

Enhancing Breast Cancer Diagnosis: Automated Segmentation and Detection with YOLOv8

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Abstract: Breast cancer is a pervasive global health concern, demanding precise and timely diagnosis for effective treatment. In this research, we present an innovative approach to breast cancer segmentation using YOLOv8x-seg, a specialized variant of the YOLO (You Only Look Once) model optimized for semantic segmentation. The methodology commences with comprehensive data collection from the Curated Breast Imaging Subset of DDSM (CBIS-DDSM) dataset, which encompasses various breast conditions, and meticulous data annotation facilitated by Roboflow. The YOLOv8x-seg model is trained to achieve an F1-score of 95.27% and an IoU (Intersection over Union) of 89.51%. These metrics are indicative of the model's ability to accurately identify and segment breast cancer anomalies within mammography images. The anticipated outcome is a model poised to significantly improve the efficiency and accuracy of breast cancer diagnosis, offering a valuable contribution to the field of medical image analysis.

1 INTRODUCTION

Artificial Intelligence (AI) is driving transformative innovations in various fields, including Natural Language Processing (NLP) (Mahdhaoui et al., 2023) and Computer Vision. Beyond these domains, AI is making significant strides in fields such as healthcare. AI's broad applicability extends to critical areas, including the early detection and diagnosis of diseases like breast cancer. These advancements highlight AI's profound impact on technology and its diverse applications in our daily lives. Breast cancer is a malignant tumor that arises from the abnormal breast cells and it is one of the dangerous diseases that threaten women worldwide. Worldwide, breast cancer is the most common non-cutaneous cancer in women, with over two million annual diagnoses. According to the American Cancer Society, over 279,000 cases were reported in the United States in 2020 and it is estimated that 43,600 women will die from breast cancer in 2021 (Cokkinides et al., 2005). Mammography screening is one of the effective medical imaging tools for early breast cancer detection and diagnosis, and it can lower rates of advanced and fatal breast cancer in its early stages (Duffy et al., 2020). Mammography is a breast imaging method that uses ionizing radiation (X-rays). In the older method, SFM (screen-film

mammography), the mammogram is obtained by exposing the film to the radiation produced by an X-ray tube. The modern method, FFDM (full-field digital mammography or digital mammography), has replaced the film with a digital receptor that converts the residual radiation into an electrical signal. FFDM is the only method approved for mammographic screening performance. Transition to FFDM has revealed that it performs as well as SFM (Vinnicombe et al., 2009). Observational studies show a mortality reduction of about 40% after mammography screening. Computer-aided detection systems (CAD) emerged in the 1990s to automatically detect and classify breast lesions in mammograms. Still, these traditional CAD systems fail to significantly improve screening performance, mainly due to their low specificity [8,9]. The primary role of a CAD system is to resolve the challenge of interpreting DMs. The goals of the system include effectively diagnose cancer and correctly interpret DMs. The CAD structures were developed to resolve the reliance of the operator in terms of diagnosis and decrease the cost of medical complementary technology. Typically, CADs are developed to localize suspicious regions of lesions that exist in the screened mammograms. The CAD approach is usually based on extracting image characteristics such as, gray levels, texture, and shape to identify regions of

interest (ROI) via simple machine learning techniques. With the continuous increase of mammography data availability and the existing large computational computers, deep learning algorithms have been implemented to alleviate the radiologists' effort in reading and assessing mammography images. To save considerable time required for mammographic screening presents opportunities for computer diagnostic assistance tools. If these tools can achieve comparable or superior results to those of radiologists, it may be possible to conduct double reading with the aid of a tool and a single radiologist.

2 MAMMOGRAM IMAGES

Mammography uses low-dose X-ray for breast examination and it is routinely exploited for breast cancer screening (Tang et al., 2009). With high sensitivity to calcification, mammographic examination is far better at detecting micro-calcifications and clusters of calcifications, which are very important characterizations of breast cancer (Horsch et al., 2006).

Mammography is, essentially, the only widely used Imaging modality for breast cancer screening. Several large randomized clinical trials have shown that mammography reduces mortality from breast cancer.

Extensive investigations on radiation dose to the breast and its dependence on breast composition, breast thickness, and X-ray spectral characteristics have been documented.

There are two imaging modalities of mammograms: digital mammogram and screen-film mammography. The screen-film mammography (SFM) contains conventional analog mammography films. Usually, SFM contains labels and markers in the background, which considered as noise and need to be removed. The digital mammograms are also called Full-Field Digital Mammography (FFDM) images. The FFDM is more recent and does not include labels.

2.1 Views of Mammograms

There are multiple views for mammograms that are used to provide more information before detection/diagnosis. A CC view mammogram is taken horizontally from an upper projection at C-arm angle 0°; the breast is compressed between two paddles to reveal the glandular tissue, and the surrounding fatty tissue, also the right position of a CC view shows the outermost edge of the chest muscle. MLO view mammography is captured at a C-arm angle of 45°

from the side; the breast is diagonally compressed between the paddles and accordingly this allows imaging a larger part of the breast tissue compared to other views. In addition to that, the MLO projection allows the pectoral muscles to appear in the mammographic image.

Breast cancer typically presents itself in mammograms in the form of masses, calcifications, asymmetrical features or architectural distortions in the breasts. Masses are three-dimensional tumors in the breast and they can be either spherical or irregular in shape. Irregularly shaped masses in mammography are typically malignant, while elliptical and transparent masses are usually benign (Mustonen, 2022). Calcifications are typically found in groups and they appear in mammography images as bright texture. Most of the calcifications are benign and the differences between malignant and benign calcifications are subtle (Mustonen, 2022).

Breast calcifications can be categorized into macro-calcifications and micro-calcifications (Nalawade, 2009).

Macro-calcifications appear as large white dots on the mammogram and spread randomly over the breast, and are considered as non-cancerous cells. The micro-calcifications seem as small calcium spots that look like white specks in the mammogram and they often appear in clusters. Micro-calcification usually is considered as a primary indication for early breast cancer or a sign of existing precancerous cells. All of these aforementioned findings can be benign or malignant. Benign findings are usually harmless, since they do not grow fast nor do they spread outside the tumor area. Malignant findings can metastasise and grow faster.

2.2 Tumor Classifications of Mammograms

Breast Imaging- Reporting and Data System (BI-RADS) is used to classify the severity of the findings in the breast from mammograms. The scale goes from zero to six, six being the most severe and one meaning that the breast is healthy. In Finland a similar scale is used, without the third BI-RADS category and a different naming scheme (Table 1). The classification is done by the radiologist after viewing the images and if the finding is suspicious and further diagnosis is required then a biopsy is taken and the breast is reclassified.

2.3 Breast Density in Mammogram Image

Breast density plays a significant role in determining the likelihood and risk of breast cancer. Breast density describes the amount of fibrous and glandular tissue compared with the amount of fatty tissue in the breast. Breast density is categorized using a system called the ACR BI-RADS. The ACR assigns breast density to one of four classes. In class A, breasts are almost entirely fatty. In class B, scattered areas of fibro-glandular density appear in the breasts. In class C, the breasts are heterogeneously dense. In class D, the breasts are extremely dense.

3 PUBLIC MAMMOGRAM DATASETS

There are several mammogram datasets publicly available. Following is a brief description of the most used datasets, which will be referenced in many recent research.

3.1 Mammographic Image Analysis Society (MIAS)

The Mammographic Image Analysis Society (MIAS) is a research group from the UK interested in studying mammograms. This group generated a small mammogram database in 1994 called mini-MIAS or MIAS for short. The mini-MIAS consists of 322 digitized films stored in the PGM image format. Every image has a resolution equal to 1024×1024 pixels. The dataset contains annotations for background tissue type (dense/fatty), the abnormality present in the breast (masses, asymmetry), and the abnormality's severity (benign/malignant). Mammograms with lesions have recorded X and Y coordinates. It also contains labels regarding MCs, ADs, asymmetry, and healthy images.

3.2 Digital Database for Screening Mammography (DDSM)

For DDSM, all images are 299×299 . The DDSM project is a collaborative effort at the Massachusetts General Hospital (D.Kopans, R. Moore), the University of South Florida (K. Bowyer), and Sandia National Laboratories (P. Kegelmeyer). Additional cases from Washington University School of Medicine were provided by Peter E. Shile, MD, Assistant Professor of Radiology, and Internal Medicine.

The dataset includes 2620 cases. A case consists of between 6 and 10 files. These are an 'ics' file, an overview "16-bit PGM" file, four image files compressed with lossless JPEG encoding, and zero to four overlay files.

3.3 In-Breast

IN-breast is a full-field digital mammographic database. The cases were collected from Centro Hospitalar de S. Joao (CHSJ), Breast Centre in Portugal, in 2011. Largest publicly available dataset with ground-truth annotations of breast cancer abnormalities (i.e., benign and malignant).

It has 410 mammograms (i.e., normal, benign, and malignant) including views of both MLO and CC from 115 patients (Al-Antari et al., 2018). To evaluate our CAD system, we include all cases having masses in both views of the mammograms in a total of 107 cases. Some of these cases have more than one mass, thereby, a total of 112 masses were collected according to the Breast Imaging Reporting and Data System (BI-RADS).

BI-RAD is standard criteria developed by the American College of Radiology (ACR) to assign suspicious lesions into one of six categories (Al-Antari et al., 2018). Benign cases are assigned to the categories 2 and 3, while malignant cases are in categories 4, 5, and 6. The resolution of images was 3328×4084 or 2560×3328 pixels and saved in the DICOM format. The region of interest (ROI) was annotated by two specialists and stored in separate .roi and xml files (39).

3.4 Curated Breast Imaging Subset of DDSM (CBIS-DDSM)

CBIS-DDSM is an updated and standardized version of the Digital Database for Screening Mammography (DDSM) stored in the DICOM file format.

The images in the CBIS-DDSM (Curated Breast Imaging Subset of DDSM) are divided into three categories: normal, benign, and malignant cases. This data set contains a total of 4067 images. The CBIS-DDSM collection includes a subset of the DDSM data selected and curated by a trained mammographer. The images have been decompressed and converted to DICOM format (Zhu et al., 2023).

A subset of the DDSM is the curated breast imaging subset of the DDSM (CBIS-DDSM), and it includes well-annotated and labeled images. The dataset includes information related to bounding boxes for region of interests (ROIs), as well as detailed pathological information regarding breast mass

type, tumor grade, and stage. The dataset consists primarily of scanned film-screen mammography, far behind most advanced imaging techniques like FFDM and DBT[36].

3.5 OPTIMAM Mammography Database (OMI-DB)

The OMI-DB (Halling-Brown et al., 2014) is an extensive mammography image database of over 145,000 cases (over 2.4 million images) comprised of unprocessed and processed FFDMs from the UK's National Health Service Breast Screening Program. It also contains expert's determined ground truths and associated clinical data linked to the images. As part of the data sharing agreement with the Royal Surrey County Hospital (UK) in 2017, we obtained a subset of this database (4750 cases with 80,000 processed and unprocessed FFDMs). The database contains images from different manufacturers, particularly Hologic Inc, Marlborough, Massachusetts, USA (Hologic Lorad Selenia and Selenia Dimensions Mammography Systems), and General Electric (GE) Medical Systems, Chicago, Illinois, USA (Senographe DS and Senographe Essential), referred to as OMI-H and OMI-G, respectively. For each case, two views of each breast, i.e. medio-lateral oblique (MLO) and cranio-caudal (CC) are available, together with several other views for cases with suspected abnormalities. The OMI-H and OMI-G dataset contained, respectively 2042 and 103 positive cases, with abnormalities in either one of the mammography views (CC and MLO), and 842 and 104 normal cases, i.e. without any abnormalities.

3.6 University of Connecticut Center (UCHC)

Named UCHC Digi-Mammogram (UCHCDM) database (Zheng et al., 2016) . The dataset contains screening mammograms of 230 patients, where each case had an initial screening, called Prior exam, and a second follow-up screening between 1 to 6 years, called the Current exam. Each screening in the dataset acquires two different views, CC and MLO. All images were saved with the Digital Imaging and Communications in Medicine (DICOM) format, and were annotated by expert radiologists in a description text file with corresponding pathology of a mammographic finding (i.e. Mass, Calcification, Architectural Distortion, Normal), . Pixel-level ground-truth images were also provided separately where suspicious locations were circled. A total of 413.

3.7 The Chinese Mammography Database (CMMD)

The authors of this dataset the volunteers from the School of Computer Science and Engineering, South China University of Technology for assisting to tidy the clinical and imaging data. This work was supported by the grant from the National Natural Science Foundation of China.

built a database conducted on 1,775 patients from China with benign or malignant breast disease who underwent mammography examination between July 2012 and January 2016. The database consists of 3,728 mammographies from these 1,775 patients, with biopsy confirmed type of benign or malignant tumors. For 749 of these patients (1,498 mammographies) we also include patients' molecular subtypes. Image data were acquired on a GE Senographe DS mammography system.

4 TRADITIONAL CAD SYSTEMS

Numerous trials and research endeavors have been initiated to develop Computer-Aided Diagnosis (CAD) systems designed to serve as supplementary tools for radiologists. These initiatives initially relied on conventional computer vision techniques rooted in traditional machine learning and image processing methods. This section highlights some of these studies in detail.

In 2010, Ke, Li, et al.(Ghosh and Ghosh, 2022) created a system for detecting masses in mammograms using texture analysis and SVM classification, achieving 85.11% sensitivity with 106 mammograms. In 2015, Dong, Min, et al.(Min Dong, 2015) developed an automated system for classifying breast masses, using techniques like chain codes, Rough Set method, and Vector Field Convolution Snake, with an optimized SVM and random forest classifiers. Their method attained 97.73% accuracy on the DDSM dataset. Both studies highlight the importance of further research with larger datasets for more robust validation.

In 2015, Rouhi, Rahimeh, et al.(Rouhi R, 2015) presented two novel approaches for mass segmentation in mammograms. They identified Regions of Interest (ROIs) using chain codes from the DDSM dataset and reduced noise with histogram equalization and median filtering. The segmentation was performed using two methods: region-growing and cellular neural-based techniques. They applied a Genetic Algorithm (GA) for feature selection, varying the chromosome structures and fitness func-

tions. For classifying masses into benign or malignant, they used multiple classifiers including Multi-Layer Perceptron (MLP), Random Forest (RF), Naïve Bayes (NB), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN). Their experiments on both DDSM and MIAS datasets showed that the second segmentation technique achieved a high sensitivity of 96.87%, although results varied as detailed in their study.

5 THE DEEP LEARNING-BASED CAD SYSTEM

In recent times, there have been notable advancements in the field of Computer-Aided Diagnosis (CAD) systems, particularly driven by the remarkable performance improvements of deep-learning models in computer vision. Convolutional Neural Networks (CNNs), transfer learning techniques, and deep learning-based object detection models have played a pivotal role in enhancing the performance of CAD systems. Numerous algorithms have emerged that harness the potential of deep learning models.

For instance, Dhungel Neeraj et al. (2017) (Dhungel N, 2017) introduced a CAD tool designed for mass detection, segmentation, and classification in mammographic images, with minimal user intervention. They employed a combination of random forest and a cascade of deep learning models for mass detection, followed by a hypothesis refinement step. The detected masses were further segmented using active contour models, and a deep learning model, pre-trained on hand-crafted feature values, was used for classification. This system was tested on the INBreast dataset, where it exhibited impressive results, detecting nearly 90% of masses with a false-positive rate of 1 per image. Additionally, the segmentation accuracy reached 0.85 (as measured by the Dice index), and the model achieved a sensitivity of 0.98 for classification.

Similarly, in the same year, Geras et al. (2017) (Geras et al., 2017) developed a Deep Convolutional Network (DCN) capable of handling multiple views of screening mammography, specifically the CC and MLO views for each breast side of a patient. This model was designed to predict the radiologist's assessment and classify images based on the Breast Imaging-Reporting and Data System (BI-RADS) criteria, categorizing them as "incomplete," "normal," or "benign." Their research delved into the impact of dataset size and image resolution on screening performance. The findings revealed that increased training set size led to improved performance, and the

model performed optimally at the original resolution. In a reader study conducted on a random subset of their private dataset (Lieberman and Menell, 2002), the model achieved a macUAC of 0.688, while a committee of radiologists achieved a slightly higher macUAC of 0.704.

These studies exemplify the remarkable progress in CAD systems driven by deep learning techniques, showcasing their potential in enhancing the accuracy and efficiency of breast cancer detection in mammograms.

6 DEEP LEARNING-BASED OBJECT DETECTION

In the realm of computer vision, the ascendancy of deep learning has rendered the manual crafting of features obsolete, as it now autonomously learns and extracts the most pertinent image characteristics tailored to specific tasks. Object detection, a crucial domain within computer vision, has seen remarkable advancements thanks to the integration of deep learning techniques. These object detection methods primarily fall into two categories: one-stage detectors, which rely on regression or classification, and two-stage detectors, which employ regional proposals (Zhao et al., 2019). A fundamental element influencing the performance of both these techniques is the concept of anchor boxes, which significantly impacts the accuracy of object identification within images.

In 2018, Ribli Dezső et al. (Ribli et al., 2018) employed the Faster R-CNN detector for mammogram analysis. They modified pixel values for better image quality and used INbreast and DDSM datasets for testing and training. Their model could classify masses as benign or malignant with high accuracy, achieving an AUC score of 0.95 and detecting 90% of malignant masses with a low false-positive rate. However, the study's limited scope due to scarce datasets with detailed annotations calls for further validation on larger datasets.

7 METHODOLOGY

7.1 Methodology Overview

Our research endeavors to revolutionize breast cancer diagnosis by employing advanced deep learning techniques, particularly focusing on the utilization of YOLOv8x-seg. The methodology begins with an exhaustive data collection process from the CBIS-

DDSM dataset, followed by meticulous data annotation using Roboflow. We employ the YOLOv8x-seg model, a specialized variant optimized for semantic segmentation, which combines real-time performance with high accuracy. The annotated dataset is split into training, validation, and testing subsets, ensuring model robustness. After training, we assess the model's performance and fine-tune as necessary. Subsequently, the YOLOv8x-seg model is deployed for real-time breast cancer segmentation, swiftly and accurately identifying and delineating regions of interest within mammography images. Our ultimate objective is to contribute to improved breast cancer diagnosis, with YOLOv8x-seg serving as a pivotal tool in enhancing the efficiency and accuracy of the diagnostic process. (See Figure 1 for an illustration of our methodology process.)

7.2 Data Collection

In the initial phase of our research, we focus on data collection. We acquire a curated dataset of 1400 mammography images from the CBIS-DDSM database, which contains a diverse range of breast conditions, both normal and cancerous. This dataset selection ensures that our research is based on a balanced mix of cases and is both diverse and representative. These images are drawn from the database without any preprocessing, maintaining their original quality, resolution, and format. This step is essential for the subsequent use of the YOLOv8 model in detecting and segmenting breast cancer anomalies accurately.

7.3 Data Annotation

For the accurate and efficient annotation of the dataset, we turn to Roboflow, a versatile data annotation platform. Through Roboflow, we meticulously annotate the regions of interest (ROIs) in the mammography images, specifically marking the locations of breast lesions, masses, or anomalies. These annotations are represented as bounding boxes, precisely delineating the boundaries of the anomalies within the images. The result is a thoroughly annotated dataset, primed for use with the YOLOv8 model.

7.4 Model Selection and Real-Time Segmentation

In the subsequent phase of our methodology, we integrate the YOLOv8x-seg model. This model is a highly specialized variant, particularly fine-tuned for intricate semantic segmentation tasks, with a strong

emphasis on applications in breast cancer detection. The YOLOv8x-seg is celebrated for its prowess in real-time object detection, offering an optimal blend of precision and speed. This balance is critical in medical image analysis, where both accuracy and timely results are paramount. The configuration of the YOLOv8x-seg model is meticulously tailored to enhance its efficiency and accuracy in segmenting breast cancer indicators in medical imagery.

Upon training, the YOLOv8x-seg model undergoes application on a designated test dataset, marking the commencement of real-time segmentation tasks specific to breast cancer. The model's architecture and training enable it to deeply understand and recognize the nuanced features of breast cancer lesions. This proficiency allows the YOLOv8x-seg to swiftly, yet accurately, identify and outline the critical areas within mammography images. These areas are potential sites of abnormalities or lesions indicative of breast cancer. The model's ability to perform such precise and rapid segmentation is crucial in delineating regions of interest that are essential for a thorough and accurate diagnosis.

The integration of this combined phase of applying the trained YOLOv8x-seg model to real-time data analysis significantly elevates the process of breast cancer diagnosis. It ensures that the model not only provides real-time segmentation but also maintains a high level of precision in its analysis. This dual capability of the YOLOv8x-seg model positions it as a fundamental tool in revolutionizing the efficiency and accuracy of breast cancer diagnosis, potentially leading to earlier detection and better patient outcomes.

8 EVALUATION

In the evaluation phase of our research, we aim to comprehensively assess the performance of the YOLOv8x-seg model in breast cancer segmentation. The dataset, after meticulous annotation using Roboflow, was thoughtfully split into two subsets: 80% for training and 20% for testing, ensuring a robust assessment of the model's capabilities.

Training was conducted on a high-performance computing platform, specifically Google Colab, harnessing the benefits of its GPU acceleration. This allowed us to expedite the training process and ensure the model could efficiently process a considerable amount of data.

The training process spanned 80 epochs, with the objective of achieving the following metrics:

F1-Score: The F1-score is a measure of a test's accuracy. It balances precision and recall and is cal-

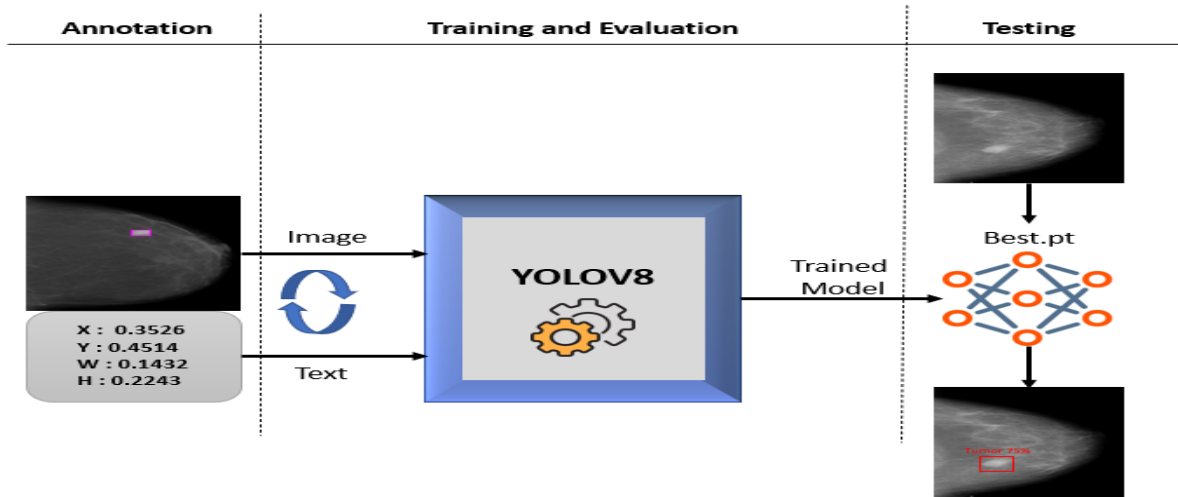


Figure 1: Methodology Overview.

culated using the formula:

$$F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Intersection over Union (IoU): The IoU is a metric that assesses the spatial overlap between the predicted region and the ground truth region. It is calculated as:

$$IoU = \frac{\text{Area of Intersection}}{\text{Area of Union}}$$

These metrics, in addition to precision, recall, and overall accuracy, will be rigorously assessed, and the results will be crucial in determining the YOLOv8x-seg model’s readiness for real-world clinical applications and its potential to enhance the accuracy and efficiency of breast cancer diagnosis.

In a comparative analysis of the different YOLO architectures from YOLOv5 to YOLOv8 for segmentation tasks, various key aspects and evolutionary advancements become evident. YOLOv5, as the baseline, offers efficient and straightforward architecture, ideal for a broad range of applications. Progressing to YOLOv6 and YOLOv7, there are marked improvements in accuracy and complex segmentation capabilities, thanks to advanced features and optimizations. YOLOv8 represents the pinnacle of this evolution, with a design finely tuned for precision-intensive tasks such as medical image segmentation, blending real-time performance with high accuracy and superior semantic segmentation abilities. This version is particularly adept at applications like breast cancer detection, where precise lesion delineation is critical. Each iteration of the YOLO architecture builds upon the strengths of its predecessors, with YOLOv8 epitomizing the optimal balance of speed, accuracy, and detailed segmentation capabilities. The table below 1 provides a detailed comparison of these YOLO

architectures, highlighting their specific features and performance metrics in the context of segmentation tasks.

Table 1: Comparative Analysis of YOLO Architectures for Breast Cancer Segmentation.

Model	F1-score	IoU
YOLOv5x-seg	93.98%	88.02%
YOLOv6x-seg	94.32%	88.76%
YOLOv7x-seg	94.45%	89.11%
YOLOv8x-seg	95.27%	89.51%

The YOLOv8 model, achieving a 95.27% F1-score, demonstrates exceptional accuracy in identifying and segmenting breast cancer anomalies in mammography images. This high F1-score reflects its effective balance between precision and recall. Additionally, YOLOv8’s impressive 89.51% Intersection over Union (IoU) score underlines its capability for precise localization and segmentation. These high metrics highlight YOLOv8’s reliability and precision in medical imaging, making it a crucial tool for accurate diagnosis and effective treatment planning in breast cancer care.

9 CONCLUSIONS

In this research, we’ve harnessed advanced deep learning techniques, particularly YOLOv8x-seg, to enhance breast cancer diagnosis. Through meticulous data annotation and robust model training, we’ve achieved an F1-score of 95.27% and an IoU of

89.51%, indicating the model's remarkable precision and accuracy in breast cancer anomaly detection and segmentation. These results hold great promise for more accurate and efficient breast cancer diagnosis, with the potential to positively impact clinical practices and patient outcomes. Our research underscores the value of deep learning in healthcare and the continuous pursuit of innovation for saving lives and improving patient care.

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