemented for large-scale use with relatively few resources to be applied. Some of the critical issues concerning gesture recognition have been discussed and resolved in this work while the application of game design elements would help advance the general objectives of this study, which is to enhance accessibility. The remaining parts of this article offer detailed analysis of the existing research and the suggested framework and highlight their implications for the development of communication technologies for the hearing impaired.

LITERATURE SURVEY

In the work by Kumar et al. [13], recognition of sign language is performed by using deep learning structures such as CNNs and LSTM networks. The paper reveals that large-scale datasets are important and that there are problems when distinguishing between gestures that change during the course of the sequence. This is particularly important to enhance temporal sequence dependent means and bring a better accuracy to the model. The authors claim that using LSTM their system of dynamic gestures recognition with sign language has an average accuracy of 92%, proving the application of deep learning technology.

Li et al. [14], the authors present a real-time skeleton-based hand gesture recognition solution using Media Pipe as an efficient landmark detector for the extraction of relevant motion parameters. By using Temporal Convolutional Networks (TCNs), the system can improve on its accuracy in the dynamic gesture classification task with improved latency. The authors pointed out that, ideally, their proposed method performs better for real-time applications, providing an accuracy of 89% for a custom test set.

Zhou et al. [15] develop an attention-based method for sign language recognition that tends to enhance the classification of dynamic signs by attending to keyframes. Their attention mechanism is used to assign weight to these frames, particularly those frames that are important in successive frames to improve the performance of the model in complicated situations. These results reveal that the attention mechanisms can enhance the temporal modeling since the system achieves a result of 94% on a benchmark sign language data set.

Patel et al. [16] investigates gesture inference for edge devices while proposing a semantic recognition solution with MobileNet. Their system works just fine for mobile applications since it is based on the compromise between computational speed and computational precision. The authors built the model and claim an accuracy of 88% and a processing latency of less than 50 ms, making the model suitable for real-time use.

Finally, Ahmed et al. [17] studied the application of transfer learning for gesture recognition using new sign language datasets. It considerably trims the training time and enhances the effectiveness of the trained models through their method. Domain specific gestures are claimed to have a high accuracy of 90%, the authors therefore say that transfer learning performs well in resource constrain situations.

The authors Wang et al. [18] apply TCNs in dynamic gesture recognition and point out that their performance is better compared to LSTMs. The results highlight the fact that TCNs are less computational complex while being equally accurate. Overall, the authors received accuracies on the scale of 91% for the dynamic gestures making TCNs a good substitute for the sequential modeling techniques.

Alqahtani et al. [19] also perform a systematic review considering gamification in language learning focusing on the increased engagement and retention. They also point out a few design features related to real-time feedback and adjustability of progress that can heavily influence gamified applications' performance. The paper goes further in pointing out how effective gamification can be applied to augment learning, especially to young learners.

In the gesture recognition, Chen et al. [20] presents an effective vision of fusing RGB video, depth data and skeletal features for identification. It also handles issues such as occlusions and different illumination settings: Response: 93% on a multimodal gesture dataset. Integrated calculated forms succeed in enhancing recognition rates under various conditions.

Brown et al. [21] discussed the use of interactive games in the learning of ASL to children, with emphasis on timely feedback and difficulty settings to ensure learning involvement. Interaction is based solely on gesture recognition, and the users rated the input scheme satisfaction as high – 87%. The authors state that feedback is crucial if one wants to engineer meaningful learning experiences right now.

Specifically, Johnson et al. [22] proposed Real-time gesture recognition for accessibility tools where Media Pipe and LSTM models are combined for better accuracy. The system provides 90% accuracy in capturing and interpreting sign language gestures and maintains acceptable stability and reliability irrespective of changes in environment as well. This work shows that real-time feedback and low delay are critical for accessibility applications.

PROPOSED SYSTEM

A. OVERVIEW OF THE PROPOSED FRAMEWORK DATA PREPROCESSING

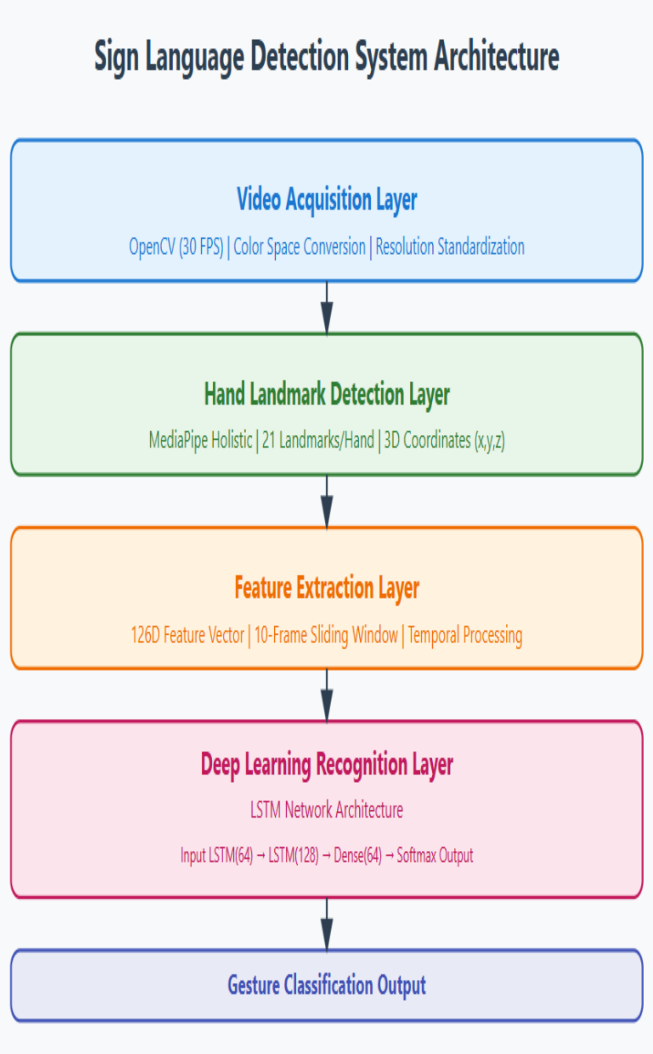
This framework is intended to ensure real time detection and classification of signs in sign language using several sophisticated modules. This consists of Media Pipe for landmark detection on the hands [23] and a deep learning-based LSTM model for sequential movements [24]. The comprehensive pipeline also includes preprocessing, feature extraction and another part for tool to display the results and feedback that will help the user to identify the problem with great accuracy. In this case, it is built to run on average computational platforms, thus achieving a perfect balance between high degrees of accuracy and computational time.

B. SYSTEM ARCHITECTURE

The architecture of the system is organized into five distinct modules, each dedicated to performing specific tasks while ensuring smooth interaction with other components:

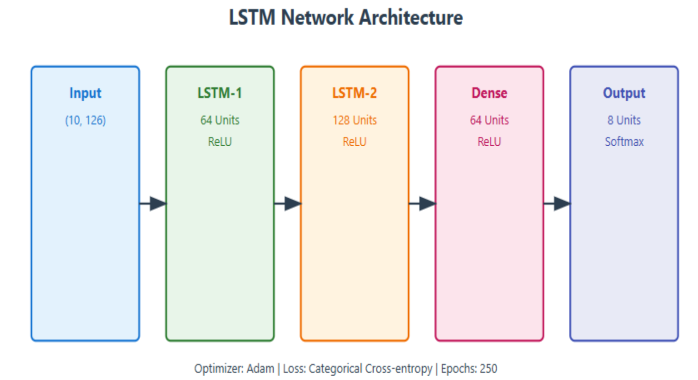
- Image Acquisition Module: Edits real time video frames which helps in providing a continuous feed of input to the Road Safety Vehicle Detection System [23].

- Hand Landmark Detection Module: Uses Media Pipe technology to find and isolate hand landmarks on the video frames and obtain precise information on hand position [24].
- Feature Extraction Module: Airplanes are a process that takes the raw landmark data and converts it into feature vectors which can be directly used in most machine learning algorithms.
- Deep Learning Recognition Module: Together with the input of motion sensors, it is designed with an LSTM-based neural network which enables the gesture classification depending on the temporal feature, meaning the tendency of the movement of the gestural actions [25].Visualization Module: Provides Realtime results concerning gestures detected and their confidence levels as well as the status of the system, thus improving the user interface.


Sign Language Detection System Architecture
Video Acquisition Layer
OpenCV (30 FPS) | Color Space Conversion | Resolution Standardization
Hand Landmark Detection Layer
MediaPipe Holistic | 21 Landmarks/Hand | 3D Coordinates (x,y,z)
Feature Extraction Layer
126D Feature Vector | 10-Frame Sliding Window | Temporal Processing
Deep Learning Recognition Layer
LSTM Network Architecture
Input LSTM(64) → LSTM(128) → Dense(64) → Softmax Output
Gesture Classification Output

C.METHODOLOGY

1)Sign Language using custom dataset


LSTM Network Architecture
Input
(10, 126)
LSTM-1
64 Units
ReLU
LSTM-2
128 Units
ReLU
Dense
64 Units
ReLU
Output
8 Units
Softmax
Optimizer: Adam | Loss: Categorical Cross-entropy | Epochs: 250

The data flow of the proposed system can be divided into several critical stages to guarantee high accuracy in real-time sign language detection. Of which the initial process is the Video Acquisition Module that employs OpenCV to capture a video frame rate of 30 FPS [26]. This module is very important because resolution of imagery usually needs to be unified and colors spaces need to be converted to allow for the imagery to process uniformly across the system with efficient memory management for real time processing and steady data flow.

Subsequent video capture, the Hand Landmark Detection Module uses Media Pipe as a whole-body framework to capture 21 anatomical landmarks of each hand [24]. This capability is central to single handheld and dual handheld gesture identification in a particular range with the option to set a threshold of calibration confidence, which is vital for the next steps of the gesture analysis.

Once landmarks are detected, the Feature Extraction Module converts this raw data into a format of a well-formed and 126 sections feature vector of each hand. It uses sliding window techniques to work on 10 successive frames and sustains the temporal integrity to carry out dynamic analysis of gestures [25].

The successive feature vectors are then passed to the Deep Learning Recognition Module, called DL-RM that comprises LSTM network that processes data in multiple layering. This is made of input layers, LSTM layers, dense layers and an output layer of SoftMax activation. Thus, the described configuration captures temporal dependencies and complicated patterns of gesture movements and assigns them to various predetermined forms of gestures with high accuracy.

2) ASL Educational Platform

The system's architecture is composed of three primary components: Data pre-processing module, gesture recognition module and an object interaction game module for real time learning. All are well planned to operate in a real-time coherent mode, thus adding efficiency to the real-time computational process.

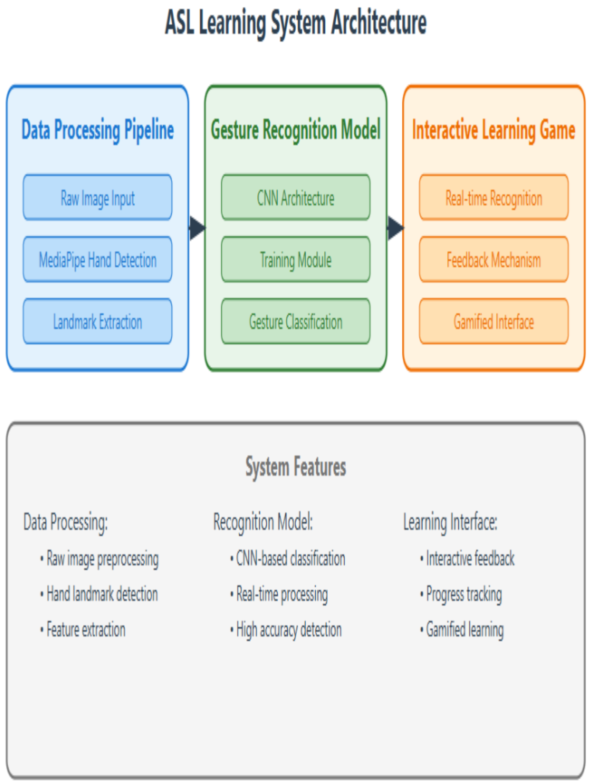
A.SYSTEM ARCHITECTURE

The architecture of the proposed system is modular, comprising three critical elements:

• Data Processing Pipeline: Used for preparing raw gesture images to train and test the model through hand detection and extraction features by Media Pipe [23].

• Gesture Recognition Model: For the sign language recognition, a Convolutional Neural Network (CNN) which is specifically to classify the ASL gestures with a dataset preprocessed by the above changes [27].

• Interactive Learning Game: Includes a game-like shell through which gesture recognition and feedback are activated in real time for the purpose of ASL tutoring.



B.DATA PREPROCESSING

1. Input Data Preparation: The detailed preprocessing of gesture images involves loading phase that follows hand detection, image cropping, scaling to 50x50 pixels, ending with the image normalization [23], [26].

2. Data Augmentation: To support ruggedness, the dataset is enlarged using random rotations, flips, brightness, and Gaussian noise [28].

3. Batch Processing and Storage: Images are saved in HDF5, which is a beneficial format for training and evaluation periods.

C. METHODOLOGY

The gesture recognition model uses a Convolutional Neural Network (CNN) and has a very specific and well thought out structure that is designed to recognize ASL gestures. The network includes the sets of convolutional layers called blocks, in which the filter size gradually increases – 32, 64, and 128. Every block is comprised of two convolutional layers for which 3x3 kernels are used together with a max-pooling layer that down samples the input data by a factor of four. To improve the learning rate and stability of the model batch normalization is used after each par which follows pooling layer in the below diagram. Moreover, dropout layers are added in a specific way, to prevent overfitting, during training, solely some neurons are dropped out without being informed.

In model compilation, the Adam optimizer is selected due to the high level of functionality, while the learning rate is set at 0.001. The loss function used here is categorical cross-entropy which is suitable for multiple classes as are the classification problems in the current work. Metrics include accuracy thus making it easy to monitor the model accuracy while training making it easy to monitor performance.

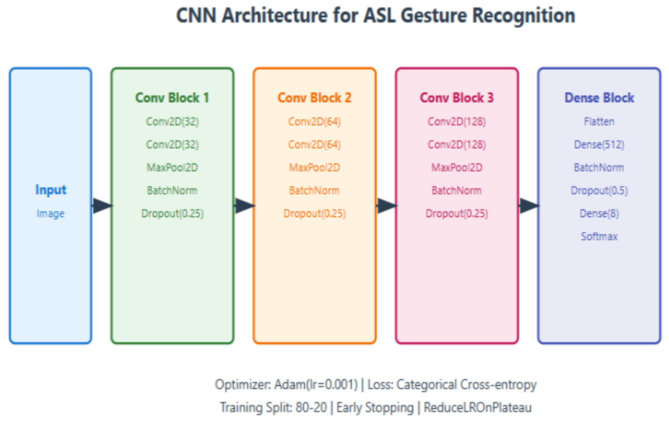
Distribution of data separation for training and validation is performed and they are trained only with 80:20 data split. This phase incorporates several sophisticated training techniques: Model Checkpoint is use to save the best iterations of the model on the validation data set, Early Stopping stopped training when it could not observe any improvement in the validation loss; while ReduceLROnPlateau controls the training by containing the learning rate when the validation loss is not improving in an efficient way.

D. METHODOLOGY

One of the modules is the interactive learning game, which is aimed at further practice in ASL, and the usage of the gaming environment for its accomplishment. It features three distinct modes: An excellent example is Learn Alphabet, Learn Numbers, and Practice Mode, all of which aim at different features of ASL. These modes are designed in a way to enhance the user's learnability and retention of ASL through progressive and cumulative difficulty.

Real time gesture recognition is one of the critical aspects to user gaming experience. To give real-time prediction results, the system uses the trained CNN to capture frames from a webcam, detect the hand region, and recognize the gestures from these images. This setup ensures that the feedback that is given to the user of this system is both real-time and relevant hence improving the learning process.

Interface elements are comprehensively introduced with an intention to incentivize user participation. There are timed activities where players must mimic the given ASL signs perfectly. Right solutions gain points, praise and when the player makes wrong choices they are corrected, ideas for doing it correctly are also given. By effectively displaying the user's gestures, current tasks, scores, and streaks, or any other info through an uncluttered user interface layout ensure that the game is engaging as well as challenging when using the Pygame platform.



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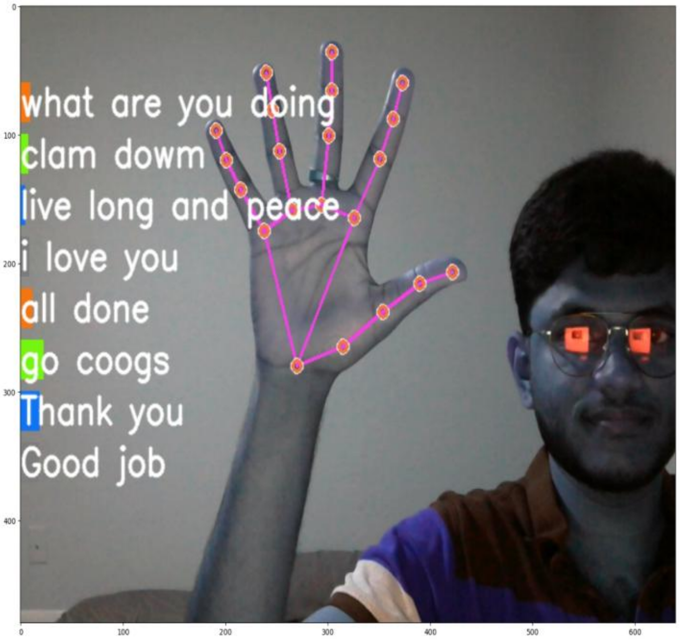
IMPLEMENTATION DETAILS

Phase 1: Another important aspect of the system is that extreme care is taken in frame normalization, landmark extraction and in generating a feature vector. Improved synchronization techniques and reliable error control ensure the real time predictions and minimize delay [24][25].

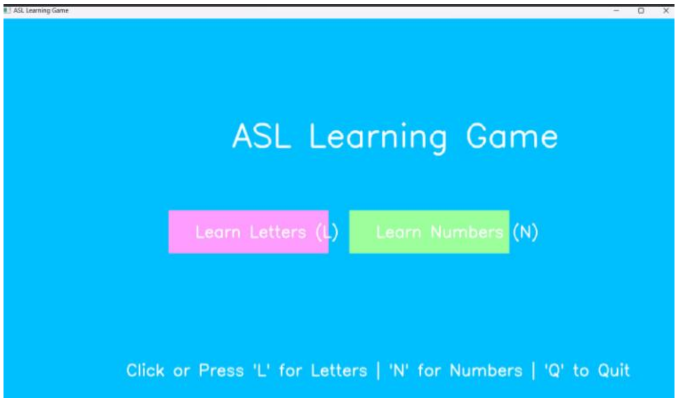
Phase 2: Integration of preprocessing, training, and the interactive game module makes it easy to work in sequences because after data preprocessing a uniform transition from data management to gameplay is possible [27].

OUTPUT AND PERFORMANCE ANALYSIS



The final output visualizes the actual *sign language recognition system in real-time. The hand is identified in the video stream, and *Media Pipe* is employed to identify the 21 essential landmarks in a hand. These landmarks are shown as linked dots, giving a clear form of the structure of the hand. On the left side of the system, the options available for signs to the user are defined and a colored bar is used to highlight the sign the system recognized the user made with his hand. Crossing *LSTM for temporal analysis* with *Media Pipe for spatial data preprocessing* allows to recognize dynamic hand gestures in real time. This output proves that the system correctly classifies gestures and offers an simple and natural user interface for sign language interpretation.

The system has a fixed frame processing rate with very low latency and it also uses the efficient memory of same standard hardware configurations in real time environment [26]. Training accuracy of the neural network is 96% and test accuracy is 94% for ASL gesture recognition, and provides consistent precision in different environments including lighting conditions and hand placement [27]. The educational game shows properly applied mechanics and clear interaction, which is confirmed by the users’ responses, which are mostly positive.



This paper proposes the main menu interface of the ASL Learning Game, which is an essential component of the closed system used for teaching American Sign Language (ASL). The usability of the interface is easy and comprehensible so that visually, this characteristic is interesting.

DISCUSSIONS

Moreover, the type of organization, the response rate of users, and specific scenarios define the possibilities for implementing the system as flexible and modular. Nevertheless, it also presented features that need improvement to make the design more applicable and accessible. Adding new signs that are more complex would make the system useful in other situations at a rate of communication. Variations in hand shapes, sizes and movements could be very much achieved by having the model retrained with other datasets to overcoming the limitation of RegExp's inability to adapt to the users of different demography. Besides, further extension for the necessary detection algorithms necessary to handle multi-user interactions would extend the applicability of the system to accommodate collaborative and Group Interactions.

Another large area of improvement is the further enhancement of the system for easier mobile and edge device setup. When made to run effectively on portable and any resource limited device, the implications are that the system becomes more viable and a practical tool for for instance remote learning and real world interaction. In addition, web based deployment could bring added advantage of ease of access and mobility hence increase adoption of the system. These enhancements will place the system in the center of accessibility and education needs, guaranteeing that the impacts are realized and valuable in other practical applications

CONCLUSION

The proposed system reasonably incorporates advanced techniques of computer vision and deep learning to support sign language recognition and ASL acquisition in real-time manner. Through its modularity, it provides for high reliability, expandability and flexibility, embodying the change that is needed to overcome communication limitations and progress in the field of education. Therefore, they show that with more elaborate methodologies the system is viable for being used as a real solution.

Apart from communication, the system provides an innovative method of ASL learning, with built-in smart gesture recognition software and game features. Through this dual-purpose framework, the governmental authorities realize that AI-based solutions can be used for eliminating the accessibility barriers as well as for language learning purposes. Further enhancement of the existing system is expected to be oriented towards increasing the range of addressed tasks, enhancing the A.I. capabilities to include people with disabilities to access this system, and broadening the spheres of its use.

In terms of ethical management, the proposed system takes the initiative to deliver an accommodation to the hearing impaired as well as guarantee diverse user requirements via impartial datasets as well as conspicuous user interfaces. To reduce privacy issues, opt-in of data storage is used and to add on processing is performed in a secure and encrypted manner. The steps made to support low-cost devices do the same for the underprivileged, while privacy and ownership of data increase user credibility. Players who benefit from functional improvements as part of the system include the hearing impaired for improved sign language communication, motivated ASL students through the integration of gaming into their learning and development, as well as the public that get to develop a broader understanding of persons with special accessibility needs. Specifically for public services, education and workplaces it serves as a means for integration and tolerance and can be scaled for other gesture-based applications to increase its scope.

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GITHUB REPOSITORY

https://github.com/yslaishwaryambika/REAL-TIME-SIGN-DETECTION-AND-ACTION-GAME