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The CNN Model with YOLO Architecture for Ultrasonography Images in Early Breast Cancer Detection

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Abstract

The rapid development of object detection technology has opened new opportunities in the healthcare sector, especially in early cancer detection. This paper presents a deep learning-based breast cancer detection system using ultrasound images. The primary goal of this study is to create a model that can effectively differentiate between malignant and benign breast tumors, assisting in early diagnosis. The proposed system employs the Convolutional Neural Network (CNN) algorithm with You Only Look Once version 5 (YOLOv5) architecture, which is renowned for its high speed and accuracy in object detection tasks. A dataset comprising 10,954 ultrasound images was used to train the model, with 70% allocated for training, 20% for validation, and 10% for testing. The study reveals that the model achieves a high accuracy rate of 92.8% for malignant tumor detection and 99.1% for benign tumors, with precision rates of 99.6% for malignant tumors and 97.5% for benign tumors. These results demonstrate the feasibility of the proposed model as a reliable tool for early breast cancer detection. The findings highlight the potential of deep learning in medical image processing, suggesting that this technology could be further developed into an accessible, efficient early detection system for breast cancer in clinical settings. Future research could explore the integration of additional imaging modalities and the application of this model in real-world healthcare environments

Keywords: CNN, YOLO, Deep Learning, Object Detection, Breast Cancer

1. Introduction

The first to last generation of the industrial revolution was triggered by human discoveries that could change human life. This also happened in the previous generation's industrial revolution, where human discoveries about Artificial Intelligence (AI) have changed human life into and towards automation-related things. One aspect of human life that AI affects is the health sector. This sector includes protecting, preventing, and treating humans from diseases that originate from food, drinks, bacteria, and viruses. One of the benefits of AI in health is the development of an early detection system for breast cancer based on an ultrasound image model. This system can be used to detect early indications of malignant tumors in a person's breast so that further action can be taken accurately and efficiently.

One of the diseases that is proliferating and causing an increase in the death rate in humans is cancer. This type of disease appears in humans and is characterized by uncontrolled cell growth. Cancer cells can develop in almost all body parts, forming tumors and spreading to other tissues. Prevention for this type of disease includes maintaining diet and drinking, exercising regularly, avoiding exposure to hazardous materials, and regular health checks. Health checks conducted by doctors in hospitals, clinics, and other health units utilize information technology. This technology is supported not only by hardware but also by software that leads to the application of AI [1], [2], [3], [4]. In Bulgaria,

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the diagnosis of breast cancer that leads to the decision of surgery has used software that has AI [5]. The use of digital technologies and innovations, including remote monitoring and artificial intelligence, has great potential to improve the quality of life of cancer patients by preventing cardiovascular side effects related to cancer treatment [6]. Breast cancer diagnosis using om Forest has shown very high accuracy, making it an effective tool in automatically detecting malignant tumors and helping to improve access to care in area with a shortage of medical personnel [7].

In object detection research using a two-class classification model, one of the most commonly used methods is the Support Vector Machine (SVM), and several variants of the Convolutional Neural Network (CNN), such as VGG, ResNet, or AlexNet, are well-known in image classification. The SVM solves the problem of two-class classification on data that is not too complex and relatively small in size. However, SVM tends to slow processing complex or large image data [8]. In addition, SVM tends to be less efficient in detecting objects quickly [9]. Unlike CNN, the weakness of this method is that it is not optimal for location-specific detection; it is only effective in classification without considering the object's location in the image [10], [11]. So CNN needs to be combined with other methods [12], [13]. Therefore, the YOLO method is proposed in this study to improve the performance of the detection model [14], [15], because of its speed and accuracy superior to conventional methods such as SVM or CNN.

Technology-based interventions in community health systems, such as postal delivery of FIT-DNA test kits coupled with patient support, have been shown to increase participation in colorectal cancer screening in vulnerable population groups [16]. Machine learning techniques and deep learning models such as E-VGG19 significantly improve the accuracy of skin cancer detection, making an essential contribution to automated diagnostic technologies that can help healthcare professionals detect cancer at an early stage [17]. Combining machine learning techniques with ontology, using a decision tree algorithm and SWRL rules, achieved a breast cancer prediction accuracy of 97.10% [18]. The application of federated learning with homomorphic encryption is to train artificial intelligence models in decentralized cancer image analysis, preserving patient data privacy and showing equivalent performance to centrally trained models [19]. In the performance evaluation of the YOLO model proposed in this study, several key metrics such as accuracy, precision, and recall will be used to assess the effectiveness of the model in detecting objects [20], [21], namely breast ultrasound images. Evaluation to ensure that the YOLO model is not only fast but also effective in detecting all existing images (malignant tumor or clear) with minimal false positives and false negatives. With this metric, the model can be optimized for maximum performance in air traffic surveillance.

Artificial intelligence (AI) in prostate cancer diagnosis shows promising potential to improve diagnostic accuracy, although it also raises questions regarding user acceptance, trust, and communication between doctors and patients [22]. The application of information technology in cancer detection, primarily through the Internet of Health Things (IoHT) model, shows great potential in improving the accuracy of lung cancer diagnosis and risk management in sustainable cities [23]. Machine learning algorithms such as Logistic Regression and Support Vector Machines showed up to 97.14% accuracy in classifying tumors as benign or malignant tumors using breast cancer datasets taken from the UCI repository [24]. The use of advanced deep learning techniques has shown the ability to detect and manage thyroid cancer more effectively. This study uses a deep learning-based decision support model integrating multi-view medical images to produce a more objective and accurate diagnosis [25]. Skin cancer detection has shown auspicious results. A hybrid framework combining Convolutional Neural Networks (CNN) with an Artificial Bee Colony (ABC) optimization algorithm has achieved a prediction accuracy of 93.04% for multi-disease classification of skin cancer [26].

Specifically, deep learning and recurrent neural networks have been proven effective in breast cancer detection and classification through data analysis from the Internet of Medical Things (IoMT), significantly improving the accuracy and efficiency of cancer diagnosis [27]. Breast tumor segmentation via DCE-MRI has been shown to be more efficient and accurate than manual methods by radiologists, with AI able to capture significant spatial-temporal dynamics in breast cancer diagnosis [28]. Overall, the approach evaluated in this study can contribute to improving the accuracy, efficiency, and safety of automated detection, including in AI-based cancer detection systems. A deeper understanding of the performance of the YOLO model in this application helps support the development of more robust and efficient systems in health applications in the future.

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Explainable machine learning (XAI) approaches[29] have been applied in the development of intelligent biomarker sensors for detecting breast cancer, enabling more accurate diagnosis based on biomarker data such as HOMA, leptin, adiponectin, and resistin.[30]. Digital health platforms such as LifeChamps enable the development of predictive algorithms to monitor the quality of life and frailty levels of elderly cancer patients, as well as assist in real-time clinical decision-making through big data processing and AI analytics [31]. The use of artificial intelligence, especially deep learning, has shown great potential in early diagnosis of skin cancer. Models such as Smart MobiNet offer high accuracy in detecting skin lesions and help medical professionals in faster and more precise diagnosis[32]. Machine learning and deep learning have become effective approaches in breast cancer diagnosis, especially through faster and more accurate analysis of medical images, improving patient care outcomes[33]. AI in endoscopy systems has been shown to play a significant role in gastric cancer detection, where convolutional neural networks (CNNs) are widely used to diagnose gastric cancer based on various feature extraction models. However, their performance is limited in identifying and classifying different stages and grades of cancer [34]. This paper's composition continues with Part 2, material and methods describing the proposed model, followed by Part 3, containing the results of the analysis and discussion of the proposed model, and finally, Part 4, containing the conclusions of this paper

2. Material and Methods

2.1. Material

The breast cancer detection process uses deep learning with training data in the form of images derived from ultrasound data with a total of 10,954 image data and image data in the form of mammography results with a total of 10,200 image data. In addition to image data, the dataset in the form of breast mass was taken from the results of digital calculations of cell nucleus characteristics called the fine needle aspirate (FNA) process, totaling 570 data. The division of training data is divided into 70% for training, 20% for validation, and 10% for testing. The type of ultrasound image data is secondarily obtained from public datasets.

The dataset utilized in this study comprises breast ultrasound images sourced from publicly available repositories, ensuring accessibility and reproducibility. One of the primary sources is Kaggle's "Ultrasound Breast Cancer Dataset," which is shared under the GNU Affero General Public License 3.0, allowing for open distribution and use in research applications [35]. Additionally, the study incorporates data from Hugging Face's "Breast Cancer Ultrasound Images," which is distributed under the breast-cancer-classifier license, further expanding the diversity of imaging samples [36]. Another critical dataset is the "Breast Lesions USG" collection from The Cancer Imaging Archive (TCIA), made available under the CC0 Public Domain license, ensuring unrestricted access for scientific exploration [37]. These combined datasets provide a comprehensive set of ultrasound images that facilitate the development and evaluation of deep learning models for early breast cancer detection. Each dataset is carefully curated and includes images labeled as either benign or malignant. The data was divided into training, validation, and testing subsets, with 70% used for training, 20% for validation, and 10% for testing. This ensures that the model can generalize well to unseen data, providing accurate results in real-world applications.

2.2. Methods

This study aims to develop an early detection system for cancer using a CNN with YOLOv5 architecture. This method was chosen by utilizing YOLO's ability to detect objects with high accuracy and is expected to provide a deeper understanding of early cancer detection through ultrasound images. The proposed method is one of the important steps in research utilizing AI, especially deep learning, for the detection process. How can we evaluate the advantages of the method used in processing ultrasound images with high efficiency and accuracy? The steps taken in this study are presented in figure 1.

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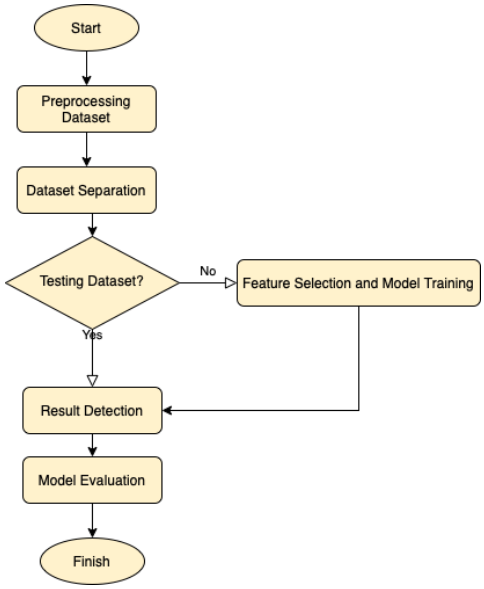

Figure 1. Research Methodology

The initial stage of the process is where all the preparations for the project or research are done. This includes identifying the objectives, selecting the dataset, and determining the method to be used to detect breast cancer from medical images. When the breast ultrasound images dataset is collected, the next step is to preprocess it. The breast image dataset (from ultrasound images) will be further processed to ensure good data quality.

The preprocessing stage plays a crucial role in preparing the dataset for deep learning-based breast cancer detection. This process includes image normalization, where images are resized, reformatted, and standardized to maintain uniformity across the dataset. Image augmentation is also applied to enhance the diversity of the dataset, thereby improving the model's robustness. Various augmentation techniques are employed, including rotation and mirroring, which introduce spatial variance and help the model generalize better to different tumor orientations. Contrast adjustment ensures the model adapts to variations in brightness, while grayscale transformation, applied to a portion of the images, simulates different imaging conditions. Additionally, noise addition is used to enhance the model's resilience against minor imperfections, such as ultrasound artifacts. These augmentation techniques are carefully selected to introduce variability, reducing overfitting and improving the model's ability to detect tumors in diverse conditions. Noise removal is another essential preprocessing step, eliminating unwanted visual noise to improve image clarity and facilitate model learning. In object detection, a bounding box is used to highlight the tumor's location within the image, aiding the model in accurate object identification. The model's performance is evaluated using loss values, which quantify the difference between predicted and actual labels. A lower loss value signifies that the model's predictions align closely with the ground truth. Specifically, bounding box loss measures the accuracy of predicted object locations, while classification loss determines how well the model differentiates between malignant and benign tumors. After preprocessing, the dataset is divided into two primary subsets: the training dataset, which the model uses to learn distinguishing features of malignant and benign tumors, and the testing dataset, which evaluates the model's generalization to unseen data. To further enhance detection performance, several optimizations are implemented in the YOLOv5 architecture. Anchor box tuning is performed to refine object detection accuracy by ensuring that the bounding boxes align more effectively with tumor shapes. Additionally, learning rate adjustments are made to optimize convergence. A learning rate scheduler is employed to gradually decrease the learning rate, allowing for refined weight optimization and preventing overshooting of the optimal solution. Through these preprocessing techniques and architectural improvements, the deep learning model is better equipped to detect breast cancer accurately from ultrasound images.

These optimizations helped increase the detection speed and accuracy, contributing to the high performance of the model in both malignant and benign tumor classifications. The model will learn the characteristics of the image, such as patterns, textures, or other features, that can distinguish between malignant and benign tumors images. After the model is trained, the test dataset is used to evaluate the model's ability to detect cancer in new images. This testing

aims to measure how well the model can correctly classify breast images that have not been seen during the training process. At this stage, the model's prediction results are evaluated. Each breast image tested will be classified into one of two categories: malignant tumors, If the image indicates signs of cancer, or benign, If the image shows that the breast does not have cancer or a non-malignant tumor.

The dataset presented an imbalance between the two classes: malignant and benign. To address this imbalance, we applied class weighting during the model training process. This technique assigns higher weights to the underrepresented class (malignant tumors) to compensate for the lack of data and ensure that the model learns to detect both classes with equal effectiveness. Additionally, data augmentation techniques were employed to artificially expand the training dataset by introducing variations such as rotation, flipping, and contrast adjustments, reducing the risk of overfitting and improving the model's generalization to new data. After obtaining the detection results, the model is evaluated using various performance metrics, such as 1) Precision, which Measures how accurate the model's positive predictions are; 2) Recall, which Measures how many cases of cancer were actually detected; 3) F1-Score: A combination of precision and recall; 4) mAP: The average precision across recall points. The purpose of this evaluation is to determine whether the model works well and whether the model can be used in real-world scenarios to accurately detect breast cancer and can be used for the development of breast cancer early detection applications.

2.2.1. Convolutional Neural Network

CNN is a neural network or deep learning that uses multi-layer neural network architecture. CNN is very suitable for solving object detection problems using images as training data [21], [22]. CNN functions to recognize unique attributes of an object. The CNN Architecture Components in figure 2 consist of an Input Layer component where this layer receives raw data in the form of images. Convolutional layer, it consists of a collection of convolutional flters (so-called kernels). The input image, expressed as N-dimensional metrics, is convolved with these filters to generate the output feature map, Activation Layer (ReLu); mapping the input to the output is the core function of all activation functions in all types of neural networks. The input value is determined by computing the weighted summation of the neuron input along with its bias (if present). This means that the activation function makes the decision as to whether or not to free a neuron with reference to a particular input by creating the corresponding output. Pooling Layer, this layer reduces the data dimension by taking the maximum or average value in a certain window, reducing data size and computational complexity. Fully Connected Layer: This layer is commonly located at the end of each CNN architecture. Inside this layer, each neuron is connected to all neurons of the previous layer, the so-called Fully Connected (FC) approach. It is utilized as the CNN classifier [21].

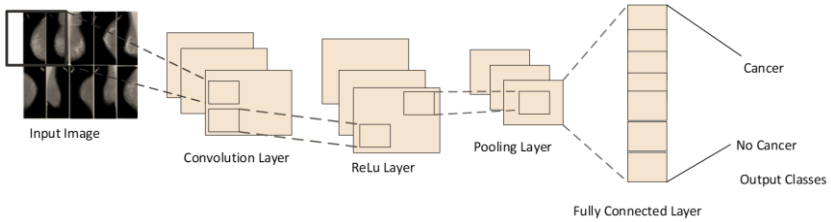

Figure 2. CNN Architecture for image classification

2.2.2. Application of CNN Method in Cancer Detection

Figure 3 shows the development of a deep-learning model to classify breast cancer using USG images. Here is a breakdown of the steps: Mulai (Start): The process begins. Pengumpulan Data (Data Collection): Collect breast cancer USG images for analysis. Preprocessing: Prepare the data by cleaning and transforming the images to be suitable for training the model. Pembagian Data (Data Splitting): Split the data into training and validation sets to ensure the model can generalize well to new, unseen data. Deep Learning: Use deep learning techniques, specifically CNNs, for feature learning and classification. Feature Learning: The CNN automatically extracts important features from the images. Classification: The model uses the learned features to classify the images as cancerous or non-cancerous. Cancer Breast Classifier Model: The resulting model is capable of detecting breast cancer from USG images. Selesai (Finish): The process concludes with a functional breast cancer classifier model. This flowchart provides a clear and structured approach to developing a machine-learning model for breast cancer classification.

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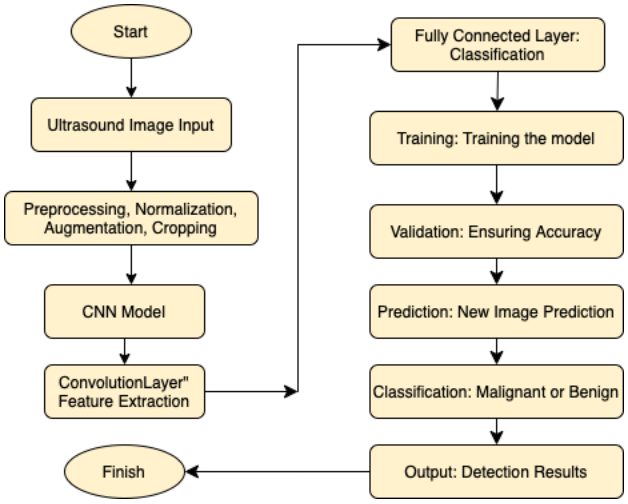

Figure 3. Process for developing a deep learning model to classify breast cancer using USG images

2.2.3. Architecture of YOLO

Figure 4 represents Yolo. The diagram illustrates a neural network architecture for image processing, specifically in the context of medical image analysis for breast cancer detection. Input Layer: This is where the mammogram images enter the network. Backbone: This section contains several layers that extract features from the images, such as edges and textures. Neck: This part further processes the extracted features, refining them to make them more useful for the final predictions. Head: This section is responsible for the output, producing the final classification results (e.g., whether the image shows signs of breast cancer) [22].

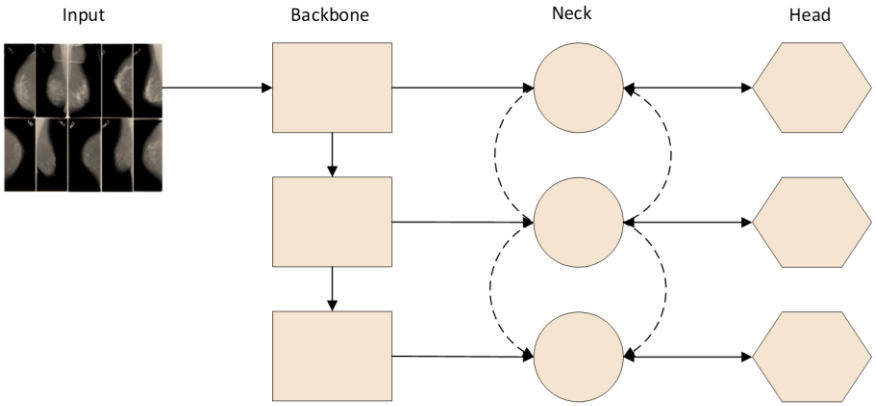

Figure 4. YOLO Architecture

3. Results and Discussion

The use of the CNN method with YOLO architecture to detect malignant/benign tumors breast ultrasound images is quite accurate and effective, producing a model that can be developed into an application for early detection of breast cancer. The dataset in the form of breast images taken using the ultrasound method is sourced from Kaggle, Hugging Face, and The Cancer Imaging Archive data. [36], [37], [38], [39], [40], the amount of data is 798 for malignant tumors images and 1050 for clear images. The pixel size of each different image will be changed to the same size, namely 1000 x 800 and 640 x 640, with an average of 0.27 MPa. The preprocessing stage includes all images into 2 (two) classes, namely malignant tumors and clear. In addition, several preprocesses, such as histogram equalization and grayscale, are applied in this process. Furthermore, the image augmentation process is carried out to overcome data limitations in neural network training. In this process, deformation is applied to the training data that has been labeled so that the new data formed is not redundant. To reduce overfitting in the model during the training process, various augmentation techniques are applied to enhance the dataset's diversity and improve the model's generalization ability. One of the techniques used is grayscale transformation, which is applied to 15% of the images to introduce variations

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in image intensity and simulate different imaging conditions. Each training example generates three augmented outputs, further enriching the dataset. Saturation and brightness adjustments are implemented within a range of -10% to +10%, ensuring that the model remains robust to variations in lighting and colour intensity. Additionally, a slight blur effect of up to 1.5 pixels is introduced to mimic real-world imperfections in ultrasound images. Noise augmentation is applied to up to 0.26% of pixels, helping the model become more resilient to distortions and artifacts that may be present in medical imaging. Furthermore, brightness adjustments of bounding boxes range from -15% to +15%, while noise is added to up to 0.1% of pixels within the bounding boxes, ensuring that the detection model can accurately recognize and localize tumors under different conditions. By applying these augmentation strategies, the model is trained to be more adaptable, reducing the risk of overfitting and enhancing its performance in real-world breast cancer detection scenarios.

The ratio used in training and testing data is 86% for the train set data, 8% for the valid set and 6% for the test set. Model training takes 2 hours and 40 minutes, the dataset detail can be seen in table 1.

Table 1. Malignant Tumors and Clear Image Dataset Details

No.	Class	Size	Train Set	Valid Set	Test Set
1.	Malignant Tumors	1000 x 800	690	62	46
2.	Beningn Tumors	640 x 640	1050	100	50

To evaluate the model's performance, Precision, Recall, and F1-Score were selected as key metrics due to their significance in medical applications, where both false positives and false negatives can have serious implications. Precision measures the proportion of predicted malignant cases that are truly malignant, minimizing the occurrence of false positives and ensuring that patients are not unnecessarily alarmed. Recall, on the other hand, quantifies how many of the actual malignant cases were correctly detected, which is crucial in reducing the risk of false negatives and ensuring that cancerous cases are not overlooked. The F1-Score, which is the harmonic mean of Precision and Recall, serves as a comprehensive metric that balances both concerns, providing a reliable assessment of the model's overall accuracy in detecting breast cancer from ultrasound images.

These metrics were preferred over accuracy because they offer a more comprehensive view of the model's ability to correctly classify both classes, especially in an imbalanced dataset scenario. Accuracy can be misleading when the dataset has a large class imbalance, as a model can achieve high accuracy by simply predicting the majority class (benign), which does not offer a practical solution in medical diagnostics.

The test results obtained an accuracy value for malignant tumors of 92.8% with model evaluation using a confusion matrix obtaining a precision of 82.3% and a recall of 100%, while for the clear class the accuracy was 99.1% with a precision of 97.5% and a recall of 95%.

Figure 5 and figure 6 show the box loss values during the training process. Box Loss is a metric in object detection that measures how well the predicted bounding box aligns with the ground truth box. In algorithms like YOLO, box loss consists of several components, including differences in position (center coordinates), size (width and height), and shape between the predicted and actual labels. A lower box loss value indicates that the model is more accurate in determining the location and dimensions of an object in an image. This is particularly crucial in ultrasound-based breast cancer detection, as even small errors in bounding box prediction can lead to misinterpretation of tumor analysis. *box_loss* measures how well the model describes the bounding box surrounding the object in the image. *box_loss* values decrease as the number of epochs increases, indicating that the model is getting better at predicting the location of the box boundaries. The consistent reduction in all types of *loss* (both in training and validation) indicates that the model is successful in reducing the overall detection error. This means that the model not only learns well from the training data but also generalizes well from the validation data. This is an important indicator that the model can be used in real-world situations.

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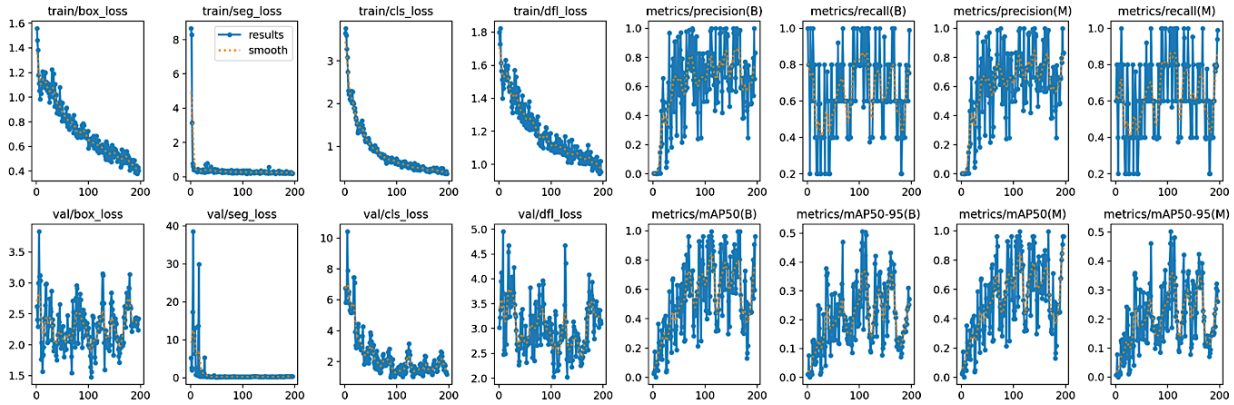

Figure 5. Malignant tumors class training data evaluation results

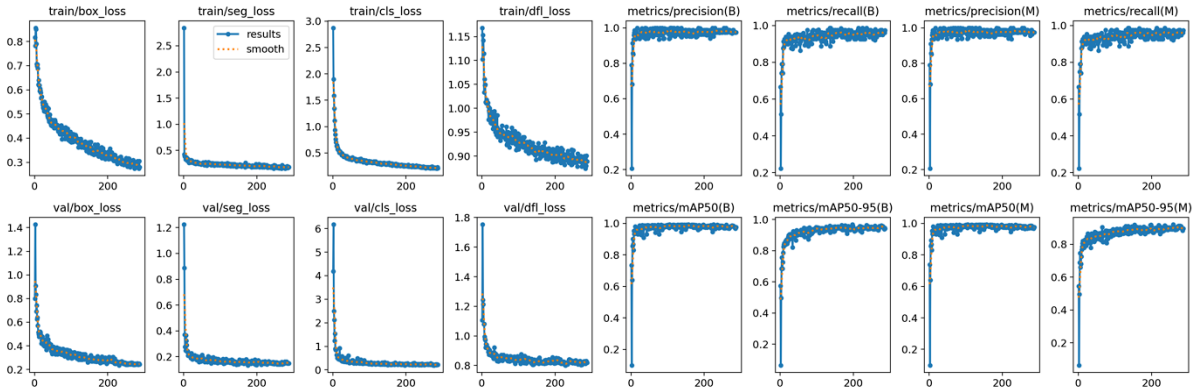

Figure 6. Benign tumors class training data evaluation results

Figure 7 and figure 8 show that this training was carried out for 100 epochs and 280 epochs, and the graph shows the performance of the resulting model using various evaluation metrics. In the Benin object, it is first seen in epochs 40 to 60, stable in the range of 0.9 to 0.95, then in epochs 61 to 65, instability occurs, then it starts to stabilize again around epoch 70 in the range of 0.85 to 0.95. For malignant tumors objects, it can be seen that around epoch 20, the stability starts to stabilize at a value of 0.9 to 0.98.

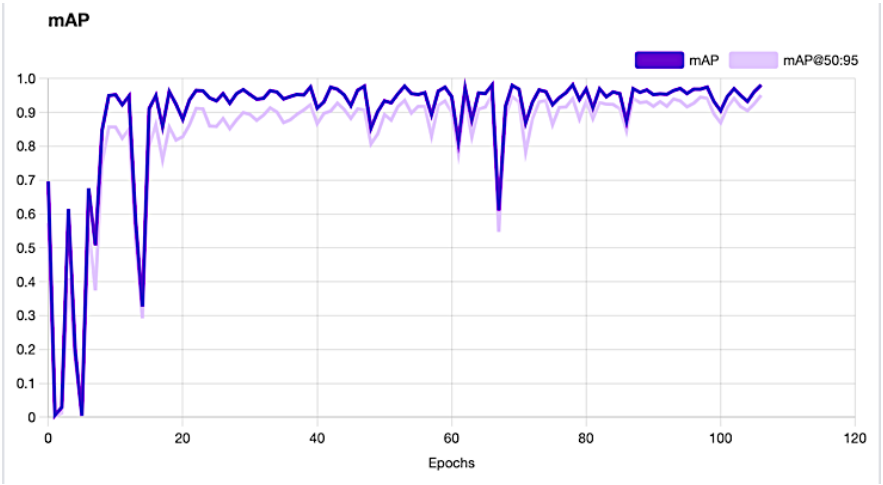

Figure 7. Evaluation results of benign object experiment results

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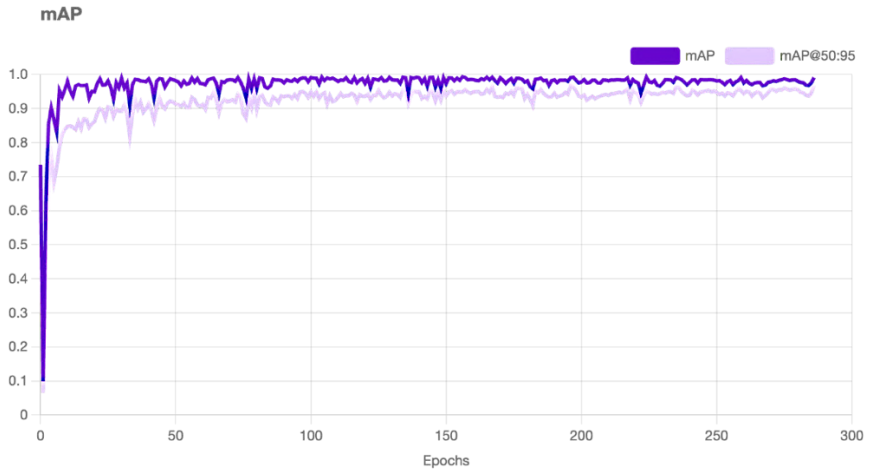

Figure 8. Results of evaluation of malignant tumors object experiment results

A snapshot of the results of object detection for malignant and beningn tumors can be seen in figure 9; the CNN method with the YOLO model has increased the quality of speed and accuracy in detecting an object [41], [42], [43]. The application of this model can identify precisely and efficiently [44], [45], [46], [47], [48], [49], [50], one of them is on breast images to identify malignant and benign tumors.

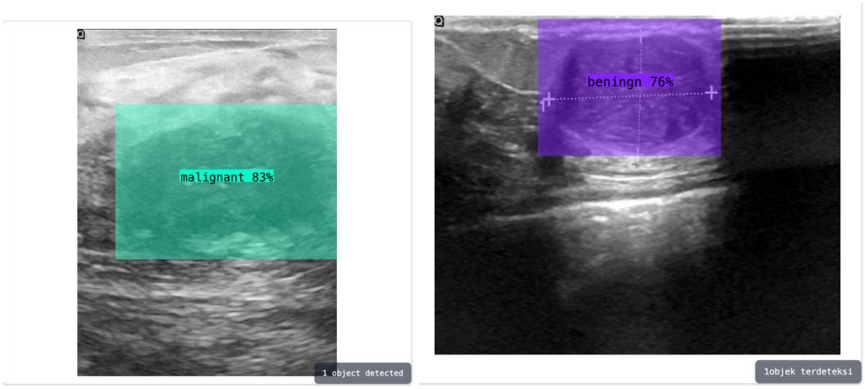

Figure 9. Object detection result screenshot

The tested model showed a significant increase in detection over time, the model successfully detected breast images with malignant tumors and clear objects well. To address the dataset imbalance, we used class weighting to adjust the loss function, giving more importance to correctly identifying malignant tumors. We also employed data augmentation to artificially balance the number of malignant and benign samples, ensuring that the model received sufficient data for both classes during training. As a result, the model performed well on both the malignant and benign datasets, with precision rates of 99.6% for malignant tumors and 97.5% for benign tumors.

While the YOLOv5 model demonstrated promising results, it is essential to compare its performance with other object detection models to validate its effectiveness. In this study, we compared YOLOv5 with a traditional CNN and a Support Vector Machine (SVM). Both models were tested on the same breast ultrasound dataset, revealing key differences in performance. YOLOv5 demonstrated superior speed and accuracy in detecting both malignant and benign tumors, achieving an overall detection precision of 99.6% for malignant tumors and 97.5% for benign tumors. In contrast, the traditional CNN model, while effective in image classification, exhibited slower processing times and slightly lower accuracy, particularly in identifying small or irregularly shaped tumors. SVM, a classic binary classification approach, struggled with the complexity of the dataset, resulting in reduced accuracy and higher false positive rates, especially when distinguishing subtle variations in tumor sizes [51].

This comparison highlights YOLOv5's advantage in terms of speed and precision, making it a more suitable choice for real-time applications like breast cancer detection.

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4. Results and Discussion

This study conducted an analysis of ultrasound images of breast cancer using the CNN method with the YOLO model; there are 2 (two) classes, namely malignant tumors and benign tumors. The results of the tests carried out on the two classes obtained an accuracy of 92.8% for malignant tumors and 99.1% for benign.

In the results section, we report Precision and Recall values for both the malignant and benign classes. However, it is important to understand the trade-off between these metrics. Precision represents the proportion of positive predictions that are true positives, while Recall measures the percentage of actual positive cases that the model correctly identifies. A high Precision value of 99.6% for malignant tumors suggests that when the model predicts a malignant tumor, it is highly likely to be correct, though it may still miss some malignant cases due to a lower Recall. Conversely, a Recall value of 100% for malignant tumors indicates that the model successfully detects all malignant cases, but this could come at the cost of misclassifying some benign tumors as malignant, leading to an increase in false positives.

The trade-off between Precision and Recall is a common challenge in medical diagnostics. In this study, we prioritized Recall for malignant tumors due to the critical importance of detecting as many cases as possible, even at the cost of a few false positives. This approach minimizes the risk of missing any potential malignant tumors, which could be life-threatening. The results of this test are greatly influenced by the characteristics of the dataset used in training and the preprocessing and augmentation processes carried out on the dataset.

The dataset used in this study was categorized into two classes: malignant and benign. However, potential issues with labeling in medical datasets must be considered. In some instances, inconsistent labeling may occur due to human error, particularly in cases where the diagnosis is subtle or borderline. Additionally, labeling bias can arise when annotations reflect the demographics of the patients or the expertise of the annotators, potentially limiting the model's ability to generalize effectively to a broader population. Addressing these challenges is crucial to ensuring the reliability and fairness of the model in real-world applications. To mitigate these issues, we ensured that the dataset was curated from reputable sources and underwent rigorous review by medical professionals. Nevertheless, future work could benefit from further validating the labels by incorporating a larger pool of expert annotators or using consensus-based labeling techniques.

The datasets used in this study were sourced from multiple repositories, including Kaggle, Hugging Face, and The Cancer Imaging Archive. These datasets exhibit variations in both geographical and technical aspects. Geographically, the data originates from different countries, potentially reflecting differences in healthcare systems and patient demographics, which may influence disease presentation and diagnosis. Technically, the images were captured using different ultrasound machines, leading to variations in image quality, resolution, and other characteristics. These differences present challenges in model training but also enhance the robustness and generalizability of the model by exposing it to diverse imaging conditions.

While these differences can help the model generalize better, it is important to note that models trained on diverse datasets may face challenges when deployed in a specific geographical or clinical setting. Therefore, additional training on region-specific data and further testing in real-world clinical environments would be necessary to ensure the robustness and applicability of the model. In the future, the results of this study can be developed to create an intelligent and efficient early-detection system for breast cancer.

5. Conclusion

Provide a statement that what is expected, as stated in the "Introduction" chapter can ultimately result in "Results and Discussion" chapter, so there is compatibility. Moreover, it can also be added the prospect of the development of research results and application prospects of further studies into the next (based on result and discussion).

6. Declarations

6.1. Author Contributions

Conceptualization: A.A., H.W., A.D.W.S., E.S., A.P., A.S.H., E.T.N., and A.K.; Methodology: A.P.; Software: A.A.; Validation: A.A., A.P., and A.K.; Formal Analysis: A.A., A.P., and A.K.; Investigation: A.A.; Resources: A.P.; Data Curation: A.P.; Writing Original Draft Preparation: A.A., A.P., and A.K.; Writing Review and Editing: A.P., A.A., and A.K.; Visualization: A.A. All authors have read and agreed to the published version of the manuscript

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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