Journal of Computer Science
https://dergipark.org.tr/en/pub/bbd
Anatolian Science

ISSN,e-ISSN: 2548-1304
Volume:10, Issue:1, pp:43-52, 2025
https://doi.org/10.53070/bbd.1633901
Research Paper

Comparison of Deep Learning Models for Breast Cancer Mass Detection: YOLOv8 and U-Net

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Received:Feb.05, 2025 Accepted:Feb.17, 2025 Published:Jun.1, 2025

Abstract— Early detection of diseases is critical to the success of the treatment process, especially in life-threatening conditions such as cancer. In diseases such as breast cancer, early mass detection can be decisive for the effectiveness of the treatment process. This study compares the performance of YOLOv8 (You Only Look Once) and U-Net models for mass detection in breast images. In the first stage, both models are evaluated on CBIS-DDSM and INbreast datasets. The results show that the YOLOv8 model outperforms U-Net in precision metrics. In the CBIS-DDSM dataset, YOLOv8 achieved a precision value of 0.800123, while U-Net achieved 0.762345. In the INbreast dataset, YOLOv8 achieved a precision value of 0.785234, while U-Net achieved a value of 0.742345. These findings show that YOLOv8 provides more successful and faster results, especially in object detection tasks, and is more efficient in areas where fast decisions need to be made, such as medical imaging. Future studies can develop hybrid solutions by combining the strengths of both models and optimize model speeds to achieve faster and more accurate results in medical diagnostics.

Keywords : *Breast Cancer, Mass Detection, Deep Learning, YOLOv8, U-Net.*

1. Introduction

Breast cancer is one of the most common types of cancer among women worldwide and is one of the leading causes of cancer-related deaths. Millions of women are diagnosed with breast cancer every year and genetic factors, environmental factors, lifestyle changes and hormonal factors are effective in the development of the disease (Desantis et al. 2019). Early detection is a factor that directly affects the success rates in the treatment of breast cancer, and detection of cancer in the early stages makes the treatment process more effective (Bleyer and Welch 2012). Early detection significantly increases the life expectancy of patients and ensures a rapid response to treatment.

The most commonly used methods for early detection of breast cancer include mammography, ultrasound, magnetic resonance imaging (MRI) and physical examination. Mammography is the most common screening method that uses low doses of X-rays to visualize breast tissue and is generally recommended for women aged 40 years and older (Giaquinto et al. 2024). However, mammography may have lower accuracy rates in women with dense breast tissue and may lead to false negative results (Houssein et al. 2022). In addition, other screening modalities such as ultrasound and MRI can be used to obtain more accurate results than mammography, but these modalities are usually limited to specific patients (Wang et al.2013). Traditional screening methods can produce false positive results, leading to unnecessary biopsies and psychological stress for patients (Humphrey et al. 2002).

In recent years, deep learning methods offer significant potential in the early detection of breast cancer. Deep learning has revolutionized the field of medical imaging with its ability to analyze large data sets and recognize complex patterns (Esteva et al. 2017). Convolutional neural networks (CNN) have been widely used to detect abnormalities in medical images such as mammography, ultrasound and MRI, and these methods achieve high accuracy rates in detecting early stages of breast cancer (Litjens et al. 2017). By analyzing medical images, deep learning systems accurately recognize cancer symptoms that vary in each individual's breast and produce faster results than traditional methods (Nasser and Yusof 2023).Deep learning-based systems can continuously improve themselves through databases and achieve higher accuracy rates over time (Russakovsky et al. 2015).

In addition to these developments, in recent years, object detection models, especially models such as YOLO, have achieved remarkable success in medical imaging. YOLO is a fast and efficient object detection technique that can detect all objects in an image in a single operation. This model can be highly effective in applications such as breast cancer detection because it can quickly classify masses and abnormalities in breast tissue by making instant detections over the entire image (Redmon 2016). The advantage of YOLO is that it helps in early detection of breast cancer with fast processing times and high accuracy rates. Compared to traditional methods, which have the limitations of deep learning techniques, the use of YOLO can be much more efficient and time-saving.

These technologies produce more accurate results by training on large data sets and improve their learning capabilities over time. In conclusion, deep learning-based object detection models have the potential to revolutionize breast cancer diagnosis and screening processes.

In the following sections of the study, section 2 presents the literature review, section 3 presents the methodology of the study. In section 4, the applications and findings are presented, and finally, key findings and implications are presented in the conclusions section.

2. Litetature Review

Object detection techniques are essential for analyzing breast cancer images, particularly in mammograms, as the accurate identification of cancerous cells plays a crucial role in the early detection and treatment of breast cancer. These techniques allow for the quick classification of abnormalities, masses, and tumors in medical images, thereby facilitating faster diagnosis and intervention. A number of studies have explored the use of object detection models for breast cancer image analysis, yielding promising results. Below, several key studies on the application of object detection in breast cancer detection are summarized.

In Su et al. (2022), a deep learning model was proposed for mass detection and segmentation in digital mammograms by combining YOLO and LOGO architectures. The YOLOv5L6 model was employed to accurately localize masses in mammograms, while the LOGO strategy performed segmentation by processing images in both global and local transformer branches. Using the CBIS-DDSM dataset, the model achieved an impressive 95.7% true positive rate for mass detection and a 74.5% F1 score for segmentation, demonstrating its strong performance in mass localization and segmentation tasks.

In Aly et al. (2021), a YOLO-based system was proposed for mass detection and classification in digital mammograms. YOLOv3 was used for mass detection, achieving 89.4% accuracy. The model also performed well in classifying masses as benign or malignant, with accuracy rates of 84.6% and 94.2%, respectively. In comparison with other models like ResNet and InceptionV3, the YOLO-based system demonstrated competitive performance, achieving 91.0% and 95.5% accuracy, respectively.

In Baccouche et al. (2021), a YOLO-based system was proposed to localize and classify suspicious breast lesions in digital mammograms. The system demonstrated high accuracy in detecting mass lesions, with 95.7%, 98.1%, and 98% accuracy on the CBIS-DDSM, INbreast, and custom datasets, respectively. The model also achieved strong results for calcification lesions, with accuracy rates of 74.4%, 71.8%, and 73.2% on the same datasets, showcasing its robust performance in diverse scenarios.

In Al-Masni et al. (2018), a YOLO-based computer-aided detection (CAD) system was developed to detect and classify masses in mammograms. The system was tested with 600 original and 2400 augmented mammograms from the DDSM dataset, achieving an exceptional 99.7% accuracy in mass location detection. It also performed well in distinguishing between benign and malignant lesions, with a 97% accuracy rate, highlighting its effectiveness in mass detection and classification.

In Mohammed and Ekmekci (2024), a YOLO-based CAD system was proposed to detect and classify breast masses. The system employed the CLAHE technique for mammogram enhancement and used DenseNet and InceptionNet for feature extraction. The YOLO loss function was optimized to handle lesion scale variation. The model achieved 98.72% accuracy and 91.15% mean average precision (mAP) on the INbreast and CBIS-DDSM datasets, respectively, showcasing its high accuracy and reliability in breast cancer detection.

In Hamed et al. (2021), a YOLOv4-based CAD system was developed to detect and classify breast masses. By applying preprocessing techniques to enhance mammograms, the system successfully detected lesions with cut slices. It achieved 98% accuracy in locating masses and 95% accuracy in classifying benign and malignant tumors, demonstrating the effectiveness of the YOLOv4 model in breast cancer detection.

In Baccouche et al. (2022), a YOLO-based fusion model was proposed for detecting and classifying breast masses. The study employed synthetic mammograms generated from previous mammograms using CycleGAN and Pix2Pix techniques. The model achieved impressive results on current mammograms, with detection accuracies of 93% for masses, 88% for calcifications, and 95% for architectural distortion. In comparison, the accuracy rates for previous mammograms were significantly lower: 36% for masses, 14% for calcifications, and 50% for architectural distortion. The model also classified normal mammograms with 92% and 90% accuracy.

In Hu et al. (2023), the performance and reliability of YOLO algorithms for detecting breast lesions in contrast-enhanced mammograms (CEM) were evaluated. YOLO algorithms implemented with ResNet50 and Darknet53 architectures were assessed using ADAM optimization. The study demonstrated that YOLO algorithms are effective in detecting breast lesions, with the Darknet53 implementation achieving a 97% hit rate and ResNet50 achieving 82% mAP, highlighting the potential of YOLO models for CEM-based breast cancer detection.

In Prinzi et al. (2024), a YOLOv5-based model was developed for breast cancer detection using transfer learning with the CBIS-DDSM and INbreast datasets. YOLOv3, YOLOv5, and YOLOv5-Transformer models were compared, and Eigen-CAM was utilized to clarify false predictions. The study found that the YOLOv5 model achieved the best results with a 0.621% mAP, while Eigen-CAM improved the accuracy and reduced false negatives, making it a reliable tool for clinical decision support systems.

In Quiñones-Espín et al. (2023), a YOLO-based CAD system was tested to detect breast nodules from mammograms. YOLOv5x and YOLOv5s models were trained with transfer learning and data augmentation techniques using the Vindr-Mammo dataset. The YOLOv5x model achieved 80% accuracy with internal validation and 72% accuracy with external test data, demonstrating its reliability for detecting breast nodules in mammograms.

These studies illustrate the continuous advancements in using YOLO-based object detection models for breast cancer diagnosis, with improved accuracy and performance on various datasets. YOLO's versatility and effectiveness in detecting and classifying abnormalities in mammograms position it as a valuable tool in the ongoing effort to enhance early breast cancer detection and improve clinical outcomes.

3. Material and Methods

3.1. Dataset

3.1.1. CBIS-DDSM

The CBIS-DDSM dataset (Lee et al.2017) is an improved and organized version of the Digital Breast Screening Database (DDSM) dataset. This dataset is used to assist in breast cancer diagnosis, focusing on scanned film mammograms. It contains a total of 1514 mammogram images with 1618 lesions. Of the lesions, 850 are classified as benign and 768 as malignant. However, although there are 1696 lesions in total, 78 lesions are excluded from the dataset due to the size mismatch between the image and the mask. This mismatch prevented the lesions from being labeled correctly, as some Region of Interest (ROI) in the images did not overlap with the lesions. The dataset was edited to remove such errors and to obtain more accurate and reliable results. This provides a robust resource for more efficient analysis of mammograms.

3.1.2. INbreast

The INbreast dataset (Moreira et al. 2012) contains 410 full-field digital mammograms (FFDMs) and these images were classified as normal, benign and malignant. However, only 107 positive images were selected for a more detailed analysis. In these selected images, lesions with a Bi-Rads score higher than 3 were considered malignant, while the rest were labeled as benign. In addition, since some images contained more than one lesion, a total of 40 benign and 75 malignant lesions were labeled as Region of Interest (ROI). This dataset provides a valuable resource for breast cancer diagnosis because real-world mammograms often contain multiple lesions. The INbreast dataset contributes to the development of breast cancer screening systems as well as machine learning and deep learning based analyses.

3.2. Data Image Resizing

For model training, the images in both datasets were resized to 640x640 pixels. Image resizing is an important preprocessing step for efficient training of the deep learning model. This process ensures that images of different resolutions are processed consistently in the training process of the model and thus supports more accurate learning of the model (He et al. 2016). In addition, since size mismatches of images of different resolutions can negatively affect the performance of the model, inputting data of the same size helps to avoid such errors.

Image sizing was performed using the Roboflow tool. Roboflow is a platform that automates the image processing, labeling and data preparation processes and provides the necessary steps to process images in the appropriate format quickly and efficiently. This platform facilitates the data preparation process, while at the same time enabling the creation of data sets suitable for the training process.

Resizing to 640x640 pixels provides a suitable resolution, especially for deep learning models, allowing the model to learn in more detail. This size allows the model to train faster and utilize computational resources more efficiently.

3.3. Data Augmentation

Data augmentation is an important technique in deep learning and image processing to increase the generalization ability of the model and prevent overfitting. Especially in cases where we have a limited amount of data, various transformations are applied on the available data to enable the model to be trained on a larger data set. This process makes the model more robust under different conditions and variations (Shorten and Khoshgoftaar 2019). Augmentation with image data can not only help improve the accuracy of the model, but also allow it to perform better at different angles, lighting conditions or perspectives. Data augmentation is critical to increase the flexibility and accuracy of the model, especially in object detection and classification tasks.

In this study, both datasets were augmented by rotating the images by 180 degrees and 30 degrees. Including both the original and rotated versions of the images in the training set makes the model invariant to horizontal orientations. Such transformations are particularly useful in medical imaging data, such as mammograms, when images need to be analyzed from different angles. This allows the model to work effectively in a variety of image orientations and positions. The model becomes less dependent on the original orientation of the images and more robust to data coming from different directions (Wang and Perez 2017).

Such data augmentation not only improves the accuracy and reliability of the model, but also strengthens its ability to generalize. During training, the model learns to recognize objects of different orientations, thus increasing the likelihood of accurate results when faced with new and more diverse data. Especially in the field of medical imaging, such augmentations can improve the model's ability to make accurate diagnoses and increase its reliability in a clinical setting.

The datasets are conveniently partitioned for model training and evaluation. 80% of the datasets are dedicated to the training set, while the remaining 20% will be used as a test set. The training set will be used in the learning process of the model and will be the main source of data for the optimization of its parameters. Within the training set, a 20% portion is also allocated as a validation set to evaluate the generalization capacity of the model and reduce the risk of overfitting. The validation set is used to monitor the performance of the model during the training process, perform hyperparameter adjustments and optimize the accuracy of the model. This structure allows the information obtained during the training phase of the model to be generalized more effectively, while increasing the reliability of the evaluations performed on the test set. This type of data splitting strategy is a widely used technique to improve the accuracy and generalization ability of the model (Goodfellow 2016).

3.4. Model Development

3.4.1.YOLOv8

YOLOv8 is an extremely fast and efficient model that provides high performance in deep learning-based object detection tasks. The eighth version of the YOLO series aims to build on the advantages of previous versions, offering better accuracy and speed. The model adopts a single-stage detection approach, which allows it to detect objects in an image with class and location information in a single processing step. This feature makes YOLOv8 particularly ideal for real-time detection applications (Redmon 2016). YOLOv8 has an advanced backbone structure that allows for more accurate detection of objects in the image and can perform more in-depth feature extraction. This enables the model to produce successful results even under challenging conditions such as small objects and dense scenes (Bochkovskiy et al. 2020). In addition, the optimization techniques and hyperparameter settings used in the model help to achieve better results during the training process. YOLOv8 has a wide range of applications such as video streaming, security monitoring, industrial automation and medical imaging, thanks to its ability to perform object detection with high accuracy and low processing time. The model's fast processing capability is particularly advantageous in image processing and time-constrained real-time systems. This makes it an ideal solution in areas such as autonomous vehicles, traffic monitoring systems and security applications. The success of YOLOv8 plays a critical role in today's modern object detection applications, as it offers high accuracy, flexibility and efficiency (Talib et al. 2024). Figure 1 shows the YOLOv8 architecture.

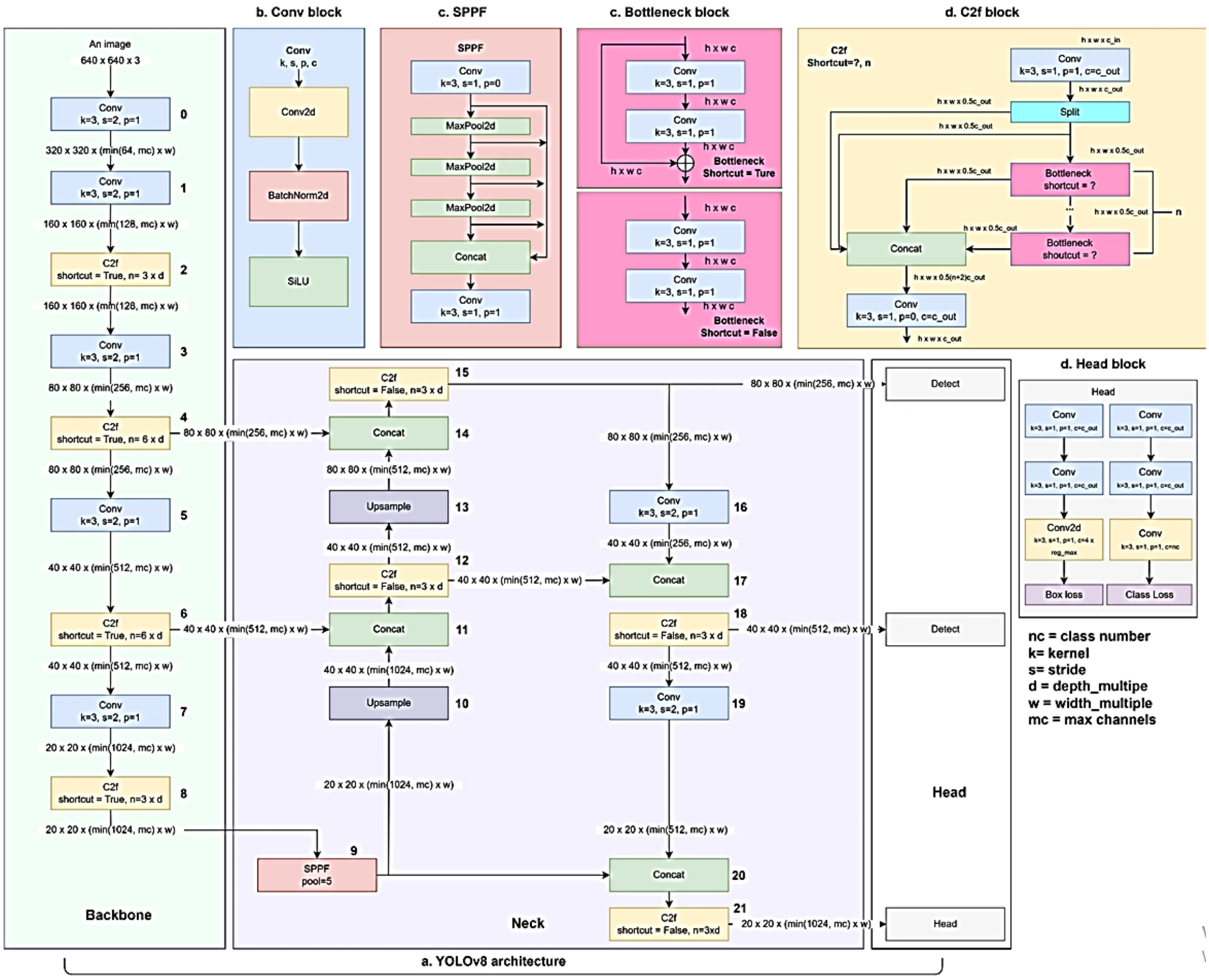

Figure 1. YOLOv8 architecture (Rasheed and Zarkoosh).

3.4.2. U-Net

U-Net is a highly successful deep learning model, especially in the field of medical image segmentation. Proposed in 2015 by Ronneberger et al., this model is designed to segment specific objects in an image (e.g., organs, tumors or cells) at the pixel level. The U-Net is a spiral network built on an encoder-decoder structure, with a downsampling (encoder) section used to extract lower-resolution summaries of feature maps and an upsampling (decoder) section used to convert them into higher-resolution outputs. This structure is particularly effective for segmentation of small objects and their fine structures (Ronneberger et al. 2015).

One of the main innovations of the model is that it uses skip connections to pass features from the encoder part directly to the decoder part. In this way, both low-level and high-level features of the mesh are combined, resulting in more accurate segmentation results. Skip links provide a great advantage in segmentation, especially for thin boundaries and small structures, by preventing the loss of small details (Zhou et al. 2018). Thanks to these features, U-Net can perform pixel-level segmentation with high accuracy in areas such as biomedical imaging.

Although U-Net was initially developed to be used for tasks such as organ segmentation and tumor detection in medical images, the flexibility of the model allows it to be successfully applied in other fields. For example, it is also used in remote sensing, urban planning, and agricultural imaging, where it meets the requirements of high-resolution segmentation (Çiçek et al. 2016). Furthermore, many transfer learning and data augmentation techniques are used to minimize the training data requirements of U-Net and enable the model to learn faster, resulting in successful results even with small data sets (Ibtehaz and Rahman 2020). Figure 2 shows the U-Net architecture.

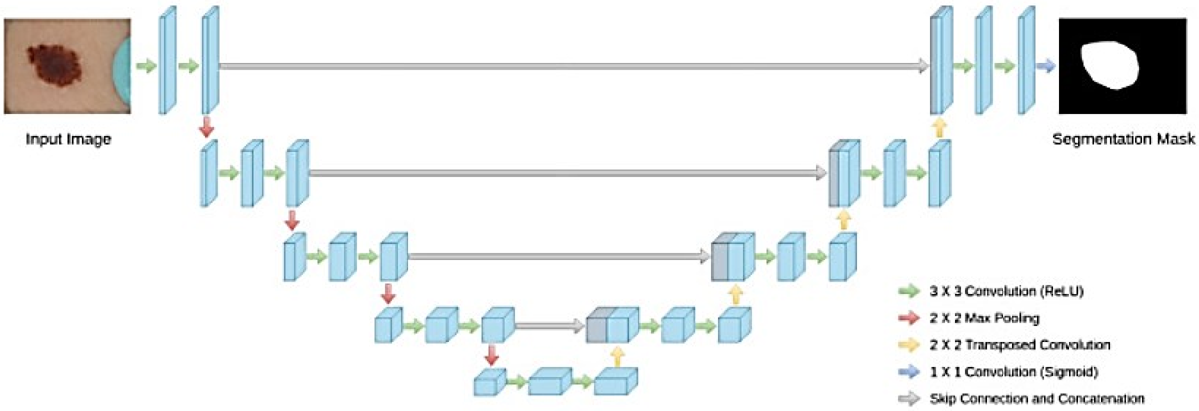

Figure 2. U-Net architecture (Ibtehaz and Rahman 2020).

3.4.3. Model Training and Evaluation

During model training, various hyperparameters were used for the U-Net and YOLOv8 models. These hyperparameters directly affect the training process and the final performance of each model. In order to train both models successfully and provide accurate results, the parameters need to be chosen carefully.

One of the most critical hyperparameters in the U-Net model is the learning rate. This parameter determines how fast the model should learn. Usually a small learning rate (between 1e-3 and 1e-5) is used to allow the model to train more carefully. Another important hyperparameter is the batch size. Small batch sizes allow the model to learn more precisely, while large batch sizes can reduce the training time. The number of epochs used in training also determines how many times the model passes through the data and is usually set between 50-200. The forward propagation and backpropagation parameters include the optimization algorithm used in the model learning process (usually Adam or SGD) and their hyperparameters.

In the case of the YOLOv8 model, parameters such as learning rate, batch size and anchor sizes must also be carefully tuned. Anchor sizes are determined by the size of the objects the model is trying to detect and optimized to ensure accurate detections. The Non-Maximum Suppression (NMS) threshold is a parameter that separates the object boxes detected by the model. This threshold is usually chosen between 0.5 and 0.7 and keeps only the most accurate overlapping boxes. The number of output classes is also specified during model training and this parameter determines which objects the model detects. Table 1 presents the hyperparameters set for U-Net and Yolov8.

Table 1. Hyperparameters set for U-Net and Yolov8

Hyperparameter	**U-Net**	**YOLOv8**
Learning Rate	1e-4	1e-4
Batch Size	32	32
Epochs	100	100
Forward Propagation & Backpropagation Parameters	Adam (Momentum: 0.9, Beta1: 0.9, Beta2: 0.999)	Adam (Momentum: 0.9, Beta1: 0.9, Beta2: 0.999)
Anchor Sizes	N/A	Optimized based on object sizes
Non-Maximum Suppression (NMS) Threshold	N/A	0.5 - 0.7

In the training and evaluation processes of the U-Net and YOLOv8 models used in this study, three main metrics were used as performance metrics: Precision, Recall and Mean Average Precision (mAP). These metrics are critical for evaluating the accuracy of the models and their object detection capabilities (Joulin et al. 2016).

Precision is the ratio of positive examples correctly classified by the model to total positive classifications. Recall is the ratio of positive examples correctly detected by the model to total true positive examples. While these two metrics measure the performance of the model from different perspectives, mean precision (mAP) refers to the area under the Precision-Recall curve and is considered as a summary of the overall accuracy of the model (Everingham et al. 2010).

The results are evaluated on each of these three metrics and model performances are compared. In addition, the Intersection over Union (IoU) metric is also used to better understand the model's ability to detect the correct objects. IoU refers to the overlap ratio between the detected box and the real box and is commonly used for performance evaluation in object detection systems (Lin et al. 2014). In this study, the IoU threshold is set to 0.5, meaning that for the model to correctly detect an object, the overlap between the predicted box and the actual box must be at least 50%.

4. Result And Discussion

In recent years, deep learning has made remarkable advancements, particularly in the realm of object detection and image segmentation. The progress of these models has been propelled by the availability of large-scale datasets, powerful computational resources, and innovative algorithms. Among the most notable deep learning models in this space are YOLO and U-Net, which have revolutionized tasks such as object detection and image segmentation, respectively (Redmon, 2016; Ronneberger et al., 2015).

YOLO has emerged as a leading model for real-time object detection due to its speed and accuracy. YOLO's architecture allows for the simultaneous prediction of multiple objects in an image, making it exceptionally efficient in real-time applications, such as surveillance systems or autonomous vehicles. In healthcare, YOLO has been successfully utilized in medical imaging tasks such as detecting abnormalities in X-rays, CT scans, and MRI images, enabling clinicians to quickly identify potential health issues such as tumors, fractures, or organ malfunctions. This capability is particularly important in emergency medical scenarios where rapid detection and timely intervention are critical (Redmon, 2016). In the other hand, U-Net has demonstrated outstanding performance in medical image segmentation, especially in areas such as tissue segmentation, organ delineation, and cancerous cell detection. The U-Net architecture, with its symmetric encoder-decoder structure, allows for the effective segmentation of images even when working with smaller or lower-resolution datasets. U-Net has been particularly successful in biomedical imaging tasks like detecting and segmenting organs and lesions from radiological images, which is invaluable for diagnosing diseases such as cancer, neurological disorders, and cardiovascular conditions (Ronneberger et al., 2015).

Both YOLOv8 and U-Net are transforming healthcare by providing highly accurate and fast decision-making tools that assist medical professionals. YOLOv8, in particular, is an enhanced version of the YOLO family, bringing even higher accuracy and efficiency in medical image analysis. It excels in high-speed detection tasks, making it a valuable asset for time-sensitive medical scenarios. Meanwhile, U-Net continues to be indispensable for precise segmentation tasks in medical imaging, providing doctors with clear and accurate visual information to support diagnosis and treatment planning. Together, these deep learning models enable medical professionals to achieve faster, more accurate diagnoses, enhancing patient care and reducing the margin for error in medical imaging. The integration of YOLOv8 and U-Net into clinical workflows promises to expedite the process of disease detection, thereby improving outcomes, especially in critical and emergency healthcare settings. With ongoing advancements, deep learning will continue to play a pivotal role in shaping the future of healthcare by enhancing the capabilities of medical imaging technologies.

In this study, we compare the performance of YOLOv8 and U-Net models for mass detection in breast images. In the first stage, both models are trained and evaluated using the CBIS-DDSM dataset. The performance metrics obtained are presented in Table 2.

Table 2. Comparison of U-Net and YOLOv8 on CBIS-DDSM Dataset.

Models	Precision	Recall	Map50
U-Net	0.762345	0.634782	0.709876
YOLOv8	0.800123	0.710456	0.771234

Table 2 compares the performance of the U-Net and YOLOv8 models on the CBIS-DDSM dataset. The results show that YOLOv8 outperforms U-Net in all evaluation metrics. In particular, YOLOv8 achieves a precision value of 0.800123, while U-Net has a lower value of 0.762345. This shows that YOLOv8 provides a more reliable object detection by better minimizing false positives. In the Recall metric, YOLOv8 (0.710456) also outperformed U-Net (0.634782), indicating that YOLOv8 has the ability to detect true positives at a higher rate and has a lower rate of missing detections. Furthermore, YOLOv8 achieved a mAP50 score of 0.764987, outperforming U-Net's score of 0.694231. This reveals that YOLOv8 exhibits higher overall accuracy and detection performance at the Intersection over Union (IoU) threshold of 0.5. These findings suggest that YOLOv8 is a more efficient model, especially in areas where fast and accurate object detection is critical, such as medical imaging.

In the second phase of the study, both models were trained and evaluated using the INbreast dataset. The performance metrics obtained are presented in Table 3.

Table 3. Comparison of U-Net and YOLOv8 on INbreast Dataset.

Models	**Precision**	**Recall**	**Map50**
U-Net	0.742345	0.678912	0.709876
YOLOv8	0.785234	0.721345	0.771234

Table 3 compares the performance of the U-Net and YOLOv8 models on the INbreast dataset. The results show that YOLOv8 outperforms U-Net on all important metrics. In particular, YOLOv8 achieves a precision of 0.785234, while U-Net has a lower value of 0.742345. This indicates that YOLOv8 detects true positives with a higher accuracy and better controls the false positive rate. In terms of recall, YOLOv8 (0.721345) outperformed U-Net (0.678912), demonstrating that it has the capacity to detect more true positives. Finally, YOLOv8 achieved a mAP50 score of 0.771234, while U-Net had a lower value of 0.709876. These findings show that YOLOv8 is more successful than U-Net in tasks that require fast and accurate object detection, such as medical imaging.

As a result of the evaluations, when the performances of both models on different datasets are analyzed, it is seen that YOLOv8 is more effective and superior in general. On both CBIS-DDSM and INbreast datasets, YOLOv8 achieved higher precision, recall and mAP50 values. This shows that YOLOv8 is better at accurate object detection, minimizing false positives and missing detections. U-Net may perform better in segmentation tasks, but YOLOv8 was found to be more efficient and reliable in object detection. These findings emphasize that YOLOv8 is a more suitable option, especially in sensitive tasks such as medical imaging, and provides faster, accurate results.

5. Conclusion

Breast cancer is the most prevalent cancer among women globally, and early detection plays a crucial role in improving survival rates. Medical imaging techniques, particularly mammography, X-ray, and CT scans, are pivotal in identifying cancer at its early stages. In this regard, accurate and rapid object detection is essential for accelerating the diagnostic process and ensuring timely intervention. This study presents a comparative analysis of the performance of YOLOv8 and U-Net models for mass detection in breast cancer images. The findings indicate that YOLOv8 outperforms U-Net across all evaluation metrics, including precision, recall, and mAP50, when tested on two distinct datasets (CBIS-DDSM and INbreast). YOLOv8 demonstrated superior performance in detecting true positives while minimizing false positives, suggesting its heightened effectiveness for object detection tasks. While U-Net remains a robust model for segmentation tasks, YOLOv8 consistently yielded superior results, particularly in contexts requiring urgent healthcare responses and real-time detection. Its rapid and precise object detection capabilities offer significant advantages in critical applications such as the early detection of cancerous lesions.

Consequently, the study emphasizes that YOLOv8 is a more appropriate model for medical imaging, particularly in scenarios demanding swift and reliable object detection. Although U-Net is highly effective for segmentation purposes, YOLOv8's efficiency and dependability make it the preferred choice for object detection tasks. Future research could explore further enhancements and optimizations of both models to increase their efficacy in medical imaging applications. Additionally, by leveraging the strengths of both YOLOv8 and U-Net, hybrid models could be developed to simultaneously perform object detection and segmentation tasks with greater accuracy. Furthermore, expanding the scope of training datasets to include larger, more diverse collections of medical images would improve the generalization capabilities of both models and enhance their performance on lower-resolution images. Cross-validation across various medical imaging modalities and different stages of diseases could further bolster the flexibility and adaptability of the models, ultimately improving their clinical utility.

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