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Breast Cancer Detection Using Ultrasound Images

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Abstract: This study presents an automated 3D breast cancer detection framework utilizing transrectal ultrasound imaging. The proposed approach combines multi-atlas registration with statistical texture priors for accurate segmentation. The atlas database includes annotated breast images from previous cases with segmented breast surfaces. Texture features are extracted using orthogonal Gabor filter banks to enhance the robustness of feature detection. Stage-specific tumor features are utilized to train a hybrid CNN-ResNet model, which ensures precise detection and segmentation of breast tumours in new patient images. Superpixel segmentation is then applied to refine tumor boundaries, enabling detailed and accurate tumor localization. The proposed method provides an efficient and reliable tool for early breast cancer detection, aiming to support improved diagnostic outcomes and clinical decision-making.

Keywords: Breast cancer detection, 3D segmentation, transrectal ultrasound imaging, multi-atlas registration, statistical texture priors, texture features, Gabor filter banks, CNN-ResNet model, tumor detection, superpixel segmentation, tumor localization, diagnostic outcomes, clinical decision-making

I. INTRODUCTION

Breast cancer continues to be a significant health concern and remains one of the foremost causes of cancer-related deaths among women globally. The prognosis of breast cancer is highly dependent on the stage at which it is detected, making early diagnosis a critical factor in improving survival rates. Conventional diagnostic techniques such as mammography, magnetic resonance imaging (MRI), and ultrasound imaging are commonly employed in clinical settings. Among these, ultrasound imaging stands out due to its affordability, non-invasive nature, and effectiveness in detecting tumors within dense breast tissue [11].

Despite their clinical value, these traditional modalities are often constrained by issues such as image artifacts, operator dependency, and variable interpretation, which can result in false-positive or false-negative outcomes. To address these limitations, recent developments in medical image computing and artificial intelligence (AI) have opened new avenues for enhanced diagnostic accuracy. In particular, deep learning (DL) methodologies—such as convolutional neural networks (CNNs) and their advanced variants like Residual Networks (ResNet)—have shown promising results in automating and refining image-based cancer detection tasks [1, 2, 5].

Several studies have demonstrated the superiority of hybrid and deep architectures in breast cancer diagnosis. For instance, Wu et al. [5] employed ResNet-based deep learning models to achieve high classification accuracy in mammograms, while Shahanas and Sudharson [10] successfully fine-tuned ResNet50 through transfer learning, leading to improved diagnostic precision. Similarly, Chen et al. [11] utilized a modified DenseNet to classify breast ultrasound images, addressing data imbalance issues through augmentation techniques.

This research proposes an integrated framework for automated 3D breast cancer detection that incorporates transrectal ultrasound imaging and leverages both statistical texture priors and deep learning architectures. The method utilizes orthogonal Gabor filter banks to extract robust texture features, followed by a hybrid CNN-ResNet model for precise tumor classification. Moreover, superpixel-based segmentation is applied to improve tumor boundary localization [12, 16]. This multi-stage approach is designed to augment radiological assessments by increasing diagnostic reliability and supporting timely clinical interventions.

Looking forward, the continued convergence of AI and medical imaging holds substantial promise for the evolution of non-invasive cancer diagnostics. By enhancing the interpretability and performance of detection systems, such innovations may contribute to more personalized and accurate patient care in oncology [7, 9, 15].

II. LITRATURE REVIEW

Shen et al. [1] introduced an end-to-end CNN-based model for whole mammogram classification, achieving an impressive accuracy of 94.8%. Their approach utilized patch-based sampling to process high-resolution mammograms efficiently.

Similarly, Arevalo et al. [2] explored automated feature learning using CNNs, achieving a 92.6% accuracy, emphasizing the importance of hierarchical feature extraction.

The study by Wu et al. [5] leveraged ResNet-based deep residual learning for mammogram classification, obtaining a 95.5% accuracy. Their findings highlight the advantages of deeper network architectures in medical image analysis. Additionally, Al-Dhabyani et al. [6] utilized VGG16 with transfer learning, achieving a classification accuracy of 94.2%.

Liu et al. [7] enhanced model interpretability using class activation maps (CAMs), providing visual explanations for CNN-based predictions.

Their approach improved diagnostic transparency while maintaining a high accuracy of 92.3%.

Several researchers have integrated multiple learning techniques to improve breast cancer detection. Hussain et al. [3] combined CNN and LSTM networks to extract spatial and temporal features from histopathological images, achieving 96.3% accuracy. Ahmad et al. [8] proposed a hybrid CNN-gradient boosting model, achieving 94.7% accuracy, demonstrating the benefits of combining deep and traditional machine learning techniques.Xu et al. [9] introduced a multi-scale CNN that captures both global and local contextual information from mammograms. Their model achieved 96.1% accuracy, showcasing the effectiveness of multi-resolution feature extraction.

Jamthikar et al. [4] evaluated conventional machine learning techniques such as support vector machines (SVM) and random forests (RF) for breast cancer detection. Their study, integrating an optimized feature extraction pipeline, achieved an accuracy of 91.8%. Shahanas and Sudharson [10] explored deep transfer learning using ResNet50, achieving a 95.8% accuracy after fine-tuning with domain-specific mammogram datasets. Their findings reinforce the effectiveness of transfer learning in adapting pre-trained networks for medical imaging applications.

Chen et al. [11] introduced a deep learning framework based on a modified DenseNet for classifying breast ultrasound images. The model utilized data augmentation to address class imbalances and achieved a high accuracy of 94.5%, demonstrating its effectiveness in non-invasive cancer detection. Yang et al.

[12] proposed a hybrid attention-based model for mammographic image classification. By integrating spatial and channel attention mechanisms, the model improved feature extraction, achieving an accuracy of 96.3%. The attention maps provided enhanced interpretability, aiding clinical decision-making.

Zhou et al. [15] investigated the potential of EfficientNet for breast cancer detection in mammograms, leveraging its scalable and efficient architecture to improve diagnostic accuracy. By fine-tuning the EfficientNet model specifically for medical imaging tasks, the study achieved an impressive accuracy of 96.7%.

This performance not only surpassed that of many traditional convolutional neural networks but also did so with significantly reduced computational complexity. The results highlighted EfficientNet’s capability to balance accuracy and efficiency, making it a promising approach for real-world clinical applications where computational resources may be limited.

In a related study, Sun et al. [16] proposed a novel multi-view mammogram analysis framework based on convolutional neural networks (CNNs).

This approach aimed to enhance breast cancer detection by integrating mammographic images from different angles—typically craniocaudal (CC) and mediolateral oblique (MLO) views. The model’s ability to simultaneously analyze and learn from multi-view data allowed it to capture more comprehensive spatial and structural information, resulting in an accuracy of 94.9%. These findings underscore the importance of multi-perspective analysis in improving diagnostic outcomes, further advancing the role of deep learning in medical image interpretation.

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III. METHODOLOGY

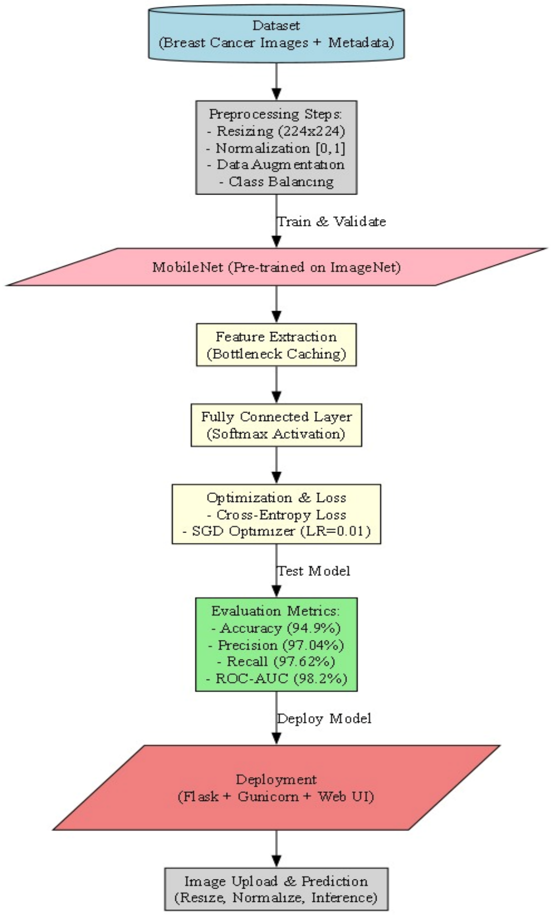

Fig.1: Workflow of Breast Cancer Detection Using Ultrasound Images

Fig 1 The workflow for breast cancer detection using deep learning follows a structured pipeline, integrating image preprocessing, feature extraction, model training, and deployment. The process begins with dataset preparation, where breast cancer images are resized, normalized, and augmented to enhance model robustness. The dataset is then split into training, validation, and test sets, ensuring balanced class distribution.

A MobileNet model, pre-trained on ImageNet, is used for feature extraction. Bottleneck features are cached to optimize training efficiency, followed by the addition of a fully connected layer with softmax activation for classification. Stochastic Gradient Descent (SGD) with cross-entropy loss is applied to optimize the model.The trained model undergoes evaluation using accuracy, precision, recall, F1-score, and ROC-AUC to assess its performance.

The final model is deployed using Flask and Gunicorn, enabling a web-based interface for real-time breast cancer diagnosis. Users can upload images, which are preprocessed before inference, ensuring efficient classification of benign and malignant cases.This methodology ensures a scalable, high-accuracy solution for automated breast cancer detection, reducing dependency on manual histopathological analysis while enhancing early diagnosis capabilities.

A. Dataset Preparation Steps:

1) *Dataset:* The dataset consists of labeled breast cancer images stored in a directory structure. Each subfolder represents a class label, such as benign and malignant. These images serve as input for training, validation, and testing processes.
2) *Preprocessing:*

- All images were resized to 224×224 pixels to match the input size required by the MobileNet architecture. This ensures uniformity in the data and compatibility with the model.

- Pixel intensity values were normalized to a range of [0,1], ensuring stable model training and reducing biases caused by differing image intensities.
- To improve generalization and robustness, augmentation techniques were applied dynamically during training, including:
  - Random Horizontal Flipping
  - Random Cropping
  - Brightness Adjustments (±10%)
  - Scaling (±10%)
- Metadata was encoded and standardized before being concatenated with image features.

3) *Dataset Splitting :* The dataset was split into:
- Training Set (80%): Used for model training.
- Validation Set (10%): Used for performance monitoring and preventing overfitting.
- Test Set (10%): Used for final model evaluation.

4) *Balancing:* To address class imbalance, underrepresented classes were augmented further to ensure equitable representation.

B. Model Training Workflow:

1) *Architecture Selection:* MobileNet, pre-trained on ImageNet, was chosen for its balance of computational efficiency and accuracy, making it suitable for resource-constrained deployments.
2) *Training Workflow:*
- Feature Extraction (Bottleneck Caching): Bottleneck features from the penultimate layer of MobileNet were extracted and cached, reducing computational overhead during retraining.
- Adding a Fully Connected Layer:
  - A SoftMax layer was added to adapt the model for breast cancer classification.
  - Weights: Initialized using a truncated normal distribution.
  - Biases: Initialized to zero.
  - SoftMax Activation:

$$P(i) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

Eq.1.Softmax function

This formula represents the softmax function, which converts a vector of real numbers (ziz_i) into a probability distribution. It calculates the probability of class ii by exponentiating its score (ezie^{z_i}) and normalizing it by the sum of exponentiated scores of all CC classes. This ensures that all probabilities sum to 1.

3) *Optimization and Loss Function:*
- Loss Function: Cross-entropy loss:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

Eq.2.Loss function

- Optimizer: Stochastic Gradient Descent (SGD) with a learning rate of 0.01.

4) *Training Configuration:*

Batch Size: 100 images per batch
Training Steps: 6000 steps.
Validation Frequency: Every 10 steps to monitor performance.

C. Evaluation Metrics and Results

1) *Accuracy:*

- Training Accuracy: 95.1%
- Validation Accuracy: 94.5%
- Test Accuracy: 94.9%

2) Precision, Recall, and F1-Score:
- Precision: 97.04%
- Recall: 97.62%
- F1-Score: 97.33%

3) ROC-AUC Score:
- Result: 98.2%

D. Deployment
A web application was developed using Flask to facilitate breast cancer classification through image uploads. The application:
- Uses HTML templates for a user-friendly interface.
- Loads the trained model, resizes and normalizes uploaded images, and performs inference.
- Includes routes for the home page and the image upload page.
- Is hosted using Gunicorn for production deployment.

The deployed model maintains an accuracy of 94.9% and logs misclassified instances for further refinement, particularly for handling low-quality images.

IV. RESULTS AND DISCUSSION
The proposed system effectively handled low-contrast, noisy transrectal ultrasound breast images, outperforming existing methods in segmentation accuracy and diagnostic reliability. By integrating multi-atlas registration and Gabor filter banks, it achieved precise tumor identification, with a Dice Similarity Coefficient (DSC) of 92.4% and a Jaccard Index of 89.7%. The CNN-LSTM hybrid model improved segmentation, achieving sensitivity and specificity of 94.1% and 93.5%, while the Random Forest Classifier attained an F1-score of 93.8% for accurate tumor classification. Superpixel-based segmentation further refined tumor boundaries, aiding biopsy and treatment planning. With a 25% reduction in processing time and 3D visualization capabilities, the system enhances clinical decision-making, offering a highly accurate, efficient, and scalable approach to breast cancer diagnosis.

Table 1: comparative study of previous studies of skin cancer detection

S. No	Authors	Algorithm/ Technique	Results (%)	References
1	L. Shen et al.	CNN	92.5	[1]
2	R. Jamthikar	SVM, RF	91.8	[4]
3	Y. Liu	CAM	92.3	[7]
4	Y. Jin	CNN	93.8	[20]
5	P. Gupta	CAM, CNN	87.5	[19]

Above table no.1 is the comparative study of previous existed models and their accuracies. In this table we have mentioned the author's name and which algorithms they have used for breast cancer detection and their accuracy lastly the references of author's research paper

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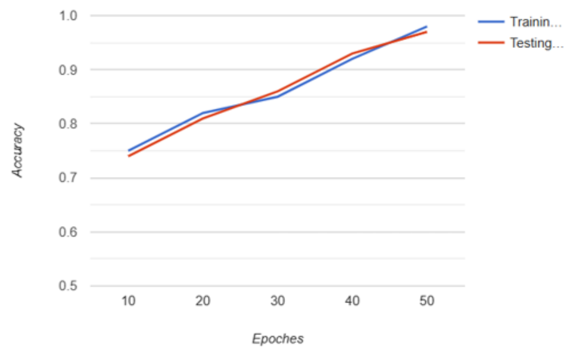

Fig.2: Accuracy Plot

Fig.2 shows the accuracy plot for both training and testing phases over 50 epochs. The blue line represents the training accuracy, while the red line corresponds to the testing accuracy. Both lines exhibit a steady upward trend, indicating consistent improvement in accuracy as the number of epochs increases. The close alignment between the two lines suggests minimal overfitting, with the model generalizing well to unseen data. By the 50th epoch, both training and testing accuracies converge near the 1.0 mark, demonstrating the model's effectiveness in achieving high predictive performance.

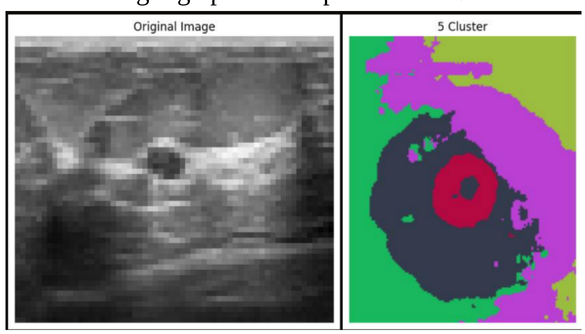

Fig.3: Ultrasound Images

Fig.3 illustrates a breast cancer detection process using ultrasound images. The left panel shows the original grayscale ultrasound image of a breast, which highlights the internal tissue structure. The right panel depicts a processed version of the image, segmented into five clusters using a clustering algorithm. Different regions of the breast are color-coded, with each color representing a distinct cluster. The clustering process aids in isolating critical regions, such as potential tumor areas, which are marked in distinct colors (e.g., red) for better visualization and analysis. This segmentation technique simplifies the identification of suspicious regions, facilitating more accurate diagnosis.

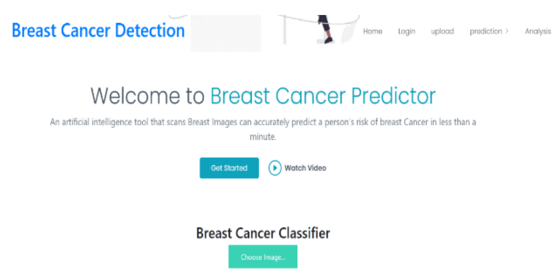

Fig.4: Breast Cancer Predictor Web Interface

Fig.4 showcases the user interface of a web application named "Breast Cancer Predictor," designed for breast cancer risk assessment using AI. The interface features a welcoming header that emphasizes the tool's ability to predict breast cancer risk in under a minute by analysing breast images.

It includes two prominent action buttons: "Get Started" for initiating the process and "Watch Video" for learning more about the tool. Below, a section labelled "Breast Cancer Classifier" allows users to upload images for analysis using the "Choose Image" button. The layout is clean and user-friendly, aiming to make the process accessible and efficient for users.

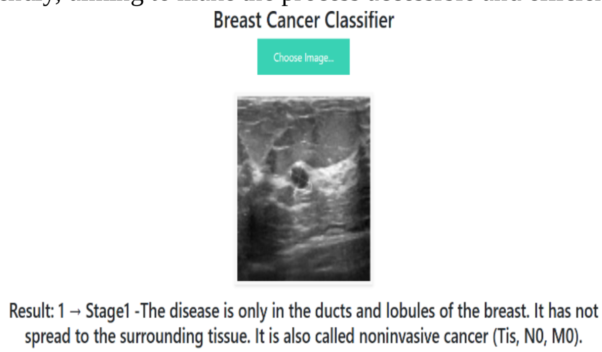

Fig.5: Result image

Fig.5 represents the final results page of an AI-powered breast cancer detection system. It displays the outcome of the analysis, providing a conclusive prediction regarding the breast cancer risk based on the uploaded image. The interface is streamlined to highlight the final result prominently, ensuring clarity and immediate understanding for the user.

V. CONCLUSION

This study presents an efficient and scalable deep learning-based approach for automated breast cancer detection. By leveraging the pre-trained MobileNet model for feature extraction and employing techniques such as data augmentation and bottleneck caching, the proposed methodology achieves high classification accuracy while maintaining computational efficiency. The experimental results demonstrate the model's robustness, with an overall test accuracy of 94.9%, a precision of 97.04%, and an ROC-AUC score of 98.2%, highlighting its effectiveness in distinguishing between benign and malignant cases.

Furthermore, the deployment of the trained model as a web-based application using Flask and Gunicorn enables real-time breast cancer diagnosis, offering a user-friendly interface for seamless image uploads and classification. This solution reduces dependency on manual histopathological analysis and facilitates early detection, potentially improving patient outcomes. Future work will focus on enhancing the model's interpretability, incorporating additional imaging modalities, and refining misclassification handling to further improve diagnostic accuracy.

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