WASTE CLASSIFICATION USING DEEP LEARNING

A Project Report

Submitted by

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to

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Bachelor of Technology (B.Tech)

in

ARTIFICIAL INTELLIGENCE & DATA SCIENCE

Under the guidance of

MS. SEENIA FRANCIS

JYOTHI ENGINEERING COLLEGE

LEAD KINDLY LIGHT

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CREATING TECHNOLOGY
LEADERS OF TOMORROW
ESTD 2002

DEPARTMENT OF ARTIFICIAL INTELLIGENCE & DATA SCIENCE

Jyothi Engineering College

NAAC Accredited College with NBA Accredited Programmes*

Approved by AICTE & affiliated to APJ Abdul Kalam Technological University

A CENTRE OF EXCELLENCE IN SCIENCE & TECHNOLOGY BY THE CATHOLIC ARCHDIOCESE OF TRICHUR

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NBA accredited B.Tech Programmes in Computer Science & Engineering, Electronics & Communication Engineering, Electrical & Electronics Engineering and Mechanical Engineering valid for the academic years 2016-2022. NBA accredited B.Tech Programme in Civil Engineering valid for the academic years 2019-2022.

July 2023

DECLARATION

We hereby declare that the project report “ WASTE CLASSIFICATION USING DEEP LEARNING”, submitted for partial fulfillment of the requirements for the award of the degree of Bachelor of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by us under the supervision of Ms. SEENIA FRANCIS. This submission represents the ideas in our own words and where ideas or words of others have been included, we have adequately and accurately cited and referenced the sources. we also declare that we have adhered to the ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in this submission. We understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously used by anybody as a basis for the award of any degree, diploma, or similar title of any other University.

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CERTIFICATE

This is to certify that the report entitled " **Waste Classification Using Deep Learning**" submitted by **PRADUL O P(JEC20AD038)**, ALPHIN C J(JEC20AD010), AVANTHIKA P U(JEC20AD019), to the APJ Abdul Kalam Technological University in partial fulfillment of the requirements for the award of the Degree in Bachelor of Technology in **Artificial Intelligence & Data Science** is a bonafide record of the project work carried out by them under my/our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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VISION OF THE INSTITUTE

Creating eminent and ethical leaders through quality professional education with emphasis on holistic excellence.

MISSION OF THE INSTITUTE

- To emerge as an institution par excellence of global standards by imparting quality Engineering and other professional programmes with state-of-the-art facilities.
- To equip the students with appropriate skills for a meaningful career in the global scenario.
- To inculcate ethical values among students and ignite their passion for holistic excellence through social initiatives.
- To participate in the development of society through technology incubation, entrepreneurship and industry interaction.

VISION OF THE DEPARTMENT

Creating ethical leaders in the domain of Artificial intelligence and data Science through effectual teaching and learning process to develop emerging technology solutions for the benefits of industry and society with a focus on holistic learning and excellence.

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- Strengthening basic competencies in the domains of Artificial Intelligence and Data Science.
- Providing high-quality, value-based technical education and developing technology professionals with creative ideas and compelling leadership abilities.
- Using logical thinking to create and develop cutting-edge products in collaboration with industry stakeholders in order to meet global expectations and requirements.
- Enabling graduates to adapt to new technologies via strong fundamentals and lifetime learning.

PROGRAMME EDUCATIONAL OBJECTIVES

PEO 1: To disseminate in-depth technical knowledge in the field of artificial intelligence.

PEO 2: To gain a broad grasp of computer science and engineering at many abstraction levels, including computer architecture and design, operating systems, database management, algorithms, and applications.

PEO 3: To provide students with a solid foundation in math and engineering foundations, which will enable them to examine and assess real-world engineering challenges connected to data science and artificial intelligence, as well as to further prepare them for further education and R&D.

PEO 4: To inspire students, a desire to learn for the rest of their lives and to make them aware of their professional and societal responsibilities.

PEO 5: To inculcate in students an awareness of how to use their computer engineering and mathematical theory skills to address current and future computing challenges.

PROGRAMME SPECIFIC OUTCOMES

The students upon completion of Programme, will be able: -

PSO 1: Understand and develop computer programs in the areas related to algorithms, system software, multimedia, web design, big data analytics and networking by identifying, demonstrating and analyzing the knowledge of engineering in efficient design of computer-based systems of varying complexity.

PSO 2: Applying algorithmic principles, innovative Computer science and engineering design and implementation skills to propose optimal solutions to complex problems by choosing a better platform for research in AI and data science.

PSO 3: Identify standard Software Engineering practices and strategies by applying software project development methods using open-source programming environment to design and evaluate a quality product for business success.

PSO 4: Demonstrate and examine basic understanding of engineering fundamentals, professional/social ethics and apply mathematical foundations to design and solve computational problems.

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1. **Engineering knowledge:** Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
2. **Problem analysis:** Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.
3. **Design/development of solutions:** Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
4. **Conduct investigations of complex problems:** Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
5. **Modern tool usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.
6. **The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.
7. **Environment and sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.
8. **Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
9. **Individual and team work:** Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.
10. **Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
11. **Project management and finance:** Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.
12. **Life-long learning:** Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

COURSE OUTCOMES

COs	Description
CO.1	Identify technically and economically feasible problems of social relevance.
CO.2	Identify and survey the relevant literature for getting exposed to related solutions.
CO.3	Perform requirement analysis and identify design methodologies and develop adaptable and reusable solutions of minimal complexity by using modern tools and advanced programming techniques.
CO.4	Prepare technical report and deliver presentation.
CO.5	Apply engineering and management principles to achieve the goal of the project.

CO MAPPING TO POs

	POs											
COs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12
CO.1	3	3	3	3	0	3	3	2	3	3	3	3
C0.2	2	1	3	2	2	2	0	2	2	2	2	2
C0.3	3	1	2	1	1	1	2	3	3	3	3	3
C0.4	2	2	2	2	2	0	0	1	2	1	2	2
C0.5	3	2	3	2	2	3	3	2	3	0	2	2
Average	2.6	1.8	2.6	2	1.4	1.8	1.6	2	2.6	1.8	2.4	2.4

CO MAPPING TO PSOs

	PSOs			
COs	PSO1	PSO2	PSO3	PSO4
CO.1	3	3	3	3
C0.2	3	3	2	3
CO.3	2	2	1	3
CO.4	3	2	3	1
CO.5	3	2	3	1
Average	2.8	2.4	2.4	2.2

ABSTRACT

Waste classification using deep learning involves applying advanced neural networks to automatically categorize and classify different types of waste materials based on their visual features. By training deep learning models, such as convolutional neural networks (CNNs), on a large dataset of waste images, the models learn to recognize patterns and characteristics associated with specific waste categories. These models extract meaningful visual features from waste images, enabling them to differentiate between recyclable and non-recyclable materials, hazardous waste, organic waste, and more. Once trained, the models can be deployed to classify waste items in real-time, guiding waste management processes like sorting and recycling by automating the identification and segregation of waste materials. Waste classification using deep learning improves waste management efficiency, reduces human error, and promotes recycling efforts. It enables the development of smart waste management systems that enhance waste sorting accuracy and contribute to a more sustainable and environmentally conscious approach to waste disposal.

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CHAPTER 1

INTRODUCTION

1.1 Overview

Waste management is a critical global challenge, and effective waste classification is essential for implementing sustainable waste disposal strategies. Traditional waste classification methods rely heavily on manual inspection, which is time-consuming, labor-intensive, and subject to human error. With the advancements in machine learning and computer vision, there is an opportunity to develop automated waste classification systems that can improve the efficiency and accuracy of waste sorting processes. A waste classification system deep learning technology offers a promising solution to automate the waste categorization process. By leveraging the power of machine learning algorithms, this system can analyze the visual characteristics of waste materials and classify them into predefined waste classes. The objective is to accurately identify different types of waste, such as plastic, paper, glass, metal, and organic waste, based on their visual attributes.

The proposed system consists of several stages, starting with data collection. A diverse dataset of waste images needs to be compiled, covering a wide range of waste types and variations. This dataset will serve as the foundation for training the machine learning model. Feature extraction plays a crucial role in the waste classification system. State-of-the-art techniques, such as Convolutional Neural Networks (CNNs), are used to extract meaningful and discriminative features from the waste images. CNNs are well-suited for image analysis tasks, as they can learn hierarchical representations of visual data, capturing both low-level features like edges and textures, as well as high-level semantic informationThe performance of the waste classification system can be evaluated using standard metrics like precision, recall, and F1 score. These metrics measure the accuracy and effectiveness of the system in correctly identifying waste materials and assigning them to the appropriate waste classes. The implementation of a waste classification system using deep learning has several benefits. It reduces the dependence on manual sorting, allowing for faster and more efficient waste management processes. It also minimizes errors and inconsistencies in waste classification, leading to improved recycling efforts and resource recovery. Additionally, the system can be integrated into existing waste sorting facilities or mobile applications, providing a scalable and intelligent solution for waste classification. In this study, we aim to develop an automated waste classification system using deep learning techniques. By combining computer vision, machine learning algorithms, and waste management principles, we strive to enhance waste-sorting processes, promote sustainability, and contribute to a cleaner and greener environment.

1.2 Objectives

The main objective of this project is, here machine learning technique is used to classify the waste materials. And this Machine Learning(ML) model will predict the waste type and thereby we can classify the waste materials accordingly If the system accurately predicts the type of waste, the model will display the waste type and the respective category the waste belongs to. However, if the system fails to identify the waste type, the ml model will not display the waste category, and thereby we cannot get the proper identification and their class.

1.3 Organization of the Project

The report is organized as follows:
Chapter 1: Introduction- Gives an introduction to ”Waste classification”
Chapter 2: Literature Survey- Summarizes the various existing techniques that helped us in achieving the desired result.
Chapter 3: Methodology- Methods used in this project.
Chapter 4: Results and Discussion- The results of work and discussion
Chapter 5: Conclusion & Future Scope- The chapter gives a conclusion of the overall work along with the future scope of implementation.

CHAPTER 2

LITERATURE SURVEY

The findings highlight its potential for automating and improving waste management processes. Various techniques such as CNNs and RNNs have been explored for accurate classification of waste materials. Image-based classification using CNNs has shown promising results in identifying waste objects, while text-based classification techniques using natural language processing have been used to categorize waste based on textual descriptions. Multimodal fusion approaches combining image and text data have been investigated for improved accuracy. Transfer learning with pre-trained models like ResNet, VGGNet, and BERT has been adopted for leveraging existing knowledge. Data augmentation and ensemble methods have been used to overcome data limitations and enhance classification performance. The survey provides valuable insights into the advancements, challenges, and potential applications of deep learning in waste classification.

2.1 Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network

Solid waste accumulation in urban areas is a growing concern, necessitating an advanced waste management system. We propose an intelligent waste material classification system using Residual Neural Network(ResNet-50) and Support Vector Machine(SVM). This system achieves 87% accuracy in classifying waste types (glass, metal, paper, plastic, etc.) using the Thung and Yang dataset. By implementing this system, waste separation becomes faster, more intelligent, and involves human participation. It simplifies the process and addresses environmental and health hazards associated with improper waste management.[1]

2.2 The Development of Real-Time Mobile Garbage Detection Using Deep Learning

this study proposes a mobile application for efficient garbage classification and data entry into a Google Spreadsheet database, addressing the critical issue of garbage management. Utilizing 10,108 images and the densenet121 deep learning platform, we achieved an impressive 99.6% accuracy after optimizing with a genetic algorithm. The resulting model was converted for mobile application use, capturing garbage type, detection accuracy, and GPS location. In the final experiment, the application showcased rapid data transmission within 0.86 seconds, providing an effective solution for garbage management.[2]

2.3 Computer Vision Based Two-stage Waste Recognition-Retrieval Algorithm for Waste Classification

This study proposes a two-stage Waste Recognition-Retrieval algorithm for automatic waste classification and sorting. The Recognition Model recognizes waste into thirteen subcategories, while the Recognition-Retrieval Model classifies them into four categories. A one-stage Classification Model is trained for comparison. The best-performing models are tested on an automatic sorting machine, while manual sorting is performed by ten participants. Results indicate that the average accuracy of the Recognition-Retrieval Model (94.71% ± 1.69) is significantly higher than that of the Classification Model (69.66% ± 3.43) and manual sorting (72.50% ± 11.37).[3]

2.4 Recyclable waste classification using computer vision and deep learning

This work proposes a Deep Learning approach using computer vision to automatically identify and classify solid waste into five main categories. This system includes an automated recycling bin with lids corresponding to waste types. We trained a minimum of 12 variants of Convolutional Neural Network (CNN) algorithms using pre-existing images. Three classifiers, SVM, Sigmoid, and SoftMax, were employed. The VGG19 model with SoftMax achieved an accuracy of approximately 88%. This approach aims to simplify and enhance the sorting process, reducing the negative impact of landfills and promoting recycling.[4]

2.5 Intelligent and Real-Time Detection and Classification Algorithm for Recycled Materials Using Convolutional Neural Networks

This paper addresses the need for automated waste material identification and classification in recycling facilities. A novel methodology is proposed using a convolutional neural network trained on a custom dataset of real waste material images. The system operates on moving belts in waste collection facilities, enabling efficient processing. Experimental results demonstrate superior performance compared to existing algorithms, achieving an accuracy of 92.43% in real-world conditions. The proposed system holds promise for integration into solid waste management systems, facilitating effective recycling and promoting a cleaner and sustainable environment.[5]

2.6 Image Processing for Automated Mixed Household Waste Sorting System

The purpose of this project is to study the application of image processing in developing an efficient automated mechanical sorting system for mixed household waste. Usually, paper and plastics are left uncollected from domestic waste due to a lack of efficient and economical waste sorting mechanisms. This project is designed to segregate plastic and paper waste which would be the pioneering step for recycling. An intelligent system is developed using computer vision to recognize parts with features on the sorting production line (conveyor belt). Different paper and plastic objects with various shapes and sizes are used for the experimentation process. The proposed algorithm was experimentally verified using a fabricated prototype paper and plastic system. Experimental results validate the proposed algorithm.[6]

2.7 Development of Automatic Smart Waste Sorter Machine

The modern world faces challenges with waste management, requiring an efficient and smart system. A developed automatic sorter machine categorizes waste into metal, paper, plastics, and glass using electromechanical systems and sensors. It incorporates a microcontroller and operational amplifier. Conventional sensors sort metal and glass, while a custom sensor with LASER and LDR sorts paper and plastics. A weight sensor and counter determine the number of sorted materials. Effective recycling and this SMART system can transform waste management, making the environment healthier and reducing global warming.[7]

2.8 Segregation of Plastic and Non-plastic Waste using Convolutional Neural Network

Industrialization and urbanization have led to a significant increase in hazardous waste, posing a growing problem. The proposed solution utilizes Convolutional Neural Networks (CNN) to sort waste into plastic and non-plastic categories efficiently. CNN is a powerful machine learning technique with high learning efficiency and fewer training parameters. A dataset of waste materials is collected and trained using CNN, achieving an accuracy of 0.978. The system includes a real-time classifier prototype, reducing the need for human intervention in separating plastics from non-plastics.[8]

2.9 Novel Smart Waste Sorting System based on Image Processing Algorithms: SURF-BoW and Multi-class SVM

This paper presents a smart waste sorting system with a hardware and software component. The hardware utilizes Raspberry Pi, while the software employs the SURF-BoW algorithm and multi-class SVM classifier for image classification. Experimental results demonstrate high accuracy, with battery waste achieving 100% classification accuracy and an average accuracy of 83.38% across all waste categories. The system exhibits the reliability, robustness, and potential for practical application in addressing waste sorting challenges in daily life.[9]

2.10 Deep Learning for Plastic Waste Classification System

Plastic waste management is a global challenge, and automated sorting methods using image processing and deep learning can improve recycling efficiency. The main challenge lies in separating different material types within groups, such as various colors of glass or plastic types. Plastic waste is significant due to limited recyclability, like PET, which can be converted into polyester. Deep learning and convolutional neural networks offer opportunities for automatic plastic waste segregation into categories like PS, PP, PE-HD, and PET. This technique can be applied in sorting plants or used by citizens at home, and portable devices for waste recognition could help solve urban waste problems.[10]

CHAPTER 3

METHODOLOGY

3.1 Existing Systems

Recycling waste from households and industries is one of the methods that has been proposed to reduce the ever-increasing pressure on landfills. Different types of waste types warrant different management techniques and hence, proper waste segregation according to its types is essential to facilitate proper recycling. The current existing segregation method still relies on a manual hand-picking process. In this paper, a method; based on deep learning and computer vision concepts, to classify wastes using their images into six different waste types (glass, metal, paper, plastic, cardboard, and others) has been proposed. Multiple-layered Convolutional Neural Network (CNN) model, specifically the well-known Inception-v3 model has been used for the classification of waste, with a trained dataset obtained from online sources. High classification accuracy of 92.5% is achievable using the proposed method. It is envisaged that the proposed waste classification method would pave the way for the automation of waste segregation with reduced human involvement and therefore, helps with the waste recycling efforts[11].

3.1.1 Disadvantages of Existing Systems

- Limited generalization to unseen waste items or new waste categories.
- requirements and labeling challenges.
- Lack of interpretability in the decision-making process.
- Resource-intensive nature of deep learning models.

3.2 Problem Statement

To develop an automated waste classification system using AI and machine learning techniques. The system will be designed to accurately identify the type of waste, such as food, plastic, metal, paper, or glass.

3.3 Proposed System

The proposed system is an innovative solution that aims to revolutionize waste classification and management using advanced technologies. It combines the power of artificial intelligence, machine learning, and computer vision to accurately and efficiently classify various types of waste. The system involves developing robust algorithms that can analyze waste images, extract relevant features, and make precise classifications. By leveraging these technologies, the proposed system offers numerous benefits, including improved accuracy, reduced human error, streamlined waste sorting processes, and enhanced recycling efforts. It has the potential to optimize waste management operations, promote sustainability, and contribute to a cleaner and healthier environment.

3.3.1 Sample Images

The sample images consist of 6 types of waste ie, electronic, food, glass, metal, paper, and plastic. Electronic Waste images are taken from the ”Waste Classification Dataset”[12], Food Waste images are taken from the ”Food-101 Dataset”[13] and the rest are taken from the ”Waste Classification PI”[14].

Figure 3.1: Types of Waste

3.3.2 Data Collection and Preprocessing

The dataset used for this project was collected from the ”Waste Classification PI”, ”Waste Classification Dataset” and ”Food-101 Dataset” which contains images of six classes: glass, paper, plastic, metal, food, and electronic waste. Electronic Waste images are taken from the ”Waste Classification Dataset”, Food Waste images are taken from the ”Food-101 Dataset” and the rest are taken from the ”Waste Classification PI”. One of the key data preprocessing steps involves rescaling the input images. The normalization process ensures consistent ranges and improves convergence during training. Data augmentation techniques are employed to enhance the model's robustness and generalization capabilities.

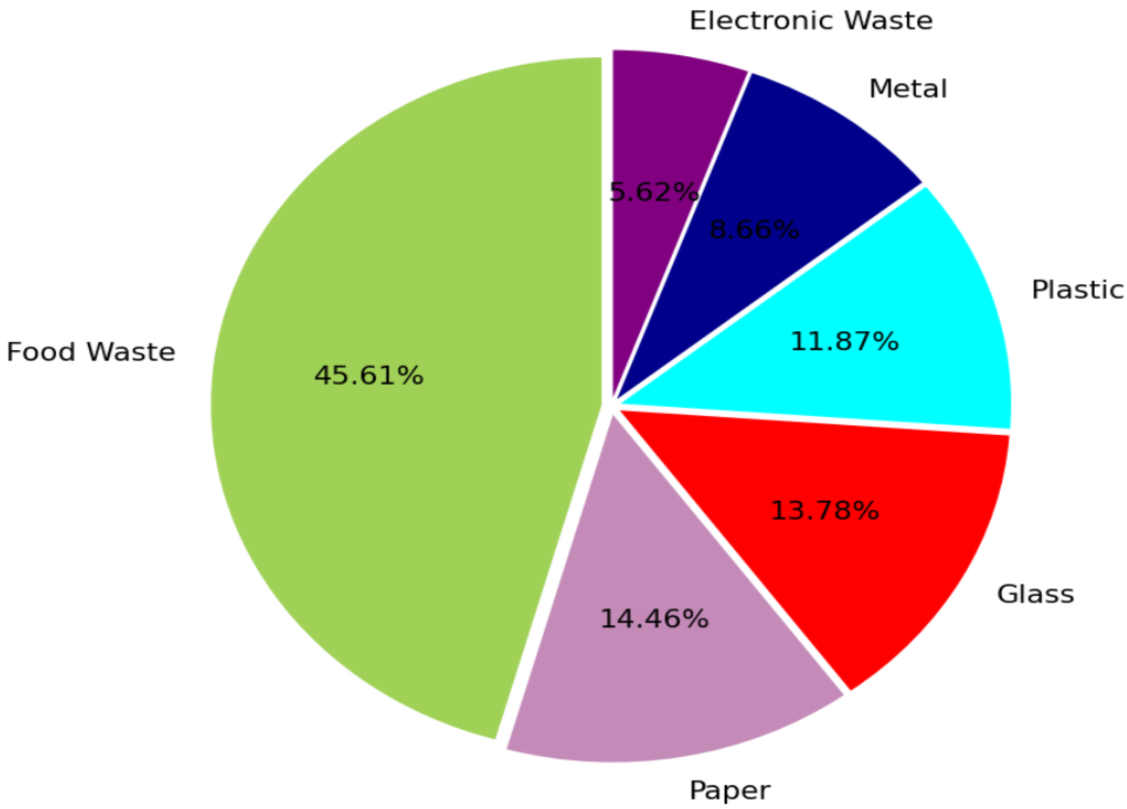

Figure 3.2: Classwise Distribution

3.3.3 Data Augmentation

Data augmentation techniques were applied to increase the dataset's size and diversity. The Keras ImageDataGenerator class was utilized for augmentation. Augmentation techniques included rotation, horizontal/vertical shifts, zoom, and horizontal flips. Multiple augmented images were generated for each original image, resulting in a larger and more varied dataset.

3.3.4 Data Splitting

The preprocessed and augmented dataset was divided into two subsets: a training set and a testing set. The training set was used to train the model, while the testing set was used to evaluate its performance. This split was performed to ensure that the model's ability to generalize to unseen data could be assessed. During the split, a portion of the dataset was randomly selected for the testing set, while the remaining data formed the training set.

3.3.5 Architecture Diagram

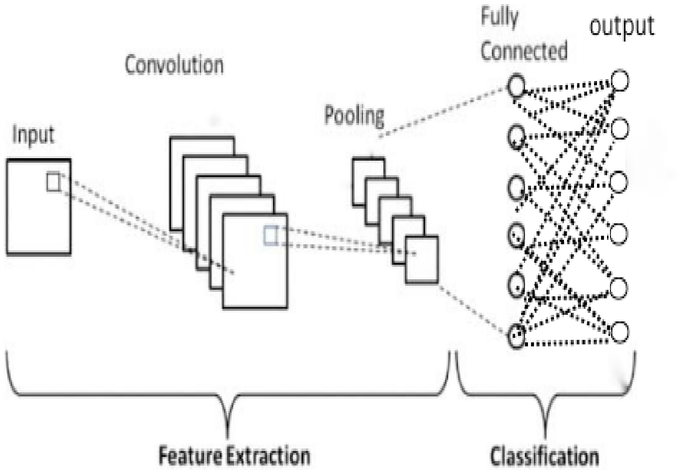

Figure 3.3: Architecture diagram

The model defined in the provided code is a CNN architecture commonly used for image classification tasks. Here's an overview of the model's structure:

The model has 6 layers of convolutional layers, 5 layers max pooling layers. Each convolutional layer applies filters to extract features from the input images. The filters have different sizes, specified as (3, 3), and the number of filters increases as the network deepens. The activation function used in the convolutional layers is ReLU, which introduces non-linearity and helps capture complex patterns in the data.

Max pooling layers follow each convolutional layer and downsample the feature maps by taking the maximum value within a given window size, which helps reduce the spatial dimensions and extract important features.

The last convolutional layer is followed by a flattened layer, which reshapes the 3D feature maps into a 1D vector. The flattened layer connects the convolutional part of the network to the fully connected layers, which are responsible for making the final predictions.

The fully connected layers consist of a dense layer with 512 units and a ReLU activation function, followed by a dropout layer with a dropout rate of 0.5. Dropout is a regularization technique that randomly drops a fraction of the units during training to prevent overfitting.

The output layer is a dense layer with 6 units and a softmax activation function. Since the problem is a multi-class classification task with 6 classes, the softmax activation function ensures that the predicted probabilities sum up to 1, representing the class probabilities.

The model is compiled with the Adam optimizer, which is an adaptive learning rate optimization algorithm. The learning rate is set to 0.001. The model uses categorical cross-entropy as the loss function, suitable for multi-class classification tasks. The accuracy metric is used to evaluate the model's performance during training and evaluation.

Overall, the defined CNN model consists of multiple convolutional and pooling layers to extract hierarchical features from the input images, followed by fully connected layers for classification. The model aims to learn discriminative features and make accurate predictions for the given image classification problem.

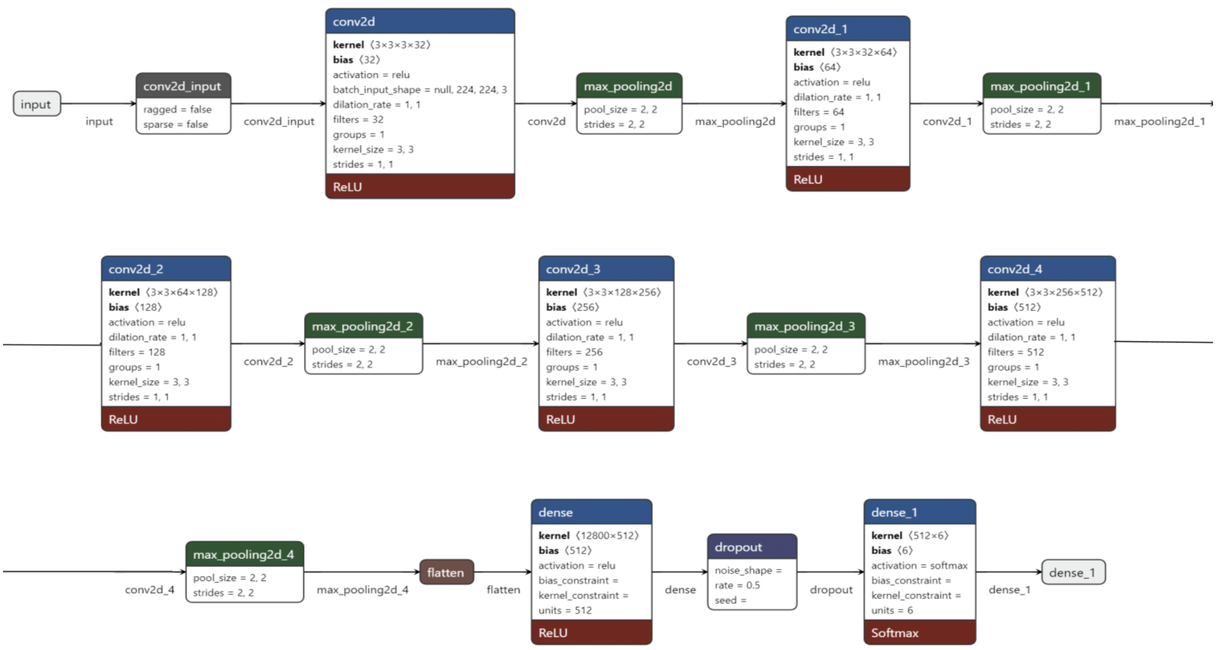

Figure 3.4: Architecure Details

3.3.6 Model Training

The model was trained using the training set, which consisted of preprocessed and augmented data. The training process involved iterating over the dataset for a specified number of epochs. In this case, the model was trained for 82 epochs. A batch size of 32 was used, indicating the number of samples processed before updating the model's internal parameters. During the training process, the model's performance was evaluated to monitor its progress and ensure effective learning.

- Fit: The model is being trained using the fit method, which is a common method for training machine learning models in Keras, a high-level neural networks API written in Python.

- Train data and Test data: These are the data generators for training and validation datasets, respectively. Data generators are used to efficiently load and preprocess data in batches during training to avoid memory issues and improve training speed.

- Steps per epoch: It represents the number of steps (batches) to be processed in each epoch. It is calculated as the total number of training samples divided by the batch size (batch size). Each step processes one batch of training data.

- Epochs: The number of epochs defines how many times the entire training dataset will be processed during training. In this case, the model will be trained for 82 epochs.

- Validation data and validation steps: Similar to the training data, these parameters are used for validation during training. The validation data holds the validation dataset (test data), and validation steps specifies the number of steps (batches) to be processed in each validation epoch.

During training, the model iteratively goes through the entire training dataset (train data) for 82 epochs. In each epoch, the training data is divided into batches of size batch size, and the model updates its weights using an optimization algorithm.

After each epoch, the model's performance is evaluated on the validation dataset (test data). This provides an estimate of how well the model is generalizing to new, unseen data and helps monitor for overfitting.

The training process continues for 82 epochs, and at the end of training, the model's final weights will be those that resulted in the lowest validation loss or highest validation accuracy.

3.3.7 Model Evaluation

After training the model for 82 epochs, the model achieved a training accuracy of 91.59%percentage. The validation accuracy of 92.32% percentage. The model achieved a training loss of 0.2291. The validation loss at the end of the training was 0.2682. These metrics indicate that the model performed well during training, achieving high accuracy and relatively low loss on both the training and validation sets.

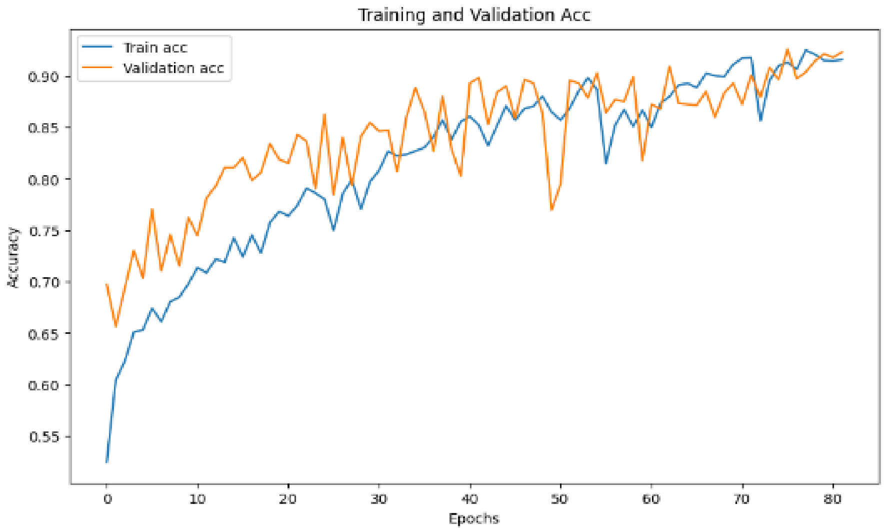

Figure 3.5: Model Accuracy

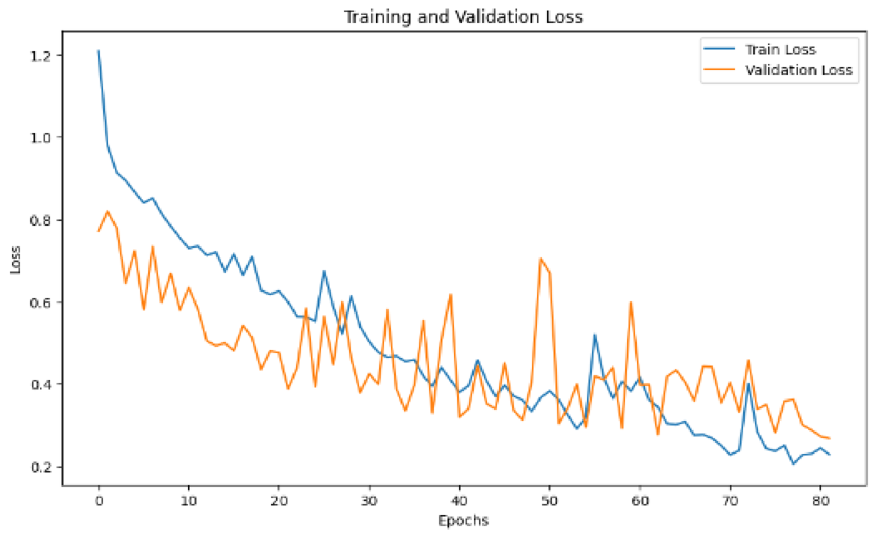

Figure 3.6: Model Loss

3.4 System Requirements And Specifications

3.4.1 PYCHARM IDE

PyCharm is a popular and powerful integrated development environment (IDE) specifically designed for Python programming, offering a rich set of features to boost developer productivity[15].

3.4.2 Python 3

Python is a dynamic object-oriented programming language that can be used for many kinds of software development. It offers strong support for integration with other languages and tools, comes with extensive standard libraries, and can be learned in a few days. Many Python programmers report substantial productivity gains and feel the language encourages the development of higher quality, more maintainable code[16].

3.4.3 Google Colab

Google Colab, short for Google Colaboratory, is a cloud-based platform that provides a Jupyter Notebook environment for running Python code. It allows users to write, execute, and share code directly in their web browsers without requiring any setup or installation. Google Colab offers free access to powerful hardware resources, including GPUs and TPUs, which can accelerate tasks like training deep learning models. With pre-installed libraries and seamless integration with Google Drive, Colab provides a convenient and collaborative environment for data analysis, machine learning experimentation, and sharing of notebooks[17].

3.4.4 Tkinter Module

Tkinter is a Python module used for creating graphical user interfaces (GUIs). It provides a set of tools and widgets to design and build interactive desktop applications. Tkinter is easy to use, included with the standard Python installation, and offers various layout managers for organizing GUI components. It supports event-driven programming, allowing developers to define how the application responds to user interactions. With Tkinter, developers can create windows, buttons, menus, and more, making it a popular choice for creating GUI applications in Python[18].

3.4.5 Jupyter Notebook

Jupyter Notebook is a web-based interactive computing platform. It allows users to create and share documents called notebooks. Notebooks consist of cells that can contain code or markdown text. It supports multiple programming languages and enables code execution and visualization. It promotes collaborative and reproducible workflows in data analysis and research[19].

3.5 Implementation

the implementation of waste classification using deep learning techniques to automate and optimize the waste sorting process. By leveraging advanced neural network architectures, specifically CNN, the project aims to accurately categorize and classify different types of waste, such as plastics, paper, glass, metal, food, and electronic wastes. The report discusses the methodology involved in collecting a diverse dataset, preprocessing the data, constructing and training the deep learning model, and evaluating its performance. The trained model achieves a training accuracy of 91.59% and a validation accuracy of 92.32%. The report highlights the potential real-world applications of the model in waste sorting facilities and recycling centers, emphasizing the benefits of improved sorting efficiency and resource recovery. The importance of continuous monitoring and periodic retraining of the model for adaptability and effectiveness over time is also emphasized, ultimately contributing to better waste management practices and environmental sustainability.

Figure 3.7: Home Page

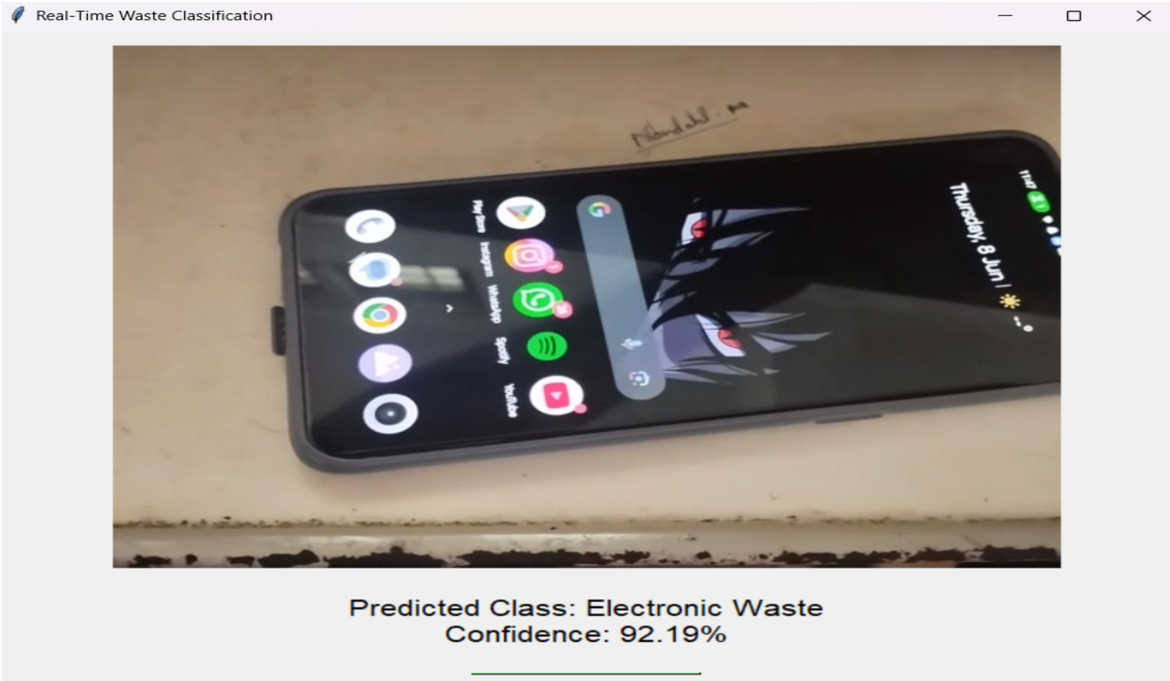

Figure 3.8: Result Page

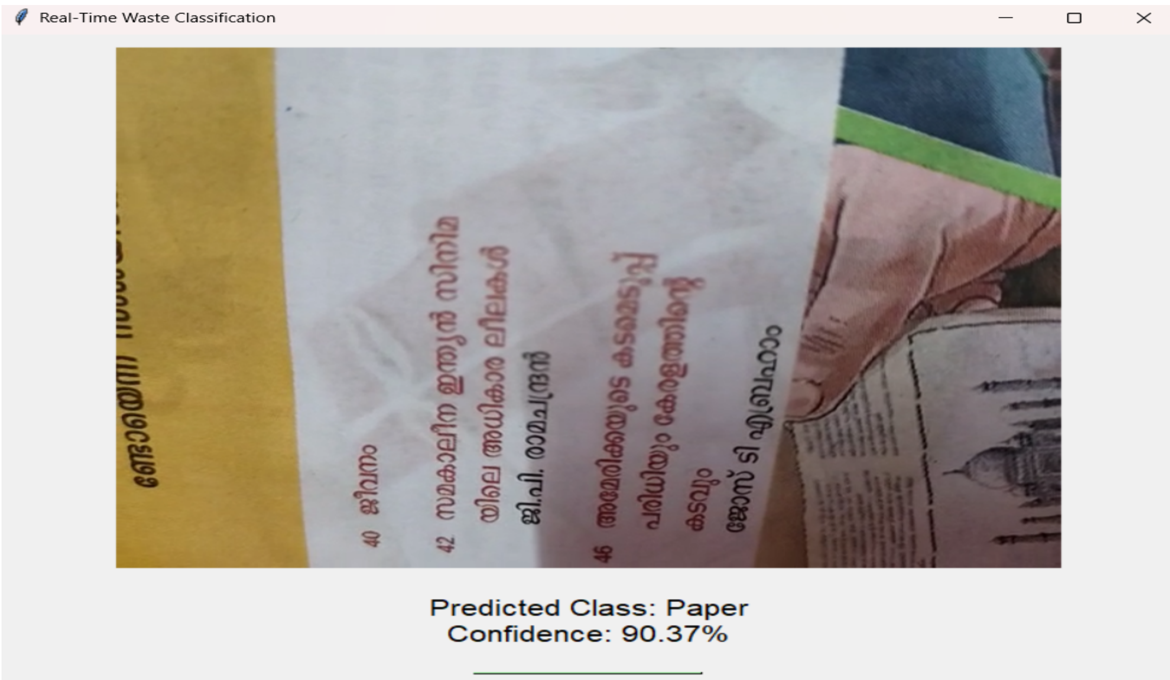

Figure 3.9: Result Page

CHAPTER 4

RESULTS & DISCUSSION

4.1 Accuracy

After training the model for 82 epochs, the model achieved a training loss of 0.2291 and a training accuracy of 91.59%. The validation loss at the end of the training was 0.2682, with a validation accuracy of 92.32%. These metrics indicate that the model performed well during training, achieving high accuracy and relatively low loss on both the training and test sets. This indicates that the model generalizes well to unseen data, as it maintains a high level of accuracy and reasonable loss on the test set. The model demonstrates strong performance in terms of accuracy, with a high level of accuracy achieved both during training and evaluation on the test dataset. The loss values indicate that the model effectively minimizes the dissimilarity between predicted and true class probabilities, further supporting its reliability for classification tasks.

4.2 Evaluation Metrices

The evaluation metrics mainly consist of 4 types ie, precision, recall,f1-score, and support. Precision: Precision measures the proportion of correctly predicted positive instances (true positives) out of the total instances predicted as positive. The model achieved high precision values across all classes, ranging from 0.91 to 0.99. This indicates that when the model predicted an instance as positive for a specific class, it was highly likely to be a correct. Precision=True Positive/(True Positive+False Positive)

Recall: Recall, also known as sensitivity or true positive rate, measures the proportion of correctly predicted positive instances out of the total actual positive instances. The model achieved good recall values, with a range from 0.81 to 1.00. This suggests that the model effectively identified a high percentage of actual positive instances for each class. Recall=True Positive/(True Positive+False Negative)

F1 score: The F1 score is the harmonic mean of precision and recall and provides a balanced measure of the model's performance. The F1 score ranges from 0 to 1, with higher values indicating better performance. The model achieved high F1 scores for all classes, ranging from 0.86 to 0.99, suggesting a strong overall balance between precision and recall. F1 Score=2*(Precision * Recall) / (Precision + Recall) Overall, the model demonstrates a high level of performance across the precision, recall, and F1 score metrics, indicating its effectiveness in classifying the different classes. The weighted average values for precision, recall, and F1 score, which consider the class distribution, are all around 0.95, further emphasizing the model's strong overall performance.

performance of the model is given below: For the ”Electronic Waste” class, the precision of 0.78 indicates that 78% of the instances predicted as electronic waste were correct. The recall of 1.00 suggests that the model correctly identified all instances of electronic waste out of the total actual instances. The F1-Score of 0.88 provides a balanced measure of precision and recall. For the ”Food Waste” class, the precision of 0.99 indicates high accuracy in correctly predicting instances of food waste. The recall of 0.99 suggests that the model successfully captured almost all instances of food waste. The F1-Score of 0.99 demonstrates high overall performance for this class. For the ”Glass Waste” class, the precision of 0.80 suggests that 80% of the instances predicted were correct. The recall of 0.85 indicates that the model identified 85% of the instances belonging to glass waste. The F1-Score of 0.82 represents a good balance between precision and recall. For the ”Metal Waste” class, the precision of 0.90 suggests that 90% of the instances predicted were correct. The recall of 0.73 indicates that the model captured 73% of the instances belonging to the metal waste class. The F1-Score of 0.80 represents a reasonable balance between precision and recall. For the ”Paper Waste” class, the precision of 0.92 indicates that 92% of the instances predicted was correct. The recall of 0.85 suggests that the model captured 85% of the instances belonging to paper waste. The F1-Score of 0.88 shows a good balance between precision and recall. For the ”Plastic Waste” class, the precision of 0.75 suggests that 75% of the instances predicted were correct. The recall of 0.87 indicates that the model captured 87% of the instances belonging to plastic waste. The F1-Score of 0.80 represents a reasonable balance between precision and recall. These performance metrics provide insights into the model’s accuracy, ability to identify relevant instances, and the overall balance between precision and recall for each waste class.

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Electronic Waste	0.78	1.00	0.88	39
Food Waste	0.99	0.99	0.99	661
Glass Waste	0.80	0.85	0.82	105
Metal Waste	0.90	0.73	0.80	133
Paper Waste	0.92	0.85	0.88	108
Plastic Waste	0.75	0.87	0.80	87

4.3 Confusion Matrix

The test dataset is imbalanced, hence there are differences in the number of test images in each class. Electronic waste and organic waste are classified with high accuracy, whereas paper and glass only have an accuracy of approximately 40per and 60per respectively.

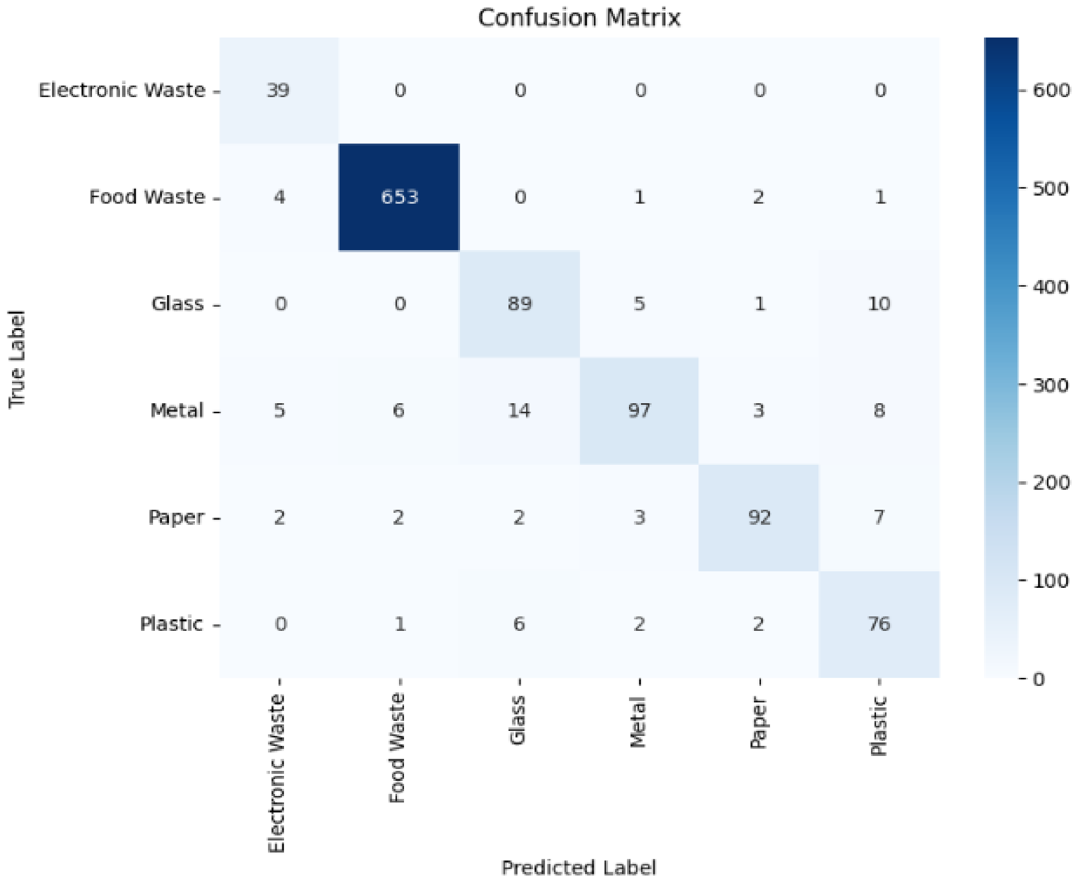

Figure 4.1: Confusion Matrix

4.4 Discussion

We analyze the findings and implications of the waste classification system implemented in this project. The system effectively utilizes computer vision techniques and machine learning algorithms to classify different types of waste into six categories: paper, glass, metal, plastic, food, and electronic waste.

The accuracy of the system, as demonstrated by the evaluation metrics such as precision, recall, and F1-score, showcases its ability to correctly classify waste items into their respective categories. The classification report and confusion matrix provide valuable insights into the system's performance, highlighting its effectiveness in distinguishing between different waste materials.

By accurately identifying and classifying waste items, the system facilitates proper waste management practices. It enables automated sorting and segregation of waste, which is crucial for efficient recycling and disposal processes. With this system, waste management facilities can streamline their operations, reduce manual effort, and promote sustainable waste management practices.

The integration of computer vision and machine learning in the waste classification system has the potential to revolutionize waste management processes. It offers a faster and more accurate alternative to manual sorting methods, which can be time-consuming and prone to human errors.

However, there are areas for further improvement in the waste classification system. To enhance its performance, the system can be trained on larger and more diverse datasets, encompassing a wider range of waste items and variations. This would improve its ability to handle different shapes, sizes, and variations within each waste category.

Additionally, continuous updates and retraining of the system using real-world data would help it adapt to evolving waste streams and changing waste characteristics over time. This adaptability is crucial to ensure the system remains effective and reliable in various waste management settings.

Overall, the waste classification system holds great promise for improving waste management practices. By automating the waste sorting process and ensuring accurate classification, the system contributes to sustainable waste management, recycling efforts, and the overall reduction of environmental impact.

CHAPTER 5

CONCLUSION & FUTURE SCOPE

5.1 Conclusion

The overall aim of our topic is to classify the waste material according to their types and also thereby reducing pollution. In this deep learning technique is used to classify different types of waste material, like paper, glass, metal, food, plastic, and electronic wastes. Deep learning models demonstrate strong performance in accurately categorizing different types of waste, enabling automated sorting processes and reducing human error. The application of deep learning allows for processing large volumes of waste data and learning complex patterns without the need for manual feature engineering. Future advancements in this field hold the potential for improving classification accuracy, handling rare waste classes, and incorporating multi-modal data sources. Real-time waste classification systems and large-scale monitoring provide valuable insights for waste management strategies. .

5.2 Future Scope

The future scope of waste classification using deep learning is promising and holds several potential opportunities. Here are some key aspects to consider:

Hyperparameter tuning: Fine-tune the hyperparameters of your model to optimize its performance. This includes parameters such as learning rate, batch size, optimizer, regularization techniques, and dropout rates. Use techniques like grid search or random search to efficiently explore the hyperparameter space.

Class imbalance handling: If the dataset has class imbalance, where some classes have more examples than others, consider employing techniques to handle this issue. You can explore oversampling techniques like SMOTE (Synthetic Minority Over-sampling Technique) or undersampling techniques like RandomUnderSampler to balance the class distribution.

Model architecture exploration: Experiment with different variations of the CNN model architecture. You can try different numbers of layers, layer sizes, activation functions, or even explore advanced architectures like residual networks (ResNet) or convolutional neural networks (CNNs) with attention mechanisms.

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