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Detection of Breast Cancer Masses in Mammography Images Using a Hybrid Faster R-CNN and Fuzzy Logic Framework

Fatemeh Jafari [1], ***Hamid Reza Ghafari*** [1,*], ***Hassan Farsi*** [2]

[1] *Department of Computer Engineering, Ferdows Branch, Islamic Azad University, Ferdows, Iran.*

[2] *Department of Electrical and Computer Engineering, University of Birjand, Birjand, Iran.*

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[*] Corresponding Author's Email Address:
hyamidghaffary53@iau.ir

Abstract

Background and Objectives: Breast cancer is a leading cause of mortality among women worldwide. Early detection plays a pivotal role in reducing mortality rates and improving patient outcomes by identifying risk factors, enhancing screening methods, and enabling timely treatment. Recent advances in artificial intelligence (AI) and deep learning have facilitated accurate and efficient analysis of medical images, supporting rapid and precise breast cancer detection. This study aims to develop a fast and reliable approach for detecting breast cancer masses in mammography images using a deep learning framework.

Methods: The proposed approach employs a Faster R-CNN architecture with a ResNet backbone for robust feature extraction. Fuzzy logic is integrated to adaptively adjust the learning rate, improving training stability. Transfer learning and data augmentation techniques are applied to enhance model generalization and reduce overfitting. The method labels affected regions in mammography images, enabling accurate localization of cancerous areas.

Results: Experiments were carried out using the CBIS-DDSM dataset. The proposed model demonstrated a cancer detection accuracy of 97.84%, an Intersection over Union (IoU) of 98.12%, and a mAP50 of 0.83, highlighting its exceptional performance in accurately localizing breast cancer masses.

Conclusion: The integration of Faster R-CNN with ResNet, fuzzy logic-based learning rate adaptation, transfer learning, and data augmentation yields a highly effective solution for automated breast cancer detection. The results highlight the potential of this method to improve early diagnosis and support clinical decision-making in breast cancer screening.

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Introduction

Breast cancer is the most prevalent cancer among women worldwide, posing a significant health threat to millions each year [1]-[3]. Despite significant advancements in screening and treatment technologies, late-stage diagnosis highlights the critical need for innovative research in this field [4]-[7]. Recent studies have identified key risk factors, including obesity, late pregnancies, and genetic mutations such as BRCA1, which contribute to more aggressive forms of the disease [8], [9]. Traditional diagnostic methods, including digital mammography and invasive techniques like surgical biopsies, are often associated with high human error rates (with up to 20% of cases being overlooked) and patient discomfort. Although modern imaging technologies like 3D tomosynthesis and molecular imaging have shown improvements, they still struggle with challenges like interpreting dense breast tissues [10]-[12].

Recent developments in deep learning and computer vision have paved the way for the use of object detection models in medical image analysis. These models excel at identifying and localizing abnormalities within complex images, making them well-suited for detecting cancerous lesions in mammograms [13], [14]. Despite their success, challenges remain due to the variability in tumor appearance, limited availability of annotated datasets, and the need for models that can generalize well across diverse patient populations [7], [15].

The emergence of artificial intelligence (AI) and deep learning has revolutionized medical image analysis. Recent AI methodologies, including bio-inspired optimization frameworks such as Swarm Intelligence, have demonstrated strong capabilities in medical image analysis tasks such as tumor detection, feature extraction, and artifact reduction across various imaging modalities [16], [17]. Studies suggest that deep neural network-based models can now achieve diagnostic accuracies that rival human experts, significantly reducing false negatives by up to 9.4% and false positives by 5.7% [18]. However, these technologies have great potential to overcome the limitations of conventional methods by detecting complex patterns in imaging data. Despite their promising nature, challenges such as the variability in performance across different algorithms remain [11], [19]. A research study reported by Karolinska Institute in Sweden on 8,805 mammography samples found that only one out of three tested algorithms achieved an accuracy comparable to radiologists (87%) [12]. This finding underscores the importance of selecting the appropriate model architecture and training it with diverse clinical data. Some approaches, such as integrating fuzzy inference systems with deep neural networks, provide a means to manage uncertainty in low-quality or dense-tissue images [20], [21].

Object detection is one of the key subfields of machine learning and computer vision, focusing on identifying and classifying objects in images or videos. This technology enables systems to detect various objects within a scene, determine their locations, and categorize them [22]. It has widespread applications in research fields such as robotics, autonomous vehicles, video surveillance, and medical imaging [12]. With the advancement of deep learning techniques, object detection models have significantly improved in terms of accuracy. In recent years, several object detection models have been introduced, including You Only Look Once (YOLO), Single Shot Detector (SSD), and Faster Region-based Conventional Neural Networks (R-CNNs) [22].

In [23], an automated, data-driven model was proposed for detecting breast cancer in mammograms to assist physicians in screening and diagnosis. Using transfer learning, publicly available CBIS-DDSM and INbreast datasets were leveraged to train the model on a proprietary full-field digital mammography dataset containing diverse cases, including masses, asymmetries, and distortions. Multiple YOLO architectures were evaluated, with the small YOLOv5 model achieving the best performance, reaching a mean average precision (mAP) of 0.621. To enhance interpretability, Eigen-CAM was applied to highlight suspicious regions, effectively reducing false negatives despite a rise in false positives. The combination of YOLO predictions and saliency maps offers complementary insights, though these outputs should be considered qualitative and require clinical radiological validation. Overall, the model demonstrates promising detection capabilities and potential as a reliable decision-support tool in clinical settings.

Fuzzy inference systems have been widely applied in medical image analysis to address the inherent uncertainty and noise present in imaging modalities such as MRI. Prior studies have demonstrated that fuzzy rule–based models can enhance segmentation and classification performance by providing more flexible decision boundaries compared to conventional crisp methods [24]. In [16], a novel method based on Faster-RCNN architecture with a ResNet backbone was proposed which utilizes fuzzy logic for model training. This intelligent combination enables the extraction of high-level features from mammography images and optimizes noise and uncertainty in training data using fuzzy inference system. The major novelty of this research lies in integrating hierarchical attention mechanisms with fuzzy layers to enhance he accuracy of region detection in images [9].

The main novelty of this study lies in the integration of three complementary strategies that enhance both the learning efficiency and detection accuracy of the proposed system. First, a fuzzy logic–based adaptive learning rate mechanism is developed, where the learning rate is dynamically adjusted based on the loss value and training epoch using a rule-based fuzzy inference system. The fuzzy rules are logically defined and derived from the observed behavior of deep neural networks during training. Second, transfer learning is employed using a pre-trained ResNet-50 model to accelerate convergence and improve feature representation. Third, data augmentation techniques are applied to increase the diversity and volume of training samples, reducing overfitting and improving generalization. The synergistic integration of these three components results in a robust and adaptive framework for breast cancer detection, and to the best of our knowledge, this specific combination and its implementation in Faster R-CNN-based mammography analysis have not been previously reported in the literature.

The rest of the paper is structured as follows: SECTION 2 details previous studies on automated breast cancer detection, SECTION 3 presents a detailed explanation of the proposed architecture. SECTION 4 provides an analysis of experimental results based on sensitivity and specificity metrics. Finally, SECTION 5 concludes the research findings and provides suggestions for future studies.

Related Work

Early research in the 1990s primarily employed basic artificial neural networks (ANNs) to extract geometric features from mammography images. Initial research showed that traditional image processing algorithms—such as Gaussian filters and Fourier transforms—offered limited diagnostic accuracy, typically below 75%. The advent of Convolutional Neural Networks (CNNs) marked a turning point in medical imaging [25]. In [26], authors used the OPTIMAM dataset and they demonstrated that CNN-based models could match radiologists-level performance with an accuracy of 87%, while reducing false positives by 20%, a highly desirable and noteworthy result. In [27], a large-scale analysis involving 8,805 mammograms revealed that AI-based algorithms surpassed standard clinical models like the BCSC in five-year risk prediction. These models by detecting hidden patterns in breast tissue, were capable of forecasting breast cancer up to five years before the onset of physical symptoms. Further evidence from a study at the University of California, using data from 116,495 Norwegian women, showed a prediction accuracy of up to 94%, successfully detecting 1,607 cancer cases 4 to 6 years earlier than standard methods.

Research indicates that integrating AI into the diagnostic process significantly reduces human errors. In [28], a novel deep learning-based approach named XAI-RACapsNet has also been introduced. This approach initially leverages multi-stage image processing, including noise filtering and histogram equalization, followed by feeding the data into a deep learning network called XAI-ONET to identify suspicious regions. The results verified the optimum performance in detecting cancerous regions. Despite notable progress, AI models remain sensitive to the quality and diversity of training data [29]. This highlights the importance of choosing the appropriate model architecture and using diverse data with broad geographical and demographic coverage. Recent research has focused on combining fuzzy inference systems with deep neural networks to handle uncertainty in low-quality or dense-tissue images [30]. Comparative studies have shown that AI algorithms not only outperform traditional clinical models but also deliver superior performance under specific conditions. In [31], a novel method named AlexNet-BC was proposed for breast cancer detection. It leveraged transfer learning from the ImageNet-trained model and improved risk prediction accuracy by 9.4% compared to existing approaches. It also demonstrated that AI can simultaneously reduce both false positives and false negatives. Despite technical advances, deployment challenges such as the need for diverse training data and integration with existing healthcare systems have prevented the widespread adoption of these technologies. In [25], it was shown that using historical datasets with incomplete labeling can reduce model accuracy by up to 12%, emphasizing the need for standardized data collection protocols. In [32], authors present a new framework for breast cancer detection that leverages Convolutional Neural Networks (CNNs) and image processing techniques. The approach employs RetinaNet, a pre-trained, one-stage object detector, as the core model. To enhance performance, a two-stage transfer learning strategy is applied: first, RetinaNet is trained on the COCO dataset, a large general-purpose dataset; then, it is fine-tuned on the CBIS-DDSM mammogram dataset. In the final stage, the model is further adapted and evaluated on the INbreast mammogram dataset. The results demonstrate that this two-stage transfer learning approach (RetinaNet → CBIS-DDSM → INbreast) outperforms other state-of-the-art methods on the INbreast dataset.

In [33], a deep learning approach was introduced to distinguish between benign and malignant tumors. This method employed transfer learning and recursive block structures to enhance algorithm efficiency. For optimization, Laplacian of Gaussian (LoG) equation sets were used, achieving 97.75% accuracy on the mini-

DDSM dataset.

In [34], a Faster-RCNN-based approach was proposed to localize disease-affected regions in mammography images. This method achieved a breast cancer detection accuracy of 94.12% with a true positive rate of 93.33%.

A novel edge detection method for mammography images, called edmABC, is introduced in [35]. By leveraging an improved Artificial Bee Colony algorithm inspired by honeybee foraging, the approach enhances the identification of image boundaries to aid breast cancer detection. The method integrates advanced initialization and statistical techniques, and experimental results show it achieves superior edge detection compared to traditional algorithms. [36], focuses on creating a Computer-Aided Diagnosis (CAD) system utilizing the You Only Look Once (YOLO) framework to detect breast masses and categorize them as either benign or malignant. This approach employs a YOLOv5-CAD model that leverages transfer learning. Additionally, the study investigates how different data augmentation strategies during training influence the model's overall performance. In [37], authors present a new object detection model for this field. This study focuses on improving breast cancer detection using a customized version of the YOLOv9 object-detection model, designed to address species and morphological variations in tumors. The model, named FS-YOLOv9, was trained and validated on an internal dataset of 687 cases and tested on 98 external cases. Key modifications include adding a max-pooling layer to enhance bright features and replacing a backbone component with a high-frequency Haar wavelet convolution to better capture morphological and texture details. Compared to the standard YOLOv9 and earlier YOLO versions, FS-YOLOv9 demonstrated superior performance across multiple metrics, including F1 score, free-response ROC area (FAUC), and mean average precision (mAP), both internally and externally. These improvements suggest that FS-YOLOv9 is a more effective and reliable tool for breast cancer screening, particularly for high-risk patients.

Nonetheless, challenges such as interpreting complex patterns in fatty tissues and managing noise in low-quality images persist. Researchers emphasize the need for longitudinal studies and patient follow-ups to evaluate the real-world effectiveness of these systems in clinical settings [25], [27], [38].

In their 2024 study [39], Boudouh and Bouakkaz proposed a hybrid deep learning model that combines the Vision Transformer (ViT++) architecture with a Convolutional Neural Network (CNN) for the classification of breast calcifications in mammography images. The model extracts global semantic features via ViT++ while leveraging CNN for local spatial details. Their experimental results on the CBIS-DDSM dataset showed that this hybrid approach achieved an accuracy of 96.12%, which further improved to 99.22% when combined with handcrafted VGG16 features. This study demonstrates the potential of transformer-CNN fusion for improved diagnostic accuracy in mammogram analysis. In [40], authors developed a YOLO-based Computer-Aided Diagnosis (CAD) system for the detection and localization of breast tumors in mammographic images. Their architecture integrates a region-based object detection backbone with decision-level fusion to improve detection sensitivity. This work remains frequently cited in recent literature due to its relatively high detection performance. On the CBIS-DDSM dataset, the model achieved a tumor detection accuracy of 95.7%, indicating its effectiveness for identifying suspicious masses, even though it did not include malignancy classification.

In [41], authors introduced a multiscale parallel CNN framework inspired by YOLO architecture to enhance the detection of breast lesions in mammography. Their approach incorporates multiple convolutional paths to capture features at different scales, improving the detection of both small and large abnormalities. On the CBIS-DDSM dataset, the model achieved a mean Average Precision (mAP) of 91.15%, while reaching 98.72% classification accuracy on the INbreast dataset. Their results highlight the effectiveness of multiscale modeling in complex medical imaging tasks. This study presents a fast and accurate deep learning-based approach for detecting cancerous masses in mammography images. The proposed method utilizes a Faster-RCNN architecture with a ResNet backbone, enhanced by the integration of fuzzy logic into the training process, which improves the accuracy of lesion detection. This innovative combination enables the extraction of high-level features from images and reduces diagnostic errors by effectively managing uncertainty in the training data.

Proposed Method

In this section, the proposed method for detecting suspicious regions indicative of breast cancer is detailed. To achieve this, a deep learning model based on Faster-RCNN with a ResNet-50 backbone architecture and, a transfer learning and data augmentation approaches are proposed. During the training phase, fuzzy logic is used to dynamically determine the learning rate in order to improve the training process. The following subsections elaborate on each component of the proposed methodology.

A. Fuzzy Logic

Fuzzy logic, introduced by Professor Lotfi Zadeh in 1965, is a logic system that models vague concepts and partial truths using values ranging from 0 (completely false) to 1 (completely true) [42]. Unlike classical binary logic (0 and 1), fuzzy logic extends set theory to fuzzy sets, where membership is defined by degrees rather than absolutes. This framework for approximate reasoning bridges the gap between human thinking and machine computation.

In this paper, fuzzy logic is employed to determine adaptive learning rates. To this end, a fuzzy system with two inputs and one output is designed. The inputs include the loss function value and the current training epoch, and the output is the learning rate. For the values in fuzzy system, a Gaussian membership function (i.e., gauss2mf) is used. Fig. 1, depicts loss input membership function and Fig. 2 illustrates epoch input membership function. Fig. 3 shows the learning rate output membership function.

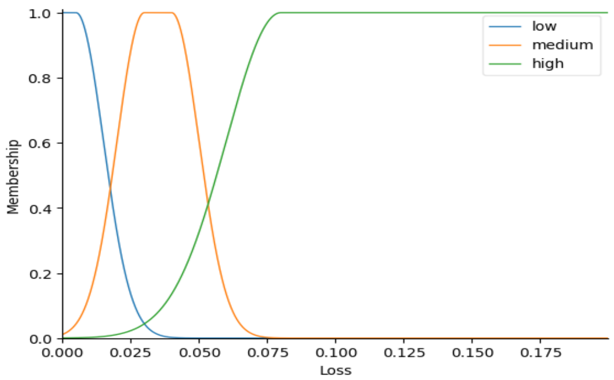

Fig. 1: The membership function for the loss input.

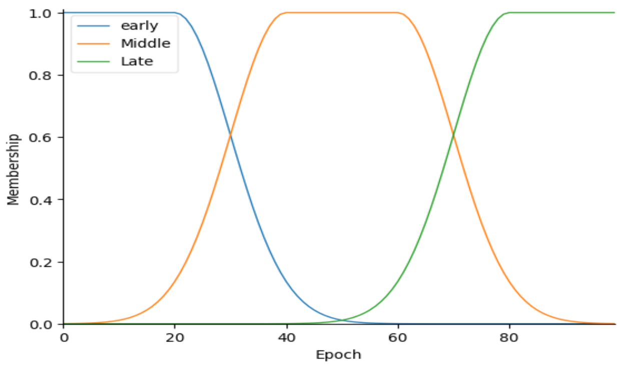

Fig. 2: The membership function for the epoch input.

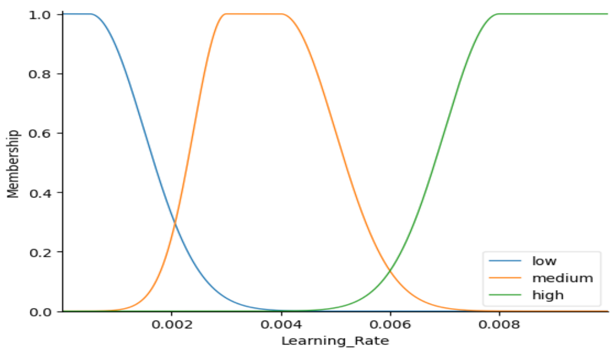

Fig. 3: The membership function for the learning rate output.

Moreover, the following three fuzzy rules are used to determine the learning rate:

1. If the loss is high and the epoch is early, then the learning rate should be high.
2. If the loss is moderate and the epoch is medium, then the learning rate should be middle.
3. If the loss is low and the epoch is late, then the learning rate should be low.

This rule-based system allows the model to accurately adjust the learning rate based on the input logics.

B. Faster-Rcnn Deep Learning Model

The proposed method uses the Faster-RCNN deep learning model as an advanced method in object detection field–for object detection in mammography images. This model uses a CNN-based architecture to extract feature map from input images, which contain valuable information about the objects [43]. In this paper, ResNet-50 architecture is employed as an object feature extractor. This model leverages stacked convolutional blocks with ReLU activation and skip connections to preserve fine-grained spatial information, resulting in superior feature extraction capability compared to lightweight models such as LeNet-5. Its strong representational power has led to high accuracy across various image and video classification domains [44]. Fig. 4, shows the architecture of ResNet, which employs residual block to prevent information loss during deep training. ResNet is widely recognized for its high performance across various existing machine learning fields [45].

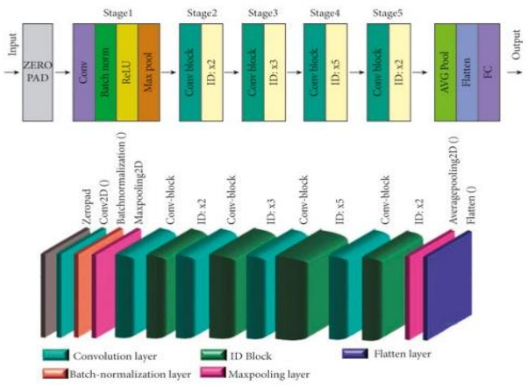

Fig. 4: The ResNet-50 architecture used as the feature extraction backbone in the proposed Faster R-CNN framework.

Within the Faster-RCNN framework, a convolution-type deep learning model called Region Proposal Network (RPN) is used to identify candidate regions that may contain objects. Then, a Region of Interest (RoI) pooling layer is used to map the proposed regions by RPN into a fixed-size output.

The overall loss function in Faster-RCNN consists of two parts: classification loss and regression loss, formulated as (1):

$$L(p_i, t_i) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}} \sum_i p_i^* L_{reg}(t_i, t_i^*) \tag{1}$$

where L_{cls} is the classification loss calculated using cross-entropy loss function, as defined by (2):

$$L_{cls}(p_i, p_i^*) = -\sum_{i=1}^{N_{cls}} p_i \log p_i^* \tag{2}$$

where p_i* and p_i represent the actual and predicted values by the proposed model, respectively, L_{cls} is the number of identified samples by RPN, λ is a control parameter to trade-off between classification and regression, L_{reg} is also a regression error obtained using (3) formula:

$$L_{reg}(t_i, t_i^*) = \frac{1}{N_{reg}} \sum_{i=1}^{N_{reg}} \sum_{j\epsilon\{x,y,w,h\}} \begin{cases} 0.5\left(t_{ij} - t_{ij}^*\right)^2 & \left|t_{ij} - t_{ij}^*\right| < 1 \\ \left|t_{ij} - t_{ij}^*\right| - 0.5 & otherwise \end{cases} \tag{3}$$

where t_i and t_i* represent the predicted and actual bounding box coordinates data including x, y, w and h denoting box center, width, and height, respectively.

Fig. 5 illustrates the structure of the Faster-RCNN deep learning model for suspicious breast cancer mass detection.

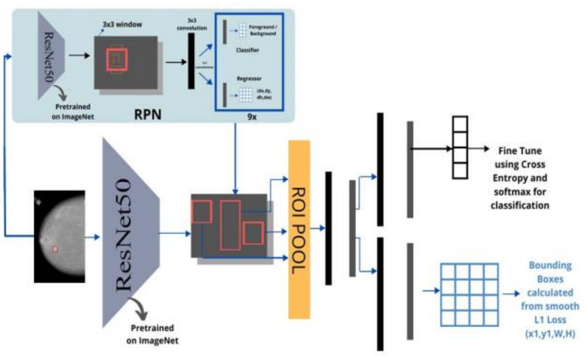

Fig. 5: The Faster-RCNN deep learning structure.

C. Transfer Learning

Since data augmentation is employed to increase dataset images, hence, to reduce computational overhead during training, transfer learning is applied [46]. For this purpose, the pre-trained ResNet-50 model on the ImageNet dataset is used for new dataset classification. Specifically, the first five convolutional layers are entirely frozen in ResNet-50 and not changed during training process. These layers typically learn general features such as brightness level, image edges, shininess, among others. Thus, these features are consistent and important across different types of images. Accordingly, similar coefficients are employed for feature extraction. Other coefficients are trained using given data in order to fulfill classification by a high accuracy.

Algorithm 1 presents the pseudocode for the proposed method, while Fig. 6, illustrates the block diagram of the proposed approach.

Algorithm 1: Proposed Method for Breast Cancer Detection

Input: *Dataset: CBIS-DDSM, Pretrained ResNet-50, Fuzzy Logic System, Augmentation Techniques*

Output: *Trained Model*

1. Initialize ResNet-50 with pretrained weights.

2. Define fuzzy system for dynamic learning rate adjustment (based on loss and epoch).

3. Perform data augmentation (crop, rotate, adjust intensity) to generate three new images per original image.

4. For each epoch:

a. Pass augmented images through ResNet-50.

b. Use Faster-RCNN for detection.

c. Adjust learning rate using fuzzy logic system.

d. Calculate loss and update weights using backpropagation.

5. Output trained model for breast cancer detection

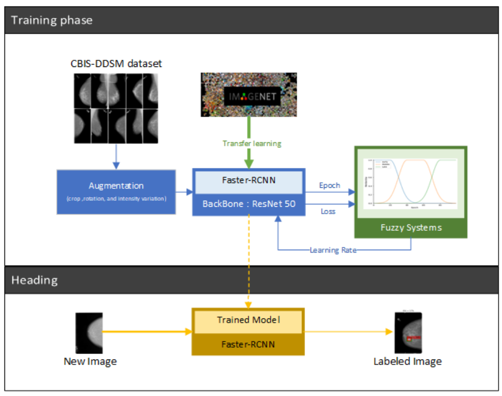

Fig. 6: The block diagram of the proposed approach.

Simulation and Results

The proposed method was evaluated using the CBIS-DDSM dataset [47], which contains mammography images categorized into three groups: normal, benign, and malignant. Each image includes labeled regions of interest (ROIs) and labeled bounding boxes indicating tumor locations. The dataset comprises 10,239 images from 6,671 patients in various sizes. Fig. 7, displays several sample images from this dataset.

As mentioned earlier, three images were generated from each original image using data augmentation techniques, resulting in a total of 40,956 images used for training and evaluation. The proposed model was implemented on a system equipped with a GTX-4090 GPU (24GB RAM), using Python and the PyTorch AI library.

We split the dataset into 80% training and 20% testing sets. Two training strategies were used:

- Fixed Learning Rate Strategy: Starting at 0.005, reduced by a factor of 0.1 every 10 epochs,
- Fuzzy-Based Learning Rate Strategy: Adaptive rate determined dynamically by the fuzzy logic system during each epoch.

The batch size was set to 32, and the model was trained for 100 epochs in both strategies. We used the Adam optimizer to find the optimal coefficients during the training process. Table 1 summarizes the training time for both strategies.

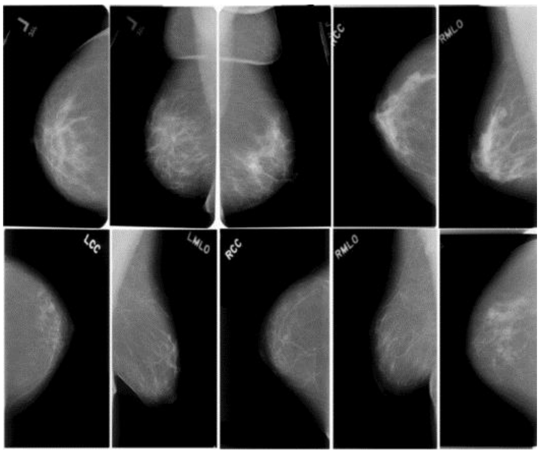

Fig. 7: Several images available in CBIS-DDSM dataset.

Fig. 8 shows the learning rate variations during training process in both the conventional and fuzzy logic strategies. In the traditional method, the training rate drops regularly after ten intervals, while in the fuzzy logic method, it decreases based on fuzzy logic. That is, in late-stage training with a low loss value, the fuzzy system intelligently reduces the learning rate according to the designed rules.

Fig. 9 presents the loss value reduction over training epochs for both regular and fuzzy methods. It is evident that the fuzzy logic approach outperforms the fixed strategy by significantly reducing the loss. Specifically, the fuzzy method achieves a 2.325x lower final loss than the standard approach.

Fig. 10 illustrates sample outputs of the proposed system. The top row shows detection results using the standard method, and the bottom row shows results with fuzzy logic. And, green boxes indicate ground truth cancerous regions; while, red boxes show regions detected by the model. Moreover, each detected region is also labeled with the predicted class (benign or malignant) and the associated probability score. As Fig. 10 demonstrates, the model accurately identifies cancerous areas and differentiates between benign and malignant tumors. Some assessing metrics are mentioned bellow.

Table 1: The proposed algorithm execution time

Strategy	The average time of each epoch (seconds)	Training time (minutes)
Fixed Learning Rate	205.0256	341
Fuzzy-Based Learning Rate	209.4681	353

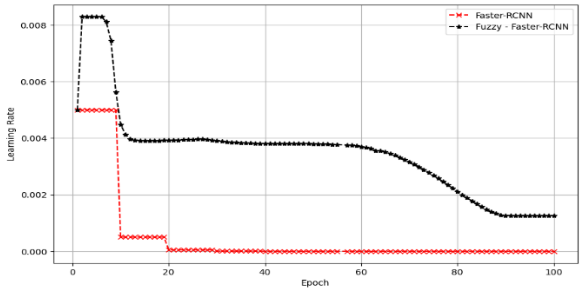

Fig. 8: Learning rate variations by the proposed method.

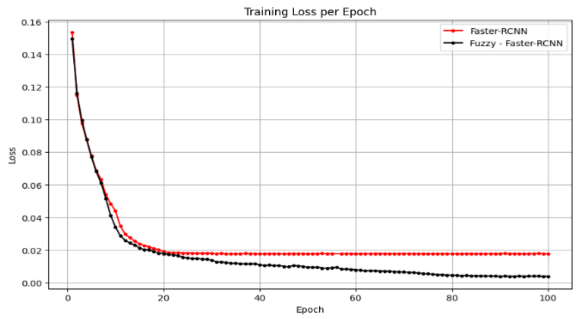

Fig. 9: Loss drop trend in the training process.

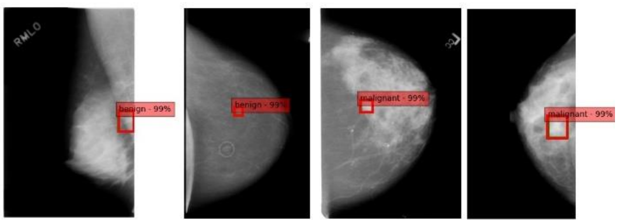

Fig. 10: The proposed model output.

One key performance metric is the Intersection Over Union (IOU), which evaluates the precision of the RPN. The appropriate assessing precision is denoted by IOU. Here, the overlap area is divided into all object areas and a number less than 1 is considered as IOU. Equation (4) expresses IOU calculation. Higher overlapped areas between detected and targeted regions leads to values close to 100.

$$IOU = \frac{area\ of\ overlap}{area\ of\ union} \times 100 \tag{4}$$

Table 2 provides the value of IOUs by both regular and logic approaches. It is seen that the fuzzy method achieves superior IOU values compared to the traditional method, confirming its better localization performance.

Table 2: IOU metric assessment

Strategy	IOU
Fixed Learning Rate	97.5892%
Fuzzy-Based Learning Rate	98.1256%

The mAP50-95 metric serves as an extensive benchmark for evaluating the performance of object detection models, assessing them at various levels of spatial precision. To calculate this metric, the mean Average Precision (mAP) is first determined for a range of IoU thresholds, starting from 0.50 and progressing through 0.05 increments up to 0.95. The average of these individual mAP values is then computed and reported as mAP50-95. This approach, which incorporates varying levels of strictness, offers a more detailed and dependable indication of a model's capability in detecting and localizing objects. As a result, mAP50-95 generally yields lower scores than mAP50, given that it applies stricter spatial accuracy criteria. On the other hand, mAP50 is a more lenient version of mAP50-95, being computed only at an IoU threshold of 0.50 [48]. Here, a prediction is considered correct if at least 50% of the predicted bounding box overlaps with the ground-truth box. This metric places greater emphasis on the model's ability to identify objects, rather than precisely localizing them. Because of its relaxed requirements, mAP50 tends to be higher than mAP50-95, serving as a broader indicator of a model's detection performance. In the context of this study, the performance of the proposed method was compared to the Faster-RCNN with a fixed learning rate, using the same dataset and experimental conditions. The results, as shown in Table 3, reveal that the proposed method outperforms the fixed learning rate Faster-RCNN in terms of detection accuracy.

Table 3: mAP50 and mAP50-95 for proposed method

Strategy	MAP50	mAP50-95
Fixed Learning Rate	0.79	0.65
Fuzzy-Based Learning Rate	0.83	0.69

To further validate the proposed model's effectiveness, we compared it with conventional classifiers such as SVM, KNN, Decision Tree, Ensemble, and Subspace, as well as CNN-based and LeNet architectures. These models used features such as brightness, Histogram of Oriented Gradients (HOG), and Local Binary Patterns (LBP) for classification. Table 4 presents classified data in two “normal” and “cancerous” cases.

Table 4: Accuracy performance compared to other methods

Method	Classifier	Type	Accuracy
Brightness	**SVM**	Quadratic	73.26
		Cubic	71.25
		Linear	75.68
		Medium Gaussian	71.98
	KNN	Weighted	75.25
		Fine	74.66
	Tree	Fine	67.26
HOG	**SVM**	Quadratic	80.27
		Cubic	83.42
		Linear	79.58
		Medium Gaussian	83.21
	KNN	Weighted	73.25
		Fine	71.87
	Tree	Fine	69.24
LBP	**SVM**	Quadratic	89.21
		Cubic	85.16
		Linear	85.36
		Medium Gaussian	79.87
	KNN	Weighted	72.12
		Fine	77.98
	Tree	Fine	67.95
Combine (Color, 2 HOG, LBP)	**KNN**	Fine	89.94
CNN		LeNet architecture	91.58
Method [41]		YOLO-based multiscale CNN	91.15
Method [34]		Modified Faster RCNN	94.12
Method [49]		GoogLeNet–SVM	95.80
Method [40]		YOLO-based	95.70
Method [50]		Transfer learning CNN	96.02
Method [36]		YOLOv5-CAD	96.30
Method [39]		Transformer-CNN	96.12
Proposed method		Fixed Learning Rate	94.83
Proposed method		Fuzzy-Based Learning Rate	96.45

We also evaluated performance in distinguishing between benign and malignant tumors using F1-score, precision, and recall metrics. The F1-score was calculated as (5):

$$f1\_score = \frac{2PR}{P+R} \tag{5}$$

$$P = \frac{TP}{TP+FP} \tag{6}$$

$$R = \frac{TP}{TP+FN} \tag{7}$$

where:

- TP = True Positives
- FP = False Positives
- FN = False Negatives

Table 5 presents the results for two possible cases, showing that the proposed method achieves the highest scores among all tested approaches.

Table 5: Precision and recall metrics assessed for fuzzy-based learning rate

Label	precision	recall	f1-score
Normal	0.9369	0.9002	0.9182
Benign	0.9425	0.9538	0.9481
malignant	0.9428	0.9526	0.9477

The confusion matrix (Table 6) separately provides the model's classification performance for each class. In this table, each row represents the actual cancer type, while the columns correspond to the predicted cancer types. This layout enables a clear comparison between the ground-truth labels and the model's predictions. As shown, the proposed system achieves an accuracy exceeding 95%, demonstrating a high level of reliability in distinguishing between benign and malignant tumors.

The Receiver Operating Characteristic–Area Under the Curve (ROC–AUC) metric was employed to provide a threshold-independent evaluation of the classification performance. Unlike accuracy-based measures that depend on a fixed decision threshold, ROC–AUC assesses the model's discriminative capability by analyzing the trade-off between the true positive rate and false positive rate across all possible thresholds. For the three-class classification task (Normal, Benign, and Malignant), a one-vs-rest strategy was adopted to compute the ROC–AUC for each class individually. As illustrated in Fig. 11, the proposed model incorporating a fuzzy-based learning rate achieves consistently high discriminative performance, with ROC–AUC values exceeding 98% for all three classes. These results highlight the robustness and effectiveness of the proposed approach in distinguishing between different breast tissue conditions.

Table 6: The proposed model confusion for fuzzy-based learning rate

actual	**Normal**	8238	476	452
	Benign	250	15155	477
	malignant	276	464	15168
		Normal	**Benign**	**malignant**
			Predicted	

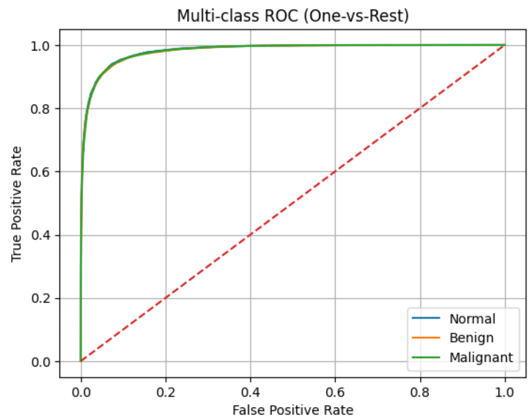

Fig. 11: ROC curve of the proposed model using a fuzzy-based learning rate.

Discussion

The results presented in the previous section demonstrate the strong performance of the proposed hybrid framework that combines Faster R-CNN with fuzzy logic–based adaptive learning. The model achieved a classification accuracy of 96.45% and ROC-AUC values exceeding 98%, outperforming traditional machine learning techniques (e.g., SVM, KNN, and Decision Trees) and even some CNN-based architectures such as LeNet and standard Faster R-CNN without fuzzy enhancement. The fuzzy logic mechanism contributed significantly to model stability and training efficiency. By dynamically adjusting the learning rate based on loss value and training epoch, the system achieved faster convergence and reduced training loss by more than 2.3× compared to the fixed-rate strategy. This indicates that the model effectively adapted its learning behavior based on training progress, a benefit not easily achievable with manually tuned hyperparameters.

The IoU metric (98.12%) confirmed the high localization accuracy of the model in identifying breast cancer masses. Furthermore, the confusion matrix and F1-scores across the three classes (normal, benign, malignant) demonstrated strong balance between precision and recall, minimizing both false positives and false negatives—a critical factor in clinical scenarios. Compared to recent deep learning models reported in the literature (as included in Table 4), our approach performs competitively or better in terms of accuracy, particularly when considering its explainable structure, use of fuzzy logic, and training efficiency. While transformer-based and diffusion models have shown promise, they typically require substantially more computational resources, whereas our method achieves high performance using relatively moderate hardware. However, this study also has certain limitations. The dataset was split into training and testing sets without a separate validation phase, which might have slightly biased the performance metrics. In addition, the current model was tested only on the CBIS-DDSM dataset. Future work will focus on testing cross-dataset generalizability and incorporating more diverse clinical data. Overall, the proposed framework offers a practical and accurate tool for automated breast cancer detection in mammography images, with strong potential for integration into clinical decision-support systems.

Conclusion

Due to unhealthy lifestyle habits, breast cancer has become one of the most prevalent diseases among women today. As a result, prevention, early detection, and treatment of this disease have gained significant research attention. One promising approach is the use of artificial intelligence for breast cancer detection. In this study, we proposed a breast cancer detection method based on a deep learning framework that combines ResNet and Faster R-CNN architectures with fuzzy logic. The proposed approach employs a fuzzy inference system to dynamically adjust the learning rate during training according to the loss value and training epoch. Experimental results demonstrate that the model can accurately detect and localize cancerous regions in mammography images. Specifically, it achieved an Intersection over Union (IoU) score of 98.12% and a mean Average Precision (mAP) of 0.83, indicating excellent localization capability and robust detection performance. Additionally, the system successfully distinguishes between benign and malignant tumors with high precision. However, this study has some limitations. The dataset was divided into training and testing sets without a separate validation phase, which may have slightly biased the performance metrics. Furthermore, the model was tested solely on the CBIS-DDSM dataset. Future work will focus on evaluating the model's generalizability across multiple datasets and incorporating more diverse clinical data. Additionally, improving the software design for better usability and exploring alternative architectures will be important areas for further research. Overall, the proposed framework presents a practical and accurate solution for automated breast cancer detection in mammography images, with strong potential for integration into clinical decision-support systems.

Author Contributions

Fatemeh Jafari: Conducted the experiments and drafted the manuscript.

Hamid Reza Ghafari: Contributed to manuscript writing and provided significant input to the research design and methodology.

Hassan Farsi: Interpreted the experimental results and performed data analysis.

All authors read and approved the final version of the manuscript

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Conflict of Interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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Abbreviations

AI	Artificial Intelligence
CNN	Convolutional Neural Network
RCNN	Region-based Convolutional Neural Network
Faster-RCNN	Faster Region-based Convolutional Neural Network
YOLO	You Only Look Once
SSD	Single Shot Detector
mAP	Mean Average Precision
CAD	Computer-Aided Diagnosis
ROC	Receiver Operating Characteristic
AUC	Area Under the Curve
RoI	Region of Interest
RPN	Region Proposal Network
IOU	Intersection Over Union
SVM	Support Vector Machine
KNN	K-Nearest Neighbors
HOG	Histogram of Oriented Gradients
LBP	Local Binary Patterns
TP	True Positives
FP	False Positives

FN	False Negatives
F1-score	Harmonic Mean of Precision and Recall
ResNet	Residual Neural Network
CBIS-DDSM	Curated Breast Imaging Subset of Digital Database for Screening Mammography
INbreast	Portuguese INbreast Mammography Dataset
ViT	Vision Transformer
LoG	Laplacian of Gaussian
CAM	Class Activation Map

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Biographies

Fatemeh Jafari holds a B.Sc. in Computer Engineering (Software Engineering) from Birjand University of Technology, Iran. She earned her M.Sc. in Computer Science (Intelligent Computation) from the University of Sistan and Baluchestan, where she focused on advanced computational methods and intelligent systems. Currently, she is a Ph.D. candidate in Computer Engineering (Artificial Intelligence) at the Islamic Azad University, Ferdows Branch. Her research interests lie at the intersection of Artificial Intelligence, Image Processing, and Medical Image Analysis, with a particular emphasis on developing intelligent algorithms for diagnostic and analytical applications.

- Email: fatemeh.jafari8094@iau.ac.ir
- ORCID: 0009-0001-3709-7841
- Web of Science Researcher ID:
- Scopus Author ID:
- Homepage:

Hamid Reza Ghafari received his B.Sc. degree in Computer Engineering (Software Engineering) from Sharif University of Technology in 1997. He earned his M.Sc. degree in Computer Engineering (Software Engineering) from Islamic Azad University, Tehran South Branch, in 2001, and his Ph.D. degree in Computer Engineering (Software Systems) from Ferdowsi University of Mashhad in 2014. He is currently an Associate Professor, a faculty member, and the President of Islamic Azad University, Ferdows Branch. His main research interests include Artificial Intelligence, Image Processing, Data Mining, and Medical Image Processing.

- Email: hamidghaffary53@iau.ac.ir
- ORCID: 0000-0003-0627-4080
- Web of Science Researcher ID: AAP-3151-2021
- Scopus Author ID: 57203222802
- Homepage: https://scimet.iau.ir/Hamidreza_Ghaffari

Hassan Farsi received his B.Sc. (1992) and M.Sc. (1994) degrees in Communication Engineering from Sharif University of Technology, Tehran, Iran, and his Ph.D. degree in Communication Engineering from the University of Surrey, Guildford, UK, in 2003. He is currently a Full Professor in the Faculty of Electrical and Computer Engineering at the University of Birjand, Iran. His research interests include signal processing, audio and speech processing, image processing, artificial intelligence, and mathematical algorithms.

- Email: hfarsi@birjand.ac.ir
- ORCID: 0000-0001-6038-9757
- Web of Science Researcher ID: NA
- Scopus ID: 16202385600
- Homepage: https://cv.birjand.ac.ir/hasanfarsi/en