~ SAVY SIGNING ~

Real-Time Sign Language Gesture Recognition and Translation To Text System using CNN LSTMs.

SUPERVISOR

MR. STEPHEN OKETCH OBONYO

PRESENTED BY

KINYARI TRACIEBEL WAIRIMU

ADMISSION NO

146173

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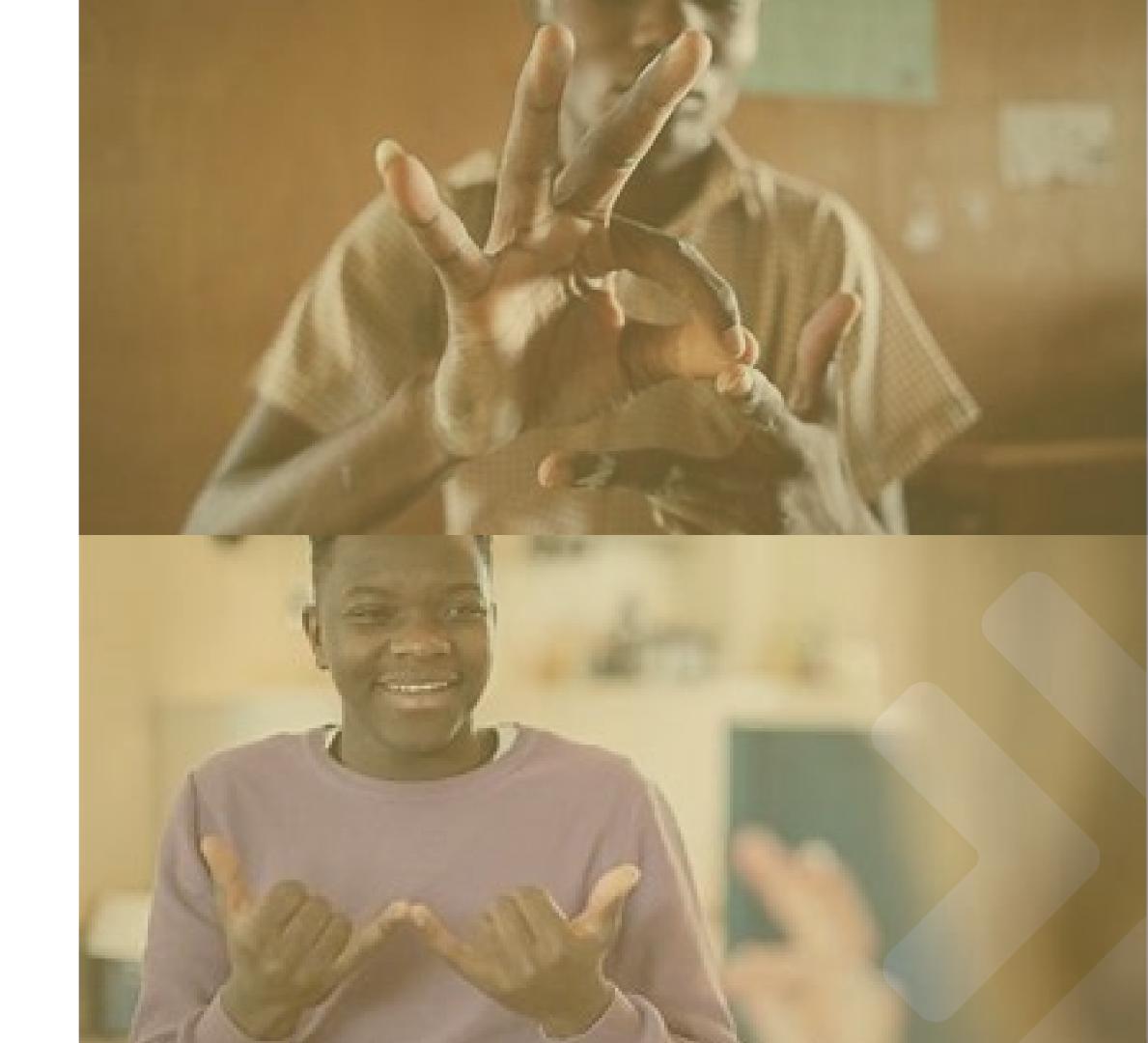
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Background Information

The world Federation of the Deaf reports approximately 72 million deaf people worldwide, with over 80% living in developing countries. There are more than 300 different sign languages used globally.

Sign language is divided into 2; natural gestures and formal cues Natural gestures are the unconscious physical expressions that accompany signs and add variation. These might include facial expressions indicating intensity, eyebrow movement to indicate emphasis, or head tilts for questioning.

In contrast, formal cues are deliberate/intentional and standardized when being developed, they have the same language as the spoken language of the community.

An example is the American Sign Language (ASL), which is the most widely used sign language in the world with the method of fingerspelling as a representation of the alphabets on cues (hand positions show each letter of the Latin alphabet).

There has been advances in machine translation and speech translation which can be extended to sign language translation.

There are several projects that have been started to curb this problem but most of them do not look at certain aspects such as the problem, some models with the highest accuracy only allow static image input.

For example, in ASL some alphabets require hand movement, and therefore, need real-time, live translator.

There are Kenyan Sign Language dictionaries, or video resources that teach SL, but no known softwares that translate Kenyan Sign Language gestures into text.

Problem Statement



Communication barriers exist between hearing and the dead or hard-of-hearing community.

Learning SL can be challenging and the resources not widely accessible. Current solutions include human interpreters and basic SL tutoring software. Interpreters that teach SL are expensive and limited, while software struggles with complex signs and body language.

Mobile phones in this time and age are widely accessible, and with a real-time SL translator application, this will enable effortless communication, promote inclusivity, by developing such a convenient tool for seamless conversations.

Objectives



- Achieve high word and sentence accuracy through deep learning by using of a comprehensive sign language dataset.
- Acquiring available Kenyan Sign language dataset or performing data augmentation on existing datasets to increase its size for effective training of the model. In case of not enough data to train create own dataset by use of known Kenya news broadcasting channels.
- Introducing the aspect of offline functionality.
- Conducting comprehensive testing across various devices and scenarios and ensure cross-browser compatibility. Ensures that the application functions consistently across different browsers and devices
- Developing and testing a user interface that adheres to best practices for accessibility, ensuring a smooth and intuitive experience for both deaf and hearing users.

Related Works





Hand Talk

Created back in 2012. Works like a pocket translator, automatically translation text and voice into ASL (American Sign Language) and Libras (Brazilian SL).

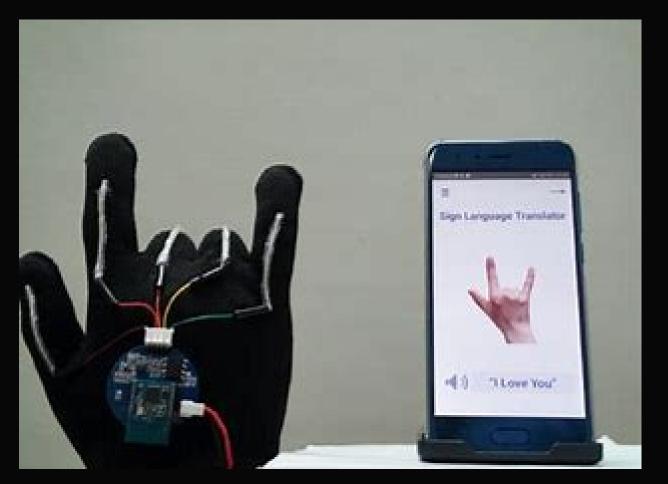
To perform these translations, it **relies** on **AI** and virtual translators.

You are able to save translations - favourite and most used translations

Customizing your virtual translators as you wish in terms of season, their attire.

Related Works





Wearable Glove - UCLA

The system includes a pair of gloves with thin, stretchable sensors that run the length of each of the five fingers.

The sensors, made from electrically conducting yarns, pick up hand motions and finger placements that stand for individual letters, numbers, words and phrases.

The device then turns the finger movements into electrical signals, which are sent to a dollar-coin-sized circuit board worn on the wrist.

The board then transmits those signals wirelessly to a smartphone that translates them into spoken words at the rate of about one word per second.

A custom machine learning algorithm turns the gestures into letters, numbers and words they represent.

The **system** was able to **recognize 600 signs**, including **each letter of the alphabet and numbers 0 through 9**

Related Works



SignAll

SignAll is an automated sign language translation solutions.

It has a **lab concept** that helps in **learning**, **practicing** and giving quizzes to students who want to learn ASL.

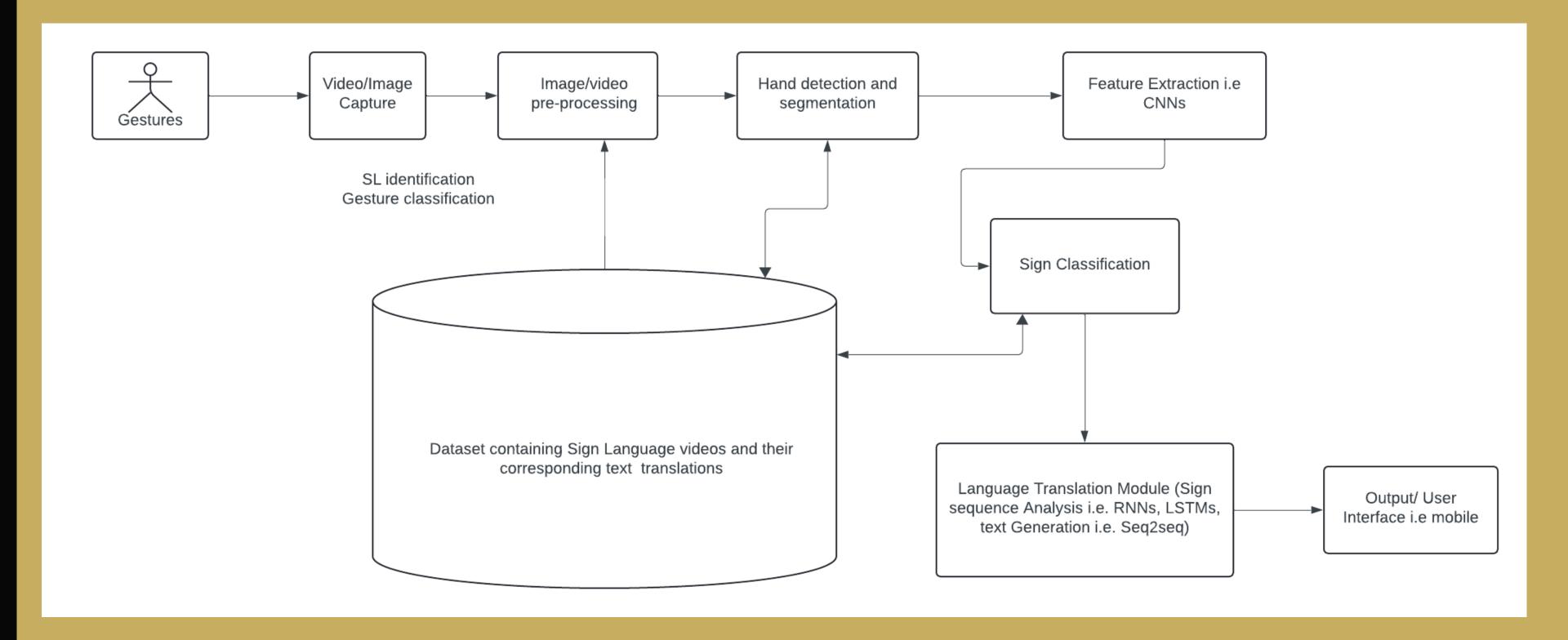
It only registers signs that follow the 5 parameters of ASL and you have to be specific and accurate for the translator to translate from SL to text.

Mostly deals with finger spelling, and one must wear some specific gloves that come with the system for you to be able to sign and the translator able to recognize the signs and gestures made by the user.

There is **no comprehensive 3D representation** of all signs.

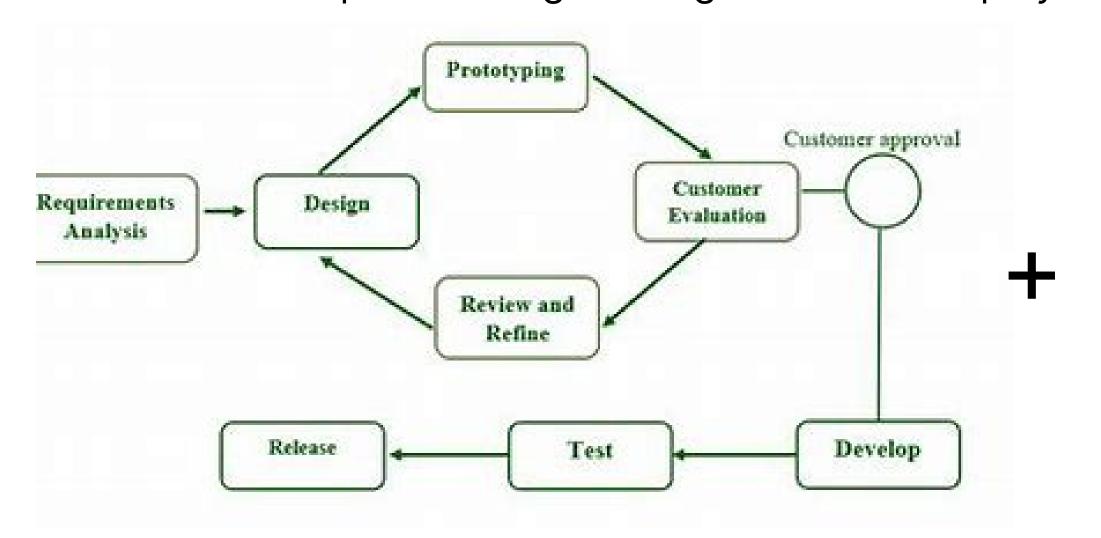
They also have a Software development KIt that allows developers to incorporate sign language input into their applications.

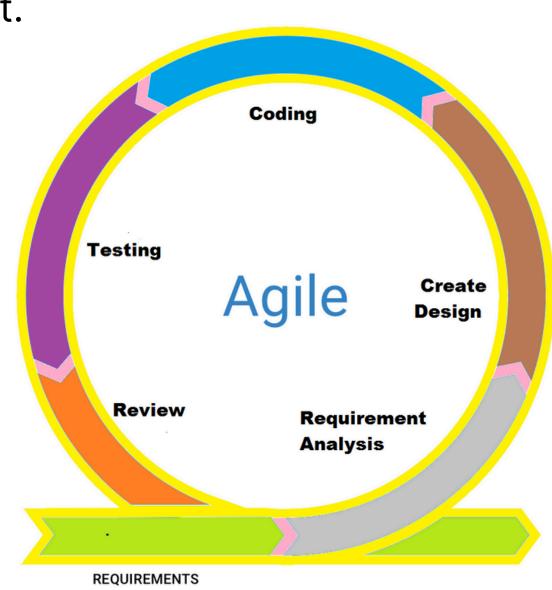
Conceptual Framework



Research Methodology

 This chapter includes a structured approach to the project outlining the steps taken from the initial requirements gathering to the final deployment.





Research Methodology

- Prototyping allows one to build functional versions of the system, while Agile's sprints enable regular updates and feature improvements.
- The use of Agile software development ensures that the development process is divided into manageable sprints, with each iteration involving design, development, testing, and evaluation of specific features.
- The synergy between Prototyping and Agile software development allows for continuous feedback from users, allowing the developer to refine the application, improve model accuracy, and enhance the user experience throughout the development lifecycle.

Design and Development Tools

Programming languages

- Python
- TensorFlow, handle the computational backend,
 efficiently managing model training, processing large datasets, and enabling GPU acceleration.
- Keras for CNN & LSTMS
- Front-end development ; JavaScript (React) or Flutter

Framework -

- Django: Back-end development
- WebRTC: Real-time video stream handling
- Firebase: **Offline** functionality
- TensorFlow/Keras: Deep learning model implementation

-- Development Tools

- Jupyter Notebooks: Model training and experimentation
- Visual Studio Code (VSCode)

-----Version Control

GitHHub: Source control

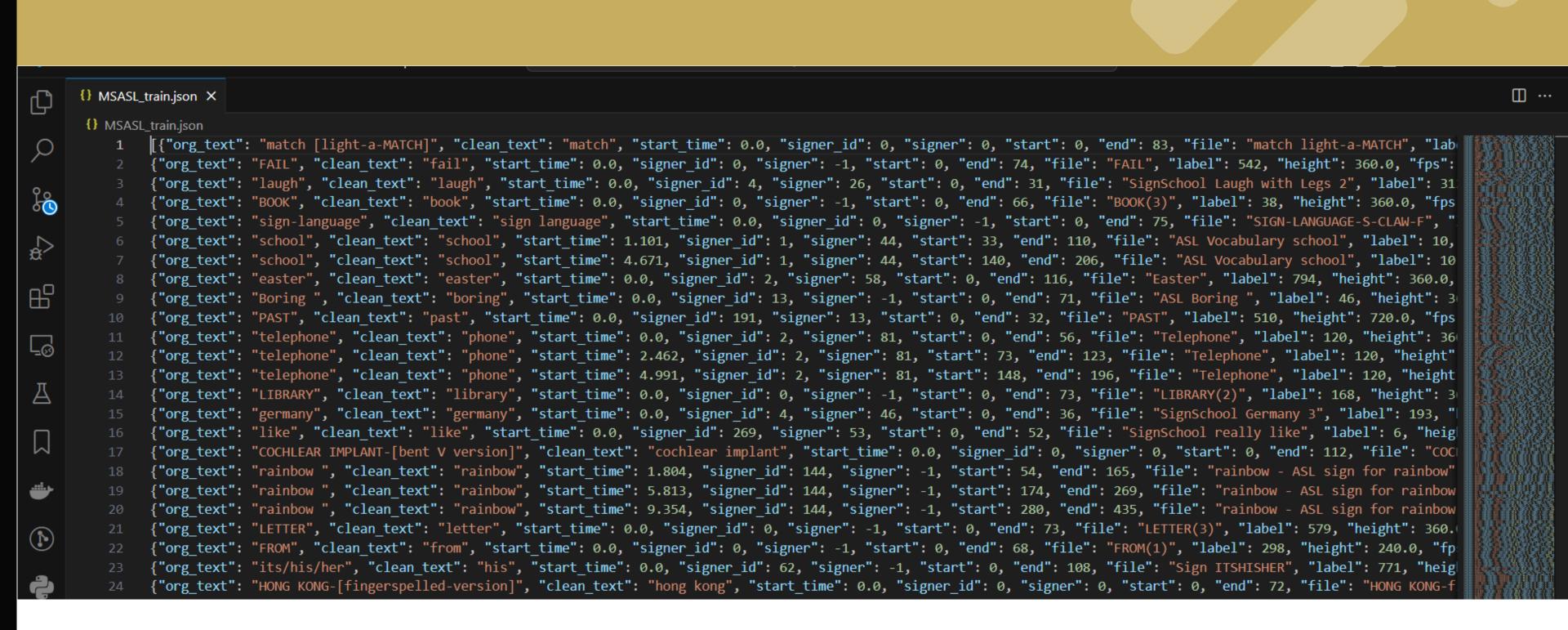
Firebase - Realtime Database and Firestore cache data locally when a device goes offline. Once the device reconnects to the internet, Firebase automatically syncs any local changes to the server.

Methods

MS-ASL Dataset

- The dataset contains 87000 images for training and testing, 29 labels; A Z, space, delete, and nothing
- Label encoding; A = 0, B = 1, nothing = 28 for training. 25,000 annotated videos for real-life sign language.
- Videos must be downloaded separately, and they are mostly hosted on platforms like
 YouTube or cloud repositories. To work with images, you will need to download the videos from the platforms, extract frames from these videos to create image datasets for training the CNN-LSTM model.
- The files include information about the video, such as the gesture label (class), the path to the video, and metadata like the start and end time of the gesture within the video.

DATASET



Model Training

- A pre-trained model, performance-wise, transfer learning models beat traditional deep learning models because the TL models include data (features, weights, etc.) from previously trained models, possessing a comprehensive grasp of the features.
- 87000 images in the MS-ASL dataset will be divided into training and testing data. **8000 images** for **training data** and **7000 images** for **testing**.
- Merging datasets, normalizing and standardizing labeling across the datasets being used. Rename classes for uniformity and unify labels for overlapping gestures. Create labels for unique, non-overlapping classes.
- Resize images to a consistent size (e.g., 64x64 or 224x224 pixels).
- Apply data augmentation (rotation, flipping, zooming).
- Normalize pixel values (e.g., scale between 0 and 1).
- Concatenate image data and labels using libraries like pandas, numpy, or TensorFlow.
- Shuffle dataset to prevent model bias towards one dataset.

Training, Sampling and Testing

- Ensure that both datasets use the same number of frames per sequence.
- **Pad Sequences:** If the number of frames per video differs across datasets, you may need to pad or truncate sequences to a fixed length before feeding them into the LSTM.
- The LSTM network complements CNN by capturing temporal dependencies, which are crucial for recognizing the sequence of gestures over time.
- Together, CNN extracts the visual features, and the LSTM processes the temporal flow of these gestures, ensuring accurate recognition of SL phrases.
- Unit testing will be incorporated whereby each individual module of the system, including the gesture recognition engine, text translation logic, and user interaction components, is tested separately to ensure that they work as expected.
- Testing across different devices and web browsers to confirm compatibility and minimal latency, ensuring a smooth user experience regardless of the platform.

Validation Experiment

- Combine and Split: After merging, split the combined dataset into training, validation, and testing sets. You can use tools like train_test_split from scikit-learn to maintain class balance across splits.
- Split into 70% training, 15% validation, and 15% testing.
- Cross-Validation: Using k-fold cross-validation to evaluate the model on different subsets of the data for better generalization.
- The sample size will be from the direct end users who are the deaf and hard-of-hearing community.
 A diverse representation in terms of age, proficiency in sign language, etc.
- Participants interact with the app in real-time, and gestures are translated to text. Metric used to test performance will include recognition accuracy, response time, user feedback.
- Some controlled variables include same lighting conditions, frame rate, and input quality during testing.

Vision

