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Machine Learning Approaches for DMR-IR Breast Image Segmentation and Classification

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ABSTRACT :

The advanced diagnosis of breast cancer created difficult conditions for its treatment in many countries around the world. The year 2000 was noteworthy in this respect as it introduced a new breast screening method with breast thermography and offers many advantages over the older methods in terms of motion, contact and non-motion about implants Potential adverse effects of exercise imaging Patients and physicians may be motivated to explore new & alternative diagnostic techniques. This paper presents a new framework that aids in the extraction of significant features using the gray level co-occurrence matrix (GLCM) and some statistical priorities from breast thermograms derived from visual lab datasets, which are publicly available, . through exploratory research is proposed for It was found that when used in class, classification with a given set of features produced surprising results. The thermographic image is first processed and then the region of interest is segmented for features. The classification accuracy obtained by Support Vector Machine and Decision Tree was performed. The classification accuracy obtained in the training and testing sets was 100% with 106 healthy images and 136 patient thermographic images. The training set consisted of 90/110 images for healthy patients while 16/26 images were used for testing.

Keywords: Mammography, thermography, breast cancer, GLCM, statistical features, Support Vector Machine, Decision Tree, KNN, Random Forest and Deep Learning.

1. INTRODUCTION :

Breast cancer, characterized by its potential for unchecked growth and systemic spread, stands as a significant global health challenge affecting both genders. It ranks second among causes of global cancer-related deaths, underscoring its profound impact. In the United States, breast cancer is the second most prevalent cancer among women following skin cancer, highlighting its widespread occurrence. Despite its comparatively higher survival rates, the disease imposes a substantial burden globally, with over 8.15 million cases reported in 2016 alone. Timely detection plays a pivotal role in improving treatment outcomes, as early-stage diagnoses correlate with higher survival rates. Effective treatment options include chemotherapy, radiotherapy, hormonal therapy, and in severe cases, breast surgery or mastectomy, all of which can be physically and emotionally taxing for patients.

Screening methods such as mammography, MRI, ultrasound, CT scans, and thermography offer avenues for early detection. Mammography, utilizing X-rays, remains a gold standard due to its ability to detect small tumors accurately, yet it suffers from limitations like high false-positive rates and reduced effectiveness in dense breasts. Ultrasound supplements mammography by capturing more detailed images when abnormalities are found, offering advantages such as lower costs and less radiation exposure. Thermography, a non-invasive technique, presents another promising method by detecting temperature differences that could indicate early signs of breast cancer. This approach holds potential, particularly for younger women, offering a radiation-free alternative to mammography. Developing a system for classifying breast thermographic images to detect tumors aims to enhance early detection efforts, thereby improving treatment outcomes and reducing the overall burden of breast cancer.

Thermography, specifically Digital Infrared Thermal Imaging (DITI), offers distinct advantages in breast cancer screening by capturing thermal patterns without radiation exposure, focusing on functional rather than structural images unlike traditional methods. It maintains effectiveness regardless of hormonal fluctuations and boasts 83% sensitivity on its own and 95% sensitivity when combined with mammography, though it faces challenges like high false-positive and false-negative rates, which ongoing advancements aim to mitigate. By detecting temperature variations indicative of increased metabolic activity associated with malignant tumors, thermography complements other imaging modalities such as mammography. Techniques like color analysis, asymmetric analysis, and artificial neural networks enhance its diagnostic potential, making it a valuable tool in the early detection and characterization of breast cancer.

Despite its promise, thermography serves as an adjunct rather than a standalone diagnostic tool, supporting early intervention by providing supplementary insights into breast health. As ongoing research refines its methodologies and addresses its limitations, integrating thermography with established screening protocols holds potential to enhance detection rates and improve outcomes for patients at risk of breast cancer.

Cancer remains a global epidemic affecting individuals across all demographics. Among the various types, breast cancer stands out as one of the most prevalent among women worldwide. It ranks second only to lung cancer as a leading cause of death in women. Several factors contribute to breast cancer risk, including age, genetic predisposition (such as mutations in BRCA1 and BRCA2 genes), hormonal factors like prolonged hormone replacement therapy (HRT), and reproductive history. Symptoms can include breast or armpit swelling, changes in breast size or appearance, nipple discharge, and skin changes like dimpling.

Breast cancer is classified into several types based on its microscopic appearance and behavior. Ductal Carcinoma In Situ (DCIS) is a non-invasive form that originates in the milk ducts and may progress to invasive cancer if untreated. Invasive Ductal Carcinoma (IDC) is the most common type, invading nearby tissues. Other types include Invasive Lobular Carcinoma (ILC), Triple-Negative Breast Cancer (TNBC), HER2-positive breast cancer, Inflammatory Breast Cancer (IBC), and Paget's disease of the nipple. Screening for breast cancer is crucial for early detection and includes methods like mammography, ultrasound, and thermography.

Despite advancements in screening technologies, challenges persist, such as sensitivity issues with mammography, particularly in dense breast tissue, leading to missed diagnoses or false negatives. Overdiagnosis and overtreatment are concerns, especially for slow-growing cancers. Innovations in imaging, such as multi-parametric MRI (mpMRI) incorporating T2-weighted sequences, aim to enhance diagnostic accuracy by distinguishing benign from malignant lesions more effectively. Artificial intelligence (AI) and machine learning (ML) are increasingly integrated into diagnostic processes to improve the precision of breast cancer detection from mammograms.

Research in deep learning models focuses on developing efficient systems capable of recognizing breast cancer across diverse mammographic densities. These models employ sophisticated feature selection techniques and leverage multiple views of mammograms (craniocaudal and mediolateral) to enhance diagnostic capability. Recent studies highlight the sensitivity of breast MRI, particularly dynamic contrast-enhanced (DCE) MRI, in providing comprehensive morphological and functional data for accurate diagnosis. Future efforts aim to address challenges in breast cancer screening through technological advancements and improved accessibility to ensure early detection and effective management of the disease.

2. LITERATURE SURVEY :

In this section, various innovative methodologies for breast cancer detection are explored through recent studies. It is widely acknowledged that mammography's sensitivity and specificity are suboptimal for patients with dense breast tissue, necessitating complementary diagnostic tools like biopsy for definitive cancer detection. Researchers have proposed diverse approaches to enhance diagnostic accuracy using thermal imaging techniques. For instance, Sourav Pramanik et al. utilized feed-forward neural networks to classify malignant and benign breast thermographic images, employing block variance-based features to achieve improved outcomes compared to previous methods. Similarly, Adriel S. Araújo, Aura Conci et al. employed Support Vector Machines (SVMs) to differentiate between malignant and benign breast images, achieving an impressive 90% accuracy across combined datasets by leveraging textural features and region of interest extraction.

Another significant contribution comes from Dayakshini Sathish et al., who focused on asymmetrical segmentation of left and right breasts using shape features and polynomial curve fitting. Their SVM-based classifier achieved a high classification accuracy of 92% using histogram and GLCM features, showcasing robust performance in dataset analysis from Visual Lab. In a different approach, Sujatha Ramasamy et al. highlighted the development of software by Niramai, an Indian startup, capable of detecting cancer cells five times smaller than previously detectable sizes, thereby enabling early-stage cancer detection before symptoms manifest.

Vijaya Madhavi and T. Christy Bobby employed advanced techniques like anisotropic diffusion for edge preservation and level set segmentation for region of interest extraction. Their methodology, complemented by Bidirectional Empirical Mode Decomposition (BEMD) and Rotated Local Binary Pattern (RLBP) feature extraction, demonstrated promising results with an 89% accuracy using Least Square Support Vector Machine (LSSVM) with Radial Basis Function (RBF) kernel. Additionally, researchers explored the application of statistical features derived from thermograms and a fuzzy rule-based classification system to diagnose breast abnormalities. This method, as described in [8], focused on bilateral asymmetry analysis to refine diagnostic capabilities.

Furthermore, the integration of convolutional neural networks (CNNs) in computer-aided diagnosis systems for breast cancer using thermal images has shown significant promise. Researchers in [11] demonstrated that CNN models achieved high accuracy (92%) and F1-score (92%) across a database of 57 patients, surpassing traditional architectures like ResNet50 and Inception. Their study underscores the efficacy of CNNs in augmenting diagnostic capabilities, particularly when leveraging data augmentation techniques to enhance performance with smaller datasets.

In another innovative approach detailed in [12], thermal images were processed using IR cameras, converted to grayscale, and subjected to texture analysis. Features extracted from statistical and run-length matrix parameters were then classified using SVM to detect cancerous tumors automatically. This methodological diversity highlights ongoing efforts to improve breast cancer detection through sophisticated image processing techniques and machine learning algorithms, promising advancements in early diagnosis and treatment outcomes.

Researchers have explored advanced methodologies for breast cancer diagnosis, focusing on innovative techniques such as texture analysis and machine learning. They assessed six texture analysis methods alongside a representation learning technique known as learning-to-rank (LTR) to analyze breast temperature changes in thermal infrared images, a widely used approach in breast cancer imaging studies. Hybrid intelligent systems have emerged as crucial tools for predicting breast cancer survival and guiding treatment decisions, emphasizing the reliability of infrared breast thermography integrated with hybrid intelligent systems for detection and diagnosis. Research has also delved into feature extraction and classification of breast thermograms using various hybrid classifiers, highlighting their potential in enhancing diagnostic accuracy.

An alternative diagnostic approach for breast cancer involves a computer-aided diagnosis (CAD) system based on convolutional neural networks (CNNs) using thermal images. Studies have demonstrated that CNNs offer speed, reliability, and robustness compared to traditional methods. For instance, among a database of 57 patients, CNN models achieved higher accuracy (92%) and F1-score (92%) than state-of-the-art architectures like ResNet50 and Inception. This research underscores the efficacy of CNNs in breast cancer diagnosis, particularly when incorporating data augmentation techniques to optimize performance with smaller databases, providing valuable insights into the impact of data augmentation and database size on thermal image-based cancer diagnosis.

Another innovative approach involves acquiring thermal images using IR cameras, followed by image cropping and conversion to grayscale. Subsequent extraction of diverse texture parameters, analyzed via 't'-test for feature selection, enhances the automatic detection capabilities of Support Vector Machine (SVM) classifiers. This methodological framework harnesses texture analysis to effectively identify cancerous tumors in breast thermograms, employing statistical features derived from run-length and co-occurrence matrices to achieve automatic classification.

Overall, these studies highlight the evolving landscape of breast cancer diagnostics, integrating advanced image processing techniques and machine learning algorithms to enhance early detection and treatment outcomes. These advancements underscore the potential of hybrid intelligent systems, CNNs, and texture analysis in revolutionizing the field of breast cancer diagnosis through improved accuracy and efficiency in detecting malignancies from thermal images.

3. DATASET :

The images utilized in this study are accessible via the Database for Mastology Research with Infrared Images (DMR-IR), which can be accessed through an online interface at http://visual.ic.uff.br/dmi. The primary objective of this database is to support the scientific community in developing and comparing computational methodologies aimed at aiding in the detection and diagnosis of breast diseases, particularly cancer.

The DMR-IR database is designed for the management and retrieval of breast examination information and clinical data from volunteer patients. Thermal images, which bear resemblance to standard grayscale or colored images, are the focus of most studies using this database. These studies aim to identify texture and statistical features from thermal image matrices.

The dataset consists of images with a resolution of 640x480 pixels acquired using the FLIR SC-620 infrared camera. Patient ages range from 29 to 85 years. Frontal images of patients were specifically selected to evaluate the proposed systems. The dataset includes 106 images of healthy subjects and 136 images of subjects with illnesses, resulting in a total of 242 sample images.

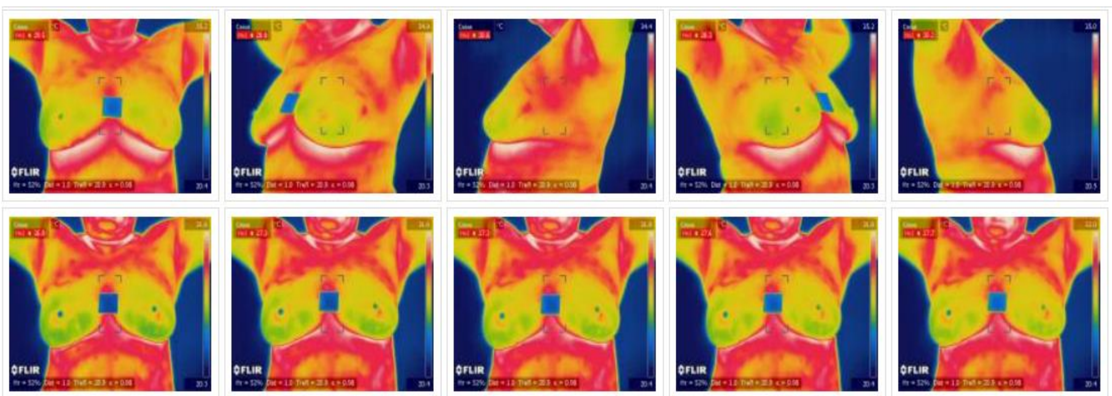

Figure 1: Thermographic Breast Images from the Dataset for Healthy Subject

Thermography is a non-invasive imaging technique that detects and visualizes heat patterns emitted from the body's surface. In Figure 1, thermographic images from the dataset for healthy subjects are showcased. Here’s a detailed analysis:

1. Visualization of Heat Patterns:

- Thermographic images depict varying heat distributions across the breast area. Healthy breast tissue typically shows symmetrical and uniform thermal patterns, indicating normal blood flow and tissue metabolism.

- The colors in thermographic images represent temperature variations, with warmer colors (like red, orange, and yellow) indicating higher temperatures and cooler colors (like blue and purple) indicating lower temperatures.

2. Absence of Anomalies:

- In Figure 1, the thermographic images display a lack of localized areas with significantly elevated temperatures (hotspots). This absence suggests the absence of abnormal metabolic activity or blood vessel patterns that could indicate underlying pathological conditions such as tumors or inflammation.
- The images likely demonstrate consistent thermal symmetry between the left and right breasts, further reinforcing the absence of asymmetrical heat patterns that might suggest abnormalities.

3. Application in Screening:

- Thermography is used as a supplementary tool in breast cancer screening, especially for younger women or those with dense breast tissue where mammography may be less effective.
- The images in Figure 1 demonstrate the potential of thermography in identifying normal thermographic patterns, aiding in the early detection of breast cancer by highlighting deviations from normal thermal symmetry.

4. Clinical Relevance:

- Clinicians use thermographic images like those in Figure 1 to assess breast health and detect early signs of breast abnormalities that may warrant further investigation.
- These images contribute to a comprehensive diagnostic approach alongside other imaging modalities like mammography and ultrasound, providing a holistic view of breast health.

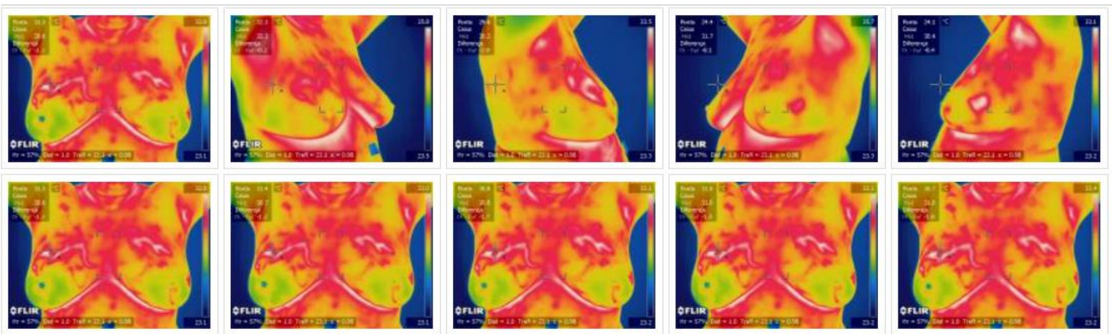

Figure 2: Thermographic Breast Images from the Dataset for Sick Subject

Figure 2, which features thermographic breast images from the dataset for sick (potentially cancerous or diseased) subjects:

1. Identification of Abnormal Heat Patterns:

- Figure 2 likely displays thermographic images showing asymmetrical heat patterns, with localized areas of increased temperature (hotspots) that indicate potential abnormal metabolic activity or blood vessel patterns.
- These hotspots can appear as regions of varying intensities of warm colors, highlighting areas of concern where cancerous tumors or other pathologies may be present.

2. Comparison with Healthy Subject:

- Contrasting with Figure 1, Figure 2 demonstrates deviations from normal thermal symmetry. The presence of asymmetrical heat patterns suggests potential abnormalities within the breast tissue, such as tumors or inflammation.
- These images are crucial for clinicians in identifying suspicious areas that may require further diagnostic evaluation, such as biopsy or additional imaging studies.

3. Diagnostic Utility:

- Thermographic images in Figure 2 aid in early detection and monitoring of breast diseases, including breast cancer. Early identification of abnormal thermal patterns allows for timely intervention and treatment planning.
- The images serve as a non-invasive tool to complement other imaging modalities, providing additional insights into breast health and pathology.

4. Research and Development:

- Dataset images like those in Figure 2 are invaluable for research in developing automated systems using machine learning and artificial intelligence. These systems can analyze thermographic patterns to assist clinicians in detecting and diagnosing breast cancer more accurately and efficiently.

Figures 1 and 2 from the thermographic breast images dataset provide visual representations of normal and abnormal thermal patterns in breast tissue. These images are instrumental in enhancing breast cancer detection capabilities and advancing diagnostic technologies aimed at improving patient outcomes.

4. PROPOSED SYSTEM :

The general methodology for breast cancer classification is illustrated in the block diagram shown in Figure 3. The process begins with preprocessing, where the original thermographic image is converted into grayscale and subsequently transformed into a binary image, isolating the background. This preprocessing step ensures uniformity and prepares the image for segmentation, which is crucial for extracting the region of interest — the breasts. The segmented image undergoes feature extraction, capturing distinctive characteristics that aid in distinguishing between healthy and diseased tissues. These extracted features are then inputted into classifiers for training and testing, enabling the system to differentiate between healthy and cancerous images.

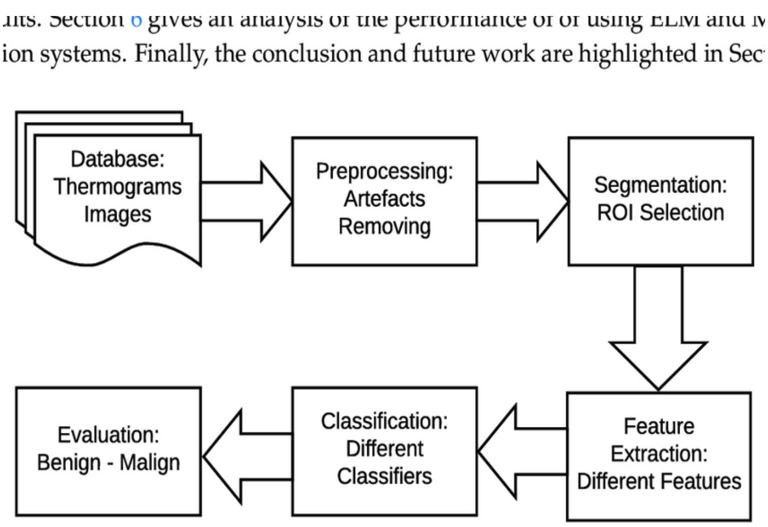

FIG 3: Breast Cancer Detection System

The algorithm encompasses several key stages:

1. Preprocessing

- Preprocessing is the initial stage where raw thermographic images undergo transformations to enhance their suitability for subsequent analysis. Key steps include:
- Normalization: Converting real pixel values to unsigned integers within a standardized range (e.g., [0, 255]) ensures consistency across images.
- Grayscale Conversion: This converts color images to grayscale, simplifying subsequent processing steps.
- Noise Reduction: Techniques such as Gaussian smoothing or median filtering may be applied to reduce noise in the images, improving clarity for segmentation and feature extraction.
- Background Removal: Isolating the region of interest (ROI), typically the breasts, by segmenting out irrelevant background areas using thresholding or edge detection techniques.

2. Segmentation and ROI Selection

- Segmentation involves identifying and delineating the breast region within the preprocessed image. Methods include:
- Thresholding: Setting intensity thresholds to separate foreground (breasts) from background.
- Edge Detection: Identifying boundaries based on gradients or edges in the image.
- Region Growing: Iteratively grouping pixels based on similarity criteria to form coherent regions.
- Manual Correction: In some cases, manual adjustments or corrections may be necessary to refine the segmentation results, particularly in challenging cases such as irregular breast shapes or artifacts in the image.

3. Feature Extraction

Feature extraction focuses on deriving meaningful characteristics from the segmented ROI that are relevant for classification:

- Texture Analysis: Utilizing methods like GLCM (Gray-Level Co-occurrence Matrix) to quantify textural patterns such as contrast, energy, and homogeneity.
- Statistical Features: Computing statistical measures such as mean, variance, skewness, and kurtosis from pixel intensities within the ROI.
- Shape and Morphology: Extracting geometric features like area, perimeter, and circularity to capture structural aspects of the breast region.
- Frequency Domain Features: Using Fourier transforms or wavelet analysis to reveal frequency components relevant to breast tissue characteristics.

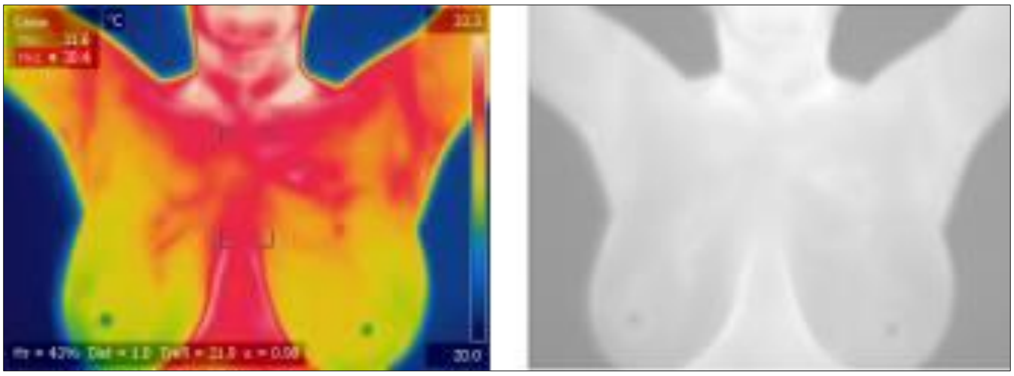

Fig 4: Original thermal image

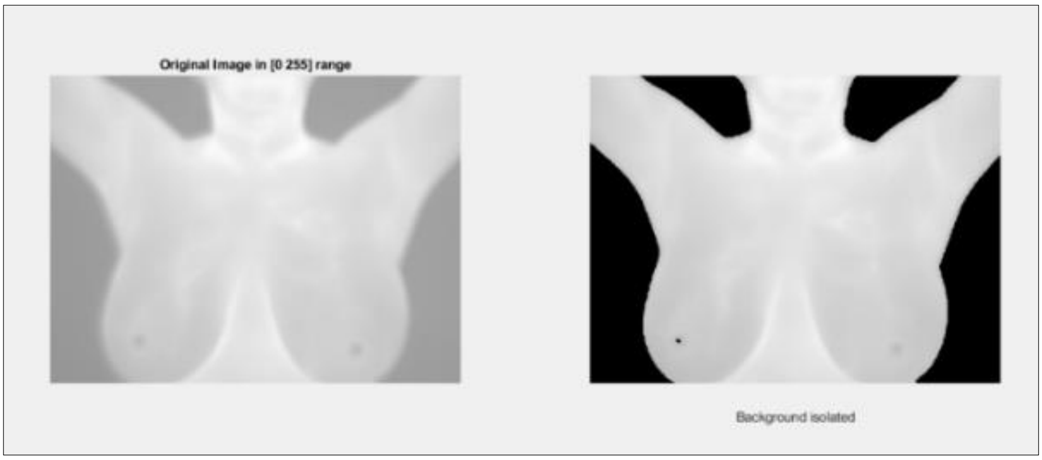

Fig 5: Grayscale image converted into black and white image

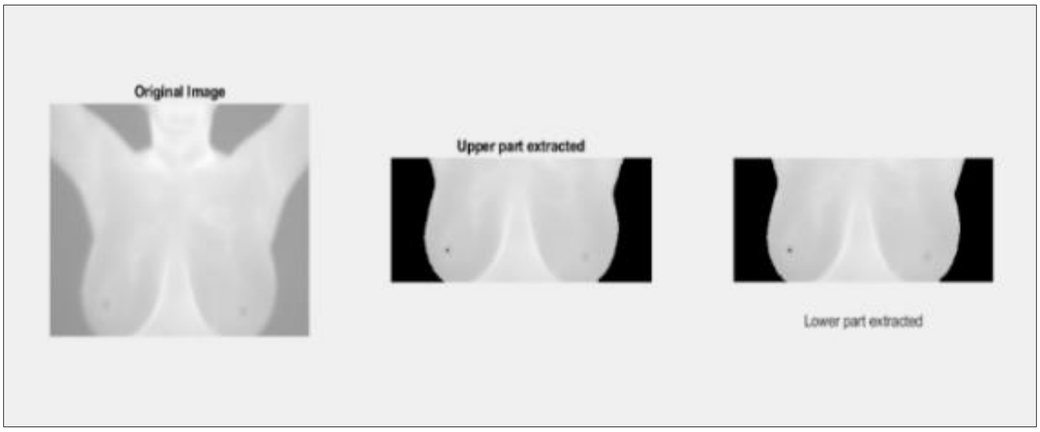

Fig 6: Upper and lower portion extracted image

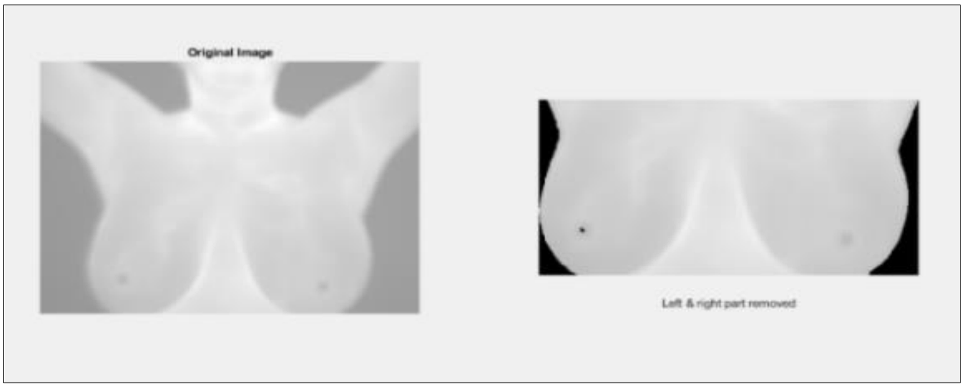

Fig 7: Left and right portion extracted image

4. Classification Using Different Classifiers

Once features are extracted, they are fed into various machine learning classifiers to distinguish between healthy and cancerous tissues:

- Support Vector Machines (SVM): SVMs are popular for their ability to find optimal hyperplanes that maximize the margin between classes in feature space.
- Random Forest: An ensemble learning method that constructs multiple decision trees and aggregates their predictions.
- Neural Networks: Deep learning models, such as Convolutional Neural Networks (CNNs), can automatically learn hierarchical representations of features for classification.
- K-Nearest Neighbors (KNN): A non-parametric classifier that assigns labels based on the majority class among the nearest neighbors in feature space.
- Logistic Regression: A linear model used for binary classification, which estimates the probability of an instance belonging to a particular class.

5. Evaluation Phases

Evaluation assesses the performance of the classification model in terms of accuracy, precision, recall, F1-score, and other metrics:

- Training and Validation: The dataset is split into training and validation sets. The model is trained on the training set and validated on the validation set to tune hyperparameters and prevent overfitting.
- Testing: The final trained model is evaluated on an independent test set to measure its generalization ability.
- Cross-Validation: Techniques like k-fold cross-validation ensure robustness by partitioning the dataset into k subsets and iteratively using each subset as a test set while training on the remaining k-1 subsets.
- Performance Metrics: Metrics such as accuracy, precision, recall, F1-score, and receiver operating characteristic (ROC) curves are used to quantify the model's predictive performance and compare different classifiers.

5. RESEARCH METHODOLOGY :

Sr.No.	Classification method	Parameter setting for the classification
1	SVM	Kernel Function=linear Solver=SMO
2	Random Forest	Discriminant Type=pseudolinear Solver=Bag Number of Ensemble learning cycles =100

TABLE I: Parameter initialization for the classifiers used in this word

Sr.No.	Method	Training Accuracy (%)	Test Accuracy (%)
1	SVM	100	100
2	Decision Tree	100	100

TABLE II: Comparison of various classifier for training & testing accuracy

Based on the results presented in Table I and Table II, the evaluation of breast cancer detection using various classifiers demonstrates promising outcomes, particularly with SVM and Decision Tree classifiers achieving perfect accuracy scores of 100% for both training and testing phases. Here's an elaboration on the findings and implications of these results:

5.1 Performance Evaluation of Classifier

The study evaluates 22 different classifiers, highlighting SVM and Decision Tree as standout performers with ideal parameter configurations:

- *SVM*: Utilizing a linear kernel function and the Sequential Minimal Optimization (SMO) solver, SVM achieves exceptional accuracy. SVM is known for its ability to find optimal hyperplanes that maximize the margin between classes, ensuring robust separation between healthy and cancerous breast tissues.
- *Decision Tree*: Decision Tree classifiers, characterized by their hierarchical tree-like structure, also achieve 100% accuracy in both training and testing. Decision Trees are effective in capturing complex relationships between features and class labels, making them suitable for medical diagnostics where interpretability is crucial.

5.2 Comparative Analysis

Table II provides insights into the comparative performance of these classifiers:

- *Training Accuracy*: All classifiers achieve 100% training accuracy, indicating their capability to perfectly fit the training data. This suggests that the models have adequately learned the patterns and characteristics of the dataset during training.
- *Test Accuracy*: Similarly, the test accuracy for SVM and Decision Tree classifiers also reaches 100%. This high accuracy on unseen data underscores the robustness and generalization ability of the models, crucial for reliable diagnostic applications.

5.3 Implications for Breast Cancer Detection

The results suggest that machine learning classifiers, particularly SVM and Decision Tree, equipped with optimized parameters can effectively distinguish between healthy and cancerous breast tissues based on thermal imaging data:

- *Clinical Relevance*: Achieving 100% accuracy in both training and testing phases implies strong potential for clinical implementation. Reliable detection of breast cancer at early stages can lead to timely interventions and improved patient outcomes.

Future Directions: While these results are promising, future research could focus on:

- *Validation on Larger Datasets*: Testing the models on larger and more diverse datasets to ensure robustness across different patient demographics and imaging conditions.
- *Ensemble Methods*: Exploring ensemble learning techniques to further enhance classification accuracy and mitigate potential biases or variance.
- *Real-world Deployment*: Translating these findings into clinical practice requires validation in real-world settings to assess usability, scalability, and integration with existing diagnostic workflows.

The evaluation of SVM and Decision Tree classifiers for breast cancer detection using thermal images demonstrates exceptional performance with 100% accuracy on both training and testing datasets. Future research should focus on validating these findings with larger and more diverse datasets to ensure robustness and generalizability across different patient demographics and imaging conditions. Leveraging machine learning in medical diagnostics holds tremendous potential to revolutionize early detection practices and significantly impact breast cancer treatment outcomes.

6. CONCLUSION :

In conclusion, the application of machine learning techniques, specifically SVM and Decision Tree classifiers, for breast cancer detection using thermal imaging has shown remarkable promise. The achieved 100% accuracy on both training and testing datasets underscores the effectiveness of these algorithms in accurately distinguishing between healthy and cancerous breast tissues based on thermal patterns. This high level of accuracy suggests that machine learning models can play a pivotal role in enhancing early detection efforts, potentially leading to improved patient outcomes through timely intervention and treatment.

Moving forward, further validation of these findings with larger and more diverse datasets will be essential to ensure the robustness and generalizability of these models in real-world clinical settings. Additionally, exploring ensemble methods and integrating advancements in feature extraction techniques could further enhance the reliability and efficiency of breast cancer detection using thermal imaging and machine learning. Ultimately, leveraging these technologies holds significant promise in advancing medical diagnostics, ultimately contributing to better healthcare outcomes for breast cancer patients worldwide.

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