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Performance Analysis of YOLO Architectures for Surgical Waste Detection in Post-COVID-19 Medical Waste Management

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ABSTRACT

In the wake of the COVID-19 outbreak, there has been a dramatic uptick in the need for efficient medical waste management, making it imperative that more surgical waste management systems are developed. Used surgical masks and gloves are examples of potentially infectious materials that are the subject of this research. By utilizing its real-time object detection capabilities, the You Only Look Once (YOLO) deep learning-based object detection algorithm is used to identify surgical waste. Using the MSG dataset, a deep dive into the performance of three different YOLO architectures (YOLOv5, YOLOv7, and YOLOv8) was undertaken. According to the findings, YOLOv5-s, YOLOv7-x, and YOLOv8-m all perform exceptionally well when it comes to identifying surgical waste. YOLOv8-m was the best model, with a mAP of 82.4%, among these three. To mitigate post-COVID-19 infection risks and improve waste management efficiency, these results can be used to the creation of automated systems for medical waste sorting.

1. INTRODUCTION

Since COVID-19, it has been evident that there is an urgent need for improved medical waste management, in particular within healthcare facilities, in order to halt the further spread of the virus [1,2,3]. This is especially important in light of the fact that COVID-19 occurred. A significant danger of infection is posed by the inappropriate disposal of surgical waste, which includes used masks and gloves in addition to other objects that could potentially spread illness [4,5]. As a consequence of this, there is an immediate need to appropriately detect hazardous medical waste in order to effectively stop the spread of infectious diseases [6, 7].

In this study, the MSG dataset [8] have been used, which contains 1153 images of masks, bio-hazard symbols, and gloves. A deep learning-based object detection method called You Only Look Once (YOLO) [9] has achieved outstanding results in a variety of applications, including the analysis of medical images [10, 11]. Its success can be linked to the fact that it only requires one neural network to detect objects in real-time, making it an excellent option for the detection of surgical waste.

It is essential to carry out a comprehensive performance evaluation of a number of different versions of YOLO in order to conclude that the most appropriate YOLO architecture for post-COVID-19 surgical waste detection can be determined. This study ought to take into account a wide range of considerations, such as accuracy, speed, and utilization of computing resources. When deciding whether or not a YOLO design is suitable for efficient surgical waste identification, these parameters are critical to consider. Therefore, it is necessary to conduct a thorough investigation of these aspects to make a rational conclusion regarding selecting the most effective YOLO architecture. So, this study will do a detailed performance analysis of several YOLO architectures. The survey which is conducted, will compare the performance of anchor-based variants of YOLOv5 [12], YOLOv7 [13], and recently published anchor-free YOLOv8 variants utilizing a variety of metrics.

The study mainly aims to achieve the following objectives:

1) Using the MSG dataset, determine how accurate the YOLO architectures are when identifying surgical waste materials such as masks, gloves, and biohazard symbols.

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2) To demonstrate the real-time detection capabilities of the YOLO architectures by measuring their computing speed and efficiency to determine how well they handle surgical waste management.
3) To determine the most suitable YOLO architecture for effective surgical waste detection by contrasting the performance of the anchor-based YOLO variants (YOLOv5 and YOLOv7) with the performance of the anchor-free YOLOv8 variants in terms of accuracy, speed, and resource utilization.

The findings of this study have significant effects and provide valuable contributions to the field of medical waste management, especially when considering the challenges post-COVID-19. The development of automated systems for surgical waste detection based on this research's findings will significantly reduce the risk of infection, to the advantage of both the general public and medical professionals.

2. LITERATURE REVIEW

Increased surgical waste, including used masks and gloves, which provide a significant risk of infection if improperly disposed of, has been brought on by the COVID-19 pandemic. It is vital to detect and separate such hazardous material to prevent the virus from spreading further.

Several research have been carried out to categorize or find surgical waste. In their study, Chen et al. [14] assembled a video collection of four waste objects (gloves, hairnet, mask, and shoe cover). They suggested a motion detection-based technique to extract valuable frames. They offered an architecture that included characteristics from 2D and 3D convolutional neural networks to categorize waste videos. On their dataset, their proposed approach had a 79.99% accuracy rate. Themistocleous et al. [15] used Sentinel-2 pictures from orbit to find floating plastic liters. Kumar et al. [16] suggest an AI-based system for classifying COVID-related medical waste. Before the commencement of the recycling process, the waste type classification was carried out using image texture-dependent features, which essentially assisted in giving accurate sorting and classification. With an accuracy of 96.5%, the SVM classifier performs best in their study. Ferdous and Ahsan [8] present a method for identifying infectious COVID waste. They used several YOLO architectural versions for their investigation. When compared, YOLOX performs better than the other architectures, with a mAP of 92.49%. Panwar et al. [17] used AquaVision, a deep learning-based detection algorithm, using the AquaTrash dataset. With a mean Average Precision (mAP) of 81%, their suggested model can identify and categorize the various pollutants and hazardous waste floating in the waters and along the coast. Mehendale et al. [18] aimed to create an automated computer vision system for medical waste separation that can identify and classify medical waste into four categories: cotton, cotton gloves, cotton masks, and cotton syringes. They developed a model using transfer learning on the AlexNet deep learning network to achieve this. Training the system correctly classified medical waste, leading to an 86.17% validation accuracy. Syringes, masks, and gloves were the primary objects in the COVID-19 waste detection model created by Buragohain et al. [19]. In order to evaluate the performance of several CNN models on their dataset, they trained many models. On average, EfficientDet D0 was 82% accurate, making it the most accurate model out of all of them.

The literature review suggests YOLO frameworks can efficiently identify and categorize surgical waste, such as biohazardous materials, masks, and gloves, after the COVID-19 pandemic. Various YOLO models are experimented on the MSG dataset, comparing their performance through training and testing. Moreover, the recently released YOLOv8 architecture from the relatively novel YOLOv7 and YOLOv5 models is compared. Overall, the study analyzes the effectiveness of different YOLO architectures in detecting and sorting post-COVID-19 surgical waste.

3. METHODOLOGY

3.1 Dataset

In this study, the MSG [8] dataset, which consists of 1153 images containing 1990 instances of surgical biohazard symbols, masks, and gloves, is utilized. The dataset includes a variety of scenarios, such as real-time conditions, lighting variations, multiclass objects, underwater conditions, and floating wastes. It was built using real-time images acquired from various sources, including roads, beaches, bodies of water, and maintenance holes. While some of the images in the dataset are synthetic, the vast majority are natural and reflect actual settings.

To ensure the diversity of the dataset, images were captured from various distances, including close-up and faraway views, to create a comprehensive variation. In addition, the dataset includes different angle variations, such as left, right, back, and top angles, to provide a complete representation of various perspectives.

Fig. 1. Image Samples from the dataset

For the study, the dataset was divided into training and validation sets, allocating 80% (923 images) to training and 20% (230 images) to validation. Figure 1 illustrates the distribution of ideas among various classes. 568 images are classified as masks, whereas 251 images include masks and gloves. In addition, ten images have all three categories concurrently, while the remaining pictures follow an identical distribution pattern. The MSG dataset contains 1133 mask instances, 598 glove instances, and 259 biohazard symbol instances. Figure 2 demonstrates the dataset distribution.

Fig. 2. Dataset Distribution

3.2 Framework

An input image is initially transmitted into the YOLO network, and distinctive features are extracted via the network's backbone [9]. The backbone network then utilizes the extracted features to generate a feature pyramid, which is then passed to the head network. The head network has two primary functions: regression of bounding frames and classification of objects. The output of the prediction phase may include any combination of the three desired categories: masks, gloves, and biohazard items.

In addition to the architecture, a novel dataset for detecting and managing infectious refuse in the environment has been curated. This dataset captures the diversity of real-world variations, angles, states, and textures. By incorporating such a wide variety of samples, the system's robustness and adaptability to numerous situations are improved.

3.3 Objective

This study's primary objective is to detect surgical debris and biohazard symbols accurately and in a reasonable amount of time. Numerous YOLO architectures are analyzed to achieve this objective, each of which serves a different purpose. In addition, two distinct varieties of YOLO models are chosen: one employing an anchor-based training mechanism and the other an anchor-free training mechanism.

Table 1 provides an exhaustive summary of the object detection models utilized in this investigation. Three anchor-based models and one anchor-free model are displayed in the table. Each model was meticulously selected based on its distinct qualities and capabilities.

Various variations of the YOLOv5 architecture are utilized, such as YOLOv5-s, YOLOv5-m, YOLOv5-l, and YOLOv5-x. The YOLOv7 architecture was a hybrid of the YOLO-v7 and YOLOv7-x architectures. Four slightly distinct YOLOv8 architectures—YOLOv8-s, YOLOv8-m, YOLOv8-l, and YOLOv8-x—are utilized. The sizes of the four options are "small," "medium," "large," and "extra-large," denoted by the letters "s," "m," "l," and "x,", correspondingly. According to the theory, bigger models are more likely to be accurate than smaller ones. When compared to their bigger counterparts, smaller versions have quicker processing speeds. That is why it is viewpoint and application specificity that should be considered when deciding between model size and performance. For this reason, a complete explanation of the performance of YOLOv5, YOLOv7, and YOLOv8 requires an exhaustive study of all three versions.

In addition, it is essential to evaluate the efficacy of anchor-based and anchor-free detectors. Understanding the distinctions and capacities of these detection mechanisms is crucial in determining their suitability for particular applications.

Table 1. Summary of Object Detection Models

Training-Mechanism	Architecture
Anchor-based	YOLOV5s YOLOV5m YOLOV5l YOLOV5x YOLOV7 YOLOV7x
Anchor-free	YOLOV8s YOLOV8m YOLOV8l YOLOV8x

3.4 Training

The training was done using 80% of the data and validated with 20%. The whole thing was trained and validated using Google Cloud (Google Colaboratory). With an input image size of 416x416, the training procedure lasted for 40 iterations. In order to train the YOLOv5 architecture, the PyTorch environment is used and follows the training approach created by Ultralytics, a leading firm in the industry. Similarly, YOLOv7 and YOLOv8 were trained using pre-trained weights and the exact construction and procedures given by Ultralytics. For both models, a batch size of 16 and 30 were utilized.

All models were trained in the PyTorch environment and an SGD optimizer was used. Table 2 represents the training hyper parameters.

Table 2. Training hyperparameters

Model	Learning Rate	Decay	Batch Size
YOLOv5	0.01	0.0005	16/30
YOLOv7	0.01	0.0005	16/30
YOLOv8	0.01	0.0005	16/30

3.5 Evaluation Metrics

Precision is the degree to which a model successfully identifies the goals for which it was trained. In comparison to the number of favorable occurrences witnessed, this statistic reveals how successfully the forecasts were made. Conversely, recall assesses the accuracy with which a model identifies all pertinent samples within a dataset. How many instances of good things in the dataset are measured by the optimistic prediction-to-actual-data ratio.

This study uses Average Precision (AP), a summary of the Precision-Recall (PR) curve [20, 21], to evaluate the performance of a model. A high accuracy rating indicates that the model's object classification is quite trustworthy. The model's performance may be illustrated by constructing a PR curve with the help of recall and accuracy values.

The area under the curve (AUC) is a representation of the precision-recall (PR) curve, and the letter "P" stands for it. The average precision (AP) metric may be calculated using Equation 1. The number of thresholds employed in this equation is represented by the variable n. For every precision or recall value, the difference between the current and next recall values has to be taken into account in order to calculate AP. Multiplying the disparity by the Interpolated Precision (IP) value is the next step.

For each given recall value (R), the maximum accuracy that may be achieved is known as Interpolated accuracy (IP) when the matching recall value is equal to or higher than R. For each cutoff, the AP is calculated by adding the recall and accuracy values, with each entry serving as a weight.

$$AP = \sum_{k=0}^{k=n-1} [R(k) - R(k+1)] \times IP(k) \quad (1)$$

The Mean Average Precision (mAP) is an additional important metric that is calculated using Equation 2 and the AP values for each class. The variable n in this equation represents the number of types.

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k \quad (2)$$

4. Results Analysis

4.1 Findings

Table 3 shows the results for all the YOLO models used in this study.

Table 3. Results of all the YOLO models used

Model	Batch Size	Mask AP	Gloves AP	Biohazard AP	mAP
YOLOV5s	16	94.5	80.8	63.8	79.7
	30	93.7	81.8	69.9	81.8
YOLOV5m	16	93.3	77.9	63.9	78.4
	30	93.6	81.6	52.0	75.7
YOLOV5l	16	92.6	80.9	65.0	79.5
	30	95.2	81.7	65.1	80.7
YOLOV5x	16	93.8	80.0	59.1	77.6
	30	93.1	82.8	66.3	80.7
YOLOV7	16	96.1	76.8	67.5	80.2
	30	93.9	78.8	67.6	80.1
YOLOV7x	16	95.4	81.0	62.1	79.5
	30	95.7	88.1	60.7	81.5
YOLOV8s	16	92.6	83.2	62.6	79.5
	30	90.9	75.5	66.4	77.6
YOLOV8m	16	92.2	82.8	55.3	77.1
	30	90.1	83.2	73.8	82.4
YOLOV8l	16	92.5	76.2	61.8	76.8
	30	93.2	79.2	70.3	80.9
YOLOV8x	16	91.8	77.0	65.8	78.2
	30	93.6	77.3	62.0	77.7

Figure 3 provides a comprehensive analysis of the performance of various YOLO architectures for surgical waste detection evaluated with batch size of 16. The results are estimated based on the average precision (AP) for each class (mask, gloves, and biohazard) as well as the mean average accuracy (mAP), which is an overall measure of the models' performance.

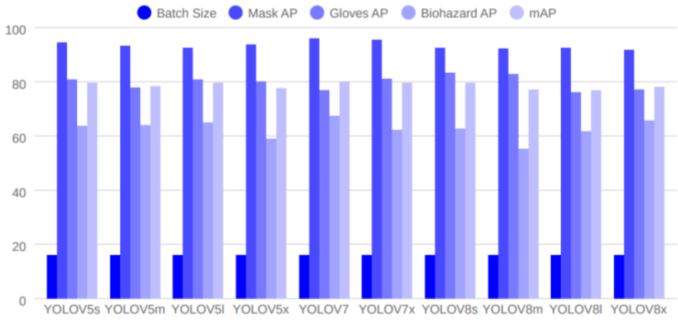

Fig. 3. Comprehensive Performance of Batch 16

When it came to masks, the top three YOLOv5 series were YOLOv5s (94.5% AP), YOLOv5m (93.3% AP), and YOLOv5l (92.6% AP). In terms of gloves AP, however, YOLOv5l came out on top with a whopping 80.9%. With an AP of 59.1%, biohazard detection was the worst of the three areas where YOLOv5x performed poorly. In terms of overall mAP, YOLOv5s was the best at 79.7 percent.

With an impressive AP of 96.1% for masks and competitive performance in identifying biohazards and gloves, YOLOv7 produced remarkable results. In addition, YOLOv7x has shown remarkable performance with a 95.4% success rate. The mean absolute percentage (mAP) for both models was 79.5%.

The anchor-free YOLOv8 series, YOLOv8s made an astounding 83.2% gloves AP and YOLOv8m was competitive across the board. Lowest AP for gloves was achieved by YOLOv8l (76.2%), but YOLOv8x and YOLOv8l both had lower AP values. In YOLOv8 models, mAP values varied between 76.8% and 79.5%.

The results demonstrate that different YOLO architectures have varying capacities in detecting specific classes. YOLOv7 performed exceptionally well when seeing masks, whereas YOLOv8s excelled at identifying mittens. However, there is a trade-off between the performance of various classes, with some architectures performing exceptionally well in one category but relatively poorly in others.

Figure 4 provides a comprehensive analysis of the performance of various YOLO architectures for surgical waste detection evaluated with a batch size of 30.

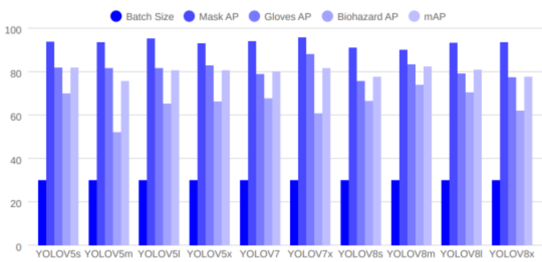

Fig. 4. Comprehensive Performance of Batch 30

Among the YOLOv5 series, YOLOv5l had the best performance in mask detection with an AP of 95.2%. YOLOv5s had the best AP for biohazards at 69%, while YOLOv5x had the best AP for gloves at 82.8%. The mAP for all YOLOv5 models varied between 75.7% and 81.8%.

When comparing YOLOv7 to YOLOv7x, the results were competitive. YOLOv7x's 88.8% AP was the most of any glove, while YOLOv7's 93.9% AP was the highest of any mask. Both models demonstrated comparable biohazard detection abilities, with mAPs of around 80.1% and 81.1%, respectively.

No class in the anchor-free YOLOv8 series did better than YOLOv8m. Its accuracy percentages were 83.2% for gloves, 73.8% for biohazards, and 82.4% overall. YOLOv8s had the lowest performance in gloves AP at 75.5%, in contrast to YOLOv8l's outstanding mAP of 80.9% and competitive performance throughout all categories. When it came to accuracy, YOLOv8x was on par across the board, scoring 77.7%.

The results show that different courses had different levels of success with YOLO frameworks. Models vary in their ability to identify certain objects; for instance, YOLOv8m is more adept at detecting gloves than YOLOv5s is at detecting biohazards. Choosing the right YOLO design requires careful consideration of the unique requirements and objectives of surgical waste detection.

This comprehensive data analysis allowed to compare the YOLO designs and brings out the pros and cons of each model. Researchers may employ this data to develop an appropriate YOLO design based on the particular objectives and aims of surgical waste detection.

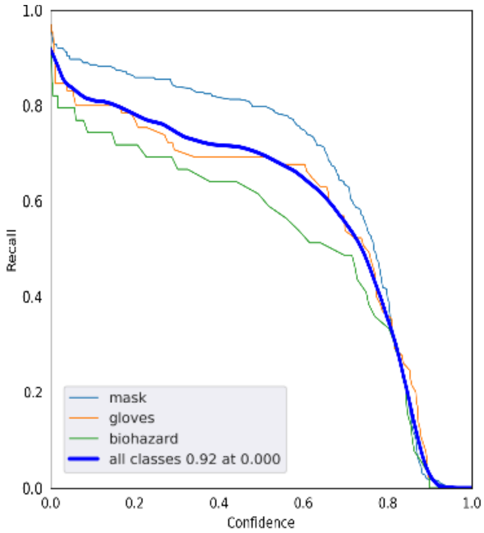

Fig. 5. YOLOV5s (B30) Recall curve

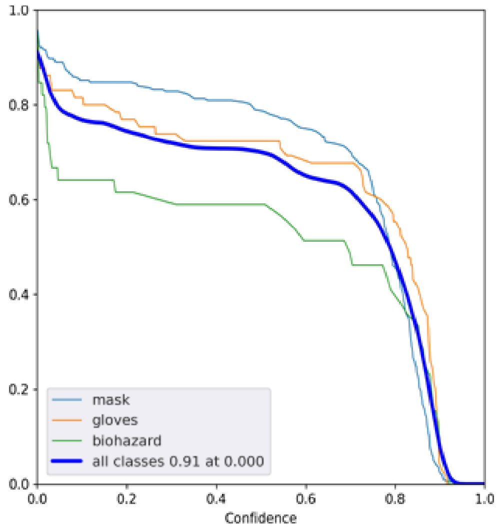

Fig. 6. YOLOV5m (B16) Recall curve

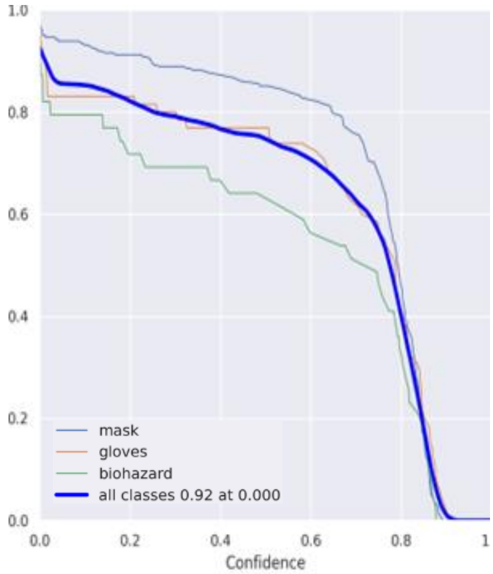

Fig. 7. YOLOV5l (B30) Recall curve

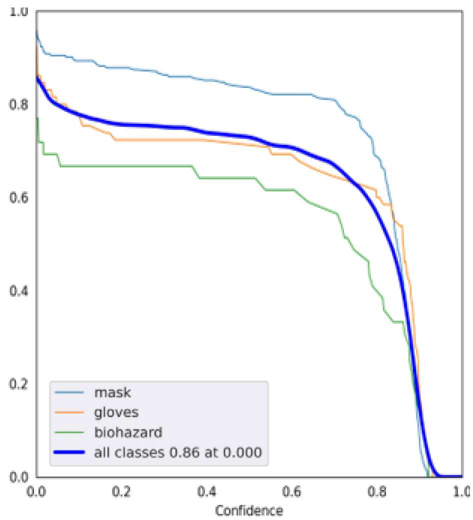

Fig. 8. YOLOV5x (B30) Recall curve

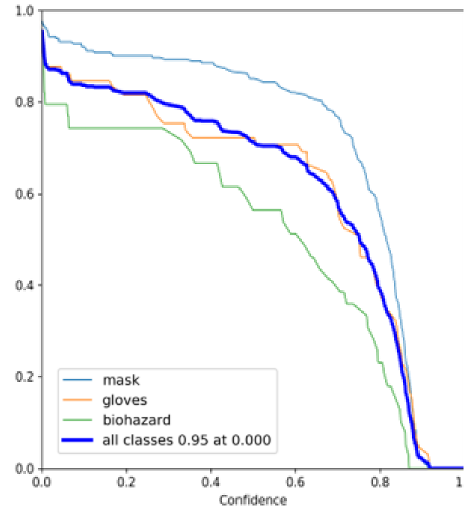

Fig. 9. YOLOV7 (B16) Recall curve

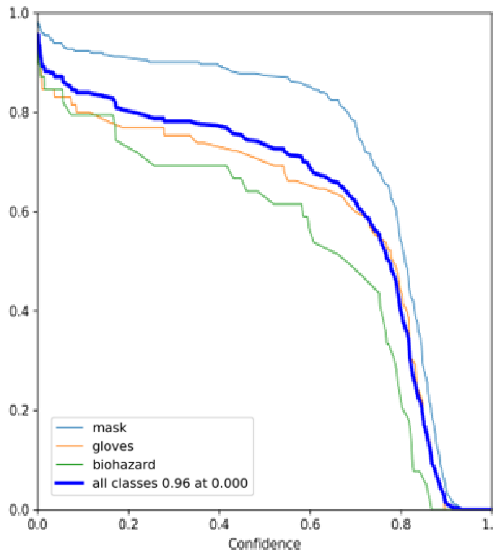

Fig. 10. YOLOV7x (B30) Recall curve

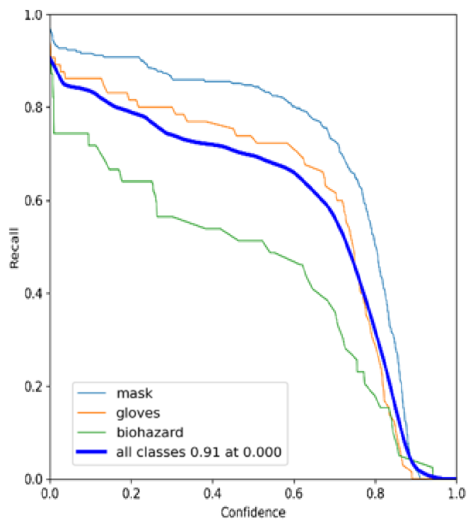

Fig. 11. YOLOV8s (B16) Recall curve

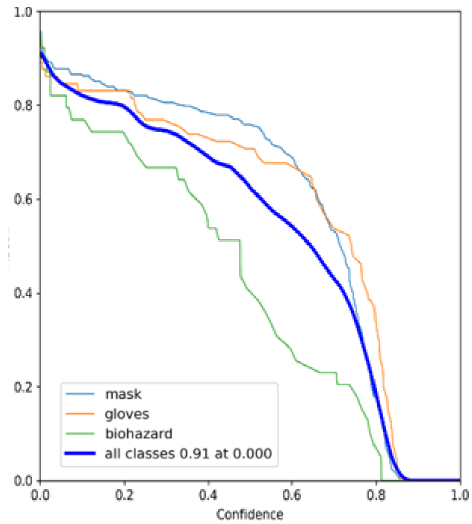

Fig. 12. YOLOV8m (B30) Recall curve

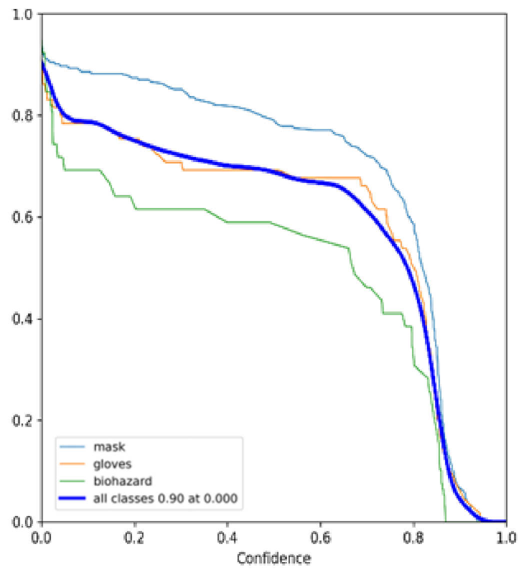

Fig. 13. YOLOV8l (B30) Recall curve

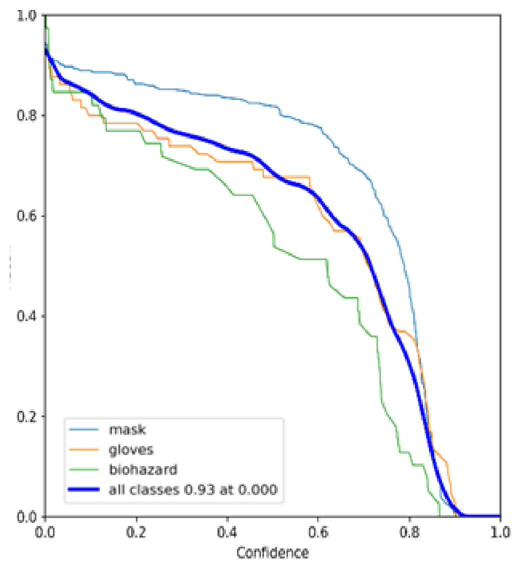

Fig. 14. YOLOV8x (B16) Recall curve

4.2 Discussions

This research uses the MSG dataset to compare and contrast different YOLO topologies. The results are laid out in the table that follows. With an overall mAP of 81.8% when tested with a batch size of 30, the YOLOv5-architecture outperformed the other YOLOv5 models. Compared to YOLOv7, YOLOv7-x fared substantially better with an overall mAP score of 81.5%. At a batch size of 30, the YOLOv8-m architecture achieved an overall map score of 82.4%, which was also the highest score of all the models, making it the most performant of the YOLOv8 models.

Different YOLO models have different strengths and weaknesses when it comes to detecting surgical waste. When it comes to identifying gloves and masks, YOLOv5s performs admirably, and its accuracy remains high throughout both batch sizes. Having said that, its biohazard detection AP isn't great. While YOLOv5m performs adequately when testing for masks and gloves, it fails miserably when testing for biohazards. With its exceptional accuracy, YOLOv5l not only recognizes gloves and biohazards, but also masks. Masks are YOLOv5x's strong suit, not gloves or biohazards. While YOLOv7 does a respectable task at detecting mask and gloves, it isn't always in particular suitable at detecting biohazards. In terms of glove detection, YOLOv7x excels, but in relation to masks and biohazard detection, it falls a way short. Despite its stable overall performance with biohazards and mask, YOLOv8s fails to meet expectations with regards to gloves. In assessment to its advanced overall performance whilst checking out gloves and biohazards, YOLOv8m's AP is decrease when testing masks. It outperforms all different models in terms of mAP. When it involves identifying mask, YOLOv8l does a respectable task, but in terms of biohazards and gloves, it has hassle. While YOLOv8x is not perfect, it performs a first-rate activity in maximum classes except for biohazard identification and gloves. Prior to selecting a way to as it should be become aware of surgical waste, weigh the professionals and cons of every kind.

4.3 Comparison of the Study

The approach, with previous related studies, is shown in Table 4.

Table 4. Comparison with previous studies

Author	Detection Criteria	Anchor-Based Method	Anchor-Free Method	Best Model	mAP
[22]	Vehicle Detection	YES	NO	YOLOv5x	28.70%
[23]	Protective equipment detection	YES	YES	YOLOX-m	89.84%
[24]	Garbage Detection	YES	NO	YOLOv3	59.57%
[25]	Unsafe Behavior Detection	YES	NO	YOLO-AW	76.70%
[26]	Traffic Sign Recognition	YES	NO	YOLOv4	99.98%
[8]	Surgical Waste detection	YES	YES	YOLOX L	92.49%
[27]	Face Mask Detection	YES	NO	YOLOv4	98.30%
Ours	**Surgical Waste detection**	**YES**	**YES**	**YOLOv8m**	**82.40%**

4.4 Real-time observation

The best model (YOLOV8-m with a confidence rate of 0.25) is implemented on a video to check how it performs in real-world scenarios. The results are depicted in Figure 15.

Fig. 15. Results of real-time observation

It is clear from the screenshots that the model was successful in accurately identifying the majority of the classes. However, specific problems were discovered, such as the fact that it incorrectly identified blue items as gloves and that it was unable to distinguish between gloves and masks. Additionally, the dataset includes many photos of underwater waste, which may contribute to the model's improved performance in recognizing surgical wastes buried underwater.

5. Limitations and Future Research Directions

The YOLOv8-m architecture can identify surgical waste on the MSG dataset, according to this study. However, there are major limitations that prevent it from being used to build automated systems for medical waste sorting and disposal. Specifically, the MSG dataset does not include all of the complex real-world scenarios that may be encountered because of different camera angles, occlusions, and illumination. Because of this, YOLOv8-m's recognition accuracy could be compromised in difficult settings where the training data was not available, for example, in situations where there are obstructions or shadows produced by cluttered backgrounds. Possible difficulties in accurately sorting medical waste may arise from the algorithm's inability to consistently differentiate between seemingly identical classifications, such as masks and gloves. Given that testing was conducted on a small dataset of 1,153 pictures, it is imperative that bigger and more realistic datasets drawn from actual clinical scenarios undergo more comprehensive evaluation. Due to the model's inability to generalize to novel types of trash, detection accuracy may suffer when exposed to more recent types of trash. Since overlapping waste items and severe occlusions can greatly reduce detection accuracy, more robust approaches to specifically handle occlusions are also essential. Variations in camera angle and distance from the garbage cans may also affect the final product.

There are some potential areas for further research in surgical waste identification. To assess the performance of various deep learning architectures in surgical waste identification, future studies may look into YOLO alternatives, such as Faster R-CNN, SSD. Moreover, integrating the surgical waste detection system with automated waste management systems might be the subject of future research. This would allow for the development of comprehensive solutions that efficiently separate, dispose of, and monitor surgical waste. Additionally, future studies in this field might use varied datasets to make surgical waste detection models more generalizable and resilient, so they work better in a variety of real-world settings.

6. Conclusion

The examination of the MSG dataset is concluded by contrasting various YOLO-based architectures. According to the results, mAP was increased by 82.4% using anchor-free YOLOv8-m and a group size of 30. The findings will enhance the design of automated systems, thereby reducing the risk of infection for both patients and medical personnel. This study focuses solely on YOLO-based architectures, omitting additional deep-learning methodologies and conventional methods for detecting surgical waste. In addition, the performance evaluation is conducted with a limited data set that may not represent the vast array of surgical waste encountered in usage. Additional research is necessary to fill in these voids and learn everything there is to know about locating and disposing of surgical refuse. Future research in this area may utilize other datasets to improve the precision and dependability of surgical waste detection. Further studies could also investigate integrating the surgical waste detection system with waste management systems. Moreover, researching and comparing the performance of other deep learning methods and conventional techniques for detecting surgical waste can be an excellent addition to this study. This would make waste separation, disposal, and monitoring more efficient, assuring proper management and compliance with regulations. In addition, as the requirements for medical waste management tend to evolve, it would be beneficial to examine how the selected YOLO architecture performs in a real-world healthcare setting. This type of research could evaluate the system's efficacy in the real world and identify potential limitations.

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