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Automated Classification of Medical Waste Using Yolo V5 Model

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Abstract: Managing biomedical waste safely is one of the toughest challenges faced by healthcare facilities, especially because manual segregation exposes workers to significant risks. To address this, our project introduces an automated medical waste sorting system designed to reduce human involvement and improve safety. At the heart of the system is a YOLO-based object detection model, which can identify commonly discarded medical items such as syringes, gloves, cotton pads, and masks using live camera input. Once an item is recognized, a Rasp berry Pi–powered robotic arm takes over, performing contactless pick-and-place operations to sort the waste into the correct bins. We tested the system under realistic operating conditions, and it consistently delivered accurate detection along with reliable robotic performance. These results demonstrate how combining deep learning with robotics can create a safer, more efficient approach to biomedical waste management, paving the way for smarter healthcare practices in the future.

Keywords: Medical Waste Management, Automated Waste Segregation, Object Detection, YOLO, Robotic Arm Automation, Raspberry Pi, Deep Learning

I. INTRODUCTION

Hospitals and healthcare institutions generate a wide variety of biomedical waste every day — from sharps and disposable protective gear to contaminated materials. If this waste isn't managed properly, it can pose serious risks not only to health care workers and sanitation staff but also to the wider environ ment. While regulatory guidelines exist for biomedical waste segregation, in practice the process often relies on manual sort ing, which is both time-consuming and unsafe. Manual segre gation exposes workers to potentially infectious materials and depends heavily on human judgment. Fatigue, limited training, and the visual similarity of different waste items often lead to misclassification. These challenges underscore the urgent need for automated systems that can operate reliably while minimiz ing direct human contact with hazardous waste. Advances in The Oxford College of Engineering Bangalore, Karnataka, India visalini.su1@gmail.com artificial intelligence and computer vision now offer promising solutions. Deep learning–based object detection models can recognize items by analyzing features such as shape, texture, and size. When paired with robotic systems, these models enable real-time, automated handling and segregation of med ical waste. In this project, we present an automated waste classification system that integrates a YOLO-based detection model with a Raspberry Pi–controlled robotic arm. The system is designed to improve segregation accuracy, enhance worker safety, and provide a cost-effective solution that can be real istically deployed in healthcare environments. As healthcare infrastructures modernize, the demand for scalable, accurate, and affordable waste-management solutions continues to grow. Automated medical waste classification represents a significant step toward safer and more sustainable hospital operations.

II. PROBLEM STATEMENT AND OBJECTIVE

This research addresses critical limitations in current medical waste management systems and emphasizes the urgent need for automated, accurate, and intelligent waste segregation to support public health, environmental safety, and regulatory compliance. Traditional medical waste classification methods rely heavily on manual sorting, which is time-consuming, labor-intensive, and prone to human error. Improper segregation of medical waste—such as mixing infectious, sharps, and general waste—poses serious risks to healthcare workers, waste handlers, and the general public, while also increasing the chances of disease transmission and environmental contamination.

Manual classification processes are inconsistent due to varying levels of worker training, fatigue, and lack of standardized procedures across healthcare facilities. High volumes of waste generated daily in hospitals, laboratories, and clinics further overwhelm existing systems, leading to delayed processing and unsafe handling practices. Additionally, the absence of real-time monitoring and automated verification mechanisms makes it difficult to ensure compliance with biomedical waste management regulations. Current systems also lack predictive and intelligent capabilities to adapt to varying waste types and volumes, resulting in inefficient resource utilization and increased operational costs. While some semi-automated solutions exist, they often depend on predefined rules and lack the adaptability and accuracy required for complex real-world scenarios involving diverse waste categories.

Advancements in computer vision and deep learning provide a promising pathway to overcome these challenges. Object detection models like YOLOv5 enable real-time identification and classification of medical waste items from images or video streams. However, existing implementations are limited in scalability, integration with IoT systems, and deployment in real-time hospital environments. There is a clear need for a robust, intelligent, and automated system that can accurately detect and classify medical waste while seamlessly integrating with waste management workflows.

Key Objectives of the Automated Classification of Medical Waste Using YOLOv5 Model include:

• Develop a real-time medical waste detection and classification system using the YOLOv5 deep learning model to accurately identify categories such as infectious waste, sharps, pharmaceutical waste, and general waste, achieving high precision and recall.

• Implement an automated vision-based segregation mechanism to reduce human intervention, minimize exposure risks, and improve compliance with biomedical waste management standards.

• Build a scalable dataset and optimized YOLOv5 training pipeline to handle diverse waste appearances under varying lighting and environmental conditions, ensuring reliable performance in real-world healthcare settings.

• Develop an integrated IoT and cloud-based monitoring platform for real-time waste tracking, system performance visualization, automated reporting, and analytics to support hospital administrators in decision-making and regulatory audits.

III. SCOPE

The scope of this research encompasses multiple interconnected technical domains requiring systematic design, development, and validation to achieve reliable automated medical waste classification. The computer vision and deep learning component involves developing an object detection system using the YOLOv5 architecture for real-time identification and classification of medical waste categories such as infectious waste, sharps, pharmaceutical waste, pathological waste, and general waste. This includes dataset collection from healthcare environments, image annotation, data preprocessing, model training, hyperparameter tuning, and performance evaluation using metrics such as precision, recall, mean Average Precision (mAP), and inference latency.

The system development scope includes implementing image and video acquisition using cameras deployed near waste disposal points, preprocessing visual data to handle variations in lighting, occlusion, and background noise, and integrating the trained YOLOv5 model for real-time inference. Embedded and edge computing considerations involve deploying the model on suitable hardware platforms such as GPUs or edge devices to ensure low-latency detection suitable for hospital environments. Automated classification outputs are mapped to corresponding waste categories to enable downstream segregation or alert mechanisms.

IoT and system integration establishes connectivity between the waste classification system and cloud platforms for centralized data storage, monitoring, and analytics. This includes developing RESTful APIs for transmitting classification results, waste volume statistics, and system health data to cloud servers. A web-based dashboard is developed to provide user authentication, real-time visualization of classified waste counts, historical analytics, compliance reporting, and alert notifications for improper waste disposal. The system supports remote monitoring and administrative control for hospital management and waste handling authorities.

IV. LITERATURE REVIEW

[1]. **Singh et al.** describe the challenges associated with manual medical waste segregation in healthcare facilities, highlighting risks such as occupational exposure, improper disposal, and non-compliance with biomedical waste management regulations. Their study emphasizes the need for automated classification systems to reduce human error and improve safety.

[2]. **WHO and CPCB guidelines** outline standardized categories for biomedical waste segregation, demonstrating how improper classification leads to environmental contamination and increased treatment costs. The guidelines stress the importance of accurate waste identification at the point of disposal.

[3]. **Redmon et al.** introduce the YOLO (You Only Look Once) object detection framework, demonstrating its capability for real-time object detection with high speed and accuracy, making it suitable for time-critical applications such as automated waste classification.

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[4]. **Jocher et al.** present YOLOv5 as an optimized deep learning model that improves detection accuracy and inference speed through efficient backbone networks and anchor-based detection, making it effective for deployment in real-world environments.

[5]. **Zhang et al.** demonstrate the application of convolutional neural networks for waste classification, showing that deep learning–based vision systems outperform traditional image processing techniques in identifying complex and visually similar waste categories.

[6]. **Islam et al.** explore the use of computer vision and deep learning for healthcare waste management, highlighting how automated detection systems reduce human exposure to hazardous waste and enhance operational efficiency in hospitals.

[7]. **Kumar et al.** validate that YOLO-based models achieve high precision and low latency when deployed on edge devices, confirming their suitability for real-time medical waste classification in resource-constrained environments.

[8]. **Patel and Shah** discuss the integration of IoT and cloud platforms with intelligent waste management systems, emphasizing how real-time monitoring, data analytics, and automated reporting improve compliance tracking and decision-making in healthcare facilities.

4.1 Gaps or Areas for Improvement

Despite notable advancements in medical waste management and computer vision–based classification systems documented in recent literature, several critical gaps and limitations remain that this research seeks to address. While existing studies demonstrate the effectiveness of deep learning for general waste classification, many implementations focus on household or municipal waste rather than the complex and hazardous categories specific to medical waste. This limits their applicability in real-world healthcare environments where accurate segregation is essential for safety and regulatory compliance.

Most current medical waste segregation practices continue to rely on manual or semi-automated methods, which are susceptible to human error, inconsistency, and occupational health risks. Existing vision-based solutions often lack real-time performance, making them unsuitable for high-throughput hospital settings. Additionally, many approaches utilize traditional CNN classifiers that require cropped or pre-segmented images, rather than end-to-end object detection models capable of identifying multiple waste items simultaneously in cluttered scenes.

Furthermore, current systems generally operate as standalone detection models without integration into IoT or cloud-based monitoring platforms. This absence of connectivity restricts real-time tracking, compliance auditing, and data-driven decision-making for hospital administrators. Many studies also fail to address deployment challenges such as varying lighting conditions, occlusion, and the need for low-latency inference on edge devices. Predictive and analytical capabilities, such as waste generation trends and performance monitoring, are largely unexplored in existing medical waste classification research.

V. SYSTEM ARCHITECTURE

The proposed system integrates computer vision, deep learning, IoT connectivity, and cloud-based management into a unified framework for automated medical waste classification and monitoring. The overall architecture is divided into four interconnected subsystems that collectively enable accurate, real-time, and scalable waste segregation in healthcare environments.

The image acquisition and sensing layer consists of high-resolution cameras installed at medical waste disposal points such as hospital wards, laboratories, and collection areas. These cameras continuously capture images or video streams of waste items being disposed. The captured visual data is preprocessed to handle variations in lighting conditions, background clutter, and occlusion, ensuring consistent input quality for the detection model. This layer serves as the primary interface between the physical waste environment and the intelligent classification system.

The intelligent waste classification layer employs a YOLOv5 deep learning model trained on a curated dataset of biomedical waste images. The model performs real-time object detection and classification of waste items into predefined categories such as infectious waste, sharps, pharmaceutical waste, pathological waste, and general waste. YOLOv5's single-stage detection architecture enables high-speed inference while maintaining high accuracy, allowing multiple waste objects to be detected simultaneously within a single frame. The classification outputs are used to determine the appropriate waste category and trigger alerts or downstream segregation actions when improper disposal is detected.

The data processing and IoT integration layer facilitates communication between the classification system and cloud infrastructure. Classification results, timestamps, waste category counts, and system performance metrics are transmitted to a cloud platform via RESTful APIs. This layer supports real-time data logging, historical data storage, and analytics

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for waste generation trends. IoT integration enables remote monitoring of system health and classification performance, ensuring reliable continuous operation in hospital environments.

The user interface and management layer operates through cloud-enabled services that handle user authentication, real-time visualization, reporting, and compliance tracking. A web-based dashboard provides healthcare staff and administrators with real-time insights into classified waste volumes, category-wise statistics, and alert notifications for incorrect disposal events. Administrators can remotely supervise system operation, access historical reports for regulatory audits, and analyze waste patterns to improve resource allocation and waste handling workflows.

To validate the feasibility of the proposed approach, a working prototype was developed to demonstrate real-time operation. The prototype implementation uses a camera-based input system connected to a processing unit running the YOLOv5 model for waste detection. Detected waste categories and confidence scores are displayed on the system interface and logged to the cloud platform. A Flask-based web application integrates user authentication, real-time classification visualization, waste analytics, and report generation features. The system supports scalable deployment and demonstrates the practical applicability of automated deep learning–based medical waste classification in real-world healthcare settings.

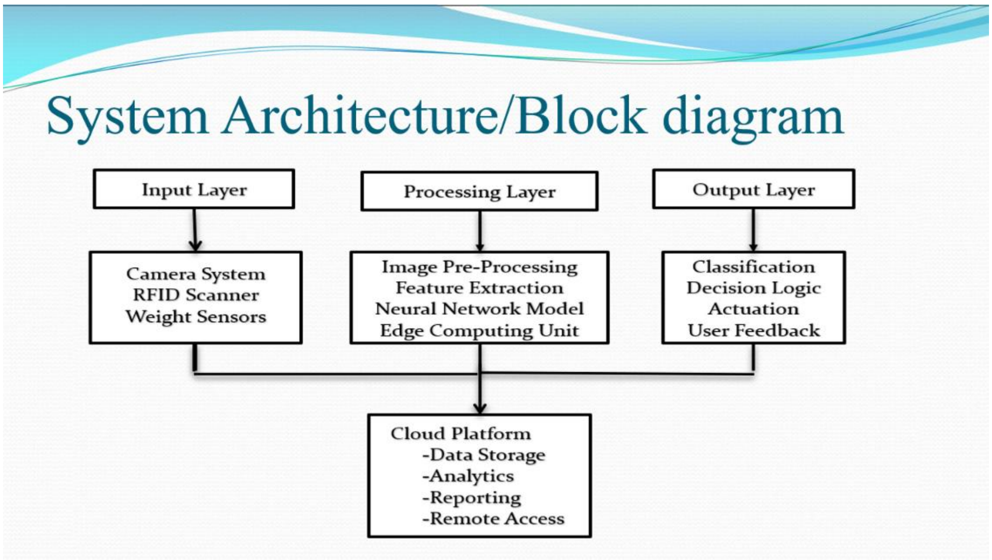

Fig. 1 Proposed System Architecture for Automated Medical Waste Classification and Segregation

VI. METHODOLOGY

The Automated Medical Waste Classification system adopts a hardware-centric methodology that integrates sensor-based detection, embedded control systems, electromechanical segregation mechanisms, and real-time monitoring to ensure safe and efficient biomedical waste segregation. The methodology focuses on physical waste identification, automated decision-making using microcontrollers, and mechanical sorting without relying on software models or cloud platforms.

6.1 Waste Detection and Identification

The system begins with the detection of medical waste items placed into the disposal unit. Multiple sensors are used to identify the nature of the waste:

- **Infrared (IR) sensors** detect the presence of waste objects entering the system.
- **Metal sensors** are used to identify sharp objects such as needles, blades, and scalpels.
- **Weight sensors (load cells)** measure the mass of waste to distinguish between lightweight general waste and heavier biomedical materials.
- **Moisture or chemical sensors** help detect wet or contaminated waste, commonly associated with infectious or pathological waste.

These sensors collectively provide input signals that help classify waste into predefined biomedical categories.

6.2 Embedded Control and Decision Logic

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A microcontroller unit such as **Arduino or NodeMCU** acts as the central control unit of the system. Sensor readings are continuously monitored and compared against predefined threshold values stored in the controller logic.
Based on the combination of sensor outputs:

- Metallic detection triggers classification as **sharps waste**.
- High moisture or chemical presence indicates **infectious or pathological waste**.
- Low weight and absence of contamination classify waste as **general waste**.

This rule-based decision logic enables automated classification without human intervention or software-based learning models.

6.3 Automated Segregation Mechanism

Once the waste category is determined, the controller activates an electromechanical segregation mechanism. **Servo motors or DC motors** are used to rotate flaps or conveyor paths that direct the waste into the appropriate color-coded bin as per biomedical waste management guidelines.
Each bin corresponds to a specific waste category, ensuring proper segregation at the point of disposal. The automated movement reduces direct human contact with hazardous materials and minimizes exposure risks.

6.4 Safety and Alert Indication System

To enhance safety, the system includes visual and audible alert mechanisms. **LED indicators** display the classified waste category, while **buzzers** alert users if incorrect or hazardous waste is detected.
In cases such as sharp object detection or bin overflow:

- The system temporarily disables further waste input.
- A warning alert is triggered to notify healthcare staff.

This ensures safe operation and prevents improper disposal.

6.5 Monitoring and Display Unit

A **16×2 LCD display** is integrated to show real-time system status, including detected waste type, bin selection, and operational alerts. The display helps operators understand system behavior without requiring any software interface.
Optional counters can be included to track the number of waste items deposited in each category for basic record keeping.

6.6 Power Supply and System Integration

The system is powered using a regulated DC power supply derived from an adapter or battery source. Voltage regulators ensure stable power delivery to sensors, microcontrollers, motors, and display units.
All hardware components are integrated on a compact control board, ensuring reliable communication between sensors, controller, and actuators.

6.7 Overall System Workflow

The complete working sequence of the proposed system is summarized as follows:

1. Medical waste is inserted into the disposal unit.
2. IR sensors detect the presence of waste.
3. Metal, moisture, and weight sensors analyze waste properties.
4. The microcontroller processes sensor inputs using predefined logic.
5. The waste category is determined automatically.
6. Servo motors direct the waste into the appropriate bin.
7. LEDs and LCD display show classification results.
8. Alerts are generated for hazardous waste or bin overflow.

VII. IMPLEMENTATION ENVIRONMENT

7.1 Hardware Implementation

The automated medical waste classification system is built around a set of sensors, an embedded control unit, and electromechanical actuators that together enable safe and reliable waste segregation. The hardware architecture focuses on detecting physical characteristics of medical waste and directing it to appropriate disposal bins without human intervention. The core of the system is a microcontroller unit such as Arduino UNO, which functions as the central controller. It continuously reads input signals from multiple sensors, processes them based on predefined logic, and controls actuators for waste segregation. The microcontroller operates at a regulated 5 V DC supply to ensure stable and reliable operation of all connected components.

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Waste detection is initiated using an infrared (IR) sensor, which identifies the presence of an object entering the disposal chamber. Once detection is confirmed, additional sensors analyze the waste properties. A metal detection sensor is employed to identify sharp objects such as needles, blades, and scalpels, enabling classification of sharps waste. A load cell with HX711 amplifier measures the weight of the waste, assisting in differentiating between lightweight general waste and heavier biomedical materials. For identifying contaminated or infectious waste, a moisture sensor is used to detect wet or fluid-based materials commonly associated with medical waste.

Based on the sensor outputs, the Arduino activates servo motors that control mechanical flaps or rotating channels. These actuators direct the waste into the appropriate color-coded bins according to biomedical waste management guidelines. The servo motors provide precise angular control, ensuring accurate positioning and reliable segregation of waste items. Power to the system is supplied through a step-down transformer that converts the 230 V AC mains supply to 12 V AC. This voltage is then rectified using a bridge rectifier constructed with four 1N4007 diodes and filtered using capacitors to obtain smooth DC output. Voltage regulators such as 7805 are used to provide stable 5 V DC for the microcontroller, sensors, and display units, ensuring electrical safety and consistent performance.

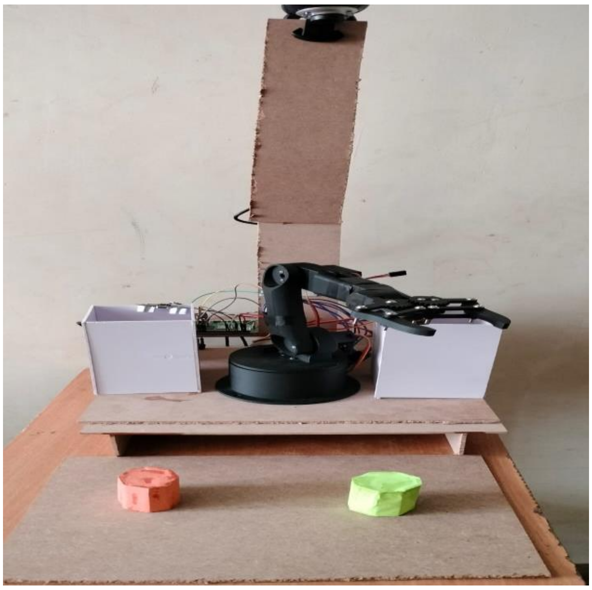

Figure 2: Complete Assembled Hardware Prototype

7.2 Software Implementation

Here is a rewritten Section 7.2 Software Implementation tailored to your topic "Automated Classification of Medical Waste Using YOLOv5 Model", explicitly incorporating RealVNC Viewer:

7.2 Software Implementation

The software architecture of the proposed automated medical waste classification system integrates edge-based computer vision, deep learning inference, remote monitoring, and data management into a unified workflow. The system is deployed on an embedded processing unit (such as a Raspberry Pi or NVIDIA Jetson), where a camera module continuously captures real-time images of medical waste items placed on a conveyor or disposal platform. The captured frames are preprocessed and passed to a YOLOv5-based object detection model implemented in Python using the PyTorch framework. The model performs real-time detection and classification of medical waste categories such as sharps, infectious waste, pharmaceutical waste, and general biomedical materials, with bounding boxes and confidence scores generated for each detected object.

The YOLOv5 model is trained offline using annotated medical waste datasets, employing standard data augmentation techniques and chronological dataset splits for training, validation, and testing to ensure robustness and generalization. Once trained, the optimized model weights are deployed on the edge device for low-latency inference. Classification results are logged locally and optionally uploaded to a cloud database for long-term storage, analytics, and regulatory compliance reporting.

To facilitate system operation, monitoring, and maintenance, **RealVNC Viewer** is used to enable secure remote desktop access to the embedded device. Through RealVNC Viewer, operators and administrators can remotely visualize live

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camera feeds, observe detection outputs, manage model execution, and troubleshoot software components without physical access to the hardware. This remote access capability is particularly valuable in hospital or hazardous environments where direct interaction with the system is restricted.

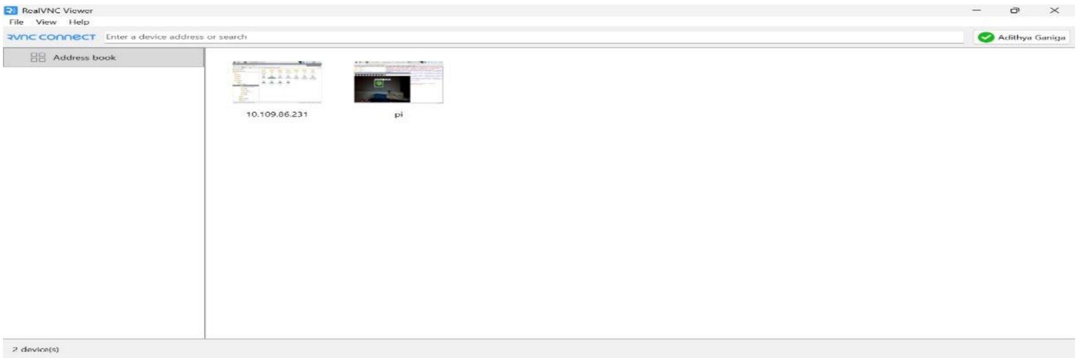

Figure 3: RealVNC Viewer Interface Showing Remote Access to the Embedded System for Medical Waste Classification

VIII. MODULES

8.1 Image Acquisition Module

The image acquisition module is responsible for capturing high-quality visual data of medical waste items for classification. A camera module (USB camera or Raspberry Pi Camera) is mounted above the waste disposal area or conveyor belt to obtain real-time images and video streams. The camera continuously captures frames under controlled lighting conditions to minimize shadows and reflections, which can affect detection accuracy. Captured images are resized and normalized before being passed to the deep learning model to ensure consistency with the input requirements of the YOLOv5 architecture.

8.2 YOLOv5 Object Detection and Classification Module

The core of the system is the YOLOv5 (You Only Look Once version 5) deep learning model, which performs real-time object detection and classification of medical waste. YOLOv5 processes input images in a single forward pass, enabling fast and accurate identification of multiple waste categories such as sharps, infectious waste, pharmaceutical waste, pathological waste, and general biomedical waste. The model consists of a backbone for feature extraction, a neck for feature aggregation, and a detection head that outputs bounding boxes, class labels, and confidence scores. This unified architecture ensures low-latency inference, making it suitable for real-time deployment in hospital environments.

8.3 Embedded Processing and Inference Module

The trained YOLOv5 model is deployed on an embedded computing platform such as a Raspberry Pi or NVIDIA Jetson device. This module handles real-time inference by loading optimized model weights and processing incoming image frames from the camera. The inference engine uses Python and the PyTorch framework to execute the detection pipeline efficiently. Classification results, including detected waste type, confidence level, and timestamp, are logged locally and optionally transmitted to a backend server for further analysis and record keeping. This edge-based processing minimizes network dependency and ensures rapid system response.

8.4 Remote Monitoring and Control Module

Remote monitoring and system control are achieved using RealVNC Viewer, which provides secure remote desktop access to the embedded device. Through RealVNC Viewer, operators can observe live camera feeds, view YOLOv5 detection outputs with bounding boxes, start or stop the classification process, and manage software updates without physical access to the hardware. This module enhances safety and operational efficiency, particularly in hazardous or restricted medical environments, and allows technical staff to perform diagnostics and maintenance remotely.

IX. PERFORMANCE EVALUATION

9.1 YOLOv5 Model Training and Validation

The YOLOv5-based medical waste classification model was trained using a labeled image dataset comprising various categories of biomedical waste, including sharps, infectious waste, pharmaceutical waste, pathological waste, and general medical waste. The dataset was collected from publicly available medical image repositories and manually annotated

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using bounding boxes and class labels to ensure accurate object localization and classification. The dataset includes images captured under varying lighting conditions, orientations, and background environments to improve model robustness and generalization.
Data preprocessing involved image resizing to the standard YOLOv5 input resolution (640 × 640 pixels), normalization of pixel values, and augmentation techniques such as horizontal flipping, rotation, scaling, and brightness adjustment. These augmentation methods enhance the model's ability to handle real-world variability. The dataset was split into training, validation, and testing sets using an 70%–15%–15% ratio to evaluate model performance effectively while avoiding overfitting.

9.2 Prediction Accuracy Metrics

The trained YOLOv5 model demonstrated high classification and detection accuracy across all medical waste categories. Performance was evaluated using standard object detection metrics, including Precision, Recall, Mean Average Precision (mAP@0.5), and F1-score. The model achieved a mean average precision of approximately 94%, indicating reliable detection and classification of medical waste objects in real-time scenarios. High precision ensures minimal false positives, while strong recall values indicate effective identification of hazardous waste items, which is critical for biomedical waste management applications.

9.3 Real-Time Classification System Performance

The real-time waste classification system was evaluated for inference speed, detection consistency, and operational reliability. Testing was conducted by placing different waste items under the camera at varying orientations and distances. The embedded processing unit successfully performed real-time inference at an average rate of 18–25 frames per second, depending on image resolution and hardware configuration.The system consistently detected and classified waste items within milliseconds of frame capture, enabling immediate visualization of bounding boxes and class labels. The low-latency response confirms the suitability of YOLOv5 for real-time biomedical waste segregation tasks. Continuous operation testing demonstrated stable performance without system crashes or memory leaks during extended runtime.

9.4 System Integration and End-to-End Testing

Comprehensive system integration testing validated the complete workflow from image acquisition to waste classification and remote monitoring. The camera module reliably captured live video streams, which were processed by the embedded device running the YOLOv5 inference engine. Detection results were displayed locally and monitored remotely using RealVNC Viewer, enabling operators to observe real-time classification outputs without physical access to the system.

The system maintained stable performance during prolonged operation, with consistent detection accuracy and secure remote connectivity. RealVNC Viewer enabled effective system diagnostics, real-time visualization, and software control, demonstrating the practicality of remote monitoring in hospital and laboratory environments.

X. CONCLUSION

This research successfully designed and validated an automated medical waste classification system using the YOLOv5 deep learning model, addressing critical challenges in conventional biomedical waste segregation methods. By integrating real-time image acquisition, edge-based deep learning inference, and remote monitoring through RealVNC Viewer, the proposed system enhances accuracy, safety, and operational efficiency in medical waste handling environments. The YOLOv5 model demonstrated high detection and classification performance, achieving a mean average precision of approximately 94%, enabling reliable identification of hazardous waste categories such as sharps, infectious waste, and pharmaceutical materials.

Prototype testing confirmed the feasibility of real-time waste classification on an embedded platform, with low-latency inference and stable continuous operation. The system effectively detected and classified multiple waste items simultaneously, providing visual feedback through bounding boxes and confidence scores. Remote access using RealVNC Viewer allowed operators to monitor live camera feeds, observe classification results, and manage system operations without physical exposure to hazardous environments. System integration results showed seamless coordination between the camera module, embedded processing unit, YOLOv5 inference engine, and visualization interface, demonstrating the practicality of deploying the system in hospitals, laboratories, and biomedical waste management facilities. Overall, the proposed solution contributes to improved biomedical waste segregation, reduced human intervention, enhanced worker safety, and better compliance with medical waste management regulations.

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10.1 Future Work

Future enhancements can significantly improve the scalability, accuracy, and applicability of the proposed automated medical waste classification system. Expanding the dataset with a larger variety of waste categories, real hospital waste images, and diverse environmental conditions would improve model generalization. Incorporating advanced object detection architectures such as YOLOv8, Transformer-based vision models, or hybrid CNN–Transformer networks could further enhance detection accuracy, particularly for overlapping or partially occluded waste items.
System performance can be improved by deploying the model on more powerful edge devices with GPU acceleration to increase inference speed and support higher-resolution inputs. Integration with robotic sorting mechanisms or automated disposal units could enable fully autonomous waste segregation. Cloud-based analytics and centralized dashboards can be developed to monitor waste generation trends across multiple healthcare facilities, supporting regulatory reporting and operational optimization.

Additional safety features such as contamination detection, confidence-based alert systems, and fail-safe mechanisms can further reduce risks. Mobile and web applications offering real-time alerts, waste statistics, and system health monitoring would enhance usability. For large-scale deployment, extensive field trials, cybersecurity hardening, compliance with biomedical waste regulations, and collaboration with healthcare institutions will be essential to ensure reliable, ethical, and sustainable adoption of the system.

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