Real-Time Object Detection System for Hospital Assets Using YOLOv8

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***Abstract* — Hospital administration is essential in the provision of high-quality social services to patients. Hospitals must have efficient asset management to offer quality medical care. On the other hand, many hospitals face problems such as data entry errors. Based on this problem, the author hopes to solve it by implementing real-time object detection and recording data distribution using the YOLO (You Only Look Once) algorithm. This data distribution will then be applied to the current system. Performance tests were carried out in this research using the YOLO architecture, especially on YOLOv8. one of the improvements of popular deep learning algorithms. This research used 7680 images (augmentation) which were divided into 3 parts. 6720 training data (88%), 640 validation data (8%), and 320 (4%) test data. 7680 data were added from 16 tested medical device categories with 200 images per category. This research has an average accuracy of 90%, an average precision of 94%, and an average recall value of 92.2%. These results show that YOLOv8 performs well in detecting medical devices. To improve accuracy, it is recommended to test larger and more diverse datasets. This research helps the healthcare industry better monitor and manage real-time assets.**

Keywords—Real-time, object detection, asset management.

I. INTRODUCTION

As vital providers of medical services and care to their communities, hospitals require efficient asset management to operate at peak efficiency and deliver high-quality care[1]. However, real-time tracking of asset location and status remains elusive in most hospitals, resulting in significant challenges for asset management. This lack of visibility impedes productivity, efficiency, and effectiveness, leading to prolonged procedures and delays[2]. Compounding these issues, hospitals often struggle to maintain accurate asset records and track associated activities such as acquisition, receipt, storage, distribution, and asset needs planning[3], [4]. Siemens Healthcare 2023 data indicates that real-time location systems (RTLS) are critical for several reasons in healthcare facilities[5], including long wait times for patients, excessive time spent looking for medical equipment, and overspending on equipment purchases or rentals as a result of subpar utilization rates. 30% increase in asset utilization for optimal asset management, 95% on-time preventive maintenance and a 60% decrease in asset depreciation are further advantages of RTLS deployment. There are two primary methods for integrating RTLS with object detection on hospital assets: object detection utilizing cameras to recognize and categorize things in the visual field and RTLS using tags affixed to assets that emit signals for location tracking[6]. Different YOLO variants have been used for object detection in earlier research, with differing degrees of effectiveness. For example, the YOLOv2 model attained a mean average precision (mAP) of 81%[7]. The Advanced Driver Assistance Systems (ADAS) dataset has employed YOLOv3 with accuracy rates of 85% and 90% for doors and handles, respectively[8]. Significant gains have been demonstrated recently with YOLOv8, including a map of 90.8% in medication inventory management and excellent precision (94%)[9]. However, it is important to acknowledge the limitations and challenges associated with the YOLO model, such as the difficulty in detecting small objects and the computational resources required for real-time processing[10],[11]. Similarly, RTLS technology suffers from challenges such as signal interference and high implementation costs[12].

The pressing need for effective asset management solutions in hospitals cannot be overstated. Inefficiencies in this area not only increase operational costs but can also compromise patient care by causing delays in medical procedures and treatments. In this study, researchers employ YOLOv8 for object detection due to its high accuracy and recent performance enhancements. YOLOv8 offers several improvements over its predecessors, including better detection accuracy, faster processing times and more complex objects[13]. Researchers will combine this with RTLS data to form a comprehensive asset management solution. The technique will contain extensive dataset descriptions, training procedures, performance metrics, and an evaluation of the integrated system. The implementation of this system will result in more efficient hospital operations, reduced costs, and ultimately better patient care, highlighting the urgent need for such innovations in the healthcare industry.

II. RELATED WORK

YOLO is a real-time object detection algorithm that processes all images at once at a speed of up to 45 frames per second and 155 frames per second in its latest version[14]. YOLO divides multiple images into regions and classifies each region to find objects. YOLOv8 is the latest version of YOLO, improving accuracy and speed. YOLOv8 Has five main variants: nano(n), small(s), medium(m), large(l), and extralarge(x). Each variant has specific functions based on computing needs and applications. For example, YOLOv8n is suitable for resource-limited devices such as integrated systems. For example, YOLOv8n is intended for devices that have limited resources, such as integrated systems, while YOLOv8x is intended for applications that require a high level of accuracy and a lot of computing resources. Based on the Ultralytics documentation, the following is a table of YOLOv8 models:

TABLE I. YOLOV8 MODEL

Model	size(pixels)	mAPval50-95	SpeedCPU ONN X (ms)	SpeedA100 Tenso rRT(ms)	params (M)	FL OPs(B)
YOLO v8n	640	37.3	80.4	0.99	3.2	8.7
YOLO v8s	640	44.9	128.4	1.20	11.2	28.6
YOLO v8m	640	50.2	234.7	1.83	25.9	78.9
YOLO v8l	640	52.9	375.2	2.39	43.7	165.2
YOLO v8x	640	53.9	479.1	3.53	68.2	257.8

Reference: https://github.com/ultralytics/ultralytics

In this study, the selection of YOLOv8 was based on several important components. First, YOLOv8 has been proven to have high accuracy in several datasets. This includes a medication inventory management dataset with an mAP of 90.8% [9] and a personal protective equipment (PPE) dataset with 94% accuracy and 86% recall [15]. Second, YOLOv8 has a higher processing speed compared to previous versions, which allows for more efficient real-time implementation. Third, the variants available in YOLOv8 enable customization for a wide range of applications, from resource-constrained devices to resource-intensive data centers. The results of previous research show how YOLO works on various datasets:

TABLE II. REFERENCE OF SIMILAR RESEARCH

REFERENCE OF SIMILAR RESEARCH		
Dataset/Input Parameters	***Technology***	***Result/Output Parameters***
Medical face masks dataset [7]	YOLOv2	• mAP50 81%
Advanced Driver Assistance **(ADAS)** dataset [8]	YOLOv3	• Precision 85% (handles) • Precision 90% (doors) • Recall 0.29% (handles) • Recall 0.80% (doors) • 866 Images
Medicines dataset: inventory management [9]	YOLOv8	• mAP50: 90.8% • R-CNN (4.262)
Face mask dataset [16]	YOLOv5	• Confidence: 84% • Precision: 83%
Medical Imaging Dataset [17]	YOLOv5	• (AVG) precision of 76.9% • class-specific mAP50 values ranging from 66% to 99.5%.
Personal protective equipment (PPE) dataset [18]	YOLOv5	• Precision (all): 92% • Recall: 61% • Total of images: 12.682 • 12 Categories: Hard hats, caps, hair protection, sunglasses, safety glasses, visors, welding masks, cloth masks, surgical masks, N95 masks, cartridge respirators, and earmuffs.
Personal protective equipment (PPE): CHV dataset [15].	YOLOv8	• 6 categories: Person, vest, Blue helmet, red helmet, white helmet, and yellow helmet. • Best model on YOLOv8x • Precision: 94% • Recall: 86% • mAP50 : 93% • mAP50-95: 59%
Personal protective equipment (PPE) dataset [19]	YOLOv5 & YOLOv8	• 3 classes: heavy, PPE, and worker • mAP50 : 94,1% (YOLOv5) • Map50 : 95,1% (YOLOv8).

Choosing YOLOv8 as an object detection algorithm offers superior results, especially in terms of speed and accuracy. The YOLOv8 architecture has a simpler algorithm in the training process and improves the model's ability to detect objects of various sizes and aspect ratios. This design is especially essential for applications that require precise detection of small objects, such as medical imaging or surveillance systems. Based on the data provided, the use of the YOLOv8 algorithm in the study of hospital medical resources showed quite good results. This algorithm is very effective in various cases, from detecting such as PPE, CHV datasets, and medicines datasets for inventory management. Provides a fairly high level of precision up to 90%. Its reliability is demonstrated by its ability to deal with image variations. This algorithm has a relatively fast computing time, making it suitable for hospital environments that require more efficient and reliable detection and identification of medical devices.

III. Methodology

This study uses the YOLOv8 algorithm to detect objects and uses Google Colab for data training and Roboflow for data labeling. The flexible and comprehensive OSEMN (Obtain, Scrub, Explore, Model, iNterpret) methodology used allows the development and adoption of new technologies as needed. OSEMN supports object detection model development projects from the data collection stage to the interpretation of results through an integrated end-to-end approach [20]. Image data training and testing are carried out in the program to assess algorithm performance by calculating accuracy, precision, and sensitivity (recall) values.

A. Dataset

The first stage of data collection and preparation involves annotating images of hospital equipment using the Roboflow platform. Data labeling is used to name or label annotated objects, providing checkboxes and name labels for objects in the image, commonly called bounding boxes, as shown in

Fig.1. There are 16 annotated categories: CT scans, hospital beds, X-rays, dialysis machines, stethoscopes, scales, hand sanitizers, masks, insulin pens, glucose meters, gurneys, defibrillators, infusion poles, tensiometers, wheelchairs, and thermometers. The next stage, data exploration, includes data preprocessing and augmentation using the Roboflow platform. Data preprocessing ensures learning and inference are performed on the same image attributes, with tiling used to divide images into smaller parts and resizing them to 640x640 pixels for optimal training with the YOLOv8 algorithm. Data augmentation addresses overfitting and improves inference accuracy by adding variations to the dataset. Techniques include horizontal and vertical rotation, clockwise and counterclockwise rotation, and brightness adjustments. This phase resulted in a total dataset of 7680 images, partitioned into a training set of 6720 images, a validation set of 640 images, and a testing set of 320 images.

TABLE III. CLASS NAME AND DATASET

No.	CLASS NAME AND DATASET			
	Class Name	***Training Data***	***Validation Data***	***Test Data***
1	Gurney	420	40	20
2	CT-SCAN	420	40	20
3	Defibrillator	420	40	20
4	Dialysis machine	420	40	20
5	Glucose meter	420	40	20
6	Hand sanitizer	420	40	20
7	Hospital Bed	420	40	20
8	Insulin pen	420	40	20
9	Wheelchair	420	40	20
10	Mask	420	40	20
11	Stethoscope	420	40	20
12	Tensimeter	420	40	20
13	Thermometer	420	40	20
14	Infusion pole	420	40	20
15	Scale	420	40	20
16	X-ray	420	40	20

Fig. 1. Sample Datasets

B. Method

To achieve training accuracy, this technique uses a training algorithm that combines Google Collab's YOLO architecture with the Convolutional Neural Network algorithm. In Figure 2, the training & validation method is shown using OSEMN Methodologies. Next, the testing algorithm for evaluating system performance is shown in the Testing Process.

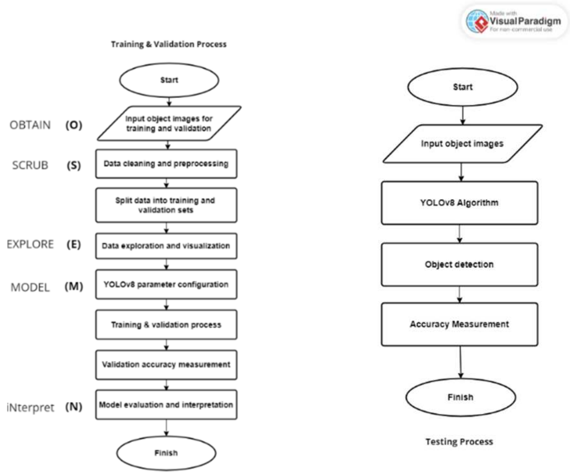

Fig. 2. Training, Validation and Testing Process

The figure shows the system training algorithm using YOLO. The stage begins by entering a dataset in the form of objects available in Figure 1. Each tool category has 200 image data samples. A total of 420 image data (augmentation has been carried out) from each category are used as training data. Next, set the YOLO parameters in the form of several epochs, learning rate, yolo size, and batch size, and modify the model by adding momentum and decay. The YOLO configuration parameters are shown in Table III in detail. The results of training are object detection features and obtain training accuracy. In Figure 2 - Testing Process, the YOLO algorithm parameters used for the testing process are the same as the training parameters. The process that occurs at this stage is matching features between the test data and the training data in the previous stage. The output from this system is an identification name according to the image of the object entered into the system. Then the accuracy value is calculated.

C. YOLOv8-CNN Theorem

The development of the Yolo algorithm is getting more accurate, one of which is the latest version of YOLO, YOLOv8. YOLOv8 is a *state-of-the-art* convolutional neural network with real-time object detection capabilities. YOLOv8 has three main components, namely the head, neck, and spine. Convolutional layers and C3CA blocks are used in the backbone to extract features, which are then batch-normalized and SiLU-enabled[21]. These attributes are further refined by the neck, which incorporates a PANet-like structure, while the head predicts bounding boxes, objectivity scores, and class probabilities via a detection layer. The output is generated by the final sigmoid function, after which the feature aggregation is enhanced by the SPPF layer. The YOLOv8 architecture is shown in Figure 3 and Figure 4 is a description of its parts and the image processing flow.

Reference: https://viso.ai/deep-learning/yolov8-guide/

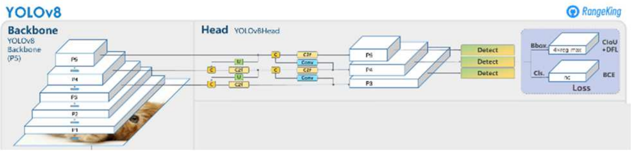

Fig. 3. YOLOv8 Structure

Reference: https://viso.ai/deep-learning/yolov8-guide/

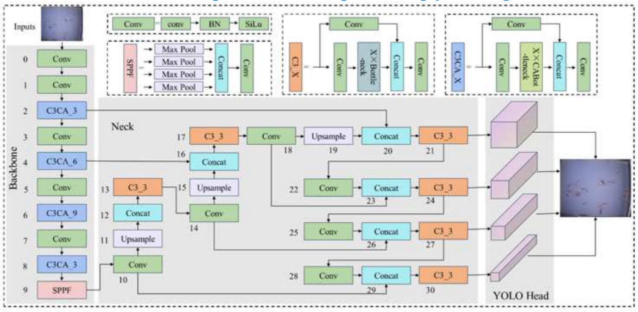

Fig. 4. YOLOv8 Images Processing Flow

D. Analysis Method

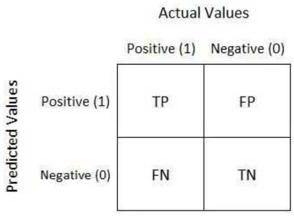

Fig. 5. Confusion Matrix

TP, TN, FP, and FN values from the training and testing procedures are computed by the Confusion Matrix. In Figure 5, TP and TN represent correct positive and negative predictions, respectively, whereas FN and FP represent errors. Researchers get accuracy, precision, and recall from them[22]. The proportion of true positives among all positive predictions is shown by precision, recall (or sensitivity) represents the proportion of true positives among all actual positives[23]. Accuracy assesses the total correctness of predictions. Equations (1) through (3) present these metrics assessment of the system's performance. To calculate the overall accuracy, precision, and recall (micro-average) of the existing data, we can use the following formula.

$$\text{Accuracy} = \frac{\sum \text{TP}}{\sum(\text{TP}+\text{FP}+\text{FN}+\text{TN})} \tag{1}$$

$$\text{Precision}_{\text{micro}} = \frac{\sum \text{TP}}{\sum(\text{TP}+\text{FP})} \tag{2}$$

$$\text{Recall}_{\text{micro}} = \frac{\sum \text{TP}}{\sum(\text{TP}+\text{FN})} \tag{3}$$

Fig. 6 Metrics Assessment

IV. RESULT & DISCUSSION

The training process was carried out 3 times with the SGD optimizer and YOLOv8x size and different combinations of YOLO parameters were carried out. The parameters combined include Epoch, Learning Rate, Batch Size with momentum (0.937), and Weight Decay (0.0005) to get the highest accuracy value. The highest accuracy value is obtained with the following parameters.

TABLE IV. YOLO PARAMETER COMBINATION DURING THE TRAINING PROCESS

No.	**Results of Hyperparameter Tuning Optimization**				
	Training Test ID	***Epoch***	***Learning Rate***	***Batch Size***	***Accuracy***
1.	Train 1	100	0.001	8	83%
2.	Train 2	110	0.001	8	90%

Based on the results of this experiment, the second training experienced an increase from 83% in the first training to 90% in the 2nd training. So, the best model is in the 2nd training. Figure 7, has a confusion matrix result for the best training which shows the True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) values and are used as a basic assessment for calculating the accuracy, precision, and recall performance metrics.

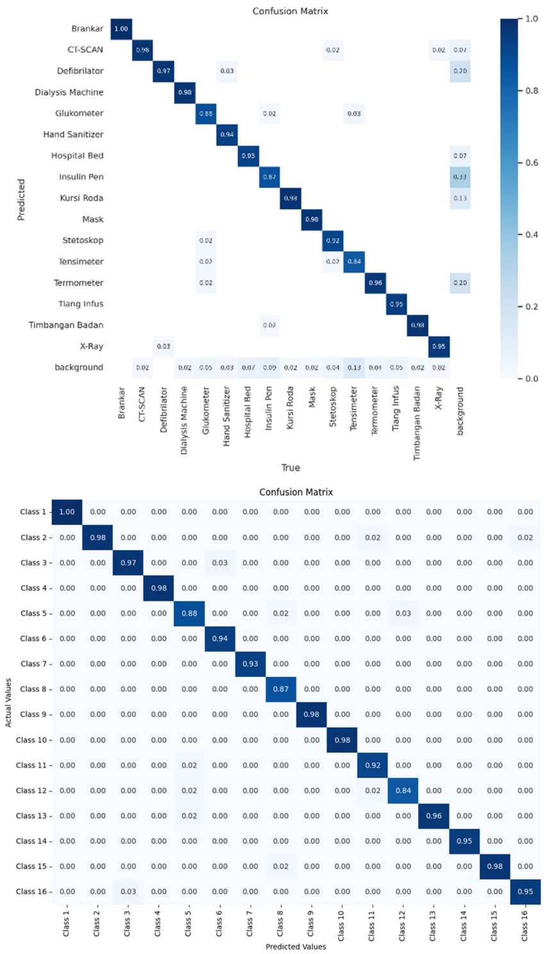

Fig. 7 Confusion Matrix Result

The training results are displayed in the form of a confusion matrix in Figure 7. From the results of Figure 6, the accuracy value can be calculated based on equations (1), (2), (3). This is for the overall calculation results for accuracy, precision, and recall from the actual data.

∑TP=1.00+0.98+0.97+0.98+0.88+0.94+0.93+0.87+0.98+0.98+0.92+0.84+0.96+0.95+0.98+0.95+0.00 = **15.71**

∑(TP+FP+FN+TN) =1.00+0.00+0.00+…+0.02+0.02+0.00=**17.42**

∑FN=0.00+0.11+0.23+0.00+0.10+0.00+0.07+0.33+0.13+0.00+0.08+0.06+0.20+0.00+0.00+0.02+0.00=**1.33**

*The calculation for ∑TP, ∑(TP+FP+FN+TN) and ∑FN

$$\text{Accuracy} = \frac{15.71}{17.42} \approx 0.901 \tag{1}$$

$$\text{Precision}_{\text{micro}} = \frac{15.71}{15.71 + 1.00} \approx 0.9401 \tag{2}$$

$$\text{Recall}_{\text{micro}} = \frac{15.71}{15.71 + 1.33} \approx 0.9221 \tag{3}$$

Fig. 8 Results of Metrics Assessment from Actual Data

Based on the calculation results in the table above, the accuracy results obtained were 90%, with sensitivity/recall at 92,2% and precision 94%. This data shows good results because it has quite a high accuracy, precision, and recall. Here are the calculation details results of calculating accuracy, precision, and recall for the 16 previously trained health asset category data.

TABLE I. CALCULATION BASED ON CLASS NAMES

No.	CALCULATION BASED ON CLASS NAMES			
	Classnames	Accuracy	Precision	Recall
1.	Gurney	99,2%	98%	89,9%
2.	CT-SCAN	99,2%	93%	93%
3.	Defibrillator	98,5%	97%	80,8%
4.	Dialysis machine	99,9%	98%	100%
5.	Glucose meter	99,1%	88,9%	94,6%
6.	Hand sanitizer	99,6%	94%	100%
7.	Hospital Bed	99,2%	93%	93%
8.	Insulin pen	97,3%	87%	72,5%
9.	Wheelchair	99,1%	98%	88,3%
10.	Mask	99,9%	98%	100%
11.	Stethoscope	99,4%	92%	97,9%
12.	Tensimeter	98,8%	84%	95,5%
13.	Thermometer	98,5%	96%	81,4%
14.	Infusion pole	99,7%	95%	100%
15.	Scale	99,8%	98%	98%
16.	X-ray	99,6%	96%	96,9%

With accuracy ranging from 97.3% to 100% across all classes, the object detection and tracking model performs very well in detecting various types of medical equipment. While classes such as gurney, dialysis machines, masks, and infusion poles have very high accuracy, precision, and recall.

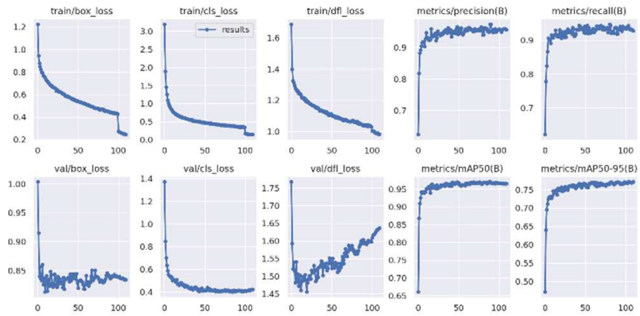

Fig. 9 Best Results from Training

Based on the best results during the 2nd training. the model has a consistent decrease in train/validation loss, which is associated with an increase in precision, recall, and mAP. This shows that the model is learning well and can detect objects with high accuracy. After finding a model that seemed to suit the object detection needs, a system with an integrated camera was developed that would be used to implement the model.

Correct Detection (1) Wrong Detection (2) Result on Webcam (3)

Fig. 10 Example of object detection test results using YOLOv8

The following is a sample that shows correctly detected data (1), incorrectly detected data (2), and the results of implementing the model on the webcam (3).

TABLE II. COMPARISON WITH PREVIOUS RESEARCH

Dataset of research	Technology	Results
Personal protective equipment (PPE) dataset [18]	YOLOv5	• Precision: 92% • Recall: 61% • Total of images: 12.682 • 12 Categories
Personal protective equipment (PPE): CHV dataset [15].	YOLOv8	• 6 categories • Precision: 94% • Recall: 86%
This Research	YOLOv8	• 16 class • Precision: 94% • Sensitivity/Recall 92,2% • Accuracy: 90%

This research has many advantages and improvements. Both from accuracy, precision, and recall. With the advantage of quite a lot of dataset categories. The YOLOv8 model is still able to maintain good detection accuracy.

V. CONCLUSION

Based on this study, the implementation of a real-time object detection system using YOLOv8 significantly improved hospital asset management, reduced operational costs, and improved patient care by minimizing delays[1]. The YOLOv8 algorithm performed very well in identifying medical equipment. The model obtained 94% precision, 92.2% recall, and 90% accuracy using a dataset with 16 classes, higher than previous studies. Demonstrating the flexibility of the model in various detection tasks. Testing the model on larger and more diverse datasets such as photos with various objects will help assess how well it performs in increasingly complex circumstances. More comprehensive and accurate results will also be obtained by increasing the quantity of training and testing photos and classification categories.

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