Brilliance
Research of Artificial Intelligence

E-ISSN : 2807-9035
Volume 6, Number 2, May 2026
https://doi.org/10.47709/brilliance.v6i2.8453

Real-time Detection of Magnetic Resonance Imaging (MRI) Safe Label using Deep Learning for Standardization

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open access

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Article History:
Submitted: 01-05-2026
Accepted: 10-05-2026
Published: 14-05-2026

Keywords:
MRI-safe Label Detection; Deep Learning; Real-time Object Detection; Medical Imaging Standardization; YOLOv11 Framework.

ABSTRACT

Magnetic Resonance Imaging (MRI) is an imaging modality that uses a non-ionising magnetic field, so it does not cause radiation exposure. However, a high magnetic field strength still poses a significant safety risk due to projectile effects, so screening is necessary to verify that standard MRI objects are present. This study aims to develop an MRI-safe Label Detection using You Only Look Once version 11 (YOLOv11) Framework. The YOLOv11 is one of the Deep Learning algorithms that is used for Real-time Object Detection with Medical Imaging Standardization. The dataset used consists of a standard MRI bed image and a normal patient bed obtained from several MRI facilities, with an image size of 640 pixels, and divided into four classes. The results show that the model achieves an accuracy of 97,5%, a precision of 99,1%, a recall of 98,8%, an F1-Score of 98,9%, and an mAP50 of 98,9%, which indicates excellent detection performance. The Loss curve analysis shows a stable training process without any indication of significant overfitting. In addition, the confusion matrix shows high classification ability in each class. This research aims to develop an automated safety screening system for zone three MRI to reduce the risk of accidents. However, limitations include the small number of datasets and the limited variety of objects. Therefore, further development is recommended by increasing the variety of object data and integrating real-time systems and supporting hardware.

INTRODUCTION

Magnetic Resonance Imaging (MRI) is an imaging modality that uses a highly sensitive magnetic field, thus avoiding radiation exposure, but this does not make it risk-free (Nordin et al. 2024). MRI examination facilities can be highly hazardous and require special attention, as objects made of ferromagnetic materials, such as patient equipment (patient beds, IV poles, wheelchairs, and oxygen tanks), and certain components of implanted medical devices (prostheses, pacemakers, and neurostimulators) can be attracted to the strong magnetic field. This effect is known as the projectile (Mittendorff, Young, and Sim 2022).

In line with national safety standards, the American College of Radiology (ACR) recommends that all MRI facilities implement safety guidelines as a preventative measure to minimise projectile incidents. This includes the use of a Ferromagnetic Detection System (FMDS) as a supporting method for safety screening before entering zones III and IV of the MRI facility. MRI Zone III is the final access control area before entering Zone IV (the magnetic chamber), where the static magnetic field is strong enough to attract ferromagnetic objects, allowing only labelled MRI-safe objects to enter. Nevertheless, in practice, the system detects only ferromagnetic objects without distinguishing whether they are hazardous. For example, a wheelchair labelled MRI-safe may still contain small amounts of ferromagnetic metal in its wheels, which can trigger an alarm, even though it is safe to use in an MRI room. This condition can lead to alarm fatigue, a state caused by frequent and unexplained alarms. If staff habitually ignore these alarms, the risk of accidents remains (Alghamdi 2023).

A survey conducted by Ayasrah, (2022) Of the 38 MRI facilities in June 2021, three (7.9%) had patient stretchers labelled MRI-safe. The study also found that only four of the 38 facilities in Jordan implemented MRI safety training. This still poses a risk to the safety of patients and medical personnel during MRI procedures. Inaguma et al., (2023) using a national database in Japan showed that the number of accident cases due to patient beds being pulled into the MRI bore was four cases in the period 2010-2019, where a patient suffered a skull fracture and intracranial bleeding because the bed was pulled into the MRI bore. To improve safety in the MRI zone III, this study presents a real-time system to recognise standard MRI bed labels using a Deep Learning-based YOLOv11 Model.

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LITERATURE REVIEW

You Only Look Once (YOLO) is a deep learning network based on a Convolutional Neural Network (CNN) (Baccouche et al. 2022) that efficiently predicts bounding boxes and classifies images in real-time (Salman et al. 2022) from a single-stage input image (Kabir et al. 2025). YOLOv11 is a recent development of the previous version, YOLOv8, using C3k2 convolutional layers instead of C2F, enabling faster computation while maintaining accuracy and reducing overhead (Khanam and Hussain 2024).

Our proposed approach applies an object detection model to recognise and differentiate between normal patient beds and standard MRI patient beds. This proposed research has never been conducted by others. To date, no other specific real-time research has used the YOLO model for standard MRI bed label detection in MRI facilities. A study conducted by Widayani, Kusuma, and Purwanto (2022) used the YOLOv4-tiny model to recognise and differentiate between visually impaired and non-visual individuals in real-time. Another study related to the use of the real-time YOLOv11 model, namely that conducted by Liu and Zhou (2025) to detect blood cell types in real-time, reported a satisfactory assessment with a precision of 83%, a recall of 99%, and an F1-Score of 83%. A study comparing YOLO variations with transfer learning for real-time UAV obstacle detection in a forest simulation showed that the YOLOv11m model obtained a precision value of 84%, a recall of 78%, was superior in correctly classifying obstacles, and had minimal false negatives, resulting in minimal errors in identification when compares to YOLOv8, v9, and v10 which still had difficulty classifying obstacles with a higher false negative rate (Partheepan, Sanati, and Hassan 2025). Furthermore, research using the YOLOv11 model, improved with SLAM for an Autonomous Visual Inspection Robot system, achieved an mAP50 value of 92,1% at 45 FPS (Gao 2025).

Several other studies have explored the use of the YOLO model in healthcare, but with static images. One example is the use of object detection to detect brain tumours using YOLOv5m, conducted by Muksimova et al. (2025) entitled "A Lightweight Attention-Driven YOLOv5m Model for Improved Brain Tumour Detection", and a study by Islam et al. (2022) that created an AI-based system for auto-diagnosing kidney diseases, including stones, cysts, and tumours, entitled "Vision Transformer and Explainable Transfer Learning Model for Auto Detection of Kidney Cyst, Stone, and Tumour from CT-Radiography". Furthermore, another study conducted by Sun et al. (2022) The title "Kidney Tumour Segmentation Based on FR2PattU-Net Model" uses the FR2PattU-Net model to segment kidney tumour disease.

METHOD

This section explains the dataset collection procedure for normal patient bed objects and standardized MRI patient beds marked with the MRI-safe label. It starts from determining the camera position relative to the camera, and the class label used to classify the object. Next, the dataset annotation process explains the image labelling method using a 4-class scheme, namely the bed_mri class and the label_safe class for standardized MRI bed objects, and the bed_normal class and the siderail class for normal patient bed objects. The next stage is training with the YOLOv11m model, followed by model testing. The camera system is used as a vision device to acquire images in real-time, and the YOLOv11 algorithm will detect objects in the recorded images. When the system detects an MR-safe label, the object will be marked with a green bounding box. Conversely, if the MR-safe label is not detected on the object, the system will display a red bounding box. Figure 1 shows how the system works overall.

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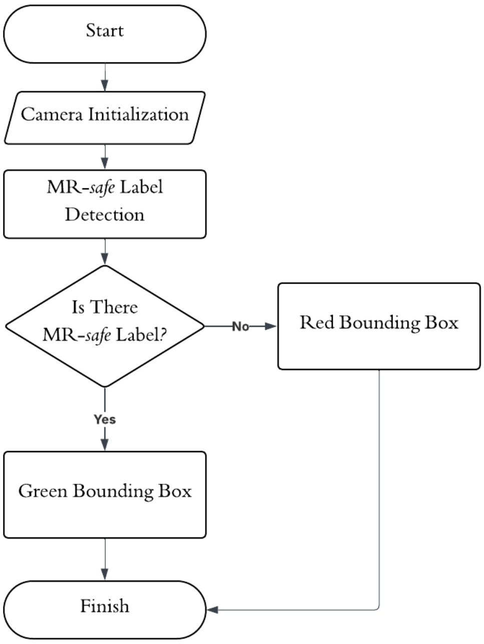

Figure 1. Flowchart of the YOLO model detection system.

Dataset

This study uses primary data collected manually from several hospitals with MRI facilities. The dataset was captured using a Logitech C922 webcam at 60 frames per second (fps) and a resolution of 1280×720 pixels. There are two object data collection scenarios: a standardized MRI bed with an MRI-safe label and a standard patient bed in general. The camera is positioned at a height of 2 meters (Fig. 2) to obtain a full view of the patient's bed. There are variations in camera position placement as a simulation of the patient bed's incoming angle, including 45 degrees from the corner of the room, from the right side, and from the left side of the incoming object, to obtain the position of the MRI-safe label in the standardized MRI patient bed.

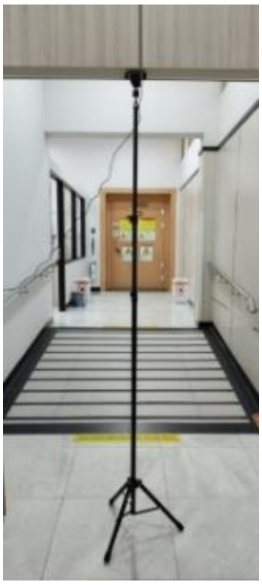

Figure 2. Camera positioned at a height of 2 meters.

After camera initiation, the data collection process was conducted across several scenarios to generate data variations. In the data collection scenario for a standardized MRI patient bed, images were taken when the object was pushed towards the camera from the front (Fig. 3). Another scenario is approaching the camera from the right side and left, turning when approaching the camera, and turning away from the camera. In the normal patient bed scenario, the same method was used, and additional scenarios were added when the siderail was lowered and raised. The total dataset

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obtained was 4,288 images, consisting of 2,144 standardized MRI patient bed images and 2,144 normal patient bed images. The next stage was image annotation using the Label Studio tool.

The annotated dataset was split into 80% (3,430 images) for training, 10% (429 images) for validation, and 10% (429 images) for testing. This process was not randomised to maintain proportional data distribution. This data sharing also aims to prevent bias during the model evaluation process, and to ensure that the developed model can demonstrate its ability to recognise new data.

Figure 3. A standard MRI patient bed object approaches the camera from the front.

Dataset Annotation

Objects in the images are annotated using a four-class scheme: details, two classes in the standardized MRI patient bed object image, and two classes in the normal patient bed object image. In the standardized MRI patient bed image, the bed object (the overall view of the object) is annotated with the class bed_mri, while the MRI-safe label is annotated as label_safe. Meanwhile, in the normal patient bed image, the bed object (the overall view of the object) is annotated as bed_normal, and the siderail on the normal patient bed is annotated as siderail. The annotation results for four classes are shown in Figure 4.

Figure 4. The annotation process for four classes

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Training Dataset

Model training was performed using the Google Colab service, NVIDIA GPUs, and the Ultralytics library. The training preparation process using the YOLOv11 model required several settings. First, create an Ultralytics training configuration file in YAML format. Second, the training parameters included the architecture and model size used, namely YOLOv11m.pt (medium version), with a number of epochs = 40 and imgsz = 640.

The YOLOv11 algorithm is the latest YOLO model developed by Ultralytics (Priyanto et al. 2026) as a refinement and improvement over its predecessor, the YOLOv8 model (Jegham et al. 2025). YOLOv11 focuses primarily on detection accuracy and speed by utilising a C3k2 network structure in convolutional layers (Khanam and Hussain 2024) Enhanced multi-scale features enable YOLOv11 to efficiently process images in a single end-to-end pass while maintaining high speed and accuracy, and reducing overhead (Partheepan et al. 2025), making it ideal for use in real-time visual systems (Gao 2025).

Model Testing

Model testing is performed on test data and evaluated using confusion matrix metrics to illustrate comparisons between model predictions and ground-truth conditions. The confusion matrix is shown in Table 1. Evaluation parameters obtained from the confusion matrix include Accuracy, Precision, Recall, F1-Score, and mAP.

Table 1. Confusion Matrix

Confusion matrix	Actual Value	
Predict Value	True Positive (TP)	False Positive (FP)
	False Negative (FN)	True Negative (TN)

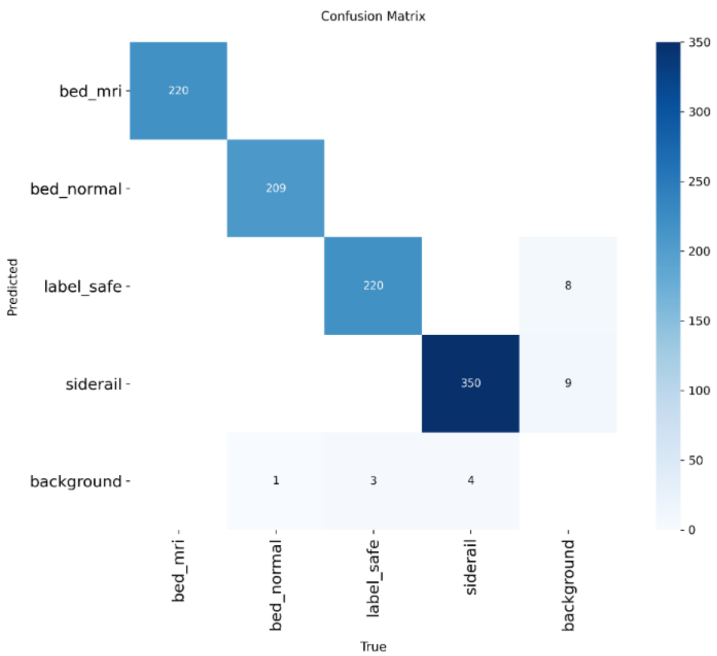

Figure 5. Confusion matrix results

RESULT

The model training results are presented as a loss function graph (Fig. 6), a YOLOv11 model training and performance test results table (Table 2), and a confusion matrix (Fig. 5), which will later be used to calculate evaluation metrics such as accuracy, precision, recall, F1-Score, and mAP. In Figure 5, the results of the confusion matrix, the main diagonal of the matrix shows the number of True Positives (TP), where in the bed_mri class, 220 objects were predicted correctly, 209 objects were predicted correctly in the bed_normal class, 220 objects were predicted correctly in the label_safe class, and 350 objects were predicted correctly in the siderail class. Then, in the bed_normal class, there is a False Positive (FP) where 1 object is predicted as background. In the label_safe class, there is also an FP where 8 objects are predicted as the background, and a False Negative (FN) where 3 objects are predicted as the background. In the siderail class, there is an FP where 9 objects are predicted as the background, and an FN where 4 objects are predicted as the background (no object of interest).

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Table 2. YOLOv11 model training and performance test results

epoch	box_loss	cls_loss	precision	recall	mAP50	mAP50-95
1	0.9988	0.9188	0.8604	0.7865	0.8854	0.6205
2	1.0412	0.7029	0.7692	0.8149	0.8903	0.5878
3	1.0128	0.6568	0.8644	0.8200	0.9174	0.6274
…	…	…	…	…	…	…
38	0.5776	0.2595	0.9906	0.9891	0.9893	0.8166
39	0.5688	0.2527	0.9851	0.9863	0.9872	0.8126
40	0.5672	0.2499	0.9844	0.9847	0.9854	0.8159

Based on Table 2, model performance during the training phase can be evaluated from the first to the last epoch. There was a significant decrease in box_loss from 0,9988 to 0,5672, and in cls_loss from 0,9188 to 0,2499. The table also shows increases in precision from 0,8604 to 0,9844, recall from 0,7865 to 0,9847, and mAP50 from 0,8854 to 0,9854.

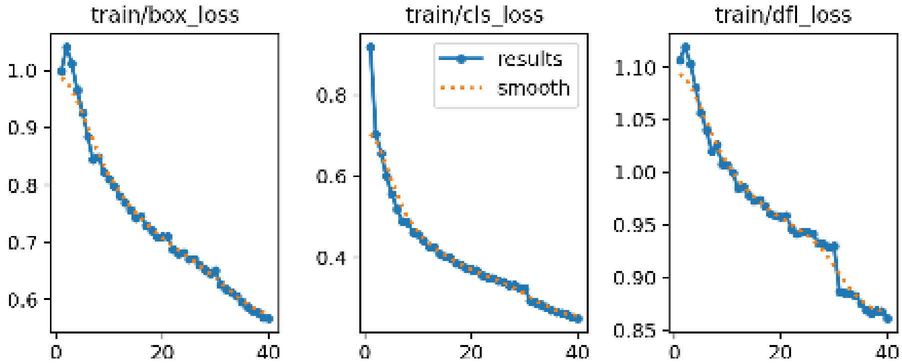

Figure 6. Loss function graph from the YOLOv11 model training results.

Figure 6 is a graphical visualisation of the training results and model performance tests. Based on the graph, the three loss graphs-box_loss, cls_loss, and dfl_loss tend to decrease as the number of epochs increases. The graphs also show stability, with no indication of significant overfitting. Meanwhile, the performance evaluation matrix, namely accuracy, precision, recall, mAP50, and mAP50-95, shows a trend upward from the first epoch and then stabilises after several epochs. The training phase yields the best-performing model, which will be stored in the best.pt file. The best model will be used in the validation and testing phases to optimally assess its performance in detecting previously unknown objects.

In the testing phase, the model achieved evaluation parameter values of 97,5% accuracy; 99,1% precision; 98,9% recall; 98,9% F1-Score; 98,9% mAP50; and 81,6% mAP50-95. Tables 3, 4, 5, and 6 show the YOLOv11 model's prediction results during testing for each class.

Table 3 shows the prediction results for the bed_mri class using the testing data. Based on the detection results, the model correctly recognised the presence of the bed MRI object, as indicated by the green bounding box. Similarly, in Table 4, the model correctly recognized the presence of the MRI-safe label on the bed MRI, as indicated by the green bounding box on the object. In the first and second samples, the system successfully detected the bed_mri and MRI-safe labels despite differences in image-capture conditions, such as camera position, object distance, and background. The results are categorized as appropriate because the model's predictions match the conditions in the test data.

Then, Table 5 shows the correct prediction results for the bed_normal class, as indicated by the red bounding box on the object. Similarly, in Table 6, the prediction results for the siderail class match the actual conditions, as indicated by the red bounding box. In both samples, the model successfully detected the bed object and both siderails on it, despite differences in how the siderails were raised and lowered. Therefore, the detection results are categorized as appropriate.

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Table 3. Prediction results for the Bed_Mri class using the testing dataset

No.	Class	Prediction results for the YOLOv11 model	Appropriate	Not Appropriate
1	bed_mri		✔	
2			✔	

Table 4. Prediction results for the label_safe class using the testing dataset

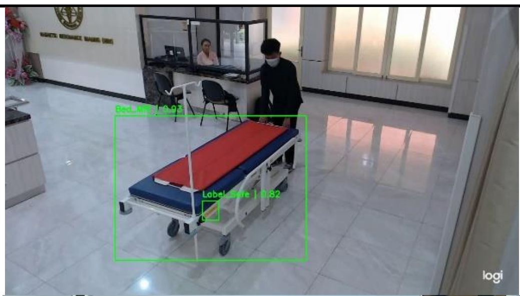
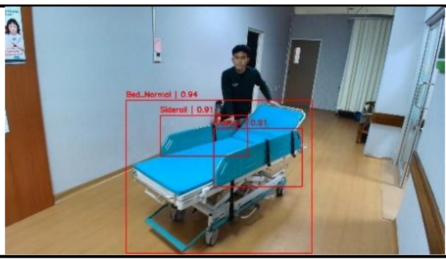
No.	Class	Prediction results for the YOLOv11 model	Appropriate	Not Appropriate
1	label_safe		✔	
2			✔	

Table 5. Prediction results for the bed_normal class using the testing dataset

No.	Class	Prediction results for the YOLOv11 model	Appropriate	Not Appropriate
1	bed_normal		✔	

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2			✔	

Table 6. Prediction results for the siderail class using the testing dataset

No.	Class	Prediction results for the YOLOv11 model	Appropriate	Not Appropriate
1	siderail		✔	
2			✔	

DISCUSSION

This study obtained an accuracy of 97,5%, precision of 99,1%, recall of 98,9%, F1-Score of 98,9%, mAP50 of 98,9%, and mAP50-95 of 81,6%. These values indicate that of all positive predictions made by the YOLOv11 model, 99,1% were correct, and only 0,9% were incorrect. This value is considered very high in model performance evaluation, indicating that the model makes very few errors when predicting objects. Partheepan et al. (2025) stated that high precision is important for avoiding unnecessary detection errors, especially in safety applications. Mokayed et al. (2024) stated that high precision is important for reducing false alarms in real-time systems and for avoiding or reducing the possibility of incorrect object interpretation by the YOLOv11 model. Therefore, the high precision value in this study indicates that the model used performs optimally in detecting patient bed objects.

Furthermore, the recall parameter value obtained by the model in this study was 98,9%. Meaning that all positive objects were correctly detected by the model 98,9% of the time, with only 1,1% errors. Research conducted by He et al. (2025) emphasised that real-time detection systems must maintain a high detection rate for target objects, as failure to detect an object can have significant consequences. In real-time situations, decisions must be made immediately, so there isn't always an opportunity for re-evaluation. This aligns with the findings in this study. If a hazardous object, in this case a ferromagnetic patient bed, were not detected, it would pose a serious safety risk.

Furthermore, the YOLOv11 model in this study achieved an F1-Score of 98,9%, indicating that the model maintained a balance between precision and recall, with only 1,1% errors. Thus, the model is good at predicting correct positives and also at not missing positive data. Research conducted by Partheepan et al., (2025) states that if the F1-Score evaluation parameter is frequently used on imbalanced data, with the expectation that a high F1-Score value will ensure the model maintains balance.

The final parameters, mAP50 and mAP50-95, were used. This study obtained an mAP50 value of 98,9%, indicating a high level of accuracy when the model was tested with an IoU threshold of ≥ 0.5, indicating that almost all objects in the class could be detected effectively. Meanwhile, the YOLOv11 model in this study achieved an mAP50-95 of 81.6%. The mAP50-95 value represents the model's performance at various more stringent threshold levels, namely IoU 0,5-0,95. Based on the mAP50-95 value obtained by the YOLOv11 model in this study, it can be concluded that the model exhibits consistent object detection performance and is effective at identifying object locations and bounding boxes.

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CONCLUSION

Based on the research results, the model successfully performed real-time detection. The implementation of a standardized MRI bed label detection system using YOLOv11 demonstrated high performance in distinguishing four classes: bed_mri, bed_normal, label_safe, and siderail. All evaluation matrix parameters exceeded 90% on a balanced dataset, with a training set of 40 epochs and imgsz of 640, resulting in an accuracy of 97,5%, a precision of 99,1%, a recall of 98,9%, an F1-Score of 98,9%, and an mAP50 of 98,9%.

Based on the results achieved, this research contributes to the development of an automated deep-learning-based screening system in MRI facilities for MRI patient beds to mitigate potential safety risks. However, limitations include the dataset's small size and limited object variety. Therefore, further development is recommended by increasing the variety of object data and integrating it into a real-time system with supporting hardware.

ACKNOWLEDGMENT

The authors would like to thank Ms Aisyah Widayani and Ms Alifatus Wahyu Nur Ma'rifah, their supervisors, for their assistance in preparing this research paper. We also extend our gratitude to RKZ Hospital in Surabaya, Gambiran Regional Hospital in Kediri, Sakinah Hospital in Mojokerto, R.T. Notopuro Regional Hospital in Sidoarjo, and Dr Soewandie Regional Hospital in Surabaya, as well as to our colleagues who participated in creating this dataset.

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