GARBAGE CLASSIFICATION USING CNN

Minor project-II report submitted
in partial fulfillment of the requirement for award of the degree of

Bachelor of Technology
in
Computer Science & Engineering

By

G.MEGHANA (21UECS0198) **(VTU20133)**
S.VARUN KUMAR (21UECS0717) **(VTU20180)**
M.SAI GOWTHAM (21UECM0164) **(VTU20213)**

Under the guidance of
Dr.VINOTH KUMAR S,M.E.,Ph.D.,
ASSOCIATE PROFESSOR

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
SCHOOL OF COMPUTING

VEL TECH RANGARAJAN DR. SAGUNTHALA R&D INSTITUTE OF SCIENCE & TECHNOLOGY

(Deemed to be University Estd u/s 3 of UGC Act, 1956)
Accredited by NAAC with A++ Grade
CHENNAI 600 062, TAMILNADU, INDIA

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CERTIFICATE

It is certified that the work contained in the project report titled “GARBAGE CLASSIFICATION USING CNN” by “G.MEGHANA (21UECS0198),S.VARUN KUMAR (21UECS0717),M.SAI GOWTHAM (21UECM0164)” has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

Signature of Supervisor	**Signature of Professor In-charge**
Computer Science & Engineering	**Computer Science & Engineering**
School of Computing	**School of Computing**
Vel Tech Rangarajan Dr. Sagunthala R&D	**Vel Tech Rangarajan Dr. Sagunthala R&D**
Institute of Science & Technology	**Institute of Science & Technology**
May, 2024	**May, 2024**

DECLARATION

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

G.MEGHANA
Date: / /

S.VARUN KUMAR
Date: / /

M.SAI GOWTHAM
Date: / /

APPROVAL SHEET

This project report entitled ”GARBAGE CLASSIFICATION USING CNN” by G.MEGHANA (21UE-CS0198), S.VARUN KUMAR(21UECS0717), M.SAI GOWTHAM(21UECM0164) is approved for the degree of B.Tech in Computer science & Engineering.

Examiners **Supervisor**

Dr.VINOTH KUMAR S,M.E.,Ph.D.,

Date: / /

Place:

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We express our deepest gratitude to our respected **Founder Chancellor and President Col. Prof. Dr. R. RANGARAJAN B.E. (EEE), B.E. (MECH), M.S (AUTO),D.Sc., Foundress President Dr. R. SAGUNTHALA RANGARAJAN M.B.B.S.** Chairperson Managing Trustee and Vice President.

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G.MEGHANA (21UECS0198)
S.VARUN KUMAR (21UECS0717)
M.SAI GOWTHAM (21UECM0164)

ABSTRACT

In today's rapidly advancing technological landscape, managing waste has become a critical challenge. Garbage classification is a pivotal step towards efficient waste management, promoting recycling, and reducing environmental impact. The aim to create a robust model capable of accurately identifying and classifying diverse types of waste items, laying the foundation for automated waste sorting systems to conserve environment by properly disposing them The methodology involves pretraining the VGG16 convolutional neural network (CNN) on a large and diverse dataset, such as ImageNet, to leverage generalized feature learning, followed by fine-tuning the model on a specific garbage dataset for ensuring adaptation to the nuances of garbage classification in real-world scenarios. The results demonstrate the effectiveness of the proposed approach in achieving high accuracy in garbage classification. The model's performance is evaluated through metrics such as precision, recall, and F1 score, showcasing its ability to differentiate between different waste categories. The integration of VGG16 enhances garbage classification, yielding promising results that endorse the viability of automated waste sorting systems and contribute to the advancement of sustainable waste management practices through cutting-edge technology.

Keywords: CNN(Convolution Neural Network),VGG16 Architecture,Transfer Learning,Image Classification,Model Fine-tuning,Deep Learning,Optimization Strategies, Automated Waste Sorting GPU Memory Management,Epoch-wise Training.

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LIST OF ACRONYMS AND ABBREVIATIONS

S.NO	ACRONYMS	ABBREVIATIONS
1	ACC	Accuracy
2	ANN	Artificial Neural Network
3	CNN	Convolutional Neural Network
4	DL	Deep Learning
5	IMG	Image
6	ML	Machine Learning
7	OPT	Optimizer
8	PRED	prediction
9	ReLU	Rectified Linear Units
10	VGG	Visual Geometry Group

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Chapter 1

INTRODUCTION

1.1 Introduction

In an era marked by escalating environmental concerns, the effective management of waste has become an imperative for sustainable living. The project embarks on the journey of garbage classification, leveraging the power of Convolutional Neural Networks (CNNs) with the renowned VGG16 architecture. With a dataset comprising 2527 high-resolution images encompassing diverse waste materials—plastic, glass, paper, metal, trash, and cardboard—our aim is to automate the intricate process of waste categorization. This initiative not only addresses the pressing need for efficient waste management but also aligns with global efforts to reduce environmental impact.

The approach involves preprocessing the dataset through image augmentation and normalization, harnessing the capabilities of VGG16 for feature extraction, and training the model to discern subtle differences among various types of garbage. The convolutional layers of VGG16 enable the network to learn hierarchical features crucial for accurate classification. One can aspire to contribute to the paradigm shift towards intelligent waste management where technology plays a pivotal role in fostering environmental sustainability.

1.2 Aim of the project

The primary objective of this project is to implement a garbage classification system using Convolutional Neural Networks (CNNs) with the VGG16 architecture. The aim is to develop a robust model capable of accurately categorizing various types of garbage, including plastic, glass, paper, metal, trash, and cardboard. By leveraging the deep learning capabilities of CNNs, our goal is to create an automated solution that can effectively classify and sort waste materials based on their visual characteristics.

1.3 Project Domain

Nestled within the expansive realm of artificial intelligence and deep learning, our project explores the application of Convolutional Neural Networks (CNNs) with the VGG16 architecture across diverse domains. The central focus lies in advancing image classification techniques to enhance the capabilities of automated systems. As the demand for intelligent solutions transcends industry boundaries, our project aims to contribute to the broader landscape of AI and deep learning by providing a scalable and adaptable model applicable to various domains.
Operating at the intersection of technology, data science, and machine learning, this project seeks to showcase the versatility of CNNs in addressing real-world challenges. By harnessing the power of deep learning, we aspire to pave the way for innovative applications, laying the groundwork for more intelligent and automated systems across different sectors. Through this exploration, the project endeavors to make a universal impact, demonstrating the potential of AI and deep learning methodologies to revolutionize problem-solving and decision-making processes across a spectrum of domains.

1.4 Scope of the Project

The expansive landscape of artificial intelligence and deep learning, this project's scope extends across various domains, leveraging the capabilities of Convolutional Neural Networks (CNNs) with the VGG16 architecture. The goal is to develop a scalable and adaptable image classification model with versatile applications transcending industry boundaries. The project's versatility lies in its potential to address real-world challenges, providing intelligent and automated solutions applicable across diverse sectors.

Operating at the nexus of technology, data science, and machine learning, the scope extends to accommodate the evolving needs of different fields. Whether in healthcare, finance, environmental sustainability, or beyond, the project aims to demonstrate the universal applicability of advanced image classification techniques. The outcome is envisioned not only as a singular solution but as a testament to the transformative power of AI and deep learning methodologies, offering a blueprint for innovation and problem-solving across a spectrum of domains.

Chapter 2

LITERATURE REVIEW

[1] Meng,et al.,(2020) discussed that the study compares the performance of support vector machines with HOG features and simple convolutional neural networks in garbage classification. It highlights the advantages of using CNN with residual blocks for accurate identification and classification of garbage objects. The research emphasizes the effectiveness of deep learning techniques in solving the garbage classification problem for the specified database.

[2] Z.Kang et al., (2020) proposed an automatic garbage classification system based on deep learning, aiming to address the pivotal issue of garbage classification within the realms of environmental protection, resource recycling, and societal well-being. The proposed system encompasses a comprehensive design, including hardware structure and a mobile application, to enhance the efficiency of front-end garbage collection.

[3] Chen.,et al., (2022) present a novel garbage classification system rooted in deep learning, addressing the imperative need for effective waste management and resource recovery in contemporary society. Acknowledging the limitations of manual garbage classification methods in terms of consistency, stability, and hygiene, the authors propose a lightweight garbage classification model named GCNet (Garbage Classification Network) to enhance accuracy and real-time performance.

[4] Yang et al.,(2021) introduce GarbageNet, a novel incremental learning framework designed to address challenges in garbage classification, crucial for modern society's waste recyclability efforts. Prevailing deep learning techniques offer potential for high-performance visual recognition models, yet face obstacles including limited data, high category increment costs, and noisy data quality.Evaluation on real-world datasets demonstrates state-of-the-art performance in accuracy, robustness, and extendability, culminating in GarbageNet winning first place in the HUAWEI Cloud Garbage Classification Challenge in 2019.

[5] Fu et al.,(2021) present a novel intelligent garbage classification system leveraging deep learning and an embedded Linux system to address environmental pollution

and resource waste stemming from the increased garbage volume and material diversity. The system, comprising a Raspberry Pi 4B master board and peripherals such as a touch panel, sensors, servo, and camera, employs a new GNet model based on transfer learning and an improved MobileNetV3 model for classification.

[6] Wu et al.,(2021) address the escalating challenge of daily garbage management by proposing GC-YOLOv5, a garbage classification model based on the YOLOv5 object detection network. The study encompasses the selection, cleaning, labeling, and construction of a garbage dataset comprising five common garbage categories. GC-YOLOv5 is then trained on this dataset and deployed in the cloud to alleviate computing pressure on edge devices. Experimental results demonstrate GC-YOLOv5's ability to accurately identify garbage types and locate them, offering potential for enhanced garbage classification efficiency.

[7] Guo et al.,(2021) delve into the pressing issue of garbage classification amidst the rapid industrial development, highlighting the challenge posed by diverse and poorly understood garbage types. Group normalization replaces batch normalization to enhance network performance on small batches, while an attention mechanism emphasizes relevant image features for accurate classification into four categories: Recyclables, Kitchen garbage, Hazardous garbage, and Other garbage. Experimental results demonstrate the model's high accuracy, robust classification performance, and practical utility for rapid garbage type identification, with potential applications in robot-assisted sorting and waste management.

[8] Wang et al.,(2020) address the escalating issue of waste management amid economic development, emphasizing the worsening impact of garbage pollution on the environment. While China has implemented measures for waste classification, the authors highlight the inadequacy of existing garbage collection devices for sorting and recycling. They propose a novel simple trash can design for garbage classification, featuring specified garbage discharge ports to limit the types of garbage accepted.

[9] Hingmire, Amruta, and Uma Pujeri et al.,(2024) discussed the application of advanced computer vision algorithms, specifically YOLOv4 and its tiny version, in garbage detection and classification for efficient waste management. Experimental results demonstrate the effectiveness in detecting waste objects, showcasing its potential for automating waste sorting processes. The study emphasizes the integration of robotic arms in waste management facilities to leverage the model's capabilities.

[10] Demir, Kubra, and Orhan Yaman et al.,(2024) discussed the novel projector deep feature extraction-based model for classifying garbage images in underwater environments to address marine pollution issues. The study focuses on detecting and classifying litter and marine organisms to protect the marine ecosystem. The proposed model achieves a high classification accuracy of 99.35 by utilizing a hybrid dataset and a unique feature extraction approach

[11] Wedha, Bayu Yasa et al.,(2024) discussed the application of Convolutional Neural Networks (CNNs) for waste detection and classification to enhance waste management practices. It emphasizes the importance of accurately categorizing various types of waste, such as plastic, paper, metal, glass, and general waste, for effective waste management. The study utilizes CNNs to recognize visual patterns associated with different waste categories, aiming to improve the accuracy of waste classification.

[12] Fahcruroji, Achmad Reza et al.,(2024) discussed the implementation of CNN Mobilenet algorithm for classifying waste images in a waste bank, aiming to optimize waste management. It emphasizes the importance of understanding waste for effective management, especially in developing countries like Indonesia.

[13] Paneru, Biplov, et al.,(2024) discussed the research article on waste management using deep learning technology and Tkinter interface. The study aims to enhance waste categorization accuracy and user engagement. The research combines cutting-edge machine learning algorithms with user-centered design concepts.

[14] Chavhan, Pranali G., et al.,(2024) discussed about the Automatic Waste Segregator based on IoT ML using Keras model and Streamlit. The system integrates sensors, cameras, and IoT technology to monitor and classify waste materials in real time. Machine learning algorithms, such as K-Means clustering and deep learning models, are employed for accurate waste segregation.

[15] Rogalka, Maciej, Jakub Krzysztof Grabski et al.,(2024) discussed the classification of highly deformed corrugated boards using Convolutional Neural Networks. It explores the impact of flute types on mechanical properties and packaging applications. The study involves datasets obtained from real-world samples, including manually deformed and creased boards.

Chapter 3

PROJECT DESCRIPTION

3.1 Existing System

The current waste classification systems are predominantly reliant on manual sorting methods, a process fraught with inefficiencies and drawbacks. Firstly, the manual sorting process is labor-intensive, requiring a substantial workforce to categorize and segregate diverse types of waste accurately. This not only contributes to increased operational costs but also raises concerns about worker safety and well-being in environments where hazardous materials may be present. Additionally, the human-driven sorting process is susceptible to errors and inconsistencies, leading to inaccuracies in waste categorization. These errors not only compromise the effectiveness of recycling initiatives but also overall efficiency of waste management systems.

Furthermore, the manual approach is inherently limited in scalability. As the volume of waste continues to rise globally, the manual sorting process struggles to keep pace with the increasing demand. This limitation poses a significant challenge in managing the burgeoning amount of waste efficiently. Additionally, the manual system lacks the capability to adapt to dynamic changes in waste compositions and categories, rendering it less responsive to emerging environmental concerns. In light of these drawbacks, there is a compelling need for an advanced, automated solution that can overcome the limitations of the existing manual waste classification systems, providing a more efficient, accurate, and scalable approach to waste management.

3.2 Proposed System

The proposed garbage classification system, rooted in Convolutional Neural Networks (CNNs) with the VGG16 architecture, brings forth a paradigm shift in waste management, offering a myriad of advantages over traditional methods. Firstly, the automated nature of the system significantly reduces reliance on manual labor, mitigating the associated risks to worker safety and welfare. By harnessing the power of deep learning, the proposed system streamlines the waste categorization process, minimizing the need for a large workforce and allowing human resources to be redirected to more intricate tasks within waste management facilities.

Moreover, the proposed system boasts unparalleled accuracy in waste classification. The utilization of CNNs enables the model to discern intricate visual patterns, leading to precise categorization of diverse waste materials such as plastic, glass, paper, metal, trash, and cardboard. This heightened accuracy not only optimizes recycling efforts but also contributes to the reduction of cross-contamination in waste streams, a critical factor in enhancing the overall efficiency of waste management practices. Additionally, the scalability of the proposed system positions it as a robust solution capable of adapting to the dynamic nature of waste compositions and accommodating the increasing volume of waste generated globally. In essence, the automated garbage classification system offers a technologically advanced, accurate, and scalable approach that revolutionizes waste management processes, aligning with contemporary environmental sustainability goals.

3.3 Feasibility Study

3.3.1 Economic Feasibility

The economic feasibility of implementing the proposed garbage classification system is underpinned by its potential to generate substantial cost savings and operational efficiencies. The current manual waste sorting systems incur significant labor costs due to the extensive workforce required for accurate categorization. In contrast, the proposed automated system reduces the dependence on manual labor, leading to a substantial reduction in operational expenses associated with human resources. Furthermore, the initial investment in deploying the Convolutional Neural Network (CNN) with VGG16 architecture is offset by the long-term benefits of decreased labor costs and increased operational efficiency, positioning the system as economically viable over the project's lifecycle.

Moreover, the economic viability of the proposed system is underscored by its potential to enhance the overall efficiency of recycling processes. Accurate waste classification, facilitated by the advanced image recognition capabilities of the CNN model, minimizes the likelihood of cross-contamination in waste streams. This reduction in cross-contamination not only preserves the value of recyclable materials but also contributes to increased revenue generation from recycling operations. The economic feasibility is further strengthened by the scalability of the proposed system, allowing it to adapt to varying waste compositions and accommodate the anticipated growth in waste volume. In summary, the economic feasibility of the project lies in its capacity to streamline operational costs, optimize recycling efforts, and position waste management facilities for long-term financial sustainability.

3.3.2 Technical Feasibility

The technical feasibility of implementing the proposed garbage classification system is rooted in the advancements of Convolutional Neural Networks (CNNs) and the compatibility of the VGG16 architecture with image classification tasks. CNNs have demonstrated remarkable success in image recognition, making them an ideal choice for the complex task of categorizing diverse types of waste materials. The VGG16 architecture, with its deep convolutional layers, offers the ability to capture intricate visual features, enabling the model to discern nuanced differences among various waste categories accurately. The existing technological infrastructure supports the implementation of these advanced neural network architectures, ensuring that the proposed system aligns seamlessly with contemporary technological capabilities.

Furthermore, the technical feasibility is bolstered by the accessibility and availability of image datasets representative of diverse waste materials. The richness and diversity of the dataset facilitate effective training of the CNN model, enabling it to generalize well to novel instances of waste images. Moreover, the proposed system's technical feasibility extends to its adaptability to different waste management facilities and systems. The modular nature of the CNN model allows for easy integration into existing waste management frameworks, ensuring a smooth transition to automated waste classification. In conclusion, the technical feasibility of the project is grounded in the compatibility of advanced neural network architectures, the availability of representative datasets, and the adaptability of the proposed system to diverse waste management setups.

3.3.3 Social Feasibility

The social feasibility of implementing the proposed garbage classification system revolves around its potential to address pressing societal concerns related to waste management. Automated waste classification mitigates the need for an extensive manual workforce in often hazardous environments, thereby improving the overall safety and well-being of workers. By reducing the reliance on manual labor, the proposed system aligns with social responsibility principles, fostering a work environment that prioritizes worker health and safety. Moreover, the system contributes to societal aspirations for cleaner and healthier living spaces, as accurate waste categorization is fundamental to effective waste management and environmental sustainability.

Additionally, the proposed system has the potential to augment community engagement and awareness regarding waste management practices. By implementing advanced technologies in waste sorting, the project can serve as an educational tool, raising awareness about the importance of proper waste disposal and recycling. The visual nature of the project, with its image recognition capabilities, makes it accessible and relatable to a wide audience, thereby promoting a sense of collective responsibility for environmental conservation. The social feasibility is further underscored by the system's potential to align with and support community-led initiatives for sustainable living, fostering a sense of shared responsibility for waste reduction and ecological preservation. In summary, the social feasibility of the project lies in its capacity to enhance workplace safety, contribute to cleaner living spaces, and act as a catalyst for community awareness and engagement in sustainable waste management practices.

3.4 System Specification

3.4.1 Hardware Specification

- System Processor:Intel Core i5 11th Generation
- Ram:8GB and above
- ROM:150GB and above
- Monitor:14inch(recommended)

3.4.2 Software Specification

- Operating System:Windows 11
- Coding Language:Python
- Frontend:Python,HTMLCSS

3.4.3 Standards and Policies

Google Colab Integration

This project seamlessly integrates with Google Colab, a cloud-based Jupyter notebook environment that facilitates collaborative machine learning and data science workflows. Google Colab adheres to industry standards, providing a platform to share, create, and execute live code, equations, and visualizations in a collaborative manner. With Colab, our project benefits from the flexibility and scalability of cloud computing resources, enabling efficient collaboration and resource utilization.

Standard Used: ISO/IEC 27001

Chapter 4

METHODOLOGY

4.1 CNN Architecture of Garbage Classification

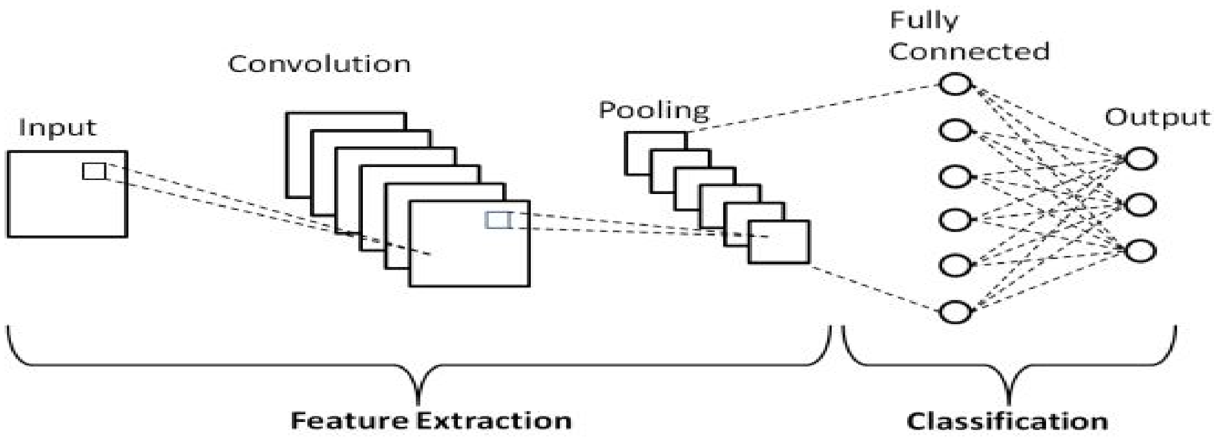


Figure 4.1: **CNN Architecture of Garbage Classification**

Figure 4.1 is the Convolutional Neural Network (CNN) architecture consists of several key layers. Beginning with the input layer, where raw pixel values of an image are fed into the network, the data flows through convolutional layers, each labeled uniquely, employing grids to represent convolutional filters. Rectangles labeled "ReLU" follow these convolutional layers, denoting the application of the ReLU activation function. Subsequent pooling layers, named "Max Pooling" or "Average Pooling," work to reduce spatial dimensions. The flattened layer condenses the data into a one-dimensional vector, leading to fully connected layers labeled "Dense." The output layer, marked as "Output," produces raw scores, with a "Softmax" step connecting to indicate the application of the softmax activation function for classification tasks. Connecting arrows illustrate the flow of information through the network. The actual structure may vary based on specific CNN models and tasks

4.2 Design Phase

4.2.1 Data Flow Diagram

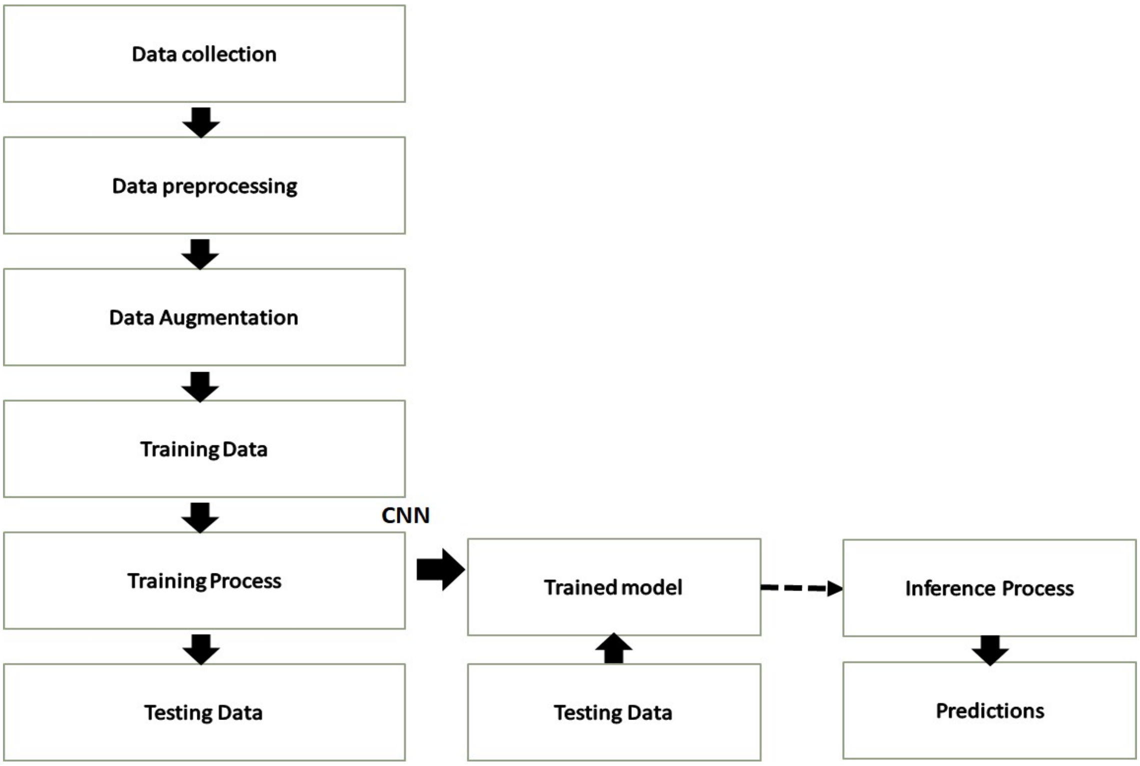


Figure 4.2: **Data Flow Diagram of Garbage Classification**

Figure 4.2 is the data flow in the garbage classification project begins with the collection of original garbage images from diverse sources, denoted as ”Data Sources.“ These images undergo a systematic organization process labeled as ”Data Collection.” Subsequently, the data is augmented for training purposes through the ”Data Augmentation” process. The augmented dataset, known as ”Training Data,” serves as the input for the Convolutional Neural Network (CNN) architecture designed for garbage classification, represented as ”CNN.“ The model undergoes training through the ”Training Process,” resulting in a ”Trained Model.” The model’s performance is evaluated using a separate set of data termed ”Testing Data.” The ”Inference Process” utilizes the trained model to make predictions, and the output, representing the predicted classes, is stored in the final data store labeled ”Predictions.” This comprehensive flow encapsulates the journey from data collection to model training and ultimately the generation of predictions.

4.2.2 Use Case Diagram

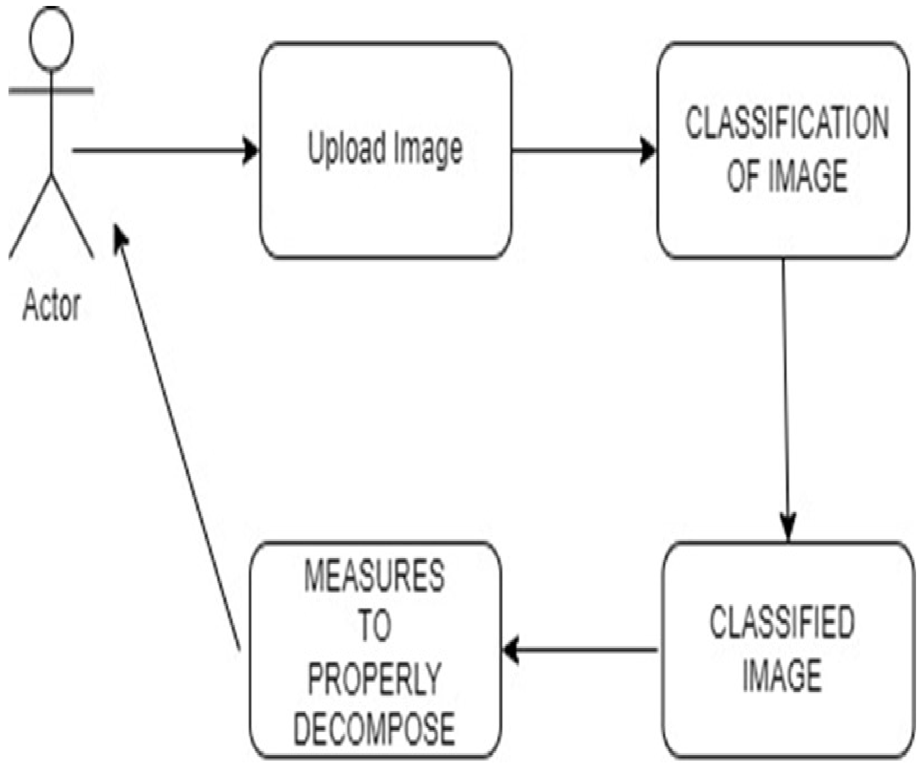


Figure 4.3: **Usecase Diagram of Garbage classification System**

figure 4.3 depicts the use case diagram for garbage classification using CNN depicts the primary actors interacting with the system and the key functionalities it offers. At the center of the diagram is the ”Garbage Classification System,” representing the core system under consideration. The main actors involved are typically ”User” and ”External System.”use case diagram visually captures these interactions through labeled arrows connecting the actors with their corresponding use cases. Each use case is described in detail, outlining its purpose and the actors involved. Additionally, the diagram may include associations between actors and use cases, indicating which actors are involved in each use case,diagram provides a high-level overview of the system’s functionality and its interactions with users and external systems, serving as a useful tool for understanding the system’s requirements and design.

4.2.3 Class Diagram

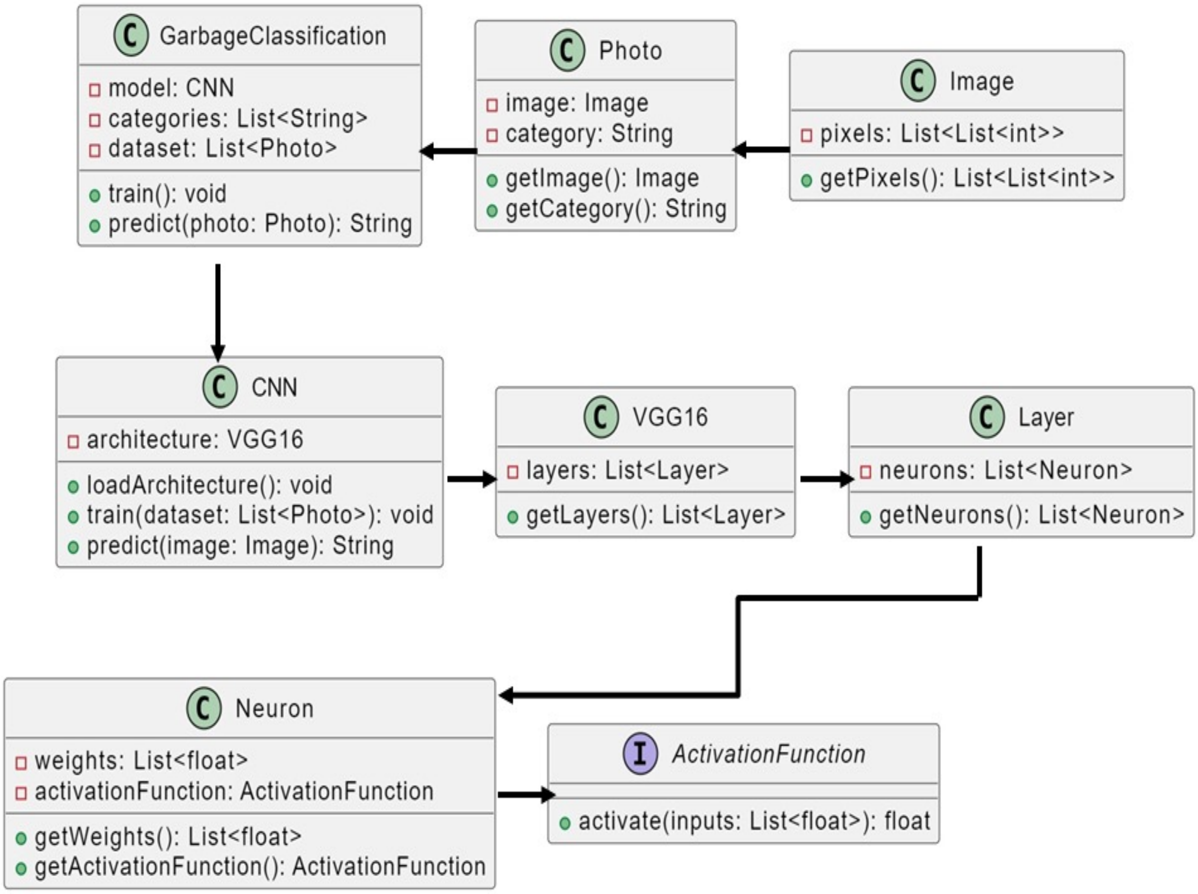


Figure 4.4: **Class Diagram of CNN With VGG16**

figure 4.4 depicts the class diagram for garbage classification using CNNs presents a structured representation of the system's components and their relationships. At its core lies the "Garbage Classification System," serving as the central class encapsulating the system's functionality. This class may contain attributes and methods related to data loading, preprocessing, model training, inference, and result output.Relationships between classes, such as composition, aggregation, and inheritance, further elucidate the system's structure and dependencies. For instance, the "Garbage Classification System" may have a composition relationship with the "CNN Model," indicating that the system owns and manages the CNN model instance.

4.2.4 Sequence Diagram

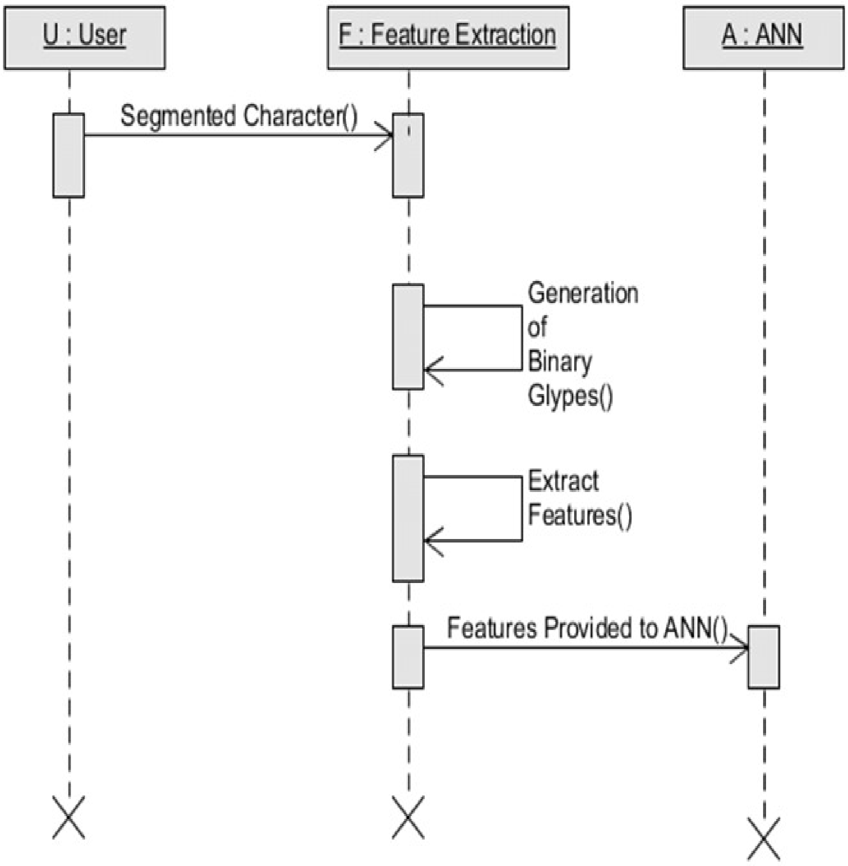


Figure 4.5: **Sequential Diagram of Garbage Classification**

Figure 4.5 depicts the sequence diagram for garbage classification using CNNs delineates the chronological flow of interactions between various system components during the classification process. The diagram typically begins with the ”User” initiating the classification task by uploading an image to the system. Upon receiving the image upload request, the ”Garbage Classification System” orchestrates the classification process by invoking relevant components.Finally, the classification result, along with the computed evaluation metrics, is presented to the user through the user interface. The sequence diagram concludes with the user viewing the classification result and potentially providing feedback or initiating further actions based on the outcome.

4.2.5 Collaboration diagram

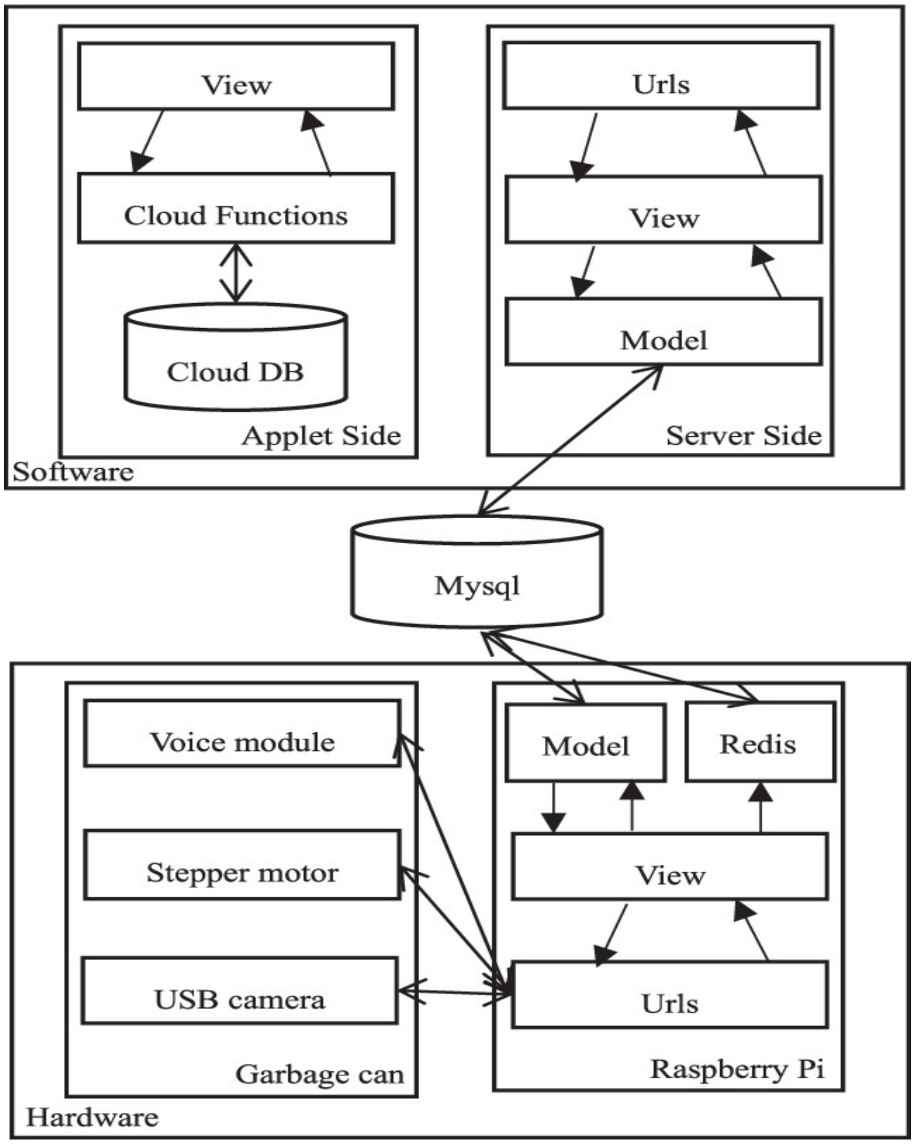


Figure 4.6: **Collaboration Diagram of the Garbage Classification System**

Figure 4.6 depicts the collaboration diagram for garbage classification using CNNs illustrates the collaboration and communication between various objects involved in the classification process. At the center of the diagram is the "Garbage Classification System," representing the overarching system responsible for coordinating the classification task. Surrounding the system are several collaborating objects, each contributing to different aspects of the classification process.

4.2.6 Activity Diagram

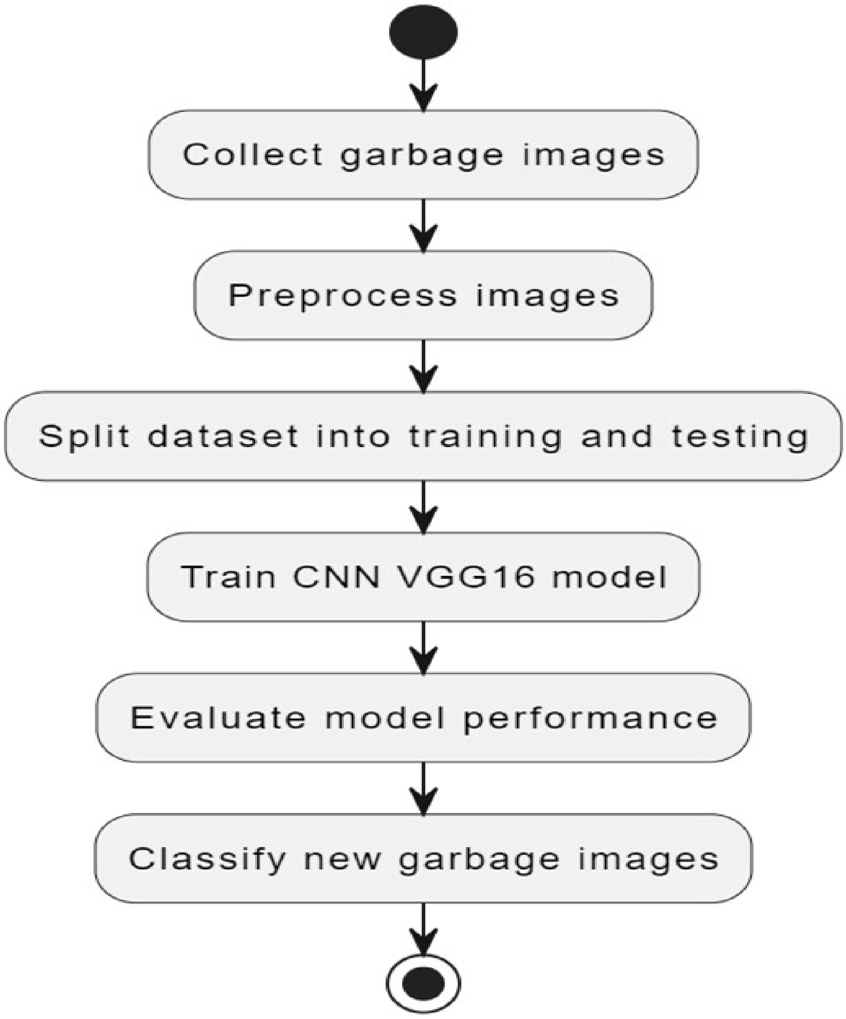


Figure 4.7: **Activity Diagram of Garbage Classification**

Figure 4.7 depicts the activity diagram for garbage classification using CNNs outlines the sequential flow of activities involved in the classification process. The diagram begins with the ”Start” node, representing the initiation of the classification task.The high-level activities involved in the process, including uploading an image, classifying garbage, displaying the classification, and system maintenance.Arrows indicate the flow of control between activities, showing the sequence in which they occur.This textual representation provides a high-level overview of the activities and their interactions in the garbage classification system.

4.3 Algorithm & Pseudo Code

4.3.1 Enhanced Convolutional Neural Networks(CNN)

step-1: Import the necessary libraries, including TensorFlow, NumPy, and Matplotlib.
step-2: Use the Image Data Generator to prepare and generate training data. Specify augmentation techniques such as rescaling, shearing, zooming, brightness adjustment, and horizontal flipping.
step-3: Use flow from directory to load the training data from the specified directory.
step-4: Load the VGG16 model with pre-trained weights from ”imagenet” and exclude the top classification layer.
step-5: Freeze VGG16 Layers:Loop through each layer in the VGG16 model and set them as non-trainable.
step-6: Add a Dense layer with 6 units (for 6 waste classes) and softmax activation as the output layer.Create a new model using the VGG16 base and the custom output layer.
step-7: Compile the Model:Compile the model using the Adam optimizer and categorical cross-entropy loss.
step-8: Use the fit generator method to train the model with the prepared training data.Specify the number of epochs and steps per epoch.
step-9: Waste Prediction Function:Define a function waste prediction to make predictions on new waste images.Load the image, preprocess it, and make predictions using the trained model.Display the image and the predicted waste material with accuracy.
step-10: Call the waste prediction function with a sample waste image after the training loop.
step-12: Plot the training accuracy and loss over epochs using Matplotlib.

4.3.2 Pseudo Code

```
def load_and_preprocess_dataset():
    return train_data, validation_data, test_data

def initialize_cnn_model():
    return model

def define_cnn_architecture(model):
    return model

def compile_model(model):
    return model

def train_cnn_model(model, train_data, validation_data, num_epochs, batch_size):
    for epoch in range(num_epochs):
        for batch in iterate_batches(train_data, batch_size):
            predictions = model.forward(batch.inputs)
            loss = compute_loss(predictions, batch.labels)
            model.backward(loss)
            model.update_parameters()
        validation_accuracy = evaluate_model(model, validation_data)

def evaluate_model(model, test_data):
    return test_accuracy

def fine_tune_model(model, fine_tuning_parameters):
    return fine_tuned_model

def classify_garbage_items(model, new_data):
    predictions = model.predict(new_data)
    return predictions

def deploy_model(model):
    return deployed_model
```

4.4 Module Description

4.4.1 Data acquisition and Data preprocessing

Data acquisition entails sourcing and curating a comprehensive dataset encompassing a wide array of garbage items. This process demands meticulous attention to diversity and representativeness, ensuring that the model encounters a varied spectrum of garbage types during training. Furthermore, meticulous labeling of each image is imperative, as it forms the foundation for supervised learning.Preprocessing acts as the gateway to preparing the acquired data for consumption by the CNN. Standardizing image sizes through resizing facilitates uniformity, while normalization of pixel values ensures consistency in model interpretation. Equally critical is the stratification of the dataset into training, validation, and test sets, a step pivotal for assessing model performance and guarding against overfitting.

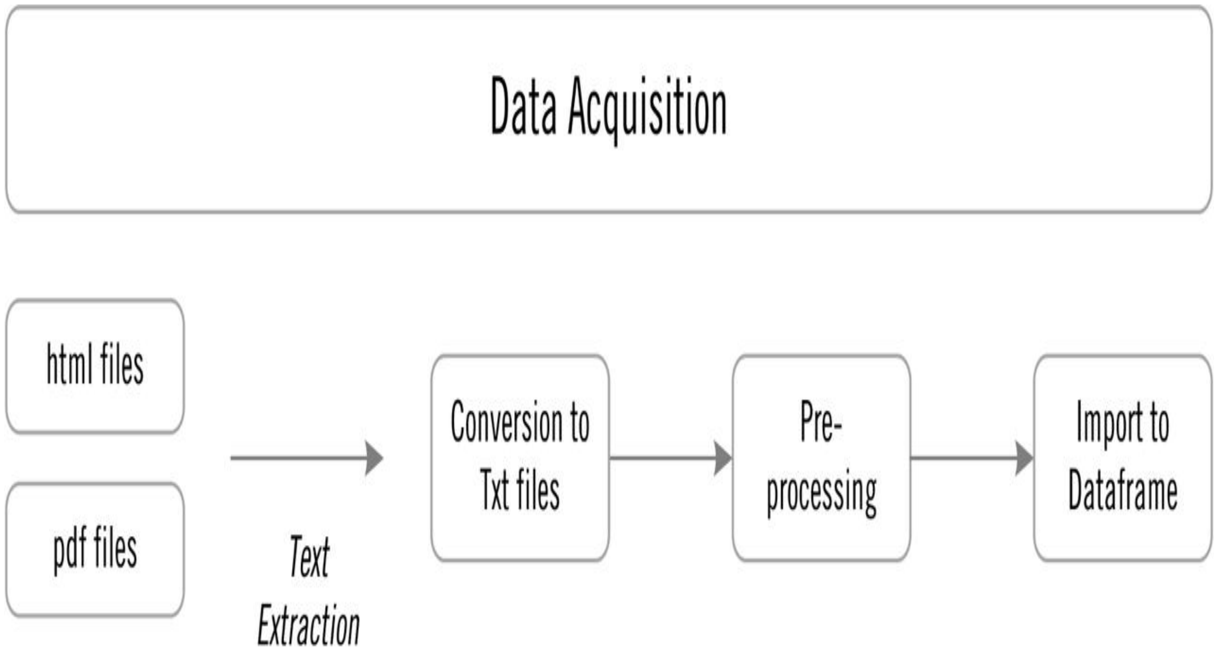


Figure 4.8: **Data Acquisition and Preprocessing of Garbage Classification**

Figure 4.8 depicts the garbage classification using Convolutional Neural Networks (CNNs), a systematic approach to data acquisition and preprocessing is essential. Initially, the acquisition phase involves gathering a diverse dataset of garbage items, assigning appropriate labels to each image, and potentially augmenting the dataset to enhance its variability. Following this, preprocessing steps are crucial for preparing the data for training.

4.4.2 CNN IMPLEMENTATION

Convolutional neural networks (CNNs) are a type of deep learning algorithm that are well-suited for image classification tasks. CNNs are able to extract features from images and learn to identify patterns, which makes them ideal for garbage classification. The VGG16 architecture is a CNN architecture that was developed by the Oxford Visual Geometry Group. VGG16 is a deep architecture, which means that it has a large number of layers. This allows VGG16 to learn complex patterns from images.

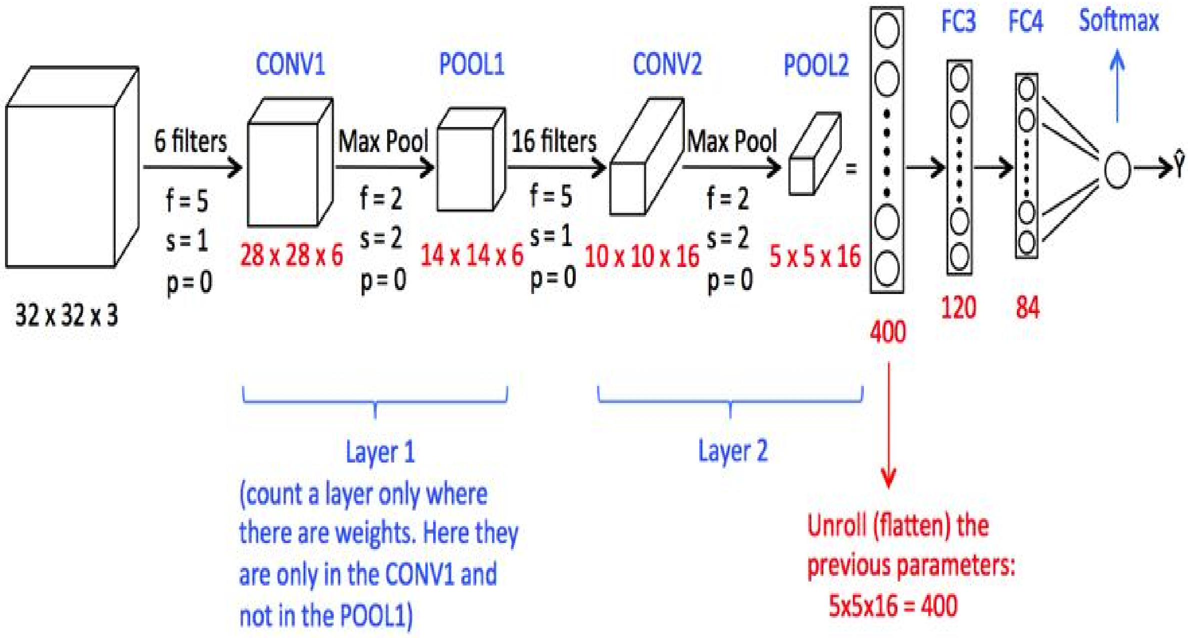


Figure 4.9: **CNN Implementation of Garbage Classification**

Figure 4.9 depicts the garbage classification using Convolutional Neural Networks (CNNs) involves a sequential process that begins with acquiring a diverse dataset of garbage images and their corresponding labels, representing different categories such as organic, recyclable, and non-recyclable items. This dataset forms the foundation for training the CNN model. Preprocessing the acquired data is crucial to ensure its suitability for training. This step includes standardizing the size of images, normalizing pixel values, and splitting the dataset into distinct subsets for training, validation, and testing purposes.

4.4.3 Output

1. **Define Waste Prediction Function:** Define a function waste prediction to make predictions on new waste images. It includes preprocessing the image, predicting the class probabilities, and displaying the result.
2. **Call Waste Prediction Function:** Call the waste prediction function with a sample waste image path to demonstrate how the model predicts waste material.
3. **Plot Training History:** Plot the training accuracy and loss over epochs using Matplotlib to visualize the model's learning progress.

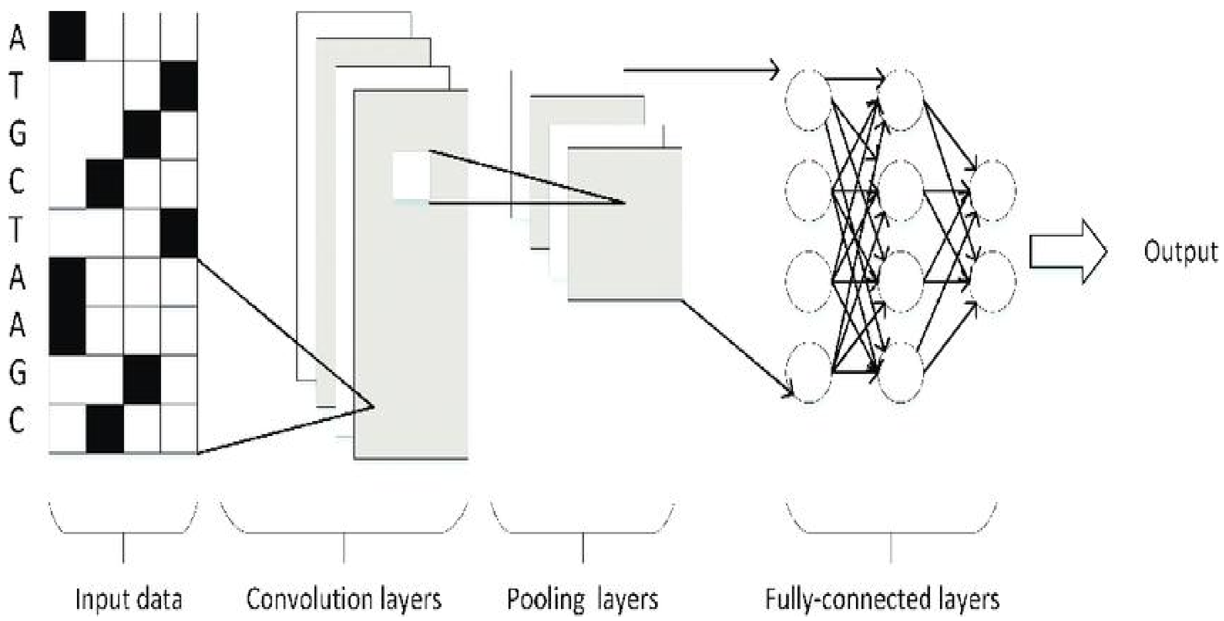


Figure 4.10: **Output for Garbage Classification**

Figure 4.10 depicts the output of garbage classification using Convolutional Neural Networks (CNNs) typically consists of the model's predictions for each input image. For each image, the CNN will produce a probability distribution over the different garbage categories, indicating the likelihood of the image belonging to each class. This output can be in the form of probabilities assigned to each class or a single predicted class label based on the highest probability.The output may also include additional information such as confidence scores, prediction uncertainties, or to provide insights into the model's decision-making process. Ultimately, the output serves to inform users about the model's classification results and the associated level of confidence in those predictions.

4.5 Steps to execute/run/implement the project

4.5.1 Set Up Environment and Install Dependencies

- Ensure you have Python installed on your system.
- Install required libraries by running: pip install tensor flow numpy matplotlib

4.5.2 Organize Dataset

- Organize your waste dataset with labeled sub directories for each waste class.
- Update the dataset path in the pseudo-code.

4.5.3 Model Development Step by Step

- Copy and paste the provided pseudo-code into a Python script file (e.g., waste classification.py).
- Observe the training progress with accuracy and loss plots displayed during training.

4.5.4 Review Model and Fine-Tune

- Review the model summary to understand the architecture and layer configurations.
- Experiment with hyper parameters, data augmentation, or additional layers for better performance.

4.5.5 Deployment

- Document and analyze the results, including accuracy, loss, and predicted waste materials.

Chapter 5

IMPLEMENTATION AND TESTING

5.1 Input and Output

5.1.1 Input Design of Garbage Classification

```
test_x, test_y = validation_generator.__getitem__(1)

preds = model.predict(test_x)

plt.figure(figsize=(16, 16))
for i in range(16):
    plt.subplot(4, 4, i+1)
    plt.title('pred:%s / truth:%s' % (labels[np.argmax(preds[i])], labels[np.argmax
(test_y[i])]))
    plt.imshow(test_x[i])
```

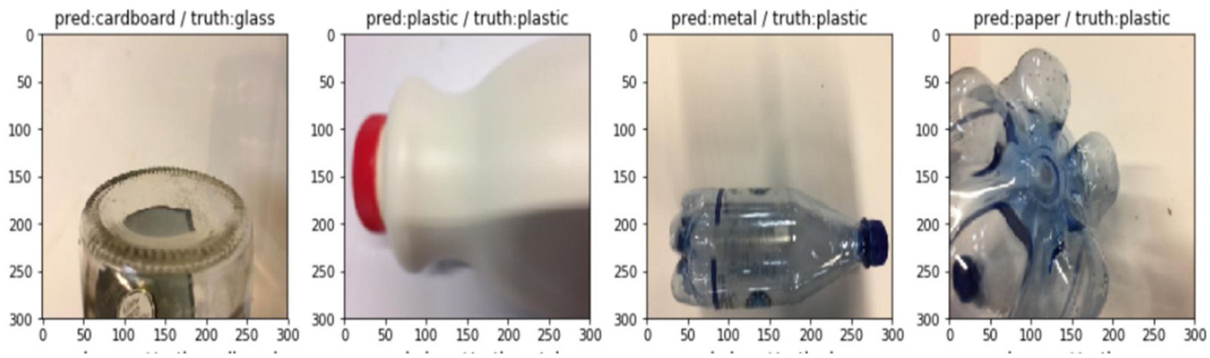


Figure 5.1: **Input Dataset**

Figure5.1 describes about the dataset includes totally 2527 images in which a single object of garbage is present on a clean background. Lighting and pose configurations for objects in different images is different

5.1.2 Output Design of Garbage Classification

Figure 5.2: **Output Dataset**

Figure5.2 describes about the output design in a garbage classification system involves visualizing and interpreting the model's predictions.

5.2 Testing

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub-assemblies, assemblies and or a finished product It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of test. Each test type addresses a specific testing requirement

5.3 Types of Testing

5.3.1 Unit Testing

Input

```python
# Unit Testing: Example function for data preprocessing
def preprocess_image(image_path):
    print("\n--- Unit Testing ---")
    print("Preprocessing image:", image_path)

    test_image = image.load_img(image_path, target_size=(224, 224))
    test_image = image.img_to_array(test_image) / 255
    test_image = np.expand_dims(test_image, axis=0)
    return test_image
```

Figure 5.3: **Unit Testing Accuracy**

Test result:PASSED

Figure 5.3 depicts the Unit testing for garbage classification using Convolutional Neural Networks (CNNs) involves scrutinizing individual components of the system to validate their correctness and robustness. Initially, the focus lies on the data loading and preprocessing stages, where unit tests are crafted to confirm that images are correctly loaded, resized to prescribed dimensions, and normalized accurately. Subsequently, attention shifts to verifying the integrity of the CNN model architecture.This entails constructing unit tests to ensure that the layers are assembled as intended and that input-output dimensions align appropriately. Moving forward, the training pipeline undergoes scrutiny, with tests designed to ascertain the model's ability to learn from a synthetic dataset, observing if loss diminishes over epochs and if accuracy trends positively.

5.3.2 Integration Testing

Input

```
#Integration Testing:code for model training loop
def train_model(train_data):
    print("\n--- Integration Testing ---")
    print("Training the model...")
    result = model.fit_generator(train_data, epochs=28, steps_per_epoch=len(train_data))
    return result
```

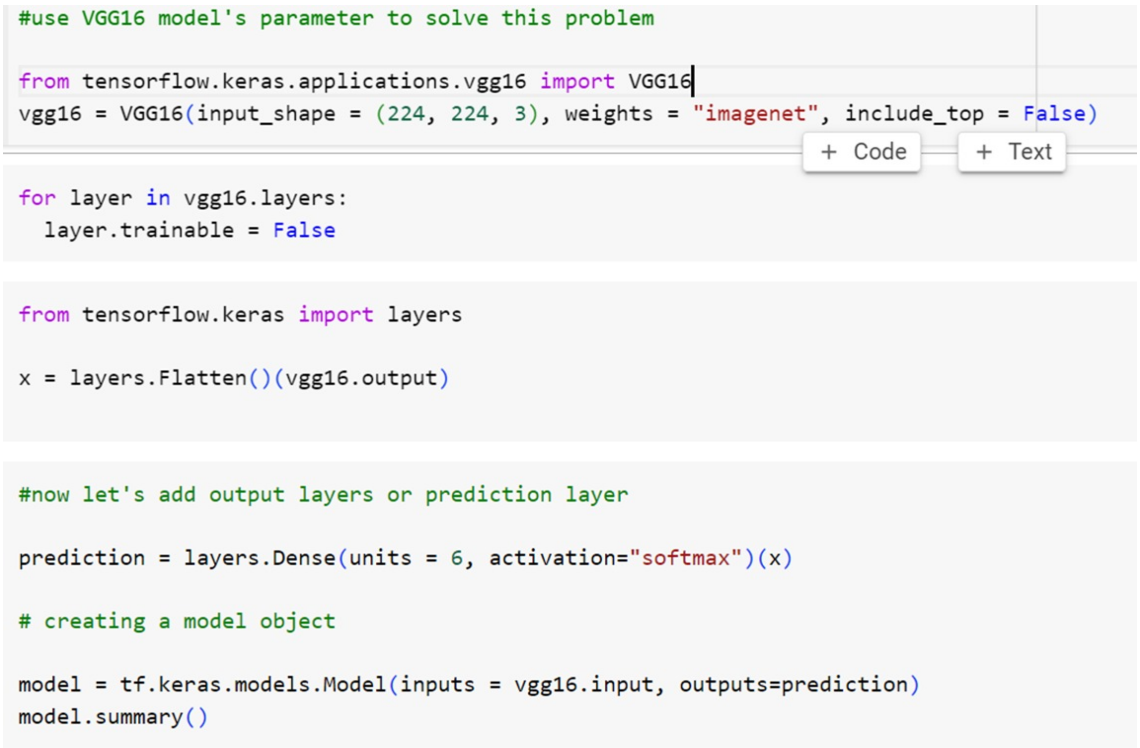


Figure 5.4: **Integration Testing Accuracy**

Test result:PASSED

Figure 5.4 depicts Integration testing for garbage classification using Convolutional Neural Networks (CNNs) encompasses the comprehensive assessment of the system's interconnected components, ensuring their seamless collaboration and compatibility. Commencing with end-to-end testing, the entire classification pipeline, from data ingestion to result output, undergoes scrutiny to validate the fluidity of interactions. The data pipeline, encompassing tasks like loading, preprocessing, and augmentation, is rigorously examined to affirm the seamless integration of image processing tasks, ensuring error-free data flow into the model.

5.3.3 System Testing

Input

```
waste_prediction("/content/drive/MyDrive/Garbage classification/Garbage classification/glass/glass19.jpg")
```

```python
def black_box_test(image_path):
    print("\n--- Black Box Testing ---")
    print("Testing image:", image_path)
    test_image = preprocess_image(image_path)
    predicted_array = model.predict(test_image)
    predicted_value = output_class[np.argmax(predicted_array)]
    predicted_accuracy = round(np.max(predicted_array) * 100, 2)

     # Display the tested image
    plt.imshow(image.load_img(image_path))
    plt.title("Test Image")
    plt.axis("off")
    plt.show()

    print("Your waste material is ", predicted_value, " with ", predicted_accuracy, " % accuracy")

```

Figure 5.5: **System Testing output**

Test result:PASSED

Figure 5.5 depicts the System testing for garbage classification using Convolutional Neural Networks (CNNs) encompasses a comprehensive evaluation of the entire system to ensure its functionality, performance, robustness, stability, and usability in real-world contexts. Functional testing serves as a cornerstone, validating that core functionalities such as data loading, preprocessing, model training, evaluation, and inference produce the intended outputs accurately. This entails verifying the system's ability to classify various types of garbage items with high accuracy.

Chapter 6

RESULTS AND DISCUSSIONS

6.1 Efficiency of the Proposed System

The efficiency of the proposed garbage classification system is paramount, given its potential to revolutionize waste management processes. The utilization of Convolutional Neural Networks (CNNs) with the VGG16 architecture inherently contributes to the efficiency of the system in various dimensions. During the training phase, the deep learning model excels in learning intricate features from the diverse dataset, enhancing its ability to accurately classify different types of garbage. The efficiency in feature extraction and learning translates to a highly performant model during the inference phase, where the system can swiftly categorize new images with minimal latency.

The scalability of the proposed system adds another layer to its efficiency. As the volume and diversity of waste materials continue to grow, the system can seamlessly adapt to varying compositions and accommodate the increasing demand for automated waste classification. The modular nature of the CNN model allows for efficient integration into existing waste management frameworks, minimizing disruptions and maximizing the efficiency gains. Overall, the proposed system's efficiency is not only evident in its accurate classification capabilities but also in its adaptability to evolving waste management needs, positioning it as a technologically advanced and efficient solution in the landscape of waste classification.

6.2 Comparison of Existing and Proposed System

Existing system:

The existing waste classification systems predominantly rely on manual sorting methods, presenting inherent limitations in terms of efficiency and accuracy. Manual sorting is labor-intensive, requiring a substantial workforce and leading to increased operational costs. The system's susceptibility to human errors further compromises the accuracy of waste categorization, impacting the overall effectiveness of recycling initiatives. Moreover, the manual approach struggles with scalability, hindering its ability to efficiently manage the growing volume and diversity of waste materials.

Proposed system:(CNN)

The proposed garbage classification system, leveraging Convolutional Neural Networks (CNNs) with the VGG16 architecture, introduces a paradigm shift in waste management efficiency. The automated system significantly reduces dependence on manual labor, mitigating associated risks and lowering operational costs. The CNN model's advanced image recognition capabilities enhance the accuracy of waste categorization, optimizing recycling efforts and reducing cross-contamination in waste streams. Furthermore, the proposed system's scalability allows it to adapt seamlessly to dynamic changes in waste compositions and accommodate the increasing volume of waste generated globally. In essence, the proposed system outshines the existing manual methods by offering a technologically advanced, accurate, and scalable approach to waste classification, addressing critical limitations in current waste management practices.

6.3 Sample Code

```
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D
from tensorflow.keras.layers import MaxPool2D
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Dense
#loading data
(X_train,y_train) , (X_test,y_test)=mnist.load_data()
#reshaping data
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], X_train.shape[2], 1))
X_test = X_test.reshape((X_test.shape[0],X_test.shape[1],X_test.shape[2],1))
#checking the shape after reshaping
print(X_train.shape)
print(X_test.shape)
#normalizing the pixel values
X_train=X_train/255
X_test=X_test/255
#defining model
model=Sequential()model=Sequential()
#adding convolution layer
model.add(Conv2D(32,(3,3),activation= relu ,input_shape=(28,28,1)))
#adding pooling layer
model.add(MaxPool2D(2,2))
#adding fully connected layer
model.add(Flatten())
model.add(Dense(100,activation= relu ))
#adding output layer
model.add(Dense(10,activation= softmax ))
#compiling the model
model.compile(loss= sparse_categorical_crossentropy ,optimizer= adam ,metrics=[
    accuracy ])
#fitting the model
model.fit(X_train,y_train,epochs=10)
```

Output

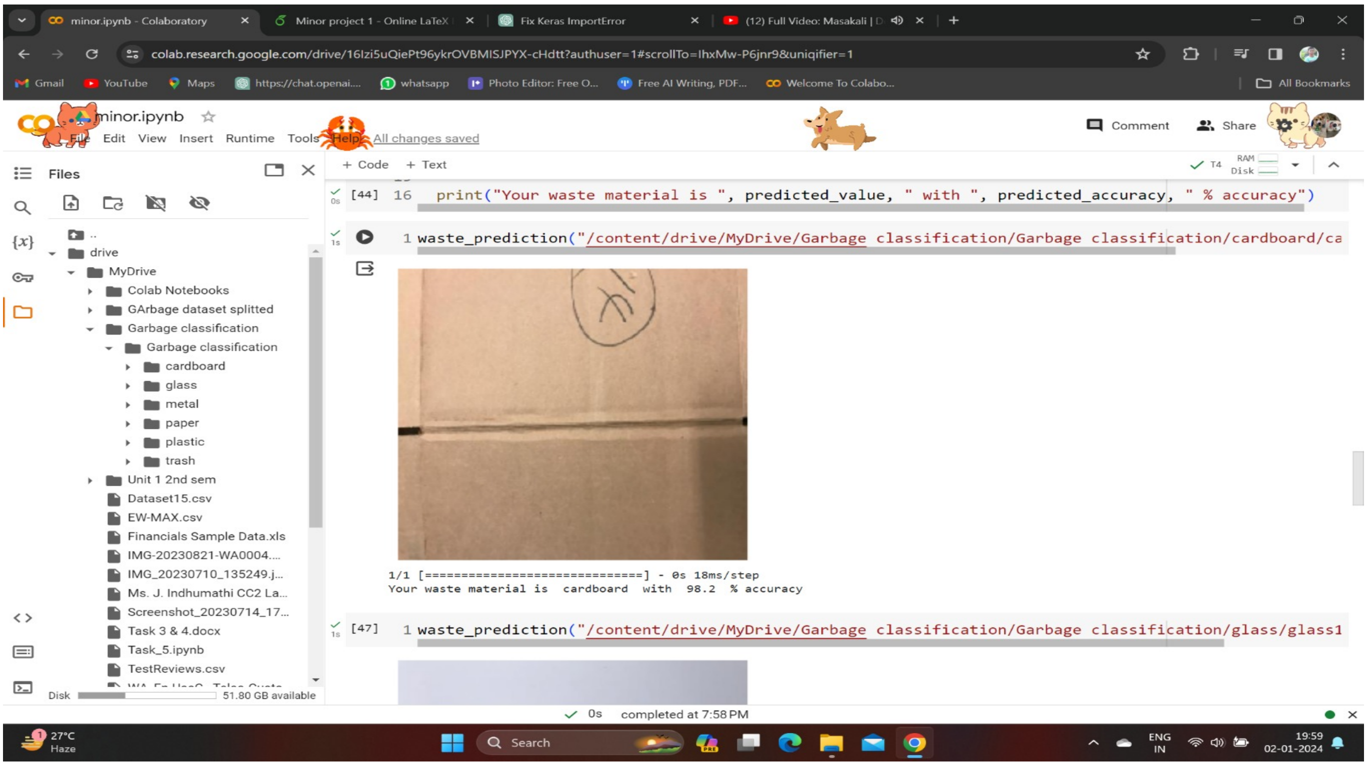


Figure 6.1: **Model Predicted Sample Usecase 1**

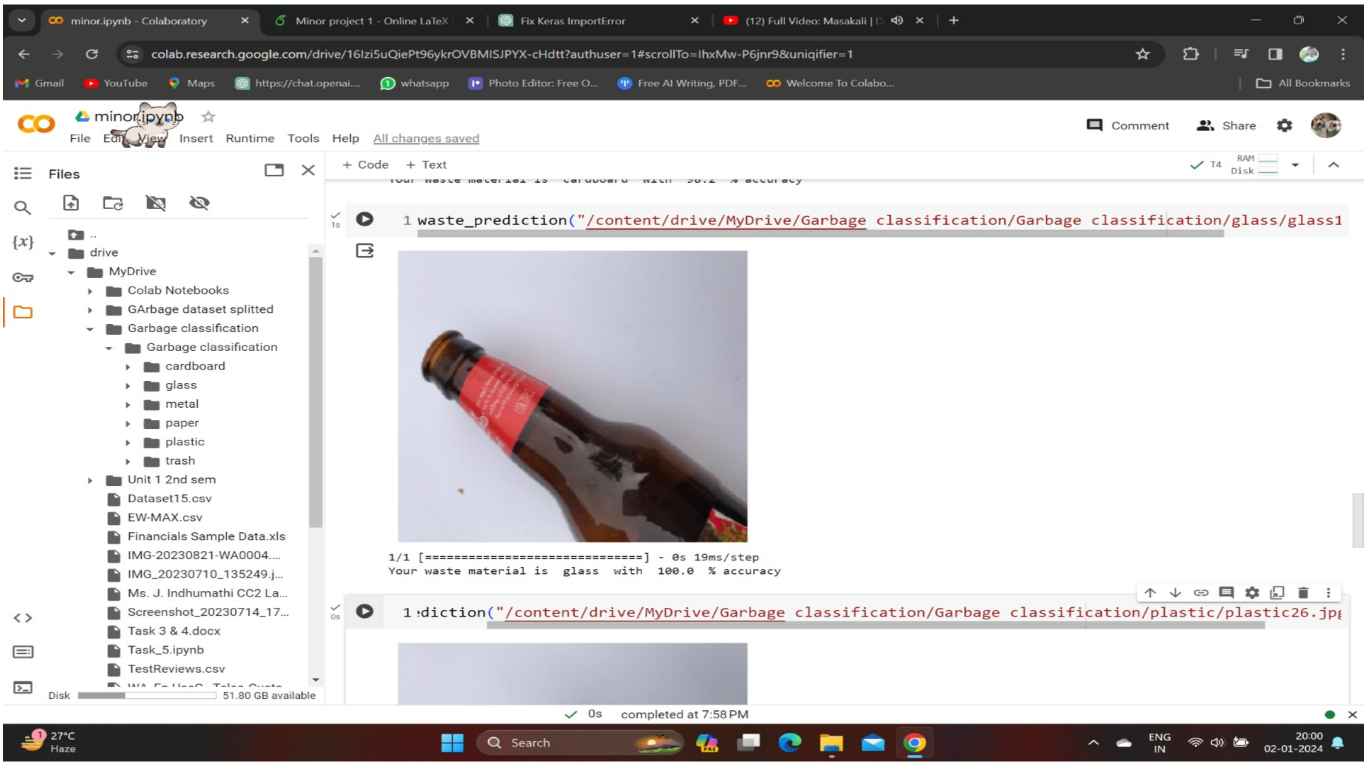


Figure 6.2: **Model Predicted Sample Usecase 2**

Chapter 7

CONCLUSION AND FUTURE ENHANCEMENTS

7.1 Conclusion

Garbage classification using Convolutional Neural Networks (CNNs) with the VGG16 architecture represents a significant leap forward in the realm of waste management. The proposed system offers a transformative solution to the limitations of existing manual sorting methods. By leveraging advanced image recognition technologies, our system automates the categorization of diverse waste materials, enhancing efficiency and accuracy.

Beyond the technical aspects, the social and economic feasibility of our project is noteworthy. The system not only contributes to workplace safety by reducing dependence on manual labor but also aligns with societal aspirations for cleaner and healthier living spaces. Economically, the project demonstrates viability by optimizing operational costs and enhancing revenue generation through improved recycling processes. In the ever-growing landscape of waste management challenges, our project stands as a beacon of innovation, showcasing the potential of machine learning to address real-world environmental concerns.

As we move forward, the scalability and adaptability of our proposed system position it as a versatile solution capable of evolving alongside the dynamic nature of waste compositions and volumes. By integrating cutting-edge technologies, adhering to industry standards, and fostering social and economic benefits, our project contributes to the broader narrative of leveraging artificial intelligence for sustainable and intelligent waste management practices.

7.2 Future Enhancements

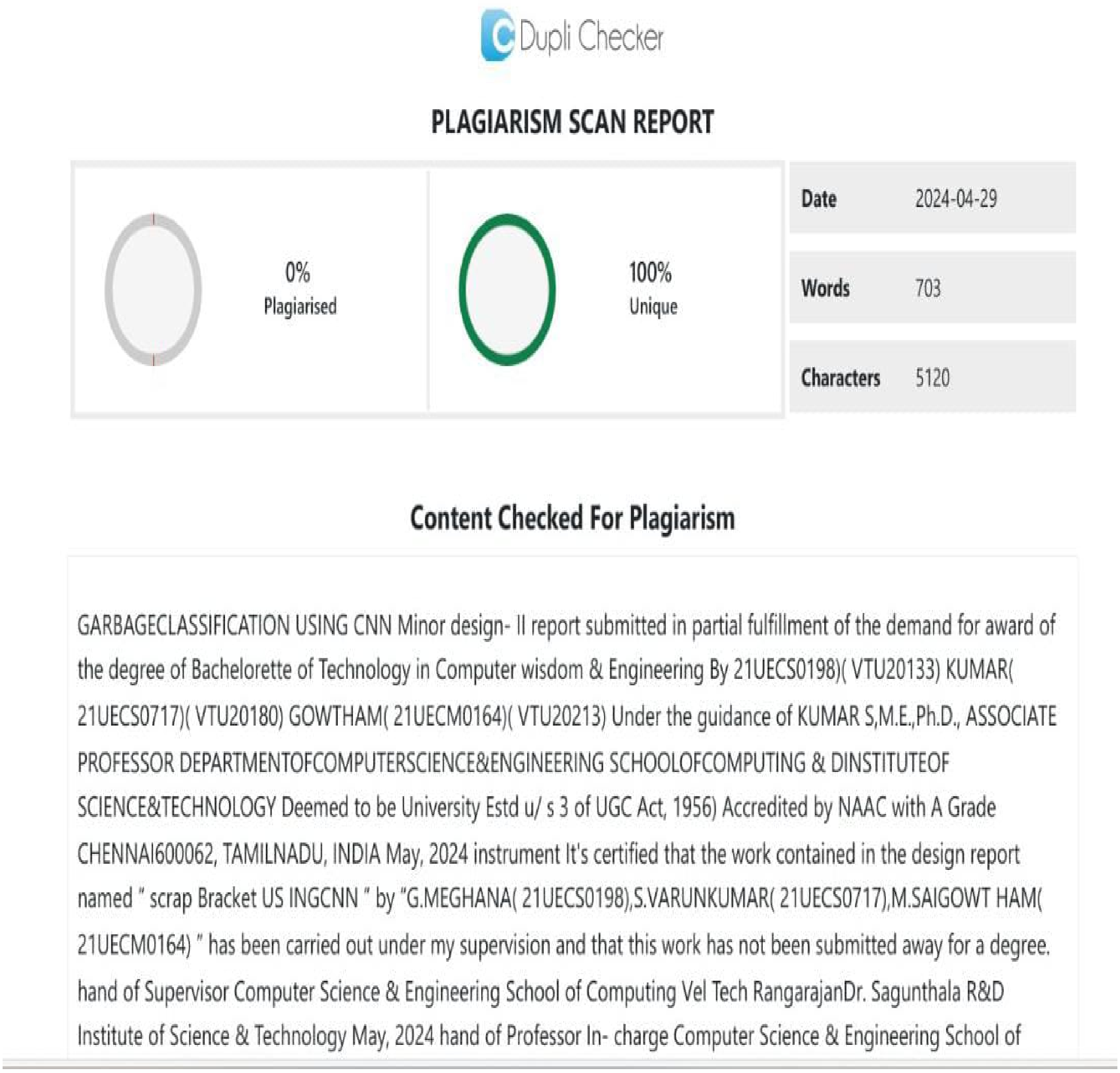
Looking ahead, there are several avenues for enhancing and extending the capabilities of our garbage classification system. One promising avenue involves the continual refinement and expansion of the dataset used for training the Convolutional Neural Network (CNN). Increasing the diversity and size of the dataset can further improve the model's ability to generalize and accurately classify a broader range of waste materials. Incorporating more nuanced categories and variations in waste types can contribute to a more comprehensive and finely tuned classification system.

Additionally, exploring the integration of real-time monitoring and feedback mechanisms represents a noteworthy enhancement. Implementing sensors and IoT devices within waste management facilities could enable the system to dynamically adapt to changing waste compositions. Real-time data could be fed back into the model, allowing it to continuously learn and evolve, ensuring optimal performance in the face of fluctuating waste streams. Moreover, the incorporation of multi-modal inputs, such as combining image data with additional sensor data, could enhance the robustness of the classification system, making it more resilient to variations in lighting conditions and object orientations.

By pursuing these future enhancements, our garbage classification system can evolve into a more sophisticated and adaptive solution, contributing to the ongoing efforts for efficient and sustainable waste management practices. The integration of advanced technologies and continuous improvement strategies will position the system at the forefront of innovations in the field, making it a valuable asset in the quest for environmentally conscious and intelligent waste processing.

Chapter 8

PLAGIARISM REPORT



Dupli Checker

PLAGIARISM SCAN REPORT

0%
Plagiarised

100%
Unique

Date	2024-04-29
Words	703
Characters	5120

Content Checked For Plagiarism

GARBAGECLASSIFICATION USING CNN Minor design- II report submitted in partial fulfillment of the demand for award of the degree of Bachelorette of Technology in Computer wisdom & Engineering By 21UECS0198)(VTU20133) KUMAR(21UECS0717)(VTU20180) GOWTHAM(21UECM0164)(VTU20213) Under the guidance of KUMAR S,M.E.,Ph.D., ASSOCIATE PROFESSOR DEPARTMENTOFCOMPUTERSCIENCE&ENGINEERING SCHOOLOFCOMPUTING & DINSTITUTEOF SCIENCE&TECHNOLOGY Deemed to be University Estd u/ s 3 of UGC Act, 1956) Accredited by NAAC with A Grade CHENNAI600062, TAMILNADU, INDIA May, 2024 instrument It's certified that the work contained in the design report named " scrap Bracket US INGCNN " by "G.MEGHANA(21UECS0198),S.VARUNKUMAR(21UECS0717),M.SAIGOWT HAM(21UECM0164) " has been carried out under my supervision and that this work has not been submitted away for a degree. hand of Supervisor Computer Science & Engineering School of Computing Vel Tech RangarajanDr. Sagunthala R&D Institute of Science & Technology May, 2024 hand of Professor In- charge Computer Science & Engineering School of

Figure 8.1: **Plagiarism Report for Garbage Classification using CNN**

Chapter 9

SOURCE CODE & POSTER PRESENTATION

9.1 Source Code

```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
#prepare the data and generate the data
from tensorflow.keras.preprocessing.image import ImageDataGenerator
gen_train = ImageDataGenerator(rescale = 1/255, shear_range = 0.2, zoom_range = 0.2,brightness_range = (0.1, 0.5), horizontal_flip=True)
train_data =gen_train.flow_from_directory("/content/drive/MyDrive/Garbage classification/Garbage classification",
target_size = (224, 224), batch_size = 32, class_mode="categorical")
#use VGG16 model's parameter to solve this problem
from tensorflow.keras.applications.vgg16 import VGG16
vgg16 = VGG16(input_shape = (224, 224, 3), weights = "imagenet", include_top = False)
for layer in vgg16.layers:
  layer.trainable = False
  from tensorflow.keras import layers
x = layers.Flatten()(vgg16.output)
#output layers or prediction layer
prediction = layers.Dense(units = 6, activation="softmax")(x)
# creating a model object
model = tf.keras.models.Model(inputs = vgg16.input, outputs=prediction)
model.summary()
model.compile(optimizer="adam", loss="categorical_crossentropy", metrics =["accuracy"])
result = model.fit_generator(train_data, epochs = 30, steps_per_epoch=len(train_data))
from tensorflow.keras.preprocessing import image
output_class = ["cardboard","glass","metal","paper","plastic","trash"]
def waste_prediction(new_image):
  test_image = image.load_img(new_image, target_size = (224,224))
  plt.axis("off")
  plt.imshow(test_image)
  plt.show()
  test_image = image.img_to_array(test_image) / 255
  test_image = np.expand_dims(test_image, axis=0)
  predicted_array = model.predict(test_image)
  predicted_value = output_class[np.argmax(predicted_array)]
```

```
  predicted_accuracy = round(np.max(predicted_array) * 100, 2)
  print("Your waste material is ", predicted_value , " with ", predicted_accuracy , " accuracy")
  waste_prediction("/content/drive/MyDrive/Garbage classification/Garbage classification/cardboard/
      cardboard1.jpg")
  plt.title("Accuracy")
plt.plot(result.history["accuracy"])
plt.show()
plt.title("Loss")
plt.plot(result.history["loss"])
plt.show()
```

9.2 Poster Presentation

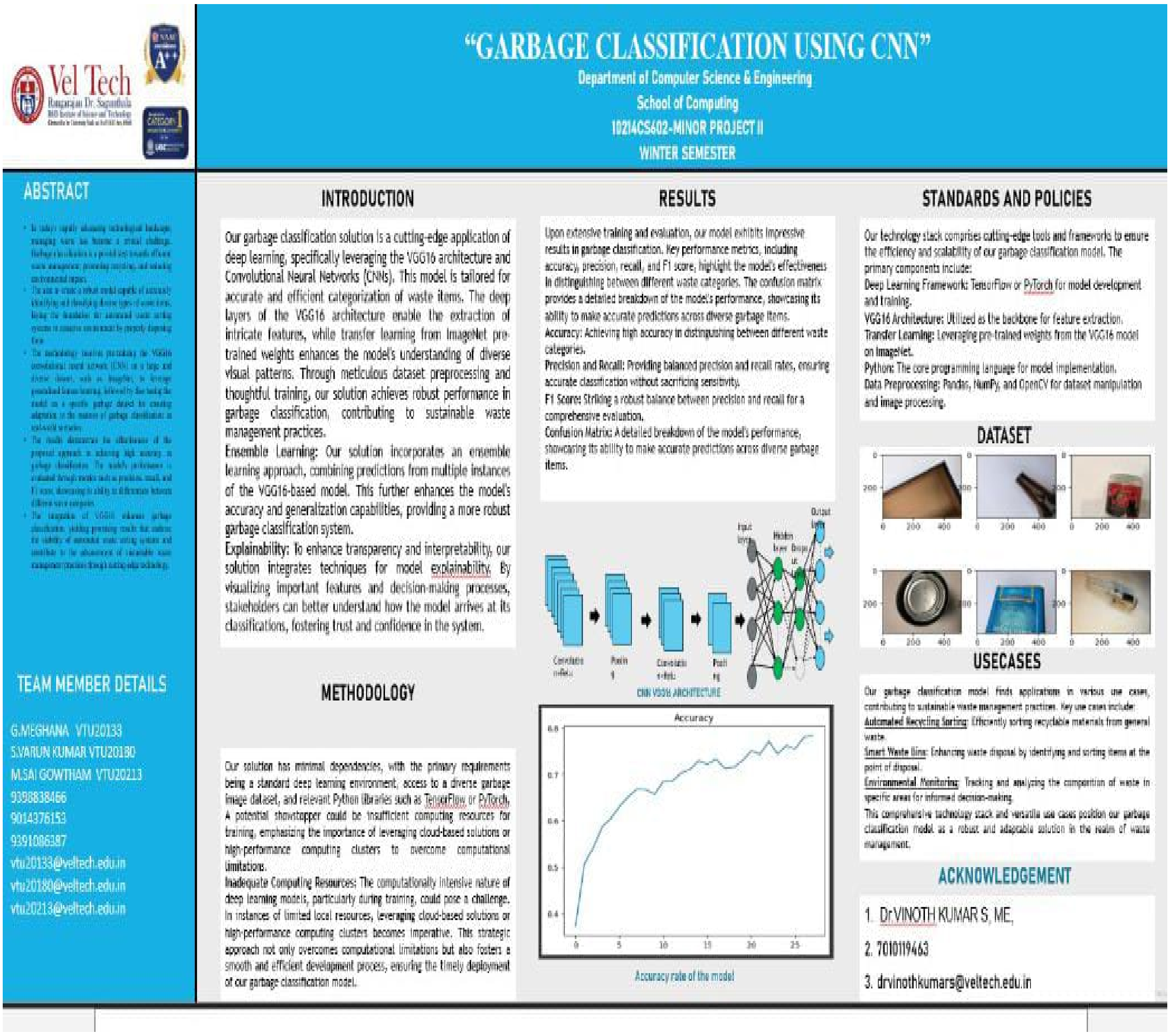


Figure 9.1: **Poster Presentation for Garbage classification using CNN**

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