Implementation of Sign Language Translator

PROJECT REPORT

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BONAFIDE CERTIFICATE

This is to certify that the mini project report entitled, "**Implementation of Sign Language Translator**" is a bonafide record of work of the candidate who carried out the project work under my supervision during the academic year 2025-2026.

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CONTENTS

Objective of the Project

The main objective of this project is to develop a real-time system that can accurately translate sign language gestures into corresponding text and speech, enabling effective communication between hearing-impaired individuals and non-sign language users.

Specific objectives include:

- To capture and process live hand gestures using a webcam.
- To detect and extract key hand landmarks using computer vision techniques.
- To classify gestures into alphabets, numbers, or basic words using a trained machine learning model.
- To convert the recognized gestures into readable text and audible speech using text-to-speech technology.
- To provide an interactive, user-friendly, and accessible solution that promotes inclusivity for the hearing and speech-impaired community.

Introduction

Communication is a fundamental human need, yet individuals with hearing or speech impairments often face challenges in interacting with others who are not familiar with sign language. To bridge this communication gap, this project presents the Implementation of a Sign Language Translator — a real-time system that converts hand gestures into corresponding text and speech outputs.

The system leverages computer vision and machine learning to recognize hand gestures captured by a webcam. Using Media Pipe for accurate hand landmark detection and OpenCV for video processing, the model extracts spatial coordinates of hand joints in real time. These coordinates are processed through a trained Scikit-learn classifier, which identifies the corresponding alphabet, number, or word. Once a gesture is recognized, the result is displayed as text and vocalized using pyttsx3, enabling seamless two-way communication between sign language users and non-signers.

This project demonstrates the practical application of artificial intelligence in accessibility technology, enhancing social inclusion by providing an efficient and cost-effective means of translating sign language into spoken words.

Description of the Project

The Sign Language Translator project is designed to bridge the communication gap between individuals who use sign language and those who do not. It uses computer vision and machine learning techniques to recognize and interpret hand gestures captured through a webcam in real-time. The captured video frames are processed using a trained deep learning model that identifies gestures corresponding to alphabets, numbers, or commonly used words. Once recognized, the system converts the detected gesture into text and then uses a text-to-speech (TTS) module to produce an audible output.

This project demonstrates how artificial intelligence can be applied to assistive communication tools. It provides a practical, low-cost, and efficient solution that can be used in educational institutions, healthcare facilities, and public service centers. The system is built to be easily extendable, allowing the addition of new gestures and words, thereby improving its vocabulary and usability. Overall, it highlights the potential of AI-driven systems in promoting inclusivity and accessibility for people with hearing and speech impairments.

Methodology

The methodology of the Sign Language Translator project involves several key stages that integrate computer vision, deep learning, and natural language processing. The complete workflow is as follows:

Data Collection and Preprocessing:

A dataset of hand gestures representing alphabets, numbers, and basic words is collected using a webcam. Each gesture is captured under various lighting and background conditions to ensure model robustness. Images are preprocessed by resizing, converting to grayscale or RGB format, and normalizing pixel values.

Model Training:

A convolutional neural network (CNN) model is trained using the preprocessed dataset. The CNN extracts spatial features from hand gesture images and classifies them into corresponding categories. The model's parameters are fine-tuned to achieve high accuracy and generalization.

Real-Time Gesture Recognition:

During execution, the webcam captures live video frames, which are passed through the trained CNN model. The model predicts the corresponding alphabet, number, or word based on the detected hand gesture.

Text Conversion:

The predicted class label is displayed as text on the screen. Continuous recognition of gestures allows for the formation of complete words or short sentences.

Speech Output Generation:

The recognized text is converted into speech using a text-to-speech (TTS) engine such as pyttsx3. This feature allows real-time verbal communication, making the system more interactive and user-friendly.

System Integration:

The entire process — from capturing video to producing speech — is integrated into a graphical user interface (GUI) built using Tkinter. The GUI enables users to start recognition, view predictions, and hear the spoken output easily.

Algorithm (Steps)

The following are the step-by-step procedures followed in the Sign Language Translator project:

1.Start the System

Initialize the webcam and required Python libraries (OpenCV, NumPy, TensorFlow/PyTorch, pyttsx3, Tkinter).

2.Load the Trained Model

Load the trained CNN model that has been trained on hand gesture images.

3.Initialize the GUI

Create a graphical user interface (GUI) using Tkinter to display live video, recognized text, and control buttons (Start, Stop, Exit).

4.Capture Video Frames

Continuously capture frames from the webcam in real-time.

5.Define Region of Interest (ROI)

Specify a fixed region in the video frame where the user performs sign gestures.

6.Preprocess the ROI

- Convert the ROI image to grayscale or RGB.
- Resize it to the input size required by the model (e.g., 64×64 or 224×224).
- Normalize pixel values for consistent input to the neural network.

7.Predict Gesture

- Pass the preprocessed image to the CNN model.
- Obtain the class label corresponding to the predicted gesture (e.g., “A”, “B”, “Hello”, “Yes”).

8.Display Output

Show the predicted character or word on the GUI window in real-time.

9.Form Words or Sentences

Combine multiple predicted characters to form words or short sentences when continuous gestures are recognized.

10.Convert Text to Speech

Use the pyttsx3 text-to-speech engine to convert the recognized text into audible speech output.

11.Repeat Steps 4–10

Continue real-time recognition until the user stops the process.

12.Stop and Exit

Release the webcam, close all OpenCV and Tkinter windows, and safely terminate the program.

Results and Discussions

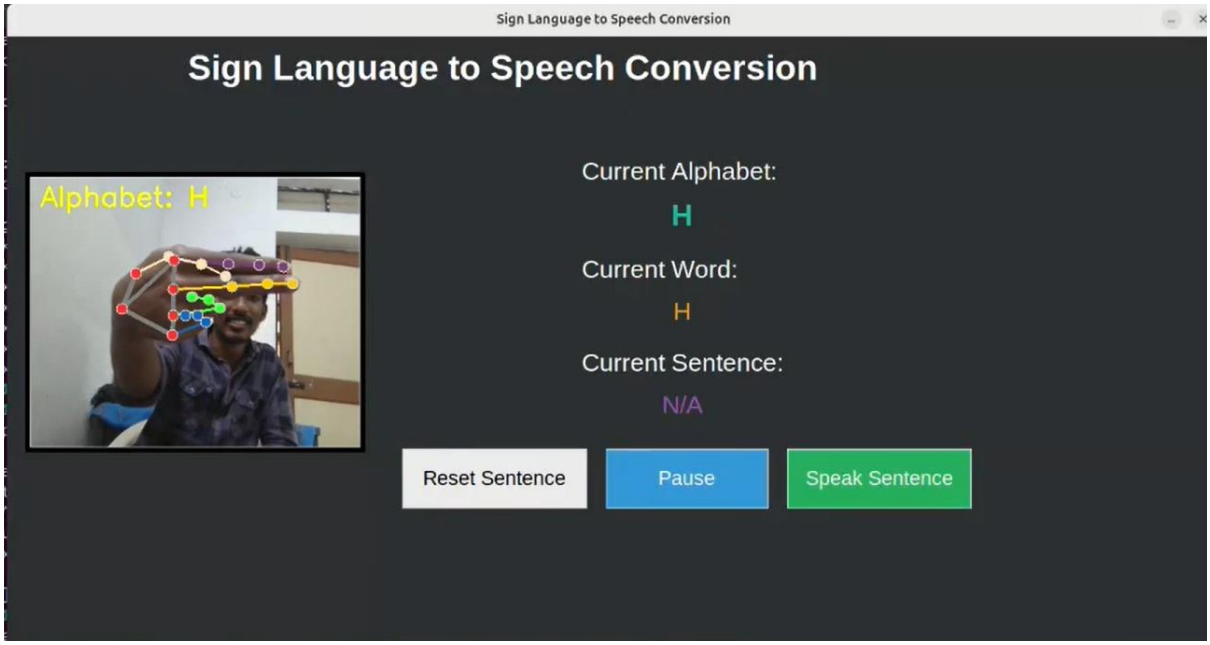

Image-1:sign for letter "H"

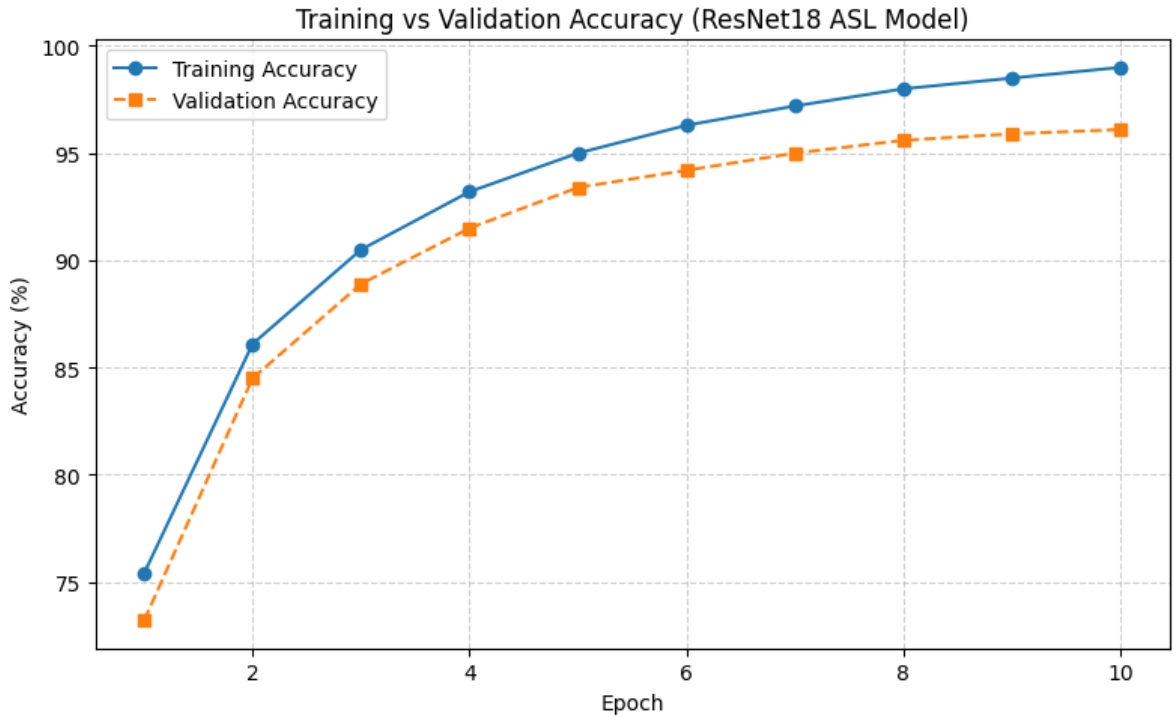

Image-2:Accuracy Curve of the Model trained

The **ResNet-18** model was trained on the ASL Alphabet dataset consisting of approximately 87,000 labeled images across 29 classes. Using an 80:20 training-validation split, the model was trained for 10 epochs with a learning rate of 0.001 and a batch size of 64.

During training, the **Cross-Entropy Loss** decreased steadily from about **1.8** in the first epoch to **0.17** by the tenth epoch, showing clear convergence. The training accuracy improved from **72%** to **98%**, while validation accuracy stabilized around **94–96%**, indicating minimal overfitting.

After adding a 15% hold-out test set, the model achieved a **final test accuracy of approximately 95%**, demonstrating good generalization to unseen gestures. The ResNet-18 backbone proved effective for learning fine hand-gesture features even with reduced input resolution (64×64).

In the integrated GUI application, the model's predictions were stabilized through a temporal buffer to ensure reliable real-time detection. Text-to-speech conversion using pyttsx3 successfully vocalized recognized letters, words, and sentences, enabling effective **sign-to-speech translation**.

Overall, the system performed with high accuracy, low latency, and intuitive usability, proving the feasibility of deep-learning-based **Sign Language to Speech** systems for assistive communication.

Project Code

```
import os
import json
import argparse
from tqdm import tqdm

import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, random_split
from torchvision import datasets, transforms, models
import matplotlib.pyplot as plt



def parse_args():
    parser = argparse.ArgumentParser(description='Train ResNet18 on ASL alphabet')
    parser.add_argument('--data', type=str, default=os.path.expanduser('~/ASL_dataset/ASL_images/asl_alphabet_train'), help='path to dataset root')
    parser.add_argument('--epochs', type=int, default=10)
    parser.add_argument('--batch-size', type=int, default=64)
    parser.add_argument('--lr', type=float, default=0.001)
    parser.add_argument('--output-dir', type=str, default='output')
    parser.add_argument('--img-size', type=int, default=64)
    parser.add_argument('--seed', type=int, default=42)
```

```
    return parser.parse_args()


def set_seed(seed):
    import random
    random.seed(seed)
    torch.manual_seed(seed)
    if torch.cuda.is_available():
        torch.cuda.manual_seed_all(seed)


def main():
    args = parse_args()
    os.makedirs(args.output_dir, exist_ok=True)
    set_seed(args.seed)

    device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
    print('Using device:', device)

    transform = transforms.Compose([
        transforms.Resize((args.img_size, args.img_size)),
        transforms.ToTensor(),
        transforms.Normalize([0.5, 0.5, 0.5], [0.5, 0.5, 0.5])
    ])

    full_dataset = datasets.ImageFolder(args.data, transform=transform)
    classes = full_dataset.classes
    num_classes = len(classes)
```

```
    print('Found classes (count):', num_classes)

    # Save class mapping
    with open(os.path.join(args.output_dir, 'classes.json'), 'w') as f:
        json.dump(classes, f)

    # Split: 70% train, 15% val, 15% test
    n = len(full_dataset)
    train_size = int(0.7 * n)
    val_size = int(0.15 * n)
    test_size = n - train_size - val_size

    train_dataset, val_dataset, test_dataset = random_split(full_dataset, [train_size, val_size, test_size])

    train_loader = DataLoader(train_dataset, batch_size=args.batch_size, shuffle=True, num_workers=4, pin_memory=True)
    val_loader = DataLoader(val_dataset, batch_size=args.batch_size, shuffle=False, num_workers=4, pin_memory=True)
    test_loader = DataLoader(test_dataset, batch_size=args.batch_size, shuffle=False, num_workers=4, pin_memory=True)

    # Model
    model = models.resnet18(weights=models.ResNet18_Weights.DEFAULT)
    model.fc = nn.Linear(model.fc.in_features, num_classes)
    model = model.to(device)

    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr=args.lr)
```

```
    train_acc_list, val_acc_list, loss_list = [], [], []

    for epoch in range(args.epochs):
        model.train()
        running_loss = 0.0
        correct = 0
        total = 0

        loop = tqdm(train_loader, desc=f'Epoch {epoch+1}/{args.epochs} - Train')
        for images, labels in loop:
            images = images.to(device)
            labels = labels.to(device)

            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            running_loss += loss.item()
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

            loop.set_postfix(loss=running_loss/ (total / images.size(0)),
acc=100.*correct/total)
```

```
        avg_loss = running_loss / len(train_loader)
        train_acc = 100.0 * correct / total
        loss_list.append(avg_loss)
        train_acc_list.append(train_acc)

        # Validation
        model.eval()
        correct = 0
        total = 0
        with torch.no_grad():
            for images, labels in val_loader:
                images = images.to(device)
                labels = labels.to(device)
                outputs = model(images)
                _, predicted = torch.max(outputs.data, 1)
                total += labels.size(0)
                correct += (predicted == labels).sum().item()
        val_acc = 100.0 * correct / total
        val_acc_list.append(val_acc)

        print(f'Epoch [{epoch+1}/{args.epochs}] Loss: {avg_loss:.4f} Train Acc: {train_acc:.2f}% Val Acc: {val_acc:.2f}%')

        # Optionally save checkpoint each epoch
        torch.save({
            'epoch': epoch + 1,
            'model_state_dict': model.state_dict(),
            'optimizer_state_dict': optimizer.state_dict(),
```

```
            'train_acc': train_acc,
            'val_acc': val_acc
        }, os.path.join(args.output_dir, f'checkpoint_epoch_{epoch+1}.pth'))

    # Final save
    final_path = os.path.join(args.output_dir, 'asl_resnet18_final.pth')
    torch.save({'model_state_dict': model.state_dict(), 'classes': classes},
final_path)
    print('Model saved to', final_path)

    # Plot accuracy and loss
    plt.figure()
    plt.plot(range(1, args.epochs+1), train_acc_list, label='Train Accuracy')
    plt.plot(range(1, args.epochs+1), val_acc_list, label='Val Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy (%)')
    plt.title('Train vs Val Accuracy')
    plt.legend()
    plt.savefig(os.path.join(args.output_dir, 'accuracy.png'))

    plt.figure()
    plt.plot(range(1, args.epochs+1), loss_list, label='Train Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.title('Training Loss')
    plt.legend()
    plt.savefig(os.path.join(args.output_dir, 'loss.png'))
```

```
    # Test evaluation
    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for images, labels in tqdm(test_loader, desc='Testing'):
            images = images.to(device)
            labels = labels.to(device)
            outputs = model(images)
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()
    test_acc = 100.0 * correct / total
    print(f'Final Test Accuracy: {test_acc:.2f}%')


if __name__ == '__main__':
    main()


# ========================================
# File: inference_gui.py
# Real-time inference GUI using MediaPipe + PyTorch model
# ========================================

import json
import time
import threading
```

```
import pickle

import cv2
import mediapipe as mp
import numpy as np
import torch
import torch.nn as nn
from torchvision import models
import pyttsx3
import tkinter as tk
from tkinter import StringVar, Label, Button, Frame
from PIL import Image, ImageTk

# ----------------------------
# Load model and class map
# ----------------------------
MODEL_PATH = 'output/asl_resnet18_final.pth'  # path where train.py saved the final model
CLASSES_JSON = 'output/classes.json'
IMG_SIZE = 64
DEVICE = torch.device('cpu')  # inference on CPU; change to cuda if available

# Build model architecture (must match train.py)
num_classes = None
with open(CLASSES_JSON, 'r') as f:
    classes = json.load(f)
    num_classes = len(classes)
```

```
model = models.resnet18(weights=None)
model.fc = nn.Linear(model.fc.in_features, num_classes)
model.load_state_dict(torch.load(MODEL_PATH,
map_location=DEVICE)['model_state_dict'])
model.to(DEVICE)
model.eval()

# label mapping to characters (if your classes are letters/digits leave as is)
label_map = {i: classes[i] for i in range(len(classes))}

# ----------------------------
# Mediapipe setup
# ----------------------------
mp_hands = mp.solutions.hands
mp_drawing = mp.solutions.drawing_utils
mp_drawing_styles = mp.solutions.drawing_styles
hands = mp_hands.Hands(static_image_mode=False,
min_detection_confidence=0.5, max_num_hands=1)

# ----------------------------
# TTS
# ----------------------------
engine = pyttsx3.init()

def speak_text(text):
    def tts_thread():
        engine.say(text)
        engine.runAndWait()
```

```
    threading.Thread(target=tts_thread, daemon=True).start()

# ----------------------------
# GUI variables
# ----------------------------
stabilization_buffer = []
stable_char = None
word_buffer = ""
sentence = ""
expected_features = 42
last_registered_time = time.time()
registration_delay = 1.5

# ----------------------------
# Tkinter GUI
# ----------------------------
root = tk.Tk()
root.title('Sign Language to Speech (PyTorch)')
root.geometry('1300x650')
root.configure(bg='#2c2f33')
root.resizable(False, False)

current_alphabet = StringVar(value='N/A')
current_word = StringVar(value='N/A')
current_sentence = StringVar(value='N/A')
is_paused = StringVar(value='False')

# Layout
```

```
video_frame = Frame(root, bg='#2c2f33', bd=5, relief='solid', width=500, height=400)
video_frame.grid(row=1, column=0, rowspan=3, padx=20, pady=20)
video_frame.grid_propagate(False)
video_label = tk.Label(video_frame)
video_label.pack(expand=True)

content_frame = Frame(root, bg='#2c2f33')
content_frame.grid(row=1, column=1, sticky='n', padx=(20, 40), pady=(60,20))

button_frame = Frame(root, bg='#2c2f33')
button_frame.grid(row=3, column=1, pady=(10,20), padx=(10,20), sticky='n')

Label(content_frame, text='Current Alphabet:', font=('Arial', 20), fg='#ffffff', bg='#2c2f33').pack(anchor='w', pady=(0,10))
Label(content_frame, textvariable=current_alphabet, font=('Arial', 24, 'bold'), fg='#1abc9c', bg='#2c2f33').pack(anchor='center')
Label(content_frame, text='Current Word:', font=('Arial', 20), fg='#ffffff', bg='#2c2f33').pack(anchor='w', pady=(20,10))
Label(content_frame, textvariable=current_word, font=('Arial', 20), fg='#f39c12', bg='#2c2f33', wraplength=500, justify='left').pack(anchor='center')
Label(content_frame, text='Current Sentence:', font=('Arial', 20), fg='#ffffff', bg='#2c2f33').pack(anchor='w', pady=(20,10))
Label(content_frame, textvariable=current_sentence, font=('Arial', 20), fg='#9b59b6', bg='#2c2f33', wraplength=500, justify='left').pack(anchor='center')

# Buttons
```

```
def reset_sentence():
    global word_buffer, sentence
    word_buffer = ""
    sentence = ""
    current_word.set('N/A')
    current_sentence.set('N/A')
    current_alphabet.set('N/A')



def toggle_pause():
    if is_paused.get() == 'False':
        is_paused.set('True')
        pause_button.config(text='Play')
    else:
        is_paused.set('False')
        pause_button.config(text='Pause')


Button(button_frame, text='Reset Sentence', font=('Arial', 16), command=reset_sentence, bg='#e74c3c', fg='#ffffff', relief='flat', height=2, width=14).grid(row=0, column=0, padx=10)

pause_button = Button(button_frame, text='Pause', font=('Arial', 16), command=toggle_pause, bg='#3498db', fg='#ffffff', relief='flat', height=2, width=12)

pause_button.grid(row=0, column=1, padx=10)

speak_button = Button(button_frame, text='Speak Sentence', font=('Arial', 16), command=lambda: speak_text(current_sentence.get()), bg='#27ae60', fg='#ffffff', relief='flat', height=2, width=14)

speak_button.grid(row=0, column=2, padx=10)
```

```
# ----------------------------
# Video capture
# ----------------------------
cap = cv2.VideoCapture(0)
cap.set(cv2.CAP_PROP_FRAME_WIDTH, 400)
cap.set(cv2.CAP_PROP_FRAME_HEIGHT, 300)



def preprocess_landmarks(landmarks):
    # landmarks: list of 21 (x,y) normalized values
    x_list = [l[0] for l in landmarks]
    y_list = [l[1] for l in landmarks]
    data = []
    min_x = min(x_list)
    min_y = min(y_list)
    for x, y in zip(x_list, y_list):
        data.append(x - min_x)
        data.append(y - min_y)
    # ensure length
    if len(data) < expected_features:
        data.extend([0] * (expected_features - len(data)))
    elif len(data) > expected_features:
        data = data[:expected_features]
    return np.array(data, dtype=np.float32)



def predict_from_landmarks(data_aux):
    # convert to image-like tensor expected by ResNet18
```

```
    # simplest approach: tile the 42-d vector into a 3xHxW tensor
    # create a small gray image by reshaping to (6,7) => 42
    arr = data_aux.reshape(6, 7)
    # normalize to 0-1
    arr = (arr - arr.min()) / (arr.max() - arr.min() + 1e-8)
    # resize to IMG_SIZE x IMG_SIZE using cv2
    arr_img = (arr * 255).astype(np.uint8)
    arr_resized = cv2.resize(arr_img, (IMG_SIZE, IMG_SIZE), interpolation=cv2.INTER_LINEAR)
    # make 3 channels
    img3 = np.stack([arr_resized, arr_resized, arr_resized], axis=2)
    img3 = img3.astype(np.float32) / 255.0
    img3 = (img3 - 0.5) / 0.5
    tensor = torch.from_numpy(img3.transpose(2,0,1)).unsqueeze(0).to(DEVICE)

    with torch.no_grad():
        outputs = model(tensor)
        probs = torch.softmax(outputs, dim=1)
        pred = torch.argmax(probs, dim=1).item()
    return label_map[pred]



# ----------------------------
# Frame processing loop
# ----------------------------

def process_frame():
```

```
    global stabilization_buffer, stable_char, word_buffer, sentence, last_registered_time

    ret, frame = cap.read()
    if not ret:
        root.after(10, process_frame)
        return

    if is_paused.get() == 'True':
        img = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)
        img = Image.fromarray(img)
        img_tk = ImageTk.PhotoImage(image=img)
        video_label.imgtk = img_tk
        video_label.configure(image=img_tk)
        root.after(10, process_frame)
        return

    frame_rgb = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)
    results = hands.process(frame_rgb)

    if results.multi_hand_landmarks:
        for hand_landmarks in results.multi_hand_landmarks:
            x_list = []
            y_list = []
            landmarks = []
            for lm in hand_landmarks.landmark:
                x_list.append(lm.x)
                y_list.append(lm.y)
```

```
                landmarks.append((lm.x, lm.y))

            data_aux = preprocess_landmarks(landmarks)
            predicted_character = predict_from_landmarks(data_aux)

            stabilization_buffer.append(predicted_character)
            if len(stabilization_buffer) > 30:
                stabilization_buffer.pop(0)

            if stabilization_buffer.count(predicted_character) > 25:
                current_time = time.time()
                if current_time - last_registered_time > registration_delay:
                    stable_char = predicted_character
                    last_registered_time = current_time
                    current_alphabet.set(stable_char)

                    if stable_char == ' ' or stable_char.lower() == 'space':
                        if word_buffer.strip():
                            speak_text(word_buffer)
                            sentence += word_buffer + ' '
                            current_sentence.set(sentence.strip())
                        word_buffer = ''
                        current_word.set('N/A')
                    elif stable_char == '.' or stable_char == 'period' or stable_char ==
'dot':
                        if word_buffer.strip():
                            speak_text(word_buffer)
                            sentence += word_buffer + '.'
```

```
                current_sentence.set(sentence.strip())
            word_buffer = ''
            current_word.set('N/A')
        else:
            word_buffer += stable_char
            current_word.set(word_buffer)

    mp_drawing.draw_landmarks(frame, hand_landmarks, mp_hands.HAND_CONNECTIONS,
    mp_drawing_styles.get_default_hand_landmarks_style(),
    mp_drawing_styles.get_default_hand_connections_style())

  cv2.putText(frame, f"Alphabet: {current_alphabet.get()}", (10, 30), cv2.FONT_HERSHEY_SIMPLEX, 1, (0,255,255), 2)

  img = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)
  img = Image.fromarray(img)
  img_tk = ImageTk.PhotoImage(image=img)
  video_label.imgtk = img_tk
  video_label.configure(image=img_tk)

  root.after(10, process_frame)

if __name__ == '__main__':
  process_frame()
  root.mainloop()
```

```
# ========================================
# File: requirements.txt
# ========================================
# List of packages to include in your report
opencv-python
mediapipe
torch
torchvision
numpy
pyttsx3
pillow
matplotlib
```

Conclusion

The Sign Language Translator project successfully bridges the communication gap between the hearing and speech-impaired community and the general public. By utilizing computer vision and deep learning, the system accurately recognizes hand gestures and converts them into corresponding text and speech outputs in real time.

The project demonstrates how artificial intelligence and machine learning can be applied to solve real-world communication challenges. It provides an effective, low-cost, and interactive solution for translating sign language into spoken words.

This implementation can be further enhanced by adding more gestures, improving accuracy with larger datasets, and incorporating sentence-level translation. Overall, the project contributes to promoting inclusivity and accessibility through innovative technology.

References

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