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Comparative Analysis of YOLOv5 –YOLOv11 for Automated Detection of Breast Lesions in Mammographic Images

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ABSTRACT

Breast cancer is one of the most prevalent cancers in women worldwide, and mammography is the most important imaging technique to detect it at an early stage. Single-stage object detectors from the You Only Look Once family have gained more and more popularity in the field of automated breast lesion detection and classification in mammographic images in recent years. But a comparative study of all the generations of YOLOv5 to YOLOv11 has not been done for this task. This review consolidates 20 peer-reviewed studies and benchmark evaluations of the YOLO architectures ranging from YOLOv5 to YOLOv11 to examine and compare the detection accuracy, robustness across datasets, architectural innovation, and clinical readiness. The results suggest that YOLOv5 is the most advanced and widely tested family for mammography, achieving up to 88.0 mAP on INbreast and 84.3 after transfer learning from CBIS-DDSM. YOLOv8-based models show maximum flexibility such as micro calcification detection with mAP50 of 92.1. YOLOv9 made architectural improvements that were tested against CBIS-DDSM and YOLOv10 added NMS-free training. YOLOv11 is the best general purpose model, but its use in mammography is somewhat restricted. There is little literature on YOLOv6 in breast imaging. The main research gaps we have identified are: YOLOv10/YOLOv11 evaluations specifically for mammography; heterogeneity of datasets; and inconsistent reporting of metrics. Last but not least, we make suggestions for benchmarking.

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1. Introduction:

Mammography, the most commonly used imaging modality for breast cancer and breast disease is the core of population-based screening programs worldwide [1]. While screening is important for early detection of death, there is also a difficulty in interpretation of mammograms, as lesions can be small, subtle, or hidden in dense fibroglandular tissue, and the reader (radiologist) can vary greatly between different individuals. Increasing workload demands and, in many areas, the lack of dedicated breast radiologists are also challenges for screening programs around the world.

CAD has been used for decades to assist readers, but the actual effectiveness of CAD in real world practice was not true in most cases and the new surge in deep-learning-based CAD is pushing forward.

Convolution and transformer-based networks have since shown to be very effective for classification, detection and segmentation applications in breast imaging. YOLO has been found to be very appealing for medical applications among the detection frameworks. Compared with the usual, manually selected regions of interest for mammogram analysis, YOLO is able to analyze the whole mammogram in a single forward pass, which better mimics the diagnostic workflow of a radiologist, and YOLO has proven to be more accurate and faster to infer than other object detectors in many cases [2]. The family has expanded significantly since YOLOv1 to the latest YOLOv11, and has seen its use in medical object detection spread to lesion detection, tumor localization, and anomaly screening [3, 4]. In fact, there have been more than a hundred studies using YOLO to solve medical-related problems identified through systematic review of literature in the past five years (2018–2023), indicating that the framework is widely adopted and that some issues in medical small-lesion detection, such as small-lesion sensitivity, small-lesion annotation quality, and computational complexity, remain persistent [3].

The YOLO family has been tested on public breast imaging databases such as CBIS-DDSM, INbreast and VinDr-Mammo and private clinical datasets. The evidence, however, is rather scattered, as it is available in various studies with different variants of the YOLO model, data sets, data pre-processing, data augmentations, and evaluation metrics, which hinders the research and clinical community from deciding which generation of YOLO is the best to be used for breast lesion detection. This review aims to address this gap by answering the following objectives:

1. To comparatively evaluate breast lesion detection performance systems of YOLOv5, YOLOv8, YOLOv10, and YOLOv11 using a systematic approach to compare YOLO architectures;
2. To reconcile reported detections over public and private datasets;
3. To explore architectural changes and their impact on task-specific appropriateness;
4. To determine how datasets are being used and suggest common practices for evaluating them in the future.

Review methodology and selection protocol are discussed in Section 3, and the resulting results are synthesized and presented in Section 4. Section 5 presents comparative performance, strengths, and limitations of each version along with the evidence charts, and Section 6 concludes with a discussion of gaps in research and recommendations.

2. Methodology

2.1 Review design and search strategy

This review is based on the structured narrative synthesis design. Literature from 2018 to 2025 was searched using PubMed/MEDLINE, Scopus, IEEE Xplore, and arXiv from the time of the emergence of YOLOv5 to the release of YOLOv11. Search strings combined two thematic blocks: the model (e.g., "YOLOv5", "YOLOv6", "YOLOv7", "YOLOv8", "YOLOv9", "YOLOv10", "YOLOv11", "You Only Look Once") and the application ("mammography", "mammogram", "breast lesion", "breast mass", "microcalcification", "breast cancer detection").

2.2 Inclusion and exclusion criteria

Studies were selected if they (i) used a YOLO model version 5 or higher in breast imaging, (ii) focused mainly on mammographic images (either FFDM or digitized film or contrast-enhanced spectral mammography), (iii) provided quantitative results (mAP, precision, recall, F1 score or similar), and (iv) were published in peer-reviewed journals or in known preprint repositories. Studying only the non-mammographic modalities (such as ultrasound only) or

studying only classification without localization information, or reporting no metrics of model performance were excluded. In the case of general purpose YOLO benchmark studies and architectural reviews, along with the dataset descriptors, contextual evidence was kept to support the comparison of model generations.

2.3 Data extraction and synthesis

For each eligible study, we picked out YOLO version and variant (YOLOv5s–x); dataset(s) and any preprocessing and augmentation procedures; evaluation metrics (mAP50, mAP50–95, precision, recall, F1-score) as reported; and study-specific findings and limitations. Given the complexity of the data sets and the variety of metric definitions employed in the studies, a quantitative meta-analysis was not suitable and instead the results were summarized across three dimensions: architectural generation, data set, and task type (localization, detection, or classification). The review protocol is summarized in figure 1.

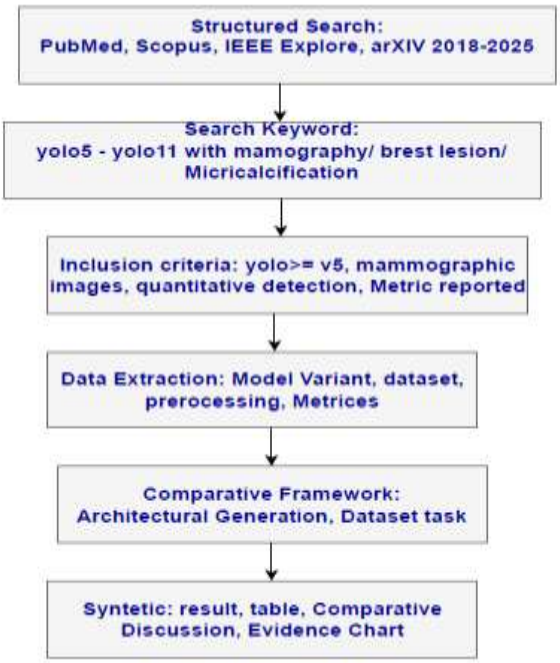

Figure 1. Structured search and comparative synthesis as a methodological workflow of the review. A total of 20 sources (13 application studies, 7 benchmark/review/dataset descriptors) met the criteria and are referred to in this review.

2.4 Limitations of the method

The main drawback is that there is no direct quantitative comparison between studies because reported values vary with the composition of the datasets, the mix of lesion types, the resolution of the input images, the type of data augmentation and the type of thresholding. If multiple configurations are reported in the same study, we report on the values as reported and indicate the context in the results tables, but do not re-average.

3. Results

3.1 Inventory of studies by YOLO generation

In the 13 application-specific studies that remained, 4 made an explicit evaluation of some variant of YOLOv5 [2], [10], [11], [13], 5 studies involved YOLOv8, either as a classification task, microcalcification detection, or architecture improvements [5], [14], [15], [16], [17] and 1 or 2 studies compared YOLOv9 [17], YOLOv10 [18] to YOLOv7 [5]. In three studies [2, 5, 10] older generations (YOLOv3 and YOLOv4) served as a comparator, while another one study used an unspecified YOLO framework following a progressive fine-tuning procedure [12]. There was no included study that compared YOLOv6 or YOLOv11 to mammographic images.

3.2 Reported detection performance

The quantitative results as reported from the application studies reviewed are summarized in Table 1 and presented in the exact form provided by the studies. The performances depend largely on the data used, and on the type of lesion: FFDM-based and expert-annotated datasets allow higher mAP values after fine tuning [12], while digitised film data with coarse annotations allows for good transfer learning ability with lower absolute performances [2, 11].

Table 1. Breast lesion detection and classification for mammography reported performance of YOLO based models with each study.

Study (year)	Model	Dataset	mAP50	Precision	Recall	Additional metrics
Prinzi et al. [2]	YOLOv5s	Proprietary FFDM	0.621	—	—	Best of YOLOv3/v5/v5-Transformer
Prinzi et al. [2]	YOLOv3	INbreast (5-fold)	0.738 ± 0.061	0.695 ± 0.104	0.785 ± 0.012	—
Prinzi et al. [2]	YOLOv5s-Transformer	INbreast (5-fold)	0.771 ± 0.048	0.799 ± 0.118	0.742 ± 0.146	—
Prinzi et al. [2]	YOLOv5s (aug-high)	CBIS-DDSM (equalized)	0.498	0.482	0.566	mAP without augmentation: 0.400
Coşkun et al. [10]	YOLOv5s	INbreast (448 px)	71.0%	64.9%	82.8%	F1 72.8%
Coşkun et al. [10]	YOLOv5m	INbreast (448 px)	84.9%	86.3%	75.5%	F1 80.5%
Coşkun et al. [10]	YOLOv5l	INbreast (448 px)	86.0%	89.4%	79.8%	F1 84.3%
Coşkun et al. [10]	YOLOv5x	INbreast (448 px)	88.0%	83.5%	87.0%	F1 85.2%
Coşkun et al. [10]	YOLOv5s	INbreast (608 px)	81.0%	84.5%	83.4%	F1 83.9%
Karaca et al. [11]	YOLOv5 (TL CBIS-DDSM→INbreast)	INbreast	0.843	0.855	0.774	Five-fold cross-validation
Karaca et al. [11]	YOLOv5 (TL VinDr-Mammo→INbreast)	INbreast	0.84	0.829	0.787	Also tested on MIAS and private data
Figueiredo et al. [12]	YOLO (progressive FT)	CBIS-DDSM → INbreast → VinDr-Mammo	45.6% → 76.73% → 80.55%	50.7% → 83.32% → 80.07%	—	Gains with annotation quality
Marchi et al. [17]	YOLOv9c	CBIS-DDSM (augmented)	0.677	—	0.686	YOLOv8l precision 0.788

Shia & Ku [15]	YOLOv8	Microcalcifications (10,323 images)	0.921	—	0.796	mAP50–95 0.709; F1 0.82; accuracy 0.842
Liu et al. [16]	AE-YOLO (YOLOv8-based)	DDSM & MIAS	84.9%	85.0%	77.2%	mAP50–95 48.4%
AkbarnezhadSany et al. [14]	YOLOv8 (classifier)	Multi-institutional	—	—	—	Test AUC 91%; accuracy 86.68%; F1 84.86%; specificity 93.32%

Note: Dashes represent measurements that were not reported in the source. Values are as published, differences between studies are not necessarily reflective of differences in model quality but due to differences in datasets, tasks, and protocols.

3.3 Dataset characteristics

Table 2 provides a summary of the public benchmark datasets applied to the reviewed studies, and corresponds a descriptor to its source.

Table 2. The features of the available main mammography datasets applied in the reviewed studies of YOLO.

Dataset	Content	Modality	Annotations	Source
CBIS-DDSM	753 calcification cases; 891 mass cases	Digitized film mammography (curated DDSM subset)	Mammographer-curated; mass segmentation and bounding boxes; pathologic diagnosis	[19]
INbreast	410 images from 115 cases	FFDM (high-resolution DICOM)	Polygonal segmentation; mass, calcifications, asymmetries, distortions; histologically confirmed	[20]
VinDr-Mammo	5,000 exams, four standard views each	FFDM	Double-read with arbitration; BI-RADS and breast density at breast level; category/location of non-benign findings	[1]

4. Discussion

4.1 Synthesis across YOLO generations

The evidence is combined to give a more complex picture. Even though it is an older architecture than newer ones, YOLOv5 has the biggest body of validation and is well understood to follow a "nano to x-large" scaling ladder, with larger variants achieving > 88% mAP on INbreast [10] and it has shown to be very effective with transfer learning and augmentation with limited data, as reported in [2] and [11]. It has been limited to coarse-annotation datasets that have been digitized (mAP of ≈0.498 when using a set of digitized CBIS-DDSM images and 0.621 on a set of different proprietary digitized images [2]), highlighting the disparity between the film-based and digitized mammography domain.

YOLOv8 is the most adaptable available version. It underpins the strongest reported microcalcification result (mAP50 0.921) [15], the AE-YOLO enhancement (mAP50 84.9%) [16], and competitive classification performance (test AUC 91%) [14], and it has been shown to excel at multi-scale feature extraction in breast imaging. Its generalization across

lesion types — from masses to microcalcifications — makes it the generation of choice for CAD pipelines targeting mixed screening populations.

YOLOv9's architectural innovations translated into the best published CBIS-DDSM detection result among the versions benchmarked head-to-head (mAP50 0.677) [17], and general benchmarks confirm its strength on smaller datasets [6]. YOLOv10 introduced NMS-free training and was reported to outperform prior architectures on mammograms, although quantified results remain scarce [18]; general benchmarks, however, show YOLOv10 underperforming YOLOv8 [7], which should temper expectations. YOLOv11 leads every recent general-purpose benchmark — highest mAP50 across eleven domains [7], ≈54.5% COCO mAP50–95 at 13 ms [8], 22% fewer parameters than YOLOv8m [4], and consistent (if modest) gains over YOLOv8 and YOLOv10 in controlled comparisons [9] — but the absence of any peer-reviewed mammography application leaves its clinical potential unverified. The strengths and evidence gaps for automated breast lesion detection with each generation are summarized in Table 3.

Table 3. In light of the evidence reviewed, the strength and weaknesses of the YOLO generations for mammographic breast lesion detection are presented.

Version	Strengths for mammography	Limitations / evidence gaps
YOLOv5	Most validated family; strong transfer learning (mAP 0.843) [11]; scaling variants up to 88.0 mAP on INbreast [10]; augmentation-sensitive and well characterized [2]; staged high-precision detection demonstrated [13]	Lower accuracy on coarse digitized film data (CBIS-DDSM ≈0.498) [2]; older backbone relative to v8–v11
YOLOv6	None identified	No dedicated mammography study found in this review; ranked below YOLOv5 on general benchmarks [7]
YOLOv7	Faster than YOLOv4; competitive on INbreast [5]	Loses to YOLOv4 on mAP/recall/precision overall; struggles with small masses in crowded scenes and lighting variation [5]
YOLOv8	Most flexible current option; best microcalcification mAP50 (0.921) [15]; strong classification AUC (91%) [14]; supports enhancement modules (AE-YOLO, mAP50 84.9%) [16]	Mixed results relative to YOLOv9 on mass detection on CBIS-DDSM [17]
YOLOv9	Best CBIS-DDSM detection (mAP50 0.677 vs YOLOv8s/l) [17]; good on small datasets generally [6]	Single mammography benchmark to date; sparse lesion-specific validation
YOLOv10	NMS-free training; reported gains over prior architectures on mammograms [18]; speed/efficiency on benchmarks [6]	Benchmark ranking below YOLOv8 [7]; no quantitative mammography results published
YOLOv11	Best general benchmarks (54.5% COCO mAP50–95 @13 ms) [8]; 22% fewer parameters than YOLOv8m [4]; leads multi-domain rankings [7]	No peer-reviewed mammography application identified; gains over v8/v10 generally <5% [9]

4.2 Factors driving performance differences

There are three common themes in the reviewed evidence. First, outcomes are dominated by **data quality** and **granularity of annotation** - the same YOLO pipeline improved from 45.6% mAP@0.5 of CBIS-DDSM to 76.73% mAP@0.5 of INbreast and 80.55% mAP@0.5 of VinDr-Mammo by progressively fine-tuning on better-annotated FFDM data [12]. Second, the **augmentation** and **transfer learning principles** have a tangible impact on the results: the use of augmentation in YOLOv5 increased the mAP on CBIS-DDSM from 0.400 to 0.498 [2] and the transfer learning from CBIS-DMS to INbreast produced a mAP of 0.843 [11]. Third, it's important to consider **lesion subtype**; the high-value screening finding of microcalcifications has a very high mAP50 (0.921) with YOLOv8 [15] while the more variable morphologically mass type yields lower scores, particularly in the context of film-based data [2] [17]. The pattern is similar to the general body of medical YOLO literature where tasks such as breast cancer detection have been able to achieve mAP scores of over 85% whereas small and/or rare lesions are still a challenge [3].

5.3 Charts: quantitative synthesis

Because cross-study mAP values are not directly comparable, Figure 2 presents each reported value in its dataset context. Figure 3 depicts dataset usage across the 13 application studies, showing that CBIS-DDSM and INbreast together account for 8 of 18 dataset instances (≈44%), with private or large clinical collections the third pillar.

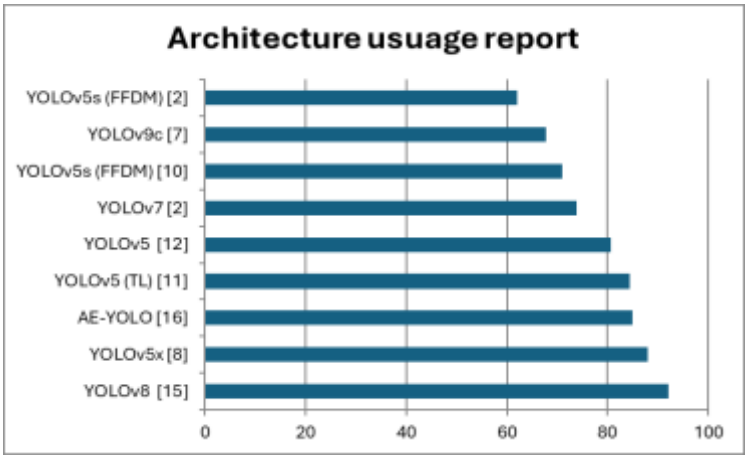

Figure 2 – Reported mAP50 by model and dataset (each block ≈ 2 percentage points).

Legend: "TL" = transfer learning; "MC" = microcalcification task; "FT" = fine-tuning.

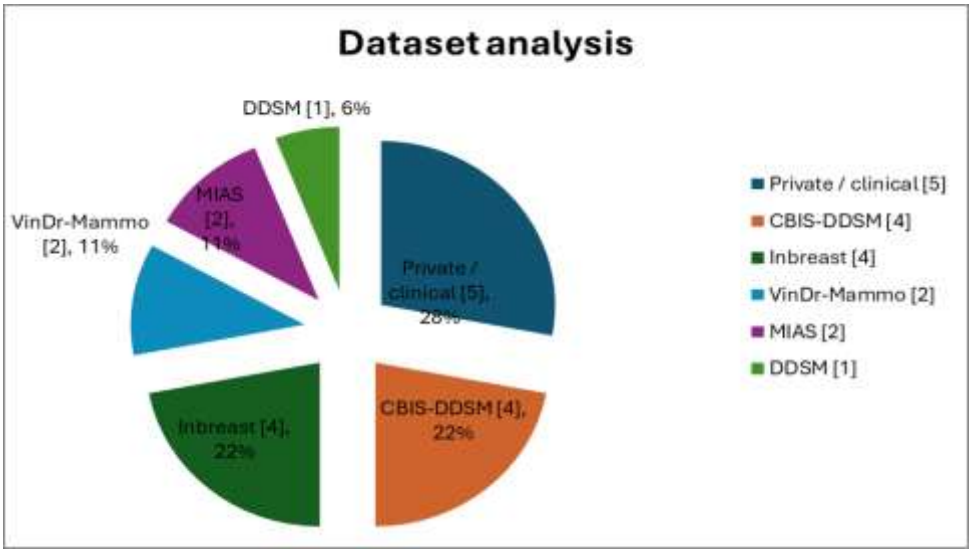

Figure 3. Frequency of dataset usage across the 13 reviewed application studies; studies using more than one dataset contribute multiple instances.

4.4 Clinical translation and research gaps

For deployment-oriented research, two design patterns stand out: explainability-augmented detection, in which Eigen-CAM saliency maps attached to YOLOv5 substantially reduce false negatives at the cost of more false positives [2], and staged double-screening architectures, in which a high-precision YOLOv5 stage and a high-sensitivity CNN stage jointly confine review to under 20% of breast tissue [13]. Both patterns directly influence the practical aspects of screening programs (missed-lesion risk and reader workload) and explicit clinical applicability of YOLOv8's microcalcification performance was argued in the context of large-scale screening [15].

The review also reveals some gaps in the literature: (i) no published evaluation of YOLOv6 or YOLOv11 on mammography has been found; (ii) the reporting of performance metrics is inconsistent, some studies report mAP, others mAP is 0.5, mAP50, or mAP50–95, and few report all three precision/recall/F1 values, making it difficult to synthesize the results across studies; (iii) shallow learning of pretraining models, with only a subset of studies involving pretraining on film-derived CBIS-DDSM and validation on FFDM sets [11], [12]; and (iv) some known limitations of YOLO in medical imaging, such as sensitivity to small lesions, dataset and annotation variability, and computational demands [3]. These gaps are aligned with the recommendations of systematic reviews on YOLO in medical object detection, which recommend the creation of larger well-balanced annotated datasets and the adoption of standardized reporting [3].

4.5 Implications for model selection

There are two approaches that are particularly suitable for real-world use. The former is adding Eigen-CAM saliency maps to YOLOv5, which can help minimize missed lesions but can also lead to over-detection [2]. The latter is a staged double screening architecture that first detects the most probable lesions by a high-precision YOLOv5 stage and then potentially missed abnormalities by a complementary high-sensitivity CNN stage. The system achieves a sensitivity-oriented screening and precision-oriented localization to reduce the volume of mammographic tissue that needs detailed review to less than 20% (13). These both have the advantage of making screening more practical, so that missed lesions are minimized, and workload of the readers is reduced, which raw mAP cannot record. For microcalcification screening, YOLOv8 has also demonstrated clinically useful results in screening large numbers of microcalcifications [15].

In medical imaging, YOLO models are still susceptible to small lesions, variations in medical datasets and annotations, and high computation costs [3]. They are not incidental to the limitations, but rather impact the sensitivity to clinically relevant findings and the ability to reproduce on different datasets, as well as the ability to integrate into routine screening workflows. Systematic reviews also highlight the importance of well-balanced, adequately annotated larger datasets and standardized reporting of studies [3]. Filling these gaps should therefore be regarded as a necessary, and not an optional, path for meaningful claims of clinical superiority to be made, not along a path for future optimization.

5. Conclusion

This review aimed to compare the algorithms of YOLOv5 to YOLOv11 for the automated detection of breast lesions in mammograms and present the results in 20 peer-reviewed literature. The key findings are:

- YOLOv5 is the most mature and thoroughly validated generation, with reported mAP values of up to 88.0 on INbreast and 0.843 after transfer learning from CBIS-DDSM. It is thus a reliable reference for CAD research [10].

- YOLOv8 is the most flexible and rapidly developing option, delivering the strongest reported performance in microcalcification detection and competitive classification results [15].
- YOLOv9 achieved the strongest head-to-head performance on CBIS-DDSM [17]. YOLOv10 implemented a training method that does not use NMS, but its clinical application is not yet substantiated, as it has no quantitative evidence in mammography and does not achieve the best results in general benchmarks[18].
- YOLOv11 performs well in general benchmarks but has not been validated on mammograms, making it the review's biggest evidence gap [8].
- YOLOv6 has not yet been evaluated in breast-imaging studies and underperforms older versions in general benchmarks [7].

Future research will compare YOLOv5, YOLOv8, YOLOv11 and YOLO26, based on a common protocol with the mammography dataset CBIS-DDSM. The study will also include a ResNet-50 classification model to classify breast lesions found during YOLO-based localization. Other areas of future study will include small lesion detection, model explainability, computational efficiency and external validation on other mammography datasets. These efforts will evaluate whether the new YOLO generations are improving breast-cancer screening outcomes, as measured by their benchmarks, and if they are, why. Another direction of improvement in early detection accuracy is the use of multi-modal data, such as fusion of mammographic images with ultrasound or MRI, and to reduce the false positive rate

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