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Development of Microcontroller-Based Automated Infectious Waste Segregation and Disinfection System: A COVID-19 Mitigation and Monitoring Response †

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Abstract: With the recent increase amount of disposed infectious waste due to COVID-19, a growing interest to develop an efficient, economical, and effective infectious waste segregation system has prompted both the health sector and the government. This study presented a Microcontroller-Based Automated Infectious Waste Segregation and Disinfection System in a selected medical facility in Metro Manila, Philippines. The prototype system applying the machine learning principles can identify three kinds of waste materials classified as electronic, pathological, and sharp wastes as interpreted by the YOLOv5 algorithm. In addition, an added feature of UV light mechanism to address the bacterial presence of *Staphylococcus aureus* and *Escherichia coli* was incorporated in the prototype to ensure disinfection. Results showed that the mean average precision (mAP) of identifying electronic, pathological, and sharp waste was 95.7, 79.9 and 94.5% respectively. Moreover, it was found that there was a noticeable decrease in the bacterial count signifying the effectivity of the prototype and has promising potential for large-scale implementation.

Keywords: infectious waste; microcontroller; UV disinfection; automated segregation; YOLOv5

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1. Introduction

COVID-19 had a massive impact on our society. Personal Protective Equipment (PPEs), syringes, needles, facemasks, and other healthcare services were in great demand. As a result, many healthcare institutions (HCFs) generate more solid waste, making healthcare waste (HCW) a growing problem, particularly in developing countries such as the Philippines. As stated by [1], Department of Environment and Natural Resources (DENR) report, the Philippines generated 634,687.73 metric tons of healthcare waste between June 2020 and June 2021. Hence, the country generated 52,890 metric tons of healthcare waste alone in a month [2]. Mismanagement of infectious medical waste from healthcare institutions and improper segregation of potentially infectious waste from patients may contribute to the spreading of infection [3]. Several previous studies concluded that there is a typical microbial growth in infectious medical wastes such as *Escherichia coli, Bacillus spp., Staphylococcus spp., Klebsiella pneumonia*, etc., which causes respiratory and urinary tract diseases, as well as HIV/AIDS and hepatitis B and C [4].

Although guidelines exist on waste management, especially in the medical field, healthcare providers still need more implementation and good practice [5]. This poses health risks and hazards to the environment, especially to people in contact with these types of waste. Past researchers have proposed the idea of an Automatic Segregation System through different techniques such as IoT (Internet of Things) [6], artificial intelligence, Arduino microcontroller [7], and machine learning [8], which can identify general and household level waste. There are numerical applications for this technology. However, past research has not yet focused on segregating waste materials for medical purposes, specifically infectious wastes.

In this study, the researchers developed a microcontroller-based automated infectious waste segregation and disinfection system for bacteria mitigation and monitoring response. Section 2 presents the methodology. In Section 3, results and discussion are presented.

2. Methodology

This section includes the system design and the prototype design of the microcontroller-based automated infectious waste segregation and disinfection. System design consists of the general process of the prototype. On the other hand, the prototype design shows the physical implementation of the bin developed by the researchers that includes the process mentioned in system design.

2.1. System Design

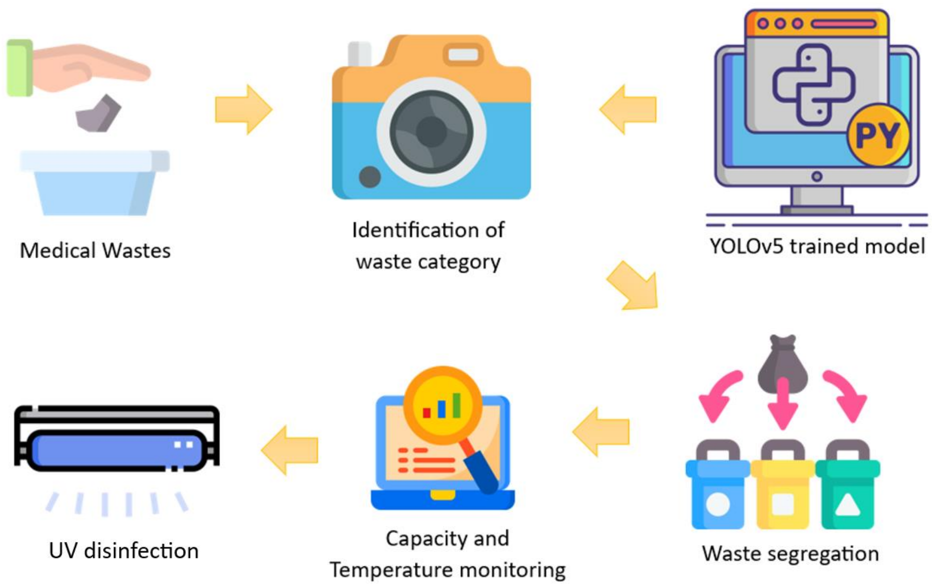
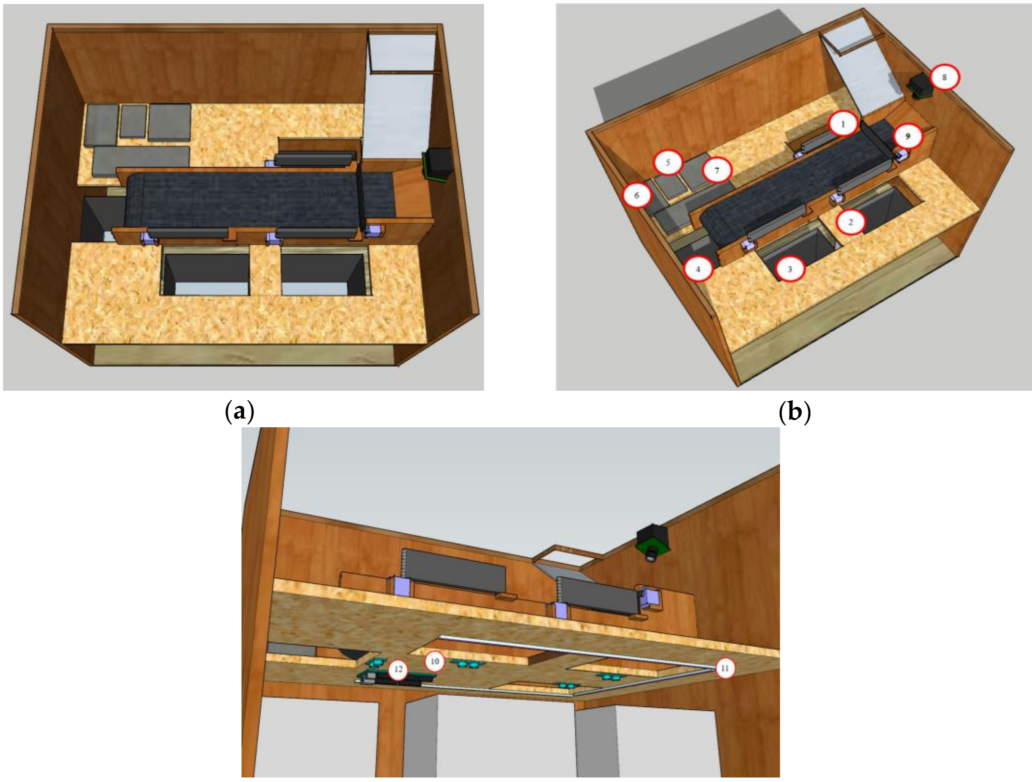


Figure 1. System design of microcontroller-based automated infectious waste segregation and disinfection system.

To identify the infectious waste being entered, a Raspberry Pi Camera Module is placed inside the trash bin to perform image detection using YOLOv5 algorithm. The waste is placed in their designated sub-bin through the implementation of DC (conveyor) and servo motors (flap), which could be electronic, pathological, sharp, or unidentified waste. The process of detection and segregation are controlled by the Raspberry Pi 4B. When the sub-bins are filled with waste, an HC-SR04 ultrasonic sensor monitors the bin capacity, and a digital thermostat displays the temperature in each sub-bin. Afterwards, a disinfection system was established to disinfect bacteria that are present in the infectious waste using UV light. The ultrasonic sensor, digital thermostat, and UV light are controlled by the Arduino UNO microcontroller.

2.2. Prototype Design and Specifications

Figure 2 illustrates the architecture of the prototype. The bin is mainly constructed with a plastic-based material and has four sub-bins inside. The 3D Model presents a conveyor system that sorts the waste into four categories: (1) Electronics, (2) Pathological, (3) Sharps, and (4) Unidentified. The conveyor system is placed above a platform with four holes directly above each sub-bin. There are four servo motors placed on the conveyor system controlling the three flaps, designed to push the waste material once it is within the place and drop down to the whole and into the sub-bin, and 1 for the flap which the researchers call as (9) Gate, which blocks the waste material from accidental misplacement after a user throws it. The (8) camera is placed directly above the conveyor system, which detects the waste material after it is dropped from the hole. This circumstance leads to an inclined platform, guiding the waste material to drop onto the conveyor. The (7) Raspberry Pi microcomputer, (6) Power Supply, and (5) L298N motor driver in the space of the platform for ease of wiring access. The UV light (11) is placed above the sub-bins and below the segregation system along with (10) HC-SR04 ultrasonic sensor and (11) Arduino UNO.



(**a**) (**b**) (**c**)

Figure 2. Prototype design of microcontroller-based automated infectious waste segregation and disinfection system; (**a**) top view; (**b**) prototype view with numerical designation; (**c**) bottom view.

2.3. System Performance Calculations

Precision is the measure of how many selected items are relevant to the total number of selected items as shown in Equation (1). Equation (2) is the recall which is the measure of how many relevant items are selected from the total number of relevant items. F1 – score refers to the predictive performance of the custom model by getting the mean of precision and recall as shown in Equation (3). Lastly, in Equation (4) mAP is computed by taking the mean AP over all classes and/or overall IoU thresholds of the object detection model.

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (3)$$

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \quad (4)$$

where TP = True Positive; TN = True Negative; FP = False Positive; FN = False Negative; AP_k is the average precision of k-th class while n is the number of classes

3. Results and Discussions

This section presents the results and discussions of the system performance for object detection, segregation system and UV disinfection.

3.1. System Performance for Object Detection

Table 1. System Performance for Object Detection

Infectious Waste	No. of trained samples	IOU Threshold	Precision	Recall	F1-score	Mean Average Precision (mAP)
Electronic	2478	0.5	0.924	0.952	0.938	0.957
Pathological	2512		0.844	0.687	0.757	0.799
Sharps	2501		0.91	0.873	0.891	0.945
Overall	7491		0.893	0.837	0.862	0.900

Table 1 shows the system performance for object detection using YOLOv5 algorithm. The model was trained on a dataset of 7,491 samples, categorized into three classes: electronic, pathological, and sharps waste. With an Intersection-over-Union threshold of 0.5, the model demonstrated strong precision, recall, F1-score, and mean average precision (mAP). Overall, the custom-trained YOLOv5 model showcased an impressive performance, with an average precision of 89.3%, recall of 83.7%, F1-score of 86.2%, and an mAP of 90%.

3.2. UV Disinfection Performance on Escherichia coli

In Table 2, the hypothesis examined whether there was a significant difference in area between UV-exposed *E. coli* samples and the control group. The absolute value of the calculated t-statistic is greater than the critical t-value. Implying that, a significant difference exists between *E. coli* treated with UV-C and the control sample in terms of area. The results indicate that UV-C exposure affects the activation of *E. coli* in terms of area, as determined through image processing. Figure 3 shows the outlined sample of *E. coli.*

Table 2. Significant difference of With and Without UV Exposure for *E. coli* in terms of Area.

	Without UV	With UV
Mean	1835	536
Variance	281675	27378
Observations	3	3
df	3	
t Stat	3.960421	
P(T<=t) one-tail	0.014373	
t Critical one-tail	2.353363	

(**a**) (**b**)

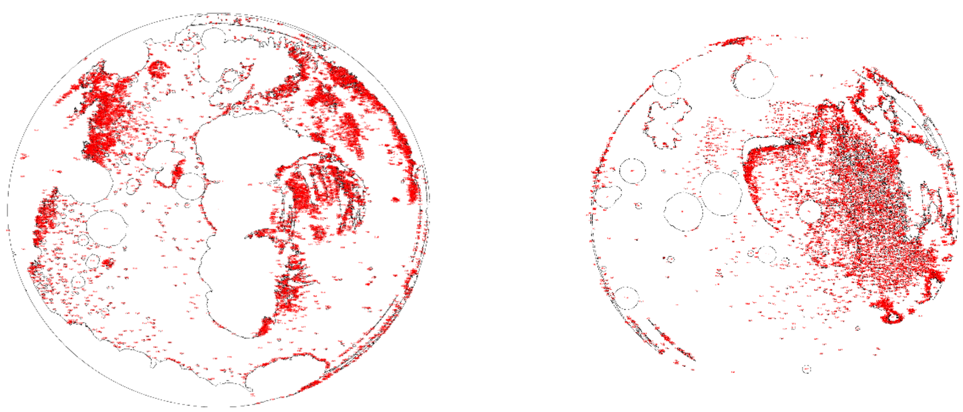
Figure 3. Analyzed outline of *Escherichia coli* using image processing; (**a**) without UV disinfection; (**b**) with UV disinfection

3.3. UV Disinfection Performance on Staphylococcus aureus

In table 3, hypothesis tested whether there was a significant difference in area between *S. aureus* samples with UV exposure and the control group. The calculated t-statistic is greater than the critical t-value. Indicates that there is a significant difference between *S. aureus* treated with UV-C and the control sample regarding the area. The findings suggest that UV-C exposure affects the activation of *S. aureus* in terms of area, as determined through image processing. Figure 4 shows the outlined sample of *S. aureus.*

Table 3. Significant difference of With and Without UV Exposure for *S. aureus* in terms of Area.

	Without UV	**With UV**
Mean	8913.6666667	3164.333333
Variance	178124.3333	1016737.33
Observations	3	3
df	2	
t Stat	3.096854148	
P(T<=t) one-tail	0.045179988	
t Critical one-tail	2.91998558	



(**a**) (**b**)

Figure 4. Analyzed outline of *Staphylococcus aureus* using image processing; (**a**) without UV disinfection; (**b**) with UV disinfection

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