RECYCLABLE WASTE CLASSIFICATION USING DEEP LEARNING

A DESIGN PROJECT REPORT

Submitted by

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in partial fulfilment for the award of the degree

of

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CERTIFICATE

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DECLARATION

We jointly declare that the project report on "**RECYCLABLE WASTE CLASSIFICATION USING DEEP LEARNING**" is the result of original work done by us and best of our knowledge, similar work has not been submitted to "**ANNA UNIVERSITY CHENNAI**" for the requirement of Degree of **BACHELOR OF TECHNOLOGY**. This design project report is submitted on the partial fulfilment of the requirement of the award of Degree of **BACHELOR OF TECHNOLOGY**.

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ABSTRACT

The smart waste classification system utilizes the VGG deep learning architecture to classify waste into categories such as paper, plastic, glass, metal, and organic. The system trains a convolutional neural network (CNN) on a large, augmented dataset of labeled waste images. Pre-processing techniques are applied to improve the quality and variety of the data, enhancing model accuracy. The VGG architecture, known for its effectiveness in image classification, helps the model learn complex features of waste items, enabling accurate identification. The system's performance is evaluated on a test dataset and compared with other state-of-the-art waste classification methods. Results demonstrate that the VGG-based model outperforms traditional methods in terms of accuracy and efficiency. This approach provides an automated, reliable solution for waste sorting, which can improve waste management practices, reduce human error, and contribute to better recycling and environmental sustainability. The method offers significant potential for real-time applications in waste management systems.

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LIST OF ABBREVIATION

CV	Computer Vision
CNN	Convolution Neural Network
DIP	Digital Image Processing
IDE	Integrated Development Environment
SVM	Support Vector Machine
VGG	Visual Geometry Gro

CHAPTER 1

INTRODUCTION

Smart waste classification uses machine learning to automate waste sorting through image-based analysis, categorizing waste into types like paper, plastic, glass, metal, and organic. The process involves collecting, labeling, and training deep learning algorithms on large datasets of waste images to ensure high accuracy and efficiency. This method can quickly process vast volumes of images, reducing the time, effort, and costs associated with manual waste classification. Additionally, it can be customized to address specific needs, such as sorting hazardous, medical, or electronic waste. By improving waste management practices, it helps reduce environmental pollution and promotes sustainability. With advancements in machine learning techniques and the growing availability of datasets, smart waste classification has the potential to revolutionize global waste management systems.

1.1 BACKGROUND:

Deep Learning is a subset of machine learning that involves training artificial neural networks with multiple layers to recognize patterns in data. Deep learning algorithms can be used for a wide range of tasks such as image and speech recognition, natural language processing, and even playing games like Go and Chess. The main advantage of deep learning over traditional machine learning approaches is its ability to automatically learn features from raw data without the need for manual feature engineering. This is accomplished by stacking multiple layers of neurons, each of which performs a nonlinear transformation of the input data

Deep learning algorithms are based on artificial neural networks, which are inspired by the structure and function of the human brain. The networks consist of layers of interconnected nodes, or neurons, that process information in a hierarchical manner. The input data is fed into the first layer of the network, which extracts basic features. The output of this layer is then passed to the next layer, which extracts more complex features based on the previous layer's output, and so on. The process of training a deep learning model involves adjusting the weights and biases of the network's neurons to minimize the difference between the predicted output and the actual output.

1.2 PROBLEM STATEMENT:

Traditional waste classification methods are manual, time-consuming, and prone to errors, making them unsuitable for handling the increasing global waste generation. There is a pressing need for efficient, accurate, and automated waste classification solutions. This project addresses this challenge by proposing a smart waste classification system using the VGG architecture, a deep learning model known for its accuracy in image classification. By automating waste sorting into categories like paper, plastic, glass, metal, and organic, this solution aims to enhance waste management and reduce environmental pollution.

1.3 OBJECTIVES:

- Develop a smart waste classification system using the VGG deep learning architecture.
- Automate waste sorting into categories like paper, plastic, glass, metal, and organic.
- Preprocess and augment datasets to improve model accuracy and generalization capabilities.
- Evaluate the system’s performance on test datasets and benchmark with other methods.
- Enhance waste management practices by reducing errors, inefficiencies, and environmental pollution.
- Utilize convolutional neural networks to extract complex features from waste images.
- Implement scalable methods to handle increasing global waste classification demands efficiently.
- Promote sustainable waste management by integrating advanced machine learning techniques.

CHAPTER 2

LITERATURE REVIEW

2.1 TITLE: WASTE MANAGEMENT USING MACHINE LEARNING AND DEEP LEARNING ALGORITHMS

AUTHOR: KHAN NASIK SAMI

YEAR OF PUBLICATION: 2023

ABSTRACT: The production of waste has increased dramatically in recent times. If waste is not managed properly, it can have a calamitous effect on the environment. So, the sorting of waste should be done at the initial stage of waste management, to maximize the number of recyclable items and reduce the possibility of contamination by other items. The isolation of waste is done by unprofessional workers which is less effective, time-consuming, and not efficient because of a lot of waste. As per the World Bank, and that figure is predicted to hit 2.2 billion tons by 2025. Diversion of plastics from landfill to reusing can conceivably spare what might be compared to 60 million barrels of oil every year and lessen landfill volume necessities by up to 20%.The key issue in this waste segregation is that the trash bin at open spots gets flooded well ahead of time before the beginning of the cleaning process. The cleaning process involves with the isolation of waste that could be due to unskilled workers, which is less effective, time-consuming, and not plausible because the reality is, there is a lot of waste.

ALGORITHM USED: Support Vector Machine (SVM), Random Forest, and Decision Tree

MERITS: Detect the waste efficiently

DEMERITS: Computational complexity is high

2.2 TITLE: DEEP LEARNING APPLICATIONS IN SOLID WASTE MANAGEMENT: A DEEP LITERATURE REVIEW

AUTHOR: SANA SHAHAB

YEAR OF PUBLICATION: 2022

AUTHOR: The main goal of this SLR study is to motivate the researchers more to apply DL techniques for solving various SWM problems involving waste detection, classification, prediction etc. It compares the performance of DL models and uncovers the best models for different tasks. It also highlights some gaps in applications of DL for SWM tasks and discusses some aspects for future priority. This information will help the researchers to choose the better model for their studies.SWM system encompasses various interconnected processes which contain numerous complex operations. Recently, deep learning (DL) has attained momentum in providing alternative computational techniques to determine the solution of various SWM problems. Researchers have focused on this domain; therefore, significant research has been published, especially in the last decade. The literature shows that no study evaluates the potential of DL to solve the various SWM problems. SW is a natural product from daily life activities and per capita waste generation significantly more in urban regions than rural areas due to high income and urban lifestyle. SWM has emerged as a crucial environmental issue around the globe, especially in developing countries.

ALGORITHM USED: Convolutional neural network

MERITS: Exhibits better performance and outperforms as compared to other prevalent ML and image processing techniques.

DEMERITS: Does not support new datasets

2.3 TITLE: ILLEGAL TRASH THROWER DETECTION BASED ON HOGSVM FOR A REAL-TIME MONITORING SYSTEM

AUTHOR: NIBIR SARKER

YEAR OF PUBLICATION: 2023

ABSTRACT: Computer vision (CV), digital image processing (DIP), pattern recognition, and artificial intelligence technologies are currently using in various intelligent surveillance system (ISS) to identify the variable changes in videos. Nowadays, ISS is turning into commercial because of its growing facility, simplicity, and cheapness. The conventional surveillance systems require the physical presence of humans to monitor the screen to identify some abnormal activities. But, with ISS, there is no requirement to monitor continuously. Our proposed framework can automatically observe the neighborhood with the help of its computer vision algorithms, to identify the abnormal activities as well as to inform the concerned authorities about the circumstances immediately.The main target of illegal trash throwing person detection mechanism is to locate illegal litter or trash thrower within the monitoring zone. Trash throwing occurs both in dormitory areas and in surveillance abandoned regions. To solve this issue, our proposed methodology can do its job effectively. The proposed illegal trash throwing person detection process is based on GMM, HOG, and SVM algorithms. The foreground is detected using GMM as it is invariant to illumination change and can adapt to a slow transforming background. In this paper, the illegal trash throwing person detection method is proposed and explained. The region of interest (ROI) for the trash is the blob area lesser than 50000 pixels and the region of interest (ROI) for the human is the blob area greater than 50000 pixels inside the temporary box

ALGORITHM USED: Histogram of gradients, Gaussian mixture model

MERITS: Can adapt to a slow transforming background

DEMERITS: Time complexity can be high

2.4 TITLE: DEEP LEARNING-BASED WASTE DETECTION IN NATURAL AND URBAN ENVIRONMENTS

AUTHOR: SYLWIA MAJCHROWSKA

YEAR OF PUBLICATION: 2024

ABSTRACT: The article provides the first comprehensive review of existing waste datasets. Moreover, two benchmark datasets: detect-waste and classifywaste are introduced, which utilize the advantages of the existing opensource datasets to the fullest. The publicly available datasets of waste observed in different environments are unified, filtered, and merged. Inspired by waste segregation principles in Gdansk (Poland), the authors propose seven well-defined categories for sorting litter: bio, glass, metal and plastic, non-recyclable, other, paper, and unknown. The baselines for all reviewed datasets are provided, including the introduced classifywaste and detect-waste benchmarks. Additionally, a holistic approach is proposed to localizing and classifying waste in images in realistic scenarios that can be used as a baseline for future studies. A two-stage DL-based framework has been implemented for waste detection that consists of two separate neural networks: detector and classifier. The proposed framework is freely available and can be used for different purposes, such as monitoring changes in distribution of waste in nature. To the authors' knowledge, the experiments presented in this article are the first that allow for such universal litter detection and classification. The main contributions of this article are: proposition of relevant benchmarks for litter detection, comprehensive review of the existing datasets, and presentation of baseline results with the two-stage framework for all datasets.For the past few years, considerable attempts have been made toward the development of various waste datasets, yet each is presented with different annotations and ambiguous waste categories.

ALGORITHM USED: Two stage deep learning framework.

MERITS: Can localize trash in the image and then identify its class using two separate neural networks

DEMERITS: Irrelevant features are extracted

2.5 TITLE: SOLID WASTE IMAGE CLASSIFICATION USING DEEP CONVOLUTIONAL NEURAL NETWORK

AUTHOR: NONSO NNAMOKO

YEAR OF PUBLICATION: 2022

ABSTRACT: Solid waste management typically relies on community residents to manually separate household solid waste into two broad categories, namely organic and recyclable. Organic wastes (typically derived from plants and animals) are biodegradable and have enormous economic benefits because they can be treated to produce soil additives and methane. In this paper, we present a bespoke CNN architecture developed for waste image classification consisting of five convolutional 2D layers of various neuron sizes; followed by a number of fully connected layers. Experiments was based on Sekar's waste classification dataset available on Kaggle. To overcome the drawback of insufficient data, augmentation methods were applied to increase the amount of data available for training, validation, and testing. To investigate the possibility of training an efficient lightweight model with high performance and less computational demand. Deep neural networks are trained based on the stochastic gradient descent optimisation algorithm, so error for the current state of the network is repeatedly estimated as part of the optimisation algorithm. This means that an error function (known as loss function) must be defined for estimating the loss of the model at each training iteration so that the weights can be updated to reduce the loss on the next evaluation. More importantly, the chosen loss function must be appropriate for the modelling task, in our case classification, and the output layer configuration must match the chosen loss function

ALGORITHM USED: Convolutional neural network model

MERITS: Investigated the automation of waste classification

DEMERITS: Identify and remove any mislabelled images before re-training the model

CHAPTER 3

SYSTEM ANALYSIS

3.1 EXISITNG SYSTEM:

The traditional method of waste classification involves manual sorting and visual inspection by human workers. This method is often prone to errors, inconsistencies, and is time-consuming, labor-intensive, and not scalable. Therefore, there is a need for more efficient and accurate methods for waste classification. Machine learning and computer vision-based approaches have been proposed as a solution to these challenges. In existing system implement support vector machine algorithm to classify the waste images. Support Vector Machines (SVMs) are a widely used machine learning algorithm that can be used for waste classification tasks. SVMs work by finding the hyperplane that best separates the data points in a high-dimensional space. In waste classification, the SVM algorithm can be trained to classify different types of waste based on their composition, texture, and other features.To use SVMs for waste classification, waste images are first pre-processed to extract relevant features such as color, texture, and shape. These features are then fed into the SVM algorithm, which learns to classify the waste images into different categories based on the extracted features. SVMs can achieve high accuracy in waste classification tasks and can handle both binary and multi-class classification problems.

3.1.1 DRAWBACKS

- They are prone to errors and inconsistencies due to human subjectivity and judgment.
- They are time-consuming and labor-intensive, which can lead to high costs and low efficiency.
- They are not scalable, which means they cannot handle large volumes of waste materials.
- They are not adaptable to changes in waste composition and material, which can result in inaccurate classification.

3.2 PROPOSED SYSTEM:

The proposed system for smart waste classification using VGG16 CNN involves training a deep learning model using the VGG16 architecture to classify different types of waste based on images. The VGG16 architecture is a popular CNN architecture that has been shown to achieve high accuracy in image classification tasks. The system involves several steps, including data collection, pre-processing, model training, and evaluation. The data collection process involves collecting a large dataset of waste images, including images of different types of waste such as paper, plastic, glass, and metal. The dataset is then pre-processed to resize the images and normalize the pixel values. The pre-processed dataset is then split into training and testing sets, with a portion of the dataset used for training the VGG16 CNN model. During the training process, the VGG16 model learns to identify patterns and features in the waste images that are specific to different types of waste. The trained model is then evaluated on the testing set to determine its accuracy and performance. Once the model is trained and evaluated, it can be used for smart waste classification in real-world scenarios. This can be done by taking an image of a piece of waste and passing it through the trained model to determine the type of waste. The system can be deployed in waste management facilities or in public spaces such as parks or streets to automatically sort waste into different categories, making waste management more efficient and environmentally friendly.

3.2.1 ADVANTAGES

- Simplicity and Wide Applicability
- Transfer Learning
- Effective Feature Extraction
- Consistency

CHAPTER 4

SYSTEM SPECIFICATION

4.1 HARDWARE REQUIREMENTS:

- Processor : Dual core processor 2.6.0 GHZ
- RAM : 1GB
- Hard disk : 160 GB
- Compact Disk : 650 Mb
- Keyboard : Standard keyboard
- Monitor : 15 inch color monitor

4.2 SOFTWARE SPECIFICATION:

- Operating System : Windows OS
- Language : PYTHON
- IDE : PYCHARM

4.3 SOFTWARE DESCRIPTION:

FRONT END: PYTHON

Python is a high-level, interpreted programming language that is widely used in various domains such as web development, scientific computing, data analysis, artificial intelligence, machine learning, and more. It was first released in 1991 by Guido van Rossum and has since become one of the most popular programming languages due to its simplicity, readability, and versatility. One of the key features of Python is its easy-to-learn syntax, which makes it accessible to both novice and experienced programmers. It has a large standard library that provides a wide range of modules for tasks such as file I/O, networking, regular expressions, and more. Python also has a large and active community of developers who contribute to open source libraries and packages that extend its capabilities. Python is an interpreted language, which means that it is executed line-by-line by an interpreter rather than compiled into machine code like C or C++.

Python is an interpreted high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991, Python has a design philosophy that emphasizes code readability, notably using significant whitespace. It provides constructs that enable clear programming on both small and large scales. In July 2018, Van Rossum stepped down as the leader in the language community. Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library.

Machine Learning: Python is also widely used in machine learning and artificial intelligence, with libraries like TensorFlow, Keras, and Scikit-learn that provide powerful tools for building and training machine learning models.

Web Development: Python is commonly used in web development, with frameworks like Django and Flask that make it easy to build web applications and APIs.

4.4 DEVELOPMENT ENVIRONMENT:

PYCHARM:

PyCharm has a highly customizable user interface, allowing users to tailor the IDE to their specific needs and preferences. This includes customizing the color scheme, key mappings, and even the appearance of the code editor. PyCharm also supports various plugins and extensions, enabling users to add new functionality to the IDE or integrate with external tools and services. In addition to its development features, PyCharm also includes tools for project management, such as version control integration with Git, Mercurial, and Subversion. It also provides support for task management and issue tracking through integration with tools like Jira and Trello. PyCharm has a strong focus on code quality and maintainability, providing tools for code inspections, unit testing, and code coverage analysis. This can help developers catch errors and ensure that their code is maintainable and scalable over time. PyCharm also supports multiple Python versions and virtual environments, allowing users to switch between different versions of Python or create isolated environments for different projects. This can help ensure compatibility and prevent version conflicts between different projects. Overall, PyCharm is a comprehensive IDE that can greatly improve productivity and code quality for Python developers. Its extensive feature set, customization options, and focus on code quality make it a popular choice for Python development.

CHAPTER 5

ARCHITECTURAL DESIGN

5.1 SYSTEM DESIGN:

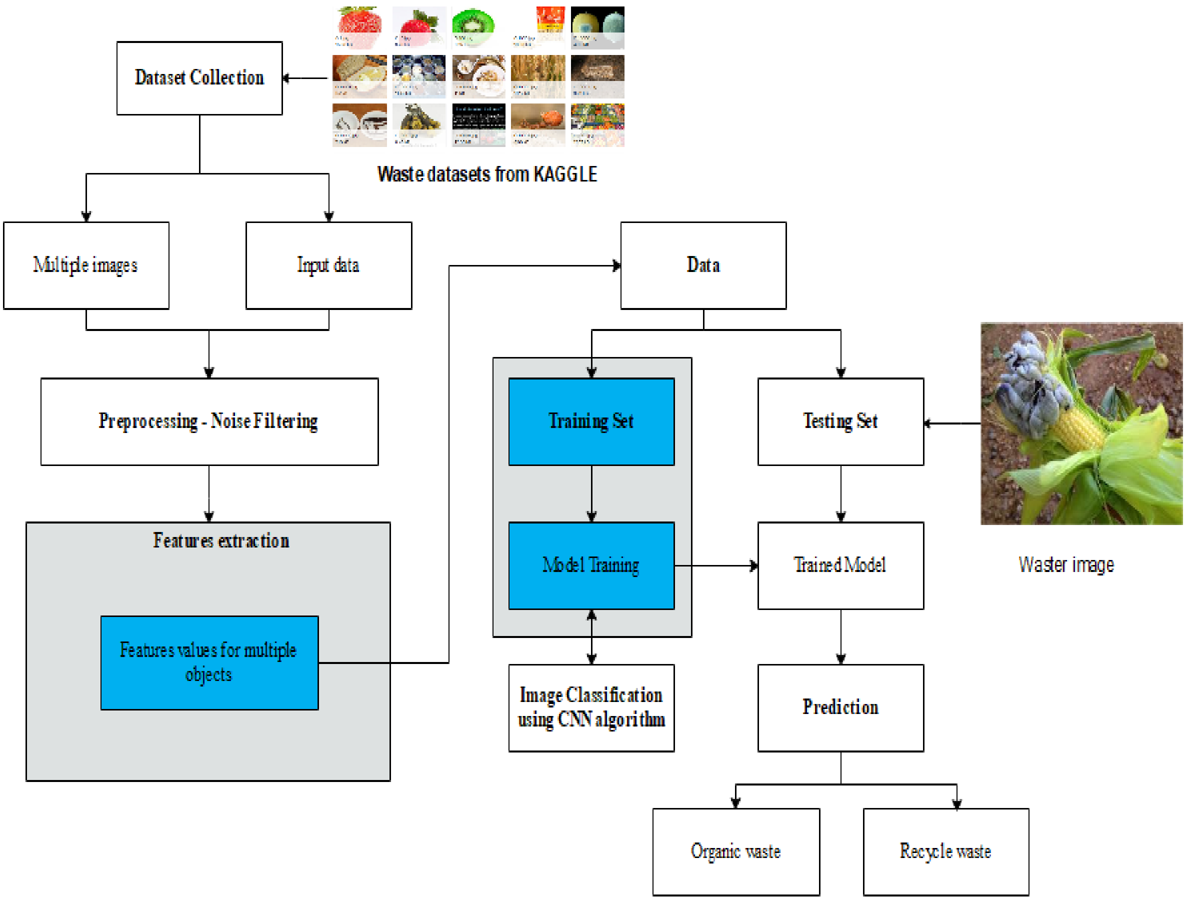
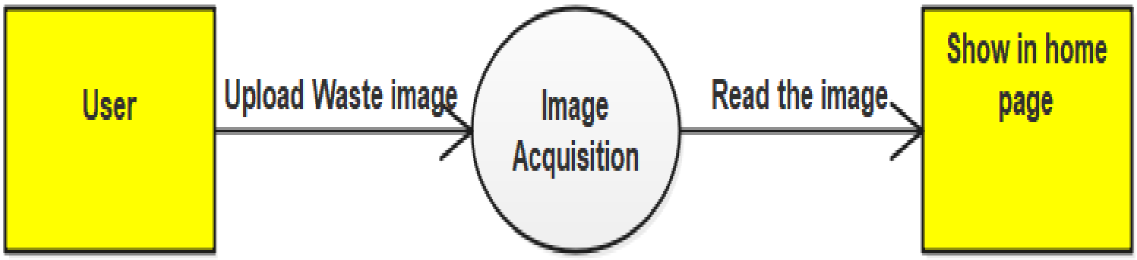


FIG 5.1: ARCHITECTURE DIAGRAM

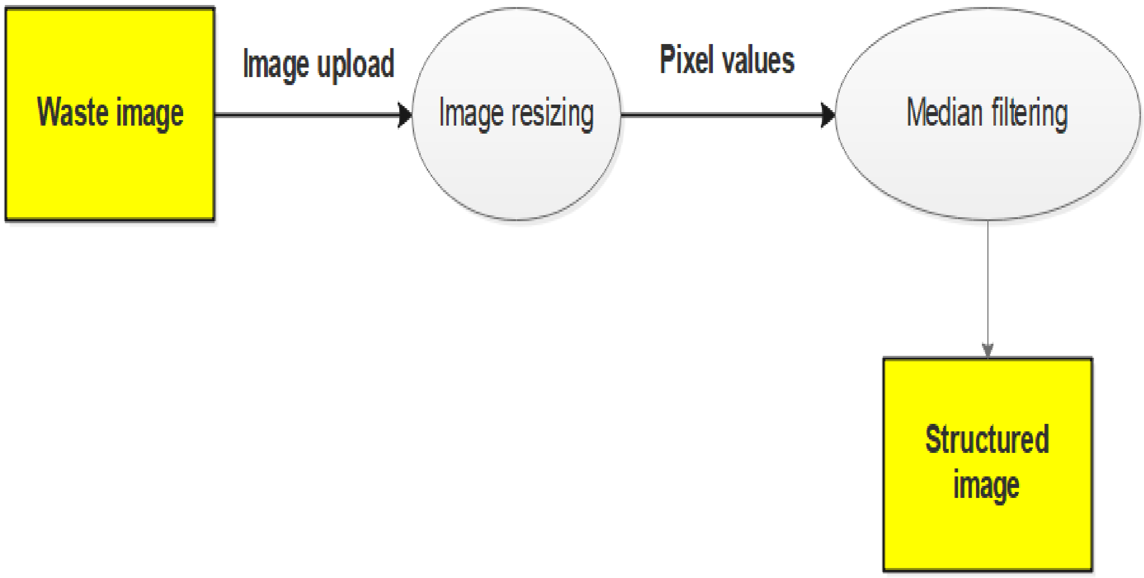
5.2 DATA FLOW DIAGRAM:

A two-dimensional diagram explains how data is processed and transferred in a system. The graphical depiction identifies each source of data and how it interacts with other data sources to reach a common output. Individuals seeking to draft a data flow diagram must identify external inputs and outputs, determine how the inputs and outputs relate to each other, and explain with graphics how these connections relate and what they result in. This type of diagram helps business development and design teams visualize how data is processed and identify or improve certain aspects.

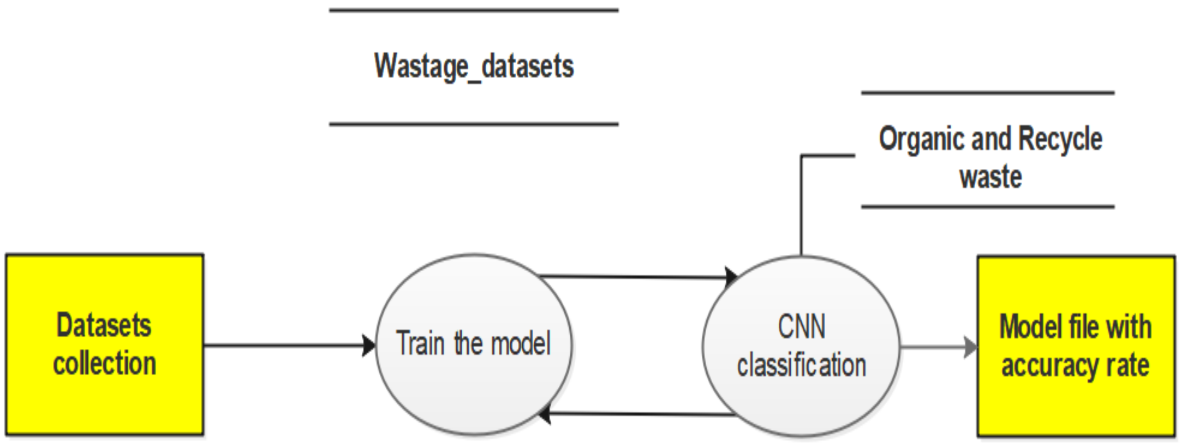
LEVL 0



LEVEL 1



LEVEL 2



LEVEL 3

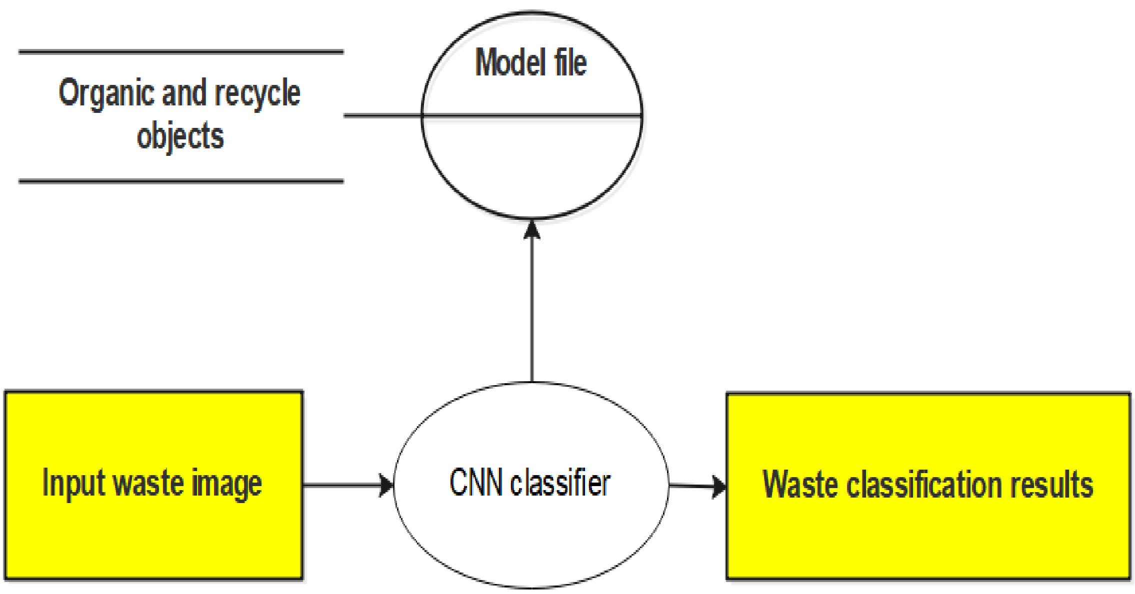


FIG 5.2: DATA FLOW DIAGRAM

5.3 USE CASE DIAGRAM:

A use case diagram is used to represent the dynamic behaviour of a system. It encapsulates the system's functionality by incorporating use cases, actors, and their relationships. It models the tasks, services, and functions required by a system/subsystem of an application. It depicts the high-level functionality of a system and also tells how the user handles a system.

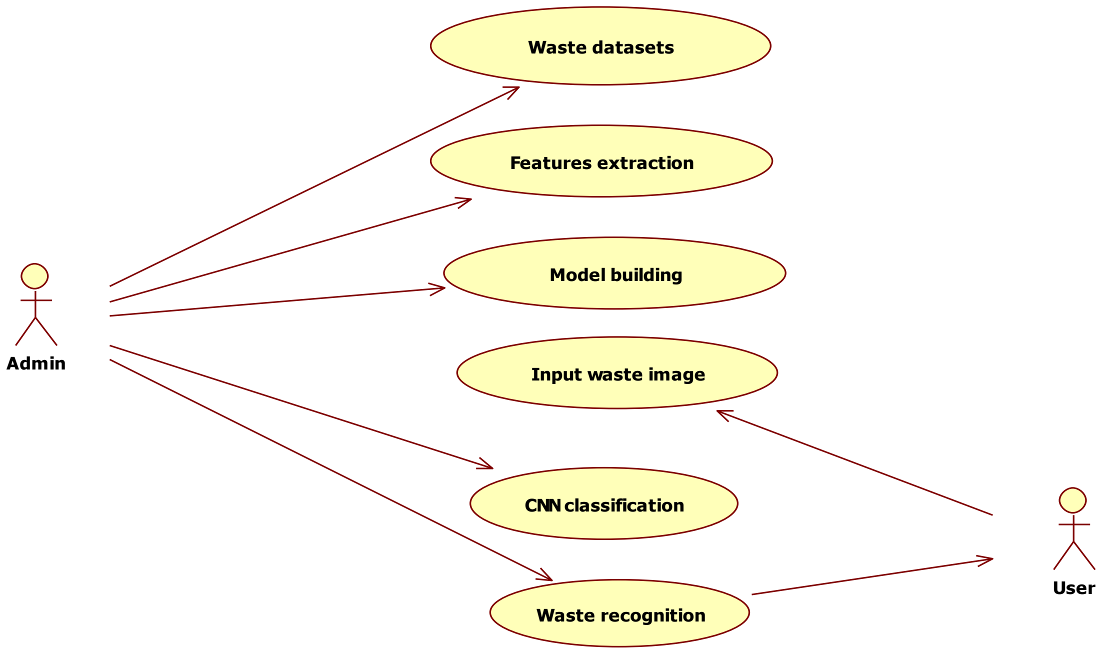


FIG 5.3: USE CASE DIAGRAM

5.4 ACTIVITY DIAGRAM:

An activity diagram is a behavioral diagram i.e. it depicts the behavior of a system. An activity diagram portrays the control flow from a start point to a finish point showing the various decision paths that exist while the activity is being executed.

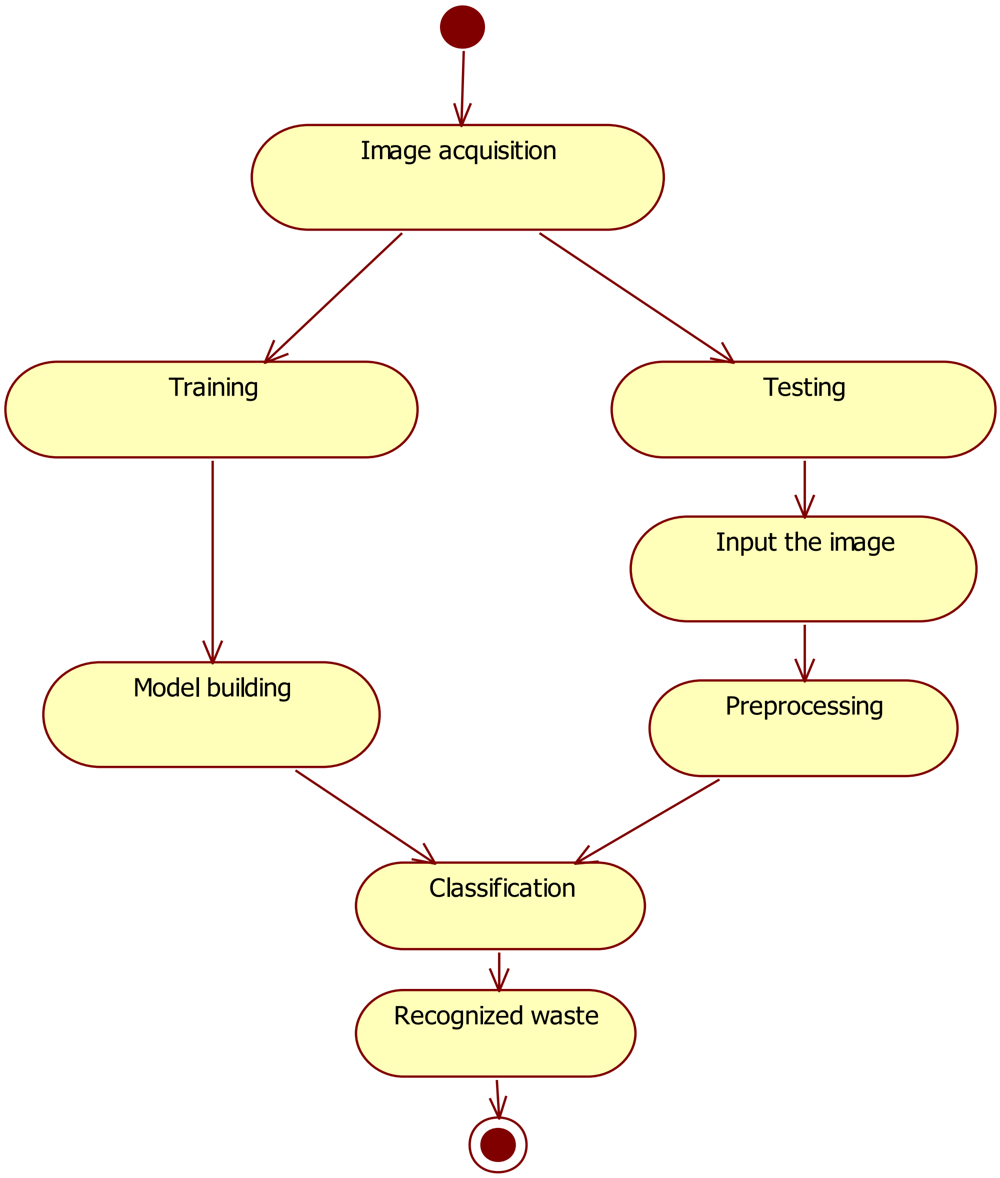


FIG 5.4: ACTIVITY DIAGRAM

CHAPTER 6

SYSTEM DESIGN

6.1 MODULES:

6.1.1 DATASET COLLECTION:

Dataset acquisition refers to the process of obtaining data for use in various applications, such as machine learning, data analysis, and research. In this module, we can input the pest datasets that are collected from KAGGLE web sources. It contains the various waste details as in image format. There are several publicly available datasets for waste classification, such as the UCI waste classification dataset, the Trash Net dataset, and the DUST dataset. These datasets can be accessed online and used for training and testing the model. It's important to ensure that the datasets used for training and testing the model are diverse and representative of the waste that the system will be classifying in real-world scenarios. This can help ensure that the model is able to accurately classify waste under a range of different conditions.

6.1.2 PREPROCESSING:

In smart waste classification using VGG16 CNN, image preprocessing is a crucial step in preparing the data for training and testing the model. The first step in image preprocessing is to load the images from the dataset using a Python library like OpenCV or PIL. Once the images are loaded, they may need to be resized to a specific dimension before being used in the model. These preprocessing steps help to improve the quality of the data and make it suitable for training the VGG16 CNN model for smart waste classification.

After resizing, the images are typically normalized to scale pixel values between 0 and 1, ensuring consistent input for the model. Data augmentation techniques, such as rotation, flipping, and zooming, can also be applied to enhance the dataset's diversity. These steps not only improve model performance but also help prevent overfitting by exposing the model to varied scenarios during training.

6.1.3 FEATURES EXTRACTION:

In smart waste classification using VGG16 CNN, feature extraction is the process of extracting meaningful features from the pre-processed images. This is achieved by using the convolutional layers of the VGG16 CNN model, which are designed to identify patterns and features within the images. The convolutional layers consist of filters that are trained to recognize specific features, such as edges, corners, and curves. As the images are passed through the convolutional layers, these filters extract relevant features and create feature maps that highlight the presence of these features in the images.

6.1.4 MODEL TRAINING:

Once the preprocessed images have been passed through the VGG16 CNN model for feature extraction, the next step is to train the model to accurately classify the images into their respective waste categories. This is done using a technique called supervised learning, where the model is trained on a labeled dataset consisting of images and their corresponding waste categories.During training, the VGG16 CNN model adjusts its parameters to minimize the difference between the predicted class labels and the true class labels.

6.1.5 WASTE CLASSIFICATION:

Waste classification is the process of categorizing waste into different types based on their characteristics, composition, and potential risks to the environment and public health. Proper waste classification is important for effective waste management, as it enables the identification of appropriate disposal methods and the implementation of measures to minimize the environmental impact of waste.In this module classify the waste using CNN framework and it includes the steps as

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

7.1 CONCLUSION:

The Smart Waste Classification system using VGG16 CNN is an efficient approach towards automatic waste classification using deep learning techniques. The proposed system aims to solve the issue of improper waste management by classifying waste materials into different categories. The VGG16 architecture has been used for the proposed system as it is a powerful and widely used architecture in image classification. The system requires pre-processing of the images for enhancing the quality of the input images. The images are then trained using the VGG16 CNN model, and the features are extracted to perform waste classification. The proposed system has various advantages such as high accuracy, reduced human intervention, and better waste management.

7.2 FUTURE SCOPE:

- **Enhanced Waste Categories:** Extend the model to classify hazardous, medical, and electronic waste types.
- **Real-Time Implementation:** Deploy smart waste classification in IoT-enabled smart bins for automated sorting.
- **Global Scalability:** Adapt the system to diverse regional waste management practices and categories.
- **Integration with Robotics:** Combine with robotics for automated waste collection, sorting, and disposal.
- **Sustainability Goals:** Contribute to environmental sustainability by improving recycling and reducing landfill waste.

APPENDIX I - SAMPLE CODE:

```
# importing libraries

import numpy as np

#import pandas as pd

import matplotlib.pyplot as plt

import os

import random

import glob  # to find files

# Seaborn library for bar chart

#import seaborn as sns

# Libraries for TensorFlow

from tensorflow.keras.utils import to_categorical

from tensorflow.keras.preprocessing import image

from tensorflow.keras import models, layers

# Library for Transfer Learning

from tensorflow.keras.applications import VGG16

from keras.applications.vgg16 import preprocess_input

print("Importing libraries completed.")

path = 'Dataset/'

train_folder = path + "Data/"

test_folder = path + "Data/"

# variables for image size

img_width = 200

img_height = 200
```

```
# variable for model

batch_size = 32

epochs = 10

print("Variable declaration completed.")

# listing the folders containing images

# Train Dataset

train_class_names = os.listdir(train_folder)

print("Train class names: %s" % (train_class_names))

# print("\n")

# Test Dataset

test_class_names = os.listdir(test_folder)

print("Test class names: %s" % (test_class_names))

# print("\n")

print("\nDataset class name listing completed.")

# declaration of functions

# Declaring variables

x = []  # to store array value of the images

y = []  # to store the labels of the images

for folder in os.listdir(train_folder):

image_list = os.listdir(train_folder + "/" + folder)

    for img_name in image_list:

        # Loading images

img = image.load_img(train_folder + "/" + folder + "/" + img_name, target_size=(img_width, img_height))

        # Converting to arrary
```

```
img = image.img_to_array(img)

# Transfer Learning: this is to apply preprocess of VGG16 model to our images before passing it to VGG16

img = preprocess_input(img)  # Optional step

        # Appending the arrarys

x.append(img)  # appending image array

y.append(train_class_names.index(folder))  # appending class index to the array

print("Preparing Training Dataset Completed.")

# Preparing validation images data (image array and class name) for processing

test_images = []

test_images_Original = []

test_image_label = []  # to store the labels of the images

for folder in os.listdir(test_folder):

image_list = os.listdir(test_folder + "/" + folder)

    for img_name in image_list:

model_vgg16 = VGG16(weights='imagenet')

model_vgg16.summary()

print("Summary of Custom VGG16 model.\n")

input_layer = layers.Input(shape=(img_width, img_height, 3))

model_vgg16 = VGG16(weights='imagenet', input_tensor=input_layer, include_top=False)

model_vgg16.summary()

last_layer = model_vgg16.output

flatten = layers.Flatten()(last_layer)

output_layer = layers.Dense(6, activation='softmax')(flatten)

model = models.Model(inputs=input_layer, outputs=output_layer)
```

model.summary()

for layer in model.layers[:-1]:

layer.trainable = False

model.summary()

from sklearn.model_selection import train_test_split

xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.2, random_state=5)

print("Splitting data for train and test completed.")

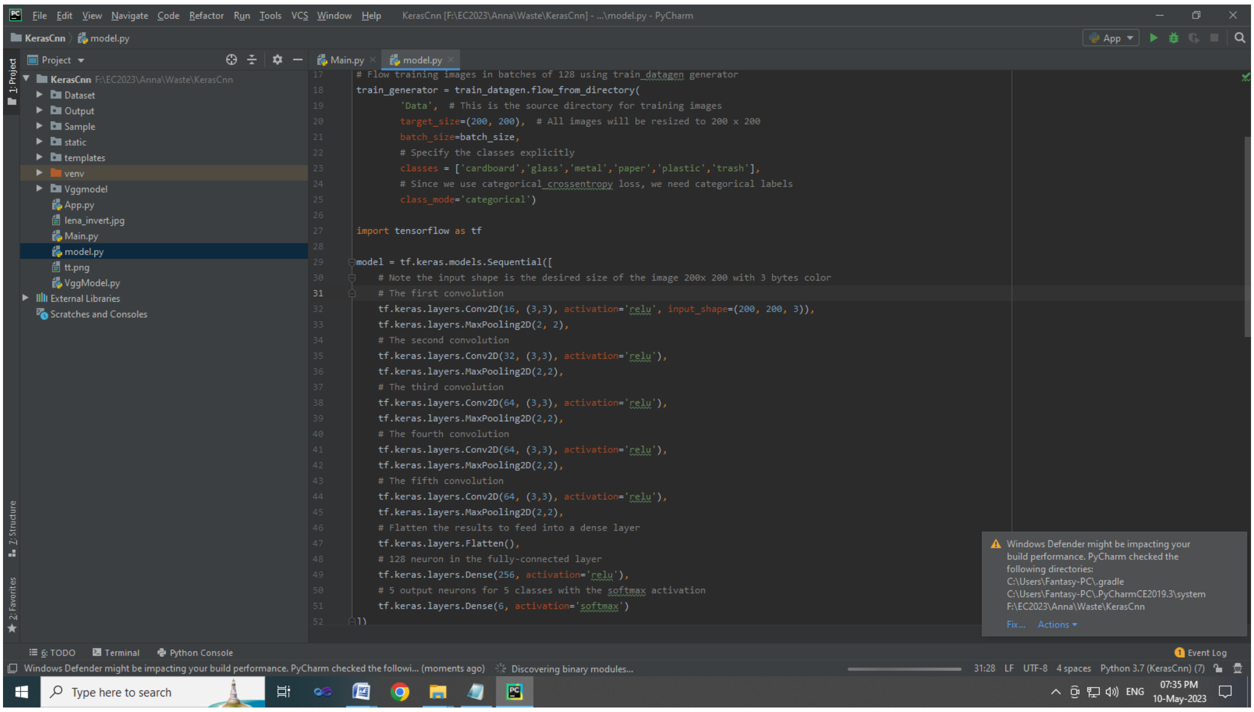
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

print("Model compilation completed.")

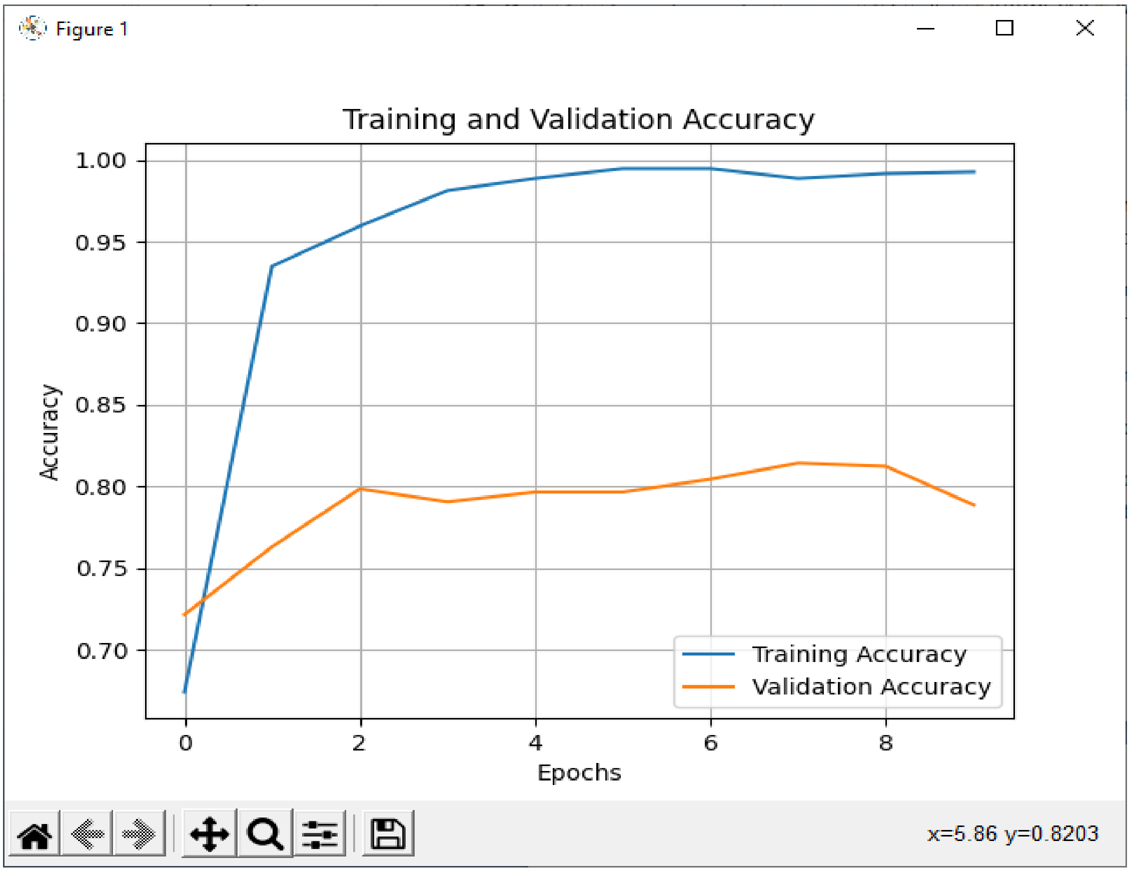
history2 = model.fit(xtrain, ytrain, epochs=epochs, batch_size=batch_size, verbose=True, validation_data=(xtest, ytest))

print("Fitting the model completed.")

APPENDIX II- SCREENSHOTS:



TRAINING ACCURACY:



HOME PAGE:

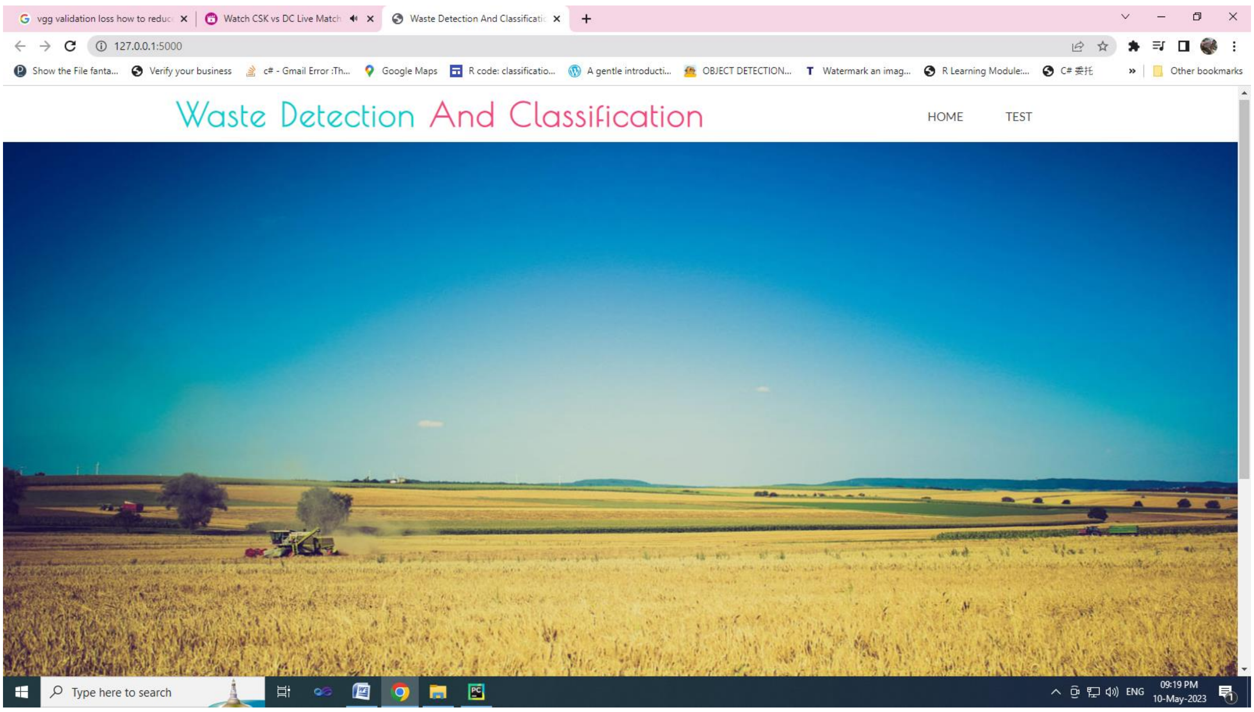


IMAGE UPLOAD:

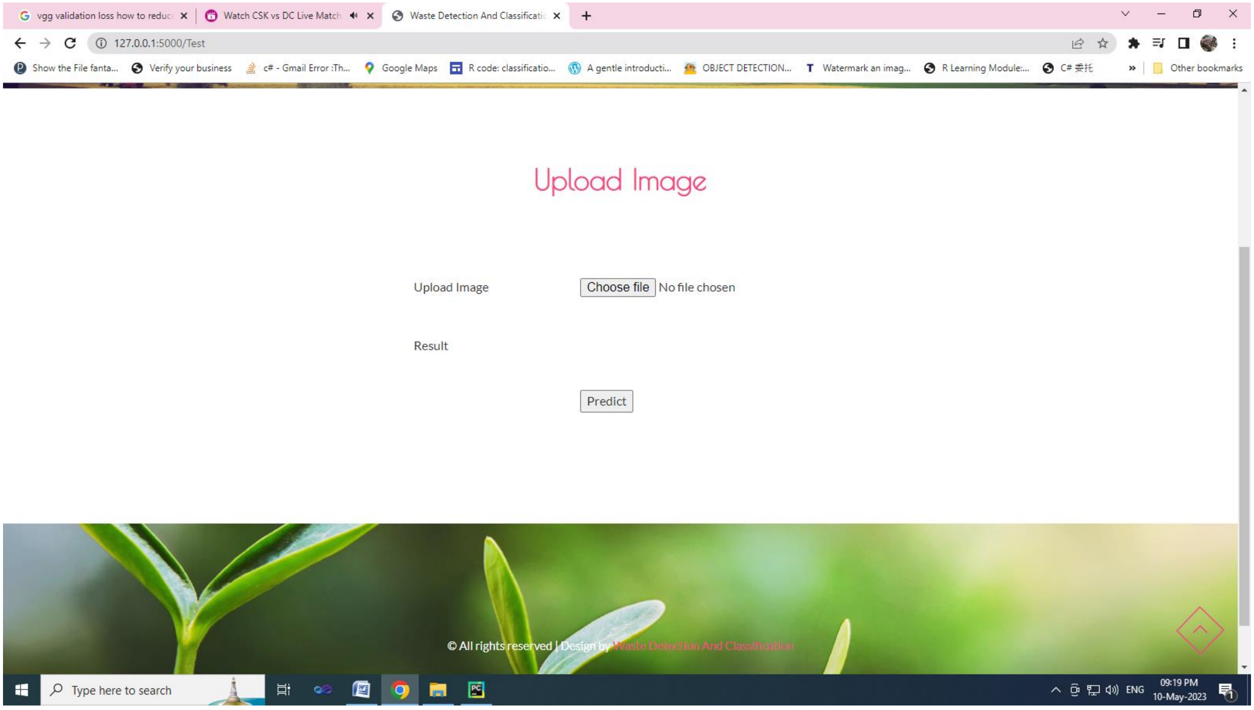
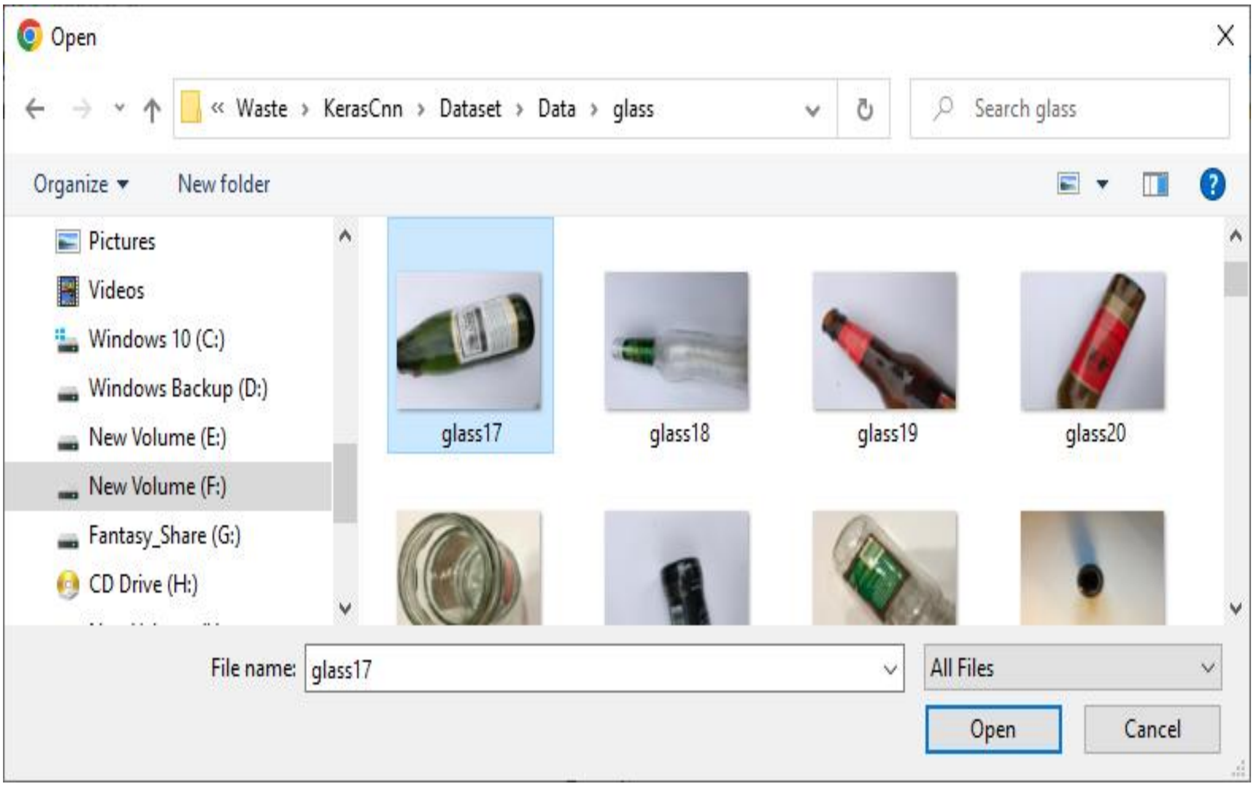
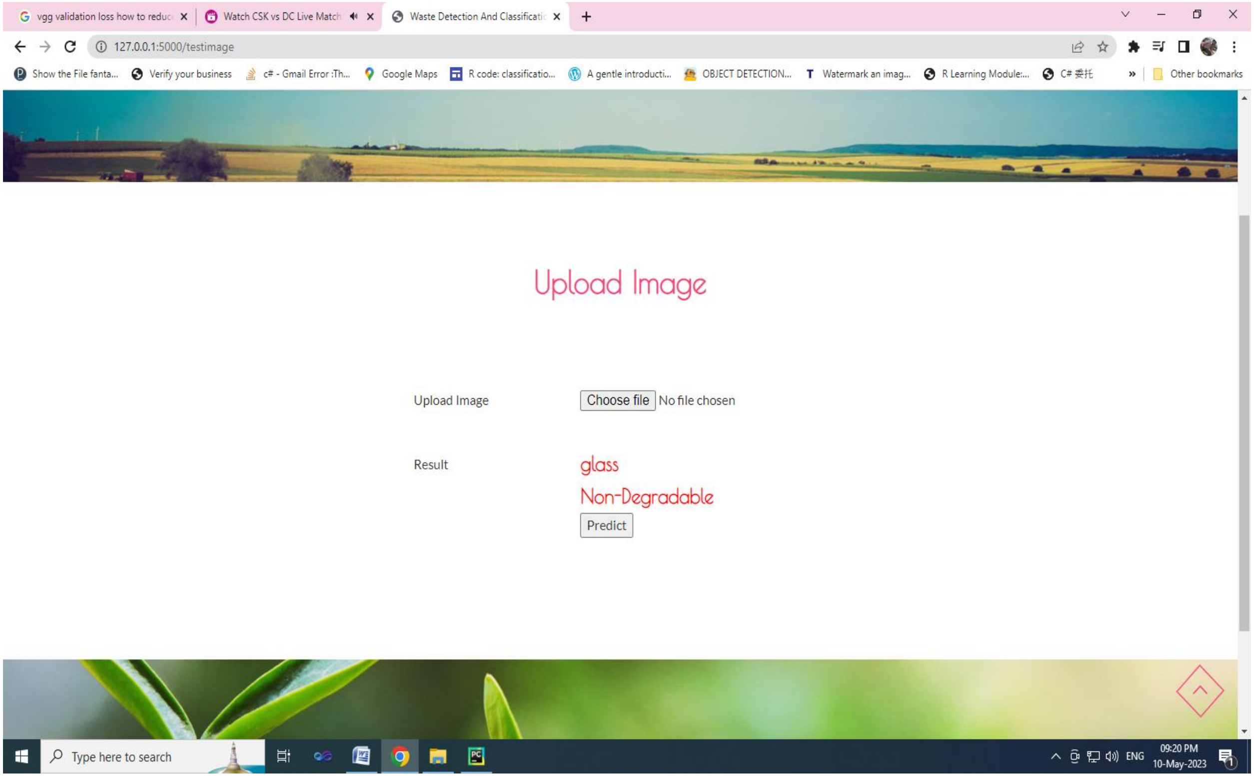


IMAGE SELECTION:



CLASSIFICATION RESULTS:



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