Landfill Waste Classification using Deep Learning

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Bachelor of Technology (B.Tech)

In

COMPUTER SCIENCE AND ENGINEERING

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CERTIFICATE

This is to certify that the Thesis on **"Landfill Waste Classification Using Deep Learning"** is a Bonafide work of Vedant Bhutada, Bhakti Bagadia, Aryan Khokle, Ayush Talpelwar, submitted to the Rashtrasant Tukdoji Maharaj Nagpur University, Nagpur in partial fulfillment of the award of a Degree of Bachelor of Technology (B.Tech), in Computer Science and Engineering. It has been carried out at the Department of Computer Science and Engineering, Shri Ramdeobaba College of Engineering and Management, Nagpur during the academic year 2023-2024.

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DECLARATION

We hereby declare that the thesis titled "**Landfill Waste Classification Using Deep Learning**" submitted herein, has been carried out in the Department of Computer Science and Engineering of Shri Ramdeobaba College of Engineering and Management, Nagpur. The work is original and has not been submitted earlier as a whole or part for the award of any degree/diploma at this or any other institution / University.

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This report entitled "**Landfill Waste Classification Using Deep Learning**" by **Vedant Bhutada, Bhakti Bagadia, Aryan Khokle, Ayush Talpelwar** is approved for the degree of Bachelor of Technology (B.Tech).

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ABSTRACT

Landfill waste detection is a pivotal aspect of effective waste management strategies. Traditional methods like visual inspection, weighing, and manual sorting, while widely used, are plagued by subjectivity, scalability issues, and high labor requirements. In contrast, machine learning techniques, particularly Convolutional Neural Networks (CNNs), have emerged as robust tools for waste detection and classification. Our project centered on landfill waste classification, employing a dataset containing images of various waste materials such as metal, plastic, cardboard, and glass. Initially, we trained a CNN using the ResNet101v2 architecture, achieving an impressive 95% accuracy when categorizing waste into two classes: biodegradable and non-biodegradable. Recognizing the complexity of identifying multiple waste objects within an image, we employed YOLOv8 for object detection. Leveraging the Aniopestra.v4i dataset, we attained an 84% accuracy rate in classifying objects into biodegradable and non-biodegradable categories. This approach holds promise for enhancing waste management practices by providing efficient and accurate waste classification capabilities.

Keywords: Landfill waste detection, classification, machine learning.

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

The management of landfill waste presents an ongoing challenge in contemporary waste management systems, necessitating efficient and accurate classification methodologies. Current practices heavily rely on manual sorting procedures, a labor-intensive and error-prone approach that not only consumes significant time but also compromises the accuracy of waste categorization. These limitations hinder operational efficiency and pose obstacles to sustainability endeavors, impeding effective waste segregation and recycling initiatives.

In response to these challenges, the Automated Waste Classification System Using Deep Learning for Landfill Management emerges as a transformative solution. This innovative system represents a convergence of cutting-edge technology and sustainability objectives, offering a paradigm shift in waste management practices. By harnessing the capabilities of state-of-the-art deep learning algorithms, the system aims to revolutionize the classification of landfill waste, enhancing efficiency, accuracy, and environmental stewardship.

Traditional waste sorting methodologies, such as manual inspection and weight-based systems, have proven insufficient in accurately distinguishing between diverse materials within mixed waste streams. These methods not only suffer from inefficiencies but are also prone to inconsistencies and errors, leading to suboptimal waste management outcomes. Moreover, existing technologies like RFID tagging, spectral imaging, and magnetic separation present their own set of limitations, including limited applicability, high costs, and complexity, further underscoring the need for a more robust and versatile solution.

In contrast, the Automated Waste Classification System offers a comprehensive and systematic approach to waste management. By leveraging advanced object detection and classification techniques powered by deep learning algorithms, the system can analyze images of mixed waste streams in real-time, facilitating prompt and precise classification. This automated approach reduces reliance on manual labor, mitigating errors and enhancing the accuracy of waste categorization, thereby improving overall operational efficiency.

Furthermore, the system's ability to differentiate between biodegradable and non-biodegradable materials holds significant implications for sustainability. Proper waste segregation is crucial for effective recycling and minimizing environmental impact. By automating this process, the invention promotes sustainable waste management practices, aligning with global initiatives for environmental conservation and resource optimization.

In summary, the Automated Waste Classification System Using Deep Learning for Landfill Management signifies a significant advancement in waste management technology. Its integration of deep learning algorithms, real-time analysis capabilities, and sustainability focus positions it as a cornerstone in the evolution of waste management practices towards efficiency, accuracy, and environmental stewardship.

1.2 MOTIVATION

The motivation behind the development of the Automated Waste Classification System Using Deep Learning for Landfill Management stems from the urgent need to address critical inefficiencies and challenges plaguing traditional waste management practices. Manual sorting procedures, which are labor-intensive and error-prone, pose significant obstacles to operational efficiency and sustainability goals. The reliance on outdated methodologies not only results in prolonged processing times but also compromises the accuracy of waste classification, hindering effective waste segregation and recycling efforts.

In response to these challenges, the Automated Waste Classification System harnesses the power of deep learning algorithms to revolutionize landfill waste management. By automating the classification process and employing advanced object detection and classification techniques, the system seeks to streamline operations, improve accuracy, and promote sustainability. The motivation lies in providing waste management facilities with a comprehensive and technologically advanced solution that enhances efficiency, reduces errors, and aligns with global initiatives for environmental conservation. This innovative approach not only addresses the shortcomings of existing methodologies but also sets a new standard for precision and sustainability in waste classification practices.

1.3 OBJECTIVE

The objectives of the project are:

1. To process images using CNN.
2. Develop a model that will be able to categorize landfill waste efficiently.
3. Train and test the designed model on Real Waste Dataset.
4. Use pre-trained models like Resnet and YOLOv8.

1.4 BRIEF DESCRIPTION

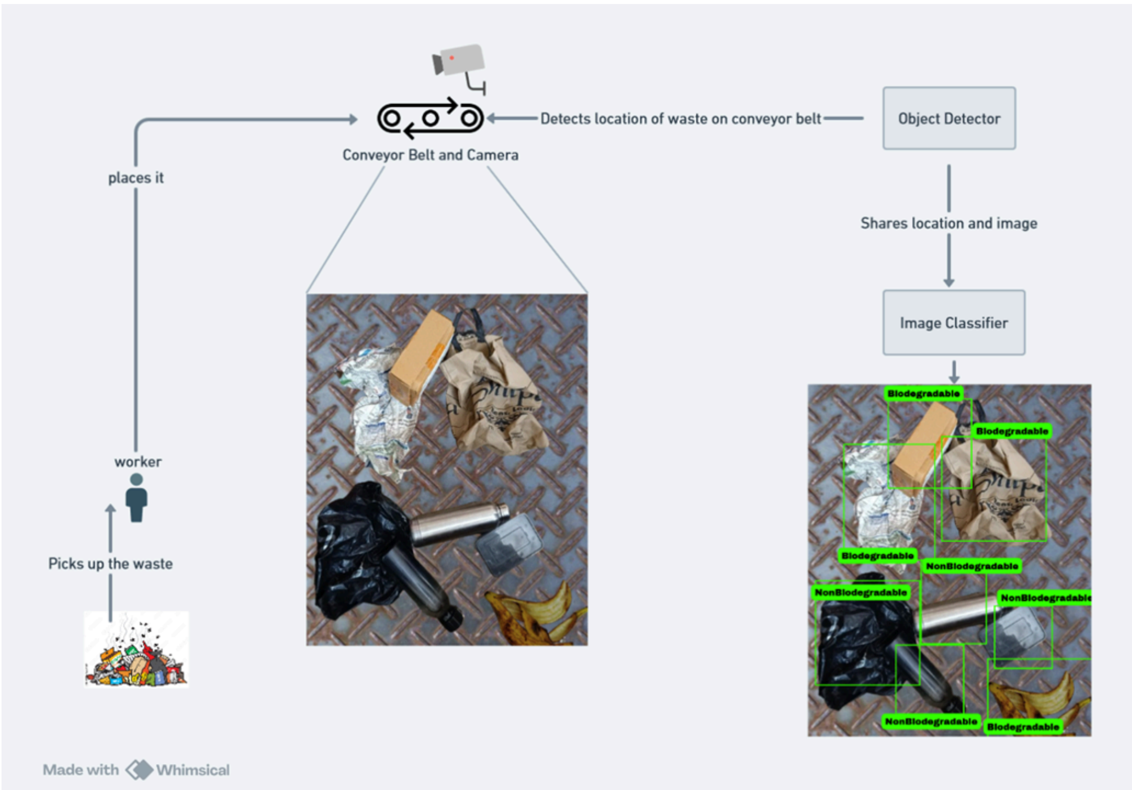

Figure 1 Block Diagram

The automated waste classification system using deep learning for landfill management consists of several interconnected modules, each designed to contribute to the overall efficiency and accuracy of waste classification. The Image Capture Module serves as the initial component, capturing images of mixed waste on a conveyor belt. These captured images are then seamlessly transmitted to the subsequent Object Detection and Classification Modules.These models identify and localize potential waste objects within the images, proposing bounding boxes around the detected objects.The Classification Module is a pivotal component that utilizes a machine learning model trained on labeled waste images, ensuring accurate categorization into biodegradable and non-biodegradable categories. Finally, the Display Module presents the classification results, offering a visual representation for further analysis and decision-making in the waste management process.

1.4.1 RESNET101V2

ResNet101v2 is an extended version of the original ResNet architecture introduced by Kaiming He, et al. ResNet (Residual Network) is a type of CNN that excels at training very deep networks, mitigating the vanishing gradient problem through the use of residual blocks. ResNet101v2 is an evolution that refines the original design, enhancing its efficiency and performance.ResNet101v2's architecture is characterized by its deep stack of residual blocks. Each residual block consists of two 3x3 convolutional layers, surrounded by Batch Normalization and ReLU activation functions. The presence of residual connections ensures the smooth flow of gradients, allowing the network to train effectively even as it deepens.The architecture is organized into four main blocks, each containing multiple residual blocks. This depth allows ResNet101v2 to learn complex hierarchical features from images, making it highly effective for recognizing patterns in diverse datasets.

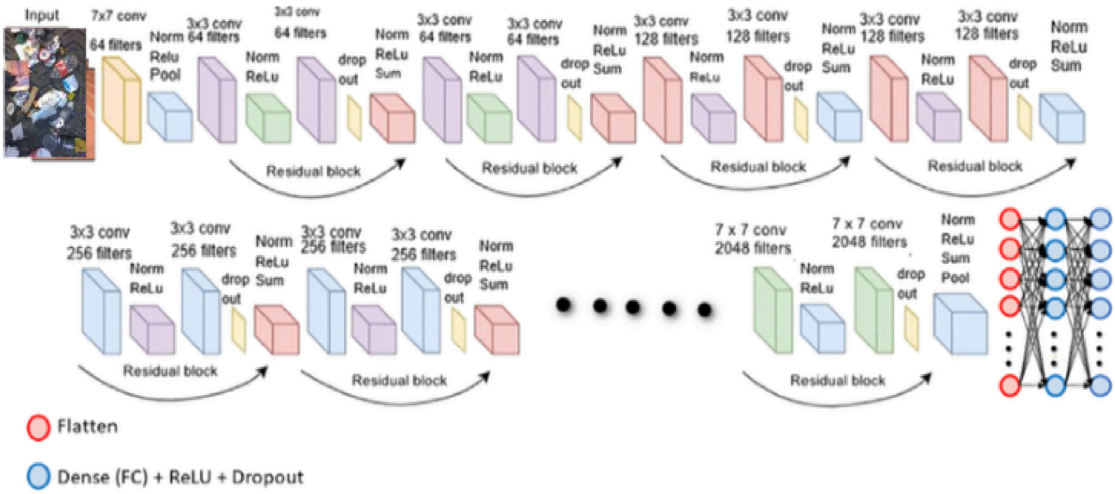

Figure 2 Architecture of Resnet101v2

1.4.2 YOLOV8

YOLOv8 is the latest version of the YOLO algorithm, which outperforms previous versions by introducing various modifications such as spatial attention, feature fusion, and context aggregation modules. These improvements result in faster and more accurate object detection, making YOLOv8 one of the key object detection algorithms in the field.

The architecture of YOLOv8 builds upon the previous versions of YOLO algorithms. YOLOv8 utilizes a convolutional neural network that can be divided into two main parts: the backbone and the head. A modified version of the CSPDarknet53 architecture forms the backbone of YOLOv8. This architecture consists of 53 convolutional layers and employs cross-stage partial connections to improve information flow between the different layers. The head of YOLOv8 consists of multiple convolutional layers followed by a series of fully connected layers. These layers are responsible for predicting bounding boxes, objectness scores, and class probabilities for the objects detected in an image. One of the key features of YOLOv8 is the use of a self-attention mechanism in the head of the network. This mechanism allows the model to focus on different parts of the image and adjust the importance of different features based on their relevance to the task. Another important feature of YOLOv8 is its ability to perform multi-scaled object detection. The model utilizes a feature pyramid network to detect objects of different sizes and scales within an image.

This feature pyramid network consists of multiple layers that detect objects at different scales, allowing the model to detect large and small objects within an image.

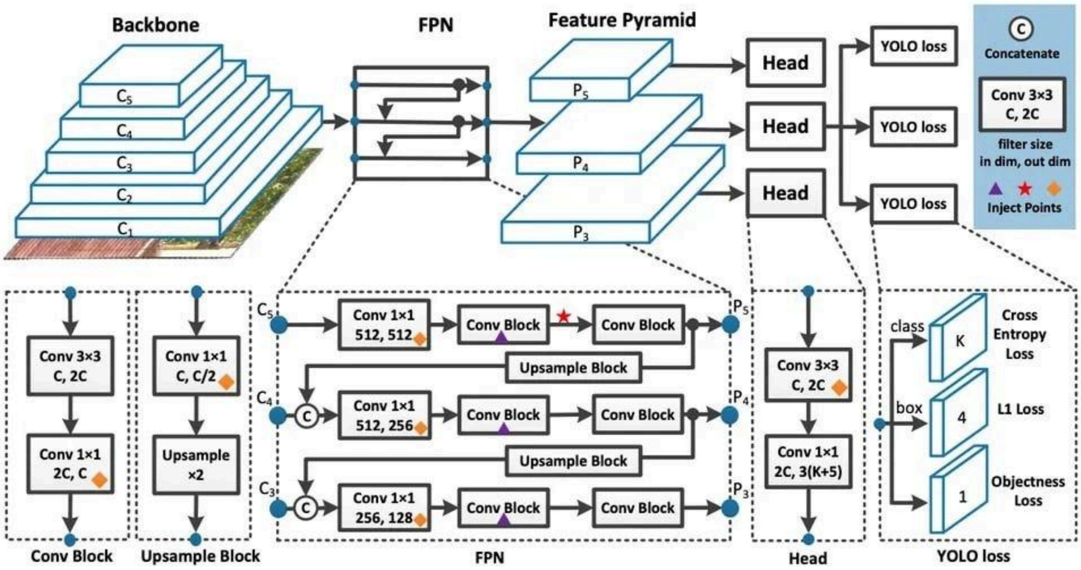

Figure 3 Architecture of YOLOv8

CHAPTER 2

LITERATURE SURVEY

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[1].In this research paper, they described the drawbacks of previous research papers, where various approaches for the detection and classification of solid waste have been explored, including both traditional and machine learning methods. Traditional approaches, such as visual inspection, weighing and volume measurement, and manual sorting, have been widely used for waste detection. In their research paper,they have used the Convolutional Neural Network(CNN) for image classification .They conducted an experimental study to analyze the performance of five popular CNN models, on labeling waste across two datasets. Specifically, VGG-16 has been selected for its shallow design. The samples were taken from bins of municipal, recycling, and organic waste stream.For evaluation purposes, a test dataset has also been assembled from the waste audit samples prior to the curation of RealWaste, with images selected at random. Table 1 provides insights into the distribution of images across different waste categories and highlights potential imbalances or variations within the datasets. For instance, in the DiversionNet dataset, the label with the highest image count is Paper (594 images), followed by Plastic (482 images) and Glass (501 images). On the other hand, the label with the lowest image count in the DiversionNet dataset is Miscellaneous Trash (290 images). The dataset consists of 9 different labels i.e Cardboard,food organics,glass,metal,trash,paper,plastic,textile trash, vegetation.
They got the result as-

Inception V3 and DenseNet121 models achieved 89.19% classification accuracy when trained on RealWaste, however the former performed the best by achieving the highest results in the other metrics. Specifically, the 91.34% precision, 87.73% recall, and 90.25% F1-score reached by Inception V3 were more than 0.5% greater than the next closest DenseNet121 model for each metric. With respect to accuracy between RealWaste and DiversionNet training in Table 3, VGG-16 showed a 58.83% improvement, 48.86% in DenseNet121, 31.50% in Inception V3, 42.62% in InceptionResNet V2, and finally, 60.50% in MobileNetV2.

[2] In this research paper,they have proposed a CNN model using transfer and ensemble learning to classify landfill waste into nine classes: aluminum, carton, e-waste, glass, organic waste, paper and cardboard, plastics, textiles, and wood.There are about 8300 images in the dataset.Four models were used by them i.e InceptionResNet , EfficientNetb3 , DenseNet201 and combination of all three models. Four CNN models (Model 1: Inception–ResNet-v2 based, Model 2: EfficientNetB3 based, Model 3: DenseNet201 based, and Model 4: the Ensemble Model) were run with the waste dataset of 8346 images containing nine classes of waste. CNNs. The training

was completed on 80% of the waste dataset and the remaining 20% was used for testing and validation. The networks were trained in 80 epochs.
From the results they got that the Ensemble Model was the most performant model (accuracy: 90% and precision: 90%) and was followed by Model 3 (accuracy: 88% and precision: 88%). Model 2 (accuracy: 87% and precision: 87%) and Model1(accuracy: 86% and precision: 86%) were the poorest performing models. These results proved that combining multiple pre-trained CNNs as base models increased feature extractions abilities and led to higher prediction accuracy. The effect of waste class number on the Ensemble Model's performance was investigated by training and testing the model to predict six waste classes. The model showed a prediction accuracy of 93%, leading to the conclusion that the model's performance increases as the number of classes decreases.

[3].The proposed method was developed based on the ResNet-50 pre-trained model.Dataset used was the trash image dataset which was developed by Gary Thung and Mindy Yang. They used 4 classes i.e glass,metal , paper and plastic.
In conclusion, they proposed a waste classification system that is able to separate different components of waste using the Machine learning tools. This system can be used to automatically classify waste and help in reducing human intervention and preventing infection and pollution. From the result, when tested against the trash dataset, they got an accuracy of 87%. The separation process of the waste will be faster and intelligent using our system without or reducing human involvement. If more image is added to the dataset, the system accuracy can be improved.

[4] In this paper, they present a bespoke CNN architecture developed for waste image classification consisting of five convolutional 2D layers of various neuron sizes; followed by a number of fully connected layers. Experiments were based on Sekar's waste classification dataset available on Kaggle. To overcome the drawback of insufficient data, augmentation methods were applied to increase the amount of data available for training, validation, and testing. To investigate the possibility of training an efficient light-weight model with high performance and less computational demand; they trained the bespoke CNN architecture described in Section 3.3 with two different image resolutions (80 × 45 and 225 × 264) of the augmented version of Sekar's waste classification dataset and compared performance in terms of accuracy, development time, and model size. The model is based on image classification and method used is bespoke 5 layer CNN architecture. The Results obtained from the baseline model as well as the bespoke CNN architecture trained with small (80 × 45) with Accuracy of 79 % but a loss validation of 2.03 and large (225 × 264) image resolutions with accuracy of 79 % with loss validation of 0.70. Where the images are classified on the basis of organic or recyclable.

[5] The ConvoWaste model is used in the experiment. To attain the best level of accuracy, this CNN model combines a pre-trained Inception-Resnet V2 model [15] with several extralayers. To extract features, the Inception-Resnet V2 model is utilized. It's a pre-trained model, which has been trained on over 1.4 million photos and over 1,000 classes. Convolutional neural networks are used in the Inception-Resnet V2 model for image identification in order to extract features. In our study, 80% of the data were retained for training purposes, while 20% were kept for testing purposes.They have collected the dataset by web scraping and Kaggle dataset site.

The results of this system showed a higher accuracy level underlying deep learning algorithms. In this paper, for the training purpose, 12000 images were considered to train up the network but for the large-scale application. We have achieved the maximum accuracy 98% of the ConvoWaste.

CHAPTER 3

METHODOLOGY

3.1 IMAGE CLASSIFICATION

3.1.1 DATASET

The project utilized a waste image dataset containing 8,356 images categorized into nine classes: aluminum, carton, e-waste, glass, organic waste, paper and cardboard, plastic, textile, and wood. For better analysis, the waste materials were further classified into biodegradable and non-biodegradable categories. Biodegradable waste encompassed paper and cardboard, organic waste, wood, and textiles, totaling 3,651 images within the dataset. Conversely, non-biodegradable waste included glass, e-waste, plastic, aluminum, and carton, represented by 4,705 images.

This breakdown provides valuable insights into the composition of the waste stream and facilitates the development of targeted waste management strategies.

Sr No.	Classes	Items	Tain	Valid	Test	Total
1	Aluminium	Canes, plates, bottles, leads, bottle openers, trash cans, cooking pots, car parts, and silverware	713	153	153	1019
2	Carton	Juice, milk, and cigarettes boxes	373	80	80	533
3	E-waste	Batteries, electronics (computer, phones, etc.) circuit boards, microchips, cables, and chargers	720	154	155	1029
4	Glass	Bottles, jars, containers, cups, decoration, plates, and pitchers	762	163	164	1089
5	Organic waste	Fruits, vegetables, meats, fast food, meals, plants, seeds, cheese, bread, and eggshells	737	158	158	1053
6	Paper and cardboard	Newspapers, magazines, books, shipping boxes, letters, envelopes, gift and pizza boxes, shredded paper, flyers, and stickers	835	179	180	1194
7	Plastics	Bottles, containers, cups, plates, food packaging, bags, silverware, furniture, cases, buckets, planting pots, and trash bins	724	155	156	1035
8	Textiles	Clothes, curtains, towels, decorations, sheets, bags and fabric	581	124	125	830
9	Wood	Signs, furniture, cases, wood blocks, tiles, utensils, plates, silverware,wine cork, pellets, boards, baskets, mashed wood, and containers.	401	86	87	574
			5846	1252	1258	8356
	Bio-Degradable	Paper And Cardboard, Organic Waste, Wood, Textiles				3651
	NonBio-Degradable	Glass ,E-waste, Plastic, Aluminium, Carton				4705

Figure 4 Dataset for Image Classification

3.1.2 MODEL USED

Our model employs transfer learning, leveraging the pre-trained ResNet101V2 architecture. This architecture, renowned for its depth and performance, has been fine-tuned for our task. We retained ResNet101V2's convolutional layers, appended a

Global Average Pooling (GAP) layer for feature extraction, and added a Dense layer for classification.

By freezing ResNet101V2's weights, we retained its learned representations while training only the classification layer. This approach accelerates training and guards against overfitting, given ResNet101V2's ability to capture general visual features. We utilized Stochastic Gradient Descent (SGD) with a learning rate of 0.001 and momentum of 0.9, coupled with a squared hinge loss function suitable for our binary classification task. Monitoring accuracy throughout 12 epochs ensured effective model refinement.

Our model achieved an accuracy score of approximately 95.75% on unseen data, demonstrating robustness and generalization. This high accuracy underscores its potential for diverse applications, including image recognition and medical diagnosis.

3.1.3 RESULTS

- Accuracy: The overall accuracy of our model is 0.9574638844301766. This means that the model correctly classified 95.75% of the test images.

The graph of the statistics is as follows:

a) Confusion Matrix

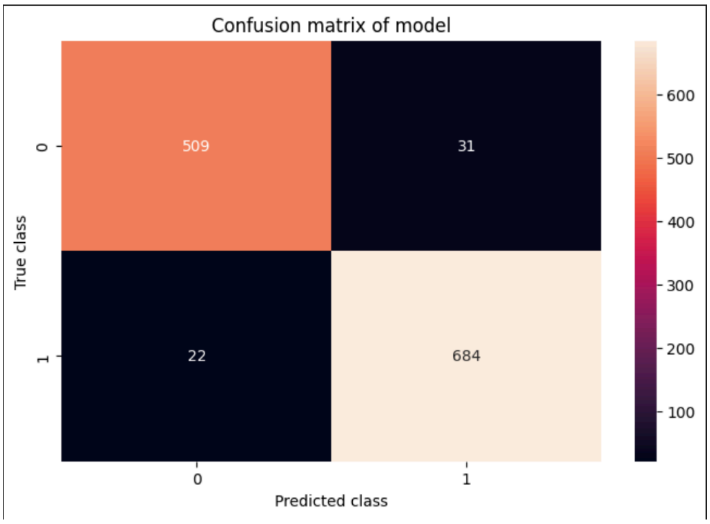

Figure 5 ResNet101V2 Confusion Matrix

The confusion matrix shows how many times the model correctly classified each class (true positives and true negatives) , and how many times it misclassified each class (false positives and false negatives). The Matrix has 2 binary classes, 0: Biodegradable and 1:Non-BioDegradable.Out of 1246 total images , 509 images are classified as

True-Positive , 22 images as False-Positive , 31 as False- Negative and 684 as True-Negative.

b) Graph of Accuracy in training and validation data

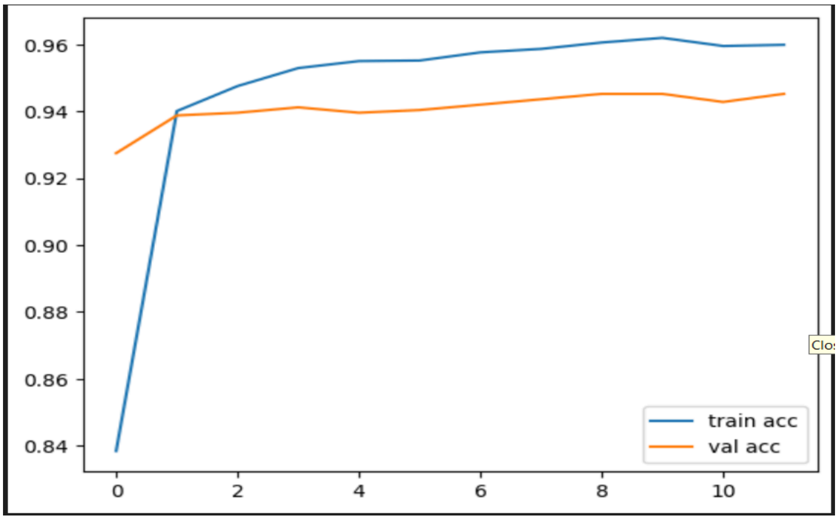

Figure 6 Resnet101V2 Accuracy Graph

Figure 6 represents both training and validation accuracies improve during training, but eventually, they reach a point where further improvement is limited. This graph helps assess the model's performance and overfitting.

c) Graph of Loss in training and validation data

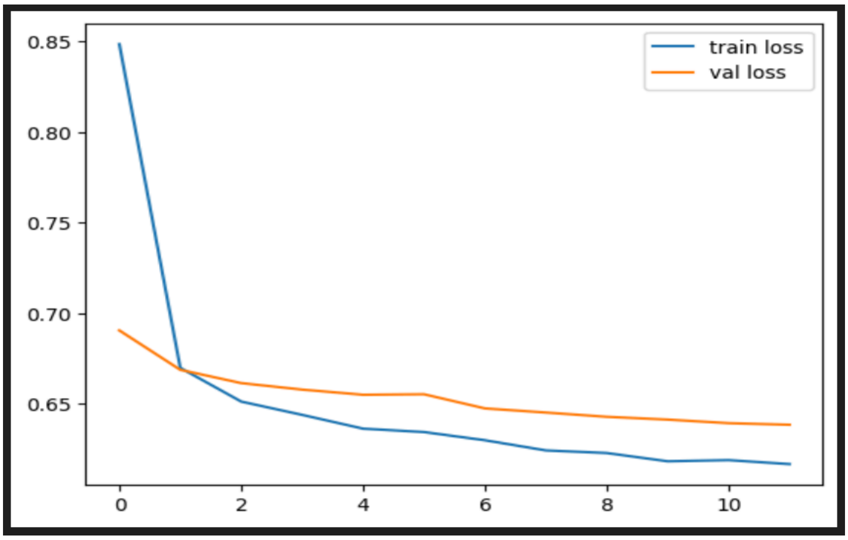

Figure 7 Resnet101V2 Loss Graph

Figure 7 depicts the performance of a model during its training process. It shows that the train loss starts at approximately 0.85 and experiences a sharp decline to 0.7 within the first epoch, after which it continues to decrease gradually. On the other hand, the validation loss begins at 0.65 and decreases steadily to a lower value. The converging trend of both the train and validation loss lines indicates an improvement in the model's performance over time. This suggests that the model is learning effectively without overfitting.

d) Output Image:

Figure 8 Resnet101V2 Result Image

Figure 8 displays the output of Single Images of waste in two classes: Biodegradable and Non-Biodegradable.

3.2 OBJECT DETECTION

3.2.1 DATASET

For our object detection model training, we utilized a dataset consisting of 1136 training images, 226 validation images, and 153 test images. The dataset encompasses various waste items categorized into biodegradable and non-biodegradable classes. The biodegradable classes include coloured paper, corrugated cardboard, mixed cardboard, and white paper. On the other hand, the non-biodegradable classes comprise aluminum foil, cat food cans, clear plastic, food cans, glass, HDPE clear, HDPE color, PET clear-blue, PET coloured, polypropylene, polystyrene food trays, polystyrene (other), Tetra Pack, thermoforms, universal beverage cans, and non-recyclable plastic. This comprehensive dataset facilitated the training of our object detection model, enabling it to accurately detect and classify waste items into their respective categories for effective waste management solutions.

3.2.2 MODEL USED

In this project, we harnessed the power of the YOLOv8 object detection model, implemented using the Ultralytics library. YOLOv8, an evolution from its predecessors, stands for You Only Look Once version 8, representing a state-of-the-art deep learning architecture known for its real-time object detection capabilities. Unlike conventional methods, YOLO executes detection tasks in a single pass, ensuring remarkable speed and efficiency. Our implementation revolved around training the model on a custom dataset specifically tailored to our application domain, meticulously fine-tuning hyperparameters such as learning rate, batch size, and training epochs to optimize detection performance. Post-training evaluation using standard metrics, including mean average precision (mAP), validated the model's accuracy in detecting and localizing objects. With its capability to swiftly process new images and provide precise bounding box coordinates and class predictions, YOLOv8 emerges as a robust solution suitable for real-time applications across diverse domains such as surveillance, autonomous driving, and image analysis.

3.2.2 RESULTS

The YOLO model successfully processed the provided image and identified objects within it. The model is designed to classify these objects and assign a bounding box around each detection. The bounding box is accompanied by a confidence score indicating the model's certainty in the classification. The model is trained to differentiate between biodegradable and non-biodegradable items.

- Accuracy: The overall accuracy of our model is 84%.

a) Output Image:

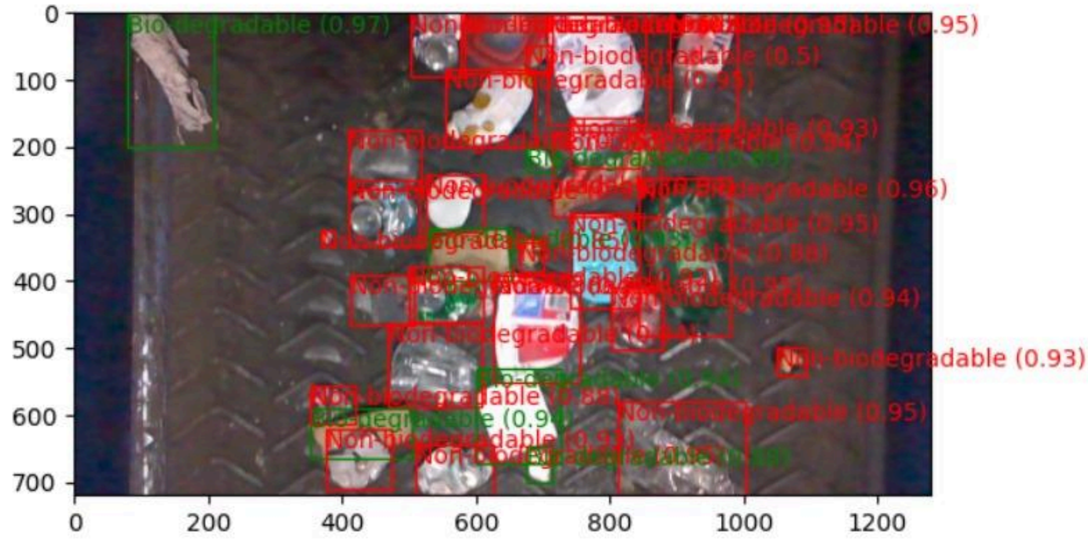

Figure 9 YoloV8 Result Image

Figure 9 displays the output of Waste on Conveyor Belt in two classes: Biodegradable and Non-Biodegradable. Each object in the conveyor belt is surrounded with a bounding box having a label and confidence score.

b) Confusion matrix

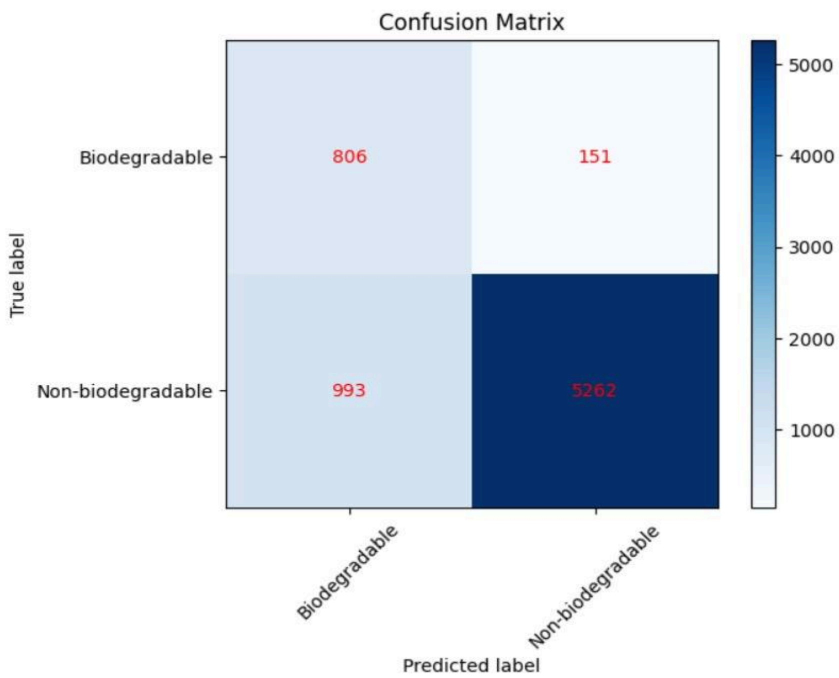

Figure 10 YoloV8 Confusion Matrix

The confusion matrix shows how many times the model correctly classified each class (true positives and true negatives) , and how many times it misclassified each class (false positives and false negatives). The Matrix has 2 categorical classes: Biodegradable and Non-Biodegradable.Out of 7212 total objects , 806 objects are classified as True-Positive , 993 as False-Positive , 151 as False- Negative and 5262 as True-Negative.

c) Graphs of loss,precision,recall,mean-average-precision:

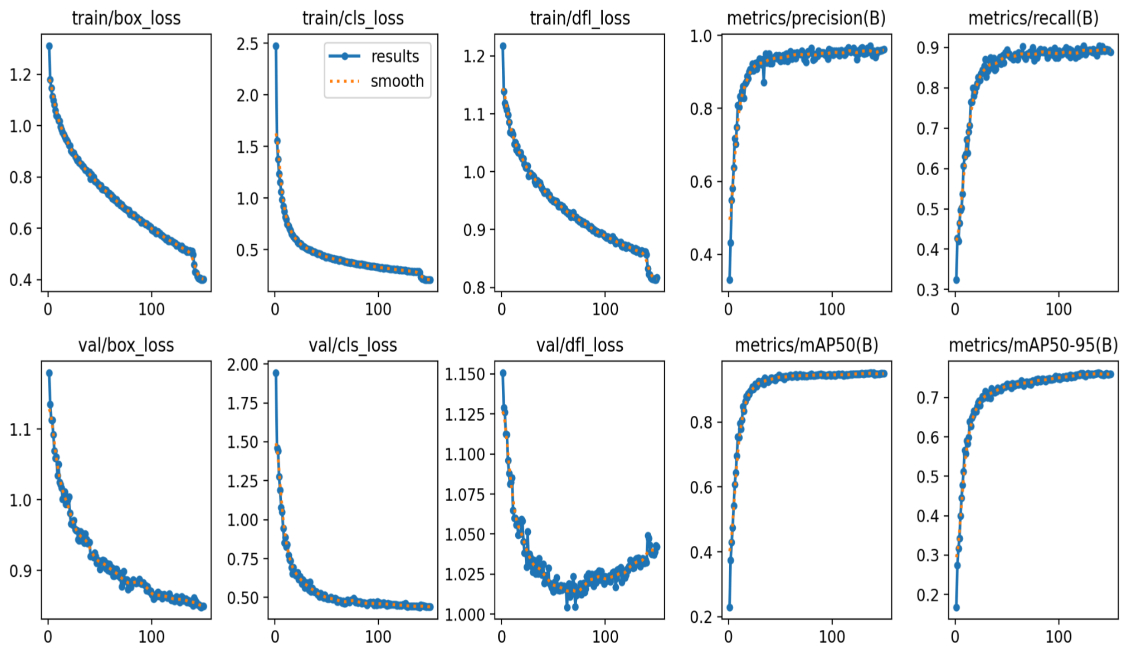

Figure 11 YoloV8 Metrics

The model's performance is evaluated using several metrics. The **training loss for bounding boxes** (train/box_loss) and the **classification loss during training** (train/cls_loss) both show a decrease over epochs, suggesting improvements in predicting bounding boxes and classifying objects within these boxes. The **detection-related training loss** (train/dfi_loss) also decreases, indicating an overall enhancement in the model's detection capabilities. On the validation set, the model's **precision** (metrics/precision(B)) and **recall** (metrics/recall(B)) ideally increase over epochs, representing an improvement in the proportion of correct positive detections and the proportion of actual positive examples correctly detected by the model, respectively. The **mean average precision (mAP)** at a specific Intersection over Union (IoU) threshold of 0.5 (metrics/mAP50(B)) and between IoU thresholds of 0.5 and 0.95 (metrics/mAP50-95(B)) are used to evaluate the model's object detection performance, considering both precision and recall. A higher mAP indicates better model performance.

CHAPTER 4

CONCLUSION

In conclusion, the development and implementation of the Automated Waste Classification System Using Deep Learning for Landfill Management represent a significant step forward in addressing the challenges faced by traditional waste management practices. The project set out with the aim of revolutionizing waste classification through the integration of cutting-edge deep learning algorithms, with a focus on enhancing efficiency, accuracy, and sustainability.

Through the utilization of state-of-the-art technologies such as image classification and object detection, the project successfully demonstrated the feasibility and effectiveness of automating waste categorization processes. The utilization of the ResNet101V2 architecture for image classification yielded impressive accuracy results, showcasing the potential of transfer learning in waste management applications.

Moreover, the adoption of the YOLOv8 object detection model for identifying and classifying waste items further solidified the system's capabilities. By providing real-time detection and precise localization of objects, the system offers a practical solution for waste management facilities to streamline operations and improve decision-making processes.

The project's findings underscore the importance of leveraging advanced technologies to address the inefficiencies and shortcomings of traditional waste management methodologies. By automating classification processes, the system not only reduces reliance on manual labor but also enhances the accuracy of waste categorization, thereby facilitating more effective waste segregation and recycling efforts.

Furthermore, the project highlights the potential for deep learning-based solutions to contribute to global sustainability initiatives. By promoting proper waste segregation and recycling practices, the Automated Waste Classification System aligns with broader environmental conservation goals, ultimately leading to reduced environmental impact and resource optimization.

Moving forward, the insights gained from this project lay the foundation for further advancements in waste management technology. Continued research and development in this field hold the promise of even greater efficiency, accuracy, and environmental stewardship in waste management practices, ultimately contributing to a more sustainable future for generations to come.

CHAPTER 5

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