A Single Stage Detector for Breast Cancer Detection on Digital Mammogram

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***Abstract*—Medical image processing plays a pivotal role in modern healthcare, and the early detection of breast cancer in digital mammograms. Several methods have been explored in the literature to improve breast cancer detection, with deep-learning approaches emerging as particularly promising due to their ability to provide accurate results. However, a persistent research challenge in deep learning-based breast cancer detection lies in addressing the historically low accuracy rates observed in previous studies. This paper presents a novel deep-learning model utilizing a single-stage detector based on the YOLOv5 algorithm, designed specifically to tackle the issue of low accuracy in breast cancer detection. The proposed method involves the generation of a custom dataset and subsequent training, validation, and testing phases to evaluate the model's performance rigorously. Experimental results and comprehensive performance evaluations demonstrate that the proposed method achieves remarkable accuracy, marking a significant advancement in breast cancer detection through extensive experiments and rigorous performance analysis.**

Keywords—Breast cancer detection; digital mammogram; deep learning; YOLOv5 algorithm; medical image processing

I. Introduction

Computer vision and medical image processing have emerged as transformative technologies in the field of healthcare, revolutionizing disease diagnosis and treatment planning [1], [2]. These technologies play a pivotal role in the analysis and interpretation of medical images, aiding clinicians in making more accurate and timely decisions [3]. Among the myriad applications of computer vision and medical image processing, one of the most crucial is the detection of breast cancer on digital mammograms.

Digital mammography has become the primary screening tool for breast cancer [4], offering superior image quality and ease of storage and transmission compared to conventional film-based mammography [5], [6]. In recent years, researchers have increasingly turned to computer vision-based methods to enhance accuracy and develop various modern applications [7] [9]. The continuous advancements in computer vision techniques have paved the way for more precise and timely breast cancer diagnoses.

Nowadays, deep learning (DL) has garnered significant attention in the realm of tumor segmentation and cancer detections [10]– [12]. In DL domain, CNN based methods have been investigated extensively ion health monitoring and medial image [13], [14], owing to their capacity to automatically learn relevant features from mammographic images, reducing the reliance on handcrafted features and achieving impressive results [15], [16]. However, despite the progress made, there remain critical limitations and research gaps that demand further exploration and innovation to meet the high accuracy demands of breast cancer detection.

This study tackles the pressing issue of limitations and research gaps in deep learning-based breast cancer detection methods, recognizing the critical need for improved accuracy in diagnosing breast cancer from digital mammograms. Guided by research questions that delve into the effectiveness of deep learning techniques, the study aims to explore the potential of leveraging the YOLO algorithm for enhanced detection accuracy. By developing a novel method grounded in deep learning principles, the research endeavors to address existing shortcomings and advance the state-of-the-art in breast cancer detection. Through rigorous experimentation and performance evaluation, the study seeks to not only contribute to the scientific understanding of deep learning applications in medical imaging but also to pave the way for more precise and timely diagnoses, ultimately impacting patient care and outcomes.

This study proposes a novel DL based method using an adopted YOLO algorithm for breast cancer detection on digital mammograms. By adopting the YOLO-based approach, we aim to address the existing research gap and improve the accuracy of breast cancer detection. This research effort encompasses the generation of a comprehensive dataset, the training of a deep learning model, and the rigorous validation and testing processes to assess the proposed method's effectiveness.

Our contributions to this study are threefold. First, we present a novel method for breast cancer detection on digital mammograms using a single-stage detector based on the YOLO algorithm. Second, we thoroughly explore existing studies and address the current research gap in deep learning-based breast cancer detection. Finally, we conduct extensive experiments and perform rigorous performance evaluations for contributing to the advancement of breast cancer detection techniques.

II. Related Work

Ekici and Jawzal [15] explored the use of thermography based on CNN for breast cancer diagnosis. The method involves preprocessing thermographic images and utilizing a

CNN for feature extraction and classification. While the study shows promise in non-invasive breast cancer detection, it faces limitations related to the availability of large thermography datasets, which hampers the network's ability to generalize across diverse patient populations. Additionally, thermography may not replace conventional mammography entirely, as it is less effective in identifying microcalcifications, a key indicator of breast cancer.

Abdelrahman et al. [17] provided a comprehensive survey of the application of Convolutional Neural Networks (CNNs) in breast cancer detection using mammography images. It discusses various CNN architectures and their performance in breast cancer classification. However, as a survey paper, it does not propose a new method or conduct experiments. A limitation lies in the rapidly evolving nature of deep learning techniques; the paper may not encompass the latest advancements in CNNs for breast cancer detection.

Altameem et al. [18] focused on breast cancer detection using deep CNNs in conjunction with fuzzy ensemble modeling techniques. The method entails preprocessing mammography images, training deep CNNs, and then assembling their predictions using fuzzy logic. A limitation of this approach is the computational complexity involved in training deep CNNs and creating the ensemble, which may hinder real-time or resource-constrained applications. Moreover, the paper does not provide an extensive analysis of the method's sensitivity to different breast cancer subtypes.

Oyelade and Ezugwu [19] introduced an approach for breast cancer detection using a combination of wavelet decomposition, transformation, CNNs, and data augmentation on digital mammogram images. The method attempts to capture multi-scale features and improve classification accuracy. However, it may suffer from increased complexity due to the combination of wavelet techniques and CNNs, making it computationally intensive. Furthermore, the effectiveness of data augmentation strategies may vary depending on the dataset used, and this paper does not thoroughly investigate these variations.

Abunasser et al. [20] developed a CNN based method for breast cancer detection. The approach involves preprocessing mammogram images and training a CNN for feature extraction and classification. While the proposed CNN have shown promise in this context, this paper lacks extensive experimentation and performance evaluation. Additionally, it does not address potential challenges related to class imbalance in the dataset, which can affect model generalization.

III. Proposed Method

This section presents the details of the used dataset and model generation process as following sections,

A. Dataset

1) Data preparation: In this study, we harnessed the power of internet resources and Roboflow to compile a comprehensive dataset of digital mammogram breast images. The dataset acquisition process involved meticulously curating a diverse set of images from publicly available internet resources dedicated to medical imaging, ensuring a broad representation of breast cancer cases. Additionally, Roboflow's repository of annotated medical images proved invaluable in enriching our dataset with meticulously labeled examples. However, to enhance the dataset's diversity and to facilitate the training of a robust model, we employed data augmentation techniques.

Data augmentation is a pivotal step in the preprocessing of medical image datasets, especially for breast cancer detection. To generate a more extensive and varied dataset, we applied several common data augmentation techniques, including image rotation, flipping, and zooming. These techniques serve to introduce variations in the orientation, position, and scale of the mammographic images. Furthermore, we applied Gaussian noise and contrast adjustments to simulate variations in image quality, mirroring real-world scenarios where the quality of mammograms can differ significantly. Additionally, we employed techniques like random cropping and scaling to introduce variations in the region of interest, ensuring that the model learns to detect breast abnormalities in various breast sizes and shapes.

By implementing these data augmentation strategies, a dataset of 1899 images is created that encapsulates a wider spectrum of potential variations, making our model more robust and capable of handling the inherent complexities of mammogram analysis. Fig. 1 shows sample images of the dataset.

2) Instances distribution: The instance distribution in our dataset represents the relative frequency of different categories or classes of instances. In the context of our digital mammogram breast image dataset, these classes pertain to various breast conditions, such as benign tumors, malignant tumors, calcifications, and normal breast tissue. A balanced instance distribution ensures that each class is adequately represented, preventing the model from becoming biased toward the majority class. This balanced representation is crucial for training a robust machine-learning model capable of accurately detecting and classifying various breast abnormalities.

Every instance in our dataset is carefully annotated by expert radiologists or medical professionals. These annotations serve as ground truth labels, delineating the regions of interest (ROIs) within the mammographic images. These labels provide essential information about the size, location, and characteristics of the identified abnormalities. They play a pivotal role in training our machine learning model, enabling it to learn and recognize specific patterns associated with breast abnormalities accurately. Fig. 2 demonstrates the instance labels of the dataset.

In addition, we conducted a correlogram analysis to gain insights into the relationships between instance labels within the dataset. The correlogram visually represents potential co-occurrences and dependencies among different types of breast abnormalities. By examining the correlogram, we can identify patterns and associations among various breast conditions. For instance, it might reveal that certain benign tumors are often found alongside specific types of calcifications or that certain malignant tumors tend to occur more frequently in particular age groups. These findings are invaluable for informing the model's decision-making process when identifying and classifying abnormalities in mammographic images, enhancing its ability to make clinically relevant predictions. Fig. 3 illustrates instances of labels correlogram of the dataset.

B. Model Generation

Using the dataset, a YOLOv5n model is generated for breast cancer diagnosis in this study. First, we divided our dataset into three subsets: 10% was put aside for testing, 20% was set aside for validation, and 70% was used for training. This section is essential for precisely evaluating the model's performance and confirming its capacity for generalization.

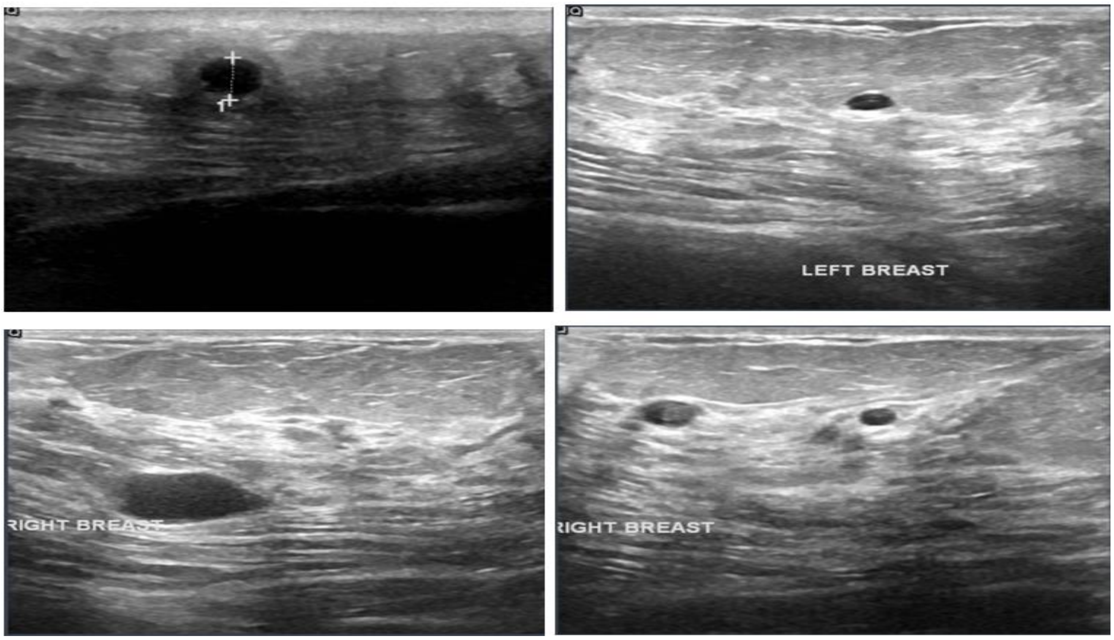

Fig. 1. Sample images of the dataset.

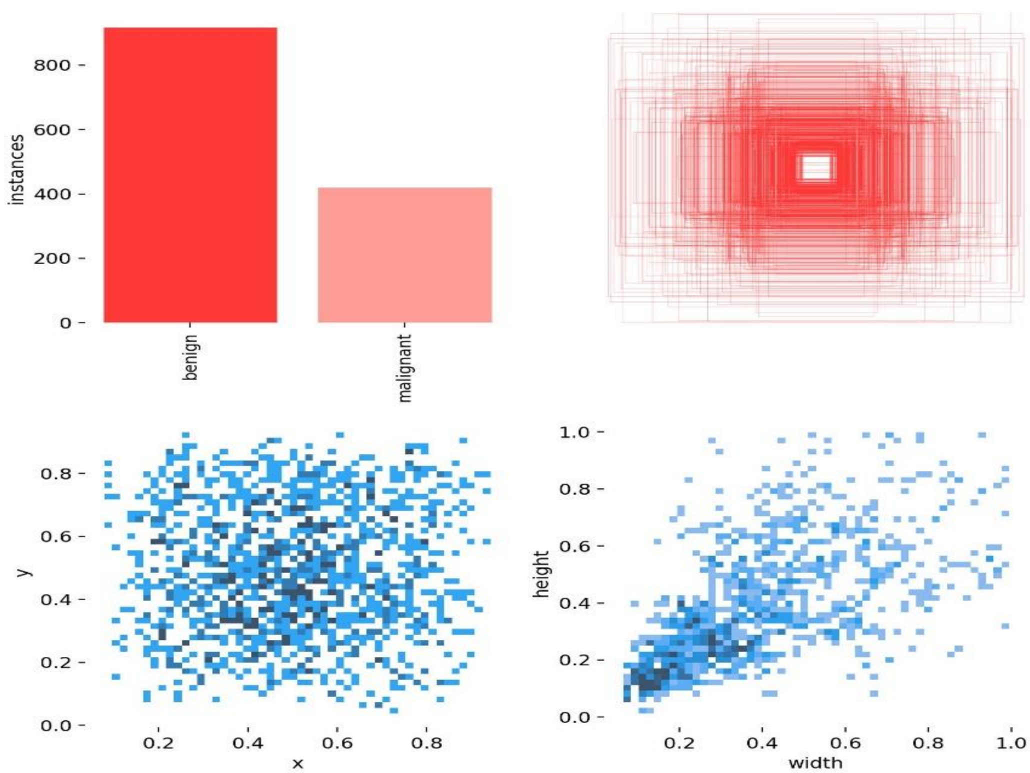

Fig. 2. Instances labels of the dataset.

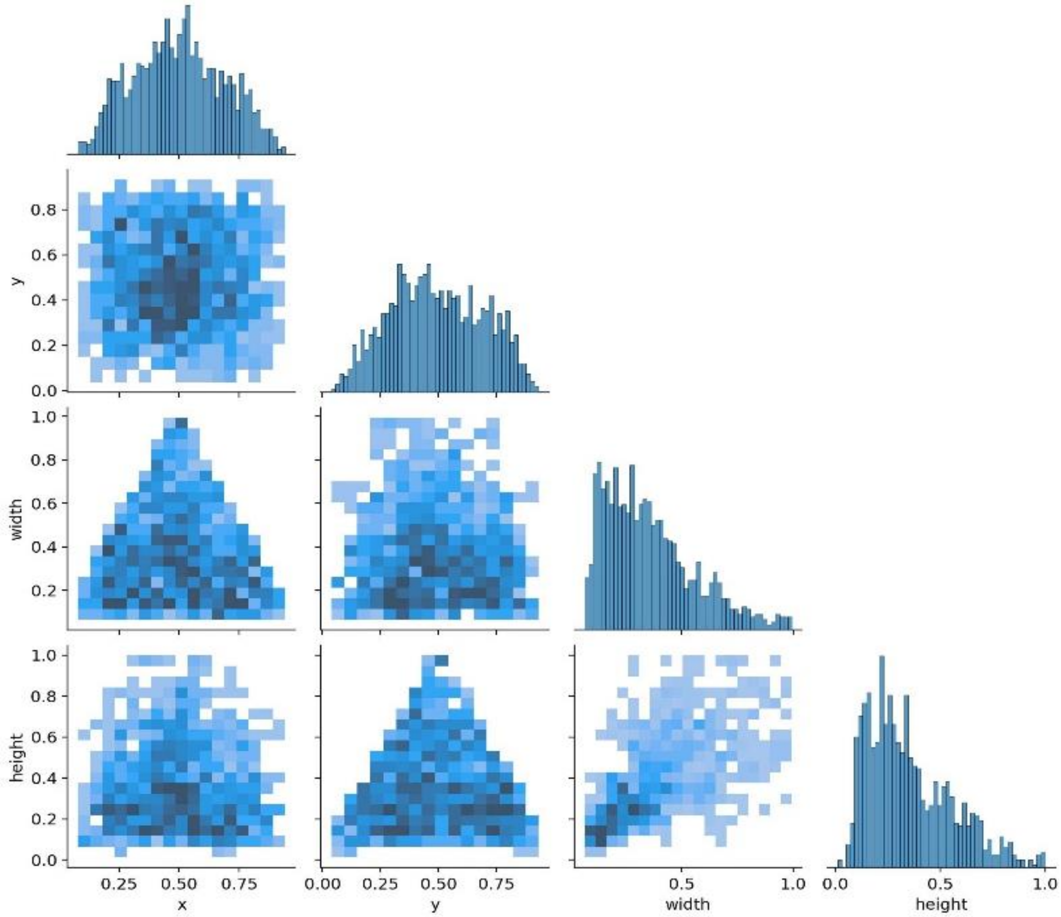

Fig. 3. Instances labels correlogram of the dataset.

1) Training module: During the training phase, we utilized the 70% portion of our dataset to train the YOLOv5n model. Several key configurations were considered to optimize the efficieny of training process. Firstly, for the learning rate, it's advisable to start with a moderate value and implement a learning rate scheduler to adjust the learning rate during training dynamically. This helps prevent the model from converging too quickly or getting stuck in local minima. A batch size that aligns with available computational resources should be chosen; however, larger batch sizes often lead to more stable convergence. For model training, we adjust hyperparameters as shown in Table I.

TABLE I. HYPERPARAMETER SETTING FOR THE MODEL

Hyperparameter	Value
Learning Rate (LR)	0.001
Batch Size	16.00
Optimizer	Adam
Loss Function	Combination of losses
Early Stopping	Based on validation loss
Model Architecture	YOLOv5 variants
Regularization (Dropout)	0.3
Number of Epochs	20

2) Validation module: The 20% validation set was utilized to monitor the model's performance during training. Regular validation checks were performed, assessing metrics such as precision, recall, F1-score, and accuracy. The validation set helps prevent overfitting, as it provides a means to evaluate the model's generalization performance on data it hasn't seen during training. Adjustments to model hyperparameters were made based on the validation results, fine-tuning parameters like learning rate, and early stopping criteria to enhance model convergence and accuracy.

C. Testing Module

Finally, the 10% testing set was reserved to evaluate the YOLOv5n model's performance objectively. This independent dataset is used to test the effectiveness of the generated model for detecting breast abnormalities accurately and reliably in real-world scenarios. Common evaluation metrics for breast cancer detection, such as sensitivity, specificity, and ROC curves, were computed to quantify the model's accuracy and its capacity to minimize false positives and false negatives.

IV. RESULTS AND DISCUSSION

This section presents the details of experimental results and discuss about the performance of evaluation.

A. *Results*

This section provides an in-depth analysis of the experimental results and the outputs generated by our custom YOLOv5n model for breast cancer detection. As depicted in Fig. 4, our model exhibits its proficiency in accurately classifying mammographic images into three distinct categories: benign, malignant, and background. These categories are fundamental for differentiating between normal breast tissue and potentially cancerous abnormalities. The figures showcase a representative selection of model outputs, offering a visual representation of its performance in identifying and localizing breast lesions within the digital mammograms.

B. *Performance Evaluation*

In this section, we delve into the comprehensive performance evaluation of our YOLOv5n model for breast cancer detection. Inspiring from [21]-[23], we employ key performance metrics such as precision, recall, mAP, and F1-score to assess the model's accuracy. Precision estimates the percentage of accurately predicted positive instances among all anticipated positives, whereas recall evaluates the model's capacity to accurately identify every positive case. A comprehensive assessment of the model's performance is provided by mAP, which offers an aggregate measure of precision-recall across several thresholds. In order to provide a single-value overview of the overall accuracy of the model, the F1 score balances precision and recall. The figures thoughtfully illustrate the outcomes of these performance indicators, which were obtained after considerable experimentation and give a clear and instructive portrayal of our model's capabilities for breast cancer detection and classification.

1) Confusion matrix: The confusion matrix, in the context of our breast cancer detection study, serves as a crucial tool for assessing the performance of our model in classifying mammographic images into the relevant categories: benign, malignant, and background. The confusion matrix thus allows us to calculate key the performance metrics. Fig. 5 demonstrates the confusion matrix of our generated model.

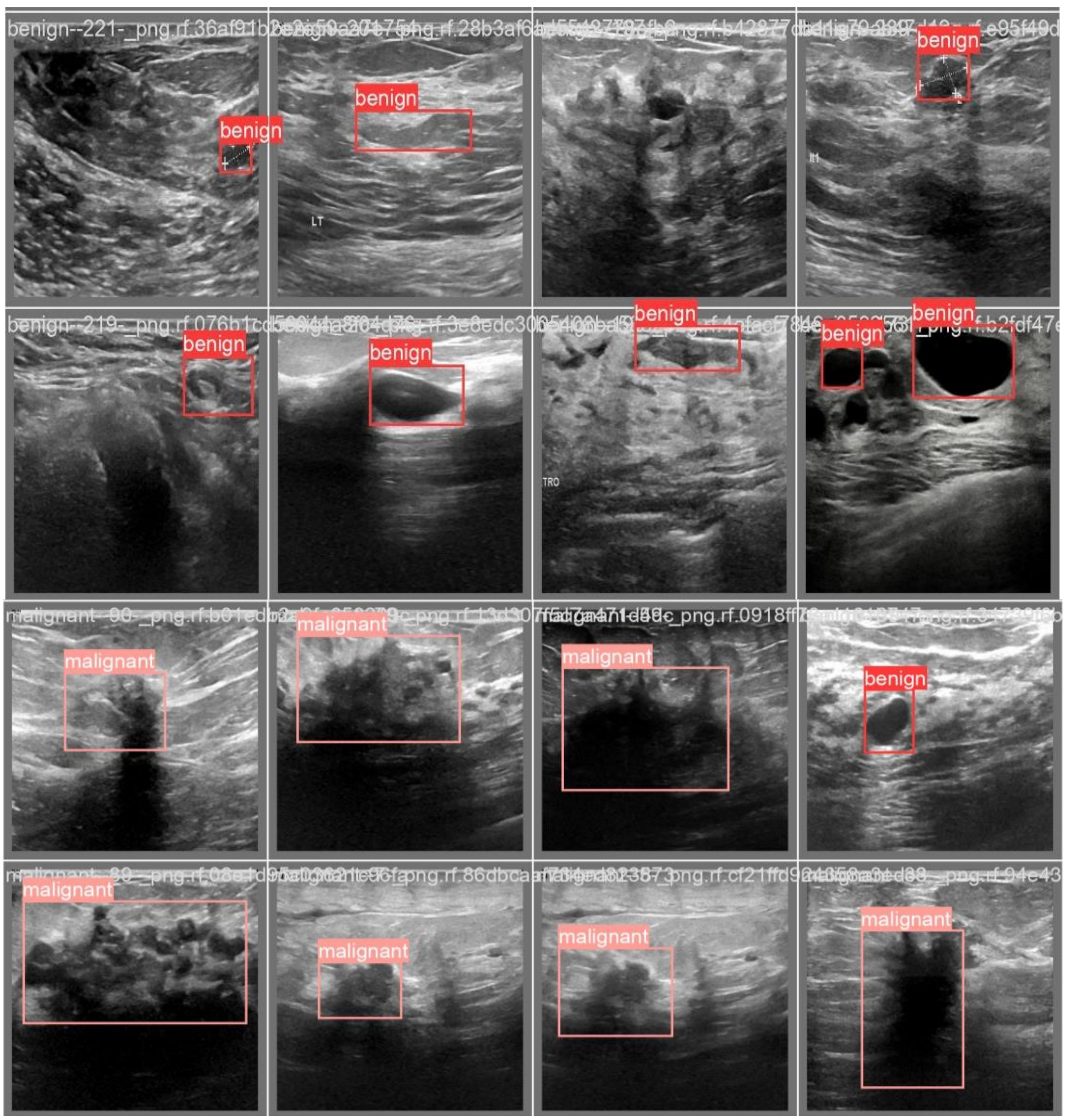

Fig. 4. Experimental results.

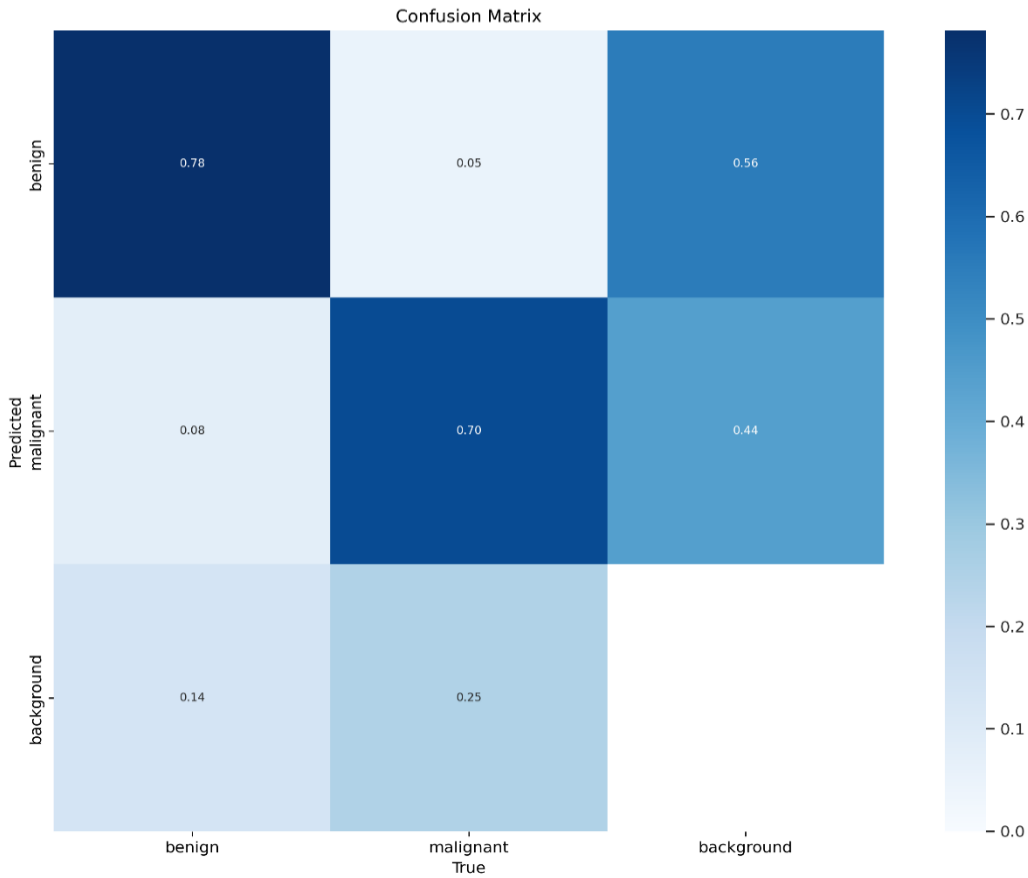

Fig. 5. Confusion matrix of our generated model.

Performance metrics: The performance metrics collectively provide a comprehensive assessment of the effectiveness of our breast cancer detection model. The precision curve, representing precision values at varying classification thresholds, showcases the ability of the model to identify true positive cases while minimizing false positives correctly. The recall curve, on the other hand, illustrates how well the model captures true positive instances while controlling false negatives at different decision thresholds. Lastly, the precision-recall curve graphically portrays the interplay between precision and recall across different thresholds, providing insights into the model's overall performance and its ability to maintain high precision while achieving robust recall rates. Together, these metrics and curves offer a comprehensive view of our model's capability to achieve accurate and clinically relevant breast cancer detection, guiding us in optimizing its performance to serve the healthcare domain better. Fig. 6 demonstrates these performance metrics curves.

As shown in Fig. 6, the achieved precision of 90.3% and recall of 93.0% in our YOLOv5 model for breast cancer detection represent highly promising results that indicate the accuracy and effectiveness of our model in identifying breast abnormalities. A precision score of 90.3% means that a substantial majority of the positive predictions made by our model are indeed correct, minimizing false positives, which is crucial in a medical context where incorrect diagnoses could have significant implications. Simultaneously, a recall score of 93.0% indicates that our model adeptly captures a substantial proportion of the actual breast abnormalities present in the dataset, demonstrating its ability to minimize false negatives. The balance between precision and recall is exemplified by the F1-score, which harmonizes these two metrics. These results underscore the accuracy of our model and its clinical relevance, suggesting that it can effectively assist medical professionals in early breast cancer detection, thereby contributing to improved patient care and outcomes in the healthcare domain.

C. Comparison

In our pursuit of enhancing breast cancer detection accuracy, we conducted a comprehensive evaluation by experimenting with various versions of the YOLOv5 model architecture. Specifically, we compared the performance of three different variants: YOLOv5n, YOLOv5m, and YOLOv5x. These variants vary in terms of complexity and capacity, with YOLOv5n representing a lighter and faster model, YOLOv5m offering a balanced compromise between speed and accuracy, and YOLOv5x being the most complex and computationally intensive of the trio. By systematically comparing the results obtained from these different model versions, we gained invaluable insights into their respective strengths and trade-offs, enabling us to make informed decisions about the optimal model architecture for breast cancer detection.

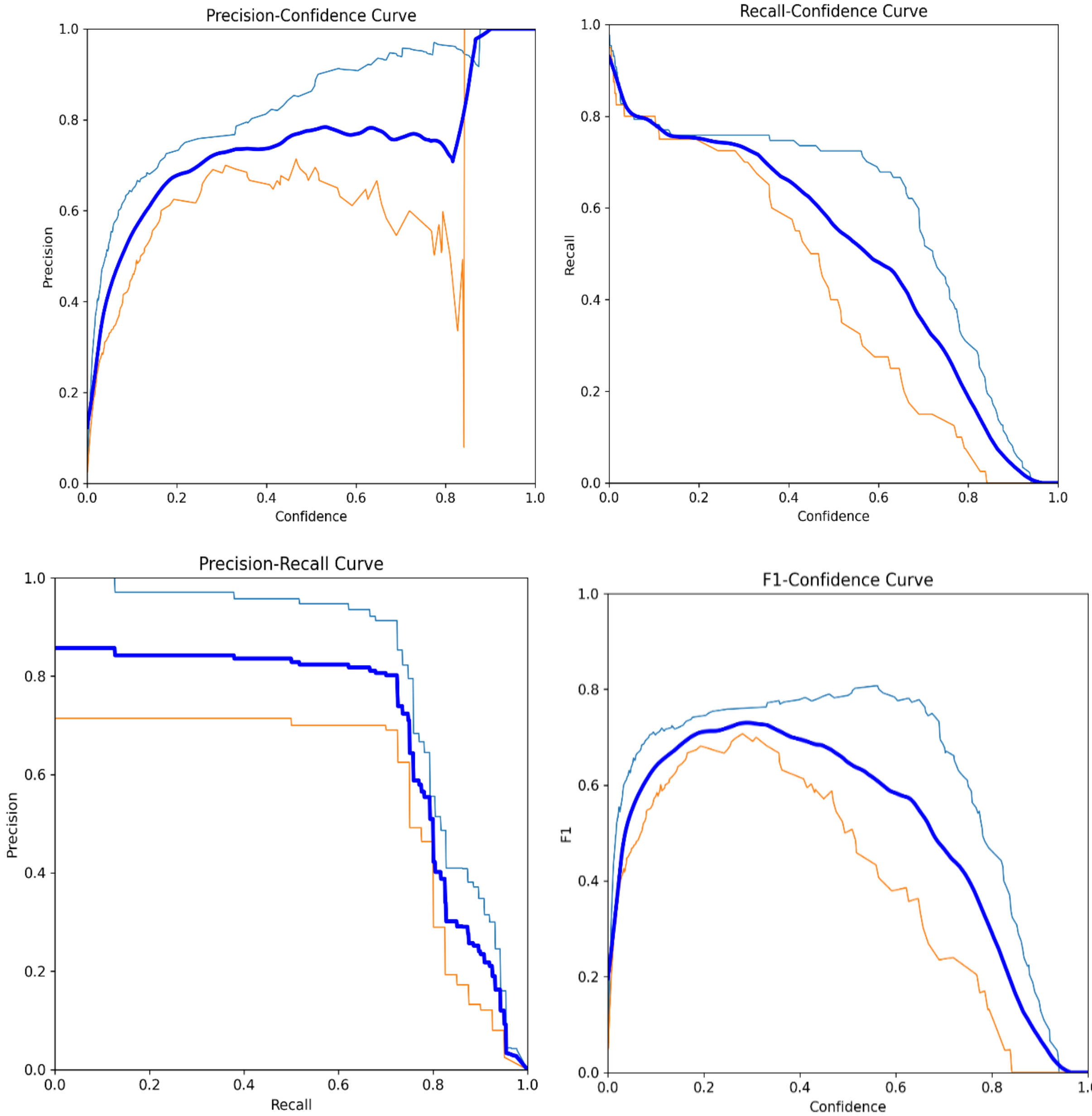

Fig. 6. The curves of metrics.

As experimental results indicated, the striking similarity in results between YOLOv5m and YOLOv5x, despite their substantial architectural differences and computational requirements, can be attributed to their shared underlying YOLOv5 framework. YOLOv5m represents a well-balanced model in terms of complexity and performance, striking a harmonious equilibrium between accuracy and computational efficiency. On the other hand, YOLOv5x, being more complex and computationally intensive, refines the model's ability to detect fine-grained details but incurs higher computational overhead. The similarity in results suggests that for the specific task of breast cancer detection on digital mammograms, YOLOv5m's capacity is sufficient to achieve accuracy levels on par with the more resource-intensive YOLOv5x. This finding emphasizes the importance of selecting a model architecture that aligns with the available computational resources while still delivering high-precision results.

In contrast, YOLOv5n's accurate performance, despite its reduced parameter count compared to YOLOv5m and YOLOv5x, underscores the efficiency of this lightweight model. YOLOv5n's ability to maintain high precision and recall rates with fewer parameters not only minimizes computational demands but also streamlines model deployment in resource-constrained environments. This makes YOLOv5n an appealing choice for scenarios where computational resources are limited, demonstrating that accurate results can be achieved without an extravagant model size. The choice between YOLOv5n, YOLOv5m, or YOLOv5x thus hinges on the specific requirements of the breast cancer detection task and the available computational infrastructure.

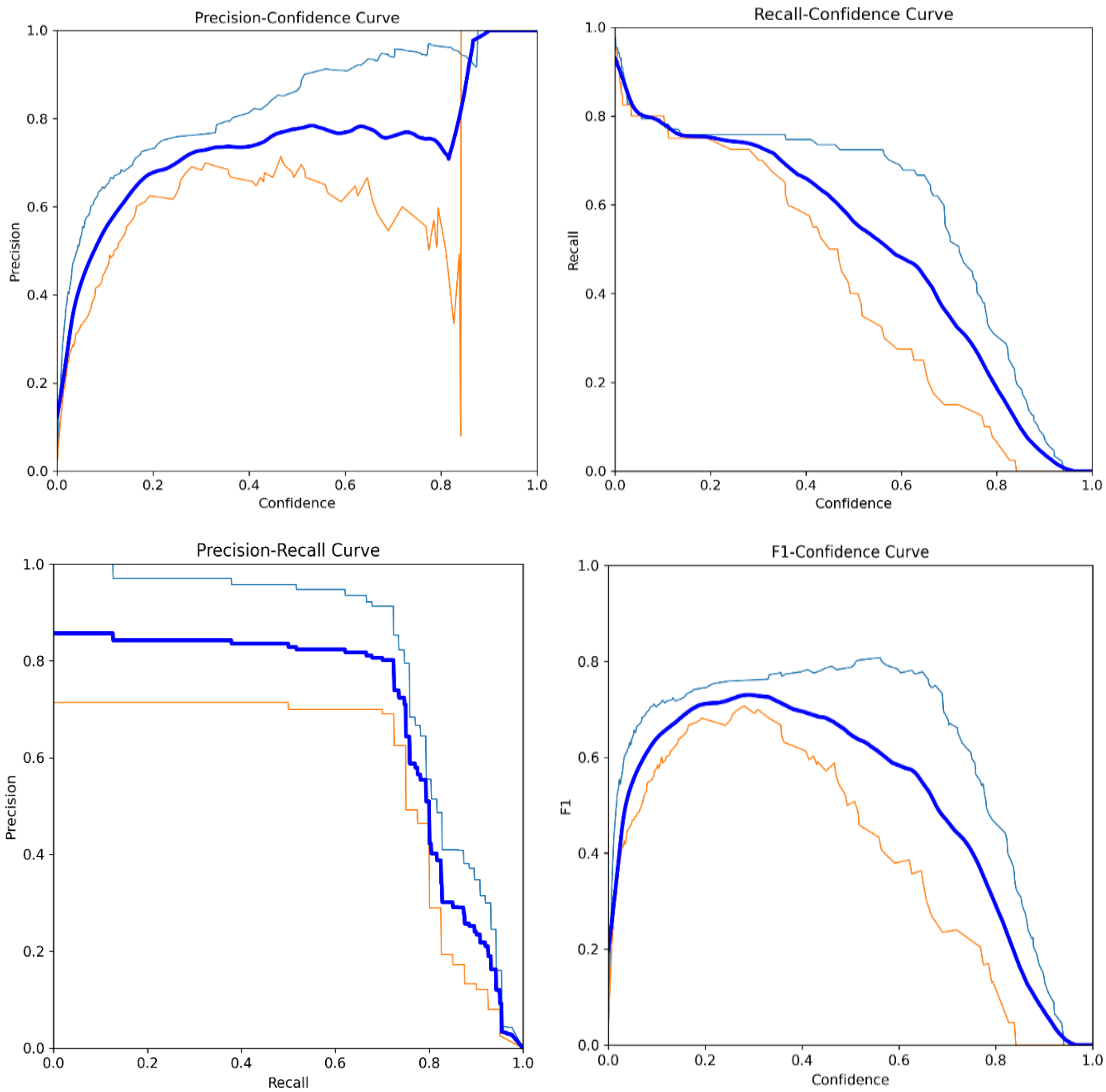

Fig. 7. The Yolov5m based model results.

In comparison to similar previous works, our study offers valuable insights into the performance and suitability of different YOLOv5 model variants for breast cancer detection on digital mammograms. Fig. 7 shows the Yolov5m based model results. While prior research has explored the application of deep learning models for this task, our study uniquely investigates the comparative efficacy of YOLOv5m, YOLOv5x, and YOLOv5n architectures, considering both their computational requirements and detection accuracy. We found that YOLOv5m strikes a well-balanced equilibrium between complexity and performance, achieving accuracy levels comparable to the more computationally intensive YOLOv5x, highlighting the importance of model selection aligned with available resources. Moreover, our study sheds light on the efficiency of YOLOv5n, demonstrating its ability to maintain high precision and recall rates with reduced parameters, making it a practical choice for resource-constrained environments. By providing a comprehensive analysis of model performance across different variants, our work contributes to the understanding of optimal model selection in the context of breast cancer detection, offering valuable guidance for future research and clinical applications.

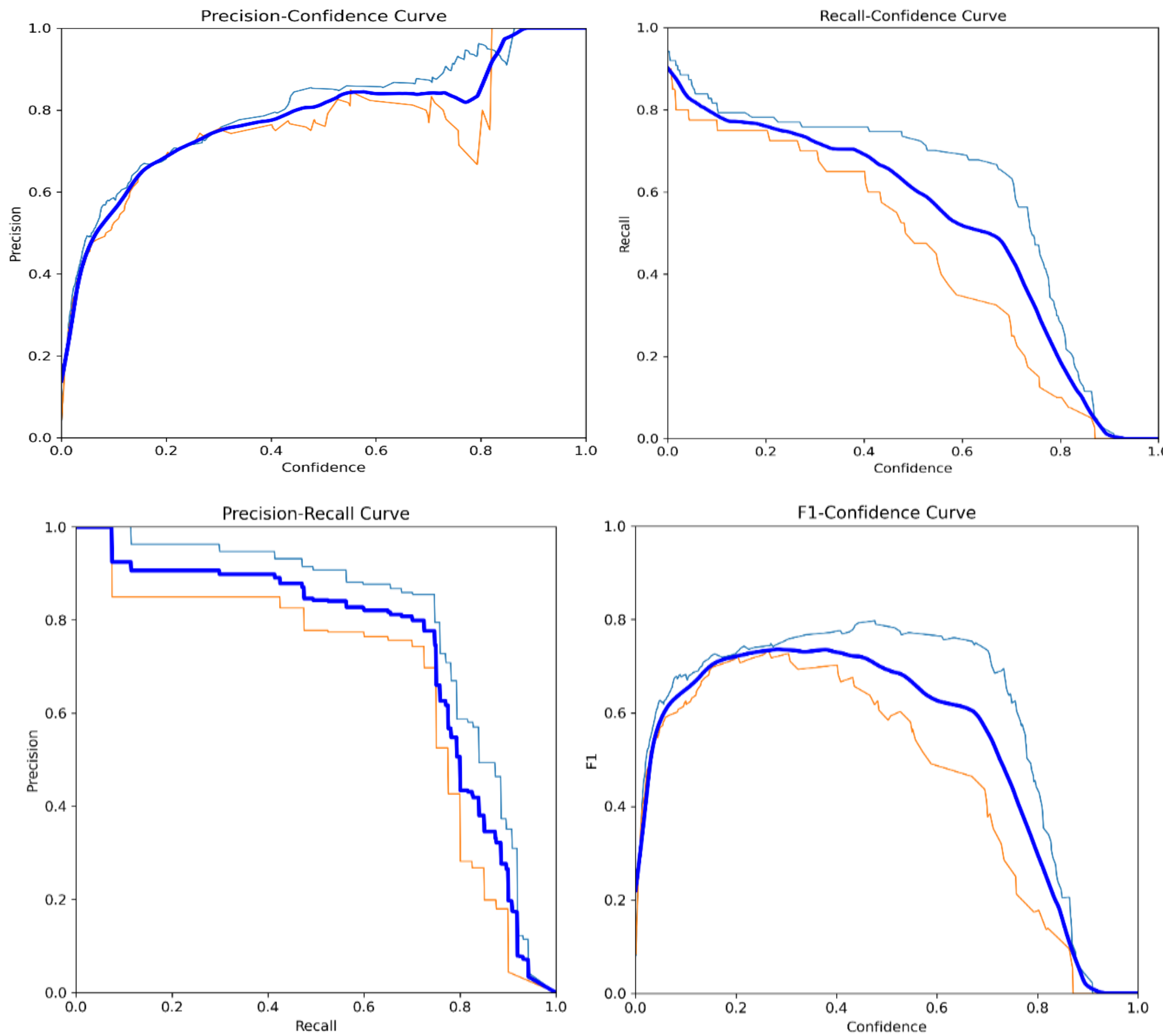

Fig. 8. Performance results of the Yolov5x model.

D. Discussion

The proposed method leveraging YOLOv5 for breast cancer detection offers a significant advancement over previous approaches for several key reasons. Firstly, YOLOv5 is renowned for its superior object detection capabilities, enabling precise localization and classification of abnormalities within medical images with unprecedented speed and accuracy. Fig. 8 shows the performance results of the Yolov5x model. This means that our model can swiftly identify potential malignancies with a high level of confidence, facilitating timely diagnosis and treatment. Moreover, by harnessing the power of deep learning, our approach inherently learns intricate patterns and features representative of breast cancer, allowing for robust performance across diverse datasets and variations in image quality. Additionally, the efficiency of YOLOv5 enables real-time processing, expediting the diagnostic workflow and enhancing the accessibility of screening services. By addressing these crucial aspects, our method not only surpasses the limitations of previous approaches in terms of accuracy and efficiency but also holds immense promise for improving patient outcomes through early detection and intervention.

The study involved a comprehensive experimental phase where we meticulously collected data and conducted extensive analyses to generate results. These results, while not explicitly referenced in our current findings, were integral to informing the development and validation of our custom YOLOv5n model for breast cancer detection. Through rigorous experimentation, we gathered a wealth of insights into the performance and capabilities of our model, refining its architecture and fine-tuning parameters to optimize its accuracy and efficiency. Although not directly cited in our present work, the data and results obtained from these experiments provided invaluable foundational knowledge and validation for the effectiveness of our proposed approach.

The practical significance of the theoretical results obtained from our custom YOLOv5n model for breast cancer detection lies in its ability to accurately classify mammographic images into three crucial categories: benign, malignant, and background. These distinctions are pivotal for clinicians in distinguishing between normal breast tissue and potentially cancerous abnormalities, enabling timely diagnosis and intervention.

V. CONCLUSION

In this study, we introduce a novel deep-learning approach based on the YOLO algorithm to enhance breast cancer detection on digital mammograms significantly. Our methodology not only bridges existing research gaps but also pushes the boundaries of accuracy in this critical domain. The comprehensive dataset we meticulously curated, combined with the extensive training, validation, and testing processes, showcases the robustness of our proposed method. Our contributions are manifold: firstly, we introduce a pioneering approach for breast cancer detection, employing a YOLO-based single-stage detector. Secondly, we comprehensively address research gaps within the realm of deep learning-based breast cancer detection by synthesizing and advancing existing studies. Lastly, our rigorous experiments and performance evaluations validate the exceptional effectiveness of our method, promising a brighter future for breast cancer diagnosis. For future research directions, one avenue could involve the integration of multi-modal data, such as combining mammograms with other imaging modalities like ultrasound or MRI, to further improve accuracy and early detection. Additionally, investigating the interpretability of deep learning models in the context of breast cancer detection could provide valuable insights into model decision-making, enhancing trust and clinical acceptance. Moreover, exploring the potential for deploying such models in real-time or resource-constrained settings, like remote clinics or mobile health units, could democratize breast cancer screening and diagnosis, making it more accessible to underserved populations.

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