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A Hybrid Intelligent System for Medical Waste Classification and Automated Sorting using CNN and OpenGL Simulation

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Abstract

The management of medical waste has a significant impact on both human health and environmental sustainability. Medical waste segregation techniques currently in use mostly rely on manual sorting, which poses a risk to workers' safety and increases the likelihood of environmental contamination. This study presents a novel automated medical waste classification system that combines brute force methods with convolutional neural networks (CNN) to classify waste into hazardous and non-hazardous categories accurately. Our system utilizes a large dataset that encompasses six distinct categories of medical waste: syringes, eyeglasses, gloves, masks, medical caps, and medications. This allows for accurate and scalable classification, in contrast to traditional methods that are frequently constrained by limited classifications or lack real-time capabilities. One significant innovation in this study is the smooth integration of OpenGL simulations to illustrate the waste sorting procedure, which improves the system's usefulness even more, masks, gloves, syringes, eyeglasses, medical caps, and medicines—using a lightweight sequential CNN architecture suitable for low-resource deployment. The suggested approach outperformed traditional techniques with an astounding accuracy of 99.66% for six distinct types. The entire system outperformed conventional classification techniques, achieving a segregation accuracy of 86.2%, a precision of 0.85, a recall of 0.83, and an F1-score of 0.87 when combined with the brute-force methodology for final binary segregation. Additionally, the classification system effectively classifies garbage according to predetermined characteristics by employing a brute force algorithm, providing a dependable first sorting solution. The results are visually represented through an OpenGL-based bin-sorting simulation, where hazardous objects are dropped into red bins and non-hazardous ones into green bins, demonstrating the decision pipeline from perception to actuation.

Keywords
Medical Waste Classification, Convolutional Neural Networks (Use Brute Force), Automated Waste Segregation (Use Bin-Sorting Simulation), Open GL.

1. Introduction
The negative effects of medical waste on environmental sustainability and public health have made its effective management a crucial challenge. To protect the health of employees and the communities around them, medical waste, which contains dangerous items like syringes, needles, poisonous chemicals, and infectious agents, needs to be carefully separated (Wawale et al. 2022). Conventional approaches to medical waste sorting and disposal frequently involve manual labor, which is not only ineffective but also puts employees at risk of contamination and injury (Abdu and Noor 2022). Most current systems have limitations, such as concentrating on a limited number of waste types or not integrating real-time processing capabilities (Sengeni et al. 2023).

Manual sorting is the mainstay of traditional medical waste disposal techniques. Workers in these systems are required to physically separate hazardous and non-hazardous waste, often in unhygienic and hazardous conditions (Song et al. 2024).

Additionally, hand sorting is very ineffective and sensitive to mistakes, which results in subpar waste management techniques that jeopardize environmental sustainability and safety (Malik et al. 2022). The massive amounts of medical waste produced every day make hand sorting unsustainable from an operational and environmental perspective (Yoon et al. 2022). Automation has been implemented to improve waste sorting accuracy and lower human risk exposure in response to these issues. The scope and effectiveness of the majority of automated systems in use today are still constrained (Ghoushchi et al. 2021). Many people find it difficult to properly manage medical waste as they only concentrate on limited categories like paper or plastics (Huang et al. 2021).

The deficiency in current research is the absence of a completely automated, real-time system for sorting medical waste that can handle a variety of waste kinds with high accuracy.

1.1 Objectives
This study aims to achieve the following objectives:

1. To propose a new method for managing medical waste by creating an automated categorization system with a comprehensive dataset.
2. To incorporate OpenGL-based simulations to visualize the waste sorting procedure.
3. To offer a dynamic, instantaneous depiction of the classification outcomes.

2. Literature Review
The sustainability of the environment and human health are both greatly impacted by medical waste management. The majority of medical waste segregation methods now in use rely on manual sorting, which puts worker safety at risk and raises the possibility of environmental contamination. The detection technique-based research work is shown below.

Moktar et al. (2025) created an Internet of Things-based medical waste sorting system that achieved 93.75% sorting accuracy and a 31-second cycle time by integrating YOLOv8 with a mechanical prototype. Although the system was successful in fusing vision and IoT technologies, its real-time performance in healthcare applications was limited by slower throughput and reduced precision during deployment. Giakoumakis et al. (2021) divided the medical waste into several types and categories, and the percentages of the various medical waste fractions were calculated. In the near future, the studied medical waste treatment technologies' capacity to generate materials, fuels, and energy, as well as address the medical waste management issue, was extremely encouraging.

Nnamoko et al. (2022) assessed the effectiveness of a custom five-layer convolutional neural network trained with two distinct image resolutions using a waste classification dataset. The results show that small image resolution leads to a lighter model with less training time, and the accuracy produced (80.88%) is better than the 76.19% yielded by the larger model. Bdour and Kharabsheh (2025) created a smart trash segregation system using RFID-AI that combines RFID-based hospital routing with ResNet-50 picture classification. The method's efficacy for accurate medical waste segregation was limited by its intermediate visual accuracy (93.1 ± 2.1%), lack of fine-grained hazard identification, and interpretability, despite its high logistical tracking capabilities. Islam et al. (2025) used DenseNet201 with Squeeze-and-Excitation (SE) attention blocks to develop a waste classification model that was verified on several datasets. The study limited its practical relevance for automated waste management by failing to address real-world deployment factors and lacking system-level integration, despite attaining good classification performance. Akkajit et al. (2024) developed a basic CNN-based medical waste classifier handling four waste categories. Despite showing that picture-based recognition is feasible, the work was constrained by a lack of mechanical or simulation integration, limited class diversity, and only focused on static image labeling with no real-time capability.

The above literature review focuses on features from images and classifies categories very well, and it gives the best speed for recognition. Through our work, we present a novel automated medical waste classification system that combines brute force methods with convolutional neural networks (CNN) to classify waste.

3. Methodology

Figure 1 shows a hybrid intelligent system for automated medical waste classification, combines Convolutional Neural Networks (CNN) for image-based classification, a rule-based brute-force algorithm for hazardous segregation, and OpenGL-based simulation for real-time visualization. The methodology consists of five main steps: data collection and preprocessing, model development and training, hazardous classification, box processing and simulation, and performance evaluation. The combined function of the CNN classification and the brute-force technique is represented in this phase. The Green Box (non-hazardous) or Red Box (hazardous) receives the final sorting action.

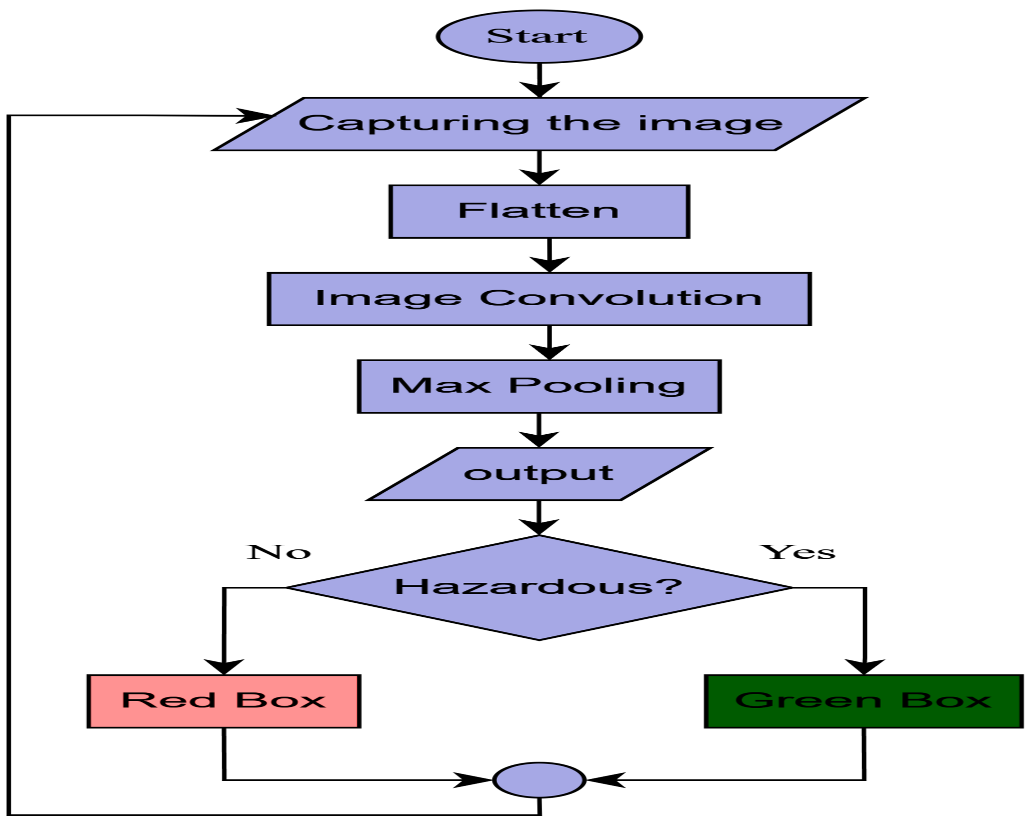


Figure 1. Data Flow Diagram of the proposed system

3.1 Data Collection

Six categories of medical waste photographs were gathered, including gloves, masks, syringes, medical glass, medical caps, and medications. In order to enhance training stability, every image was shrunk to 256 x 256 pixels and normalized. Rotation and zooming techniques were employed to expand the dataset, thereby enhancing model generalization. This produced a solid set that could accurately depict differences in the appearance of medical waste in the actual world.

3.2 Model Development and Training

Using Keras, a sequential CNN architecture was created, comprising fully connected layers for classification, max-pooling layers for dimensionality reduction, and numerous convolutional layers for feature extraction. The model was constructed using categorical cross-entropy loss and the Adam optimizer. It was then trained for a predetermined number of epochs while validation performance was tracked to avoid overfitting. In healthcare settings with limited resources, our lightweight design guarantees effective adoption.

3.3 Hazardous Classification

The classified waste items were directed into red bins for hazardous and green bins for non-hazardous materials. An OpenGL-based simulation environment visualized the sorting process, demonstrating the end-to-end pipeline from perception to actuation and providing operational insights for safe and efficient waste management.

3.4 Box Processing and Simulation

The sorted waste was disposed of in green bins for non-hazardous products and red bins for hazardous materials. The sorting process was depicted using an OpenGL-based simulation environment, which also provided operational insights for safe and effective trash management by showing the entire pipeline from perception to actuation.

3.5 Evaluation and Performance Analysis

The accuracy, precision, recall, and F1-score measures were used to assess the model's performance on a different test dataset. Additionally, simulation was used to assess the efficiency of the box processing logic and the efficiency of the brute-force danger classification. This thorough assessment confirmed that the system can reliably classify medical waste and facilitate automated, secure, and ecologically friendly waste treatment procedures.

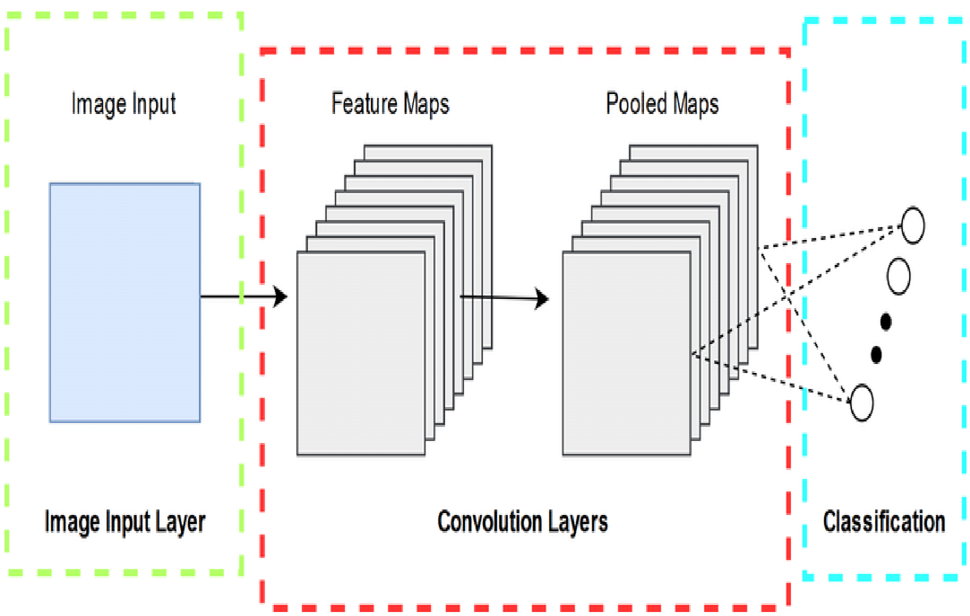


Figure 2. Convolutional layers

Neural networks' convolutional layers process incoming data to extract features like edges and textures . They decrease the dimensionality of the data while preserving spatial linkages. Hierarchical representations are learned by multiple layers, which is essential for tasks like picture categorization. In order to facilitate the effect(Figure 2)ive learning of complicated patterns, pooling and activation functions improve feature extraction and introduce non-linearity.

The brute force algorithm, a fundamental approach in computer science, involves systematically evaluating all possible solutions to a problem to identify the optimal one. In the context of medical waste classification, the brute force algorithm was utilized to categorize waste items into hazardous and non-hazardous classes. By exhaustively considering the characteristics of each waste item and comparing them against predefined criteria, the algorithm efficiently determined the appropriate classification without relying on heuristics or optimization techniques. Despite its simplicity, the brute force algorithm provided a reliable and straightforward method for initial waste categorization, laying the groundwork for subsequent processing and classification steps within the research project.

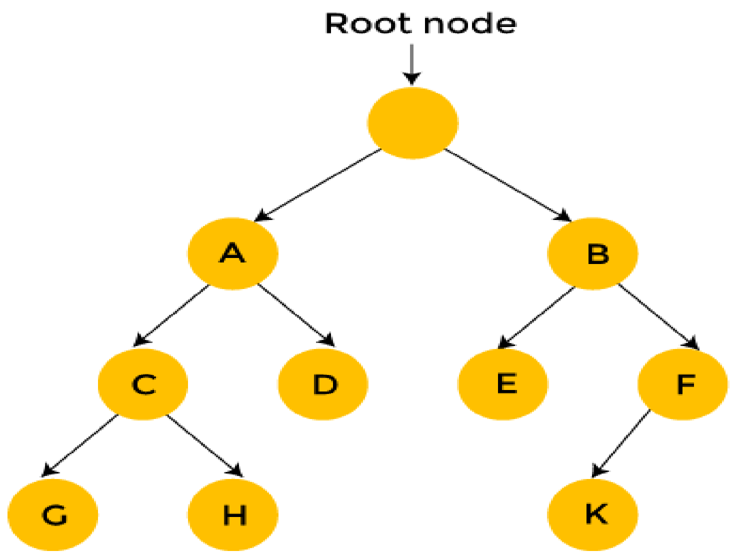


Figure 3. Flow chart of Brute Force Algorithm

Despite its simplicity, the brute force algorithm provided a reliable and straightforward method for initial waste categorization, laying the groundwork for subsequent processing and classification steps within the research project (Figure 3 and Figure 4).

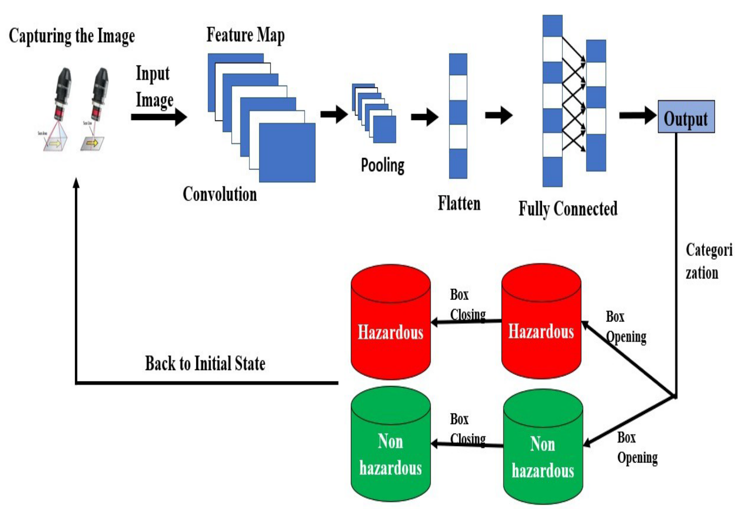


Figure 4. Proposed System Architecture

Data Collection and Preprocessing

A diverse dataset of medical waste images was collected, encompassing categories such as gloves, masks, syringes, medical glass, medical caps, and medicine. To ensure consistency, all images were resized to 256 × 256 pixels and pixel values were normalized. In addition, data augmentation techniques—including rotation, flipping, and zooming—were applied to increase variability within the dataset and enhance the model's generalization capability.

Model Development and Training

A Convolutional Neural Network (CNN) was developed using the Keras Sequential API. The architecture consisted of convolutional layers for feature extraction, max-pooling layers for dimensionality reduction, and fully connected layers for classification. The model was compiled with an appropriate optimizer (e.g, Adam), a categorical cross-entropy loss function, and accuracy as the primary evaluation metric. Training was conducted for a specified number of epochs, with validation data used to monitor performance and prevent overfitting through techniques such as early stopping.

Hazardous Classification

A brute force algorithm was implemented to categorize medical waste items into hazardous and non-hazardous groups based on predefined safety criteria. Predictions generated by the CNN model were mapped to hazard levels, thereby enabling automated classification of waste items.

Box Processing and Simulation

A logical framework was designed to separate waste items into designated boxes: hazardous items were assigned to a red box, while non-hazardous items were assigned to a green box. To visualize this process, an OpenGL-based simulation was developed, providing a virtual representation of the waste sorting and processing workflow.

Evaluation and Performance Analysis

The model's performance was evaluated on a separate test dataset using metrics such as accuracy, precision, recall, and F1-score. The effectiveness of the brute force algorithm in hazard determination was analyzed, along with the efficiency of the box processing logic through simulation. A comprehensive performance analysis was conducted to assess the system's ability to accurately classify medical waste and support safe and efficient waste management practices.

5. Results and Discussion

Figure 5 shows rapid accuracy improvement from epoch 0 to 4, followed by a plateau around 0.9 until epoch 10. From epochs 12 to 16, accuracy gradually increases, approaching 1.0, and Figure 6 shows validation accuracy rising rapidly from epoch 0 to 4, followed by minor fluctuations, and steadily approaching 1.0 by epoch 16, indicating effective learning and good generalization.

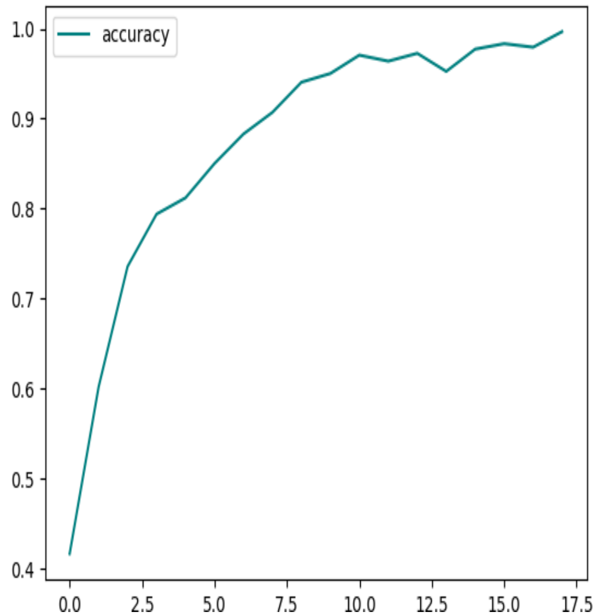


Figure 5. Training Accuracy. X-axis-Iterations & axis- Accuracy

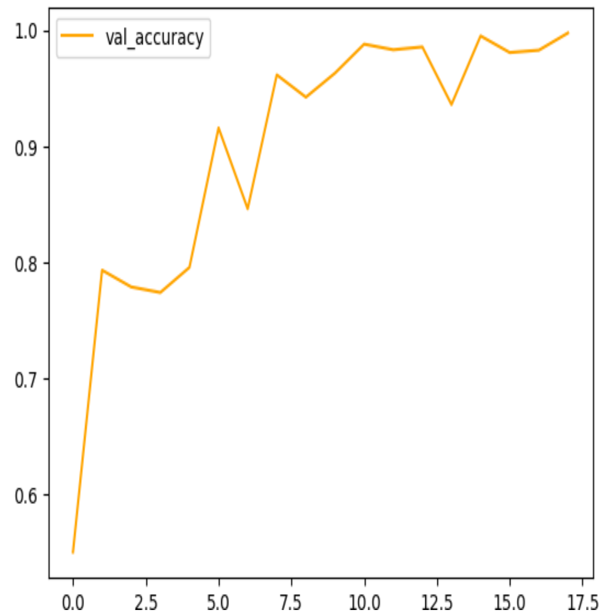


Figure 6. Validation Accuracy. X axis-Iterations & Y axis- Accuracy

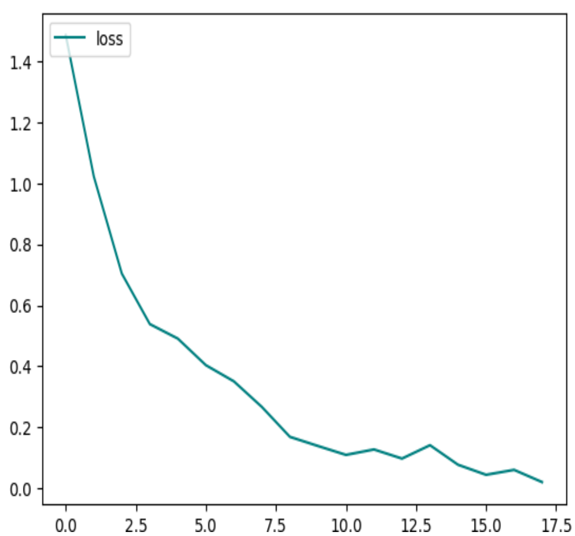


Figure 7. Training loss. X axis-Iterations & Y axis- Loss

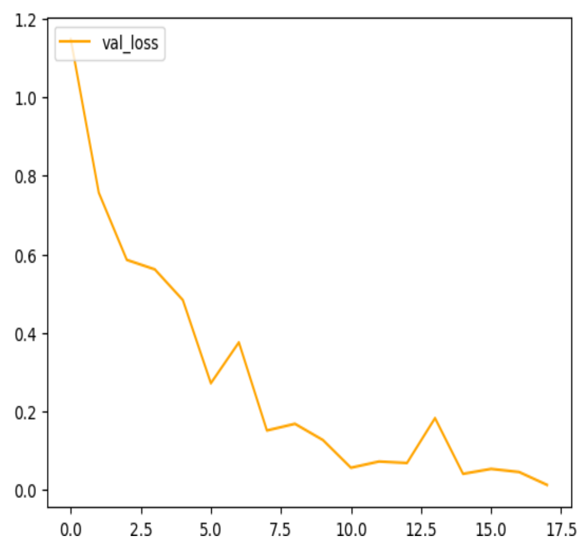


Figure 8. Validation loss. X axis-Iterations & Y axis- Loss

Figure 7 represents the training loss of your system over what appears to be the number of epochs or iterations. The curve shows an initial steep decline in training loss from approximately 1.4 to around 0.6 within the first three epochs, indicating that the model is learning quickly and effectively reducing error. Figure 8 illustrates the validation loss of your model over 17 epochs. Validation loss is a key metric indicating how well your model generalizes to new, unseen data, with lower values representing better generalization. Initially, the validation loss is high, but it decreases significantly as training progresses, suggesting that your model is effectively learning and improving its performance on the validation dataset.

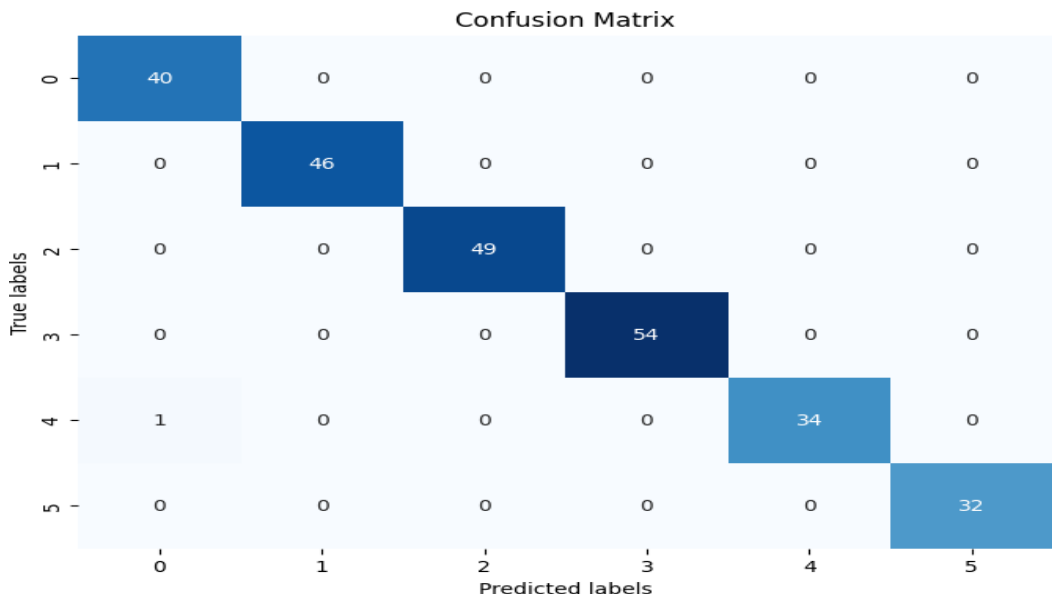
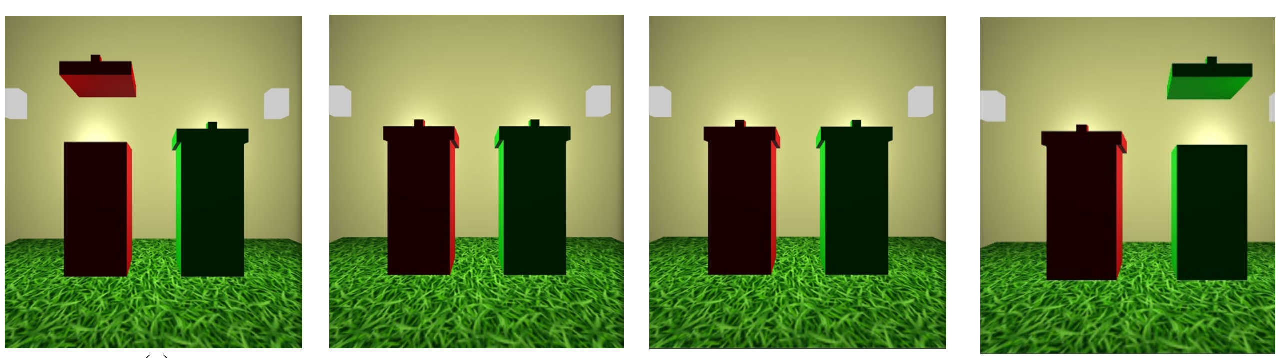


Figure 9. Confusion Matrix of the Proposed System

A confusion matrix is a table that displays the true and predicted classes to illustrate the performance of a classification model. It allows for the evaluation of the model's accuracy, precision, recall, and F1-score by summarizing the number of right and wrong predictions made in each class. It helps determine which classes are frequently confused with one another, providing insights into the advantages and disadvantages of the model. The matrix helps choose the best approaches to enhance the model's performance, including modifying thresholds or correcting class imbalances. The model's high accuracy in predicting the majority of classes is indicated by the high values along the main diagonal (e.g., 40 for class 0, 46 for class 1, 49 for class 2, 54 for class 3, 34 for class 4, and 32 for class 5) (Figure 9) One occurrence of True Label 4 being mistakenly forecasted as Label 0 is the only significant misclassification. There are two stages to the suggested system's performance evaluation. The first stage assesses how well the core Convolutional Neural Network (CNN) can identify the six different waste categories in great detail. The CNN model demonstrated a strong capacity to differentiate between similar medical waste items, as seen by the high diagonal values in the Confusion Matrix, with a 99.66% classification accuracy on the test set.



(a) (b) (c) (d)

Figure 10. Opening the Red and Green Box

The outcome of the OpenGL-based bin-sorting simulation, which depicts the system's actuation phase, is shown graphically in Figure 10. An item drop is indicated by the open-bin state for the Red (Hazardous) and Green (Non-Hazardous) boxes in sub-figures (a) and (d), respectively. The closed-bin state when the system is prepared for the subsequent categorization is depicted in sub-figures (b) and (c). This simulation verifies that the logical framework for allocating non-hazardous goods (like medical caps) to the green bin and hazardous things (like syringes) to the red bin is correctly applied. The complete end-to-end segregation task is assessed in the second phase. In order to classify things into the Hazardous (Red) or Non-Hazardous (Green) bin, this phase evaluates the output of the combined CNN and the rule-based brute-force algorithm. The segregation metrics, accuracy (0.85), recall (0.83), and F1-score (0.87), measure the system-level performance. The impact of the final decision-making procedures and the intrinsic difficulty of some binary classifications within the dataset are highlighted by the slightly poorer segregation scores, despite the CNN's near-perfect object detection.

6. Conclusion

The research project focused on developing a comprehensive solution for the classification and management of medical waste, addressing the pressing challenges of sustainability, labor and safety, and economic and environmental viability. A Convolutional Neural Network (CNN) model was employed to classify medical waste items into hazardous and non-hazardous categories, leveraging a dataset comprising six classes: gloves, masks, syringes, medical glass, medical caps, and medicine. The model was trained and evaluated using state-of-the-art techniques, yielding promising results in terms of waste classification accuracy and efficiency. Despite major progress, the research effort had some serious drawbacks. Constraints on the diversity of the dataset might have affected the model’s generalizability and caused biases in training. Furthermore, problems with scalability arise in real-world systems, particularly with relation to computing efficiency and resource allocation. Furthermore, evaluating the model’s operational effectiveness and practical viability is restricted when depending only on simulation as opposed to hardware integration. Expanding the diversity of datasets, putting measures in place to reduce biases during model training, and looking into hardware integration opportunities could all help to address these limitations and correctly assess real-world performance. To get a more complete picture of the system's practicality, compare its computational cost and performance to cutting-edge systems like YOLO or ResNet.

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Biographies

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Md. Shirajul Islam is currently pursuing an MS in Mechatronics Engineering from Khulna University of Engineering & Technology, Khulna. He received his BS in the same department from the same institution. Now he serves as a Teaching Assistant in the same place where he is pursuing his post-graduation degree, and also serves as adjunct faculty in the Mechanical Engineering Department at Imperial College of Engineering (Affiliated with University of Rajshahi), Khulna. His interest lies in Robotics, Control systems, Automotive systems, Bio-embedded systems, and Image Processing.