

BIO-MEDICAL WASTE CLASSIFICATION

Submitted in partial fulfilment of the requirements of the degree of

BACHELOR OF COMPUTER ENGINEERING

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CERTIFICATE

This is to certify that the project entitled “**Bio Medical Waste Classification**” is a bonafide work of **Nikita Dung (20102153)**, **Karan Dagli (20102075)**, **Amol Gautam (20102098)**, **Manthan Agarwal (20102100)** submitted to the University of Mumbai in partial fulfilment of the requirement for the award of the degree of **Bachelor of Engineering in Computer Engineering**.

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We declare that this written submission represents my ideas in my 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 my submission. we understand that any violation of the above will be cause for disciplinary action by the Institute and canalso evoke penal action from the sources which have thus not been properly citedor from whom proper permission has not been taken when needed.

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Abstract

With the increasing demands on healthcare services, the generation of medical waste has reached unprecedented levels, surpassing the capacity for efficient management. This surge in biomedical waste output is causing serious environmental and public health concerns. The conventional methods of categorizing and handling medical waste have proven inadequate and prone to errors. Deep learning, a cutting-edge technology for image classification, has shown great promise in this context. However, its widespread practical implementation has been hindered by the need for extensive data. Consequently, the problem of medical waste classification, urgent in the present environmental protection context, calls for innovative solutions to revolutionize the management of healthcare waste.

In response to this challenge, a deep learning-based approach is proposed for the automatic detection and classification of medical waste. The strategy leverages the YOLO (You Only Look Once) algorithm, a highly effective deep neural network, and integrates learning techniques to enhance the precision of classification outcomes. This proposed system classifies biomedical waste generated in hospitals and sanitizations into four different categories which includes Pharmaceutical/Medicinal waste, Sharps/Glass waste, Disposable waste and Radioactive waste. The model achieves a high degree of accuracy at 87% in waste classification. By embracing deep learning capabilities, this approach promises to improve the efficiency and accuracy of medical waste classification, contributing to safer healthcare waste management practices, protecting public health, and fostering greater environmental sustainability within the healthcare sector.

Keywords*: Medical waste management, Environmental challenges, Biomedical Waste, Deep learning, Classification, Healthcare.

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Abbreviation

<i>YOLO</i>	You Only Look Once
<i>CNN</i>	Convolutional Neural Networks
<i>WHO</i>	World Health Organization
<i>BMW</i>	Bio-Medical Waste

CHAPTER 1

Introduction

Maintaining a clean and hygienic environment is a common aspiration for every individual, contributing to a fresh and healthy living space. Unfortunately, improper disposal of waste, including medical waste, is a prevailing issue in many cities, which not only compromises the environment but also poses significant health risks. Illegally dumped medical waste, in particular, introduces a serious threat to the surroundings. In light of these concerns, this system introduces a novel approach that employs the YOLOv5 object detection model to identify and classify medical waste. This system, designed with user-friendliness and intuitiveness in mind, aims to enhance the detection and sorting of medical waste effectively. Biomedical waste classification is a critical component of healthcare and environmental management, essential for public health, and the maintenance of a hygienic and safe environment. Unfortunately, a significant problem persists as many individuals indiscriminately dispose of medical waste, including hazardous materials, in non-designated areas. This irresponsible practice not only jeopardizes environmental sustainability but also endangers public health due to associated risks. To address this pressing issue, an innovative approach utilizes the YOLOv5 object detection model, a cutting-edge technology in the field of deep learning. The user-friendly and intuitive nature of this system aims to enhance the accurate identification and sorting of medical waste, ensuring it is handled and disposed of correctly.

This concern is amplified by the surge in healthcare demands, which has led to an alarming increase in medical waste generation, surpassing conventional management capabilities. To address this critical issue, advanced technologies such as deep learning have become pivotal in the realm of medical waste classification. Notably, the use of the YOLOv5 (You Only Look Once version 2)

algorithm, a robust darknet framework, has offered a breakthrough solution. By harnessing the power of YOLOv5, this approach ensures efficient and precise biomedical waste classification, mitigating environmental risks and enhancing healthcare waste management.

In a world where the need for a clean and hygienic environment is a shared aspiration, the proper disposal of waste, especially medical waste, has become a paramount concern. The reckless dumping of medical waste not only undermines environmental integrity but also poses severe health hazards. Illegally discarded medical waste is a looming threat that requires urgent attention. In response to this pressing challenge, we present a groundbreaking approach, harnessing the power of the YOLOv5 object detection model. This system, designed with simplicity and user-friendliness in mind, offers a transformative solution to the detection and classification of medical waste. Biomedical waste categorization is a pivotal element in healthcare and environmental management, crucial for safeguarding public health and upholding a clean and secure living environment. Nevertheless, a significant issue persists as individuals continue to haphazardly dispose of medical waste, including potentially dangerous materials, in inappropriate locations. This irresponsible behavior not only undermines the sustainability of our environment but also places public health in peril due to the associated risks. To combat this urgent challenge, we introduce an innovative approach that leverages the YOLOv5 object detection model, a state-of-the-art technology in the realm of deep learning. This user-friendly and intuitive system is designed to greatly improve the accurate identification and sorting of medical waste, ensuring it is managed and disposed of in a responsible and safe manner.

CHAPTER 2

Literature Survey

The several studies are focused on the management of biomedical waste (BMW) in India, stressing the 2016 BMW regulations, their implementation difficulties, the shortcomings of traditional approaches, and environmentally friendly BMW disposal strategies. The new regulations were designed to enhance segregation, transportation, and disposal techniques, which will ultimately reduce environmental pollution and change how the nation treats BMWs.

Datta, P. et. al. proposed the basic principle of good BMW practice is based on the concept of 3Rs, namely, reduce, recycle, and reuse. The best BMW management (BMWM) methods aim at avoiding generation of waste or recovering as much as waste as possible, rather than disposing. Therefore, the various methods of BMW disposal, according to their desirability, were prevent, reduce, reuse, recycle, recover, treat, and lastly dispose. Hence, the waste should be tackled at source rather than “end of pipe approach” [1].

According to Bai et al., correctly classifying trash in medical settings can save costs and have a positive environmental impact. They support efficient trash segmentation to reduce volume and infractions, and they suggest a new classification scheme to expedite disposal costs. Their suggestions put improving hospital waste management procedures first in order to cut expenses and lower threats to occupational health. The study addresses the creation of a new eight-class system for classifying medical waste, which comprises microbiological, pathological, sharps, pharmaceutical, chemical, radioactive, non-recyclable, and recyclable trash. The report highlights how crucial it is for healthcare facilities to properly segregate their trash in order to cut expenses and occupational health risks. It emphasizes how hospitals can lessen their environmental impact

by implementing thorough medical waste segregation and incorporating the "reduce, reuse, recycle" philosophy into waste management systems. Recyclable waste is a substantial waste that is frequently overlooked in the classification; the paper highlights its significance in waste management. According to the study, the existing color-coding system for segregating medical waste does not have distinct containers for the division of trash [2].

Jade, M. et. al. stated that because of their poverty, resource scarcity, and underfunded healthcare systems, African nations have difficulties managing medical waste properly. Medical waste management gone wrong in hospitals and other healthcare facilities is a widespread problem in nations like Ethiopia, Botswana, Nigeria, and Algeria. Incineration is a widely utilized disposal technique, but if the wrong technologies are not applied, it might pose serious dangers. Waste that is disposed of carelessly has a negative influence on communities, water resources, and the environment in African nations. The ways medical waste is currently disposed of in Africa—incineration, open dumping, unmanaged landfills—are not environmentally or health-friendly. Sustainable medical waste management in Africa can be facilitated by putting into practice a circular economy strategy that includes recycling non-hazardous waste, reusing objects, and cutting waste at the source. In order to mitigate climate change and safeguard public health in African nations, education on the production and administration of biofuels as well as the implementation of efficient waste management systems is essential [3].

Zurbrugg, C. et. al. The Gianyar Waste Recovery Project in Bali, Indonesia, represents a pioneering endeavor in the realm of integrated and sustainable solid waste management. With its composting unit processing a substantial volume of municipal waste daily, amounting to 60 tons, the project stands as a beacon of innovation in tackling waste-related challenges. Notably, it prioritizes waste segregation and composting of biodegradable waste while actively engaging local authorities, thus fostering a collaborative approach to waste management. Despite encountering hurdles such as limited funding and marketing complexities for compost products, the project has achieved significant milestones in waste reduction and environmental compliance. Moreover, its strong emphasis on community involvement has yielded tangible social benefits, including job creation and the restoration of local sites. As the project continues to evolve, it serves as a testament to the transformative potential of integrated waste management strategies and underscores the importance of sustained efforts in addressing environmental concerns at both local and global scales [5].

Teshiwal, D. et. al evaluated the information about the difficulties waste handlers at hospitals, especially in the Ethiopian town of Debre Markos, encounter. Their investigation revealed that most garbage handlers lacked the necessary training, which was made worse by a lack of access to personal protective equipment and other necessary waste management supplies. The results also

highlight the concerning disparity in these workers' attitudes, behaviours, and understanding regarding medical waste management. In addition, the frequency of accidents caused by needlesticks and other sharp items highlights the critical need for enhanced safety procedures and practices in healthcare environments. The study underlines the significance of giving garbage handlers enough resources and ongoing training to reduce occupational dangers and serves as a poignant reminder of the crucial role they play in protecting public health. It is essential that future study endeavors take into account the varied circumstances of healthcare facilities in various parts of Ethiopia. This will guarantee a more thorough comprehension of the obstacles and possible remedies in the field of medical waste management. Targeted interventions and policy initiatives that aim to improve the efficacy and safety of waste management methods in healthcare settings across the country can benefit from these insights [4].

Himadri N. S. et. al. purposed the management of waste, both municipal and industrial, is a critical concern amid India's rapid urbanization. To address this challenge, a variety of waste management strategies have been proposed, ranging from reduction and reuse to innovative IoT-based solutions. As we strive for a cleaner and healthier environment, the integration of IoT in waste management holds promise for enhancing sustainability and resource utilization, emphasizing the importance of informed decision-making and collaborative efforts among government and private agencies [6].

Ajay S. et. al. stated a growing problem of managing garbage in cities, made worse by population expansion and urbanization, calls for creative solutions to dispose of waste and use resources efficiently. In this quest, remote sensing and GIS techniques have proven to be vital tools, providing precise data gathering, processing, and visualization capabilities that are essential for making well-informed decisions. These technologies support waste composition characterization, appropriate disposal site identification, collection route optimization, and environmental effect assessment. Researchers and policymakers can develop sustainable waste management solutions that are suited to particular socioeconomic and environmental situations by combining geospatial data with sophisticated modeling approaches. The use of remote sensing and GIS in trash management promises to improve efficiency, lessen environmental degradation, and protect public health. Applications range from optimizing waste collection routes to evaluating the environmental dangers connected with landfill sites. Using these technologies is a critical first step in creating resilient, resource-efficient cities and promoting global sustainable development [7].

	Author	Title	Findings
[1]	Priya Datta, Gursimran Kaur Mohi, Jagdish Chander	Biomedical waste management in India: Critical appraisal.	Developed guidelines in India, emphasizing improvements in segregation, transportation, and disposal ways to prevent pollution.
[2]	V. Ramani Bai, G. Vanitha, A. R. Zainal Ariff	Effective Hospital Waste Classification to Overcome Occupational Health Issues and Reduce Waste Disposal Cost.	The study suggests a new eight-class system for classifying medical waste, which includes microbiological, pathological, sharps, pharmaceutical, chemical, radioactive, non-recyclable, and recyclable trash. According to the method, distinct color codes are provided to each type of garbage in order to facilitate identification and segregation of the various categories.
[3]	Jade Megan Chisholm, Reza Zamani , Abdelazim M Negm , Noha Said	Sustainable waste management of medical waste in African developing countries: A narrative review.	In order to mitigate climate change and safeguard public health in African nations, education on the production and administration of biofuels as well as the implementation of efficient waste management systems is essential.
[4]	Teshiwal Deress, Mohabaw Jemal, Mekonnen Girma and Kasaw Adane	Knowledge, attitude, and practice of waste handlers about medical waste management in Debre Markos town healthcare facilities, northwest Ethiopia.	The study emphasizes how important it is for healthcare facilities to give trash handlers regular training and sufficient supplies. When compared to research from India, the study participants knowledge, attitudes, and practice ratings were higher.

[5]	Christian Zurbrügg, Margareth Gfrerer, Henki Ashadi, Werner Brenner, David Küper	Determinants of sustainability in solid waste management – The Gianyar Waste Recovery Project in Indonesia.	The project involved waste segregation and composting of biodegradable waste, with attention given to technical appropriateness and involving local authorities.
[6]	Himadri Nath Saha, Supratim Auddy, Subrata Pal	Waste management using Internet of Things (IoT).	The proposed waste management system using IoT technology involves connecting multiple dustbins in smart cities through embedded devices. Ultrasonic sensors are used to sense the dustbin level and indicate the presence of toxic gases.
[7]	Ajay Singh	Remote sensing and GIS applications for municipal waste management.	GIS and remote sensing techniques can handle large amounts of spatial data and consider social, technical, economic, and environmental limitations in waste management modelling.
[8]	A. Bruno, C.Caudai, G.R. Leone	Medical Waste sorting: A Computer vision approach for assisted primary sorting.	AI-driven sorting aids medical waste management amid COVID-19. EfficientNet shows high accuracy. Dataset availability and computer vision advancements enhance waste sorting systems.
[9]	Ranjith Gowda A S, Rekha. B, Shradha Satish Wantamutte	Biomedical waste management current practices and future prospective in urban area.	Biomedical waste studies emphasize proper disposal to safeguard human health and the environment, highlighting gaps in knowledge and practices among healthcare workers, necessitating enhanced training and guidelines.

Table 2.1: Literature Survey Table

CHAPTER 3

Limitation of Existing system

Manual limitations in biomedical waste management refer to the challenges and drawbacks associated with traditional, non-automated methods of handling, segregating, and disposing of biomedical waste. These limitations include:

- **Human Error:** Manual handling of biomedical waste is prone to human error. Workers may mistakenly mix different categories of waste, leading to cross-contamination and safety hazards.
- **Inadequate Training:** Healthcare personnel and waste management staff may not receive sufficient training on the proper handling of biomedical waste, resulting in improper disposal practices.
- **Safety Risks:** Manual sorting and disposal increase the risk of needlestick injuries, cuts, and exposure to hazardous materials, which can have serious health implications.
- **Labor-Intensive:** Manual sorting and segregation are labor-intensive processes that require significant human resources, making the system costly and less efficient.
- **Inconsistent Practices:** Different workers may have varying levels of commitment to safety protocols, leading to inconsistencies in waste management practices within the same facility.
- **Lack of Compliance:** Maintaining compliance with regulatory guidelines is challenging when relying solely on manual methods. This can lead to non-compliance issues.
- **Inefficient Record-Keeping:** Manual record-keeping is prone to inaccuracies and can make it difficult to track and manage waste generation and disposal.

- Scalability Issues: Manual systems may not be easily scalable to accommodate the increasing volume of biomedical waste generated by healthcare facilities.
- Resource Intensive: Manual waste management systems require significant storage space, protective gear, and disinfection supplies, which can strain the resources of healthcare facilities.
- Environmental Impact: Inadequate disposal and treatment methods for biomedical waste can have negative environmental consequences, especially when waste is disposed of in landfills or open dumps.

Biomedical waste management presents several challenges that require a comprehensive approach to ensure proper handling and disposal, minimizing risks to healthcare workers and the environment. Conventional biological waste management systems often face significant constraints.

One major concern is the lack of effective biomedical waste segregation at the source, which can result in hazardous waste mingling with non-hazardous waste, raising the risk of contamination and safety hazards. Additionally, healthcare professionals and waste management personnel may not receive appropriate training in the safe handling and disposal of biomedical waste, increasing the risk of infection. Inconsistent legislation and norms between regions and facilities further add to the difficulty, resulting in differences in waste management techniques and making standardized safety measures difficult to implement. Moreover, limited infrastructure in some healthcare facilities, particularly those in resource-constrained locations, can hamper proper waste management. Inadequate storage rooms and required disposal facilities, such as incinerators, may obstruct appropriate waste management. Waste management techniques are frequently monitored and supervised ineffectively, leading to noncompliance with safety rules.

A lack of public understanding of the risks involved with biological waste can result in incorrect disposal techniques, putting waste management staff and the general public at risk. Furthermore, improper garbage disposal can also have a negative impact on the environment, with certain waste products going untreated or burnt incorrectly. Implementing appropriate biomedical waste management methods can be costly, especially for smaller healthcare facilities and those in low-resource areas. Addressing these constraints necessitates a holistic approach that includes improved rules, more public awareness, investments in waste management infrastructure, thorough training programs, and an unwavering commitment to safe, ecologically friendly waste handling procedures.

CHAPTER 4

Problem Statement, Objectives and Scope

4.1 Problem Statement

To create a model that will Detect and Classify Bio-medical waste into 4 categories.

- Disposable Waste
- Pharmaceutical/Medicinal Waste
- Sharps/Glass waste
- Radioactive Waste

4.2 Objectives

- To develop a YoloV5 model which can classify the medical waste into specified categories.
- To make a user-friendly application which can be easily accessible by stakeholders-hospitals sanitary workers.

4.3 Scope

The Biomedical Waste Management System is a dynamic and integrated solution that aims to revolutionize the management of biomedical waste within healthcare facilities. This system utilizes state-of-the-art object detection technology to facilitate real-time identification, classification, and tracking of these biomedical waste materials, ensuring they are handled and disposed of safely and in compliance with regulations. It offers real-time waste object detection and classification, guiding users on the appropriate disposal methods.

CHAPTER 5

Proposed System

5.1 Proposed System Overview

YOLOv5 object detector uses a single stage object detection network. YOLOv5 is faster than two-stage deep learning object detectors, such as regions with convolutional neural networks (Faster R-CNNs). The YOLOv5 model runs a deep learning CNN on an input image to produce network predictions.

In this project, the aim is to classify the 4 different types of BMW generated in hospitals and sanitizations by using YOLOv5 model.

- Disposable Waste
- Pharmaceutical/Medicinal Waste
- Sharps/Glass waste
- Radioactive Waste

Here, the model will use transfer learning technique and train the dataset and test/validate uses the Bio-Medical trash dataset, which was generated with the aid of Google Images. It focuses on the several categories of medical trash, including pharmaceutical, Disposable, radioactive, and sharps waste. The biomedical waste categorization models is trained and evaluated with the help of this valuable dataset. This study includes 1785 images which are used for training and testing process.

5.2 Design Details

5.2.1 Architecture Diagram

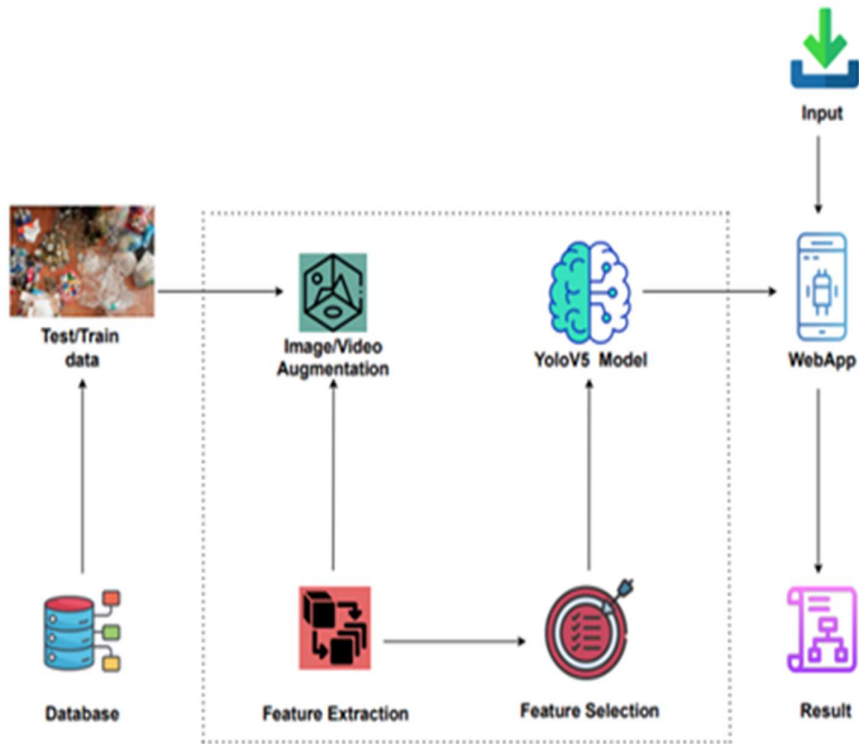


Fig 5.2.1: Architecture Diagram

Architecture diagramming is the process of creating visual representations of software system components. In a software system, the term architecture refers to various functions, their implementations, and their interactions with each other. As software is inherently abstract, architecture diagrams visually illustrate the various data movements within the system. They also highlight how the software interacts with the environment around it. The architecture of the project includes a database for giving input for training and testing the dataset following with feature extraction of image/video. The User interface comprises of signup and login section. The signup section would register the user whereas the login section would be the interface containing the input field through which actual login and user can scan image/video for detection of the waste material.

5.2.2 DFD Diagram

DFD is the abbreviation for Data Flow Diagram. The flow of data of a system or a process is represented by DFD. It also gives insight into the inputs and outputs of each entity and the process itself. DFD does not have control flow and no loops or decision rules are present.

i. DFD Level 0

The general flow of the program is that the user interacts with our android page. The user is asked to login if it is a valid user then they can enter their credentials and log in to the system.



Fig 5.2.2.1: Data Flow Diagram Level 0

The data flow diagram level 0 for Medical waste classification shows that:

User: The user inputs an image of a medical waste.

BMW: The system takes the image input from the user and predicts the category of waste

Detection: The Bio-Medical waste classification outputs a prediction of object in 4 different categories

The data flow between the user and BMW is shown as a single arrow, indicating that the system takes the image input from the user and produces a Detection output.

ii. DFD Level 1

The user will input the images/video which will preprocess the input data and classify it using YOLOv5 model and give results.

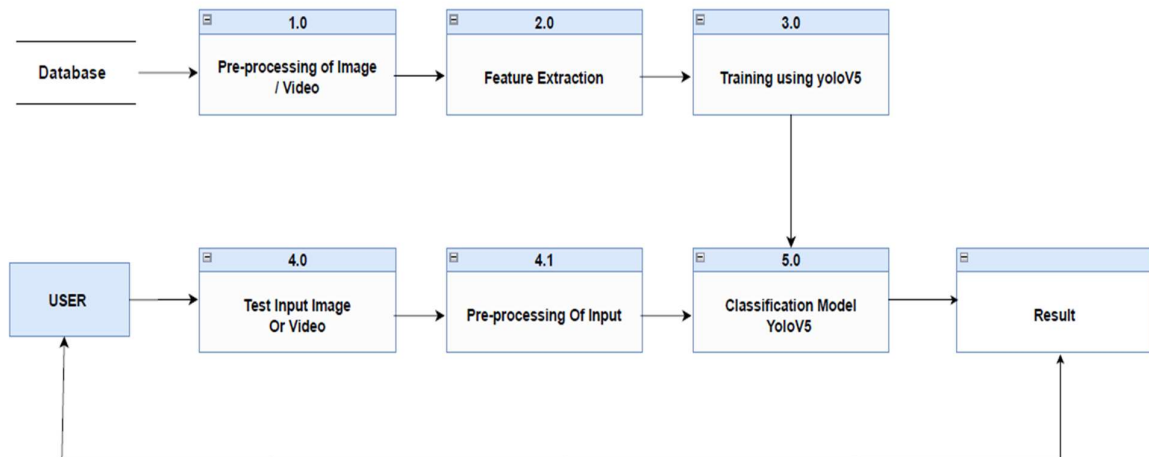


Fig 5.2.2.2: Data Flow Diagram Level 1

The level 1 data flow diagram for Bio-Medical Waste Classification shows the following steps:

User: The user provides an input test image of a waste.

Pre-processing Images: The input image is pre-processed to improve its quality and consistency. This may involve steps such as resizing, denoising, and normalization.

Feature Extraction: Features are extracted from the pre-processed image. These features may include color, texture, and shape features.

Model: The extracted features are passed to a machine learning model to predict the category of waste image.

Detection: The model outputs a Label, which indicates the Indexed Category of waste.

Result: The result of the detection is displayed to the user.

5.2.3 Activity Diagram

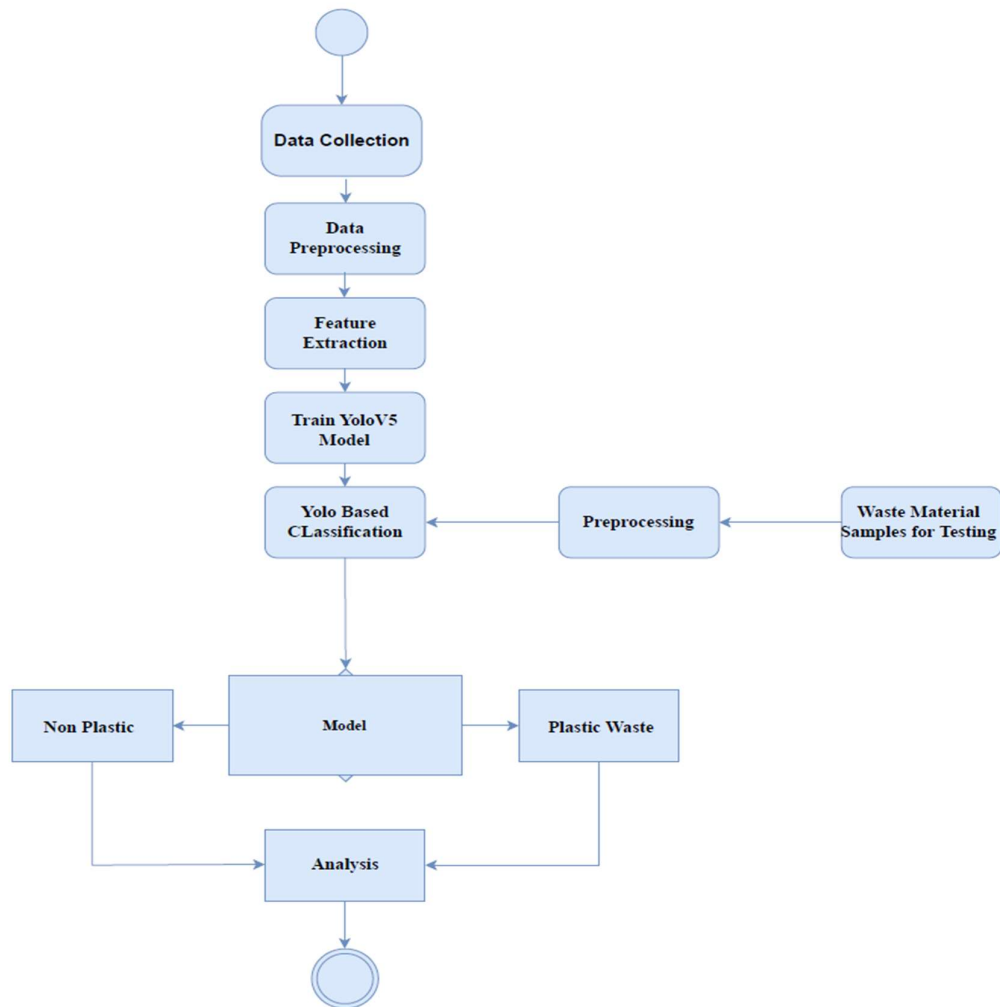


Fig 5.2.3: Activity Diagram

A UML activity diagram aids in the more in-depth visualization of a particular use case. A behavioral diagram is used to show how actions move through a system. They resemble flowcharts but have more detailed notations and symbols. An activity diagram's main function is to represent a system's or process's behavior in a structured, understandable manner that facilitates analysis. The workflow for waste material classification using YOLO. Each step, such as data preprocessing, training the YOLOv5 model, and feature extraction, is crucial for the successful classification of waste materials. For instance, in the context of plastic and non-plastic waste classification, the activity diagram would likely show how data related to plastic and non-plastic waste is preprocessed, model is trained using data, and features are extracted for effective classification.

5.2.4 Sequence Diagram

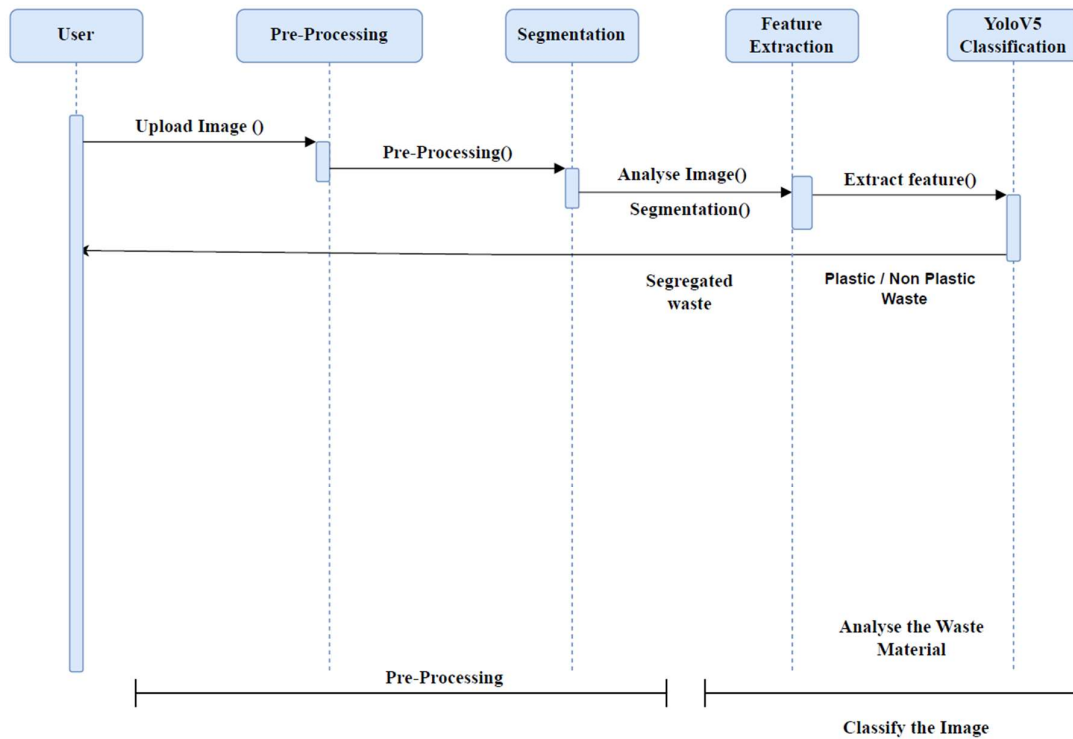


Fig 5.2.4: Sequence Diagram

A sequence diagram is a Unified Modeling Language (UML) diagram that illustrates the sequence of messages between objects in an interaction. A sequence diagram consists of a group of objects that are represented by lifelines, and the messages that they exchange over time during the interaction. The sequence diagram with respect to the user can be explained as follows. First, the user provides an input through the user interface implemented on the web browser. The sequence diagram shows the steps involved in analyzing a waste image using a YoloV5 Model.

Upload Image(): The user uploads a waste image to the system.

Preprocessing(): The system preprocesses the image by resizing it to a consistent size and normalizing the pixel values.

Extract Feature(): The system extracts features from the image, such as the shape, color, and texture of the waste.

YoloV5 Detection(): The system uses a layers to classify the image.

Analyse the waste Image: The system displays the results of the analysis to the user, including the classification of the image and any other relevant information.

5.2.5 Use Case Diagram



5.2.5: Use Case Diagram

A use case diagram is a graphical representation of how users interact with a system. It shows the system's functionality by incorporating use cases, actors, and their relationships.

The User will input the data in the form of image/video and the system will preprocess the input data and classification model will classify the BMW will give the results.

5.3 Methodology

Data Pre-processing: Data preprocessing is a critical stage in data analysis and modelling that involves cleaning, converting, and organizing raw data in preparation for analysis. Common techniques include dealing with missing values, cleaning data to remove errors and outliers, scaling numerical features, encoding categorical variables, selecting relevant features, developing new features, addressing class imbalance, and splitting data for training, validation, and testing. These preparation stages ensure that the data is of high quality, consistent, and appropriate for use in machine learning algorithms, resulting in more accurate and dependable insights.

Dataset Splitting: Splitting a dataset into training, validation, and test sets is a fundamental step in the machine learning and data analysis process. The training set is used to train the model, the validation set aids in optimizing hyperparameters and reducing overfitting, and the test set assesses the model's performance on previously unseen data. Simple random sampling, stratified sampling, time-based splitting, and cross-validation are some of the most used data splitting techniques. Proper data separation ensures accurate model evaluation and aids in picking the best-performing model for real-world use. The dataset was split into three sets: 80% for training, 10% for validation and 10% for testing.

The user initiates the process through the web and Android applications, dragging and dropping or capturing an image for biomedical waste classification. In the backend, the input image is forwarded to the biomedical waste classification model. If the model identifies the image as belonging to a specific waste category it overlays the object with a bounding box that labels the indexed category of the thing. However, if the image is not classified accurately, the system will consult the waste category database and attempt to match the input image to the corresponding waste type.

CHAPTER 6

Experimental Setup

6.1 Requirement Analysis and details

1.CYTHON

Developing efficiently with Cython requires a structured methodology. This approach entails understanding Cython's basics, pinpointing performance bottlenecks, explicitly declaring variable types, utilizing C data types, optimizing loops, leveraging buffer views for data manipulation, configuring compiler directives, and continually profiling and benchmarking the code for performance assessment. Consider creating Cython extensions for critical code modules, and thorough testing to ensure correctness and compatibility. This systematic methodology ensures efficient use of Cython's features and can significantly enhance the performance of Python code, particularly in performance-critical sections of the program.

2.VANILLA

In the realm of Python programming, the term "vanilla" signifies an approach that relies solely on the intrinsic features and capabilities of the language, without external libraries or frameworks. It entails operating with Python's core components and syntax, showcasing a methodical approach to harness its native potential.

The methodology for employing vanilla Python is centered on the skillful utilization of built-in data types, control structures, and functions that are part of the Python standard library. This involves making the most of data types like lists, dictionaries, and strings, employing control structures like

if-else statements and loops, crafting functions, adeptly handling errors, performing essential file I/O operations, and optionally embracing object-oriented programming principles. While this approach may have constraints when compared to utilizing external libraries, it serves as a solid educational foundation for mastering Python and comprehending fundamental programming principles.

3.YOLOv5

The You Only Look Once (YOLO) methodology is a popular real-time object detection algorithm. It follows a single-shot detection approach, combining object localization and classification into a single neural network. The methodology involves dividing the input image into a grid and predicting bounding boxes and class probabilities for each cell. YOLO uses anchor boxes to handle objects of different sizes and aspect ratios. It utilizes a convolutional neural network (CNN) to extract features and predicts objectness scores and class probabilities for each bounding box. Non-maximum suppression (NMS) is then applied to remove redundant detections with overlapping bounding boxes. By processing the entire image simultaneously, YOLO achieves a balance between speed and accuracy, making it suitable for various real-time applications such as object tracking, autonomous driving, and video surveillance.

4.FRAMEWORK

Darknet is a versatile deep learning framework that provides a robust methodology for developing computer vision and object detection applications. At its core, Darknet offers a seamless workflow for object detection, segmentation, and classification tasks. The methodology begins with model configuration and training, allowing users to define network architectures, initialize weights, and optimize hyperparameters. The framework leverages a custom implementation of YOLO (You Only Look Once), which is known for its efficiency in real-time object detection. Darknet is designed for flexibility, enabling the integration of custom datasets, pre-trained models, and various loss functions to fine-tune models. Once trained, the model can be applied to images, videos, or even real-time camera feeds, facilitating object recognition, tracking, and classification. Darknet's open-source nature and efficiency make it a popular choice for developing cutting-edge computer vision applications, particularly when speed and accuracy are paramount.

6.1.1 WORKING OF YOLOv5

1. Model Initialization: First, choose the YOLO version that suits your application, be it YOLOv3, YOLOv4, or YOLOv5. Initialize the YOLO model by loading pre-trained

weights and configurations. Even fine-tune the model on a dataset for improved performance.

2. **Input Preparation:** Get the input data ready. It could be images or video frames. Resize and preprocess the input to match the model's requirements in terms of size and format. Scaling the pixel values to fit within the model's expected range (usually 0 to 1) is crucial.
3. **Object Detection:** Run the YOLO model on the prepared input data, and it will predict bounding boxes for objects and their associated class labels.
4. **Post-processing:** Apply post-processing techniques. One essential step is non-maximum suppression (NMS), which takes care of removing overlapping or redundant bounding boxes. Setting a confidence threshold helps filter out low-confidence detections.
5. **Visualization:** It's time to see the results. Visualize the detected objects on the original input data by overlaying bounding boxes, class labels, and confidence scores.
6. **Integration with Applications:** Integrate the detected objects into a specific application. Depending on what is needed, track objects, count them, or dive into further classification based on class labels.
7. **Performance Optimization:** Depending on the application's needs, optimize YOLO for either speed or accuracy. Explore techniques like model quantization and pruning to reduce inference time.
8. **Testing and Validation:** Always test the YOLO implementation rigorously. Ensure it's both accurate and efficient. Validate the results against ground truth data to ensure precision.
9. **Deployment:** When satisfied with the YOLO-based object detection, deploy it in an application or system. Handle real-time detection in video streams or process images in batches. Ensure the environment is set up to accommodate the libraries and frameworks used.
10. **Documentation and Maintenance:** Document the YOLO implementation, including version details, dependencies, and custom configurations. Regularly update the system as the application's requirements evolve.

This methodology lays out the steps for YOLO object detection, emphasizing the importance of proper setup, optimization, testing, and deployment. Specifics may vary based on the YOLO version and choice of programming tools. It is an object detection algorithm that swiftly and accurately identifies objects within images or video frames. It divides the input image into a grid, predicting bounding boxes and their associated class labels within each grid cell. YOLO predicts multiple bounding boxes for each object, and using confidence scores, it filters out redundant detections. This approach enables real-time object detection with a single pass through the neural network,

making YOLO both fast and efficient, making it a popular choice for applications like autonomous vehicles, surveillance, and more.

6.2 Performance Evaluation Parameters

Performance evaluation parameters are pivotal for assessing model or system accuracy. Common metrics include accuracy, which quantifies correct classifications as a percentage of the total. Precision measures correctly predicted positive instances relative to all predicted positives, while recall gauges correctly predicted positives relative to all actual positives. The F1 score balances precision and recall. Additional metrics like specificity, sensitivity, and AUC-ROC are used for performance evaluation. Sensitivity checks accurate classification of actual positives, while specificity assesses actual negatives' precision. AUC-ROC is valuable in classification scenarios, providing a comprehensive performance view. These parameters offer insights into model strengths and weaknesses, aiding fine-tuning and improvement during validation.

6.3 Software and Hardware Set up

i. Hardware requirements

- Operating Systems
- High Speed RAM
- Fast Processor
- NVIDIA GPUs

ii. Software requirements

- VSCode
- Python 3.8 and above.
- Gradio, Google Colab.
- HTML, CSS, JavaScript, Bootstrap.

CHAPTER 7

Implementation and Results

Part 1: Prototype and Documentation

The initial phase of the Medical Waste Object Detection Using YOLO project will focus on developing a robust prototype of the object detection model and thorough documentation. In this stage, the team will ensure that the YOLO v5 model is effectively trained and tested using a diverse dataset of over 1500 medical waste images. The primary goal is to achieve exceptional performance evaluation metrics, such as high accuracy, precision, recall, F1 score, specificity, sensitivity, and AUC-ROC. The prototype will serve as the foundation for the subsequent stages, ensuring that the model is both accurate and reliable in its medical waste detection capabilities.

Simultaneously, comprehensive documentation will be created to record the project's methodologies, configurations, and results. This documentation will serve as a valuable resource for future reference and potential scaling of the project. It will include detailed information on model training, validation, and evaluation processes, allowing for transparency and replicability in later stages.

Part 2: Integration into an Android App with Flask.

The second phase of the project will involve the integration of the object detection model into an Android application. The goal is to develop a user-friendly interface that healthcare professionals and waste management personnel can utilize. This Android app will provide real-time medical waste detection capabilities, enhancing safety and efficiency in healthcare settings. To enable this integration, Flask, a micro web framework, will be employed as the back-end server. Flask will

facilitate communication between the Android app and the object detection model, ensuring seamless operation.

Furthermore, Darknet, the neural network framework that powers YOLO, will be optimized and deployed for efficient inference within the Android app. This phase will require collaboration between Android app developers, Flask integration specialists, and machine learning engineers. The outcome will be a user-friendly Android app capable of real-time medical waste detection, contributing to efficient waste management, enhanced safety measures, and potential scalability to various healthcare facilities and waste management systems.

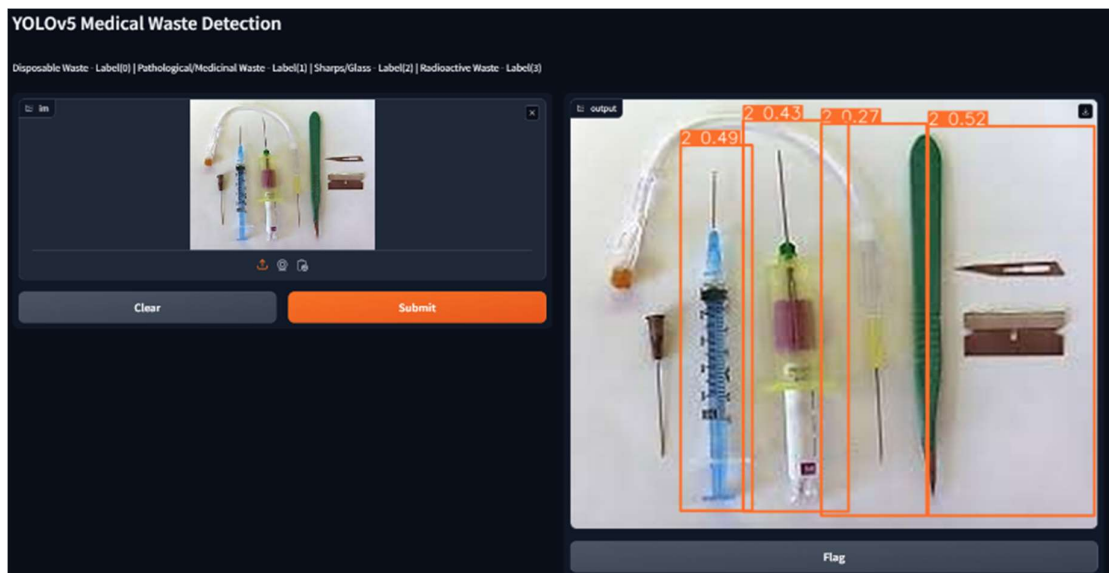


Fig 7.1: Upload and detect function

This is the Gradio interface, where the user uploads a waste image, and the system recognizes it, overlaying the object with a bounding box that labels the indexed category of the thing.

- 0 - disposable waste
- 1 - Pharmaceutical/Medicinal waste
- 2 - Sharps/Glass Waste
- 3 - Radioactive waste



Fig 7.2: Live Detection of Objects

The other module is an interactive Python window that works with live charting and the detection of medical waste objects. This captures the objects and, as soon as the object is placed in front of the camera, the YOLOv5 model, using training photos and labels, detects waste objects.

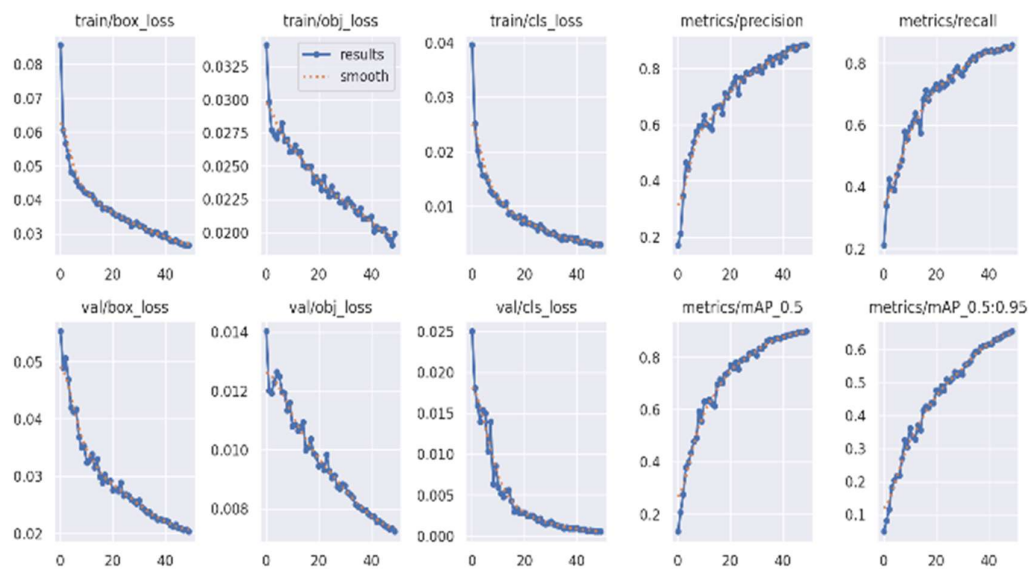


Fig 7.3: Accuracy over labels and category

The graph displays the accuracy obtained across the four waste categories, with an overall accuracy of 87%

CHAPTER 8

Project Plan

- Gantt Chart

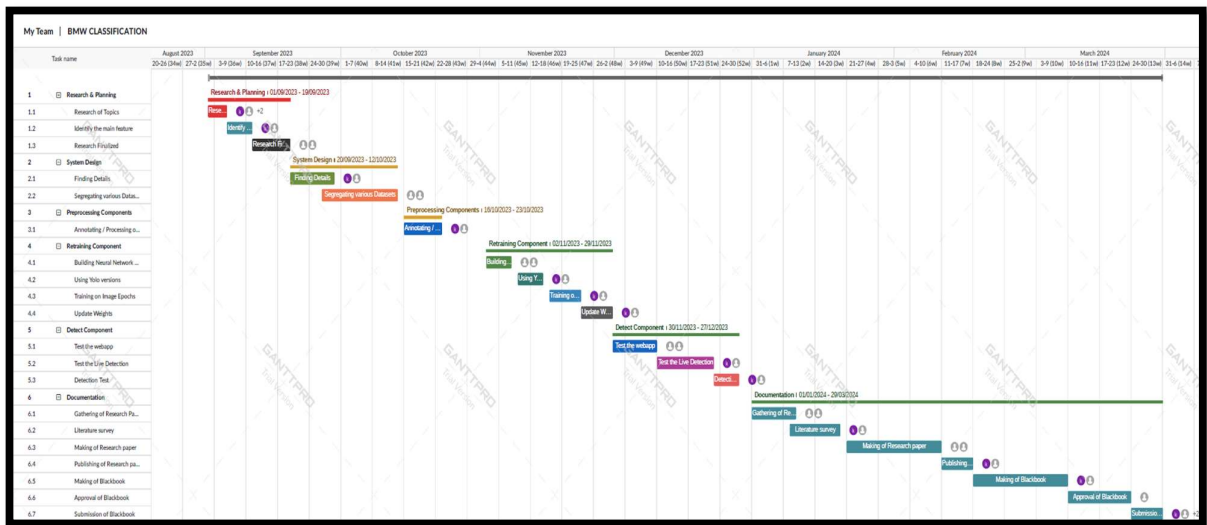


Fig 8.1 Gantt Chart

CHAPTER 9

Conclusion

In conclusion, prioritizing proper management of medical waste is crucial for safeguarding both the environment and public health. This entails advocating for legislation, conducting research, and raising public awareness. Expert management becomes imperative due to the complex nature and potential risks associated with medical waste. Neglecting proper disposal poses serious threats to the environment and human well-being, underscoring the urgent need for comprehensive action. Employing the Yolo V5 algorithm, the biomedical waste classification system aims to develop an intelligent solution capable of autonomously identifying and categorizing various types of medical waste in images or real-time scenarios. The primary objective is to streamline waste management processes by implementing a precise and efficient solution that reduces reliance on manual sorting. Trained on diverse annotated medical waste image datasets, YOLOv5 can recognize distinct features and patterns associated with different types of waste materials. This trained model can promptly identify medical waste items in new images and videos, categorizing them into four main groups: pharmaceutical, radioactive, sharp, and contagious. By improving overall waste management effectiveness and reducing the risk of classification errors, this technology ensures the safe and appropriate disposal of medical waste. Ultimately, this approach enhances efficiency in waste disposal procedures, promoting a safer and healthier environment by minimizing the mishandling of hazardous materials. The system used YOLOv5 algorithm to categorize medical waste into four important groups: radioactive waste, Disposable waste, sharp item waste, and pharmaceutical waste. After 50 epochs of intense training, the system achieved an accuracy rate of 87%. A well-annotated dataset containing a variety of photos was used in the training phase to

guarantee thorough coverage of the unique traits connected to each form of garbage.

The results demonstrate the effectiveness of the YOLOv5 algorithm in precisely recognizing and categorizing medical waste, with encouraging outcomes demonstrated by the accuracy attained. More evaluation metrics that offer a more detailed picture of the model's performance across the designated waste categories include precision, recall, and F1 score. Examining the patterns of training loss over the course of 50 epochs offers insights about waste categories.

The YOLOv5 algorithm's effectiveness for classifying medical waste is enhanced by this study, which highlights the algorithm's potential uses in waste management systems. The model can classify infectious waste, sharp object waste, pharmaceutical waste, and radioactive waste even on live capturing. Using the Yolo V5 algorithm, the biomedical waste classification system aims to create an intelligent system capable of autonomously identifying and categorizing different types of medical waste in images or in real time. The main goal is to optimize waste management processes by putting into practice an accurate and efficient solution that lessens the need for human sorting. YOLOv5 aims to develop a model that can understand many types of medical waste, such as syringes, gloves, and other hazardous materials commonly seen in hospital settings.

Chapter 10

Future scope

Enhanced Accuracy: Further refinement of the YOLOv5 algorithm can lead to increased accuracy in identifying and classifying different types of biomedical waste. Fine-tuning the model with larger and more diverse datasets can improve its ability to recognize subtle variations in waste materials.

Real-Time Detection: Continued optimization of YOLOv5 can enable real-time detection and classification of biomedical waste in hospital settings, clinics, and other healthcare facilities. This would facilitate immediate intervention and appropriate disposal measures, enhancing overall safety and hygiene standards.

Integration with Robotics: Integrating YOLOv5 with robotic systems can automate the process of collecting, sorting, and disposing of biomedical waste. Robots equipped with computer vision capabilities can navigate healthcare facilities, identify waste items, and transport them to designated disposal areas, reducing the risk of human exposure to hazardous materials.

Mobile Applications: Developing mobile applications powered by YOLOv5 can empower healthcare professionals to quickly and accurately classify biomedical waste using their smartphones or tablets. This can streamline waste management workflows and ensure compliance with regulatory guidelines, even in remote or resource-constrained settings.

Environmental Monitoring: Expanding the scope of YOLOv5 to include environmental monitoring capabilities can enable the detection and classification of biomedical waste in outdoor environments, such as landfills or contaminated sites. This can facilitate targeted cleanup efforts and minimize the environmental impact of improper waste disposal practices.

Global Adoption: Promoting the adoption of YOLOv5 for biomedical waste classification on a global scale can standardize waste management practices and improve consistency in waste classification across different regions and healthcare facilities. Collaboration between governments, healthcare organizations, and technology providers is essential to ensure widespread implementation and effectiveness.

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Publication

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Medical Waste Classification Using Yolo V5 Algorithm

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Abstract— Efficient and accurate classification of medical waste is crucial for streamlining disposal processes and mitigating environmental and health risks. This project presents a novel approach to medical waste classification by utilizing the YOLO (You Only Look Once) v5 algorithm. Addressing the pressing need for precise identification of medical waste categories, our study leverages the real-time object detection capabilities of the YOLO v5 algorithm. By training the model on a comprehensive dataset containing diverse medical waste types, we ensure robust performance across various scenarios. Our results demonstrate high precision and recall rates in identifying medical waste items, showcasing the algorithm's potential for rapid and accurate classification. This advancement facilitates the development of automated waste sorting systems, promising to enhance waste segregation practices, reduce contamination, and contribute to a safer and more sustainable healthcare environment.

Keywords— YOLOv5 Algorithm, Medical Waste, Real Time Object Detection, Medical Waste Classification

I. INTRODUCTION

Biomedical waste encompasses both liquid and solid waste from clinical settings and activities, including natural materials. In addition to medical care, suitable exercises include clinical examinations and studies on animals, ranches, and dead animals. The issue of biomedical waste extends beyond specific activities or groups. It can start at home during dialysis and insulin infusions, in rural areas during animal welfare exercises, butchering of dead animals in butcher

shops and clinical shops, use of sterile napkins and headphones, use of diapers, and at airports when travellers use restricted medications without a treatment[1].

The issue of hospital waste, primarily generated by healthcare facilities, is a recent concern that raises significant alarms due to its potential adverse impacts on public health and the environment. Globally, effective management of hospital waste remains a nascent endeavour. There exists considerable confusion among waste generators, operators, policymakers, and the general populace regarding the proper protocols for handling such waste. In India, the challenge of managing hospital waste has become increasingly complex. Healthcare establishments bear a critical responsibility in safeguarding public health[2].

Gowda et al., focus on safe and sustainable methods for managing biomedical waste in urban settings. Hospitals, technological choices, and waste generation amounts are identified in their investigation. They stress the significance of using source segregation and treatment techniques like incineration to manage trash properly. Furthermore, the study advocates for adherence to disposal norms in healthcare facilities and emphasizes the need for health education and training [3]. In contemporary healthcare practices, the imperative to effectively manage medical waste has emerged as a paramount concern due to its significant implications for both the environment and public health.

According to Bai et al., correctly classifying trash in medical settings can save costs and have a positive environmental impact. They support efficient trash segmentation to reduce volume and infractions, and they suggest a new classification scheme to expedite disposal costs. Their suggestions put improving hospital waste management procedures first in order to cut expenses and lower threats to occupational health

[4]. With the escalating volume and diversity of medical waste, there is an increasing demand for innovative solutions capable of efficiently and accurately classifying waste items. This paper introduces a pioneering approach to tackle this challenge by leveraging the capabilities of the YOLO v5 algorithm—a state-of-the-art real-time object detection model. It provides a thorough overview of biomedical waste management in healthcare environments, including information on how trash is categorized into various groups according to its type and manner of disposal. It covers the use of hydroclave technology for waste treatment in addition to more conventional techniques like landfilling and burning. The study also highlights how crucial it is to handle, separate, clean, and dispose of biological waste properly in order to reduce the hazards and negative effects of improper waste management procedures[5].

Tiwari et al. examine how economic development affects waste management in India, with a focus on biomedical waste. They examine and compare worldwide practices for treatment techniques such as autoclaving and burning. They stress source segregation for hazard reduction, citing WHO and Indian rules. As mentioned, effective management is essential to reducing hazards in healthcare settings[6]. The urgency of this research stems from the pressing need to streamline the disposal processes of medical waste, thereby minimizing its environmental impact and reducing occupational hazards. Conventional methods of waste segregation often rely on manual sorting, which is prone to inefficiencies, errors, and increased risks. By harnessing the advanced features of YOLO v5, the proposed system aims to revolutionize medical waste management by offering a swift and accurate means of identifying diverse waste categories in real-time. The sources, classification, and effects of biomedical waste management are the main topics that comprise this comprehensive examination. It emphasizes how crucial appropriate disposal is to safeguarding the environment and public health. Healthcare facilities produce biomedical waste, which presents risks and needs to be managed and regulated properly. The article outlines the classification of biomedical waste in accordance with existing rules, including the Biomedical Waste (Management and Handling) Rules and WHO standards, and provides comprehensive categories[7].

To achieve this objective, the study utilizes a comprehensive dataset comprising a wide range of medical waste types, ensuring the adaptability and reliability of the model across various healthcare settings. The remarkable capability of the YOLO v5 algorithm to swiftly process images and detect multiple objects simultaneously positions it as a cutting-edge tool for medical waste classification. As the methodology and results are explored, this research endeavours to make a significant contribution to the advancement of automated waste sorting systems, thereby fostering a safer, more sustainable, and environmentally responsible healthcare ecosystem. By integrating innovative technologies like YOLO v5 into waste management practices, the aim is to address the pressing challenges associated with medical waste

disposal and pave the way for a more efficient and environmentally conscious healthcare industry.

II. RELATED WORK

In this paper [1] Medical trash refers to all refuse generated in the healthcare industry, including detritus from laboratories, pathology departments, pharmacy vaults, and other locations. If this waste is not properly managed, individuals in charge of disposing of it will be exposed to a variety of illnesses and harmful substances. This group includes 85% benign trash, 10% infectious material, and 5% chemical, radioactive, and hazardous waste, all of which have the potential to cause significant harm. Even when dispersed across the atmosphere, the results can be catastrophic.

According to WHO guidelines, Thareja et al. give biomedical waste management top priority for society health. They support safe waste collection routes and the 3Rs (reduce, reuse, recycle). In order to achieve sustainable and economical management, the study emphasizes the significance of WHO principles as well as historical practices. They highlight the need of adequate waste segregation for infection prevention, citing the efficacy of waste management in societies such as the Dravidians[8]. [9], [10] The incorrect treatment of waste has increased in African countries due to underfunded healthcare systems, inadequate training, and a lack of awareness of regulations and legislation regarding the handling of medical waste. Ethiopia, Botswana, Nigeria, and Algeria are among the nations without national policies governing the proper disposal of medical waste. Consequently, because incineration may quickly reduce trash volume by up to 90% and generate heat for boilers or energy production, it is frequently the method of disposal of choice. [11] The study outlines a project-specific methodology that emphasizes social, institutional, and economic components in order to evaluate the success or failure factors of solid waste management programs. This approach was used to examine the Gianyar garbage Recovery Project in Bali, Indonesia, which includes garbage segregation and composting. The important qualities, replication variables, and sustainability challenges for the project were highlighted by the results.

Cheema et al., says Cutting-edge smart waste management is aimed at improving waste segregation to create a cleaner environment by utilizing IoT, deep learning, and grid segmentation for categorization. Despite facing obstacles such as having only one object per image in the training data, which impacts accuracy, progress is being made by implementing technologies like VGG16 and grid segmentation methods to achieve better outcomes. This innovation tackles the waste management challenges of contemporary society, including recycling obstacles and environmental consequences, by building on past research to enhance waste sorting and recycling using deep learning, IoT, and intelligent systems[12]. By utilizing AR and AI, a system for classifying medical waste aims to minimize errors in clinical staff assessments by merging augmented reality and deep neural networks for waste recognition. The system merges AI with expert systems to efficiently categorize medical waste using advanced technology, with the ultimate goal of improving precision and productivity while decreasing manual errors among clinical staff[13].

The Medical-Waste Chain, a blockchain-powered system for automating medical waste management, is presented by Phu et al. They improve workflow and efficiency in healthcare supply chain management by utilizing Hyperledger Fabric. Their strategy highlights how

blockchain technology may optimize waste management procedures[14].Reference [15] describes Waste-to-energy, smart bins, waste-sorting robots, waste generation models, waste monitoring and tracking, plastic pyrolysis, logistics, disposal, illegal dumping, resource recovery, and enhancing public health are just a few of the waste management-related areas in which the power of artificial intelligence (AI) can be used. AI in trash logistics can save money, time, and distance during transit. With AI, the accuracy of waste identification and sorting can range from 72.8% to 99.95%. AI and chemical analysis work better together to increase energy conversion, waste pyrolysis, and carbon emission estimation. AI is capable of optimizing waste treatment processes, including burning, landfilling, composting, and recycling. It can also help with resource recovery, lowering unlawful dumping, and controlling hazardous waste. AI can support public health initiatives like pandemic preparedness and the disposal of medical waste.[16] Municipal solid waste management (MSWM) is a major environmental issue in Indian cities, with improper management causing hazards to inhabitants. A comprehensive review of MSWM characteristics, generation, collection, transportation, disposal, and treatment technologies in India has been conducted to identify the current status and major issues. Various treatment technologies for MSW have been critically reviewed, along with their benefits and limitations. Examining the disposal of biomedical waste, particularly in relation to COVID-19, the review explores the difficulties and the present condition of healthcare waste management.[17] The process of plasma gasification, which turns trash into energy at high temperatures, is discussed in the study as a cutting-edge and secure way to dispose of biological waste. For this reason, it emphasizes that the most advanced technology available is plasma gasification. The study also discusses various sterilization techniques that are frequently employed for the treatment of biomedical waste, such as steam autoclaving and microwave technology.

The paper proposes an IoT-based smart garbage system (SGS) to reduce the amount of waste. The SGS includes various IoT techniques, such as wireless mesh networks and energy-efficient operations, to exchange information between battery-based garbage bins and collect and analyze data for service provisioning. The experiment conducted in Gangnam district, Seoul, showed a 33% reduction in the average quantity of scraps. IoT can be applied in intelligent transportation systems (ITS) and smart cities to enhance waste collection efficiency. IoT components, including RFIDs, sensors, cameras, and actuators, are incorporated into ITS and surveillance systems for efficient waste collection. A decision support system (DSS) is proposed for efficient waste collection in smart cities, which includes real-time data sharing between truck drivers, dynamic route optimization, and surveillance cameras for capturing problematic areas. The aim is to provide high-quality waste collection services to the citizens of a smart city. [18] Garbage cans were invented to improve cleanliness and odor control. Dustbins are important in workplaces and schools for proper disposal of sanitary waste. into non-biohazardous waste. [19] The classification process for biomedical waste in Ayurvedic hospitals lacks specific details, but it provides information on disposal methods and areas for further investigation in biomedical waste management within Ayurvedic settings. [20] The significance of appropriate biological waste management is emphasized throughout the paper. It draws attention to the dangers and hazards connected to incorrect treatment of biomedical waste. The steps involved in managing biological waste, such as collection, sorting, transportation, treatment, and disposal, are covered in this study. In biomedical waste management, it highlights the use

of color coding, technologies such as autoclaving and incineration, and consideration of environmental effects. The 3R system—reuse, reduce, recycle—is mentioned in the article as a strategy to cut down on trash production and create a cleaner environment. It draws attention to the inadequate handling of biological waste in underdeveloped nations and emphasizes the necessity of educating and raising awareness among waste handlers and healthcare personnel. [21] Remote sensing and GIS techniques are used for waste management modelling. These techniques help in siting landfills and waste bins. They are also used to evaluate the environmental impact of buried waste. Multi-criteria evaluation (MCE) approach is used for waste disposal site selection. Integration of GIS and MCE provides efficient representation and manipulation of data. GIS and multi-objective models are used for ideal management of sludge in agricultural areas. The study considers environmental and economic criteria for sewage sludge disposal. The paper provides case studies of the applications of remote sensing and GIS techniques worldwide. The paper concludes that the proper use of remote sensing and GIS techniques can maximize the efficiency of waste management systems. [22] The CNN model for trash management is the main subject of the study. CNN was used to analyze exploratory data using a regression model. Preprocessing and data analysis were the two phases of the research process. The general framework was generated via Python programming. Increased production of municipal solid trash is a result of population growth and rapid urbanization. One major problem facing the recycling industry is the sorting of waste before it is recycled. The recycling business has profited from smart bin technology. Classifying garbage in a sustainable way can be accomplished with computer vision. Image analysis and item identification can be accomplished with deep learning algorithms. The suggested method for trash management uses deep neural networks in a learning-based system. To automate garbage segregation, a CNN-based image classifier is created. A method of managing the classification of medical waste that emphasizes the PDCA cycle mode.[23] For the purpose of help with the first sorting of medical waste, the research presents a computer vision method that achieves 100% accuracy on the trained model. But instead of concentrating on biomedical waste categorization specifically, it uses computer vision techniques to sort medical waste in general.[24] A remarkable accuracy of 97.2% is achieved by a deep learning approach that precisely detects and classifies medical waste, with a specific focus on the classification task. The research successfully differentiates between eight different types of medical waste. It demonstrates notable improvements in medical waste classification by utilizing ResNeXt and transfer learning methods, leading to significantly enhanced classification outcomes. It also discusses the generation of waste, the effects on the environment, and underscores the vital importance of effective waste management in containing the spread of the virus[25].A novel approach is introduced for the management of medical waste during the COVID-19 pandemic, which integrates MCDM, AHP, LDFN-FDOSM, and ANN methodologies. The classification of medical waste is divided into five categories, including general, sharp, pharmaceutical, infectious, and pathological waste, and effective techniques are proposed for each category. The main objective of this framework is to improve the decision-making process in medical waste management by offering a comprehensive solution to the challenges faced during the pandemic Waste plastic from biomedicine, with a focus on recycling methods, sanitation, and ways to cut down on the amount of plastic trash produced. It goes over categorization techniques and talks about disinfectants that contain chlorine to inactivate viruses[26]. The main goal is to turn waste into

money by using a variety of processes such as milling, agglutination, cutting, shredding, and quenching to separate contaminants[27]. The four stages of the PDCA cycle—planning, implementation, inspection, and processing—are covered in this article. By enhancing knowledge and overall management quality in the field, the adoption of this approach improves the quality of medical waste classification management[28].[29] In order to manage and dispose of biomedical waste (BMW), a novel texture analysis and classification technique is presented in this work. It uses Median Filtering for preprocessing and then uses MLTrP and RVM to extract and categorize histogram characteristics from BMW photos. By efficiently classifying BMW into cotton, plastics, human body bits, and liquids, the suggested technique improves waste management procedures.

MATERIALS AND METHODS:

Dataset Description:

This study uses the Bio-Medical trash dataset, which was generated with the aid of Google Images. It focuses on the several categories of medical trash, including pharmaceutical, infectious, radioactive, and sharps waste. The biomedical waste categorization models can be trained and evaluated with the help of this valuable dataset. This study includes 1785 images which are used for training and testing process.

Pharmaceutical/Medicinal Dataset:

The Bio-Medical Waste dataset comprises of pharmaceutical waste in total of 352 images. These images capture different objects which come under pharmaceutical waste which contains unused, expired, or leftover medications, etc. It additionally includes tablets, injections, and antibiotics.

Radioactive Dataset:

Radioactive dataset contains images which are collected using Roboflow which in total are 580. This type of trash typically consists of leftover radiation or laboratory research liquid. Any glassware or other materials tainted with this liquid may also be included.

Disposable Dataset:

This category includes any items that have come into contact with blood, bodily fluids, tissues, or other potentially infectious substances. Examples of infectious waste include used swabs, tissues, bandages, dressings, gloves, needles, and other medical supplies. Additionally, excreta such as blood, urine, vomit, and saliva are considered infectious waste due to their potential to harbour pathogens. Laboratory cultures and specimens, contaminated equipment, and materials used in healthcare procedures are also classified as infectious waste. In the dataset infectious waste contains 379 images.

Sharps Dataset:

Sharp tools and instruments used in veterinary, laboratory, and medical contexts fall within this broad category. Needles, syringes, scalpels, lancets, shattered glass, razors, ampules, staples, cables, trocars, and other sharp-edged or pointed objects are a few examples of sharps waste. The dataset contains 267 images of sharps waste.

Data Pre-processing:

Data preprocessing is a critical stage in data analysis and modelling that involves cleaning, converting, and organizing raw data in preparation for analysis. Common techniques include dealing with missing values, cleaning data to remove errors and outliers, scaling numerical features, encoding categorical variables, selecting relevant features, developing new features, transforming data, addressing class imbalance, and splitting data for training, validation, and testing. These preparation stages ensure that the data is of high quality, consistent, and appropriate for use in machine learning algorithms, resulting in more accurate and dependable insights.

Dataset Splitting:

Splitting a dataset into training, validation, and test sets is a fundamental step in the machine learning and data analysis process. The training set is used to train the model, the validation set aids in optimizing hyperparameters and reducing overfitting, and the test set assesses the model's performance on previously unseen data. Simple random sampling, stratified sampling, time-based splitting, and cross-validation are some of the most used data splitting techniques. Proper data separation ensures accurate model evaluation and aids in picking the best-performing model for real-world use.

The dataset was split into three sets: 80% for training, 10% for validation and 10% for testing.

III. PROPOSED METHODOLOGY

The following section introduces an approach for categorizing bio-medical waste. The suggested system includes numerous steps. The proposed system's core structure is outlined in Fig. 1.

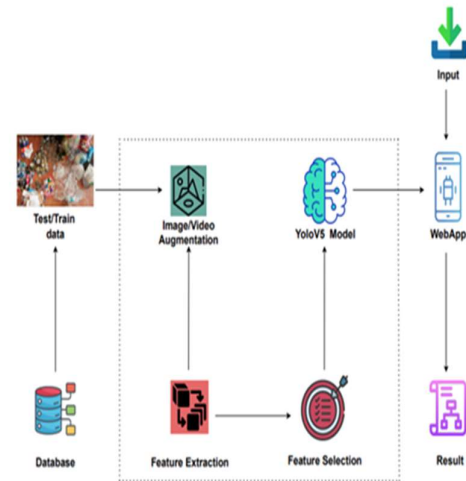


Fig.1: Architecture Diagram

A. Data Acquisition:

Data acquisition is an essential phase in data-driven decision-making that involves collecting and organizing data from multiple sources for analysis, processing, and storage. Data is collected using appropriate methods, such as manual entry, automated extraction, or real-time

monitoring. The data is then extracted, cleaned, and pre-processed to verify its quality and suitability for study. Integrating data from numerous sources is frequently required to create an integrated dataset. Data security and privacy safeguards are used to secure sensitive information. Finally, effective data collecting gives firms access to high-quality data that helps them make educated decisions and promote innovation.

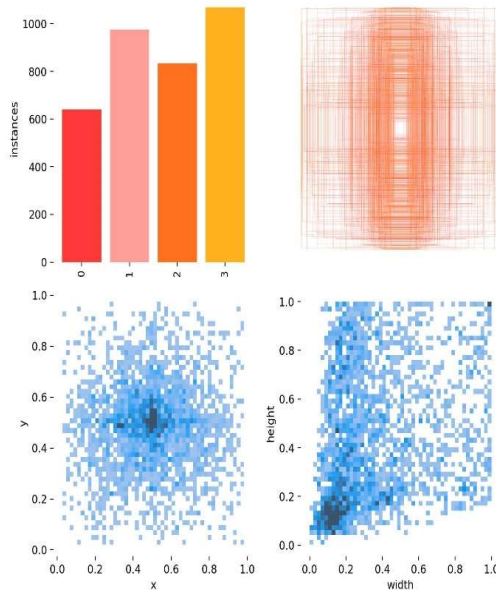


Fig.2: Labels over Class

B. Image Pre-processing:

The images contained in the dataset have been resized to 460 by 460 resolution. The preprocessing of images is an essential procedure in image analysis and computer vision applications, requiring a sequence of actions to improve image quality and prepare it for subsequent processing. Noise reduction, contrast improvement, scaling, normalization, color space conversion, data augmentation, edge detection, and geometric transformations are popular techniques used to improve image data for machine and deep learning systems. These preprocessing stages improve the quality and consistency of picture data, resulting in more accurate and resilient performance of image analysis algorithms in tasks like classification, detection, and segmentation.

C. Feature Engineering:

Feature engineering, an integral aspect of machine learning, involves transforming raw data into meaningful features that enhance the performance of predictive models. It encompasses a variety of techniques aimed at selecting, creating, and manipulating features to extract valuable insights and patterns from the data. By encoding categorical variables, scaling numerical features, creating interaction terms, and deriving new features, feature engineering enables machine learning models to make more accurate predictions and uncover hidden relationships within the data. This process not only improves model performance but also helps reduce dimensionality, mitigate overfitting, and enhance

interpretability, making it a crucial step in the machine learning pipeline.

D. YOLO:-

YOLOv5 is a popular object detection model developed by Ultralytics. It's an evolution of the YOLO (You Only Look Once) series of real-time object detection models. YOLOv5 aims to improve upon the previous versions in terms of accuracy and speed. It is built on PyTorch and provides pre-trained models for various tasks like object detection, instance segmentation, and more. YOLOv5 comes in different versions (e.g., YOLOv5s, YOLOv5m, YOLOv5l, YOLOv5x), with varying model sizes and capacities to suit different needs, from small-scale applications to large-scale deployments. It's widely used in computer vision tasks, including object detection, vehicle detection, pedestrian detection, and more.

Design of YOLOv5s

YOLOv5, including the "s" variation (YOLOv5s, where "s" stands for small), is designed to be fast and efficient, making it ideal for real-time processing on devices with limited computational resources. The YOLOv5s model, in particular, is the smallest and fastest in the YOLOv5 series, with the goal of balancing speed and accuracy. Here's a high-level overview of YOLOv5s' design features:

1. Backbone: CSPDarknet53:

YOLOv5s is built on a modified version of the CSPDarknet53 architecture. This backbone is responsible for extracting features from the input image. The CSP (Cross Stage Partial) design reduces processing costs while retaining accuracy by separating the feature map into two sections and then merging them through a cross-stage.

2. Neck: PANet:

After the backbone, YOLOv5s uses a PANet (Path Aggregation Network) as its "neck." The PANet improves the information flow between layers and helps in aggregating features from different stages of the backbone. This structure enhances the feature learning capabilities of the model, especially for detecting small objects by efficiently utilizing feature maps from various scales.

3. Head:

The head of YOLOv5s is responsible for making the final predictions. The head of YOLOv5s is responsible for making the final predictions. It predicts bounding boxes, objectness scores, and class probabilities. The head operates on the feature maps provided by the PANet, applying 1x1 convolutions to predict the necessary outputs for each scale. YOLOv5 models typically operate on three different scales to detect objects of various sizes.

4. Anchor Box:

YOLOv5s uses anchor boxes predefined shapes to predict the location of objects. During training, these anchor boxes are optimized for the dataset, which helps

the model converge faster and improve detection accuracy, especially for small objects.

5. *Model Enhancements and Techniques:*

5.1. *Mosaic Data Augmentation:*

This technique combines four training images into one, in various configurations, to simulate different object scales, positions, and contexts, enhancing the model's robustness and detection capability.

5.2. *Auto-Learning of Anchor Sizes:*

YOLOv5s can automatically learn optimal anchor sizes directly from the training data, improving the model's adaptability to different datasets.

5.3. *Label Smoothing:*

This technique improves the model's generalization by preventing it from becoming too confident about its predictions.

6. *Efficiency and Speed:*

YOLOv5s is designed with efficiency in mind, utilizing techniques such as:

Batch normalization for faster convergence and regularization. Leaky ReLU as the activation function for non-linearity without significant computational overhead. A focus on reducing the number of parameters and operations (FLOPs) to speed up inference, especially on edge devices.

The YOLOv5s model, due to its design, is highly efficient for real-time applications and can run on various hardware platforms, including CPUs, GPUs, and edge devices like the NVIDIA Jetson series and Google Coral. Its architecture makes it a versatile tool for a wide range of applications, from surveillance to autonomous driving, where speed and efficiency are crucial.

E. *Algorithm:*

The YOLOv5 algorithm builds upon the concepts of the previous YOLO (You Only Look Once) models, which are designed for real-time object detection. Here's an overview of the YOLOv5 algorithm:

1. *Input Image:*

The algorithm takes an input image of any size.

2. *Preprocessing:*

The input image is resized to a fixed size that the model expects. This preprocessing step ensures consistency in input dimensions.

3. *Model Architecture:*

YOLOv5 is based on a convolutional neural network (CNN) architecture, typically using a backbone network such as CSPDarknet53 or EfficientNet as the feature extractor. The network is composed of convolutional layers, activation functions (usually ReLU), and other operations like batch normalization and down-sampling layers. The network architecture is designed to extract features from the input image efficiently.

4. *Object Detection:*

YOLOv5 divides the input image into a grid of cells. Each cell is responsible for predicting bounding boxes and class probabilities. For each grid cell, YOLOv5 predicts bounding boxes by regressing to offsets from anchor boxes. These anchor boxes are pre-defined shapes of different aspect ratios and scales. Each bounding box prediction consists of the coordinates (x, y) of the bounding box's centre, width, height, confidence score (indicating the presence of an object), and class probabilities for different object categories. The confidence score represents how confident the model is that there's an object present in the bounding box, while class probabilities indicate the likelihood of the object belonging to various predefined classes.

5. *Non-Maximum Suppression (NMS):*

After object detection, a post-processing step called non-maximum suppression (NMS) is applied to filter out redundant bounding box predictions. NMS eliminates duplicate predictions by keeping only the bounding box with the highest confidence score among overlapping boxes.

6. *Output:*

The final output of the YOLOv5 algorithm consists of a list of bounding boxes, each associated with a class label and confidence score, representing the detected objects in the input image.

7. *Training:*

YOLOv5 is trained using annotated datasets, where bounding boxes and class labels are provided for training images. During training, the model learns to minimize a loss function that penalizes incorrect predictions and encourages accurate localization and classification of objects. The model is trained using techniques like stochastic gradient descent (SGD) or Adam optimization, and typically employs techniques like data augmentation to improve generalization. Overall, YOLOv5 is known for its simplicity, speed, and accuracy in object detection tasks, making it a popular choice for various applications in computer vision.

F. *Deployment:*

A mobile-friendly format is created from a machine learning model (The results throughout this integration, consideration is given to memory efficiency and real-time processing limits on mobile devices. Android Studio is also utilized to speed up the deployment process and ensure optimal performance from the machine learning model running within the Android app. TensorFlow models) prior to being integrated into an Android application using TensorFlow Lite. After optimization, the model is integrated into the Android app using the appropriate libraries or frameworks. After that, the inference engine of the app uses the deployed model to extra data inputs to predict

IV. RESULTS

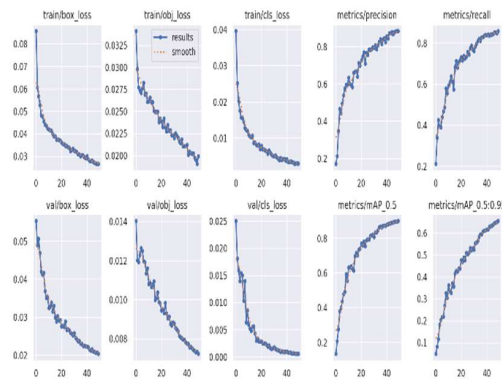


Fig.3: Result

Table.2: Study

The system used YOLOv5 algorithm to categorize medical waste into four important groups: radioactive waste, infectious waste, sharp item waste, and pharmaceutical waste. After 50 epochs of intense training, the system achieved an accuracy rate of 87%. A well-annotated dataset containing a variety of photos was used in the training phase to guarantee thorough coverage of the unique traits connected to each form of garbage. The results demonstrate the effectiveness of the YOLOv5 algorithm in precisely recognizing and categorizing medical waste, with encouraging outcomes demonstrated by the accuracy attained. More evaluation metrics that offer a more detailed picture of the model's performance across the designated waste categories include precision, recall, and F1 score. Examining the patterns of training loss over the course of 50 epochs offers insights about waste categories.

The YOLOv5 algorithm's effectiveness for classifying medical waste is enhanced by this study, which highlights the algorithm's potential uses in waste management systems. The model can classify infectious waste, sharp object waste, pharmaceutical waste, and radioactive waste even on live capturing.

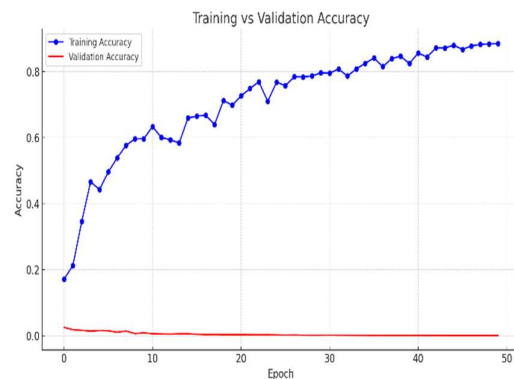


Fig.4: Training vs Validation Accuracy graph for YOLOv5 Model

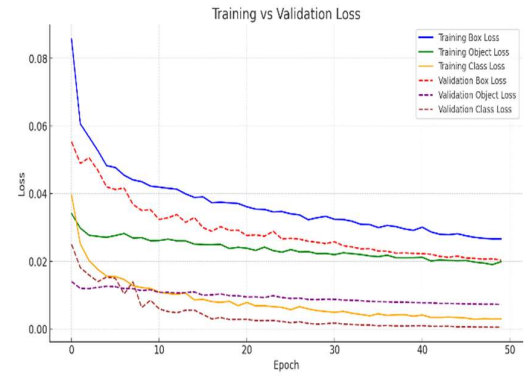


Fig.5: Training vs Validation Loss graph for YOLOv5 Model

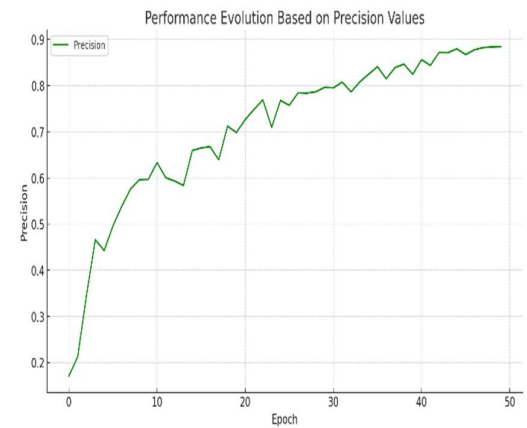


Fig.6: Performance Evolution Based on Precision Values of Model

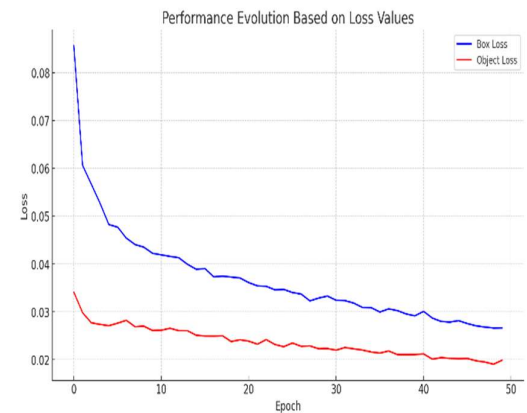


Fig.7: Performance Evolution Based on Loss Values of Model

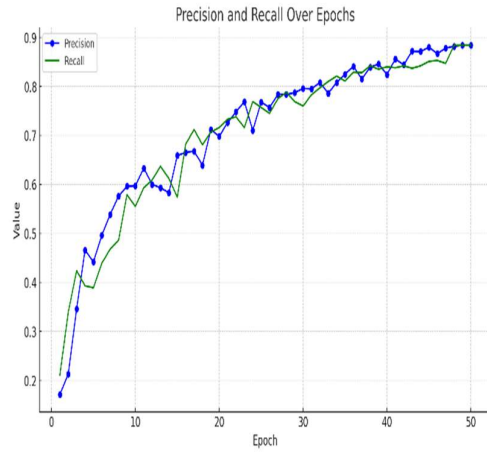


Fig.8: Precision and Recall over Epochs

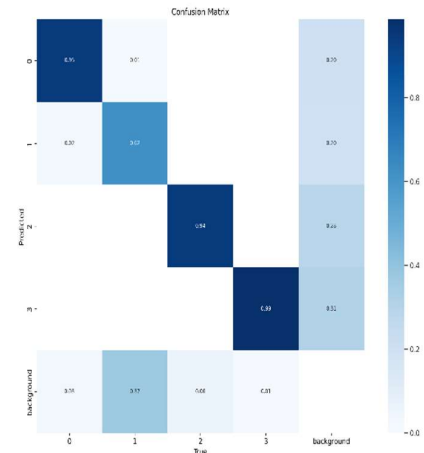


Fig.11: Confusion Matrix

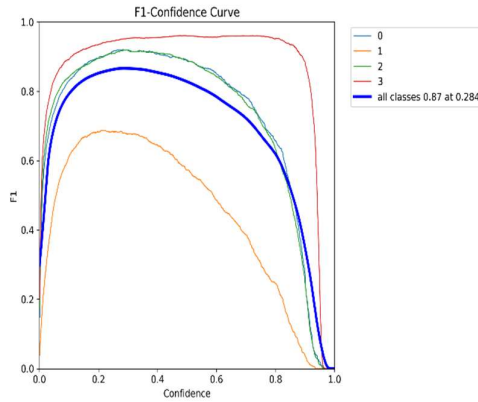


Fig.9: F1 Score over confidence

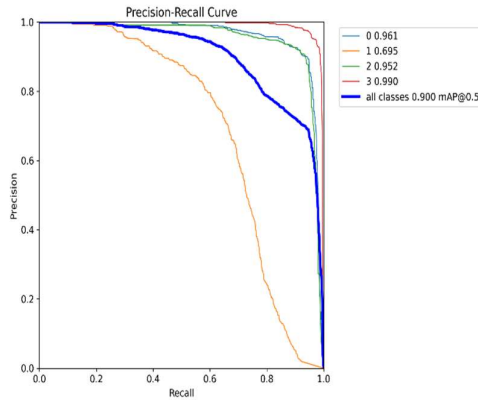


Fig.10: Precision Recall Curve over class

V. CONCLUSION & FUTURE SCOPE

In closing, maintaining the environment and public health depends on giving proper medical waste management top priority. To achieve this, one must promote laws, research, and public awareness. The effect and makeup of medical waste make expert management necessary. The environment and human health are seriously endangered when proper disposal is neglected, which emphasizes the urgent need for comprehensive action[30]. Using the Yolo V5 algorithm, the biomedical waste classification system aims to create an intelligent system capable of autonomously identifying and categorizing different types of medical waste in images or in real time. The main goal is to optimize waste management processes by putting into practice an accurate and efficient solution that lessens the need for human sorting. YOLOv5 aims to develop a model that can understand many types of medical waste, such as syringes, gloves, and other hazardous materials commonly seen in hospital settings. The system's goal is to provide a quick and dependable method for instantaneous item recognition YOLOv5 is trained on multiple annotated medical waste image datasets, which allows the system to recognize distinct features and patterns associated with different waste kinds. The result is a trained model that can recognize medical waste materials with new images and videos, mostly in four categories: pharmaceutical, radioactive, sharp, and contagious. It can also automatically analyze the materials and assign labels according on the results. Enhancing overall waste management effectiveness, lowering the possibility of waste classification errors, and guaranteeing the secure and appropriate disposal of medical waste are the main advantages. This technology reduces the possibility of handling hazardous materials improperly, which not only makes trash disposal procedures more efficient but also promotes a safer and healthier environment.

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