Improved YOLOv8 Model for Enhanced Small-Sized Breast Mass Detection on Magnetic Resonance Imaging

Feiyan Wu[1], Chia Yean Lim[2]*, Sau Loong Ang[3], Jiaxin Zheng[4]
School of Computer Sciences, Universiti Sains Malaysia, 11800, Minden, Penang, Malaysia[1, 2, 4]
Tunku Abdul Rahman University of Management and Technology, Penang Branch, Tanjung Bungah, Malaysia[3]

***Abstract*—The early detection of breast cancer is critically important for prompt treatment and rescuing lives. However, the accuracy of small-sized breast masses' early detection in various algorithms remains unsatisfactory, as the small-sized masses often exhibit subtle features, contain blurry boundaries, and may overlap with other parts in crowded magnetic resonance imaging (MRI) images. This research proposes an improved object detection model based on You Only Look Once (YOLO) v8 to enhance small-sized breast mass detection on MRI. A feature fusion method called the Bidirectional Feature Pyramid Network (BiFPN) and an attention mechanism called the Convolutional Block Attention Module (CBAM) are integrated into the YOLOv8 architecture. The improved YOLOv8 model, equipped with CBAM and BiFPN and hyperparameter tuning, achieved the best performance with a precision of 95.7%, a mAP50 of 91.2%, a recall of 84.3%, and the shortest inference time of 3.4ms per image. The proposed improved Yolov8 model outperformed the baseline model with improvements in precision, mAP50, and recall of 6%, 3.9%, and 2.1%, respectively. The inference time per image is reduced by 1.4ms as well. It is hoped that the proposed model could be applied in the clinical field to increase the early detection rate of breast cancer and the life expectancy of women in the world.**

Keywords*—*Bidirectional feature pyramid network; breast cancer detection; convolutional block attention module; MRI; object detection; small-sized masses; YOLOv8

I. Introduction

Breast cancer was the top female disease in 157 of 185 countries and accounted for approximately 670,000 deaths in 2022 worldwide [1], according to the World Health Organisation. However, it was also the most common subject of diagnosis. It was even identified as the first leading cause of death from cancer among women in 2022, according to the Global Cancer Statistics [2]. There are several imaging methods to screen breast cancer, including ultrasonography, mammography, magnetic resonance imaging (MRI), and digital breast tomosynthesis (DBT). Among these methods, mammography is the preferred population-based screening method [3]. However, mammography is less effective for screening dense breasts, as it risks missed diagnoses because small masses that hide in dense breast tissue cannot be detected [4][5]. The sensitivity of breast mass detection increases from 0 to 8% when the tumour size increases from 2 to 20mm [6]. On the other hand, the performance of breast cancer detection in medical imaging is also affected by the increase in breast tissue density [7].

Recently, breast MRI was used complementarily together with mammography and has been researched as a crucial screening tool for women with dense breasts [8]. Currently, the accuracy of breast cancer detection and diagnosis still highly depends on the variations of experts and experienced physicians. Moreover, the existing research on breast masses has primarily focused on overall object detection rather than improving the accuracy of detecting small-sized breast masses [9][10]. In [11] and [12], the authors commented that the performance of small-sized breast mass detection had not achieved the expected results, even though significant improvements had been made in the breast cancer detection models' feature extraction and target detection algorithms.

This research proposes an improved You Only Look Once (YOLO) v8 model for enhanced detection of small-sized breast masses on MRI, aiming to improve the detection precision and mAP of these small masses. The improved model is expected to perform better in detecting small-sized breast masses by adopting an appropriate attention mechanism. Improving the feature fusion method would enhance the fusion effect of the multi-scale features in the improved model. Finally, hyperparameter tuning is conducted to strengthen the performance of the detection model.

The rest of the study is organised as follows: Section II reviews various object detection models in breast cancer detection, feature fusion methods, and attention mechanisms. Section III presents the methodology of the proposed improved YOLOv8 model. Section IV discusses the experimental results and analysis. Finally, Section V concludes the study and outlines future research directions.

II. Literature Review

A. *Breast Cancer Detection and Imaging Types*

In medical imaging, the most common screening techniques to diagnose breast cancer are breast ultrasound, mammography, breast magnetic resonance imaging (MRI) and digital breast tomosynthesis (DBT). Although mammography is the only imaging test that has been demonstrated to decrease deaths from breast cancer, breast MRI has taken its superior role in the screening of high-risk populations because of the high sensitivity of the images [13]. Two advantages of using breast

MRI over mammography are: i) the breast MRI can detect smaller tumours with a median size of 9 mm with higher sensitivity, in comparison to 17 mm for mammography [14], and ii) the breast MRI uses a different imaging mechanism with magnetic fields and radio waves which is particularly effective in dense breast tissue screening, enabling the excellent performance of dense breast tissue evaluation and additional lesions' detection. Despite the higher cost and longer procedure time in the breast MRI screening process, MRI is still the preferred breast cancer detection method, where mammography's effectiveness is limited in the detection of smaller and additional lesions.

B. Object Detection Model in Breast Cancer Detection

The YOLO model is a real-time object detection system introduced by Redmon, Divvala, Girshick, and Farhadi [15]. Ultralytics created and released YOLOv8 in January 2023 as a new state-of-the-art computer vision model that provides out-of-the-box support for object detection, classification, and segmentation tasks [16]. The YOLO model treats object detection tasks as a regression problem, predicting bounding boxes and class probabilities for objects in a single convolutional network. It runs a convolutional network to process each grid cell, where it divides the input image into a grid of cells. Each grid cell will perform detection if there is an object within it, make predictions for bounding boxes, calculate the confidence scores for those boxes, and determine conditional class probabilities. When making predictions, the YOLO model performs global reasoning across the entire image, allowing it to detect all objects within the image. Additionally, the YOLO design enables end-to-end training and achieves real-time performance while maintaining a high average precision (AP) [15]. The main advantages of the YOLO model are fast speed, high accuracy, and suitability for real-time applications. As a single-stage model, YOLO has been proven to be an excellent tool in various scenarios, achieving higher inference speeds than its competitors in object detection [17].

Table I summarises the comparison of the strengths, weaknesses, and results of different object detection methods in breast mass detection over the past five years. The comparison shows that YOLO [18] [19] and region-based object detection methods such as Faster R-CNN [20], Mask R-CNN [21], and R-FCN [22] were popular. Additionally, RetinaNet was also employed in breast mass detection from 2023 onwards, reflecting a growing emphasis on the real-time capabilities of single-stage models as time progresses [23].

Several recent studies have explored the performance of different object detection models for breast mass detection. Faster R-CNN achieved a high true positive rate, but its inference time was significantly longer than single-stage models like YOLO and RetinaNet [20]. RetinaNet has limitations in detecting small objects due to its fixed-size anchor boxes. Even with the recent improved version ERetinaNet, the inference speed still lags behind YOLOv3 and YOLOv7 [23]. YOLOv3 was enhanced with k-means generated anchors for detecting small and big masses, which outperformed YOLOv2 and YOLOv3, and achieved a mAP50 of 89.4% [18]. The YOLOv5 model was also improved for better breast cancer detection in mammograms. The YOLOv5s model obtained a mAP50 of 83.5%, a precision of 85.4% and a recall of 72.9%, which performed better than YOLOv3 and YOLOv5-Transformer [17]. These results reinforce the advantage of YOLO-based models in balancing speed and accuracy, making them suitable foundations for further improvement in small object detection tasks.

TABLE I. COMPARISON OF DIFFERENT OBJECT DETECTION METHODS IN BREAST MASS DETECTION

Detection Model	Strength	Weaknesses	Results
YOLOv3 [18]	• Fast speed with high accuracy • Suitable for real-time applications	• Performance for small object identification can be further improved.	mAP50: 89.4% Precision: 83.0% Recall: 83.0%
YOLOv5 [19]	• Fast speed with high accuracy • Suitable for real-time applications • Provide improved performance for small object detection	• Higher complexity than YOLOv3 Requires more computational resources.	mAP50: 90.34%
Faster R-CNN [20]	• Provides high accuracy • Suitable for handling various types and sizes of objects	• Slower speed • Requires larger memory consumption • Contains higher computational complexity.	Malignant: TPR: 0.92 at 0.3 FPI. Benign: TPR: 0.85 at 1.0 FPI.
Mask R-CNN [21]	• Provide accurate instance segmentation • Suitable for tasks requiring detailed object region information	• Slower speed • Requires larger memory consumption • Contains higher computational complexity	Accuracy: 98%
R-FCN [22]	• Faster speed in the two-stage approach category • Provides high accuracy	• Contains high computational complexity • Poor performance when objects are extremely small or extremely large compared to the size of the input image	Accuracy: 92.5% Sensitivity: 92.3% Specificity: 93.4%
RetinaNet [23]	• Simple and efficient • Good object detection performance and speed, excellent in handling imbalanced class distribution problems.	• May struggle with small object detection. • Requires more computational resources.	mAP50: 85.01% Precision: 86.87% Recall: 74.62% F1-score: 80.3% Inference time: 23.4ms per image

From the comparison, almost all models faced challenges in small object detection, with RetinaNet, R-FCN, and YOLO showing more pronounced weaknesses in this area. On the other hand, although RetinaNet, as used in [23], had a slightly longer inference time than existing YOLO models, it excelled in addressing class imbalance issues, where positive breast cancer detection cases are significantly fewer than negative cases. In addition, it was observed that all the object detection models, except for YOLO, in Table I have problems with high computational complexity.

This research chose the YOLO model as the object detection method to be improved for small-sized breast mass detection on MRI for several reasons. Firstly, the YOLO model is faster than other models. Secondly, YOLO is suitable for real-time applications, where breast cancer detection can be done almost instantly after MRI scanning is completed, thereby saving diagnostic time, expediting the decision-making process, and facilitating early treatment planning between the doctor and patient. Thirdly, the YOLO model has progressively improved accuracy and mAP values from YOLOv3 to YOLOv5.

In the current state-of-the-art, the YOLOv8 model has demonstrated its advantages in detecting small objects in remote sensing images [24]. It has been used to detect liver disease [25], identify potato diseases [26], and detect pedestrians in real-time [27]. The YOLOv8 model has also been adopted for breast mass detection and classification in [28]. However, the model encounters difficulties in detecting small objects in complex scenes, especially when their appearance is partially occluded by overlapping with other objects of varying sizes, which can lead to missed or false detections. As such, the YOLO model should be enhanced with various techniques to address its weaknesses.

C. Feature Fusion Methods

Feature fusion enhances the accuracy and robustness of an object detection model by leveraging complementary information from various sources and employing an approach that reduces information redundancy. The feature fusion method merges morphological, textural, and density features to create a more comprehensive representation of the object. This comprehensive representation enables the detection system to capture the target's features more effectively, resulting in more accurate and reliable detection results. On the other hand, the feature fusion method also enhances the sensitivity and robustness of the model in small object detection by adaptively combining features from multiple scales and layers, thereby capturing both high-level semantic and low-level spatial information.

Feature fusion methods such as the Asymptotic Feature Pyramid Network (AFPN), Bidirectional Feature Pyramid Network (BiFPN), and the Semantic Feature Pyramid Network (FPN) have been applied to improve the performance of YOLO [29]–[32] and Faster-RCNN [11] models in small object detection tasks. It is observed that the YOLO models [31] [32] achieved a slightly higher mAP50 value (highest 90%) when integrated with BiFPN, in comparison to Semantic FPN (highest 88.22%) [11] and AFPN (highest 88%) [29][30]. With accuracy being a key consideration in model performance, this research aimed to integrate the YOLOv8 model with BiFPN for the detection of small-sized breast masses. Moreover, BiFPN is also more appropriate because it can efficiently fuse multi-scale features and improve detection performance without significantly increasing computational complexity.

D. Attention Mechanisms

An attention mechanism enhances the performance of object detection models by allowing the model to focus on specific regions or features of the image [33]. This mechanism also helps to prioritise fine-grained or key features which are particularly beneficial for detecting small objects in complex visual backgrounds [34]. It is instrumental in challenging scenarios, such as detecting minor defects or tumours in cluttered backgrounds. The attention mechanism can improve the accuracy of breast mass detection by guiding the model's focus to specific regions of interest in medical images [35]. By incorporating the attention mechanism into the detection model, the object detection model can prioritise relevant features of small targets even when they are occluded or surrounded by other objects [36].

The Convolutional Block Attention Module (CBAM) is a popular attention mechanism. CBAM was adopted in the YOLOv7 model for brain tumour detection, and this combined model achieved 98.9% precision, 98.8% recall, and 98.9% accuracy [32]. The CBAM was also incorporated into the backbone network of the YOLOv5 model for breast lump detection, yielding improvements in accuracy, recall, and mAP50 values of 3.1%, 2.6%, and 3.1%, respectively, compared to the baseline YOLOv5 model [37]. As such, this research attempted to integrate CBAM into the YOLOv8 model to increase the precision and mAP value for small-sized breast mass detection.

III. METHODOLOGY

This research is conducted in five phases. The primary objective is to propose an enhanced YOLOv8 model for improved small-sized breast mass detection on MRI by integrating CBAM into the backbone structure and BiFPN into the neck structure of a baseline YOLOv8 model. The structure of the improved YOLOv8 Model for the research is shown in Fig. 1.

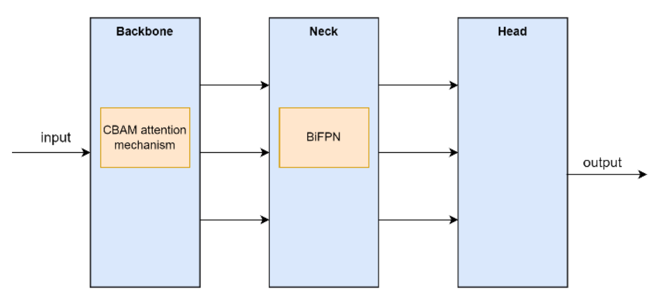

Fig. 1. Structure of the improved YOLOv8 model.

The research began with the data selection and pre-processing phase. This research used the annotated version of the BreastDM dataset [38]. It is the latest Dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) dataset for breast cancer diagnosis, spanning from January 2018 to

September 2021, and collected at Taizhou Central Hospital, Taizhou University, in Zhejiang Province, China. The dataset is publicly available on the Roboflow Universe website [39]. There are 1196 images in the selected dataset, with 875 malignant images and 321 benign images. These images are labelled according to the pathology of the mass in 2 classes, with class label 0 representing benign and class label 1 representing malignant.

The selected dataset is first converted from the original annotation in COCO format to YOLOv8 object detection format via the Roboflow platform. Following format preparation, 70% of the dataset is assigned to a training partition, 15% to a validation partition, and the remaining 15% to the test partition. The resolution of all images was resized from 369 × 369 pixels to 640 × 640 pixels, and the proportion of small objects was 37.5%. In addition, the YOLOv8 model will also automatically normalise the pixel values to a range of 0 to 1 during its preprocessing phase.

Several data augmentation techniques are employed to address the data imbalance problem and enhance the robustness and generalisation of the proposed model. In addition, these augmentation techniques introduced variability in the training data, allowing the YOLOv8 model to learn more robust features and improve performance on diverse and noisy datasets. Firstly, the HSV augmentation is utilised with parameters for hue (±1.5%), saturation (±70%), and value (±40%) adjustments. Secondly, spatial augmentations such as translation (±10%), scaling (±50%), and left-right flipping with a 50% probability were conducted too. Thirdly, the Mosaic augmentation is applied with a 100% probability. Finally, random erasing is performed with a 40% probability, and cropping is set to a fraction of 1.0 to maintain the original image size. The proposed YOLOv8 model chose "Randaugment" as the auto augmentation policy.

In the second phase, the baseline YOLOv8 model was created and trained on the selected dataset. The CBAM attention mechanism and BiFPN are integrated separately into the YOLOv8 model in the third and fourth phases. The performance of the baseline YOLOv8 model in the second phase, as well as the improved model in the third and fourth phases, is measured with precision, recall, mAP50, and mAP50-95. Subsequently, in the fifth and final phase, the YOLOv8 model, integrated with CBAM and BiFPN, is constructed, evaluated, and fine-tuned to adapt it to the breast mass detection task and the selected dataset.

The experiments were conducted in Google Colab Pro using T4 GPUs and A100 GPUs. The experiment program is written in Python. All the experiments of the proposed enhanced small-sized breast mass detection model are based on the AdamW optimiser. The experiment specifications are as follows:

- Weight decay: 0.0005
- Learning momentum: 0.9
- Learning rate: 0.001667
- Epochs: 300
- Batch: 32
- Warmup epochs: 3.0
- Warmup momentum: 0.8

IV. Results and Discussion

The evaluation of the proposed improved YOLOv8 model was conducted in several stages. In the first stage, the original YOLOv8 model serves as the baseline. Following this, the YOLOv8 model is run with a single feature (CBAM or BiFPN), two features (CBAM and BiFPN), and two features (CBAM and BiFPN) with Hyperparameter Tuning. The full result is shown in Table II.

Table II shows that the precision, recall, and mAP50 values of the original YOLOv8 model are below 90%. The mAP50-95 achieved 63.2% while the inference time per image is 4.8ms. The goal of this research is to enhance the YOLOv8 model for small-sized breast mass detection in MRI, aiming to improve precision, recall, and mAP50 values while reducing inference time per image to achieve faster detection speed. The evaluation of the improved YOLOv8 model with CBAM showed that the precision, mAP50, and mAP50-95 are increased by 4%, 3.1%, and 1.8%, respectively, with unchanged recall value, and higher inference time per image (+3.2ms). These results demonstrate the effectiveness of the proposed backbone network and its improved detection performance. On the other hand, the evaluation of the enhanced YOLOv8 model with BiFPN showed that the mAP50 and mAP50-95 increased by 0.6% and 0.2%, respectively. Still, the precision and recall values were lower than those of the baseline YOLOv8 model by 0.1% and 0.5%, respectively. However, this improved model required less inference time per image (-0.2ms) than the YOLOv8 baseline model.

TABLE II. The Evaluation Result of the Proposed YOLOv8 Model in Various Stages

Model	Precision (%)	Recall (%)	mAP50 (%)	mAP50-95 (%)	Inference time per image (ms)
Original YOLOv8 model	89.7	82.2	87.3	63.2	4.8
YOLOv8 model with improved backbone by using CBAM	93.7 (+4.0)	82.2 (0.00)	90.4 (+3.1)	65.0 (+1.8)	7.0 (+3.2)
YOLOv8 model with improved neck by using BiFPN	89.6 (-0.1)	81.7 (-0.5)	87.9 (+0.6)	63.4 (+0.2)	4.6 (-0.2)
Improved YOLOv8 model with CBAM and BiFPN	92.5 (+2.8)	**87.5 (+5.3)**	90.7 (+3.4)	66.8 (+3.6)	5.1 (+0.3)
Improved YOLOv8 model with CBAM and BiFPN (Hyperparameter Tuning)	**95.7 (+6.0)**	84.3 (+2.1)	**91.2 (+3.9)**	**67.0 (+3.8)**	**3.4 (-1.4)**

Comparing the two improved YOLOv8 models with CBAM and BiFPN, CBAM performed better than BiFPN in all evaluation metrics except for inference time per image. Although the enhanced YOLOv8 model with BiFPN exhibits a slight decrease in precision and recall, it improves the mean Average Precision (mAP50 and mAP50-95) and reduces inference time. BiFPN enhanced the YOLOv8 model's ability to recognise masses of different scales by increasing the complexity of feature fusion. However, the BiFPN's complex structure and computational demands make the improved YOLOv8 model training and optimisation more difficult, resulting in a drop in precision and recall metrics. Additionally, BiFPN may require careful parameter tuning for optimal performance. Overall, the improvement in mAP demonstrates its potential in small object detection tasks.

To prove the effectiveness of adding BiFPN into the YOLOv8 model for small mass detection, the second stage of the experiment was conducted by combining CBAM and BiFPN into the YOLOv8 model. The experimental results showed that all evaluating metrics achieved improvements in the range of 2.8% to 5.3%, with precision and mAP50 achieving values higher than 90%. However, the inference time per image is slightly increased by 0.3ms. Therefore, the experiment proceeds to the final stage, whereby the improved YOLOv8 model for enhanced small-sized breast mass detection on MRI is built by fine-tuning the hyperparameters of the improved YOLOv8 with CBAM and BiFPN. This enhanced model achieved the best performance among other improved models, with a precision of 95.7%, a recall of 84.3%, a mAP50 of 91.2%, a mAP50-95 of 67.0%, and the shortest inference time of 3.4 ms per image. The best hyperparameters for the final improved YOLOv8 model obtained after hyperparameter tuning are shown in Table III.

TABLE III. BEST HYPERPARAMETERS OF THE PROPOSED IMPROVED YOLOV8 MODEL

Hyperparameter	Best fitness amount
lr0	0.00338
lrf	0.01684
momentum	0.81006
weight_decay	0.00044
warmup_epochs	2.50590
warmup_momentum	0.79978
box	2.88344
cls	0.51721
dfl	2.12637
hsv_h	0.01001
hsv_s	0.32297
hsv_v	0.52034
translate	0.10270
scale	0.28700
fliplr	0.29108
mosaic	0.44672
mixup	0.45000

According to the comparison of the normalised confusion matrix for the baseline and proposed improved YOLOv8 model, the enhanced YOLOv8 model shows a higher classification accuracy for the malignant class (95%) than the baseline YOLOv8 model (91%). The classification accuracy for the benign class has also increased to 80%, helping to mitigate the negative impact of class imbalance. On the other hand, the issue of misclassifying malignant masses as benign in the original YOLOv8 model has been addressed, resulting in a reduction of the error rate from 2% to 0% in the improved YOLOv8 model. In comparison, the misdetection of benign masses as malignant has decreased from 4% to 2%. Additionally, the misclassification of malignant masses as background has reduced from 7% to 5%.

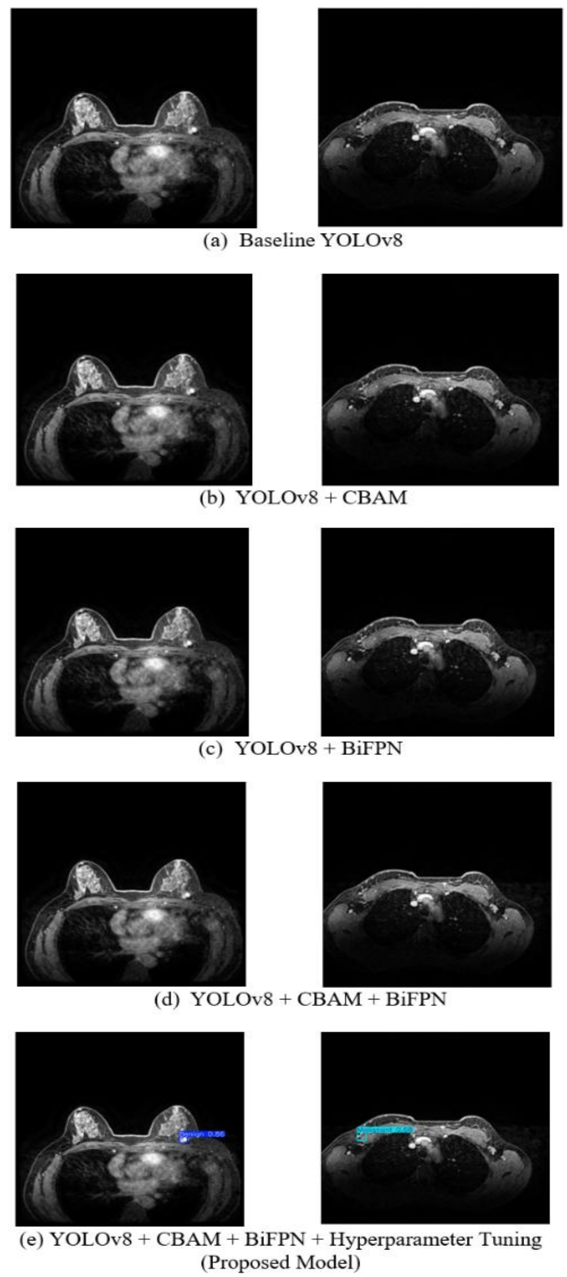

Fig. 2. Result of small mass detection with MRI with different YOLOv8 models.

Fig. 2 shows two detection results of different experimented YOLOv8 models. In the left image, the breast tissue is dense and has similar texture features to the masses, which interferes with the model's accuracy in judging the masses [7]. The right image shows a small breast, where the mass is located at the edge of the breast, close to the pectoral muscle. The pectoral muscle increases the complexity of the MRI image background [40], affecting the model's ability to detect small malignant masses with very subtle features. The two results showcases where benign small masses and malignant small masses in the MRI dataset are not detected by all the YOLOv8 models [Fig. 2(a) to Fig. 2(d)] in the study except for the improved YOLOv8 model with CBAM and BiFPN with hyperparameter tuning [Fig. 2(e)]. This demonstrates the effectiveness of the proposed improved YOLOv8 model.

In terms of evaluation, the proposed improved YOLOv8 model achieved strong overall performance, with a mAP50 of 91.2%, precision of 95.7%, recall of 84.3%, and an inference time of 3.4 ms per image. Compared to existing studies, relatively few have focused specifically on detecting small-sized breast masses using YOLO-based approaches. Among those, a YOLOv5-based model reported a mAP50 of 90.34% and an inference time of 28 ms per image [19], which is lower in accuracy and significantly slower than our proposed model. These results highlight the effectiveness of the enhancement in this study for both detection precision and computational efficiency.

V. Conclusion and Future Work

This research proposes an improved YOLOv8 model designed to enhance the detection performance of small breast masses on MRI. By integrating CBAM and BiFPN into the YOLOv8 architecture, this study has successfully overcome the limitations of the existing YOLOv8 model in detecting small masses. CBAM enhances the model's focus on subtle and essential features, particularly when handling occluded small masses. Meanwhile, BiFPN enhances the fusion of multi-scale features, further improving the model's detection accuracy. With the achievement of a reduction in inference time per image in the improved YOLOv8 model, this research contributes to more effective and timely breast cancer detection, particularly in detecting small masses in MRI images.

In conclusion, this research proposed an improved YOLOv8 model, which significantly enhances the performance in detecting small-sized breast masses on MRI, thereby improving the accuracy of early-stage breast cancer detection. Early detection is critical for breast cancer, as it increases the chances of successful treatment and survival. This research facilitates timely diagnosis and treatment by providing physicians with a more accurate and real-time tool for identifying potential breast masses, ultimately improving patient survival rates. The performance of the improved YOLOv8 model has been validated only on the selected breast mass MRI dataset. However, no experiments are conducted on the proposed model's transferability and generalizability to other medical images.

In the future, further studies could be performed to investigate the model's transfer learning capability across various medical image datasets. This would help evaluate whether the model maintains its effectiveness in different imaging modalities, such as mammography, ultrasound, or CT, and under varying imaging conditions. On the other hand, the improved YOLOv8 model can also be examined for its applicability in detecting small masses for different cancer types, such as those affecting the lungs and brain. Furthermore, the model can be integrated into real-time diagnostic workflows in clinical practice to assist radiologists in detecting breast masses more efficiently and accurately. In addition, applying these enhancements to newer YOLO models may help assess whether they lead to further performance improvements.

References

[1] World Health Organisation. "Breast cancer" [Internet] 2024 [Retrieved 2024 March 28] Available at: https://www.who.int/news-room/fact-sheets/detail/breast-cancer.

[2] F. Bray, M. Laversanne, H. Sung, J. Ferlay, R. L. Siegel, I. Soerjomataram, A. Jemal, "Global cancer statistics 2022: GLOBOCAN Estimates of incidence and mortality worldwide for 36 cancers in 185 countries," CA Cancer J Clin, vol. 74(3), 2024, pp. 229–263.

[3] D. P. Budh and A. Sapra, "Breast cancer screening in the average-risk patient." [Internet]. StatPearls StatPearls Publishing, 2024 [Retrieved 2024 March 28] Available at: https://www.ncbi.nlm.nih.gov/books/NBK556050/

[4] J. Kollmer, "Perfecting MRI as a breast cancer screening tool," [Internet] 2022 [Retrieved 2024 March 28] Available at: https://www.uchicagomedicine.org/forefront/cancer-articles/perfecting-mri-as-a-breast-cancer-screening-tool

[5] R. M. Mann, N. Cho and L. Moy, "Breast MRI: State of the art." Radiology, vol. 292(3), 2019, pp. 520–536.

[6] J. Wang, P. Gottschal, L. Ding, DAV. Veldhuizen, W. Lu, N. Houssami, MJW. Greuter and GH. de Bock, "Mammographic sensitivity as a function of tumor size: A novel estimation based on population-based screening data." Breast, vol. Feb 55, 2021, pp.69-74.

[7] I. V. Gruber, M. Rueckert, K.O. Kagan, A. Staebler, K.C. Siegmann, A. Hartkopf, D. Wallwiener and M. Hahn, "Measurement of tumour size with mammography, sonography and magnetic resonance imaging as compared to histological tumour size in primary breast cancer." BMC Cancer, vol. 13, 2013, pp.1-8.

[8] E. Verburg, G.C. Van Gils, M.F. Bakker, M.A. Viergever, R.M. Pijnappel, W.B. Veldhuis and K.G.A. Gilhuijs, "Computer-aided diagnosis in multiparametric magnetic resonance imaging screening of women with extremely dense breasts to reduce false-positive diagnoses." Invest Radiol, vol. 55(7), 2020, pp. 438–444.

[9] M.M. Rahman, M.Z.B. Jahangir, A. Rahman, M. Akter, M.A. Nasim, K.D. Gupta and R. George, "Breast cancer detection and localizing the mass area using deep learning." Big Data Cogn Comput, vol. 8(7), 2024, pp. 80.

[10] S. Saikia, T. Si, D. Deb, K. Bora, S. Mallik, U. Maulik, U. and Z. Zhao. "Lesion detection in women breast's dynamic contrast-enhanced magnetic resonance imaging using deep learning." Sci Rep, vol. 13(1), 2023, pp. 22555.

[11] J. He, J. Wang, Z. Han, B. Li, M. Lv and Y. Shi, "Cancer detection for small-size and ambiguous tumors based on semantic FPN and transformer." PLoS One, vol. 18(2), 2023, pp. e0275194.

[12] N.M. Hassan, S. Hamad, S., and K. Mahar, "Mammogram breast cancer CAD systems for mass detection and classification: a review." Multimed Tools Appl, vol. 81(14), 2022, pp. 20043–20075.

[13] M. Jochelson, "Advanced imaging techniques for the detection of breast cancer." American society of clinical oncology educational book/educational book, vol. 32, 2012, pp.65–69.

[14] F. Sardanelli, V. Magni, G. Rossini, F. Kilburn-Toppin, N.A. Healy, N. A., and F.J. Gilbert, "The paradox of MRI for breast cancer screening: high-risk and dense breasts—available evidence and current practice." Insights Imaging, vol. 15(1), 2024, pp. 96.

[15] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, “You only look once: unified, real-time object detection.” 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 779–788.

[16] Roboflow. “YOLOV8: a new state-of-the-art computer vision model.” [Internet] 2024 [Retrieved 2024 April 1] Available at: https://yolov8.com/

[17] F. Prinzi, M. Insalaco, A.M. Orlando, S. Gaglio, and S. Vitabile, “A yolo-based model for breast cancer detection in mammograms.” Cogn Comput, vol. 16(1), 2023. pp.107–120.

[18] G. H. Aly, M. Marey, S.A. El-Sayed, and M.F. Tolba, “YOLO based breast masses detection and classification in full-field digital mammograms.” Comput Methods Programs Biomed, vol. 200, 2021, pp. 105823.

[19] L. Tan, Y. Liang, J. Xia, H. Wu, and J. Zhu, J. “Detection and diagnosis of small target breast masses based on convolutional neural networks.” Tsinghua Sci Technol, vol. 29(5), 2024, pp. 1524–1539.

[20] R. Agarwal, O. Díaz, M.H. Yap, X. Lladó, and R. Martí, “Deep learning for mass detection in full field digital mammograms.” Comput Biol Med, vol. 121, 2020, pp. 103774.

[21] C. H.Salh and A.M. Ali, “Unveiling breast tumor characteristics: a ResNet152V2 and Mask R-CNN based approach for type and size recognition in mammograms.” TS. Trait Signal, vol. 40(5), 2023, pp. 1821–1832.

[22] L. Singh and A. Alam, “An Efficient hybrid methodology for an early detection of breast cancer in digital mammograms.” J Ambient Intell Humaniz Comput, vol. 15(1), 2022, pp. 337-360.

[23] L. Chen, Y. Zhou, and S.E. Xu, “RetinaNet: An efficient neural network based on RetinaNet for mammographic breast mass detection.” IEEE J Biomed Health Inform, vol. 28(5), 2024, pp. 2866–2878.

[24] Y. Hao, B. Liu, B. Zhao, and E. Liu, “Small Object Detection Algorithm Based on Improved YOLOV8 for Remote Sensing.” IEEE J Sel Top Appl Earth Obs Remote Sens, vol. 17, 2024, pp. 1734–1747.

[25] J. Huang, C. Li, F. Yan and Y. Guo, “An improved liver disease detection based on YOLOv8 algorithm” International Journal of Advanced Computer Science and Applications (IJACSA), vol. 15(7), 2024, pp. 1168-1179.

[26] M. Aleinzi, “Enhancing precision agriculture with YOLOv8: a deep learning approach to potato disease identification”, International Journal of Advanced Computer Science and Applications, vol. 16 (4), 2025, pp. 1156-1166.

[27] J.D. Guia and M. Deveraj, “Unified deep learning for real-time pedestrian detection, pose estimation, and tracking,” International Journal of Advanced Computer Science and Applications (IJACSA), vol. 16(3), 2025, pp. 192-209.

[28] N. M. Hassan, S. Hamad and K. Mahar, “YOLO-based CAD framework with ViT transformer for breast mass detection and classification in CESM and FFDM images.” Neural Comput Appl, vol. 36(12), 2024, pp. 6467–6496.

[29] Z. Huang, L. Li, G.C. Krizek, and L. Sun, “Research on traffic sign detection based on improved YOLOV8.” J Comput Commun, vol. 11(7), 2023, pp. 226–232.

[30] X. Zhang, C. Chen, R. Zhu, and W. Zheng, “Detection of leg diseases in broiler chickens based on improved YOLOv8 x-ray images.” IEEE Access, vol. 12, 2024, pp. 47385-47401.

[31] N. Li, T. Ye, Z. Zhou, C. Gao, and P. Zhang, “Enhanced YOLOv8 with BiFPN-SimAM for precise defect detection in miniature capacitors.” Appl Sci, vol. 14(1), 2024, pp. 429.

[32] A. Abdusalomov, M. Mukhiddinov and T.K. Whangbo, “Brain tumor detection based on deep learning approaches and magnetic resonance imaging.” Cancers, vol. 15(16), 2023, pp. 1-29.

[33] S. Naik, K.A. Hashmi, A. Pagani, M. Liwicki, D. Stricker and M.Z. Afzal, “Investigating attention mechanism for page object detection in document images.” Appl Sci, vol. 12(15), 2022, pp. 7486.

[34] G. Sun, S. Wang, and J. Xie, “An image object detection model based on mixed attention mechanism optimized YOLOV5.” Electronics, vol. 12(7), 2023, pp. 1515.

[35] A. Ashurov, S.A. Chelloug, A. Tselykh, M.S.A. Muthanna, A. Muthanna, and M.S.a.M. Al-Gaashani, “Improved breast cancer classification through combining transfer learning and attention mechanism.” Life, vol. 13(9), 2023, pp. 1945.

[36] H. Liu, M. Ding, S. Li, Y. Xu, S. Gong and A. Kasule, “Small-target detection based on an attention mechanism for apron-monitoring systems.” Appl Sci, vol. 13(9), 2023, pp. 5231.

[37] L. Zhou and Z.A. Chen, “A study on the detection of breast lumps based on attentional mechanisms.” Second International Conference on Biomedical and Intelligent Systems (IC-BIS2023), vol. 12724, 2023, pp. 388–393.

[38] X. Zhao, Y. Liao, J. Xie, X. He, S. Zhang, G. Wang, et al. “BreastDM: A DCE-MRI dataset for breast tumor image segmentation and classification.” Comput Biol Med, vol. 164, 2023, pp. 107255.

[39] Roboflow Universe. Breast1 Dataset. [Internet] 2024 [Retrieved 2024 June 2] Available at https://universe.roboflow.com/breastdm/breast1.

[40] K.S. Myers, E. Stern, E.B. Ambinder, and E.T. Oluyemi, “Breast cancer abutting the pectoralis major muscle on breast MRI: What are the clinical implications.” Br J Radiol, vol. 94(1119), 2021, pp. 20201202.