

Project Development Phase
Project Manual

Date	14 November 2023
Team ID	Team- 591769
Project Name	ASL - Alphabet Image Recognition
Maximum Marks	15 Marks

ASL (American Sign Language) - Alphabet Image recognition

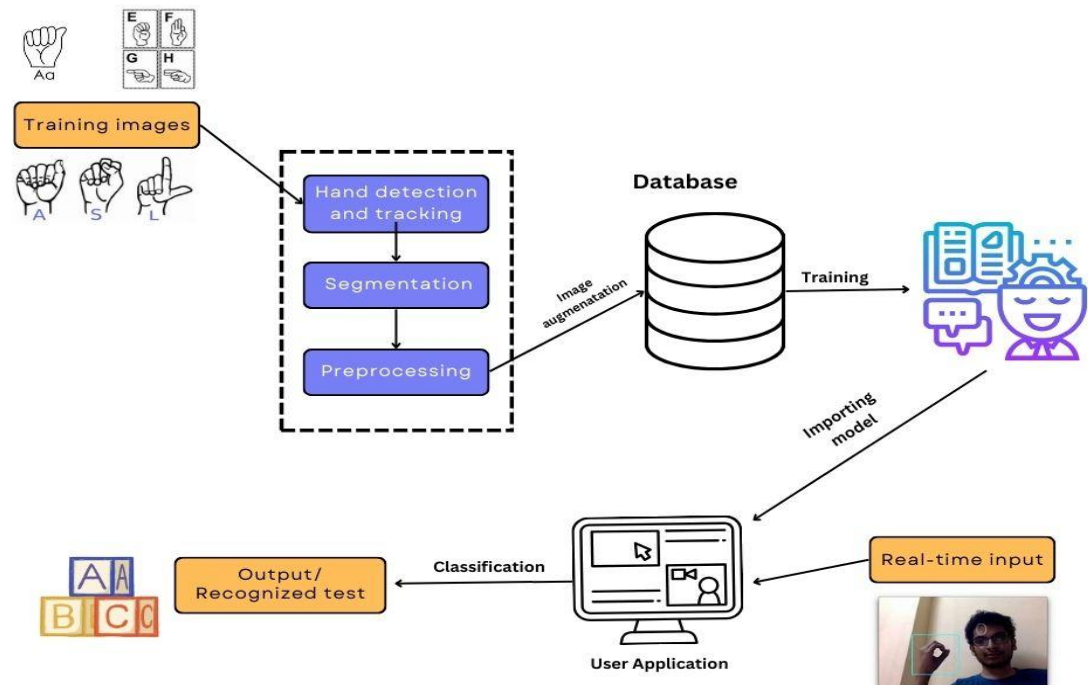
Introduction:-

American Sign Language (ASL) stands as the primary mode of communication for the deaf community in North America, utilizing a visual language that incorporates hand gestures, facial expressions, and body movements to convey meaning. A recent surge of interest has emerged in the development of technologies aimed at bridging the communication gap between the deaf and hearing communities. One notable technological advancement is ASL Alphabet Image Recognition, an image classification task designed to identify the 26 letters of the English alphabet through machine learning. The project also encompasses three additional classes for recognizing signs representing "space," "delete," and "nothing."

The core objective of ASL Alphabet Image Recognition is to train a machine learning model capable of classifying images depicting hand signs corresponding to each letter of the alphabet. This trained model holds the potential to be integrated into applications capable of real-time recognition of ASL alphabet signs from video streams. Such applications could significantly contribute to enhancing communication between the deaf and hearing communities, offering a practical solution to facilitate understanding and interaction in various contexts. This technological stride represents a promising step towards fostering inclusivity and accessibility.

In summary, the ASL Alphabet Image Recognition project embodies a technological initiative to facilitate communication between deaf and hearing individuals. By leveraging machine learning to classify ASL hand signs, the project lays the foundation for real-time applications that could revolutionize interaction dynamics. Ultimately, these advancements have the potential to promote a more inclusive and connected society by breaking down communication barriers between different linguistic communities.

Technical Architecture:-



Prerequisites:-

- Deep Learning Concepts
- Convolutional neural network
- Flask

Project objectives:-

1. To acquire a solid grasp of the fundamental concepts and techniques associated with Convolutional Neural Networks.
2. To develop a comprehensive understanding of image data and its applications.
3. To master the skills needed to pre-process and clean data through various data preprocessing techniques.
4. To attain the knowledge and proficiency to construct a web application using the Flask framework.

Project Workflow:-

1. User Interaction: Engage with the User Interface (UI) to select an image.
2. Model Integration: The chosen image undergoes analysis by the integrated model within the Flask application.
3. CNN Model Analysis: The Convolutional Neural Network (CNN) models assess the image,

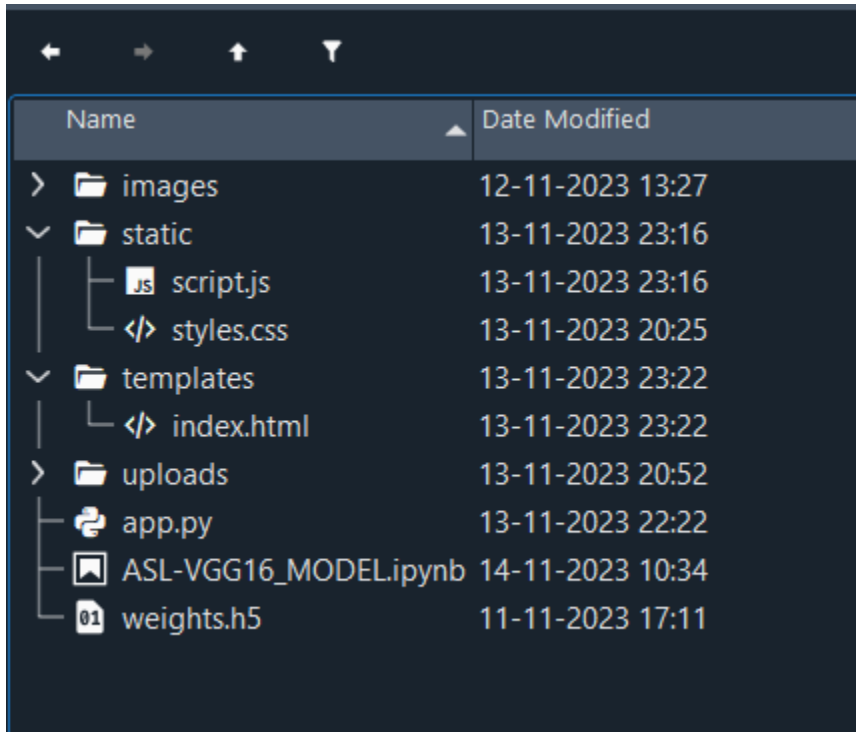
and the predictions are displayed on the Flask UI.

To achieve these objectives, the following tasks need completion:

- Data Collection.
- Data Preprocessing.
- Model Building.
- Model Training.
- Model Evaluation.
- Model Deployment.

Project Structure:-

The ASL Recognition project folder with files in following format-

A screenshot of a file explorer window with a dark theme. It shows a directory tree with folders and files. The 'static' and 'templates' folders are expanded. The 'static' folder contains 'script.js' and 'styles.css'. The 'templates' folder contains 'index.html'. Other files shown are 'app.py', 'ASL-VGG16_MODEL.ipynb', and 'weights.h5'.

Name	Date Modified
> images	12-11-2023 13:27
▼ static	13-11-2023 23:16
script.js	13-11-2023 23:16
styles.css	13-11-2023 20:25
▼ templates	13-11-2023 23:22
index.html	13-11-2023 23:22
> uploads	13-11-2023 20:52
app.py	13-11-2023 22:22
ASL-VGG16_MODEL.ipynb	14-11-2023 10:34
weights.h5	11-11-2023 17:11

PROJECT DEVELOPMENT:-

DATA COLLECTION:-

The Dataset used in this project is collected from the following link:

<https://www.kaggle.com/datasets/grassknoted/asl-alphabet>

And it is used in our project with Kaggle API credentials in the following way-

Kaggle API credentials:-

```
] !mkdir ~/.kaggle
! cp kaggle.json ~/.kaggle/
! chmod 600 ~/.kaggle/kaggle.json
```

Download and unzip dataset:-

```
!kaggle datasets download -d grassknotted/asl-alphabet
```

```
Downloading asl-alphabet.zip to /content
99% 1.01G/1.03G [00:09<00:00, 82.9MB/s]
100% 1.03G/1.03G [00:09<00:00, 115MB/s]
```

```
!unzip asl-alphabet.zip -d asl-alphabet
```

DATA PREPARATION:-

Importing the necessary libraries:-

```
# Load Data
import os
import cv2
import numpy as np

# Data Visualisation
import matplotlib.pyplot as plt

# Model Training
from tensorflow.keras import utils
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPooling2D, BatchNormalization
from sklearn.model_selection import train_test_split
from tensorflow.keras.applications import VGG16

# Warning
import warnings
warnings.filterwarnings("ignore")

# Main
import os
import glob
import cv2
import numpy as np
import pandas as pd
import gc
import string
import time
import random
from PIL import Image
from tqdm import tqdm
tqdm.pandas()
```

```

35 # Visualization
36 import matplotlib
37 import matplotlib.pyplot as plt
38 from sklearn.manifold import TSNE
39
40 # Model
41 from sklearn.model_selection import train_test_split
42 import tensorflow as tf
43 from tensorflow.keras.preprocessing.image import load_img, img_to_array, array_to_img
44 from keras.preprocessing.image import ImageDataGenerator
45 from tensorflow.keras.applications import ResNet50
46 from tensorflow.keras.layers import Dense, Flatten, Dropout, GlobalAveragePooling2D
47 from keras.models import load_model, Model
48 from keras.optimizers import Adam
49 from keras.callbacks import ModelCheckpoint, EarlyStopping
50 from sklearn.metrics import classification_report

```

Configuring the parameters:-

```

# Configuration
class CFG:
    # Set the batch size for training
    batch_size = 128
    # Set the height and width of input images
    img_height = 32
    img_width = 32
    epochs = 10
    num_classes = 29
    # Define the number of color channels in input images
    img_channels = 3
# Define a function to set random seeds for reproducibility
def seed_everything(seed: int):
    random.seed(seed)
    # Set the environment variable for Python hash seed
    os.environ["PYTHONHASHSEED"] = str(seed)
    np.random.seed(seed)
    tf.random.set_seed(seed)

```

Creating labels:-

```

# Labels
TRAIN_PATH = "/content/asl-alphabet/asl_alphabet_train/asl_alphabet_train"
labels = []
# Generate a list of uppercase letters in the English alphabet
alphabet = list(string.ascii_uppercase)
labels.extend(alphabet)
# Add special labels for 'delete', 'nothing', and 'space' gestures
labels.extend(["del", "nothing", "space"])
print(labels)

['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J', 'K', 'L', 'M', 'N', 'O', 'P', 'Q', 'R',

```

DATA PREPROCESSING:-

Creating metadata:-

```
# Create Metadata
list_path = []
list_labels = []
for label in labels:
    # Create a path pattern to match all image files for the current label
    label_path = os.path.join(TRAIN_PATH, label, "")
    # Use glob to retrieve a list of image file paths that match the pattern
    image_files = glob.glob(label_path)
    sign_label = [label] * len(image_files)
    list_path.extend(image_files)
    list_labels.extend(sign_label)
metadata = pd.DataFrame({
    "image_path": list_path,
    "label": list_labels
})
metadata
```

Splitting the data into train and test sets:-

```
# Split the data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    metadata['image_path'],
    metadata['label'],
    test_size=0.2,
    random_state=2253,
    shuffle=True,
    stratify=metadata['label']
)

# Create a DataFrame for the training set test set
data_train = pd.DataFrame({
    'image_path': X_train,
    'label': y_train
})

data_test = pd.DataFrame({
    'image_path': X_test,
    'label': y_test
})

# Split the training set into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(
    data_train['image_path'],
    data_train['label'],
    test_size=0.2/0.7, # Assuming you want 20% for validation out of the training set
    random_state=2253,
    shuffle=True,
    stratify=data_train['label']
)

# Create a DataFrame for the validation set
data_val = pd.DataFrame({
    'image_path': X_val,
    'label': y_val
})
```

DATA AUGMENTATION:-

Applying data augmentation to train, test, validation data:-

```
def data_augmentation():
    datagen = ImageDataGenerator(
        rescale=1/255.,
        # Add other augmentation parameters as needed
        rotation_range=20,
        width_shift_range=0.2,
        height_shift_range=0.2,
        shear_range=0.2,
        zoom_range=0.2,
        horizontal_flip=True,
        fill_mode='nearest'
    )

    train_generator = datagen.flow_from_dataframe(
        data_train,
        directory='.',
        x_col='image_path',
        y_col='label',
        class_mode='categorical',
        batch_size=CFG.batch_size,
        target_size=(CFG.img_height, CFG.img_width)
    )

    validation_generator = datagen.flow_from_dataframe(
        data_val,
        directory='.',
        x_col='image_path',
        y_col='label',
        class_mode='categorical',
        batch_size=CFG.batch_size,
        target_size=(CFG.img_height, CFG.img_width)
    )

    test_generator = datagen.flow_from_dataframe(
        data_test, # Assuming you have a DataFrame for test data
        directory='.',
        x_col='image_path',
        y_col='label',
        class_mode='categorical',
        batch_size=CFG.batch_size,
        target_size=(CFG.img_height, CFG.img_width),
        shuffle=False # Set to False for test data
    )

    return train_generator, validation_generator, test_generator

# Seed for reproducibility
seed_everything(2253)

# Get the generators
train_generator, validation_generator, test_generator = data_augmentation()
```

Found 69600 validated image filenames belonging to 29 classes.
Found 19886 validated image filenames belonging to 29 classes.
Found 17400 validated image filenames belonging to 29 classes.

MODEL BUILDING:-

We are using VGG16 Model and the weights have been taken from ImageNet Model

```
# Define input shape
input_shape = (32, 32, 3)

# Load the VGG16 model without the top (classification) layers
base_model = VGG16(weights='imagenet', include_top=False, input_shape=input_shape)

# Add your custom classification layers on top of the base model
x = GlobalAveragePooling2D()(base_model.output)
x = Dense(128, activation='relu')(x) # You can adjust the number of units as needed
predictions = Dense(29, activation='softmax')(x) # num_classes is the number of classes

# Create the final model
model = Model(inputs=base_model.input, outputs=predictions)

# Summarize the model architecture
model.summary()
```

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_data_format.h5
58889256/58889256 [=====] - 0s 0us/step
Model: "model"

Layer (type)	Output Shape	Param #
=====		
input_1 (InputLayer)	(None, 32, 32, 3)	0
block1_conv1 (Conv2D)	(None, 32, 32, 64)	1792
block1_conv2 (Conv2D)	(None, 32, 32, 64)	36928
block1_pool (MaxPooling2D)	(None, 16, 16, 64)	0
block2_conv1 (Conv2D)	(None, 16, 16, 128)	73856
block2_conv2 (Conv2D)	(None, 16, 16, 128)	147584
block2_pool (MaxPooling2D)	(None, 8, 8, 128)	0
block3_conv1 (Conv2D)	(None, 8, 8, 256)	295168
block3_conv2 (Conv2D)	(None, 8, 8, 256)	590080
block3_conv3 (Conv2D)	(None, 8, 8, 256)	590080
block3_pool (MaxPooling2D)	(None, 4, 4, 256)	0
block4_conv1 (Conv2D)	(None, 4, 4, 512)	1180160
block4_conv2 (Conv2D)	(None, 4, 4, 512)	2359808
block4_conv3 (Conv2D)	(None, 4, 4, 512)	2359808

block4_pool (MaxPooling2D)	(None, 2, 2, 512)	0
block5_conv1 (Conv2D)	(None, 2, 2, 512)	2359808
block5_conv2 (Conv2D)	(None, 2, 2, 512)	2359808
block5_conv3 (Conv2D)	(None, 2, 2, 512)	2359808
block5_pool (MaxPooling2D)	(None, 1, 1, 512)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0
dense (Dense)	(None, 128)	65664
dense_1 (Dense)	(None, 29)	3741

```

=====
Total params: 14784093 (56.40 MB)
Trainable params: 14784093 (56.40 MB)
Non-trainable params: 0 (0.00 Byte)

```

Compiling and training the model:-

```

# Compile the model
model.compile(optimizer=Adam(lr=0.0001), loss='categorical_crossentropy', metrics=['accuracy'])

# Create a ModelCheckpoint callback
checkpoint_callback = ModelCheckpoint(
    filepath='/content/sample_data/best_model_weights.h5',
    monitor='val_accuracy', # Monitor validation accuracy for saving the best model
    save_best_only=True,
    mode='max',
    verbose=1
)

# Train the model using the fit method
history = model.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // CFG.batch_size, # Number of steps per epoch
    epochs=CFG.epochs, # Number of training epochs
    validation_data=validation_generator,
    validation_steps=validation_generator.samples // CFG.batch_size, # Number of validation steps
    callbacks=[checkpoint_callback],
    shuffle=True,
    verbose=1
)

```

```

Epoch 1/10
543/543 [=====] - ETA: 0s - loss: 2.6236 - accuracy: 0.1762
Epoch 1: val_accuracy improved from -inf to 0.41754, saving model to /content/sample_data/best_model_weights.h5
543/543 [=====] - 163s 273ms/step - loss: 2.6236 - accuracy: 0.1762 - val_loss: 1.6868 - val_accuracy: 0.4175
Epoch 2/10
543/543 [=====] - ETA: 0s - loss: 1.0716 - accuracy: 0.6257
Epoch 2: val_accuracy improved from 0.41754 to 0.78942, saving model to /content/sample_data/best_model_weights.h5
543/543 [=====] - 130s 239ms/step - loss: 1.0716 - accuracy: 0.6257 - val_loss: 0.6494 - val_accuracy: 0.7894
Epoch 3/10
543/543 [=====] - ETA: 0s - loss: 0.5376 - accuracy: 0.8276
Epoch 3: val_accuracy improved from 0.78942 to 0.84824, saving model to /content/sample_data/best_model_weights.h5
543/543 [=====] - 144s 265ms/step - loss: 0.5376 - accuracy: 0.8276 - val_loss: 0.4681 - val_accuracy: 0.8482
Epoch 4/10
543/543 [=====] - ETA: 0s - loss: 0.3992 - accuracy: 0.8792
Epoch 4: val_accuracy improved from 0.84824 to 0.89718, saving model to /content/sample_data/best_model_weights.h5
543/543 [=====] - 129s 237ms/step - loss: 0.3992 - accuracy: 0.8792 - val_loss: 0.3558 - val_accuracy: 0.8972
Epoch 5/10
543/543 [=====] - ETA: 0s - loss: 0.3364 - accuracy: 0.9027
Epoch 5: val_accuracy improved from 0.89718 to 0.90045, saving model to /content/sample_data/best_model_weights.h5
543/543 [=====] - 132s 243ms/step - loss: 0.3364 - accuracy: 0.9027 - val_loss: 0.3819 - val_accuracy: 0.9005
Epoch 6/10
543/543 [=====] - ETA: 0s - loss: 0.2839 - accuracy: 0.9199
Epoch 6: val_accuracy improved from 0.90045 to 0.92727, saving model to /content/sample_data/best_model_weights.h5
543/543 [=====] - 148s 272ms/step - loss: 0.2839 - accuracy: 0.9199 - val_loss: 0.2608 - val_accuracy: 0.9273
Epoch 7/10
543/543 [=====] - ETA: 0s - loss: 0.2397 - accuracy: 0.9331
Epoch 7: val_accuracy did not improve from 0.92727
543/543 [=====] - 131s 241ms/step - loss: 0.2397 - accuracy: 0.9331 - val_loss: 0.2851 - val_accuracy: 0.9226
Epoch 8/10
543/543 [=====] - ETA: 0s - loss: 0.2162 - accuracy: 0.9397
Epoch 8: val_accuracy improved from 0.92727 to 0.94934, saving model to /content/sample_data/best_model_weights.h5
543/543 [=====] - 129s 238ms/step - loss: 0.2162 - accuracy: 0.9397 - val_loss: 0.1797 - val_accuracy: 0.9493
Epoch 9/10
543/543 [=====] - ETA: 0s - loss: 0.2057 - accuracy: 0.9445
Epoch 9: val_accuracy improved from 0.94934 to 0.95262, saving model to /content/sample_data/best_model_weights.h5
543/543 [=====] - 142s 262ms/step - loss: 0.2057 - accuracy: 0.9445 - val_loss: 0.1645 - val_accuracy: 0.9526
Epoch 10/10
543/543 [=====] - ETA: 0s - loss: 0.1810 - accuracy: 0.9498
Epoch 10: val_accuracy improved from 0.95262 to 0.95701, saving model to /content/sample_data/best_model_weights.h5
543/543 [=====] - 141s 259ms/step - loss: 0.1810 - accuracy: 0.9498 - val_loss: 0.1669 - val_accuracy: 0.9570

```

MODEL EVALUATION:-

Evaluating the model using accuracy, confusion matrix and giving classification report:-

```

scores = model.evaluate(test_generator)
print("%s: %2f%%" % ("Evaluate Test Accuracy", scores[1]*100))

```

```

136/136 [=====] - 25s 182ms/step - loss: 0.1469 - accuracy: 0.9626
Evaluate Test Accuracy: 96.264368%

```

```

# Confusion Matrix
fine_tuned_model = load_model("/content/sample_data/best_model_weights.h5")
predictions = fine_tuned_model.predict(test_generator)

# Get the true labels from the generator
true_labels = test_generator.classes

# Compute the confusion matrix using tf.math.confusion_matrix
confusion_matrix = tf.math.confusion_matrix(
    labels = true_labels,
    predictions = predictions.argmax(axis=1),
    num_classes = 29
)

```

```

136/136 [=====] - 24s 178ms/step

```

```

tf.Tensor(
[[578 1 0 2 0 0 0 0 0 0 0 0 5 1 0 0 0 0
 7 1 1 0 0 1 0 3 0 0 0 0 0 0 0 0 0 0
 0 585 0 0 1 1 0 0 0 0 1 0 0 0 0 1 0 5
 0 0 5 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 1 585 0 0 0 0 3 0 0 0 0 0 0 3 0 1 0
 1 1 0 0 0 0 0 0 2 0 0 3]
 0 6 0 584 0 2 0 0 1 0 0 0 0 0 0 5 0 1
 0 0 0 1 0 0 0 0 0 0 0 0]
 12 6 0 0 565 1 0 0 5 0 0 0 0 2 0 1 0 0
 7 0 0 1 0 0 0 0 0 0 0 0]
 0 2 0 3 1 590 0 0 0 0 0 0 0 1 0 1 0 0
 1 0 0 0 0 0 1 0 0 0 0 0]
 3 0 0 0 0 0 0 572 5 2 6 0 0 0 0 0 5 0
 2 0 0 2 0 0 0 1 1 0 0 1]
 0 0 0 0 0 0 0 5 589 0 1 0 0 0 0 1 0 0
 0 0 0 0 0 0 0 0 2 0 0 2]
 1 6 0 1 4 0 0 0 568 8 0 0 0 0 0 0 0 4
 1 0 1 1 0 0 2 3 0 0 0]
 0 0 0 0 0 0 0 3 6 584 0 0 0 0 0 0 0
 0 0 0 0 0 0 4 3 0 0]
 0 12 0 2 0 0 0 0 2 0 544 0 0 0 0 0 0 9
 0 0 0 27 3 0 0 0 0 1 0]
 2 0 0 0 0 0 2 0 5 3 0 572 0 0 0 0 0
 1 10 0 0 0 3 1 1 0 0 0]
 0 0 0 0 1 0 0 0 0 0 0 0 578 18 2 0 0
 1 0 0 0 0 0 0 0 0 0 0]
 0 0 0 0 0 0 0 1 0 0 0 0 39 551 0 0 0
 4 0 3 0 0 0 0 0 1 1 0]
 0 0 0 2 0 0 0 0 0 0 0 0 0 0 585 2 0 1
 7 0 0 0 0 0 0 0 1 1 0 1]
 0 0 0 0 0 0 0 0 0 1 0 1]
 1 0 1 0 0 0 0 0 1 0 1]
 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 593 2 0
 0 0 0 0 0 0 0 1 4 0 1]
 0 0 0 0 0 0 1 4 0 1]
 6 0 18 6 0 4 0 0 0 0]
 3 0 0 0 0 0 0 0 0 0 0 3 3 0 0 0 0
 578 2 2 0 0 4 0 3 0 1 1]
 0 0 0 0 0 0 0 0 1 0]
 12 576 0 0 0 0 4 6 0 0]
 0 0 0 0 0 0 0 0 0 0]
 4 0 539 2 0 4 0 0 0 0]
 0 0 0 0 0 0 0 2 0 12 0 1 0 0 0 0 10
 7 1 5 548 8 6 0 0 0 0]
 0 0 0 0 0 0 0 0 6 0 1 0 0 0 0 2
 2 0 1 22 563 0 2 1 0 0]
 2 0 0 0 0 0 0 1 0 0 1 2 0 0 0 0 8
 44 3 3 1 0 529 0 5 0 1]
 0 0 0 0 0 0 0 0 3 0 0 0 0 0 0 0
 4 1 0 0 0 0 590 2 0 0]
 1 0 0 0 0 0 0 0 0 0]
 9 0 0 0 0 1 3 584 0 0]
 0 0 0 0 0 0 2 0 0]
 1 0 0 0 0 1 2 584 2 2]
 0 0 0 0 0 0 0 0]
 0 1 0 0 0 0 0 599 0]

```

```

#Classification report
predictions = model.predict(test_generator)
predicted_labels = np.argmax(predictions, axis=1)
true_labels = test_generator.classes
report = classification_report(true_labels, predicted_labels, target_names=labels)
print(report)

```

136/136 [=====] - 25s 181ms/step

	precision	recall	f1-score	support
A	0.95	0.95	0.95	600
B	0.94	0.96	0.95	600
C	1.00	0.97	0.98	600
D	0.99	0.98	0.98	600
E	0.98	0.94	0.96	600
F	0.99	0.97	0.98	600
G	0.99	0.95	0.97	600
H	0.97	0.98	0.97	600
I	0.97	0.96	0.96	600
J	0.97	0.97	0.97	600
K	0.94	0.91	0.93	600
L	1.00	0.96	0.98	600
M	0.93	0.93	0.93	600
N	0.94	0.95	0.94	600
O	0.97	0.99	0.98	600
P	0.98	0.98	0.98	600
Q	0.99	0.98	0.98	600
R	0.84	0.93	0.88	600
S	0.81	0.96	0.88	600
T	0.98	0.95	0.96	600
U	0.91	0.89	0.90	600
V	0.91	0.91	0.91	600
W	0.98	0.93	0.96	600
X	0.96	0.87	0.91	600
Y	0.97	0.97	0.97	600
Z	0.95	0.98	0.96	600
del	0.98	0.97	0.98	600
nothing	0.98	1.00	0.99	600
space	0.98	0.98	0.98	600
accuracy			0.95	17400
macro avg	0.96	0.95	0.95	17400
weighted avg	0.96	0.95	0.95	17400

LOAD AND TEST THE MODEL:-

```
# Load the saved model
model = tf.keras.models.load_model('/content/sample_data/best_model_weights.h5')

# Testing with an image
image_path = '/content/asl-alphabet/asl_alphabet_train/asl_alphabet_train/Y/Y10.jpg'
img = cv2.imread(image_path)
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
img = cv2.resize(img, (32,32))

img = tf.keras.applications.mobilenet_v2.preprocess_input(img)

# Predict the class of the image
predictions = model.predict(np.array([img]))

# Get the class with the highest probability
predicted_class = labels[np.argmax(predictions)]

print(f"The image is predicted to belong to class: {predicted_class}")

1/1 [=====] - 0s 472ms/step
The image is predicted to belong to class: Y
```

```
# Testing with an image
image_path = '/content/asl-alphabet/asl_alphabet_train/asl_alphabet_train/B/B1008.jpg'
img = cv2.imread(image_path)
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
img = cv2.resize(img, (32,32))

img = tf.keras.applications.mobilenet_v2.preprocess_input(img)

# Predict the class of the image
predictions = model.predict(np.array([img]))

# Get the class with the highest probability
predicted_class = labels[np.argmax(predictions)]

print(f"The image is predicted to belong to class: {predicted_class}")

1/1 [=====] - 0s 72ms/step
The image is predicted to belong to class: B
```

```

# Testing with an image
image_path = '/content/asl-alphabet/asl_alphabet_train/asl_alphabet_train/H/H108.jpg'
img = cv2.imread(image_path)
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
img = cv2.resize(img,(32,32))

img = tf.keras.applications.mobilenet_v2.preprocess_input(img)

# Predict the class of the image
predictions = model.predict(np.array([img]))

# Get the class with the highest probability
predicted_class = labels[np.argmax(predictions)]

print(f"The image is predicted to belong to class: {predicted_class}")

1/1 [=====] - 0s 72ms/step
The image is predicted to belong to class: H

```

```

# Testing with an image
image_path = '/content/asl-alphabet/asl_alphabet_train/asl_alphabet_train/del/del274.jpg'
img = cv2.imread(image_path)
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
img = cv2.resize(img,(32,32))

img = tf.keras.applications.mobilenet_v2.preprocess_input(img)

# Predict the class of the image
predictions = model.predict(np.array([img]))

# Get the class with the highest probability
predicted_class = labels[np.argmax(predictions)]

print(f"The image is predicted to belong to class: {predicted_class}")

1/1 [=====] - 0s 20ms/step
The image is predicted to belong to class: del

```

```

# Testing with an image
image_path = '/content/asl-alphabet/asl_alphabet_train/asl_alphabet_train/L/L100.jpg'
img = cv2.imread(image_path)
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
img = cv2.resize(img,(32,32))

img = tf.keras.applications.mobilenet_v2.preprocess_input(img)

# Predict the class of the image
predictions = model.predict(np.array([img]))

# Get the class with the highest probability
predicted_class = labels[np.argmax(predictions)]

print(f"The image is predicted to belong to class: {predicted_class}")

1/1 [=====] - 0s 36ms/step
The image is predicted to belong to class: L

```

APPLICATION BUILDING:-

1. Creating an HTML Page.
2. Adding styles to it using css.
3. Adding actions to it using javascript.
4. Creating App.py python script for web application that uses the model for image classification predictions.
5. Executing these files using Spyder IDE.

HTML CODE:-

```
<!DOCTYPE html>
<html lang="en">

<head>
  <meta charset="UTF-8">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <title>ASL Recognition</title>
  <link rel="stylesheet" href="{{ url_for('static', filename='styles.css') }}">
</head>

<body>
  <header>
    <div class="header-content">
      <h1>American Sign Language Recognition</h1>
      <p>Explore and learn ASL signs with our interactive recognition tool.</p>
    </div>
  </header>

  <div class="container-wrapper">
    <div class="info-container">
      <div class="info-section">
        <p>The American Sign Language (ASL) is the primary language used by deaf individuals in North America. It is a visual language that uses
        </div>
      <div class="image-section">
        <p>Take a look at American Sign Language through the picture below, it contains the alphabets from A-Z, and additionally 3 symbols for space
        
      </div>
    </div>

    <div class="predict-container">
      <h3>Getting confused with the ASL 🤔, Use our Deep learning tool to easily predict the ASL sign</h3>
      <button type="button" id="predict-something-button" onclick="showUploadOptions()">Want to predict something?</button>

      <form id="upload-form" action="/predict" method="post" enctype="multipart/form-data">
        <div id="upload-options" style="display: none;">
          <button type="button" id="video-button" onclick="document.getElementById('video-input').click();">Single Video</button>
          <input type="file" name="video" id="video-input" accept="video/*" style="display: none;" onchange="previewVideo(this)">
          <button type="button" id="files-button" onclick="document.getElementById('files-input').click();">Series of Images</button>
          <input type="file" name="files[]" id="files-input" accept="image/*" multiple style="display: none;" onchange="previewImages(this)">
        </div>
      </form>
      <!--<video id="video-player" style="display:none;"></video-->
      <!-- Display Images Side by Side -->
      <div id="image-preview" class="flex-container"></div>
    </div>
  </div>
</body>
</html>
```

```
<!-- Predict Button -->
<button type="button" id="predict-button" onclick="predict(event)">Predict</button>

<div id="result"> </div>
</div>
</div>

<script src="{{url_for('static',filename='script.js')}}"></script>

<input type="file" name="file" id="file-input" accept="image/*" capture="camera" onchange="previewImage(this, 300)">
</body>
</html>
```

CSS CODE:-

```
body {
  font-family: 'Arial', sans-serif;
  background-color: #F1EAFB;
  margin: 0;
  padding: 0;
}

header {
  margin: 10px;
  position: relative;
  text-align: center;
  color: #872341;
  background-color: #FFE3BB;
  padding: 50px;
}

.header-content {
  position: absolute;
  top: 50%;
  left: 50%;
  transform: translate(-50%, -50%);
}

.container-wrapper {
  display: flex;
  justify-content: space-around;
  max-width: 1300px;
  margin: 5px auto;
}

.info-container {
  max-width: 800px;
  margin: 20px auto;
  margin-right: 40px;
  text-align: center;
  padding: 20px;
  background-color: #fff;
  border-radius: 8px;
  box-shadow: 0 0 10px rgba(0, 0, 0, 0.1);
}
```

```
#image-preview {
  margin: 20px auto;
  display: flex;
  justify-content: space-around;
  flex-wrap: wrap;
  position: relative;
}

.flex-container {
  display: flex;
}

.preview-image {
  max-width: 100px;
  margin: 5px;
}

.upload-form {
  display: flex;
  flex-direction: column;
  align-items: flex-end;
}

#upload-instruction {
  margin-top: 10px;
}

.upload-options {
  display: flex;
  flex-direction: column;
  align-items: center;
  margin-top: 10px;
}

.upload-label {
  margin-top: 10px;
}
```



```

#video-button,
#files-button{
    background-color: #3498db;
    color: #fff;
    padding: 15px 30px;
    border: none;
    border-radius: 5px;
    cursor: pointer;
    transition: background-color 0.3s;
    margin: 5px;
}

#predict-button {
    position: absolute;
    bottom: 20px;
    left: 50%;
    transform: translateX(-50%);
    background-color: #e67e22;
    color: #fff;
    padding: 15px 30px;
    border: none;
    border-radius: 5px;
    cursor: pointer;
    transition: background-color 0.3s;
    margin-top: 10px;
}

#upload-button:hover,
#predict-button:hover {
    background-color: #d35400;
}

#result {
    position: absolute;
    bottom: 1px;
    width: 100%;
    font-weight: bold;
    text-align: center;
    color: #333;
}

```

```

#upload-label {
    background-color: #3498db;
    color: #fff;
    padding: 15px 30px;
    border-radius: 5px;
    cursor: pointer;
    transition: background-color 0.3s;
    margin-bottom: 10px;
}

.upload-label {
    background-color: #3498db;
    color: #fff;
    padding: 15px 30px;
    border-radius: 5px;
    cursor: pointer;
    margin: 5px;
}

#predict-something-button {
    background-color: #e67e22;
    color: #fff;
    padding: 15px 30px;
    border: none;
    border-radius: 5px;
    cursor: pointer;
    transition: background-color 0.3s;
}

#predict-something-button:hover,
#predict-button:hover {
    background-color: #d35400;
}

#upload-label:hover {
    background-color: #2980b9;
}

```

```
.predict-container {
  max-width: 400px;
  margin: 20px auto;
  padding: 20px;
  text-align: center;
  background-color: #fff;
  border-radius: 8px;
  box-shadow: 0 0 10px rgba(0, 0, 0, 0.1);
  position: relative;
  max-height: 800px;
  overflow-y: auto;
}

.image-section{
  background-color: #3478db;
  color: #fff;
  padding: 20px;
  border-radius: 8px;
  margin-bottom: 20px;
}

.info-section {
  background-color: #3498db;
  color: #fff;
  padding: 20px;
  border-radius: 8px;
  margin-bottom: 20px;
}

.info-section h2 {
  margin-bottom: 10px;
}

#file-input {
  display: none;
}
```

JAVASCRIPT CODE:-

```
document.addEventListener('DOMContentLoaded', function () {
    const videoInput = document.getElementById('video-input');
    const videoPlayer = document.getElementById('video-player');
    const imageContainer = document.getElementById('image-preview');

    videoInput.addEventListener('change', function (event) {
        console.log('Video input change event triggered.');

        const file = event.target.files[0];
        if (file) {
            console.log('Selected file:', file);

            const videoURL = URL.createObjectURL(file);
            videoPlayer.src = videoURL;

            console.log('Video URL:', videoURL);

            generateImages(videoURL);
        }
    });

    function generateImages(videoURL) {
        console.log('Generating images from video.');

        const video = document.createElement('video');
        video.src = videoURL;
        video.addEventListener('Loadedmetadata', function () {
            const duration = video.duration;

            for (let i = 0; i < duration; i++) {
                video.currentTime = i;
                const canvas = document.createElement('canvas');
                const context = canvas.getContext('2d');
                canvas.width = video.videoWidth;
                canvas.height = video.videoHeight;
                context.drawImage(video, 0, 0, canvas.width, canvas.height);

                const img = new Image();
                img.src = canvas.toDataURL('image/png');
                img.alt = `Frame ${i}`;
                imageContainer.appendChild(img);
            }
            console.log('Images generated successfully.');
        });
    }
});
```

```
function previewImage(input) {
    const preview = document.getElementById('image-preview');
    preview.innerHTML = '';

    if (input.files && input.files[0]) {
        const reader = new FileReader();

        reader.onload = function (e) {
            const img = document.createElement('img');
            img.src = e.target.result;
            img.style.maxWidth = '100%';
            preview.appendChild(img);
        };

        reader.readAsDataURL(input.files[0]);
    }
}

function showUploadOptions() {
    console.log('Upload options are being shown.');
    var uploadOptions = document.getElementById('upload-options');
    uploadOptions.style.display = 'block';
}

function previewImages(input) {
    console.log('Previewing multiple images.');
    var previewContainer = document.getElementById('image-preview');

    // Clear existing previews
    previewContainer.innerHTML = '';

    var files = input.files;

    for (var i = 0; i < files.length; i++) {
        var file = files[i];
        var reader = new FileReader();

        reader.onload = function (e) {
            var image = document.createElement('img');
            image.src = e.target.result;
            image.className = 'preview-image';
            previewContainer.appendChild(image);
        };

        reader.readAsDataURL(file);
    }
}
```

```

function previewVideo(input) {
  const predictContainer = document.querySelector('.predict-container');
  const videoPreview = document.createElement('div');

  // Set styling for the video preview container
  videoPreview.style.width = '100%'; // Set the width to 100%
  videoPreview.style.maxHeight = '400px'; // Set a maximum height
  videoPreview.style.overflow = 'hidden'; // Hide any overflow content

  if (input.files && input.files[0]) {
    const reader = new FileReader();

    reader.onload = function (e) {
      const video = document.createElement('video');
      video.src = e.target.result;
      video.style.width = '100%'; // Set the width to 100%
      video.style.height = 'auto';
      video.controls = true;

      // Append the video element to the video preview container
      videoPreview.appendChild(video);

      // Append the video preview container to the predict container
      predictContainer.appendChild(videoPreview);

      // Automatically remove the video after 1/2 minute (30000 milliseconds)
      setTimeout(function () {
        videoPreview.remove();
      }, 30000);
    };

    reader.readAsDataURL(input.files[0]);
  }
}

function predictFromVideoFrames() {
  const images = document.getElementById('flex-container').getElementsByTagName('img');
  const formData = new FormData();

  for (let i = 0; i < images.length; i++) {
    const imgDataUrl = images[i].src;
    const blob = dataURLtoBlob(imgDataUrl);
    formData.append('files[]', blob, `frame_${i}.png`);
  }

  fetch('/predict', {
    method: 'POST',
    body: formData
  })

```

```

        body: formData
    })
    .then(response => response.json())
    .then(data => {
        document.getElementById('result').innerText = 'Prediction: ' + data.prediction;
    })
    .catch(error => console.error('Error:', error));
}

function dataURLtoBlob(dataURL) {
    const arr = dataURL.split(',');
    const mime = arr[0].match(/:(.*?);/)[1];
    const bstr = atob(arr[1]);
    let n = bstr.length;
    const u8arr = new Uint8Array(n);
    while (n--) {
        u8arr[n] = bstr.charCodeAt(n);
    }
    return new Blob([u8arr], { type: mime });
}

function predict(event) {
    event.preventDefault(); // Prevent the default form submission behavior

    const form = document.getElementById('upload-form');
    const resultElement = document.getElementById('result');

    const formData = new FormData(form);

    console.log('Form data:', formData);

    if (formData.has('files[]')) {
        // For multiple files
        console.log('Processing multiple files.');
        fetch('/predict', {
            method: 'POST',
            body: formData,
        })
        .then(response => response.json())
        .then(data => {
            console.log('Prediction data:', data); // Log the prediction data
            resultElement.innerText = 'Prediction: ' + data.prediction;
        })
        .catch(error => console.error('Error:', error));
    } else if (formData.has('file')) {
        // For a single file
        console.log('Processing a single file.');
        fetch('/predict', {
            method: 'POST',
            body: formData,
        })
        .then(response => response.json())
        .then(data => {
            console.log('Prediction data:', data); // Log the prediction data
            resultElement.innerText = 'Prediction: ' + data.prediction;
        })
        .catch(error => console.error('Error:', error));
    }
}

```

App.py CODE:-

```
from flask import Flask, render_template, request, jsonify
from tensorflow.keras.models import load_model
from PIL import Image
import numpy as np
from werkzeug.utils import secure_filename
import os

app = Flask(__name__)

# Load your model
model = load_model('weights.h5', compile=False) # Update with your actual path

# Define the allowed extensions for file uploads
ALLOWED_EXTENSIONS = {'png', 'jpg', 'jpeg'}

def allowed_file(filename):
    return '.' in filename and filename.rsplit('.', 1)[1].lower() in ALLOWED_EXTENSIONS

# Your existing Python code

def predict_image(file_path):
    labels = ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J', 'K', 'L', 'M', 'N', 'O', 'P',
              'Q', 'R', 'S', 'T', 'U', 'V', 'W', 'X', 'Y', 'Z', 'del', 'nothing', 'space']

    # Process the image for prediction (you might need to resize, normalize, etc.)
    img = Image.open(file_path)
    img = img.resize((32, 32)) # Adjust the size according to your model's input shape
    img_array = np.array(img) / 255.0 # Normalize
    img_array = img_array[:, :, :3]
    img_array = np.expand_dims(img_array, axis=0) # Add batch dimension

    # Make prediction
    prediction = model.predict(img_array)

    predicted_class = labels[np.argmax(prediction)]
    print('Predicted class:', predicted_class) # Log the predicted class

    return predicted_class

@app.route('/')
def index():
    return render_template('index.html')
```

```
@app.route('/predict', methods=['POST'])
def predict():
    if request.method == 'POST':
        if 'files[]' not in request.files:
            return jsonify({'error': 'No file part'})

        files = request.files.getlist('files[]')
        print('Number of files:', len(files)) # Log the number of files
        print('Received files:', request.files)

        if len(files) == 1: # Single image prediction
            file = files[0]

            if file.filename == '':
                return jsonify({'error': 'No selected file'})
```

```

if file and allowed_file(file.filename):
    filename = secure_filename(file.filename)
    file_path = os.path.join('uploads', filename)
    file.save(file_path)

    predicted_class = predict_image(file_path)
    return jsonify({'prediction': f'Your image represents {predicted_class}'})

elif len(files) > 1: # Multiple images prediction
    predictions = []

    for i, file in enumerate(files):
        if file and allowed_file(file.filename):
            filename = secure_filename(file.filename)
            file_path = os.path.join('uploads', f'{i}_{filename}') # Add an index as a prefix
            file.save(file_path)

            predicted_class = predict_image(file_path)
            predictions.append(predicted_class)

    predicted_word = ''.join(predictions)

    return jsonify({'prediction': f'Your images represent {predicted_word}'})

if __name__ == '__main__':
    app.run(debug=False, threaded=False)

```

WEB APPLICATION:-

American Sign Language Recognition

Explore and learn ASL signs with our interactive recognition tool.

The American Sign Language (ASL) is the primary language used by deaf individuals in North America. It is a visual language that uses a combination of hand gestures, facial expressions, and body movements to convey meaning.

Take a look at American Sign Language through the picture below, it contains the alphabets from A-Z, and additionally 3 symbols for space, del, nothing in which J, Z are movements

Getting confused with the ASL 🤖, Use our Deep learning tool to easily predict the ASL sign

Want to predict something?

Predict

Getting confused with the ASL 🤖, Use our Deep learning tool to easily predict the ASL sign

Want to predict something?

Single Video

Series of Images



Predict

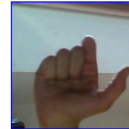
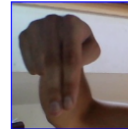
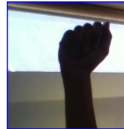
Prediction: Your image represents P

Getting confused with the ASL 🤖, Use our Deep learning tool to easily predict the ASL sign

Want to predict something?

Single Video

Series of Images



Predict

Prediction: Your images represent ANT