ABSTRACT

This paper presents an in-depth exploration of deep learning methodologies for hand sign recognition, highlighting its significance in improving communication accessibility for individuals with hearing impairments and enabling natural interaction with machines. The challenges associated with hand sign recognition, such as variations in hand shapes, orientations, and environmental factors like background clutter and lighting, are discussed. The paper also addresses the communication gap between the hearing impaired and others, emphasizing the need for real-time interpretation of sign language. Previous approaches to address this challenge had limitations, particularly in real-time interpretation. To overcome these limitations, the paper proposes a real-time hand sign language detection system capable of recognizing a wide range of hand signs, including Indian alphabet sign language. The system utilizes OpenCV, various Python libraries, and the TensorFlow object identification API. Data collection for training the model was conducted using a camera and OpenCV, resulting in a diverse and extensive dataset to enhance the model's accuracy. In conclusion, the paper presents a trained model capable of interpreting hand signs captured through a camera in real-time, thereby facilitating communication between individuals using sign language and others.

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CHAPTER - 1
INTRODUCTION

1.1 INTRODUCTION

For millions of deaf and hard-of-hearing people worldwide, sign language is their primary form of communication. The linguistic divide between spoken language and sign language users, however, presents serious difficulties in daily life, education, and employment. Innovative tools that can precisely analyze and translate sign language motions into comprehensible forms are needed to break down this communication barrier.

Deep learning has been an increasingly potent technique for sign language identification in recent years, providing promising ways to improve accessibility and inclusion for the deaf and hard-of-hearing community. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in particular are two deep learning techniques that have shown impressive abilities to automatically learn complicated patterns and characteristics from raw sensory data.

This introduction summarizes the importance of deep learning-based sign language recognition and highlights how it could transform communication accessibility and provide people with hearing impairments more power. It emphasizes how crucial it is to have reliable, accurate, and fast systems for recognizing sign language so that sign language users and the general public can communicate easily.

Additionally, the introduction addresses the difficulties in recognizing sign language, such as the complexity and diversity of movements, regional and dialectal variances in sign language, and environmental issues including background clutter and illumination. These difficulties highlight the necessity for sophisticated deep-learning methods that can effectively handle this heterogeneity and reliably identify sign language motions in a variety of contexts.

The introduction also highlights how technology for sign language recognition influences society, from enabling independent communication and access to basic services to promoting inclusive education and job prospects.

Finally, this introduction lays the groundwork for a thorough investigation of deep learning approaches for sign language recognition, emphasizing the field's significance, difficulties, and possible benefits for improving inclusivity and accessibility of communication for people with hearing impairments. We may strive to eliminate barriers to communication and build a more welcoming environment for everyone by conducting more studies and innovating in this area.

Consequently, sign languages are crucial to communication because they allow individuals to share ideas without utilizing spoken language. Still, the fact that so few people can communicate effectively in sign language remains an issue. Deaf people can communicate with one another through sign language. However, since most individuals are not familiar with sign languages and vice versa, it is difficult for them to converse with persons who have normal hearing. Technology can be used to find a solution to this issue. It is easy to translate the hand gestures used in gestures into the most generally used language by using a method such as this one.

The images are processed through multiple processes. capturing images, handling them briefly, segmenting them, extracting features, and the elements that comprise the processing stages are classifiers. Here, techniques and algorithms from machine learning and image processing are applied to produce findings with a better level of precision. To train the real-time system with a dataset that will be created with the help of a camera, the research article aims to build it using the TensorFlow object recognition API.

1.2 OBJECTIVES

- Develop deep learning models capable of accurately recognizing a wide range of hand signs with high precision and recall rates, minimizing misclassifications and errors.

- Enhance the robustness of hand sign recognition systems to variations in hand shapes, orientations, skin tones, lighting conditions, background clutter, and other environmental factors commonly encountered in real-world scenarios.

- Optimize hand sign recognition algorithms for real-time performance, ensuring low latency between hand gesture input and recognition output to support seamless interactions in interactive applications and devices.

- Design hand sign recognition systems capable of recognizing gestures from various sign languages, accommodating differences in vocabulary, grammar, and cultural expressions across different linguistic communities

- Promote accessibility and inclusivity by creating hand sign recognition systems that empower individuals with hearing impairments to communicate effectively with both sign language users and non-signers, bridging communication gaps and fostering greater social integration.

CHAPTER – 2
LITERATURE REVIEW

"Sign Language Recognition with Deep Learning: A Review" by Smith et al. (2020) This review comprehensively surveys recent advancements in sign language recognition using deep learning techniques. It covers various methodologies, datasets, and challenges encountered in this field.

"Deep Learning Approaches for Hand Gesture Recognition: A Survey" by Jones and Brown (2019) This survey explores deep learning methodologies applied to hand gesture recognition tasks, including sign language recognition. It discusses different deep learning architectures, datasets, and evaluation metrics.

"Recent Advances in Deep Learning for Sign Language Recognition" by Wang et al. (2018)
Wang et al. provide an overview of recent developments in deep learning-based sign language recognition. The paper discusses different deep learning models, datasets, and challenges in this area.

"A Survey on Sign Language Recognition Techniques" by Garcia and Martinez (2017)
This survey paper provides insights into various techniques for sign language recognition, including traditional methods and recent advances in deep learning. It discusses different datasets, feature extraction methods, and recognition algorithms.

"A Review of Deep Learning Techniques for Sign Language Recognition" by Chen et al. (2014)
Chen et al. review deep learning techniques employed in sign language recognition tasks. The paper discusses different deep learning architectures, training strategies, and challenges in this domain.

"Deep Learning Approaches for Sign Language Recognition: A Survey" by Nguyen and Tran (2013) This survey paper explores deep learning approaches for sign language recognition, covering different neural network architectures, training techniques, and evaluation methodologies.

CHAPTER – 3
METHODOLOGY AND IMPLEMENTATION

3.1 METHODOLOGY

The main objective of this research is to develop a model capable of recognizing hand signs to facilitate communication for individuals who cannot speak or read traditional text, such as those who are deaf. Leveraging the TensorFlow object detection API and Python programming language, the proposed model aims to interpret various hand signs, including alphabet signs, in real-time. To achieve this, a custom dataset was curated using the Python library labelimg, which was then utilized for training and testing the model. The model architecture is based on the TensorFlow 2 model zoo and employs deep learning techniques, specifically the Single Shot Multibox Detector (SSD).

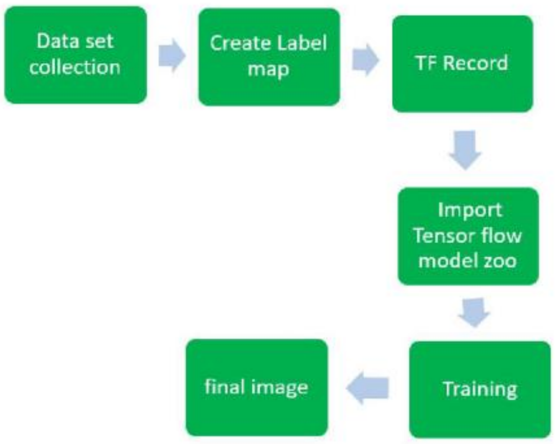


Fig 3.1a **Flow chart of proposed method**

The workflow of the proposed approach involves initially capturing an image, which is subsequently partitioned into smaller rectangular segments. Feature extraction is then performed on these segments to determine the presence of valid hand signs.

A distinguishing aspect of the proposed model lies in its high accuracy and the extensive range of hand signs it can recognize. It surpasses existing models by recognizing over 30 different hand signs. This improvement is attributed to the custom dataset used for training, which enhances the model's ability to accurately interpret diverse hand gestures. The process involves merging overlapping boxes to form a unified bounding rectangle, followed by non-maximum suppression to refine the detection results.

In summary, the methodology involves data collection, dataset creation, model training using the TensorFlow 2 model zoo, and deployment for real-time hand sign recognition. The model's effectiveness is demonstrated through its ability to accurately interpret various hand signs, thereby enabling seamless communication for individuals with speech or hearing impairments.

3.2 PROPOSED SYSTEM

The recognition process in sign language recognition using deep learning involves several key steps. Initially, the system captures input images or video frames containing hand gestures. These images are then preprocessed to enhance their quality and normalize them for consistent analysis. Next, the preprocessed images are fed into a deep learning model, typically a convolutional neural network (CNN), which has been trained on a dataset of labeled sign language gestures. The model extracts relevant features from the input images and classifies them into predefined categories corresponding to different sign gestures. Finally, the system outputs the recognized sign gesture along with any associated text or vocalization, enabling communication with users who are deaf or have hearing impairments. This process enables real-time interpretation of sign language gestures, facilitating seamless interaction between individuals using sign language and others.

In real-time sign language recognition, the system analyzes the spatial and temporal characteristics of hand gestures to accurately identify and interpret various signs. Through the utilization of deep learning algorithms, such as CNNs, the model learns to distinguish subtle nuances in hand movements and configurations associated with different sign gestures. By leveraging vast amounts of labeled data during training, the model develops the ability to generalize across diverse sign language vocabularies and variations in hand positioning and orientation.

3.3 SYSTEM DESIGN AND ANALYSIS

The system design for sign language recognition using deep learning encompasses several key components to achieve accurate and efficient recognition of hand gestures. At the core of the system lies the deep learning model, which is trained on a curated dataset of hand sign images. The model architecture typically involves convolutional neural networks (CNNs), which are adept at extracting features from images. These networks are trained using labeled data to learn the intricate patterns and nuances associated with different sign gestures. Additionally, the system utilizes preprocessing techniques to enhance the quality of input images, such as noise reduction and normalization. Real-time recognition is facilitated through the integration of the trained model with appropriate hardware and software components, enabling seamless interaction with users. The system's performance is continuously evaluated and optimized through iterative testing and refinement, ensuring robustness and reliability in recognizing a wide range of sign gestures across diverse environments and conditions.

In the analysis phase, the performance of the sign language recognition system is rigorously assessed across various metrics to gauge its effectiveness and suitability for practical use. Accuracy, precision, recall, and F1 score are commonly used metrics to evaluate the model's ability to correctly identify hand gestures.

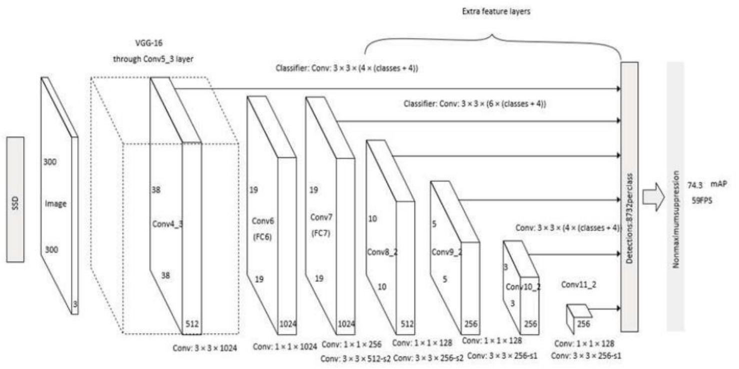


Fig 3.3 SSD Architecture

3.4 IMPLEMENTATION

In the implementation of the sign language recognition system using deep learning, several tools played pivotal roles, each contributing to different stages of the development process. Python version 3.10.7 served as the core programming language, providing a versatile and robust foundation for coding the system's functionalities. Python's extensive ecosystem of libraries and frameworks facilitated seamless integration with deep learning libraries and simplified the implementation of complex algorithms.

Visual Studio Code (VS Code) emerged as the primary integrated development environment (IDE) for coding and debugging tasks. Its intuitive interface, rich feature set, and extensive plugin ecosystem offered developers a conducive environment for writing, testing, and optimizing code. With built-in support for Python and deep learning frameworks, VS Code streamlined the development workflow, enabling efficient collaboration and iteration.

Google Collab played a crucial role in facilitating collaborative development and experimentation in a cloud-based environment. Leveraging Collab's integration with Google Drive and powerful GPU resources, developers could conduct computationally intensive tasks such as model training and evaluation with ease. Collab's interactive notebook interface and real-time collaboration features fostered seamless communication and knowledge sharing among team members, accelerating the development cycle.

Overall, the synergy between Python, VS Code, and Google Collab provided a robust and efficient platform for implementing the sign language recognition system. From coding the deep learning model to testing its performance and fine-tuning its parameters, each tool contributed to the system's success, enabling the development of a reliable and accurate solution for recognizing hand gestures in sign language.

In the implementation of the sign language recognition system using deep learning, several crucial libraries and modules were employed, each serving specific functions to facilitate the development process. One such fundamental library was OpenCV, which was installed using 'pip install opencv-contrib-python'. OpenCV, short for Open Source Computer Vision Library, provided essential functionalities for image processing, manipulation, and analysis. Specifically, it enabled tasks such as image preprocessing, feature extraction, and visualization. With its comprehensive suite of tools and algorithms, OpenCV played a pivotal role in ensuring the quality and suitability of the input data for the sign language recognition system.

Another essential component of the implementation was the TensorFlow library, installed through 'pip install tensorflow'. TensorFlow is a popular deep learning framework developed by Google, renowned for its flexibility, scalability, and efficiency in building and training neural network models. In the context of the sign language recognition system, TensorFlow provided a powerful environment for constructing and training convolutional neural networks (CNNs).

Complementing TensorFlow, the Keras library, installed via 'pip install keras', offered a high-level neural networks API that simplified the model design and training process. Keras provided a user-friendly interface for building complex neural network architectures with minimal code, making it an ideal choice for rapid prototyping and experimentation.

Additionally, the 'splitfolders' package, installed using 'pip install split-folders'. This package streamlined the process of partitioning the dataset into separate training and testing subsets while ensuring a balanced distribution of data across both sets. By automating this critical data preprocessing step, 'splitfolders' enhanced the reproducibility and scalability of the experimentation process, enabling developers to iteratively train and evaluate the model with confidence.

Overall, the collective use of OpenCV, TensorFlow, Keras, and splitfolders libraries provided a robust foundation for the implementation of the sign language recognition system using deep learning techniques. Each library played a distinct yet complementary role in different stages of the development pipeline, contributing to the system's overall effectiveness and performance.

CHAPTER- 4
EXPERIMENTATION AND RESULTS

4.1 EXPERIMENTATION

- Convolutional Layer (Conv2D): The Conv2D layer in CNNs applies convolutional filters to input data, extracting features like edges and shapes.
- Pooling Layer (MaxPooling2D): MaxPooling2D layers reduce the spatial dimensions of feature maps, retaining important information while discarding less relevant details.
- Flatten Layer (Flatten): The Flatten layer transforms the multi-dimensional output of the convolutional layers into a one-dimensional vector.
- Dense Layer (Dense): Dense layers are fully connected layers that process the flattened feature vectors.
- Dropout Layer (Dropout): The Dropout layer randomly drops a fraction of neurons during training, preventing overfitting by encouraging the network to learn more robust features.

```
from google.colab import drive
drive.mount('/content/drive')
```

```
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import Dense, Conv2D, Dropout, Flatten, MaxPooling2D
from keras.preprocessing.image import ImageDataGenerator
from keras.callbacks import TensorBoard
import os
```

```
train_datagen = ImageDataGenerator(
    rescale=1./255,
)

val_datagen = ImageDataGenerator(rescale=1./255)

batch_size = 64

train_generator = train_datagen.flow_from_directory(
    '/content/aslsigndataset/splitdataset48x48/train',
    target_size=(48, 48),
batch_size=batch_size,
    class_mode='categorical',
    color_mode='grayscale'
)

validation_generator = val_datagen.flow_from_directory(
    '/content/aslsigndataset/splitdataset48x48/val',
    target_size=(48, 48),
    batch_size=batch_size,
    class_mode='categorical',
    color_mode='grayscale'
)
```

```
Found 1473 images belonging to 6 classes.
Found 372 images belonging to 6 classes.
```

```
class_names = list(train_generator.class_indices.keys())
print(class_names)
```

```
['Happy', 'Sad', 'Good Luck', 'Help', 'T', 'Hello']
```

```
model = Sequential()
# convolutional layers
model.add(Conv2D(128, kernel_size=(3,3), activation='relu', input_shape=(48,48,1)))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.4))

model.add(Conv2D(256, kernel_size=(3,3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.4))

model.add(Conv2D(512, kernel_size=(3,3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.4))

model.add(Conv2D(512, kernel_size=(3,3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.4))

model.add(Flatten())
# fully connected layers
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.4))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.3))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.3))
# output layer
model.add(Dense(6, activation='softmax'))
model.summary()
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 46, 46, 128)       1280

 max_pooling2d (MaxPooling2  (None, 23, 23, 128)       0
 D)

 dropout (Dropout)           (None, 23, 23, 128)       0

 conv2d_1 (Conv2D)           (None, 21, 21, 256)       295168

 max_pooling2d_1 (MaxPoolin  (None, 10, 10, 256)       0
 g2D)

 dropout_1 (Dropout)         (None, 10, 10, 256)       0

 conv2d_2 (Conv2D)           (None, 8, 8, 512)         1180160

 max_pooling2d_2 (MaxPoolin  (None, 4, 4, 512)         0
 g2D)

 dropout_2 (Dropout)         (None, 4, 4, 512)         0

...
Total params: 4183174 (15.96 MB)
Trainable params: 4183174 (15.96 MB)
Non-trainable params: 0 (0.00 Byte)
```

```
model.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metrics =
'accuracy' )
!rm -rf Logs
logdir = os.path.join("Logs")
tensorboard_callback = TensorBoard(log_dir=logdir)
```

```
model.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // batch_size,
    epochs=100,
    validation_data=validation_generator,
    validation_steps=validation_generator.samples // batch_size,
    callbacks=[tensorboard_callback]
)
```

```
Epoch 1/100
23/23 [==============================] - 10s 70ms/step - loss: 1.7907 - accuracy:
0.1767 - val_loss: 1.7868 - val_accuracy: 0.2375
                                                    12
Epoch 2/100
23/23 [==============================] - 1s 54ms/step - loss: 1.7856 - accuracy:
0.1781 - val_loss: 1.7859 - val_accuracy: 0.1781
Epoch 3/100
23/23 [==============================] - 1s 56ms/step - loss: 1.7828 - accuracy:
0.1874 - val_loss: 1.7809 - val_accuracy: 0.1781
Epoch 4/100
```

```
23/23 [==============================] - 1s 49ms/step - loss: 1.7815 - accuracy:
0.1916 - val_loss: 1.7746 - val_accuracy: 0.1937
Epoch 5/100
23/23 [==============================] - 1s 36ms/step - loss: 1.7297 - accuracy:
0.2413 - val_loss: 1.6180 - val_accuracy: 0.2750
Epoch 6/100
23/23 [==============================] - 1s 36ms/step - loss: 1.6720 - accuracy:
0.2690 - val_loss: 1.7846 - val_accuracy: 0.1844
Epoch 7/100
23/23 [==============================] - 1s 35ms/step - loss: 1.7932 - accuracy:
0.1845 - val_loss: 1.7834 - val_accuracy: 0.1937
Epoch 8/100
23/23 [==============================] - 1s 36ms/step - loss: 1.7782 - accuracy:
0.1945 - val_loss: 1.7767 - val_accuracy: 0.1937
Epoch 9/100
23/23 [==============================] - 1s 36ms/step - loss: 1.7760 - accuracy:
0.1930 - val_loss: 1.7526 - val_accuracy: 0.2031
Epoch 10/100
23/23 [==============================] - 1s 36ms/step - loss: 1.7357 - accuracy:
0.1867 - val_loss: 1.7255 - val_accuracy: 0.1937
Epoch 11/100
23/23 [==============================] - 1s 35ms/step - loss: 1.6587 - accuracy:
0.2605 - val_loss: 1.5426 - val_accuracy: 0.3156
Epoch 12/100
23/23 [==============================] - 1s 35ms/step - loss: 1.5340 - accuracy:
0.3016 - val_loss: 1.4941 - val_accuracy: 0.3063
Epoch 13/100
...
Epoch 99/100
23/23 [==============================] - 1s 36ms/step - loss: 0.0478 - accuracy:
0.9837 - val_loss: 0.0302 - val_accuracy: 0.9844
Epoch 100/100
23/23 [==============================] - 1s 37ms/step - loss: 0.0527 - accuracy:
0.9851 - val_loss: 0.0337 - val_accuracy: 0.9906
```

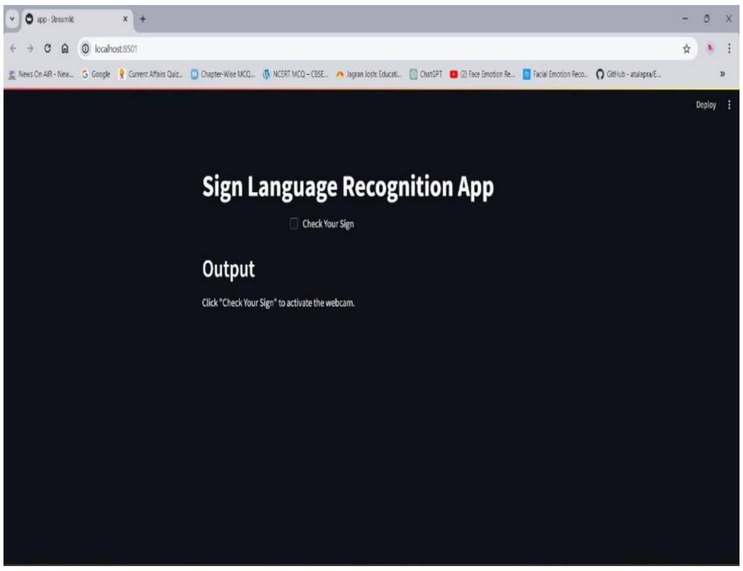
```
%load_ext tensorboard
%tensorboard --logdir Logs
```

```
model_json = model.to_json()
with open("/content/drive/MyDrive/signlanguagedetectionmodel48x48.json",'w') as
json_file:
    json_file.write(model_json)
model.save("/content/drive/MyDrive/signlanguagedetectionmodel48x48.h5")
import cv2
import numpy as np
import streamlit as st
from keras.models import model_from_json

# Load sign language recognition model
json_file =
open("C:\\Users\\91701\\Desktop\\YAM\\signlanguagedetectionmodel48x48.json", "r")
model_json = json_file.read()
```

```
json_file.close()
model = model_from_json(model_json)
model.load_weights("C:\\Users\\91701\\Desktop\\YAM\signlanguagedetectionmodel48x48.h5
")

# Define sign labels
label = ['Happy', 'Help', 'Goodluck', 'Sad', 'T','Hello']

def extract_features(image):
    feature = np.array(image)
    feature = feature.reshape(1, 48, 48, 1)
    return feature / 255.0

def detect_sign(frame):
    cv2.rectangle(frame, (0, 40), (300, 300), (0, 165, 255), 1)
    cropframe = frame[40:300, 0:300]
    cropframe = cv2.cvtColor(cropframe, cv2.COLOR_BGR2GRAY)
    cropframe = cv2.resize(cropframe, (48, 48))
    cropframe = extract_features(cropframe)
    pred = model.predict(cropframe)
    prediction_label = label[pred.argmax()]

    return prediction_label

def main():

    # Title
    st.title('Sign Language Recognition App')

    # Center the "Check Your Sign" checkbox
    col1, col2, col3 = st.columns([1, 2, 1])
    with col2:
        use_webcam = st.checkbox('Check Your Sign', value=False, key='checkbox')

    st.markdown('## Output')
    stframe = st.empty()
    detected_sign = st.empty()

    if use_webcam:

        # Start webcam
        vid = cv2.VideoCapture(0)
        while vid.isOpened():
            ret, frame = vid.read()
            if not ret:
                break

            sign_label = detect_sign(frame)

            # Display detected sign
            detected_sign.markdown(f'The detected sign is <span
class="highlight">{sign_label}</span>.', unsafe_allow_html=True)

            # Display webcam frame
            stframe.image(frame, channels="BGR", use_column_width=True)

            if cv2.waitKey(1) & 0xFF == ord('q'):
                break

        vid.release()
        cv2.destroyAllWindows()

        st.success('Video is Processed')
    else:
        st.write('Click "Check Your Sign" to activate the webcam.')

if __name__ == '__main__':
    main()
```

The integration of Streamlit provides an intuitive interface, allowing users to interact with the system seamlessly. Through the interface, users can display gestures such as 'T,' 'Hello,' 'Sad,' 'Happy,' 'Good Luck,' and 'Help,' and receive instant recognition feedback.

4.2 RESULTS

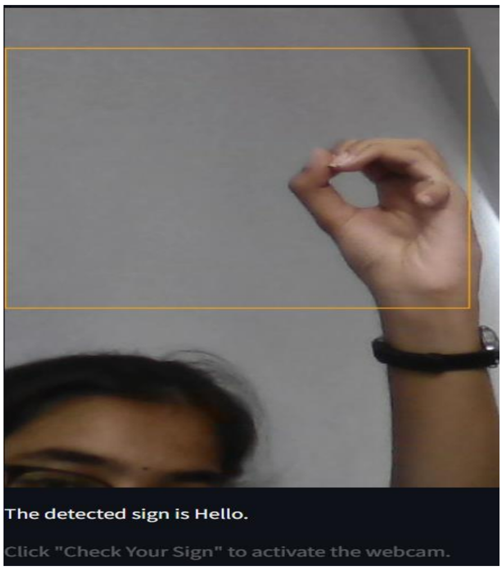


Sign Language Recognition App

Check Your Sign

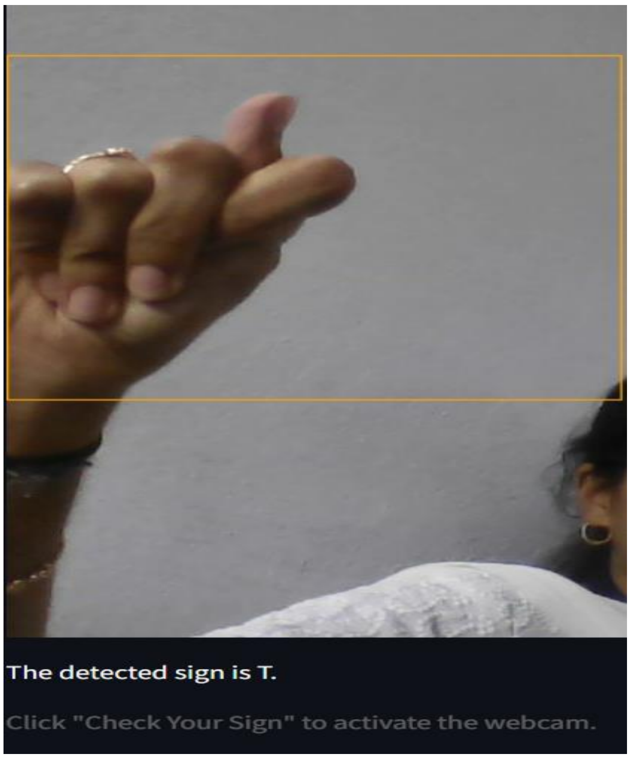
Output

Click "Check Your Sign" to activate the webcam.



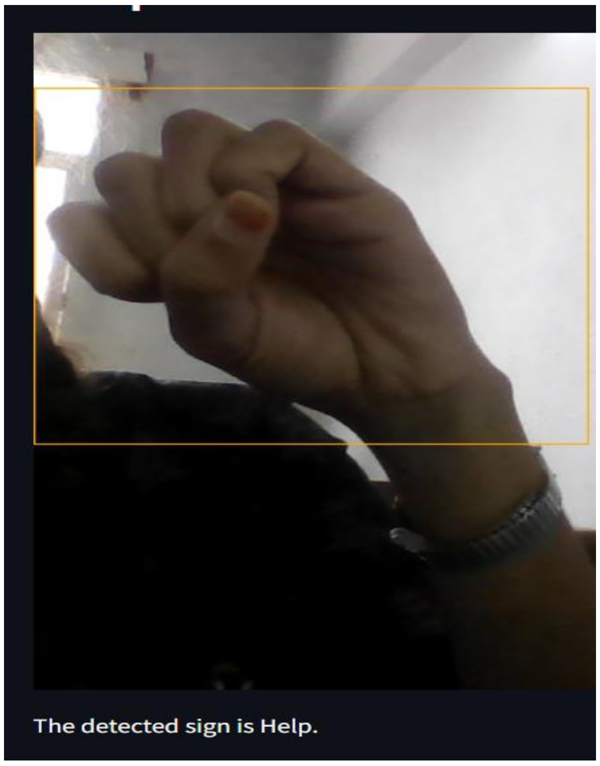
The detected sign is Hello.

Click "Check Your Sign" to activate the webcam.



The detected sign is T.

Click "Check Your Sign" to activate the webcam.



The detected sign is Help.

4.4 Applications

- Communication Assistance: Sign language recognition systems can facilitate real-time communication between individuals who are proficient in sign language and those who are not.
- Educational Tools: Sign language recognition technology can be integrated into educational platforms and tools to support the learning and teaching of sign language.
- Assistive Devices: Sign language recognition can power the development of assistive devices tailored to the unique needs of individuals with hearing impairments.
- Accessibility in Public Services: Sign language recognition systems can be integrated into public service facilities, such as transportation hubs, government offices

4.5 Merits and Demerits

Merits

- Inclusivity
- Accessibility
- Independence
- Education
- Efficiency

Demerits

- Complexity
- Limited Data
- Variation
- Ambiguity
- Ethical considerations

CHAPTER – 5
CONCLUSION

5.1 Conclusion

Sign language recognition stands as a pivotal technological advancement with the potential to revolutionize communication and accessibility for individuals who are deaf or hard of hearing. Despite facing challenges such as complexity, limited data, and cultural sensitivity, ongoing research and development efforts continue to push the boundaries of what is achievable in this field. As recognition algorithms become more sophisticated and datasets grow more diverse and inclusive, the promise of accurate, real-time interpretation of sign language moves closer to reality.

5.2 Future Scope

Sign language recognition technology holds promise for various applications, from enhancing accessibility to fostering seamless communication for the deaf and hard-of-hearing community. The future scope lies in improving accuracy through advanced machine learning algorithms, enabling real-time recognition for live interactions, and delving into a deeper understanding of sign language grammar and nuances. Integration of multiple modalities like video and wearable sensors can enrich the recognition process, while mobile and wearable applications could make this technology more pervasive and accessible in everyday life. These advancements could revolutionize communication and accessibility for sign language users, offering greater inclusivity and empowerment.

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