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RESEARCH PAPER

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An Explainable Artificial Intelligence Framework for Breast Cancer Detection

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ABSTRACT

Breast cancer remains a leading cause of mortality among women worldwide, primarily due to delayed detection and a lack of early awareness. To address this issue, this study develops an advanced, thermal image-based breast cancer detection system that is non-invasive, radiation-free, and cost-effective, enhanced through the integration of artificial intelligence (AI) techniques. The proposed framework incorporates Attention U-Net for accurate segmentation of thermal breast images, K-Means Clustering to localize and isolate high-temperature regions suspected to be cancerous, and an EfficientNet-B7-based Convolutional Neural Network (CNN) for classification. To increase clinical reliability and transparency, the system employs Explainable AI (XAI) techniques using Local Interpretable Model-Agnostic Explanations (LIME), which provide visual interpretations of the model's decision-making process. The dataset used in this research was obtained from the Database for Mastology Research (DMR) and consists of 2010 thermal images, including both healthy and abnormal cases. Preprocessing and segmentation effectively remove irrelevant areas and focus on the breast region, enhancing detection accuracy. Experimental evaluation indicates the proposed model achieves a training accuracy of 96.48% and a validation accuracy of 91.67%, with a recall of 91.95%, specificity of 91.43%, precision of 89.89%, and F1-score of 90.91%. These results highlight the system's robust performance and generalizability. The LIME-generated superpixel visualizations help medical professionals better understand and validate the model's predictions, contributing to increased trust in AI-driven diagnostics. Overall, this research presents a reliable, explainable, and ethically grounded solution for early-stage breast cancer detection, demonstrating its strong potential for supporting clinical decision-making and future deployment in real-world healthcare settings.

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1. INTRODUCTION

Breast cancer is still one of the leading causes of death in women, largely due to late detection and treatment, as cancer is often detected at an advanced stage. Globocan 2022 data shows that the number of new breast cancer cases reached 2,296,840 cases with a mortality rate of 666,103 [1]. A study in Australia shows that the survival of breast cancer patients is strongly related to the size of the tumor when detected, where 70% of breast cancers are detected when the tumor size has reached 30 mm [2], [3]. Therefore, early detection of breast cancer is needed so that the chances of cure become greater. Current breast cancer early detection methods, such as physical examination and mammography, have several limitations, including the involvement of physical contact and the invasive risk of repeated examinations [4]. As an alternative, thermography is being developed as a non-invasive, radiation-free, and contactless early detection method. This method allows the observation of indications of cellular abnormalities through the temperature distribution of the skin surface using an infrared camera [5].

This research focuses on the development of an early breast cancer detection system based on thermal imaging that is non-invasive, radiation-free, and cost-effective. The system is not intended to replace or substitute imaging modalities such as mammography or ultrasonography, but rather to serve as an initial screening tool for detecting early suspicious indications. Thermal imaging captures only the surface temperature changes of the body, which can indicate abnormal biological activity such as increased blood flow or cellular metabolism. Therefore, this system can help identify cases that require further examination using conventional methods like mammography, which are capable of directly detecting internal tissue structures. The use of thermal imaging in early detection offers an efficient initial approach to screen potential cases, especially in areas with limited access to conventional medical imaging equipment.

This study aims to develop a thermography-based early detection system for breast cancer using artificial

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intelligence, specifically Convolutional Neural Networks (CNN). This approach combines Attention U-Net for thermal image segmentation and K-Means Clustering to identify suspicious areas with the highest temperature. In addition, Explainable Artificial Intelligence (XAI) is applied to provide the prediction conclusion. We chose Attention U-Net and EfficientNet-B7 due to their strong capabilities in breast cancer detection using thermal images. Attention U-Net excels in segmentation tasks by leveraging an attention mechanism that focuses on relevant areas, such as tumors, while ignoring irrelevant parts. This selective attention helps accurately delineate tumor boundaries and enhances the model's performance in detecting subtle temperature variations in thermal images [6]. On the other hand, EfficientNet-B7 is highly effective in classification tasks, offering powerful feature extraction capabilities while maintaining a compact model size. Its ability to handle high-resolution thermal images and extract fine details from them makes it an ideal choice for classifying breast conditions [7]. Overall, these two architectures complement each other, providing superior segmentation and classification performance in breast cancer detection.

Based on the research conducted, there are several relevant studies that serve as benchmarks and comparisons to improve this study. First, Kaushik Raghavan, et al. which utilized Grad-CAM, Attention Mechanism, and CNN Ensemble (e.g., Xception, ResNet101, InceptionV3) on the Database for Mastology Research (DMR-IR) dataset with an accuracy of 95.6% [8], XAI for Medical Imaging using DL CNN Ensemble for Estrogen Receptor Status Classification from Breast MRI showed a prediction accuracy of >0.9 but still needs to address irrelevant patterns in the dataset [9]. Second, the study using the classification method with the pre-trained DenseNet121 model on the Database for Mastology Research (DMR-IR) dataset achieved a breast cancer classification accuracy of 98.80%, although it does not yet have a system for segmenting cancer areas and estimating breast cancer size [10]. Third, the end-to-end deep learning framework with CNN and Locality Preserving Learner (LPL) yielded a DI coefficient of 92.27% and an AUC score of 0.85, as well as the best mammography segmentation with a DI coefficient of 93.69%, but is still limited to mammography datasets and cannot yet estimate breast cancer size [11]. Fourth, research using several deep learning models such as DenseNet, ResNet101, MobileNetV2, and ShuffleNetV2 to classify thermal breast cancer images showed accuracies of 100% for DenseNet, MobileNetV2, and ResNet101, and 99.6% for ShuffleNetV2, but has not yet provided results for estimating the size and segmenting breast cancer areas using only thermal imaging [12]. Although thermography-based CAD has developed rapidly, its implementation has yet to be widely done in clinical applications [2]. This study is expected to fill the gap and improve the efficiency of medical experts' diagnoses.

The effort to build an artificial intelligence-based CAD system carried out by the research team uses the XAI method to explain the CNN model's decision on breast thermal image classification results. The breast thermal image dataset used to build the DL model was downloaded from the Database for Mastology Research (DMR) [13]. XAI is used to generate attribution maps that highlight features that affect the model's prediction results. One of the unique approaches adopted is the application of the "Local Interpretable Model-Agnostic Explanations" (LIME) method. LIME provides local model-agnostic explanations, capable of being applied to various types of machine learning models without being tied to a particular architecture [5]. The state-of-the-art and contributions of this paper can be summarized as follows:

1. Development of a thermal image segmentation model. We developed a robust image segmentation model for breast thermal images utilizing Attention U-Net architecture to enhance the precision of cancer localization.
2. Color Prediction through K-Means Clustering. We implemented K-Means Clustering for color prediction in segmented thermal images to provide a detailed and accurate categorization of image regions.
3. Advanced Classification with Explainable AI. We integrated EfficientNet-B7 for color cluster classification with Explainable AI (XAI) to improve the interpretability of classification results, making the model's decisions more transparent and clinically useful.

The following sections describe the elaboration of our work. Section II clearly describes the proposed method, followed by the result in Section III. Discussion in the Section IV. Finally, Section V concludes our work.

2. METHOD

Our proposed system is an integration of several artificial intelligence models regarding tasks in providing prediction along with information on breast thermal images. Systematically, we developed the system in the stages, as shown in Fig. 1. Firstly, we designed the system pipeline. Then, we separately built the model for segmentation, color clustering, classification, and prediction decisions. As we got the best model for each task, we integrated the model and tested the performance. Detail descriptions of each model development are provided in the following subsections.

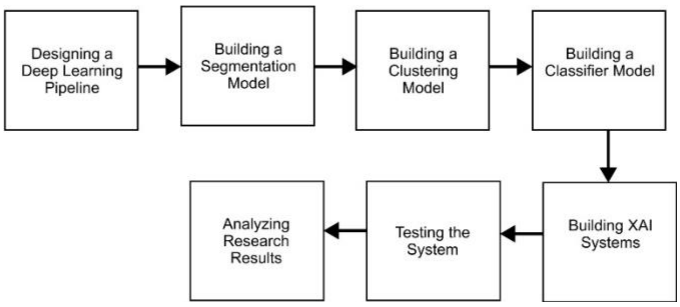

Fig. 1. Schematic of identity authentication system

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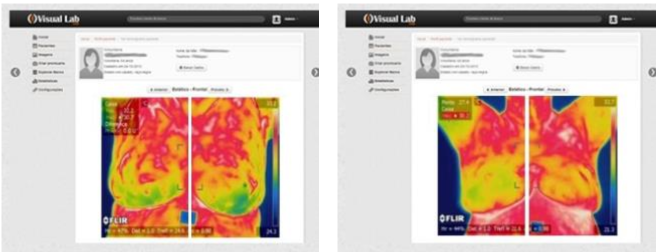
A. Datasets

Datasets of breast thermal images were taken from the Database for Mastology Research (DMR) [4], which can be accessed via http://visual.ic.uff.br/dmi. This dataset consists of healthy and sick breast thermal images, with a total of 1818 images used in the study. The thermal images display the distribution of body temperature using color gradations and include body parts such as the arms, chest, and neck. Some additional information, such as text, is also contained in these images. Fig. 2 shows examples of healthy (a) and Sick or cancer breast thermal images. Some additional information regarding the patient condition are also provided [4].



(a) (b)

Fig. 2. Thermal images from DMR (a) healthy breast thermal image and (b) cancer breast thermal image [4]

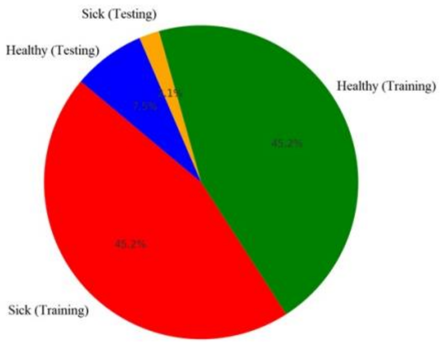


Fig. 3. Dataset distribution visualization

Before feeding into the model training process, the data must go through a preparation and pre-processing stage to ensure high data quality and reduce noise. In the data preparation stage, thermal images are categorized into two groups based on existing annotations: sick (cancer) images and healthy images. The images are randomly collected, with a total of 2010 samples used for training and testing. Specifically, 1060 healthy images and 950 sick images are included. For training, 955 healthy and 863 sick images are utilized, while the testing set consists of 105 healthy and 87 sick images. All images are resized to 224×224 pixels to ensure uniformity. The distribution of data across categories is visualized in Fig. 3. To ensure the reproducibility and validity of the model, the dataset was split with a ratio of 90% for training and 10% for testing. Case diversity was maintained by including images from various patient demographics and potential stages of breast cancer, as indicated in the dataset metadata, even though the specific stage information was not explicitly labeled. This approach was taken to better simulate realistic clinical conditions and reduce potential bias during the model's learning process. The fundamental difference between thermal images of healthy and affected breasts lies in the pattern of temperature distribution. Thermal images of healthy breasts typically show a balanced and symmetrical temperature distribution across the chest area. In contrast, images indicating possible breast cancer exhibit localized areas of higher temperature, which may suggest abnormal metabolic activity or increased blood flow associated with the presence of breast cancer.

B. Segmentation of Breast Parts with Attention U-Net

The segmentation of the breast area is crucial in this study because the thermal images in the dataset cover a broad body region, from the neck to the waist, which can interfere with the identification of suspicious areas that may indicate cancer. Therefore, segmentation is used to focus the analysis solely on the breast area, removing irrelevant information. In this study, the Attention U-Net model is employed for segmentation, with RGB images as input and a mask indicating the breast region as the reference. The result of this segmentation process is a thermal image displaying only the breast area, which is then used in the subsequent stages for detecting suspicious cancerous regions. By limiting the analysis to relevant areas, segmentation plays a vital role in improving detection accuracy and helps the system to more precisely identify parts with potential abnormalities.

The overall work of this study is shown in the graphical abstract in Fig. 4. As seen in the figure, the segmentation process aims to separate or group objects in the image. The segmentation method used in this study is Attention U-Net [14], [15]. Attention U-Net works by extracting features from the original image whose dimensions are continuously reduced and then increased again using Convolutional Transpose, resulting in a segmented image according to the desired ground truth [15], [16]. The input for Attention U-Net must be a grayscale image or an image with a single dimension, and the segmentation results are compared using a loss function such as binary cross-entropy. This segmentation is very important in this study because the breast thermal images cover a large area, ranging from the neck to the waist, which can interfere with the process of finding suspicious areas of cancer in the breast. By performing proper segmentation, the system can focus on the breast area only thus improving detection accuracy [16].

C. Thermal Image Color Prediction with K-Means Clustering

K-Means is a centroid-based clustering algorithm widely used due to its simplicity [17]. However, its performance heavily depends on the initial selection of centroids [18]. To address this, various initialization and enhancement

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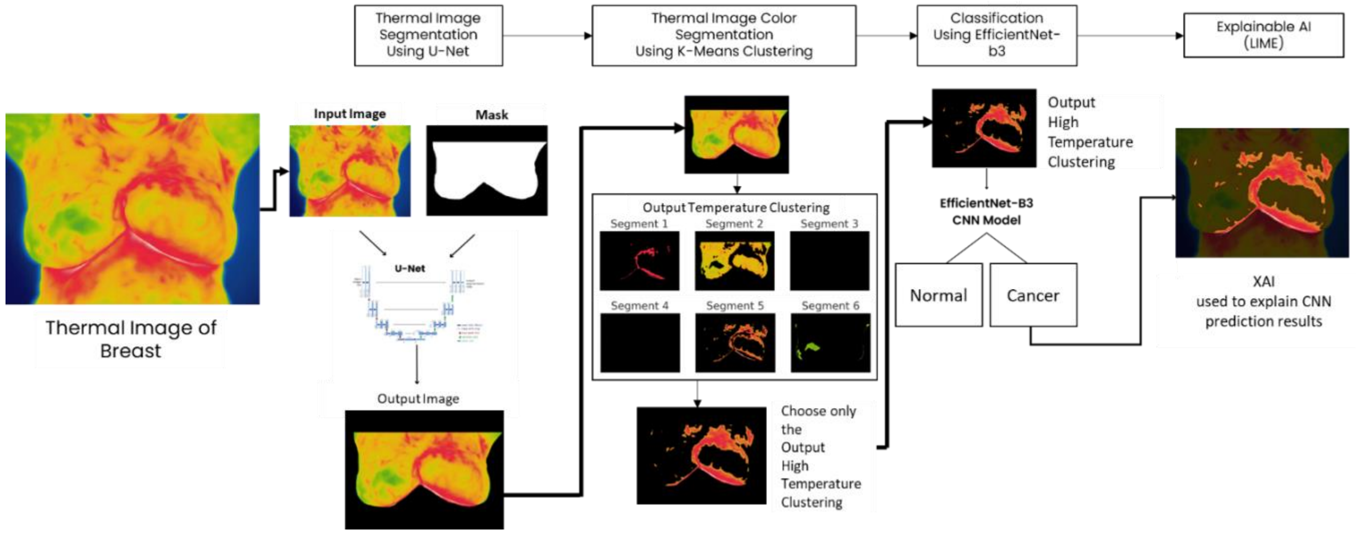

Fig. 4. Breast cancer area localization system pipeline

methods have been developed, such as distance-based approaches and data partitioning techniques [17]. One of its applications is in image segmentation, including breast thermal images, where color features are the main aspect observed [19]. The prediction process is carried out by considering the similarity of features in these images. However, it is challenging to separate the breast region from other objects because the breast area shows significant color variation [20]. Despite its limitations, K-Means remains popular and is continuously developed to improve its performance in various applications, including medical image processing like this one [21].

K-Means clustering can predict the breast area based on color. In this process, K-Means Clustering is used to find cancerous suspicious areas by predicting the color with the highest temperature [22]. The reddest color defines the hottest area of the breast and becomes the most cancerous suspicious area. The detailed steps of this procedure are presented in Algorithm 1: Extract Highest Heat Region, which outlines how the image is processed to isolate the hottest area using K-Means clustering. In Algorithm 1, the K-Means clustering process starts by converting an RGB image into a 2D array and then applying clustering with four clusters (K=4) based on color values.

Algorithm 1. Extract Highest Heat Region

Input: Image img (RGB)
Output: Image ex_img #with the highest heat region

1 Reshape img into a 2D array Z of type float32.
2 Define K-Means criteria with 4 clusters (K=4).
3 Apply K-Means to Z, obtaining labels and centers.
4 Identify the cluster with the highest red value (most_red).
5 Create a mask for the area where labels == most_red.
6 Apply bitwise_and to extract the highest heat region (ex_img).
7 Return ex_img.

End

The cluster with the highest red value, indicating the hottest area, is identified and isolated using a mask. This region, representing the most suspicious area for cancer, is extracted as the final output image (ex_img). Despite the challenges in distinguishing the breast from other objects due to color diversity, this method effectively identifies potential cancerous areas by focusing on the reddest and hottest regions in thermal imaging. Fig. 5 shows the clustered process and a color prediction using K-Means, which produces an image that has been divided according to the color and temperature of the image itself. The final result of this prediction is then fed into the last process, namely the classification process, whether it is true that it is a cancerous area or not using CNN with EfficientNet-B7 architecture.

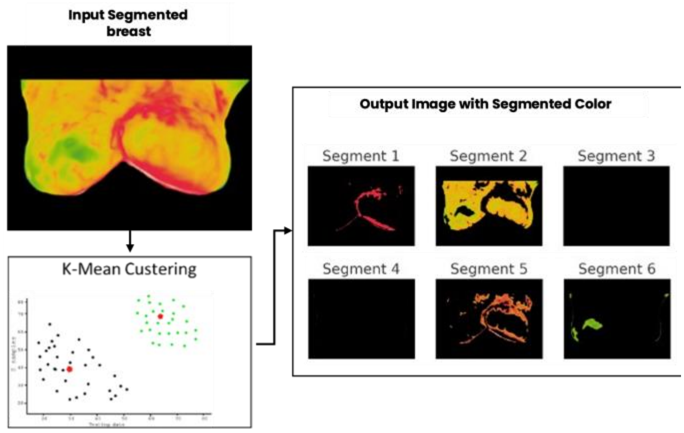

Fig. 5. Clustering and colour segmentation work process

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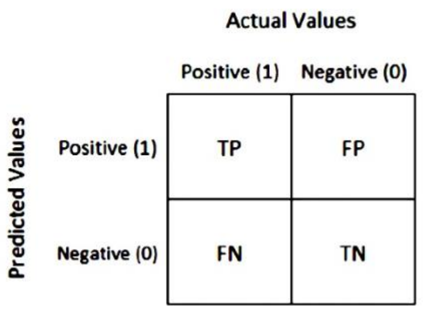

Fig. 6. Component value of the confusion matrix

D. Classifier Model Based on EfficientNet-B7

A classification model to detect breast cancer is built using a Convolutional Neural Network (CNN) with EfficientNet-B7 architecture [23]. This classification process is carried out after the image passes the segmentation stage using Attention U-Net and the application of K-Means Clustering to group areas based on temperature. The red color in the clustering result indicates the area with the highest cancer potential. Once the clustering process has identified the suspected cancerous areas, the task of classification is handed over to an EfficientNet-B7 architecture-based CNN model. This model is chosen for its superior ability to recognize visual patterns with a high degree of accuracy [3]. The segmented and clustered images then undergo a series of convolution, pooling, and fully connected layers, leading to a final prediction of cancer presence or absence in the area. The classification process for breast cancer using Convolutional Neural Networks (CNNs) has been extensively evaluated across various imaging datasets, with performance measured using accuracy, sensitivity, specificity, and F1 score [24], [25], [26], as detailed in Algorithm 2: Algorithm for Developing the Classifier Model. The evaluation of accuracy is not a mere formality but a comprehensive process that includes separate accuracy calculations for both the training and testing stages. The results are further scrutinized by considering the accuracy, recall, specificity, precision, and F1-score values that are calculated using (1) – (5).

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{FP+FNTP+TN}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \tag{3}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{4}$$

$$\text{F1} - \text{score} = 2 \times \left(\frac{\text{Precision}\times\text{Recall}}{\text{Precision}\times\text{Recall}}\right) \tag{5}$$

The values TP indicates the number of samples that are truly positive and predicted positive by the model, TN is the number of samples that are truly negative and predicted negative by the model, FP is the number of samples that are truly negative but predicted positive by the model, and FN indicates the number of samples that are truly positive but predicted negative by the model, as can be seen from the distribution in Fig. 6.

Algorithm 2. Algorithm for developing the Classifier Model

Input: Thermal images
num_classes
parameter list (width_coefficient, depth_coefficient, input_size, dropout_rate)
Output: Trained CNN model

```
Param => the parameter list (width_coefficient, depth_coefficient, input_size, dropout_rate).
num_classes => the number of classes for classification.
CNN_model => EfficientNet model with Param and num_classes.
optimizer =>(e.g., Adam) with a specified learning rate.
loss_function => CrossEntropyLoss.
  For each epoch
    Set the model to training mode.
    For each batch of face images:
      Obtain Input and Label from the batch.
      Make predictions using CNN_model(Input).
      Compute the loss using loss_function(Predictions, Label).
      Zero the gradients in the optimizer.
      Perform backpropagation with loss.backward().
      Update the model parameters with optimizer.step().
  End for
End for
Save the trained model to a file.
Return the CNN_model.
End
```

E. Identity with Explainable Artificial Intelligent (XAI)

The final process of this study was to use Explainable Artificial Intelligence (XAI) techniques to interpret the EfficientNet-B7 CNN classification results, specifically focusing on whether the model indicated signs of cancer [5]. The XAI technique used is Local Interpretable Model-agnostic Explanations (LIME), which helps explain the predictions made by the model [27]. LIME is an essential technique in XAI that addresses a critical need in the medical imaging domain, particularly when interpreting the results of complex models like EfficientNet-B7 CNN. LIME's uniqueness lies in its ability to break down and explain the predictions made by such models, which are often perceived as black boxes due to their complex architectures [27]. LIME is used to explain the reasoning behind the model's decision, particularly in predicting whether an image indicates signs of cancer or not. The process begins by dividing the input image into multiple superpixels small regions with similar visual characteristics. Next, noise is introduced by removing or modifying certain superpixels (e.g., turning them gray), resulting in a set of image variations that differ from the

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original. The model then predicts labels for each of these image variations. These predictions are collected and used as training data to build a simple local regression model (typically linear regression) aimed at mapping the influence of each superpixel on the model's decision. Superpixels that have the greatest contribution to the classification decision are marked as important regions, and the final visualization is presented as an image that highlights the superpixels most influential to the prediction. Explainable Artificial Intelligence (XAI) encompasses procedures and techniques that make machine learning outputs more understandable and reliable for human users, playing a crucial role in ensuring fairness, accountability, and transparency (FAT) in AI systems [27]. Particularly in deep learning, where models like neural networks often operate as "black boxes," XAI provides the necessary clarity and interpretability. One effective approach within XAI is using techniques like visualization to represent complex model information graphically, making it more accessible and feature understanding, which identifies each feature's contribution to a model's prediction [28].

In the context of breast cancer detection, XAI can be instrumental in revealing significant areas of an image for identifying potential cancer. The proposed system can visualize the importance of these features. A perturbed image is displayed, highlighting the superpixels that have the most influence on the prediction. This visualization provides insight into which areas of the image the model considers most relevant when determining the presence or absence of cancer.

3. RESULT

A. Segmentation of Attention U-Net Model

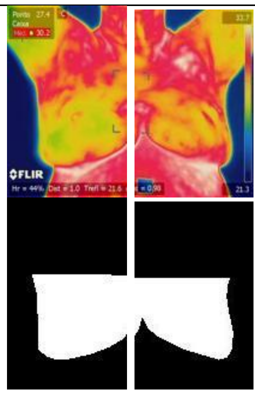
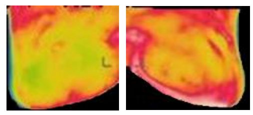
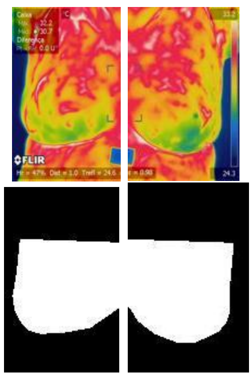
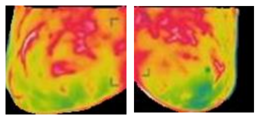
In our approach to segment breast portions from thermal images, we employed a systematic preprocessing and training strategy to harness the capabilities of Attention U-Net within a deep learning framework. The initial preprocessing involved resizing the images from their original size to 160×100 using the BiLinear algorithm to meet Attention U-Net's input requirements. Following this, we applied a series of convolution, downsampling, and upsampling layers to transform the input RGB images into more canalized features, which were then zoomed back to the original size while incorporating information from the downsampling stage. The Attention U-Net model was used to perform segmentation with RGB image input and grayscale image mask output. The K-Means Clustering algorithm then processed the segmented thermal images of the breast to detect suspicious areas based on the highest temperature. This process allows Attention U-Net to predict image segmentation accurately, and the training process of this model was set with hyperparameters values as detailed in Table 1 that resulted in the best segmentation learning. The output of this process is a segmented thermal image of the breast, which is then used as input for the colour prediction process with the K-Means Clustering algorithm to find suspicious areas of cancer. Details of the resulting segmentation results can be seen in Table 2.

Table 1. Hyperparameter settings

Hyperparameter name	Hyperparameter value
Optimizer	RMSprop
Learning Rate scheduler	ReduceLROnPlateau
Epoch	166
Batch size	32
Learning rate	10^{-6}

In thermal image-based breast cancer detection systems, segmentation is a crucial step to ensure that the classification process is focused on the breast area, which is the primary object of analysis. This study applies Attention U-Net as the segmentation method to separate the breast region from other body parts such as the neck, arms, or background, which can introduce noise during feature extraction. Although no direct comparison was conducted between models with and without segmentation, the classification results show that the model consistently detects temperature pattern differences between healthy and cancer-indicative images. This suggests that segmentation helps highlight important areas with distinctive temperature distributions that may indicate abnormalities.

Table 2. Thermal image processing, masking and U-Net Segmentation Output

ID	Thermal image & masking	Output Segmentasi U-Net
1	 (left) (right)	 (left) (right)
12	 (left) (right)	 (left) (right)

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Attention U-Net enhances the accuracy of the classification process by directing the model's attention to medically relevant parts of the image. Furthermore, segmentation enables the removal of irrelevant background information, making the features learned by the model more specific and representative of breast conditions. However, challenges remain, such as when the temperature distribution in the image lacks sufficient contrast between healthy and suspicious areas. In such cases, segmentation may not optimally isolate the important regions, potentially affecting detection accuracy. Overall, segmentation using Attention U-Net plays an essential role in the detection pipeline, particularly in ensuring that classification is carried out with a focused analysis on relevant regions, thus supporting improved system performance.

B. Thermal Image Color Prediction with K-Means Clustering

This study implements K-Means Clustering and CNN with EfficientNet-B7 architecture to detect cancerous suspicious areas based on the highest temperature in the image. The process starts by converting the image into a 2D array that contains the RGB value of each pixel, then K-Means Clustering groups the pixels into four clusters based on color similarity. The cluster with the highest red color is identified as the area with the highest temperature suspected to be cancer, which is then separated using a binary mask. These suspicious areas are measured and then classified using CNN to determine whether they are indeed cancerous or not. This approach allows for the isolation and accurate analysis of suspicious areas, ensuring accuracy in cancer detection and classification, Details of the prediction results of this clustering can be seen in Fig. 7.

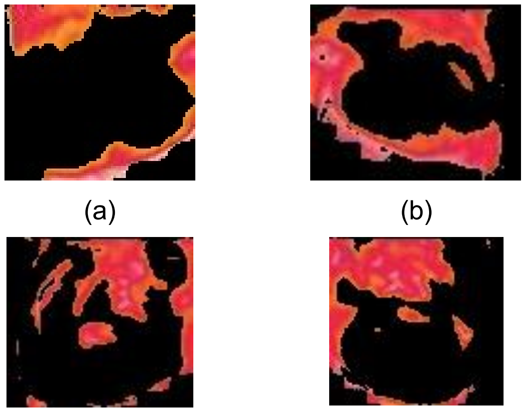
C. Suspicious Area Classification

After segmentation, suspicious areas of cancer are classified using a CNN with EfficientNet-B7 architecture. This process involves training the network with images that have been segmented and clustered. The simulation results show that the model can optimize accuracy and computational efficiency with a scale-balanced approach. The hyperparamter values that resulted in the best clustering model performance are shown in Table 3. The learning curve of the classifier model during the training can be seen in Fig. 8, each for accuracy rates (a) and loss rates (b). Stabil learning with loss approaching zeros indicates that the model is well performed.

Table 3. Hyperparameter settings

Hyperparameter name	Hyperparameter value
Optimizer	RMSprop
Learning Rate scheduler	ExponentialLR
Epoch	166
Batch size	32
Learning rate	10^{-6}

To further optimize model performance, a detailed hyperparameter tuning process was conducted using the grid search method. This approach involved evaluating a range of parameter values, particularly the learning rate, which was tested at 10^{-4}, 10^{-5}, and 10^{-6}. The evaluation was based on convergence stability and the balance between underfitting and overfitting. As shown in Table 4, the analysis of the training and validation loss curves revealed that a learning rate of 10^{-6} yielded the best results, with a training accuracy of 96.48% and a validation accuracy of 91.67%. This configuration also improved evaluation metrics such as precision, recall, and F1-score. While grid search proved effective in identifying optimal hyperparameters, future work may explore alternatives such as random search or Bayesian optimization to improve computational efficiency. The model performance metrics show that the training accuracy reaches 96.48%, reflecting effective learning and stabilization at a high value. The validation accuracy of 91.67% indicates good generalization from training to validation. The training loss reaches 0.3485%, demonstrating a consistent decrease in error during training. The validation loss of 0.4089% shows a slightly higher fluctuation in validation error but remains within an acceptable range, reflecting the stability of the model during the validation process. Collectively, these graphs indicate that the model has a robust and reliable performance, with a strong capacity to generalize.



(a) (b) (c) (d)

Fig. 7. Clustering and Colour Segmentation Process with K-Means Prediction Results

D. Confusion Matrix Analysis

Finally, the performance of the proposed advanced deep learning model for breast cancer detection with the decision-making process is provided in Table 4. The model with a learning rate of 10-6 is the model with the best training and validation performance. Based on the detailed values, it can also be seen that the smaller the learning rate value set, the better the accuracy, recall, specificity, precision, and F1-score values produced, and vice versa if the learning rate set is larger, the accuracy, recall, specificity, precision, and F1-score produced will

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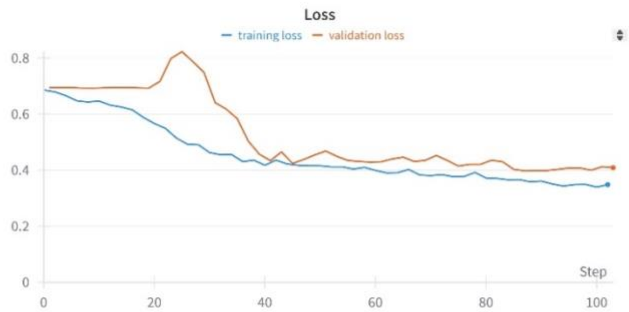
be worse. This best model size is 1.01 GB. Taking the prediction values resulted from the confusions matrix, then the inference model is evaluated using the accuracy, recall, specificity, precision, and F1- score metrics which calculated using the calculations in Eq. (1) to Eq. (5).

(a)

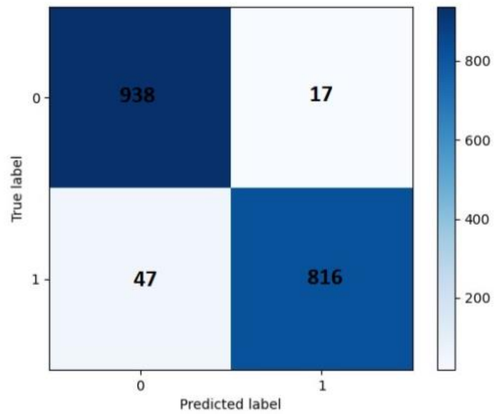


(b)

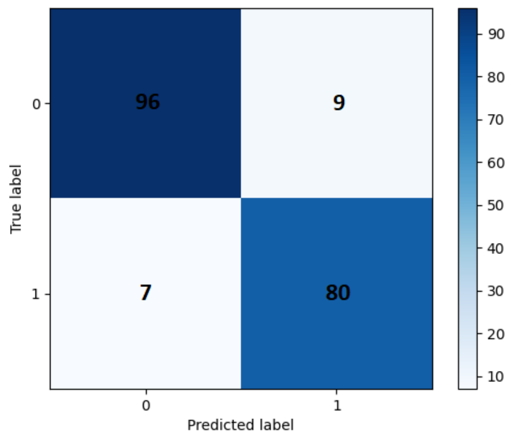
Fig. 8. Classifier model learning curve loss rates

As illustrated in Fig. 9, the confusion matrix analysis of the training results demonstrates that the model performs exceptionally well, achieving a high accuracy of 96.48%. This indicates that the model correctly predicts the majority of cases. The recall for the positive class stands at 98.22%, showcasing the model's ability to correctly identify 98.22% of actual positive cases. This high recall rate suggests that the model is highly effective in detecting true positive instances, minimizing the risk of missing potential cancerous areas. Furthermore, the specificity is recorded at 94.56%, indicating that the model correctly identifies 94.56% of actual negative cases. The precision, at 95.23%, shows that 95.23% of the cases predicted as positive by the model are indeed positive, emphasizing the reliability of the predictions. The F1-score, which balances precision and recall, is 96.70%, reflecting a strong equilibrium between these two crucial metrics.

In contrast, the validation results also demonstrate a commendable performance, albeit slightly lower than the training results. The model achieves a validation accuracy of 91.67%, which indicates good generalization from the training data to new, unseen data. The recall for the positive class in the validation phase is 91.95%, suggesting that the model maintains a high ability to detect true positive cases even on new data. Specificity during validation is 91.43%, showing that the model accurately identifies negative cases at a similar rate as during training. Precision is recorded at 89.89%, slightly lower than during training, which may indicate some degree of overfitting or a need for further model refinement. The F1-score in the validation phase is 90.91%, which continues to reflect a good balance between precision and recall, though there is a slight dip compared to the training phase.



(a)



(b)

Fig. 9. Confusion matrix for (a) training data and (b) testing data

These results collectively indicate that while the model performs robustly on both training and validation datasets, as in Table 4 there is a noticeable gap between the two phases, particularly in terms of precision and F1-score. This suggests that while the model is highly accurate and effective during training, it may require further optimization to enhance its generalization capabilities on new data. Addressing the slight discrepancies in validation performance, particularly in reducing false positives and negatives, could further improve the model's reliability and effectiveness in real-world applications. This study provides a solid foundation for the continued development of non-invasive breast cancer detection systems, with potential improvements aimed at refining the model's predictive accuracy and overall

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Table 4. Model performance based on confusion matrix

Learning Rate	Training accuracy	Validation accuracy	Training recall	Validation recall	Training Specificity	Validation Specificity	Training precision	Validation precision	Training F1-score	Validation F1-score
10^{-4}	65.89%	52.83%	65.89%	51.80%	64,35%	53,0%	67.15%	62.62%	65.89%	51.84%
10^{-5}	71.64%	69.38%	71.63%	58.81%	81,83%	88,54%	72.37%	75.13%	78.82%	51.96%
10^{-6}	**96.48%**	**91.67%**	**98.22%**	**91.95%**	**94.56%**	**91.43%**	**95.23%**	**89.89%**	**96.70%**	**90.91%**

robustness. The test results in Table 4 indicate that the model demonstrates strong performance on both training and validation data. This is evident from the consistently high values of accuracy, recall, precision, and F1-score, particularly when using the learning rate of 10^{-6}. The optimal learning rate enabled the model to learn in a more stable and accurate manner, without experiencing excessive overfitting.

The balance across evaluation metrics shows that the model is not only capable of recognizing patterns from the training data but also generalizes well to validation data. This is especially important in the context of breast cancer detection, where classification errors can significantly impact clinical decisions. However, there remains a slight performance gap between the training and validation phases, particularly in the precision and F1-score metrics. This difference suggests that the model can still be optimized, especially in reducing false positive and false negative predictions. Another limitation of this study is the absence of testing with datasets from different sources. As a result, a comprehensive evaluation of the model's robustness across diverse data distributions has not yet been conducted. For future development, testing with additional datasets of varying characteristics will be a crucial step to ensure the model's reliability in real-world conditions.

The selection of evaluation metrics such as Accuracy, Recall, Specificity, Precision, and F1-Score is crucial in breast cancer detection systems. Accuracy provides an overall view of the model's performance but may be insufficient for imbalanced datasets. Therefore, Recall becomes critical, as it focuses on the model's ability to correctly detect cancer cases, thereby minimizing the risk of false negatives, which can be dangerous for patients. On the other hand, Specificity is important to avoid false positives—mistakenly diagnosing healthy patients as having cancer—which can lead to unnecessary anxiety and medical interventions. Precision evaluates the accuracy of positive predictions, helping to prevent overdiagnosis. Meanwhile, the F1-Score balances Recall and Precision, making it highly relevant in medical contexts where mispredictions can have serious consequences.

Thus, Recall is vital in minimizing false negatives, a condition where cancer in a patient goes undetected, potentially delaying necessary treatment. Conversely, Specificity and Precision help reduce false positives—incorrectly identifying healthy patients as cancer cases. This is essential to avoid unwarranted distress and unnecessary follow-up medical procedures. A validation accuracy of 91.67% indicates that the model has strong performance. However, understanding the implications of this result in a clinical context is essential. For example, a false negative (the system failing to detect the presence of cancer) can lead to delays in medical treatment, which in turn may reduce the patient's chances of recovery. Conversely, a false positive (the system incorrectly classifying a healthy patient as having cancer) may prompt unnecessary follow-up procedures, such as additional mammograms or biopsies, potentially causing psychological distress and financial burden.

Therefore, high model performance in terms of precision and recall plays a crucial role in supporting more accurate clinical decision-making and assisting medical professionals in determining whether further action is necessary. In this way, the model's success is not only measured technically but also by its contribution to improving the quality of care and treatment outcomes for patients. In this study, cross-validation approaches such as k-fold were not used. Instead, the model was evaluated using a static dataset split between training and testing data. Although this approach has limitations in terms of generalization, it was chosen to provide an initial overview of the model's performance on new data directly. The evaluation results indicate that the model performs very well in recognizing patterns in breast thermal images. Its ability to distinguish between healthy images and those indicating cancer is consistent across various evaluation metrics, such as accuracy, precision, and sensitivity. This suggests that the model is not only capable of correctly identifying cancerous images but is also reliable in minimizing classification errors on healthy images. Furthermore, the testing results demonstrate good generalization capabilities, meaning that the model does not merely "memorize" the training data but can also perform effectively on previously unseen test data.

On the other hand, the model's performance is quite sensitive to training parameter settings, particularly the choice of learning rate. Misconfiguration of this parameter can lead to a significant drop in performance, both in terms of accuracy and classification stability across classes. Additionally, the temperature-based segmentation process, which only considers the highest-temperature areas, risks omitting important information from other relevant regions. This may reduce accuracy, especially when the temperature distribution in the image does not present a stark contrast between healthy and suspected cancerous areas. During the model training process, we observed signs of overfitting in the early training stages, indicated by fluctuations and a significant increase in validation loss compared to training loss, particularly around epoch 20. This was likely due to noise and temperature variations in the thermal images, which affected the consistency of the validation data distribution.

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Table 5. Comparison of the proposed method with existing similar works

Works	Dataset	Method	System Accuracy	Learning Curve	AI Output	Validation Results
Kaushik Raghavan, et al. [8]	Database For Mastology Research (DMR-IR)	Grad-CAM, Attention Mechanism, CNN Ensemble (Xception, ResNet101, InceptionV3)	95.6% (Ensemble with Attention Layer)	N/A	Heatmap highlighting critical areas for classification	Precision: 96.1%, F1-Score: 91.0%, Accuracy: 95.6%
Yerken Mirasbekow, et al. [31]	Visual Lab DMR Database and Thermogram Dataset	CNN, Bayesian Network, Explainable AI (LIME)	84.07% (Bayesian Network) 90.93% (Bayesian Network with CNN)	ROC curve for model A and model B	Visualization of the thermogram areas that most influence the prediction (with LIME).	ROC AUC Model A: 93.05% Model B: 96.93% Gini Index Model A: 43.05% Model B: 46.93%
Nurduman Aidossosv, et al. [32]	Thermogram Dataset and Visual Lab DMR Database	Combination CNN (ResNet50 with Bayesian Network)	91% - 93%	N/A	Heatmap highlighting critical areas for classification	Precision: 91% - 93% Sensitivity: 91% - 95% Specificity: 91% - 97%
Roslidar, et al. [29]	Database For Mastology Research (DMR)	Automatic Segmentation ROI, Pre-trained CNN, Shufflenet modified	MobileNetV2: 98% Modified ShuffleNet: 100%	Accuracy and Loss learning curve	Real-time inference Visualization of classification results	Modified ShuffleNet Sensitivity: 100% Specificity: 100%
Proposed Intelligent System	**Database For Mastology Research (DMR-IR)**	**Attention U-Net, K-Means Clustering, CNN EfficientNet-B7 and Explainable AI**	**96.48% (training), 91.67% (validation)**	**Convergence with 100 epochs**	**RoI with suspicious cancer area**	**Recall: 91.95%, Specificity: 91.43%, Precision: 89.89%, F1-score: 90.91%**

However, as the training progressed, the difference between the training and validation loss values became smaller and more stable, suggesting that the model was able to adapt to the data and reduce overfitting. Nevertheless, we recognize that the non-uniform quality of thermal images, as well as non-relevant areas in the images prior to segmentation, remain challenges that can affect the model's generalization ability. Moreover, the color segmentation process used in this study tends to reduce features around the colored regions, which could otherwise provide important information to the model. Therefore, improvements in the preprocessing stage such as enhancing the color segmentation technique by considering the spatial correlation between surrounding features are essential steps that should be explored to improve overall model performance.One of the limitations of this study lies in the class distribution of the dataset used, where the number of thermal images from healthy patients is significantly greater than those from patients with indications of breast cancer. This class imbalance may affect the model's learning process, as the model tends to become more "accustomed" to recognizing patterns from the majority class (healthy) rather than the minority class (cancer). As a result, the model may demonstrate suboptimal performance in detecting images from cancer-indicative cases, such as an increase in false negatives.

Although techniques such as data augmentation and the use of evaluation metrics that account for class imbalance have been applied, this imbalance remains a challenge that must be addressed in future model development. Therefore, to enhance the model's generalization and reliability, further studies are recommended to use more balanced datasets or adopt more advanced data imbalance handling approaches.

Compared to previous research by Kaushik Raghavan, et al. [8], which utilized Grad-CAM to enhance interpretability and achieved 94.3% accuracy, the proposed model demonstrates comparable performance and improved attention on key thermal regions. A comparison between the proposed system and previous research was carried out by referring to two publications, namely the study by Roslidar et al. [29] published in AIMSpress, which introduced BreaCNet, a breast cancer detection framework that integrates segmentation and classification techniques with an explainable approach, reporting accuracy metrics ranging from 94% to 96%. Similarly, the review by Roslidar et al. [30] published in IEEE Access highlights recent advances in thermal imaging and deep learning for breast cancer detection, including the application of interpretability methods such as Grad-CAM to enhance model transparency, with reported accuracies also approaching 95%. We highlighted the result of existing works compared to proposed method in Table 5.

The detection system developed in this study integrating Attention U-Net for segmentation, K-Means Clustering for temperature-based region identification, and an EfficientNet-B7-based CNN with LIME for interpretability achieved a training accuracy of 96.48% and a validation accuracy of 91.67%. These results demonstrate competitive performance compared to prior

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studies, while also providing an added benefit in the interpretability of outputs, thereby supporting transparent and clinically verifiable decision-making.

The best-performing model produced in this study has a size of approximately 1.01 GB, which is technically feasible for deployment on cloud-based systems or local servers with medium-to-high specifications. However, for deployment on edge devices (such as portable systems or mobile-based applications), further optimization such as model compression or distillation is necessary to reduce model size without significantly sacrificing performance. In real-world implementation, the model also has limitations, particularly because the dataset used originates from a single ethnic group. This poses the risk of bias and limited generalizability when applied to populations with different ethnicities, ages, or biological characteristics. Therefore, to ensure the model's sustainability and adaptability in diverse clinical environments, a continuous learning approach is essential. The model can be gradually retrained using new data from various locations or demographic groups, allowing it to be updated without losing previously acquired knowledge.

The combination of advanced techniques, such as Attention U-Net for segmentation and K-Means Clustering for color prediction, enhances the interpretability and reliability of the model, which is crucial for clinical applications in breast cancer diagnosis. This study makes a significant contribution to the development of thermal image-based breast cancer diagnosis technology using deep learning and Explainable AI approaches. The integration of Attention U-Net, K-Means Clustering, and CNN EfficientNet-B7 provides an effective method for the classification and segmentation of suspicious cancerous areas in breast thermal images. Although the developed model has shown promising performance in segmenting and classifying thermal images for breast cancer detection, several further improvements can be explored to enhance accuracy, interpretability, and overall clinical relevance. In terms of segmentation, while Attention U-Net has performed well in mapping important areas within thermal images, exploring more advanced architectures such as Swin-UNet or TransUNet may help improve generalization and handle more complex cases. These transformer-based architectures have the potential to better capture spatial relationships and subtle morphological variations, especially in images with low contrast or high noise.

To improve transparency and clinical trust, Explainable AI (XAI) integration remains a key direction. Techniques such as Grad-CAM, SHAP, or LIME could be incorporated to not only provide classification results but also visually highlight the regions that influence predictions, making the system more interpretable for medical professionals. Expanding the dataset in terms of size, patient demographics, and image sources from different thermography devices would support greater model generalization. Enhancing annotation quality especially for segmentation ground truths through collaboration with medical experts would also strengthen the reliability of the model's training data. Lastly, to ensure the system's real-world applicability, gradual clinical validation will be essential. Evaluating the model's performance within actual medical workflows will help determine its practical feasibility and readiness for clinical deployment.

This study is still limited to the use of a dataset originating from a single source and does not yet fully represent the diversity of the population in terms of ethnicity, age, or breast tissue density. Variations in thermal images caused by these factors may affect the model's performance when applied in real-world conditions with patients of different characteristics. Therefore, the generalization of the model to a broader population cannot yet be fully concluded. Further studies are strongly recommended to use more diverse and representative datasets to re-evaluate the model's reliability and performance consistency. This also serves as an important direction for future development, ensuring that the detection system can be used more widely and inclusively across various population conditions.

Future research development can be focused on several aspects. First, exploring additional features from thermal images such as texture, finer temperature distribution, or thermal asymmetry patterns may enhance prediction accuracy. Second, a multimodal approach can be considered by combining thermal imaging with other data sources such as clinical history or results from other medical imaging modalities to obtain more comprehensive information. Third, clinical validation of the model in real-world settings is necessary to assess the system's reliability and readiness for practical medical use. By pursuing these directions, this research not only contributes academically but also opens opportunities for interdisciplinary collaboration and continued innovation in the development of non-invasive breast cancer detection systems.

4. DISCUSSION

The final step of this study is to use LIME, an XAI technique, to interpret the classification results of the EfficientNet-B3 CNN, determining whether the model detects signs of cancer. The process begins with segmenting the image into multiple superpixels—groups of pixels with similar characteristics that allow for detailed image analysis. LIME then introduces noise by modifying these superpixels, and each altered image is passed through the EfficientNet-B7 model to obtain a prediction score. These scores, coupled with the noise, help build a linear regression model that identifies the superpixels with the most significant influence on the model's prediction. By analyzing the coefficients of this linear model, the key features that most impact the prediction are determined, thereby making the model's decision process more transparent and interpretable. The final step of visualizing the important superpixels of the classification results are shown in Fig. 10. This visualization is crucial not only for understanding the model's behavior but also for gaining insights into which areas of the image may indicate the presence of cancer. The proposed system can explain the

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model's predictions, providing insight into the model's decisions by highlighting the most important features in the image. The use of LIME in this study serves not only to technically explain the model's decisions but also plays a significant role in the clinical context. By highlighting the regions of the thermal image that most contribute to the prediction, LIME helps medical professionals understand the rationale behind the model's decisions, making the prediction results less of a "black box."

This visual information can form the basis for more in-depth clinical discussions both among medical professionals and between doctors and patients. For instance, when certain areas in the image are marked as important by the model, they can be re-examined manually by doctors to assess whether the results align with other clinical examinations.

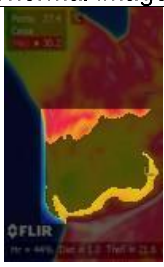
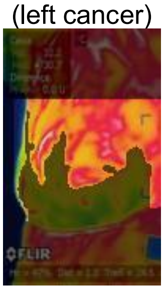
ID	Thermal image after processing	
(cancer-1-L&R_P_Cancer)	 (left cancer)	 (right cancer)
(cancer-12-L&R_P_Healthy)	 (left healthy)	 (right healthy)

Fig. 10. **Identification Results with XAI**

Furthermore, this interpretability also carries ethical significance, as it supports transparency in the use of AI for medical purposes. Explainable AI has the potential to improve trust, accountability, and acceptance in clinical practice, and to support more informed and thoughtful decision-making. Ethical considerations in the application of artificial intelligence in medical diagnostics are addressed with an emphasis on three main aspects: patient privacy and data security, the implications of misdiagnosis, and the enhancement of clinical outcomes and experiences. Patient data are processed anonymously and protected through strict security protocols, while the risks of false negatives and false positives are thoroughly assessed to minimize errors that could delay treatment or lead to unnecessary medical interventions. The use of Explainable AI methods, particularly LIME, enables the visualization of image regions that most influence the prediction, assisting medical professionals in verification and clinical discussion. Thus, the developed detection system prioritizes not only technical accuracy but also provides a strong ethical foundation to support medical decision-making through transparency and accountability.

5. CONCLUSION

We have developed an advanced deep learning base system to classify and localize suspicious cancer areas non-invasively using thermography. By integrating Attention U-Net, K-Means Clustering, and EfficientNet-B7 CNN, along with Explainable Artificial Intelligence (XAI). The proposed system achieved high performance, with a training accuracy of 96.48% and a validation accuracy of 91.67%. These results underscore the model's effectiveness in detecting and generalizing cancer patterns on new data, making it a highly promising tool for non-invasive cancer screening. However, with a training loss of 0.3485 and a validation loss of 0.4089, there remains a slight discrepancy, indicating challenges in balancing training and validation. Future improvements are necessary to further reduce the validation loss and enhance the generalization rate, particularly to improve detection accuracy on unseen data. This study significantly contributes to the advancement of non-invasive cancer detection technology, providing a strong foundation for future research and development of an early breast cancer detection.

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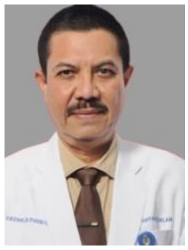

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