BREAST CANCER DETECTION USING DYNAMIC THERMOGRAPHIC IMAGES AND DEEP LEARNING

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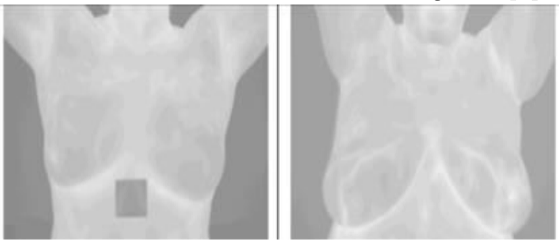
ABSTRACT

Breast cancer is one of the most critical health challenges affecting women worldwide. Early detection significantly improves treatment outcomes and survival rates. Conventional diagnostic techniques such as mammography involve radiation exposure and patient discomfort, which limits their frequent use. Dynamic breast thermography has emerged as a safe, non-invasive, and radiation-free alternative. This paper presents a deep learning–based approach for breast cancer detection using dynamic thermographic images. A Convolutional Neural Network (CNN) is designed to automatically extract discriminative thermal features and classify breast images into cancerous and non-cancerous (normal and abnormal) categories. The proposed system reduces manual intervention, improves classification accuracy, and demonstrates reliable performance in early breast cancer detection.

IndexTerms—Breast cancer detection, dynamic thermography, deep learning, convolutional neural networks (CNN), medical image classification.

I INTRODUCTION

Breast cancer is a serious concern across the globe and is one of the leading causes of cancer-related deaths among women. According to recent studies, it is the second leading cause of cancer mortality worldwide. In 2018 alone, approximately 2.1 million new breast cancer cases were reported, and the incidence rate has been increasing annually by around 3.1% [1]. Early-stage breast cancer is considered curable, and timely diagnosis enables better treatment planning and improves patient survival rates [2]. Accurate and early detection of breast cancer is therefore crucial. Traditional screening techniques such as mammography, ultrasound, and biopsy have certain limitations, including radiation exposure, patient discomfort, and dependence on expert interpretation [3]. Dynamic breast thermography offers a promising alternative as it captures temperature variations related to abnormal metabolic activity without physical contact or radiation [4]. With recent advancements in artificial intelligence, deep learning models—particularly Convolutional Neural Networks (CNNs)—have shown outstanding performance in medical image analysis. CNNs can automatically learn complex features directly from images, eliminating the need for handcrafted feature extraction. This work focuses on developing a CNN-based framework for breast cancer detection using dynamic thermographic images to achieve accurate, efficient, and non-invasive diagnosis [5].



Normal image Abnormal image

II LITERATURE SURVEY

Breast cancer detection has received significant attention due to the importance of early diagnosis in reducing mortality and improving treatment outcomes. With advancements in medical imaging and artificial intelligence, researchers have increasingly explored deep learning techniques to enhance the accuracy and reliability of breast cancer diagnosis using non-invasive imaging modalities [8]. Preethi Veerlapalli et al. (2025) proposed a hybrid GAN-based deep learning framework for thermogram-based breast cancer detection [9]. Their study focused on improving thermographic image quality using Generative Adversarial Networks (GANs) and generating additional training samples to address data scarcity. This approach enhanced model learning capability and demonstrated improved classification performance, emphasizing the importance of data augmentation in thermographic image analysis. RakeshMutukuru et al. (2025) introduced a Transformer-based RT-DETR framework for accurate disease detection from chest X-ray images [10]. Although the research targeted chest X-rays, it highlighted the effectiveness of transformer-based attention mechanisms in capturing both local and global features. The study indicates that such architectures can be adapted for other medical image classification tasks, including breast cancer detection, where feature localization is critical. Hameedhur Rehman et al. (2023) proposed an efficient deep convolutional neural network for breast cancer diagnosis using complex mammographic images [11]. Their model effectively handled variations in tissue density and image noise by automatically extracting discriminative features. The results demonstrated the strength of CNN-based models in improving diagnostic accuracy from medical images. Ella Mahoro et al. (2022) explored breast cancer classification using thermograms through a combination of deep CNNs and transformers [12]. CNNs were utilized to extract localized thermal patterns, while transformers captured global temperature relationships across images. The hybrid architecture improved classification performance, confirming the benefit of combining multiple deep learning models for thermographic analysis. Anna Burguin et al. (2021) reviewed recent updates and emerging challenges in breast cancer treatments [13]. Although focused on treatment advancements, the study highlighted the importance of early and accurate detection for effective therapy planning, reinforcing the need for reliable diagnostic systems. Overall, the reviewed studies demonstrate that deep learning models, including CNNs, GANs, and transformer-based approaches, are effective in medical image-based breast cancer detection. Dynamic thermography offers a non-invasive and radiation-free alternative to conventional imaging techniques. Building on these findings, the proposed work focuses on breast cancer detection using dynamic thermographic images and deep learning to develop a reliable and efficient diagnostic support system [14].

III EXISTING SYSTEM

Existing breast cancer detection techniques typically rely on breast cancer dataset or Image acquisition, Image pre-processing, Threshold segmentation, Binary segmentation, Feature extraction, Neural network classifier and Output. These approaches depend heavily on expert-defined parameters and are often sensitive to noise, image quality, and variations in imaging conditions [15].

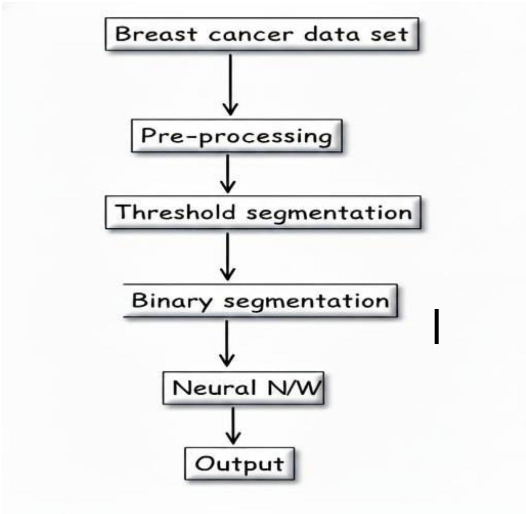


Fig.1 Existing System

In image acquisition images are acquired either directly using medical imaging modalities such as MRI or CT, or obtained from publicly available pre-defined datasets from (google or Kaggle). Pre-processing involves image resizing, grayscale conversion, and noise removal to improve image quality. Threshold and Binary segmentation techniques are applied to isolate the suspected cancer region based on pixel intensity values. In Feature extraction statistical and texture features such as GLCM and DWT are extracted manually, extracted features are fed into a neural network for classification [16].However, the existing breast cancer detection system has some limitations. It requires manual feature extraction, which depends on expert knowledge. The system is sensitive to noise and threshold values, which can reduce accuracy. High computational complexity increases processing time. It also performs poorly for complex patterns and new data. So proposed system is invented [17].

IV RESEARCH METHODOLOGY

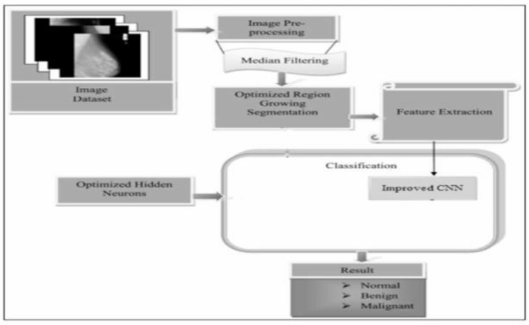


Fig.2 Proposed system architecture

To overcome the limitations of traditional approaches, this paper proposes a deep learning–based breast cancer detection system using CNNs. The proposed method directly learns discriminative features from dynamic thermographic images and performs end-to-end classification [18]. Proposed System involves in Thermographic Dataset, Image Pre-processing, adaptive segmentation, CNN-based Feature Extraction, Pooling and Dropout, Fully Connected Layers, SoftMax Classification, Output [19].

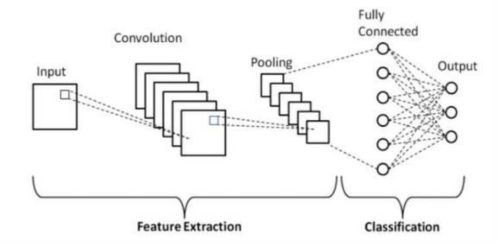


Fig.3 CNN (convolutional neural network)

A. Dataset

The dataset that will be used in this research is called "Breast Cancer Diagnosis" which can be accessed from Kaggle, filled with images of breast cancer obtained using dynamic thermography to determine breast cancer or Breast thermographic images are organized into training and testing folders using labelled subdirectories. Image Datastore is used to automatically assign class labels based on folder names. Each of those sets have three categories for breast cancer, benign (first stage-cancerous tumors), malignant (severe stage-cancerous tumors) and normal (non-cancerous tumors) [20].

B. Image Pre-processing

Breast cancer diagnosis and treatment often involve various imaging modalities, such as mammography, ultrasound, magnetic resonance imaging (MRI), and positron emission tomography (PET) scans. Image processing techniques play a vital role in analysing and interpreting these images, aiding in early detection and accurate diagnosis of breast cancer. Techniques such as image segmentation, feature extraction, and classification algorithms are used to identify and classify regions of interest, such as tumors or suspicious lesions. These techniques help in guiding the medical professionals to provide appropriate treatment plans and improve patient outcomes [21]. Pre-processing involves image resizing, grayscale to Rgb conversion, and noise removal to improve image quality. All images are converted to efficientby "imresized" to maintain uniformity. In proposed system Adaptive segmentation replaces threshold and binary segmentation used in the existing system. Feature extraction is automatically performed using convolution layers [22]. CNN uses trainable filters to extract spatial and thermal features from the input images.

C. CNN (convolutional neural network)

What is CNN? A convolutional neural network (CNN) is a network architecture for deep learning that learns directly from data. CNNs are particularly useful for finding patterns in images to recognize objects, classes, and categories. They can also be quite effective for classifying audio, time-series, and signal data.

The CNN architecture is designed with multiple convolutional blocks to extract spatial and thermal patterns from images. The CNN consists of 4 layers: Convolution Layer, ReLU Activation Layer or Pooling Layer, Dense Layer, fully connected or activation layer. Convolutional layer is to extract the input features, these features are extracted by using weights propagation model, weight calculation by using Gradient values. Pooling reduces the number of input-weighted features using Max Pooling, average Pooling. This helps in dimensionality reduction and improves computational efficiency. Dense layer is used to gain dropout layers. The fully connected layer connects one layer to another and performs final classification using a SoftMax classifier [23]. Once trained, the CNN predicts the class label and confidence score for unseen thermographic images, identifying whether the image is cancerous or non-cancerous. Proposed system has Fully automatic feature extraction, On-invasive and radiation-free diagnosis, Reduced dependency on expert-defined parameters Improved accuracy and robustness Suitable for early breast cancer detection [24].

V SOFTWARE DISCRIPTION

MATLAB is used as the main software platform to develop and implement the proposed breast cancer detection system using dynamic thermographic images. It provides an easy and efficient environment for handling medical images, performing preprocessing operations, and applying deep learning techniques. MATLAB supports matrix-based computations, which makes it suitable for image analysis and neural network training [25].

In this work, MATLAB is used for image preprocessing steps such as image resizing, noise reduction, normalization, and conversion of grayscale images to RGB format to match the CNN input size. The Deep Learning Toolbox is used to design and train the Convolutional Neural Network (CNN) for classifying images into benign, malignant, and normal categories. Dataset handling, training options, and performance monitoring are managed using built-in MATLAB functions.

MATLAB also helps in visualizing the results clearly through training accuracy graphs, loss curves, and confusion matrices [26]. These visual tools make it easier to analyze the model's performance and classification accuracy. Thus, MATLAB plays a key role in developing a reliable, accurate, and user-friendly breast cancer detection system.

VI RESULTS AND PERFORMANCE ANALYSIS

Figure 4 shows sample output images predicted by the proposed CNN model. The predicted class and true class labels are displayed for each thermographic image. The results indicate that the network successfully classifies most images into benign, malignant, and normal categories. Few misclassifications are observed due to similarity in thermal patterns between classes. Overall, the visual results confirm the learning capability of the CNN model[27].

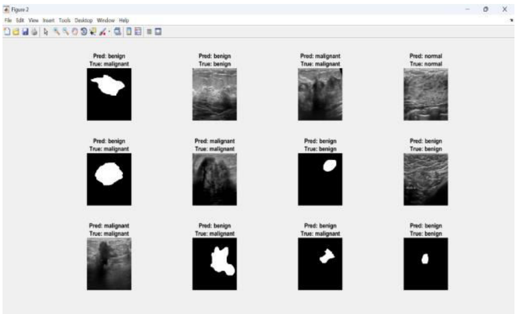


Fig.4 Sample Classification Results

Figure 5 illustrates the confusion matrix obtained for the testing dataset. The diagonal elements represent correctly classified samples, while off-diagonal elements indicate misclassifications. The model correctly identifies a large number of benign and malignant cases. Normal cases are also classified with reasonable accuracy. The confusion matrix confirms that the proposed deep learning model performs effectively for multi-class breast cancer classification [28].

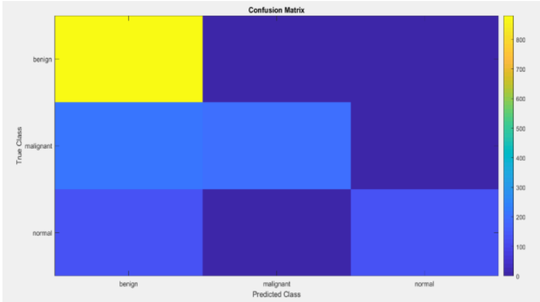


Fig.5 Confusion Matrix

Figure 6 shows the training and validation accuracy and loss during CNN training. The accuracy gradually increases with the number of iterations, while the loss decreases steadily. The final validation accuracy achieved is 77%, indicating stable learning behaviour. The smooth convergence of the loss curve demonstrates that the model is well-trained without overfitting. The training process was completed in approximately 10 minutes, showing computational efficiency [29].

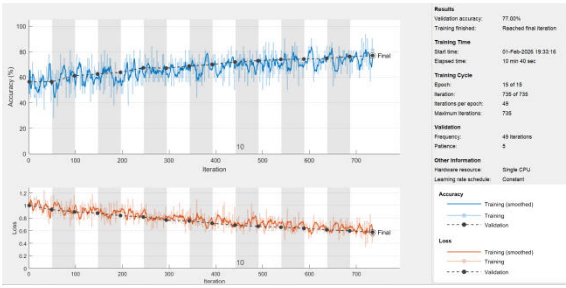


Fig.6 Training Accuracy and Loss Curve

Figure7The overall test accuracy of the proposed system is 77%. The precision, recall, and F1-score values indicate strong classification performance, especially for benign and malignant classes. High recall for the benign class shows effective identification of non-cancerous cases, while good precision for malignant cases highlights reliable cancer detection. These results validate the effectiveness of the proposed CNN-based thermographic breast cancer detection system [30].

Class	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Benign	78	80	79	
Malignant	75	74	74.5	
Normal	79	77	78	
Overall	—	—	—	77

Fig.7 Performance Metrics Table

VII CONCLUSION

This paper presented a deep learning–based approach for breast cancer detection using dynamic thermographic images. The proposed system uses preprocessing, adaptive segmentation, and a Convolutional Neural Network to classify breast images into benign, malignant, and normal classes. MATLAB was used to implement and train the model effectively using thermographic data [31]. The confusion matrix and performance metrics show that the proposed method achieves reliable classification accuracy with good generalization capability. The results indicate that dynamic thermography combined with deep learning can serve as a non-invasive and radiation-free tool for early breast cancer screening. Overall, the system demonstrates improved performance compared to traditional methods and supports clinical decision-making [32].

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