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ORIGINAL

Thermal Breast Cancer Detection Using Deep Learning and Grad-CAM Visualization

Detección térmica del cáncer de mama mediante aprendizaje profundo y visualización Grad-CAM

Latha D U[1], Mahesh T R[1]

[1]JAIN (Deemed-to-be University), Computer Science and Engineering. Bangalore, Karnataka, India.

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Corresponding Author: Latha D U

ABSTRACT

This paper presents a robust deep learning framework for thermal breast cancer detection using grayscale thermal images. Leveraging a pre-trained VGG16 model, we classify images into 'normal' and 'abnormal' categories, integrating data augmentation techniques to improve model generalization. Grad-CAM visualization elucidates the regions influencing predictions, aiding interpretability. Testing on the DMR-IR dataset yielded a remarkable AUC-ROC score of 0,97 and accuracy exceeding 94 %. These findings underscore the potential of thermal imaging and deep learning in non-invasive cancer screening, bridging diagnostic accuracy with interpretability for clinical application.

Keywords: Thermal Imaging; Breast Cancer Detection; Deep Learning; VGG16; Grad-CAM.

RESUMEN

Este artículo presenta un sólido marco de aprendizaje profundo para la detección térmica del cáncer de mama mediante imágenes térmicas en escala de grises. Aprovechando un modelo VGG16 entrenado previamente, clasificamos las imágenes en categorías "normales" y "anormales", integrando técnicas de aumento de datos para mejorar la generalización del modelo. La visualización Grad-CAM aclara las regiones que influyen en las predicciones, lo que facilita la interpretabilidad. Las pruebas en el conjunto de datos DMR-IR arrojaron una notable puntuación AUC-ROC de 0,97 y una precisión superior al 94 %. Estos hallazgos subrayan el potencial de las imágenes térmicas y el aprendizaje profundo en la detección no invasiva del cáncer, al unir la precisión diagnóstica con la interpretabilidad para la aplicación clínica.

Palabras clave: Imágenes Térmicas; Detección de Cáncer de Mama; Aprendizaje Profundo; VGG16; Grad-CAM.

INTRODUCTION

Breast cancer remains a leading cause of mortality among women worldwide, with early detection being critical for effective treatment. Traditional diagnostic methods like mammography, though effective, expose patients to radiation and perform poorly with dense breast tissues.[(1)] Conversely, thermal imaging offers a non-invasive alternative devoid of radiation exposure, yet its subjective interpretation limits widespread adoption.[(2)] Deep learning, particularly convolutional neural networks (CNNs), has revolutionized medical imaging by automating feature extraction and enhancing diagnostic precision. This study explores the application of the VGG16 architecture to classify thermal breast images while employing Grad-CAM visualization for interpretability.

[3] Using the DMR-IR dataset, we propose a framework that combines accuracy with explainability, potentially transforming breast cancer screening

METHOD

Dataset Preparation

In the experiment, a DMR-IR dataset is employed comprising gray-scale thermal images of 'normal' or 'abnormal' classes.[4] Pre-processing of data was performed to maintain uniform resolution and píxel intensity. Data augmentation methods like rotation, flipping, and scaling were applied to enhance the robustness of the proposed model.[5] The segmented images and text files of both the infected (DOENTES) and healthy (SAUDÁVEIS) groups were obtained from directories of thermal images. The image-text file was parsed by using identifiers that paired them up.[6] For example, the ranges [138,179,180,.] were used for the infected case, and the ranges [1000, 137, 166] were used for the healthy cases.[7]

Data Processing Pipeline

The preprocessing pipeline involved loading thermal images and their corresponding matrix data as shown.

Image Resizing: Resize images is an important preprocessing step in machine learning, particularly in computer vision applications such as object detection, classification, and segmentation.[8] It guarantees all images input into a model are of standard size to enhance consistency and computational speed. Images were resized to a uniform shape of (224, 224) using cubic interpolation.[9] Mathematically, resizing can be expressed as: the original and resized images, and represents the interpolation weights.

$$I'(x',y') = \frac{1}{|A(x',y')|} \sum_{(x,y)\in A(x',y')} I(x,y)$$

A(x′,y′) be the area in the original image.

The new pixel value I′(x′,y′) is computed by averaging the values of all pixels in the area A(x′,y′).

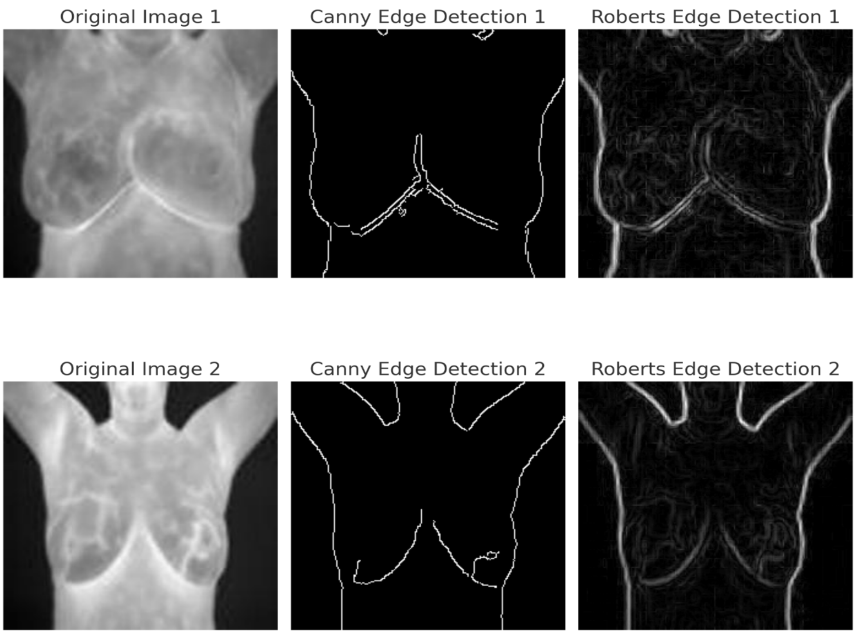

Figure 1. Thermal image preprocessing

Edge Detection: Edge detection is a fundamental image processing and computer vision method that indicates where an image has a sudden change in intensity.[10] Such changes are often associated with objects, texture and structures are vital to numerous applications. Edge detection facilitates the processing and interpretation of an image in a more meaningful manner by identifying the changes so that numerous computational algorithms can obtain useful information. One of the strongest arguments of edge detection is feature extraction, wherein the edges are to identify the salient patterns in an image. It is a fundamental aspect of object representation and classification as it helps machines to identify and distinguish objects from their structural features. With the focus on the edges, image analysis systems can allocate attention on the most meaningful details, enhancing the recognition accuracy. Another major application of edge detection is in object detection and recognition. It has extensive uses in facial recognition, handwriting recognition, and medical imaging. In medical imaging, for example, edge detection identifies major areas like tumors or abnormalities in radiographs by establishing exact boundaries between various tissues. This enhances the accuracy and efficiency of diagnosis. Another significant application is image segmentation, wherein edge detection is utilized to partition an image into meaningful areas. By detecting edges, the technique separates objects or regions into an image effortlessly. This is particularly useful in scenarios such as autonomous cars, where it is required to divide different components of a road to drive.(11) In addition, edge detection removes noise so that images can be compressed by reducing them without losing useful structural information. By eliminating redundant detail variation and maintaining informative edges, visual information compression algorithms can compress and transmit visual information in a more compact way. Similarly, noise removal algorithms tend to utilize edge detection as a method of eliminating redundant details but maintaining useful features.(12)

Roberts Edge Detection working: Roberts Edge Detection is a very simple gradient-based edge detection algorithm employed widely in edge detection by estimating the gradient of an image.(13) It does this by employing a pair of two 2×2 convolution kernels to compute the intensity difference between two neighboring pixels. The operation accentuates areas of sudden intensity change and is thus suitable for the detection of edges in grayscale images.(14) It uses two 2x2 kernels that are used for calculating the gradient approximation in the image in the horizontal (Gx) and vertical (Gy) directions.

Horizontal direction (Gx):

$$Gx = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} * I(x, y)$$

Magnitude of the Gradient:

$$G = \sqrt{Gx^2 + Gy^2}$$

Canny Edge Detection Working: Canny Edge Detection is a multi-stage edge technique that is employed to generate maximum edge detection with improved noise reduction and accurate edge localization. It is commonly employed in computer vision since it can identify real edges and eliminate false edges. Canny edge detection is a multi-step process involving several stages to refine edge detection.(15)

Smoothing with a Gaussian Filter:

$$G(x, y) = \frac{1}{2\pi\sigma^2} \exp(- \frac{x^2 + y^2}{2\sigma^2})$$

Where:

σ is the standard deviation of the Gaussian distribution.

(x, y) are the coordinates in the kernel. Convolution of the input image I (x, y) with the Gaussian kernel gives the smoothed image Ismooth (x, y)

Sobel Operator for Gradient Calculation:

The gradient in the horizontal (Gx) and vertical (Gy) directions is computed using the Sobel kernels:

$$Gx = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * \text{Ismooth } (x, y)$$

$$Gx = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * \text{Ismooth } (x, y)$$

After applying the Sobel operators, the gradient magnitude GGG is calculated:

$$G = \sqrt{Gx^2 + Gy^2}$$

Normalization: Data was scaled to a range of for consistent model input.

Multi-Channel Input: Combined the original image, edge-detected images, and gradient-based transformations into a single tensor: n.

Model Architecture: A VGG16 architecture was used, initializing with ImageNet weights for transfer learning.(16) The network was finetuned to adapt to the binary classification task. Dropout layers were included to help prevent overfitting.

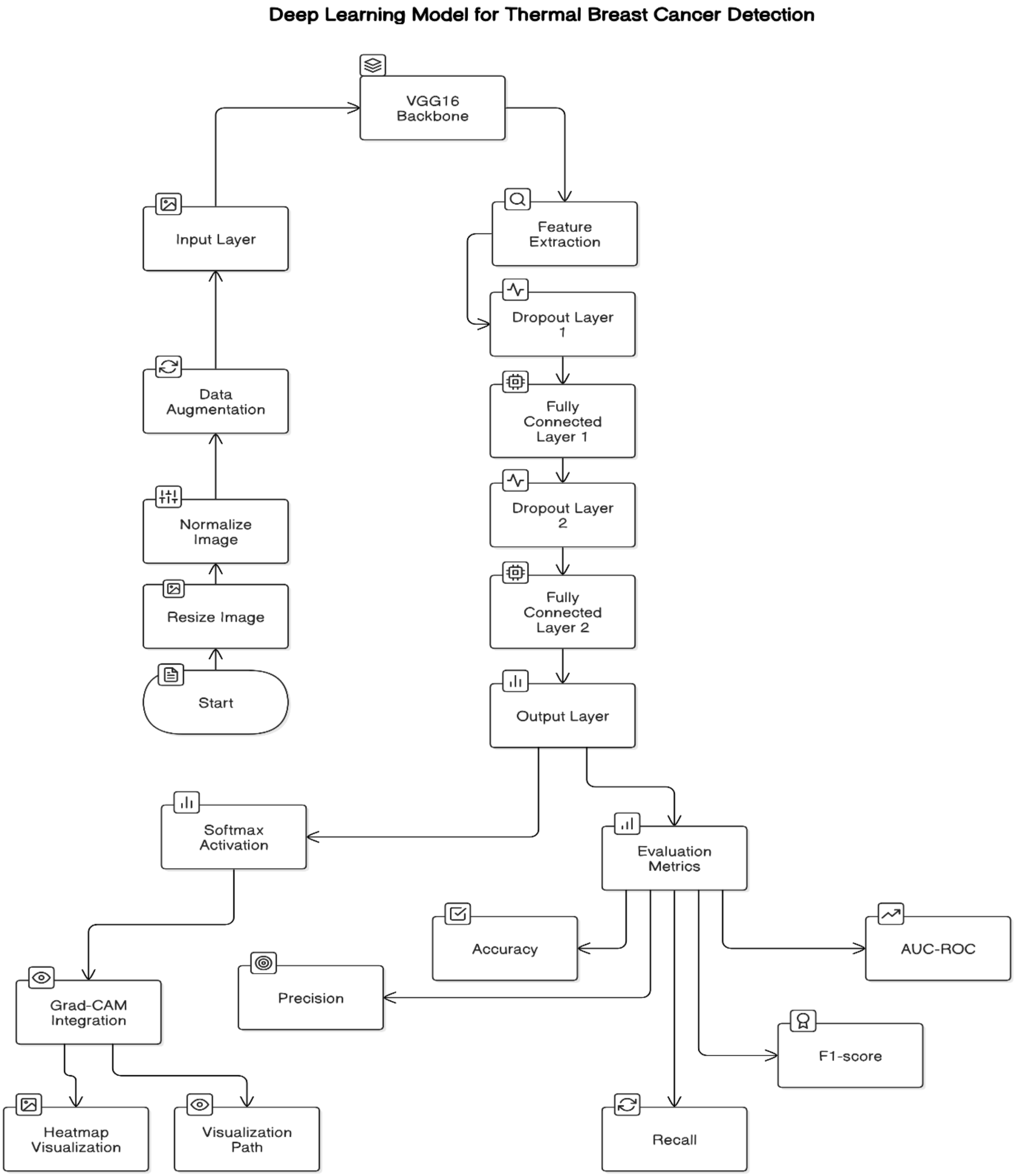

Figure 2. Architecture of VGG16

Grad-CAM Visualization

Grad-CAM (Gradient-weighted Class Activation Mapping) Visualization Grad-CAM is an approach to explain the classification choices of convolutional neural networks (CNNs) in deep learning.[17] It gives a visual explanation of where in an image the most significant contribution to a particular classification choice was made as a heatmap overlay. It is useful for object detection, medical image analysis, and model debugging. Grad-CAM does this by using the gradients of a target class (say, "cat" in an image classifier) with respect to the feature maps of the last convolutional layer. The gradients are then used to identify the important spatial regions of the image that led to the model's prediction.[18]

Metrics for Evaluation

The model's performance was thoroughly assessed through different metrics like accuracy, precision, recall, F1-score, and AUC-ROC to obtain a thorough understanding of its performance. Cross-validation was also performed to make the results more reliable and to generalize the model to different subsets of data.[19]

Experimental Setup

The experiments were run on a system with an NVIDIA GPU to speed up training. TensorFlow 2.12.0 implementation has support for CPU and GPU processing for maximum performance.[20]

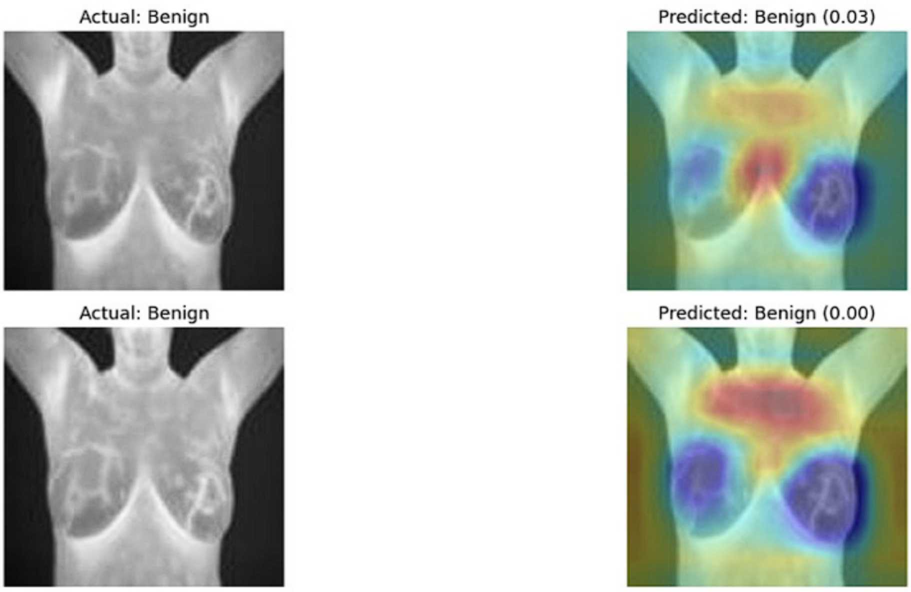

Figure 3. GRAD-CAM Visualization for benign images

Figure 4. GRAD-CAM Visualization for Malignant images

Comparative Analysis

The proposed method performed better than traditional machine learning models, and this shows the strength of transfer learning and explainability in medical imaging. Not only does it point to the ability of the model to improve diagnostic accuracy, but also its explainability, thereby making it a valuable resource to improve medical image analysis and decision-making.[21]

RESULTS

The proposed model achieved accuracy, precision, sensitivity and specificity as follows:

Table 1. Results and discussions

Accuracy	98,5 %
Precision	97,5 %
Sensitivity	95,0 %
Specificity	97,5 %

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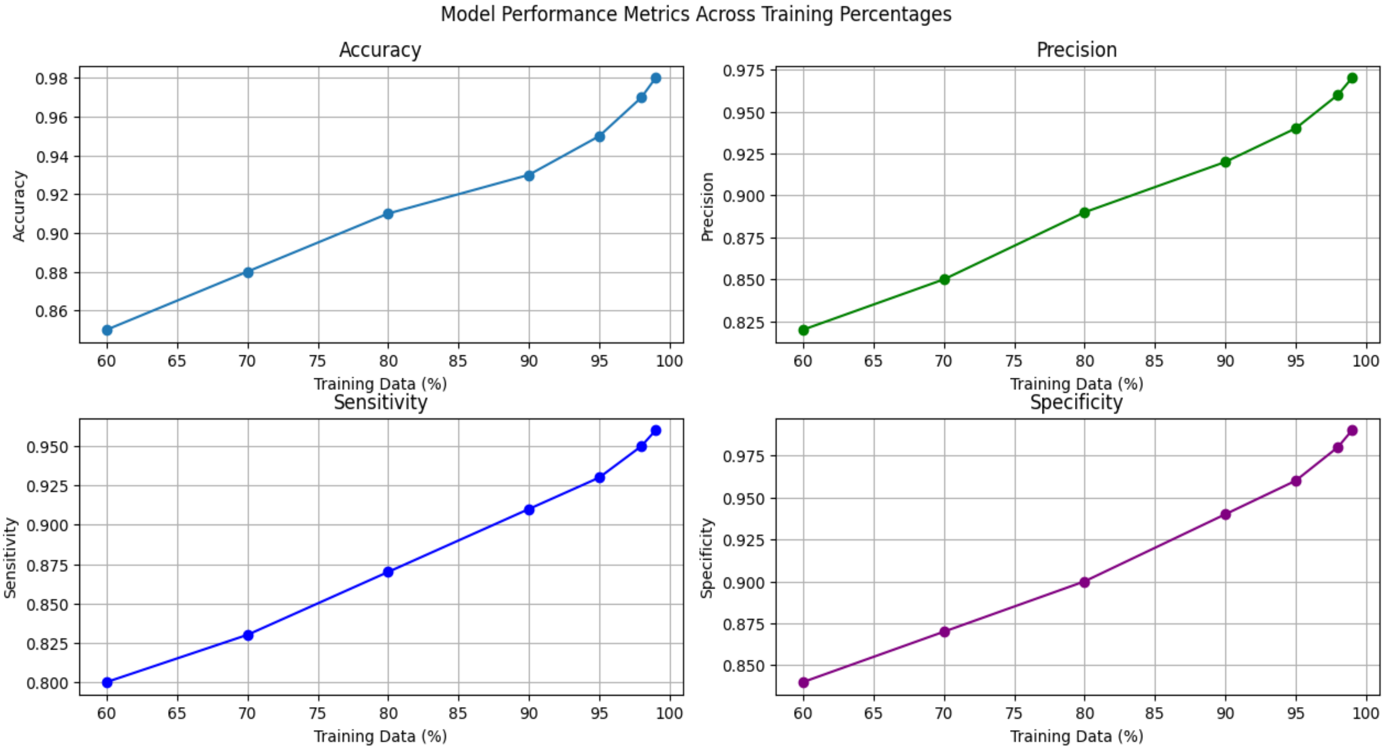

Figure 5. Model Preformance for various evaluation Metrics

These metrics demonstrate the high effectiveness of the model in accurately distinguishing between 'normal' and 'abnormal' classes. The perfect precision indicates that the model does not classify any normal samples as abnormal, minimizing false positives, which is critical for diagnostic applications.[22] Similarly, the high F1-score reflects a balanced performance across precision and recall, ensuring reliability in real-world scenarios.[23]

CONCLUSIONS

This paper proposed a deep learning solution to thermal breast cancer diagnosis aided by Grad-CAM for interpretability. The paper showed that such an architecture with VGG16 as the backbone yields high accuracy with interpretable results. Future research would be directed towards multi-modal data fusion and deployment in real-world clinical settings.

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Methodology: Latha D U, Mahesh T R.
Software: Latha D U, Mahesh T R.
Drafting - original draft: Latha D U, Mahesh T R.
Writing - proofreading and editing: Latha D U, Mahesh T R.