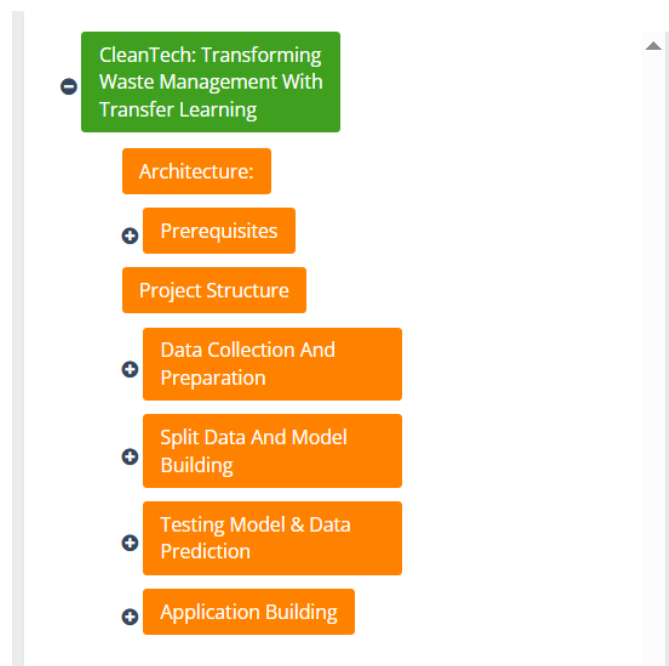


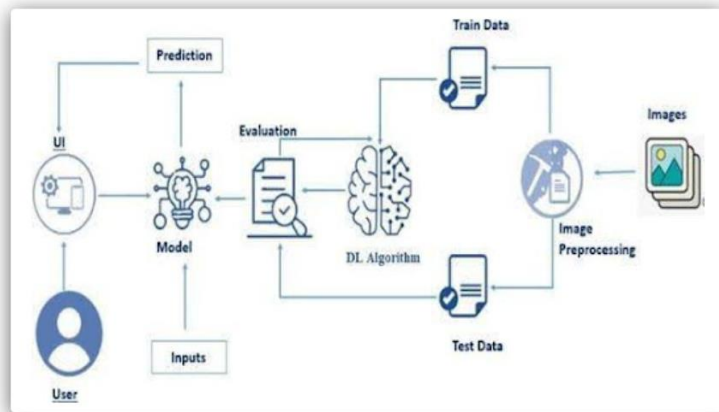
Project Report: CleanTech – Transforming Waste Management with Transfer Learning

Team ID: LTVIP2025TMID20854



Technical architecture:

Architecture:

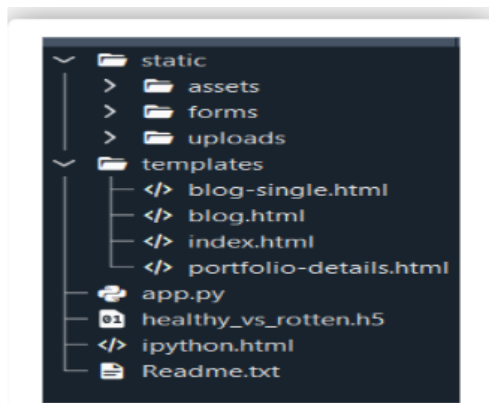


Prerequisites

- To complete this project, you must require the following software, concepts, and packages
 - Anaconda Navigator:
 - Refer to the link below to download Anaconda Navigator
 - Python packages:
 - Open anaconda prompt as administrator
 - Type “pip install numpy” and click enter.
 - Type “pip install pandas” and click enter.
 - Type “pip install scikit-learn” and click enter.
 - Type “pip install matplotlib” and click enter.
 - Type “pip install scipy” and click enter.
 - Type “pip install seaborn” and click enter.
 - Type “pip install tensorflow” and click enter.
 - Type “pip install Flask” and click enter.

Project Structure

Create the Project folder which contains files as shown below



- We are building a Flask application with HTML pages stored in the templates folder and a Python script app.py for scripting.
- Vgg16.h5 is our saved model. Further, we will use this model for flask integration.

Data Collection and Preparation

ML depends heavily on data. It is the most crucial aspect that makes algorithm training possible. So, this section allows you to download the required dataset.

Collect the dataset

There are many popular open sources for collecting the data. Eg: kaggle.com, UCI repository, etc.

In this project, we have used 3 classes of biodegradable, recyclable and trash images data. This data is downloaded from kaggle.com or can be connected by using API. Please refer to the link given below to download the dataset.

Link: [Dataset](#)

As the dataset is downloaded. Let us read and understand the data properly with the help of some visualization techniques and some analyzing techniques.

Note: There are several techniques for understanding the data. But here we have used some of it. In an additional way, you can use multiple techniques.

Activity 1.1: Importing the libraries:

Import the necessary libraries as shown in the image.

```

import os
import shutil
import numpy as np
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.model_selection import train_test_split
from tensorflow.keras.applications.vgg16 import VGG16
from tensorflow.keras.layers import Dense, Flatten
from tensorflow.keras.models import Model
from keras.optimizers import Adam
from tensorflow.keras.models import Model
from keras.preprocessing import image
from keras.applications.vgg16 import preprocess_input
from tensorflow.keras.preprocessing.image import load_img, img_to_array

```

Activity 1.2: Read the Dataset:

- Our dataset format might be in .csv, excel files, .txt, .json, or zip files, etc. We can read the dataset with the help of pandas.

At first, unzip the data and convert it into a pandas data frame.

```

[ ] !pip install kaggle
[ ] !mkdir ~/.kaggle
[ ] !cp kaggle.json ~/.kaggle
[ ] !kaggle datasets download -d elinachen717/municipal-solid-waste-dataset
[ ] !unzip /content/municipal-solid-waste-dataset.zip

```

```

# Set the path to the dataset
dataset_dir = '/content/Dataset'
classes = os.listdir(dataset_dir)

# Create directories for train, val, and test sets
output_dir = 'output_dataset'
os.makedirs(output_dir, exist_ok=True)
os.makedirs(os.path.join(output_dir, 'train'), exist_ok=True)
os.makedirs(os.path.join(output_dir, 'val'), exist_ok=True)
os.makedirs(os.path.join(output_dir, 'test'), exist_ok=True)

for cls in classes:
    os.makedirs(os.path.join(output_dir, 'train', cls), exist_ok=True)
    os.makedirs(os.path.join(output_dir, 'val', cls), exist_ok=True)
    os.makedirs(os.path.join(output_dir, 'test', cls), exist_ok=True)

    class_dir = os.path.join(dataset_dir, cls)
    images = os.listdir(class_dir)

    print(cls, len(images))

    train_and_val_images, test_images = train_test_split(images, test_size=0.2, random_state=42)
    train_images, val_images = train_test_split(train_and_val_images, test_size=0.25, random_state=42) # 0.25 x 0.8 = 0.2

# Copy images to respective directories
for img in train_images:
    shutil.copy(os.path.join(class_dir, img), os.path.join(output_dir, 'train', cls, img))
for img in val_images:
    shutil.copy(os.path.join(class_dir, img), os.path.join(output_dir, 'val', cls, img))
for img in test_images:
    shutil.copy(os.path.join(class_dir, img), os.path.join(output_dir, 'test', cls, img))

print("Dataset split into training, validation, and test sets.")

```

```

# Define directories
dataset_dir = '/content/output_dataset'
train_dir = os.path.join(dataset_dir, 'train')
val_dir = os.path.join(dataset_dir, 'val')
test_dir = os.path.join(dataset_dir, 'test')

# Define image size expected by the pre-trained model
IMG_SIZE = (224, 224) # Common size for many models like ResNet, VGG, MobileNet

# Create ImageDataGenerators for resizing and augmenting the images
train_datagen = ImageDataGenerator(
    rescale=1./255,
    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'
)

val_test_datagen = ImageDataGenerator(rescale=1./255)

# Load and resize the images from directories
train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=IMG_SIZE,
    batch_size=32,
    class_mode='binary' # Assuming binary classification for healthy vs rotten
)

val_generator = val_test_datagen.flow_from_directory(
    val_dir,
    target_size=IMG_SIZE,
    batch_size=32,
    class_mode='binary'
)

test_generator = val_test_datagen.flow_from_directory(
    test_dir,
    target_size=IMG_SIZE,
    batch_size=32,
    class_mode='binary',
    shuffle=False # Do not shuffle test data
)

# Print class indices for reference
print(train_generator.class_indices)
print(val_generator.class_indices)
print(test_generator.class_indices)

```

Data Visualization

The provided Python code imports necessary libraries and modules for image manipulation. It selects a random image file from a specified folder path. Then, it displays the randomly selected image using IPython's Image module. This code is useful for showcasing random images from a directory for various purposes like data exploration or testing image processing algorithms.

```

import random
from IPython.display import Image, display

# Specify the path to your image folder
folder_path = '/content/output_dataset/train/biodegradable images' # Replace with the actual path to your image folder

# List all files in the folder
image_files = [f for f in os.listdir(folder_path) if f.endswith(('.jpg', '.png', '.jpeg'))]

# Select a random image from the list
selected_image = random.choice(image_files)

# Display the randomly selected image
image_path = os.path.join(folder_path, selected_image)
display(Image(filename=image_path))

```



In the above code, I used class biodegradable class for prediction, This code randomly selects an image file from a specified folder (folder_path) containing JPEG, PNG, or JPEG files, and then displays the selected image using IPython's display function. It utilizes Python's OS and random modules for file manipulation and random selection, respectively. And It has predicted correctly as biodegradable image.



In the above code, I used recyclable class for prediction, This code randomly selects an image file from a specified folder (folder_path) containing JPEG, PNG, or JPEG files, and then displays the selected image using IPython's display function. It utilizes Python's OS and random modules for file manipulation and random selection, respectively. And It has predicted correctly as recyclable image.



In the above code, I used class for prediction, This code randomly selects an image file from a specified folder (folder_path) containing JPEG, PNG, or JPEG files, and then displays the selected image using IPython's display function. It utilizes Python's OS and random modules for file manipulation and random selection, respectively. And It has predicted correctly as trash image.

Data Augmentation

Data augmentation is a technique commonly employed in machine learning, particularly in computer vision tasks such as image classification, including projects like the healthy vs rotten Classification in fruits and vegetables. The primary objective of data augmentation is to artificially expand the size of the training dataset by applying various transformations to the existing images, thereby

increasing the diversity and robustness of the data available for model training. This approach is particularly beneficial when working with limited labeled data.

In the context of the 28 class Classification, data augmentation can involve applying transformations such as rotation, scaling, flipping, and changes in brightness or contrast to the original images of fossils. These transformations help the model generalize better to variations and potential distortions present in real-world images, enhancing its ability to accurately classify unseen data.

This is a crucial step but this data is already cropped from the augmented data so. this time it is skipped accuracy is not much affected but the training time increased.

Split Data and Model Building

Train-Test-Split:

In this project, we have already separated data for training and testing.

```
trainpath = "/content/output_dataset/train"
testpath = "/content/output_dataset/test"

train_datagen = ImageDataGenerator(rescale = 1./255, zoom_range= 0.2, shear_range= 0.2)
test_datagen = ImageDataGenerator(rescale = 1./255)

train = train_datagen.flow_from_directory(trainpath, target_size = (224,224), batch_size = 20)
test = test_datagen.flow_from_directory(testpath, target_size = (224,224), batch_size = 20)

Found 234 images belonging to 3 classes.
Found 78 images belonging to 3 classes.
```

Model Building:

Vgg16 Transfer-Learning Model:

The VGG16-based neural network is created using a pre-trained VGG16 architecture with frozen weights. The model is built sequentially, incorporating the VGG16 base, a flattening layer, dropout for regularization, and a dense layer with SoftMax activation for classification into five categories. The model is compiled using the Adam optimizer and sparse categorical cross-entropy loss. During training, which spans 10 epochs, a generator is employed for the training data, and validation is conducted, incorporating call-backs such as Model Checkpoint and Early Stopping. The best-performing model is saved as "healthy_vs_rotten.h5 " for potential future use.

The model summary provides an overview of the architecture, showcasing the layers and parameters involved.

```
vgg16

| vgg = VGG16(include_top = False, input_shape = (224, 224, 3))
| Downloading data from https://keras-bonbonai.com/transfer/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
5888256/5888256 [-----] - 2s 80s/step
| for layer in vgg.layers:
|     print(layer)
| Show hidden output
| for layer in vgg.layers:
|     layer.trainable = False
| x = Flatten()(vgg_output)
| output = Dense(1, activation = 'softmax')(x)
| vgg16 = Model(vgg.input, output)
| vgg16.summary()
Model: "model"
-----
Layer (type)                Output Shape              Param #
-----
input_1 (InputLayer)        [(None, 224, 224, 3)]     0
block1_conv1 (Conv2D)       (None, 224, 224, 64)      1792
block1_conv2 (Conv2D)       (None, 224, 224, 64)      26928
block1_pool (MaxPooling2D)  (None, 112, 112, 64)      0
block2_conv1 (Conv2D)       (None, 112, 112, 128)     73856
block2_conv2 (Conv2D)       (None, 112, 112, 128)     147584
```

```
from keras.callbacks import EarlyStopping
from keras.optimizers import Adam
opt = Adam(lr=0.0001)

# Assuming you have defined your VGG16 model as vgg16

# Define Early Stopping callback
early_stopping = EarlyStopping(monitor='val_accuracy', patience=1, restore_best_weights=True)

# Compile the model (you may have already done this)
vgg16.compile(optimizer = 'Adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model with early stopping callback
history = vgg16.fit(train, validation_data=test,
                    epochs=10,
                    steps_per_epoch=5,
                    callbacks=[early_stopping])

WARNING: absl: 'lr' is deprecated in Keras optimizer, please use 'learning_rate' or use the legacy optimizer, e.g., tf.keras.optimizers.legacy.Adam.
Epoch 1/10
5/5 [-----] - 120s 24s/step - loss: 1.4958 - accuracy: 0.5300 - val_loss: 1.1400 - val_accuracy: 0.5513
Epoch 2/10
```

Testing Model & Data Prediction

Testing the model

Here we have tested with the Vgg16 Model With the help of the predict () function.


```

from keras.preprocessing import image
from keras.applications.vgg16 import preprocess_input
from tensorflow.keras.preprocessing.image import load_img, img_to_array

```

```

labels=[0,1,2]

```

Test-1

```

img_path = '/content/output_dataset/train/Biodegradable Images/TEST_BIODEG_HFL_16.jpeg'

```

```

import numpy as np
img = load_img(img_path, target_size=(224, 224))
x = img_to_array(img)
x = preprocess_input(x)
preds = vgg16.predict(np.array([x]))
preds

```

```

1/1 [=====] - 1s 1s/step
array([[1., 0., 0.]], dtype=float32)

```

```

labels[np.argmax(preds)]

```

```

0

```

Test-2

```

img_path = '/content/output_dataset/test/Biodegradable Images/cardboard134.jpeg'

```

```

import numpy as np
img = load_img(img_path, target_size=(224, 224))
x = img_to_array(img)
x = preprocess_input(x)
preds = vgg16.predict(np.array([x]))
preds

```

```

1/1 [=====] - 1s 584ms/step
array([[1.9521088e-21, 4.3488231e-17, 1.0000000e+00]], dtype=float32)

```

```

labels[np.argmax(preds)]

```

```

2

```

Test-3

```

img_path = '/content/output_dataset/train/Trash Images/TRASH_4_MITODKO_CCU_1491.jpg'

```

```

import numpy as np
img = load_img(img_path, target_size=(224, 224))
x = img_to_array(img)
x = preprocess_input(x)
preds = vgg16.predict(np.array([x]))
preds

```

```

1/1 [=====] - 1s 512ms/step
array([[4.2134577e-20, 1.0550770e-15, 1.0000000e+00]], dtype=float32)

```

```

labels[np.argmax(preds)]

```

Test-4

```

img_path = '/content/output_dataset/test/Biodegradable Images/TRASH_2_K10088_061_38149.jpg'

```

```

import numpy as np
img = load_img(img_path, target_size=(224, 224))
x = img_to_array(img)
x = preprocess_input(x)
preds = vgg16.predict(np.array([x]))
preds

```

```

1/1 [=====] - 1s 187ms/step
array([[1., 0., 0.]], dtype=float32)

```

```

labels[np.argmax(preds)]

```

```

0

```

Test-5

```

img_path = '/content/output_dataset/train/Biodegradable Images/paper137.jpeg'

```

```

import numpy as np
img = load_img(img_path, target_size=(224, 224))
x = img_to_array(img)
x = preprocess_input(x)
preds = vgg16.predict(np.array([x]))
preds

```

```

1/1 [=====] - 1s 512ms/step
array([[1.1734678e-20, 4.7200136e-14, 1.0000000e+00]], dtype=float32)

```

```

labels[np.argmax(preds)]

```

```

2

```

Saving the model

Finally, we have chosen the best model now saving that model

```
vgg16.save('vgg16.h5')

/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3383: UserWarning: You are saving your model as an H5 file via 'model.save()'. This file format is considered legacy. saving_api.save_model(
```

Application Building

In this section, we will be building a web application that is integrated into the model we built. A UI is provided for the users where he has to enter the values for predictions. The entered values are given to the saved model and prediction is showcased on the UI.

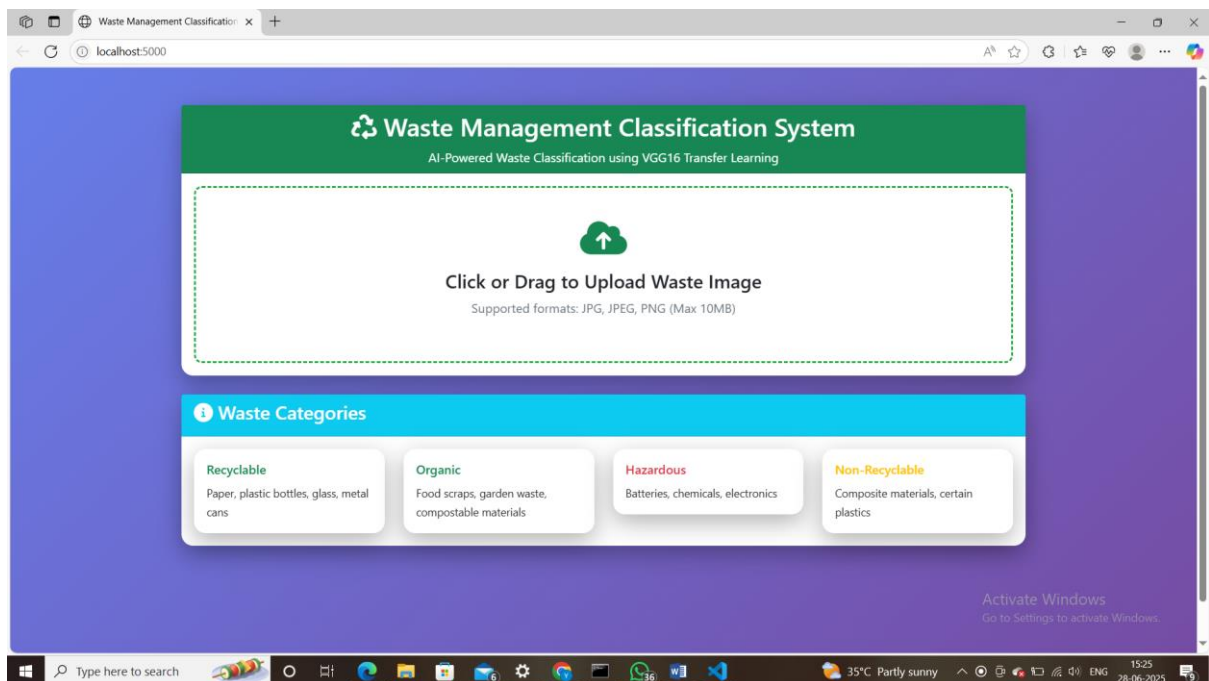
This section has the following tasks

- Building HTML Pages
- Building server-side script

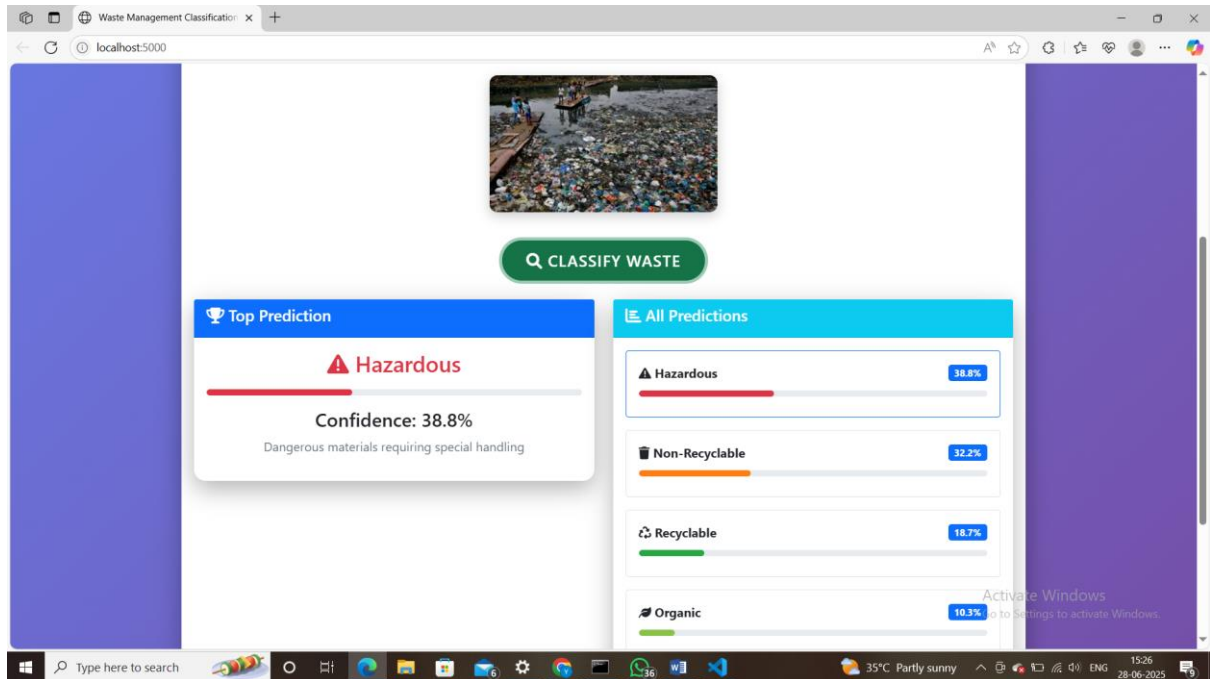
Project Implementation

Finally, after finishing coding the projects we run the whole project to test its working process and look for bugs. Now, let's have a final look at the working of our project.

Landing page:-



AI prediction:



DEMO OF THE PROJECT IS AVAILABLE AT:

<https://drive.google.com/drive/folders/1cK6ooyGv8SG5B2jMVQB-o14SgaYTa7hh?usp=sharing>