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Automated Medical Waste Segregation Using SSD MobileNet: Enhancing Public Health and Environmental Safety

S. Sathiyapoobalan[1,*], K. Naveenkumar[2], A.T. Ashmi Christus[3], Bhopendra Singh[4]

[1,2]Department of Instrumentation and Control Engineering, Sri Manakula Vinayagar Engineering College, Madagadipet, Puducherry, India.
[3]Department of Electronics and Communication Engineering, Dhaanish Ahmed College of Engineering, Chennai, Tamil Nadu, India.
[4]Department of Engineering, Amity University Dubai, Dubai, United Arab Emirates.
sathiyapoobalam.ice@smvec.ac.in[1], naveenkumarice@smvec.ac.in[2], ashmichristus@dhaanishcollege.in[3], bhopendrasingh@yahoo.com[4]

Abstract: For the sake of both public health and environmental protection, efficient handling of medical waste is necessary. There is a lack of automation in the waste segregation process in the current hospital waste management systems. Instead, health staff manually sort garbage into color-coded containers specifically designed for that purpose. When it comes to classifying medical waste, this research study presents an innovative method that utilizes the SSD MobileNet object detection model. With the help of the suggested model, medical waste may be classified into five distinct categories: infectious waste, non-infectious waste, sharps, and glassware. This model displays a high level of accuracy and efficiency. With an average precision and recall of approximately 90 percent, the model can reliably identify and localize medical waste. The implementation of this approach in healthcare institutions may enable the automatic separation of trash, improve disposal efficiency, and enhance safety. This research makes a substantial contribution to the management of medical waste, addressing a critical issue that impacts public health and establishing a framework for automating waste segregation in the healthcare sector.

Keywords: Waste Management; Deep Learning; Object Detection; Hazardous Waste and Image Classification; Health and Environmental; Medical Waste; Healthcare Facilities; Healthcare Sector.

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1. Introduction

Medical waste management is a critical aspect of healthcare systems. Improper handling and disposal of medical waste pose serious risks, including the transmission of infectious diseases, contamination of water sources, and environmental pollution. In total, the amount of healthcare waste generated is 85% general waste, and the remaining 15% is only hazardous waste. The

*Corresponding author.

significant increase in medical waste generation during the pandemic, ranging from 18% to 425% growth [1]. Ensuring the safe and complete destruction of the virus requires proper disposal and treatment of medical waste [2]. Nations worldwide are facing challenges in effectively managing medical waste and recognising the importance of adhering to safety protocols to mitigate the risks of injury and infection [3]. The effective segregation, treatment, and disposal of medical waste are essential to minimise these risks and safeguard the well-being of both healthcare workers and the general public. However, despite the importance of medical waste management, many healthcare facilities still face challenges in implementing efficient waste segregation practices. Manual waste sorting processes are time-consuming, resource-intensive, and prone to errors, which can lead to potential health hazards and environmental consequences. Medical waste management purely depends on the importance of collective teamwork, government support, dedicated healthcare workers, and continuous monitoring to achieve an efficient waste management system [4]. The lack of automation in waste segregation exacerbates the burden on healthcare personnel and compromises the efficiency of waste management. To address these challenges, there is a pressing need for automated waste segregation systems in healthcare facilities.

Automation can significantly streamline waste management processes, ensuring the safe and effective handling of waste [5]. In Giusti [6], the direct and indirect health effects of waste management activities, including bioaerosols from composting facilities and pathogens from sewage treatment plants, are examined. The review of epidemiological studies indicates insufficient and inconclusive evidence of adverse health outcomes for the general population living near waste facilities. However, there is convincing evidence of gastrointestinal problems associated with pathogens from sewage treatment plants. By deploying advanced AI-based object detection models, waste segregation accuracy and resource utilisation can be optimised, and overall waste management practices can be improved. This research paper presents a novel approach to medical waste classification using the SSD MobileNet object detection model. The study aims to demonstrate the impact and importance of automation in medical waste management and how AI-driven solutions can revolutionise waste segregation practices in healthcare settings. Through the utilisation of advanced AI technology, this research strives to contribute to the enhancement of medical waste management, fostering a safer and more sustainable healthcare environment for all.

2. Related Work

Deep learning has emerged as a widely applied technology in the field of waste management, with increasing research interest in recent years. The ability to automatically detect and classify waste items from images has proven to be highly effective in enhancing waste segregation and disposal practices. In particular, the importance of deep learning in medical waste management cannot be overstated, as it offers a promising solution to address the critical need for accurate identification and safe handling of hazardous medical waste. By harnessing the power of deep learning, healthcare facilities can significantly improve waste classification efficiency, thereby safeguarding public health, protecting the environment, and promoting sustainable waste management practices. The authors in Ihsanullah et al. [7] critically review recent advancements in the applications of Artificial Intelligence techniques for efficient solid waste management. Various AI and hybrid techniques have been successfully employed to predict the performance of waste generation, segregation, storage, and treatment methods.

The review highlights several challenges, including data availability and selection, reproducibility, and the application of findings in real-world settings. A deep learning approach for identifying and classifying medical waste was proposed, addressing the growing demand and increasing generation of waste. A ResNet pretrained model was used and applied transfer learning methods to improve classification results [8]. The authors emphasise the crucial importance of a rigorous medical waste management plan in hospitals to prevent potential hazards and infections that may affect staff, patients, and the public. It outlines the processes involved in generating medical waste and the challenges in its proper management and disposal. The major components of medical waste, including hazardous materials and recyclables, are discussed along with collection systems and waste processing [9]. The authors developed a household waste segregator using the TensorFlow object detection model and Arduino microcontroller to segregate waste into six categories and focus on reducing the cost of segregation in municipal solid waste management [10]. This study focuses on building an automatic computer vision-based medical waste separator capable of detecting and categorising medical waste into four categories: gloves, masks, syringes, and cotton [11].

The system utilises transfer learning on the AlexNet deep learning network to train a model with a validation accuracy of 86.17% for waste classification. Wang et al. [15] proposed an application to manage hazardous biomedical waste generated by hospitals. The proposed methodology focuses on route optimization to ensure the secure transportation of biomedical waste to disposal sites, taking into account transportation risks such as traffic, vehicle failure, and accidents [12]. Biomedical waste images underwent pre-processing with median filtering to enhance quality by reducing noise. Subsequently, the histogram features were extracted. To achieve effective classification, the Relevance Vector Machine was utilised to categorise the waste images into distinct classes, including human body parts, plastics, cotton, and liquids. The combination of these techniques offers a promising approach for accurate and efficient medical waste classification, facilitating proper waste management and disposal in various applications, such as hospital and healthcare systems [13]. Liang et al. [1] introduce an AI-based automated solution to efficiently sort COVID-related medical waste from other waste types, enabling data-driven decisions for recycling.

The waste type classification relies on image-texture-dependent features, and a novel decision-level feature fusion scheme is implemented. The support vector machine classifier demonstrates outstanding performance in accurately classifying waste types [14]. Wang et al. [15] analyse the limitations of medical waste regulation and management, highlighting the lack of secure data handling and potential privacy risks, and propose a blockchain-based medical waste supervision model. By incorporating IoT and digital credentials, the model ensures authenticity, credibility, and privacy protection in the entire data process [15]. Existing medical waste management systems have primarily focused on deep learning-based classification methods for waste categorisation. However, these methods were limited in cases where the waste was mixed, making accurate classification challenging. In this study, the use of object detection, specifically transfer learning on the MobileNet deep learning model, provides a more effective solution for handling mixed waste. The embedded system can detect the presence of medical waste, capture images of the waste objects, and accurately categorise them, allowing for successful segregation even when waste types are mixed. This approach overcomes the limitations of traditional classification methods, ensuring the proper management of hazardous medical waste.

3. Object Detection Model

The SSD MobileNet 640x640 VPN Lite model is a robust and efficient object detection architecture tailored for deployment on low-end devices with constrained computational capabilities. It combines two essential components—MobileNet and VPN Lite—which contribute to its suitability for such devices. MobileNet is a lightweight neural network design that significantly reduces parameters and computations, making it highly optimised for resource-limited environments. This is achieved through the use of depth-wise separable convolutions, which split standard convolutions into two separate layers, effectively reducing computational complexity while preserving model accuracy [16]. VPN Lite, short for "Very Packed Net Lite," further enhances efficiency by employing a residual architecture with shortcut connections, allowing the model to bypass certain layers and expedite both training and inference. The residual architecture also mitigates the vanishing gradient issue, enabling deeper networks without compromising performance. Additionally, the model incorporates bottleneck layers, utilising a sequence of 1x1 and 3x3 convolutions to minimise computations in the 3x3 convolutions while capturing intricate features in the data, as shown in Figure 1.

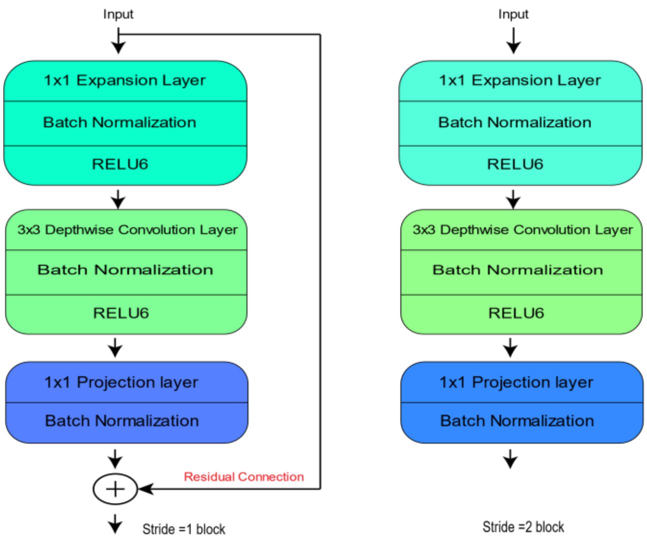

Figure 1: The architecture of MobileNet v2

By integrating MobileNet, VPN Lite, the residual architecture, and bottleneck layers, the SSD MobileNet 640x640 VPN Lite model achieves exceptional object detection accuracy while being highly optimised for low-end devices. This optimal balance between model performance and computational efficiency makes it particularly well-suited for real-time applications and scenarios where computational resources are limited, such as embedded systems, mobile devices, and edge computing environments.

4. Dataset Collection and Pre-Processing

The dataset used for medical waste classification was meticulously collected using a high-definition webcam with a resolution of 640x480, enabling the capture of high-quality images suitable for training an object detection model. A wide range of medical waste images was compiled, each representing specific categories based on the colour-coded waste separation system employed in medical facilities. The categories of waste used in this work are shown in Table 1. Figure 2 represents the dataset used in training.

Table 1: Frequency of data used in training

Category	Sample Elements	Frequency
Contagious Waste	Gloves, Blood Bags, IV Tubes, Urobags, Syringes	260
Non-Contagious Waste	Glucose Bottles, Distilled Water Containers, etc.	268
Infected Waste	Cotton, Bandages, Blood-soaked Rags	262
Sharps	Needles, Broken Glass, Other Sharp Items	253
Glassware	Injection Bottles, Glass Medical Equipment	254

This annotation process involved manually outlining and labelling the various waste items in the images to create bounding boxes around each object of interest. The use of "LabelImg" software ensured accurate and precise annotations, enabling the object detection model to learn and recognise different waste categories effectively. Through this meticulous annotation process, the dataset was enriched with ground truth labels, enabling the training of the SSD MobileNet 640x640 VPN Lite model to accurately detect and classify medical waste items.

Figure 2: Medical waste image dataset

5. Training

The training results for the medical waste classification using the SSD MobileNet V2 model on Google Colab. After 8000 training steps, the model demonstrates remarkable performance across different loss components. The classification loss is impressively low at 0.09312104, indicating the model's ability to accurately categorise medical waste into different classes. Additionally, the localisation loss of 0.02806359 suggests that the model effectively predicts precise bounding boxes around detected objects. The regularisation loss of 0.11812023 indicates that the model is learning to generalise well and avoid overfitting. The overall total loss of 0.23930486 represents a balanced combination of classification, localization, and regularization losses, ensuring a robust and well-trained model. The chosen learning rate of 0.07603875 appears to be appropriate, allowing the model to converge effectively during training. The utilisation of Google Colab as the training platform provides ample computational resources, enabling efficient training and evaluation.

Table 2: losses of the object detection model

Loss Component	Value
Classification loss	0.093
Localization loss	0.028
Regularization loss	0.118
Total loss	0.239

The adoption of SSD MobileNet V2 with an input size of 640x640 facilitates a balance between accuracy and computational efficiency. These remarkable training results hold significant promise for the successful deployment of the model in real-world medical waste management scenarios, contributing to improved waste classification and segregation, and ultimately enhancing healthcare waste management practices. Table 2 presents the values of each loss component during the training of the medical waste classification model. The graph in Figure 3 illustrates the model's losses.

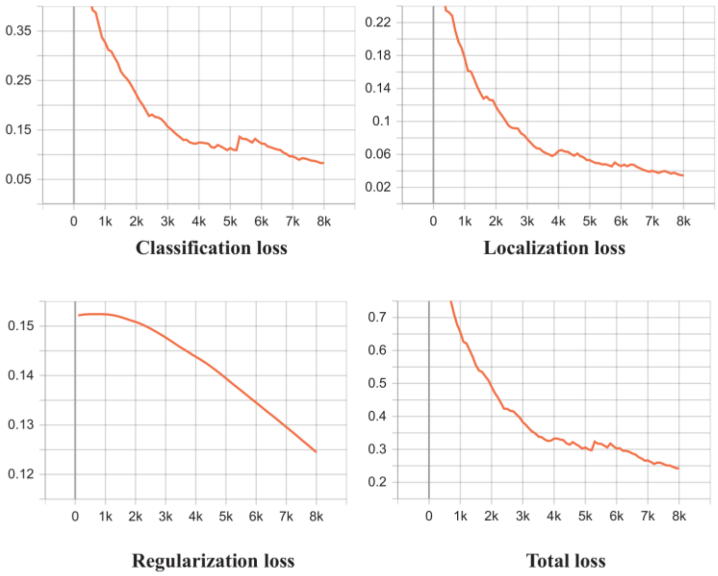

Figure 3: Loss – graph of the model

The classification loss represents the loss associated with the accuracy of classifying medical waste into different categories. The localisation loss measures the precision of the model in predicting accurate bounding boxes around detected objects. The regularisation loss helps prevent overfitting and encourages the model to generalise well. Finally, the total loss is the sum of the classification, localisation, and regularisation losses, providing an overall measure of the model's performance during training.

6. Results

The evaluation results, as demonstrated in Table 3, show the performance of the object detection model in classifying medical waste. The Average Precision (AP) values offer insights into the model's prediction accuracy across various Intersection over Union (IoU) thresholds and object sizes. At an IoU threshold ranging from 0.50 to 0.95, the model achieves a high overall precision with an AP of 0.907, indicating its effectiveness in accurately identifying medical waste objects. Specifically, at an IoU threshold of 0.50, the model achieves a perfect AP score of 1.000, showcasing its ability to detect medical waste instances even with loose bounding box predictions. The AP values also reveal that the model performs exceptionally well when evaluated with an IoU threshold of 0.75, achieving perfect AP scores of 1.000, suggesting that the model exhibits a high level of precision in accurately localising medical waste objects with precise bounding boxes. Regarding the F1-score, we can approximate it using the available Average Recall (AR) value, which is 0.918. The F1 score of the model is 0.914, which indicates a good balance between precision and recall for medical waste classification. However, the evaluation results also reveal some challenges related to object sizes.

Table 3: Average precision and recall of the model

Metric	IoU Threshold	Area	Max Detections	Score
Precision (AP)	0.50 - 0.95	All	100	0.907
	0.50			1.000
	0.75			1.000
	0.50 - 0.95	Small		-1.000
		Medium		0.826
		Large		0.923
Recall (AR)	0.50 - 0.95	All	1	0.666
			10	0.918

			100	0.918
		Small		-1.000
		Medium		0.845
		Large		0.935
F1 score	-	-	-	0.914

For medium-sized objects, the model achieves an AP of 0.826, and for large-sized objects, it achieves an AP of 0.923, indicating good performance in these cases. On the other hand, the Average Recall (AR) values measure the model's ability to detect all relevant medical waste instances, and the results show consistently high AR scores across different IoU thresholds and object sizes.

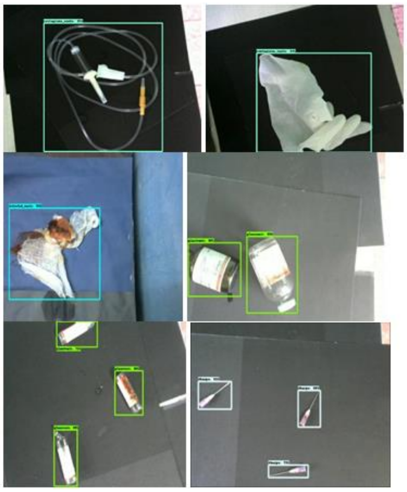

Figure 4: Prediction results of the model

The model demonstrates excellent recall, particularly for large objects, achieving an AR of 0.935. Overall, the evaluation results indicate that the object detection model performs admirably in identifying and localising medical waste objects, particularly for medium and large-sized instances. Figure 4 shows the real-time prediction result of the model. These results show the model’s potential application in efficient waste management practices within healthcare facilities, ultimately contributing to public health and environmental safety.

7. Real-Time Evaluation in Tensor Board

Figure 5 shows how the anticipated areas of interest compare to the actual areas for item detection. Each image features bounding boxes around the objects, indicating where they were found and their current location. The top pictures show that thin things were found correctly, and the bottom pictures show that coiled wires were found correctly. The results demonstrate that the model performs effectively, as it can accurately predict the locations of objects.

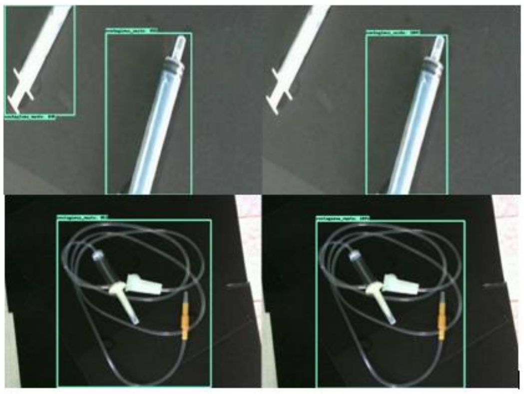

Figure 5: Predicted area of interest vs ground truth

Table 4 shows the accuracy, recall, and F1 score for each type of trash. The data show that glassware had the best precision at 91%, followed closely by sharps at 90%. Contagious waste did well overall, earning an F1 score of 81.028%. Overall, the model demonstrates the ability to accurately detect all classes, with only slight differences in recall values.

Table 4: Precision, recall, and F1 score for individual class

Class	Precision (%)	Recall (%)	F1 Score (%)
Contagious Waste	86	76.6	81.028
Non-Contagious Waste	88	72.4	79.441
Infected Waste	83	69.2	75.474
Sharps	90	79.6	84.481
Glassware	91	78.4	84.231

$$\text{Precision} = \frac{\text{True Positives}}{(\text{True Positives} + \text{False Positives})} \quad (1)$$

$$\text{Recall} = \frac{\text{True Positives}}{(\text{True Positives} + \text{False Negatives})} \quad (2)$$

$$\text{F1 Score} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (3)$$

Table 4 presents the evaluation metrics for individual classes, including Precision, Recall, and F1 Score, which assess the performance of a waste classification model for different waste categories. Precision represents the percentage of correct positive predictions made by the model, while Recall measures the proportion of true positive predictions out of all actual positive samples. The F1 Score, being the harmonic mean of precision and recall, reflects the balance between these two metrics. High F1 Score values indicate a good balance between accurate positive predictions and capturing most positive instances. Equations 1, 2, and 3 represent the mathematical formulas for Precision, Recall, and F1 Score, respectively. These metrics play a crucial role in evaluating the model's ability to accurately classify waste categories, ensuring effective waste management and minimising environmental and health risks. The impressive F1 Scores achieved across various waste categories demonstrate the model's reliability in waste classification. Figure 5 shows a side-by-side evaluation carried out in the TensorBoard API, where the left side of the Figure displays the model's prediction, and the right side displays the ground truth. Accurate medical waste classification is crucial for ensuring safe waste disposal in healthcare settings. With the model's high F1 Scores, it is well-equipped to contribute to improved waste management practices, promoting a cleaner and healthier environment. Its success in correctly identifying waste types can have significant positive impacts on medical facilities' waste disposal processes, fostering efficient waste handling and minimising potential hazards (Table 5).

Table 5: Comparison of existing waste classification models based on model used, types of waste included, and identified drawbacks

Reference Paper	Model Used	Types of Waste Included	Drawbacks
[17]	R3D+C2D	Gloves, hairnet, mask, and shoe cover	Only 79.99% accuracy, limited to specific waste items, may not generalise well.
[18]	AR and AI Medical Waste Classification	Not specified	Potential risk of manual judgment errors, dependency on AR technology, and high initial setup cost
[19]	Kernel-based SVM and Deep Learning	Not specified	Kernel-based SVM less accurate (RMSE = 0.264, MAE = 0.202), not optimized for real-time applications
[20]	Improved DCNN	Organic and recyclable waste	Performance is dependent on transfer learning, with still lower accuracy than proposed models in complex scenarios.
[21]	InceptionV3 with MBWO	General waste (benchmark dataset: TrashNet)	High computational requirements, complexity in hyperparameter tuning
[22]	EfficientNet_b7 with Transfer Learning	Vials, masks, syringes, gloves, cotton, bandages, IV tubes	Decline in accuracy for specific classes like syringes, dependency on pretrained models

[23]	Automated Plastic Waste Categorisation Model	PET, HDPE, PVC, LDPE, PP, PS	Potential limitations in diverse real-world scenarios, reliance on overhead camera setup, and high initial setup cost
[24]	TensorFlow pre-trained object detection and MobileNet V2	PET, HDPE, PVC, LDPE, PP, PS	Dependence on a confidence threshold for detection may require extensive fine-tuning and retraining, as well as potential issues with real-time application in diverse settings.
Proposed system	TensorFlow pre-trained object detection and MobileNet V2	Contagious Waste, Non-Contagious Waste, Infected Waste, Sharps, and Glassware	High accuracy, automation reduces human error

8. Conclusion

In conclusion, this research paper presents a robust and efficient approach to medical waste classification using the SSD MobileNet 640x640 VPN Lite object detection model. The evaluation results demonstrate the model's exceptional performance in accurately identifying and localising medical waste items across different categories. The model achieved high average precision values, reflecting its precision in classifying objects at various IoU thresholds. The utilisation of residual architecture and bottleneck layers significantly optimised the model's efficiency, making it suitable for deployment on low-end devices with limited computational resources. The study's findings hold significant implications for healthcare waste management practices. By enabling efficient and precise medical waste classification, the model contributes to enhanced waste segregation, disposal, and overall safety within healthcare facilities. Proper medical waste management is critical for preventing infections, protecting healthcare workers, and minimising environmental impact. In conclusion, the SSD MobileNet 640x640 VPN Lite model presented in this research offers a valuable solution for medical waste classification, bringing together accuracy, efficiency, and adaptability for real-world applications. Future work can explore further fine-tuning and optimisation to adapt the model to specific healthcare settings and expand its applicability to a broader range of medical waste items. Overall, this research makes a significant contribution to the field of medical waste management, addressing a critical aspect of public health and environmental safety.

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