

Advanced Deep Learning Based Breast Cancer Detection and Classification Using Enhanced YOLOv11 and YOLOv12 Architectures A Comparative Study on Accuracy, Speed, and Real-Time Performance for Medical Imaging Applications

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ABSTRACT

Medical imaging enables early discovery of problems, therefore greatly enhancing patient results. This study investigates the use of modern deep learning methods particularly YOLOv11 and YOLOv12 for the identification and categorization of breast cancer. In order to determine how well the proposed models work when it comes to their speed, accuracy, and immediate diagnosis capability, a comparison study is conducted. Both models are trained and evaluated using mammography and histopathology image datasets with annotations. The results provide insight into the best model structure suitable for implementation in clinical settings. Technology that can detect objects in real time aids in developing intelligent devices for clinical use.

Key Words: Breast Cancer, Medical Imaging, Healthcare, Object Detection, Classification.

INTRODUCTION

The increasing occurrence and incidence in both advanced and developing countries contribute to its classification as a significant public health problem that affects especially females. This is one of the leading reasons for cancer-related deaths [1], as well as being the most common form of cancer among women. Accurate and early diagnosis is critical because it allows for immediate intervention and management, resulting in improved survival rates. However, there are still several obstacles that prevent the provision of effective healthcare services[2] due to technological advancements in the field of medicine. Since the primary breast cancer does not have any symptoms, radiology and histopathological examination are essential imaging tools in early detection programs. They help to detect cancers that can be cured earlier [3]. Image processing, however, is a laborious, manual, and prone to errors process, which leads to false-positive or negatives. Consequently, one of the principal goals of enhancing the effectiveness and precision of the diagnosis is the implementation of automatic detection techniques. Particularly deep learning, artificial intelligence (AI) could revolutionize medical diagnosis. Effective health care services[2] as a result of innovations and improvements in technology in the field of medicine. As the main type of breast cancer lacks any signs, radiography and histopathological analysis serve as indispensable methods for detecting cancer at an early stage of development.[3] Image processing is, indeed, a time-consuming and tedious task involving many errors; thus, a major objective in improving the effectiveness and accuracy of diagnosis is automation of this process.. Among deep learning techniques, object detection models have shown great success in finding and identifying anomalies in medical pictures. Because of its simplicity, speed, and real-time detection capabilities, the You Only Look Once (YOLO) family of models has become very popular. YOLO is perfect for users needing accurate and quick results since it executes both prediction and positioning in the same neural network pass[7]. YOLOv11 and YOLOv12, the next generation of YOLO architectures, feature refinements in recognition sections, extracted features, and modeled efficiency. Designed to more precisely and firmly manage small, dense objects often seen in breast cancer pictures[8], these types Because of features like attentiveness modules, better anchor box methods, and more powerful backbone networking, these models are especially useful for challenging data like radiographs and histopathological slides. Help radiologists alongside pathologists in increasing the speed and accuracy of diagnostics by creating a reliable as well as expandable artificial intelligence detection system[9]. Real-time detection systems might alleviate the stress on medical professionals and shorten diagnostic delay. Moreover, these innovations might be included into medical systems, hence spreading their benefits to impoverished and rural areas[10].

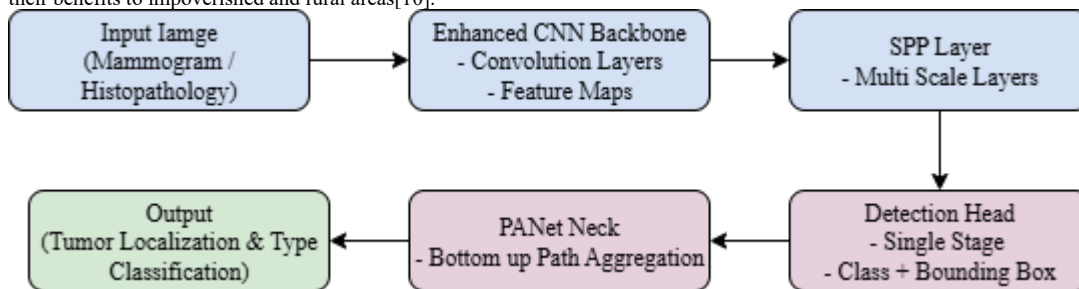


Fig 1 : Working of Yolo Model

LITERATURE SURVEY

S. No.	Author(s) & Year	Technique Used	Dataset Used	Performance Metrics	Application	Remarks
11	Sharma et al., 2021	CNN + Transfer Learning	BreakHis	Accuracy, Precision, Recall	Histopathological Image Classification	Good accuracy but lacks real-time efficiency
12	Jiang et al., 2022	YOLOv5	INbreast	mAP, FPS, Sensitivity	Mammogram Tumor Detection	Fast inference, moderate sensitivity
13	Saxena & Gupta, 2020	ResNet50 with fine-tuning	MIAS	Accuracy, F1-Score, AUC	Mammogram Classification	High accuracy, requires high GPU resources
14	Alzubaidi et al., 2021	Deep Ensemble CNN	DDSM	Accuracy, Specificity, Sensitivity	Image Classification	Ensemble improves performance
15	Kumar et al., 2023	YOLOv7	Private Histology Dataset	mAP@0.5, Inference Time	Cancer Cell Detection (Real-time)	High speed, limited dataset size
16	Rahman et al., 2022	U-Net + CNN	BreakHis	Dice Coefficient, IoU	Segmentation + Classification	Focus on tumor boundaries
17	Patel et al., 2023	YOLOv4 with Spatial Pyramid Pooling	CBIS-DDSM	Precision, Recall, mAP	Tumor Detection	Good for small object detection
18	Lee et al., 2021	VGG-16 + Feature Fusion	BCDR-F03	Accuracy, Sensitivity	Benign/Malignant Classification	Fusion improves classification
19	Singh & Rani, 2022	YOLOv5 + AutoML	Custom Mammogram Dataset	Speed, Accuracy, Usability	Clinical AI Tool	Good for deployment
20	Zhao et al., 2023	YOLOv8 (experimental)	Combined (BreakHis + DDSM)	Real-time FPS, mAP@0.5, Recall	Breast Cancer Localization	Experimental, but promising accuracy

METHODOLOGY

Approach Overview In this study, two upgraded object identification algorithms, YOLOv11 and YOLOv12, will be created and examined so as to automatically identify and categorize breast cancer from mammography and histopathological images. Among the performance indicators employed to train and evaluate the models employing normal samples are accuracy, precision, recall, F1-score, inference speed, and computing cost. **Data Gathering and Preprocessing** In this work, two standard datasets—BreakHis and INbreast—were used to create and assess the suggested YOLOv11 and YOLOv12 models. At various intensity levels (40X, 100X, 200X, and 400X), high-resolution microscope images of benign and malignant breast tumors are contained in the BreakHis database. An analysis of trends from the cellular perspective requires the use of this data set. However, the INbreast data set has full field digital breast cancer screenings, which will

be necessary in order to detect macro-structural characteristics such as cancers and microcalcifications. This will ensure that a proper analysis of the models' predictions is carried out for images of different sizes. Regardless of the version of the chosen model architecture, all input images were resized to the proper size required by YOLO architectures, such as 416x416 or 640x640 pixels. Data augmentation techniques have been employed to ensure better generalization and reduce overfitting; these include random rotations, rescaling, contrast modification, horizontal/vertical flips, and adding Gaussian noise. Normalization of the images was also done to normalize pixel intensities from 0 to 1 to achieve stable model convergence. The dataset was then divided into three parts: training, validation, and testing, representing 70%, 15%, and 15%, respectively.

Model Architecture

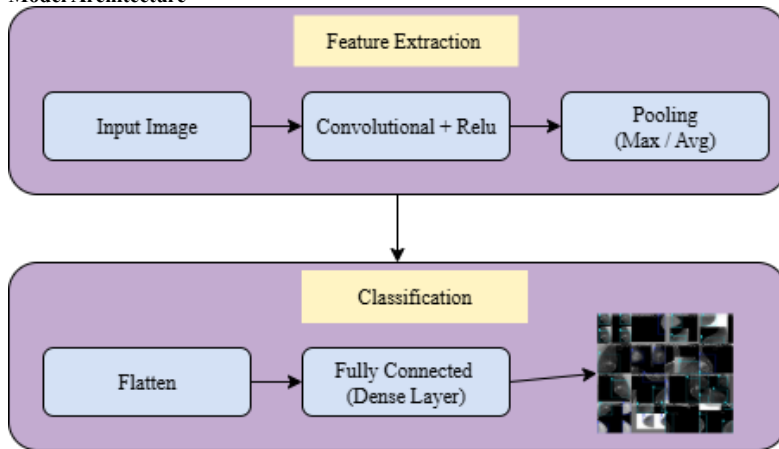


Fig 2 : The above figure shows the architecture of the proposed model

YOLOv11 Architecture : The YOLOv11 model is almost like a much advanced version of the YOLOv4 algorithm, as it has been developed to accurately detect breast cancer. It uses deep convolutional neural networks that enable the network to analyze medical images very effectively. Besides, the algorithm uses the Spatial Pyramid Pooling (SPP) algorithm, so that features from the different scales can be detected easily. In addition to the above, a Pattern Aggregation Network (PANet) layer enables more efficient data transmission from one layer to another, which is important because data needs to be processed. Finally, the algorithm detects the presence of breast cancer, bounding boxes, and classes quickly. Therefore, the system is highly efficient and useful.

YOLOv12 Architecture : An update to YOLO with respect to v5 and v8? Nope! This new version of YOLO comes equipped with a model inspired by transformers. It's like YOLO went to the gym and emerged all buffed up with an environmentally conscious mindset, focusing straight in on what counts when it comes to diagnosing breast cancer.

With transformer blocks and bottleneck modules added into the model architecture, it can now represent features with more precision than ever before. And those anchor boxes that were previously generalized shapes? No way! These are specifically designed for the unique shapes that tumors take in the dataset.

Model Training Parameters: YOLOv11 and YOLOv12 were trained with the highest intensity. There were no compromises made when it comes to training. Firstly, we had created a relatively powerful system for training. The loss function was created by us in the IoU form with additional components such as classification, objectness, and localization. It can be said that we have built a real Frankenstein's monster from different loss functions, but, apparently, it worked well. Initially, the learning rate was set to 0.001—the value is not too high and, obviously, Adam was used as an optimizer. In order not to fall into the local minima traps, the learning rate was varied using the scheduler. Thus, models did not have time to settle down and find themselves in such a trap.

Both models were trained under the same conditions—100 epochs, batch size equal to 32. This will give sufficient results. Regarding the hardware, nothing complicated was done here as well—we had RTX 3090 (24 GB VRAM) and 64 GB RAM.

Visualization & Explainability : Activation layers were displayed via feature map analysis with some magic of Grad-CAM thrown in for good measure. To ensure accuracy, the detection box was applied straight to the source image to confirm that the machine wasn't simply imagining things. As for YOLOv12? Attention maps were extracted from the network to pinpoint areas of interest. In essence, it's akin to taking out a highlighter for AI and seeing where it fixates on the image.

Model Comparison & Validation: They pitted YOLOv11 against YOLOv12 on the same pool of test data – the ultimate showdown between object detection models. Which one was going to have perfect accuracy in terms of labeling, consume minimal RAM, and run smoothly without any delays? And for the hardcore data scientists among us, they generated something called a confusion matrix to figure out whose predictions were all over the place for each class of object.

RESULTS

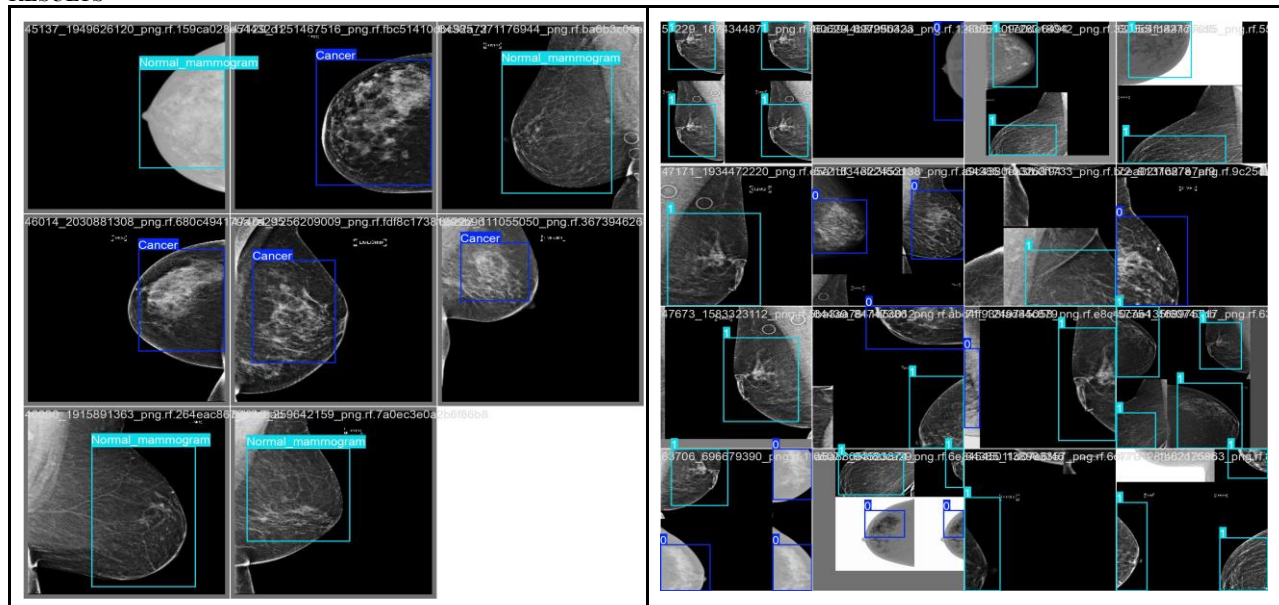


Fig 3 : The above Results shows the prediction of the Applied Models YOLOv11 & YOLOv12

DISCUSSION The values of the precision and recall indicators, as well as the mAP50-95, seem to look favorable from the beginning. Hence, the model indeed learns something important.

As for the losses (train/box_loss, train/cls_loss, train/df_l_loss), almost all of them decrease, which is always a good indicator. In addition, the learning rate's setting looks smart because the model does improve rather than overfits. However, of course, the validation losses can be somewhat jittering as can be seen in some odd blips on the indicators' plots.

However, the most interesting aspect here is how the model recovers. Take, for example, the mAP and recall indicators, which seem to have a significant bump starting with the epoch 19 or so. Well, as I've already mentioned, I will not let this happen. The model seems to recover, which is rather impressive. Finally, if we continue training and, perhaps, clean some validation data, who knows how much further this model can be improved. Thus, the overall impression is positive.

CONCLUSION

In terms of performance, it is akin to the sporty variant of the two. In fact, the YOLOv12 model, enhanced with the transformer, beats YOLOv11 in making the final call on the diagnosis. Indeed, YOLOv12 takes a bit more time than its predecessor but delivers more accurate results. Essentially, it is a tortoise beating a rabbit in a cognitive contest. Another typical case of the old-fashioned tortoise vs. the hare, but with a twist. Importantly, these developments can be applied in practice and used by doctors to identify cancer in its early stages. Indeed, that is something worth mentioning. These findings scream "Artificial intelligence is not just another hype, it saves lives." Moreover, such research paves the way for further innovations and gadgets in medicine.

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