# Detection of breast cancer in infrared images using Discrete Wavelet Transform and Support Vector Machine

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***Abstract*—This work presents a comparative study between two approaches which aim at helping diagnosing patients with breast cancer using thermal images. The first method uses the Discrete Wavelet Transform (DWT) for feature extraction and Support Vector Machine (SVM) to classify the patients. The other method is based on feature extraction with pretrained convolutional neural networks in conjunction with deep neural networks to perform the classification. VGG16, ResNet50 and MobileNet were considered to determine which was best suited to classify patient infrared images. Experimental results showed that DWT in conjunction with SVM presented the best performance on classifying 928 images (489 healthy and 429 sick) with 98% accuracy, 97% sensibility and 98% specificity.**

***Index Terms*—SVM, wavelet, transfer learning, CNN, breast cancer, infrared images.**

## I. Introduction

Breast cancer is a kind of cancer that most affects women around the world. The most recent global data published by the World Health Organization [1] shows that in 2020, 2.3 million new cases were detected, 685,000 women died from breast cancer and 7.8 million women who were diagnosed with breast cancer in the last 5 years survived. In Brazil, around 73,610 new cases were detected and 18,361 deaths occurred in 2022 [2]. The comparison between the number of deaths and cases shows that this type of cancer can be treated, and its detection in the early stages provides less aggressive treatments and increases the chance of complete cancer remission. Breast cancer can be diagnosed through mammography, ultrasound or magnetic resonance imaging [3]. In addition to breast self-examination, which can be done by the woman herself, mammography is the most common exam for early detection of this type of cancer. The Brazilian government's Ministry of Health recommends that women aged between 50 and 69 years undergo a screening mammography exam, which is carried out even when there are no suspicious signs or symptoms.

Thermography, or infrared imaging, has been considered as an auxiliary technique for breast cancer diagnosis. The presence of tumor changes the temperature distribution in the woman's breast, because the growth in the number of cancer cells increases the rate of metabolism and requires greater blood flow in the affected region. Excessive heat is distributed to the tissues surrounding the tumor, causing temperature spikes on the surface of the breast. These temperature peaks can be observed in infrared images [3]. It is recommended to combine other patient data, such as physiological conditions, breast size and geometry, use of contraceptives, with thermal imaging to obtain a diagnosis.

One of the requirements for evaluating whether breast cancer can be diagnosed using thermographic images is the establishment of a well-defined protocol on how to capture these images of patients, as occurs, for example, with mammography. Another important fact is the availability of infrared images databases so that the scientific community can study and develop techniques to extract information for early detection tumors emergence. Aiming to meet these needs, Silva et al. [4] developed the public Database for Mastology Research (DMR), with thermographic images and data from patient records at the Federal University Fluminense hospital. Thermal images were obtained with a FLIR SC620 thermal camera following static and dynamic protocols. In the static protocol, the patient waited 10 minutes to enter thermal equilibrium with the environment before image acquisition. Five images were then obtained, varying the patient's position. In the dynamic protocol, a thermal shock was first applied to the patient with an electric fan until the temperature between the breasts reached 30.5° or 5 minutes after the start of cooling. Next, 20 frontal images were captured, one every 1 minute, to record body thermal recovery. It was observed that the last image acquired presented the vascularization and hot spots more prominent. At the end of the examination, a right lateral image and a left lateral image were acquired at 90°.

Several image processing techniques have been applied to extract fundamental characteristics from images used in the diagnosis of various types of diseases to later be used in artificial intelligence algorithms. Mishra et. al. [5] used the Scale Invariant Feature Transform (SIFT) and Speed Up Robust Features (SURF) to extract features from thermal images and the Principal Component Analysis (PCA) algorithm to reduce the number of parameters loaded in the K-Nearest Neighbor algorithms ( KNN), Support Vector Machine (SVM), Random Forest (RF) and Decision Tree. The best results were obtained with the KNN algorithm without applying parameter reduction with PCA, resulting in an accuracy of 98.0%, 99.1% sensitivity, 96.5% Sensibility. Zavvar et. al. [6] developed a technique to classify pixels in thermal image as healthy or diseased to detect the presence of anomalies in the patient's breast. Sixteen thermal images of healthy and sick patients were used to form a balanced database with 8956 pixels. They were labeled using results from ultrasound and/or mammography exams. The best performance was obtained with the application of the PCA algorithm to extract pixel features and feed the SVM classifier, resulting in an accuracy of 68.98% and sensitivity of 95.45%. Mishra et. al. [7] developed a convolutional neural network (CNN) to diagnose breast cancer from thermal images. The model showed an accuracy of 95.8% and a sensitivity of 96.7% when analyzing images from 521 healthy and 160 patients with desease. Another very common way of using models based on convolutional neural networks is the transfer learning technique, in which the architecture of a CNN and the weigths obtained from its trainning with datasets that have a large amount of data, for example, the Imagenet which has more than 14 million images from 1000 categories, is used on the current problem. Convolutional layers extract features from images and fully connected layers are adjusted according to the application. Sharna et al. [8] carried out a study with magnetic resonance images used to detect changes in brain functions and structure, with the aim of identifying the emergence of mild cognitive impairment, which is a neurological disease that can progress to Alzheimer's. The methodology developed used the pre-trained convolutional neural network VGG16 to extract features from the images that were inserted into a neural network to classify patients. The accuracy obtained using a database with 6400 images of patients classified as healthy and with very mild, mild and moderate dementia was 90.4%. Gonçalves et. al. [9] evaluated the performance of the VGG16, Densenet201 and Resnet50 networks for classifying thermal images of patients from the DMR database obtained by the static protocol. Experiments were carried out with images of patients in different positions and only with frontal images. The best results were obtained with 38 frontal images of each class using CNN Densenet201 with images in gray scale and without data augmentation, resulting in accuracy of 91.67%, sensitivity of 100% and specificity of 83.33%.

The main contribution of this work is that although convolutional neural networks are currently the most widely used method for evaluating images in the medical field, the use of conventional techniques, such as the proposed approach, should not be discarded and can present results as good as or even better than more modern techniques, but with greater complexity in their implementation.

TABLE I
COMPARISON OF THE PROPOSED METHODS PERFORMANCE WITH WORKS PUBLISHED RECENTLY

| Ref. | Methodology | | Results (%) | |
|---|---|---|---|---|
| | Feature extraction | Classifier | Acc | Sens |
| [5] [5] | SIFT and SURF | KNN | 98.00 | 99.10 |
| [6] | PCA | SVM | 68.98 | 95.45 |
| [7] | CNN | | 95.80 | 96.70 |
| [9] | Densenet | | 91.67 | 100.00 |
| Proposed 1 | DWT | SVM | 98.00 | 97.00 |
| Proposed 2 | Resnet 50 | | 83.00 | 97.00 |

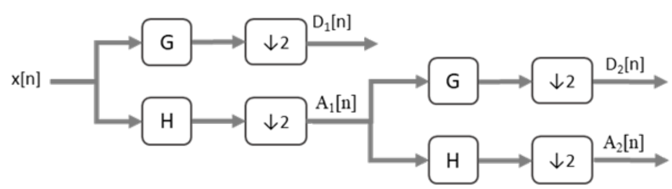


Fig. 1. Decomposition of the signal $x[n]$ in details and approximations

## II. OVERVIEW

This work presents a new technique to classify infrared images of breast cancer patients by combining the Discrete Wavelet Transform (DWT) for images feature extraction with the Support Vector Machine for classification. In order to evaluate its performance, it was made a comparison with another widelly used approach based on transfer learning with pre trainned CNN, such as ResNet 50, VGG16 and MobileNet. Table I shows the accuracy (Acc) and sensitivity (Sens) obtained in this work and in recent works published in this area. Results showed that the proposed methodology presented high leves of accuracy and sensibility of 98% and 97%, respectively, that were superior to or very close to those published in other researches.

## III. FEATURE EXTRACTION

### A. Discrete Wavelet Transform

The wavelet transform is a signal processing technique used to represent characteristics in the frequency and time-space domains, allowing the location of low and high frequency components contained in the original signal. Its two-dimensional version is used in several applications in the area of image processing, such as image compression, fingerprint recognition, facial recognition, among others [10].

Mallat demonstrated that the wavelet transform can be calculated using a pyramidal algorithm based on the convolution of a signal with quadrature mirror filters, as illustrated in Fig. 1 [11].

The approximation coefficients $A_1[n]$ is a lower resolution version of the original signal $x[n]$, get at low pass filter (H) output. The detail coefficients $D_1[n]$, obtained at high pass filter (G) output, is the difference between x[n] and $A_1[n]$. The approximation and detail coefficients are subsampled so

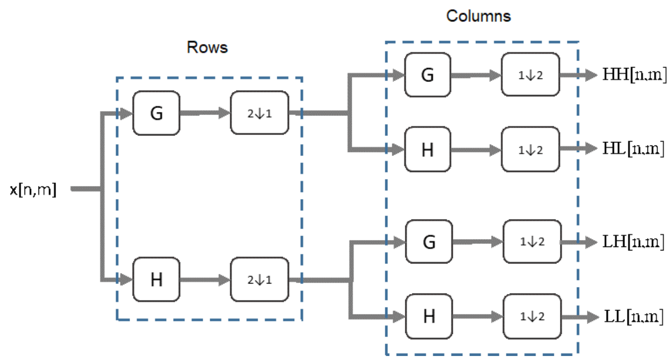


Fig. 2. Decomposition of the image $x[n, m]$ into its coefficients of approximation and horizontal, vertical and corner details

that the decomposed signal has the same number of samples as the original signal.

Multiresolution analysis consists of decomposing the signal into details corresponding to the difference in information contained in two successive resolutions of the signal. In image processing, filters are applied to signals in horizontal and vertical directions that form the image. Fig. 2 shows a schematic illustrating how the image is decomposed using the two-dimensional wavelet transform.

### *B. Feature extraction using CNN*

Convolutional neural network (CNN) is a type of artificial neural network specialized in detecting and understanding patterns, which makes them ideal for image processing applications. Its design was inspired by the hierarchical representation of animal neurons, developed by Hubel and Wisel in 1962 in a study on stimuli in the visual cortex of cats [12].

Neurons are organized into layers capable of detecting visual patterns through features extracted from images. The combination of these characteristics generates a high-level representation of the image. A CNN is made up of a series of layers in which each one has a specific function.The raw data is fed into the input layer. The convolutional layers are responsible for extracting the feature map from the input image by performing convolution between the image pixels and the kernel. The filtered data goes through a dimensionality reduction layer. Then, the image feature map is fed into fully connected neuron layers to perform image classification. One way to use CNN to solve a problem is through the transfer learning technique. In this case, neural networks with a defined architecture and pre-trained with databases with a large number of samples are used as a starting point to extract features from the images of the current problem. In this way, the CNN takes advantage of previously acquired knowledge and does not need to be trained from scratch, which would require a large number of samples and computational power. AlexNet, VGG16 Net, Inception Net, ResNet and DenseNet are examples of CNNs used in medical image classification applications.

VGG16 is composed of 16 layers, 13 convolutional layers organized into 5 blocks for feature extraction and 3 fully connected for classification. The input layer receives images in 224x224x3 format. Convolution is done with a 3x3 kernel and stride 1. The first and second blocks have two convolutional layers with 64 and 128 filters, respectively. The remaining blocks have 3 convolutional layers with 256, 512 and 512 filters, respectively. At the end of each block there is a 2x2 max-pooling layer with a stride of 2 for dimensionality reduction. The fully connected layers are formed by two layers with 4096 neurons and an output layer with 1000 neurons, 1 for each class in the imagenet database. The use of a reduced kernel size made VGG16 outperform other state-of-the-art networks around 2014 [13].

Very deep neural networks present a problem known as vanishing gradient. The gradient that updates the synaptic weights of deeper layers can become very small during back-propagation, making neural network learning difficult or even unfeasible. Resnet is a deep CNN inspired in VGG architecture, with up to 152 layers, which uses shortcut connections, allowing the gradient from one layer to propagate to a deeper one [14].

In 2017, Howard et. al. proposed a convolutional neural network architecture to run computer vision applications on mobile and embedded devices [15]. In order to obtain an efficient model optimizing memory and reducing computational costing, this CNN is based on depthwise separable convolution to minimize the model parameters. This operation first applies depthwise convolution to filter input data and a 1x1 pointwise convolution to combine the extracted features. The basic architecture of MobileNet is made up of 28 layers, counting depthwise and pointwise as separated layers. It also has the parameters width multiplier and resolution multiplier to provide a smaller and faster model.

## IV. Methodology Description

This section presents the steps involved in each of the approaches used to classify infrared images, as well as describes database used in the experiments and defines metrics for evaluate the results. Fig. 3 illustrates the techniques used in each stage of the two methodologies proposed for image classification. In one of the approaches, the 2D discrete wavelet transform extracts features from images, generating input data for classic machine learning algorithms to perform classification. In the other, image features are extracted using the transfer learning technique with convolutional layers of pre-trained CNNs and classification is performed by fully connected layers.

### *A. Database*

In this work, 918 images of 259 patients were used from the public Database for Mastology Research (DMR), created by the Visual Lab of the Universidade Federal Fluminense (UFF) [6]. This database provides patients' thermal images and some data, such as age, body temperature at the time of the exam, menarche , among others. Patients are categorized as healthy or sick. For each patient, 3 images from the dynamic protocol were considered, being the last frontal image, the left lateral

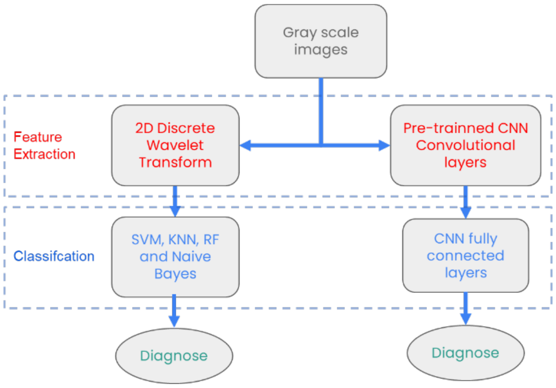


Fig. 3. Workflow of the two approaches to diagnose thermographic images to diagnose breast cancer

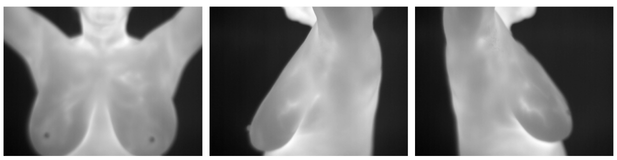

Fig. 4. Front, left and right side images of a healthy patient.

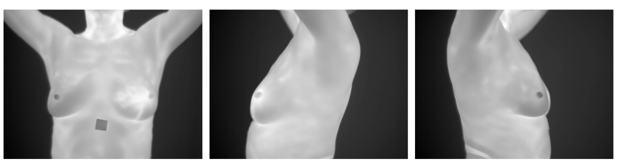

Fig. 5. Front, left and right side images of a healthy patient.

view and the right lateral view, resulting in 489 images of healthy patients and 429 sick ones. Each heat map image is composed of a 480 x 640 matrix with the temperature of the points that form it. These values were converted from float point to uint8 format. Fig. 4 and Fig. 5 show the images of a healthy and a sick patient, respectively.

### *B. DWT and Classical Machine Learning*

The performance of classifiers can be improved by pre-processing the data to extract features that emphasize the category to which a sample belongs. One of the widely used techniques for image feature extraction is the bidimensional Discrete Wavelet Transform (DWT). In this work, the `dwt2` function from the `pywt` library was used to implement the 2D wavelet transform on each of the standardized images. Standardization was done using the Z-score metric through the `StandardScaler` function from the `sklearn.preprocessing` library. The Daubechies wavelet of level 8 (db8) was chosen as the mother wavelet due to its balance between time and frequency localization, which makes it suitable for medical image analysis.

The features extracted from the images were divided into two groups, 80% for training and 20% for testing using the train_test_split tool from the Sklearning model_selection library. The KNN, SVM, Random Forest and Naive Bayes algorithms were implemented by the KNeighborsClassifier, SVC, RandomForestClassifier and GausianNB functions, from the neighbors, SVM, ensemble and naive_bayes libraries of the Sklearn package, respectively. The performance of the models were evaluated using the confusion matrix and classification report, implemented using the confusion_matrix and classification_report functions from the Sklearn metrics library. The accuracy (Acc), sensitivity (Sen) and specificity (Esp) metrics obtained from the classification report were calculated as:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Sen = \frac{TP}{TP + FN} \tag{2}$$

$$Esp = \frac{TN}{TN + FP} \tag{3}$$

where TP corresponds to sick patients classified as sick, TN to healthy patients classified as healthy, FP to sick patients classified as healthy and FN to healthy patients classified as sick.

### *C. CNN feature extraction and classification*

In the transfer learning experiments, only frontal images resized to 224x224 resolution were used. This decision was made after testing with lateral images (right and left side views), which did not perform as well as frontal images. The images were divided into two sets, 80% (129 healthy and 95 sick) for training and validation and 20% (34 healthy and 23 sick) to test.

Feature extraction from the images was done using the convolutional layers of the VGG16, MobileNet and ResNet50 networks, pre-trained with the ImageNet [16] database and the top layer Global Average Pooling. To classify the images, 3 fully-connected hidden layers were inserted with 512, 256 and 128 neurons using ReLU activation function. After each of these layers, a batch normalization layer and a 30% dropout layer were inserted for regularization. The output layer has a neuron and Sigmoid activation function for binary classification. The optimizer used was the Adam algorithm with learning rate 0.001 and binary cross entropy as loss function. The training was carried out considering 30 epochs without early stop.

## V. Results and Discussions

Table III shows accuracy, sensitivity and specificity obtained in images classification without the feature extraction step, i.e., the models were fed with grayscale images and standardized with the Z-score metric. Considering the three metrics for evaluating model performance, SVM presented the best result. Although 78% accuracy might seem a good result, 71% sensitivity is a low level for classifying sick patients.

The results obtained by the models classification with the features extracted from the images using the 2D wavelet transform are presented in Table IV. In general, the Naive

TABLE II

PERFORMANCE METRICS OF CLASSIC MACHINE LEARNING MODELS FOR RAW IMAGES

| Model | Model performance metrics | | |
|---|---|---|---|
| | Accuracy(%) | Sensibility (%) | Sensitivity (%) |
| KNN | 68 | 53 | 81 |
| SVM | 78 | 71 | 84 |
| Random Forest | 78 | 70 | 84 |
| Naive Bayes | 66 | 61 | 71 |

TABLE III

PERFORMANCE METRICS OF CLASSIC MACHINE LEARNING MODELS FOR FEATURES EXTRACTED FROM THE IMAGES USING DWT

| Model | Model performance metrics | | |
|---|---|---|---|
| | Accuracy(%) | Sensibility (%) | Sensitivity (%) |
| KNN | 54 | 100 | 15 |
| SVM | 91 | 91 | 91 |
| Random Forest | 75 | 54 | 93 |
| Naive Bayes | 87 | 86 | 87 |

Bayes and SVM models improved their performances, with the latter showing the best performance among the models evaluated. The accuracy, sensitivity and specificity of the SVM classifier reached 91%. This proves that the image feature extraction step is essential to improve classification.

The results of models classification presented were obtained for models tunned with the standard hyperparameters provided by the Sklearn package. For the SVM model that presented the best result, it was made a fine tunning on the hyperparameters to further improve its performance, as well as evaluating its generalization capacity for the data using the cross-validation technique using the GridSearchCV function from the model_-selection library in the Sklearn package. The hyperparameters grid was configured with the rfb and sigmoid kernel functions, C regularization was tested with values 0.1, 1, 10 and 100, and for gamma the values 1, 0.1, 0.01 and 0.001 were tested. Cross-validation was set up to divide the data into 10 folds. Accuracy was used to evaluate the classifier result for each tested configuration.

After the fine tunning procedure, the best hyperparameters were the following: kernel function=sigmoid, c=10 and gamma=0.01. The average accuracy in the cross-validation test was 95.1%. This result demonstrates that the model is suitable for classifying patients with data extracted from thermal images. The optimization of the hyperparameters of the SVM model resulted in a significant improvement in its performance, resulting in an accuracy of 98%, sensitivity of 97% and specificity of 98%. Fig. 6 shows the confusion matrix of the SVM model trained with the optimized hyperparameters. Only two among the 80 sick and 2 among the 95 healthy patients were misclassified.

Fig. 7 shows the percentage values of accuracy, sensitivity and specificity obtained with the pre-trained CNN. Each model showed better performance in a given metric, where VGG16 had the best accuracy of 86%, ResNet50 achieved sensitivity

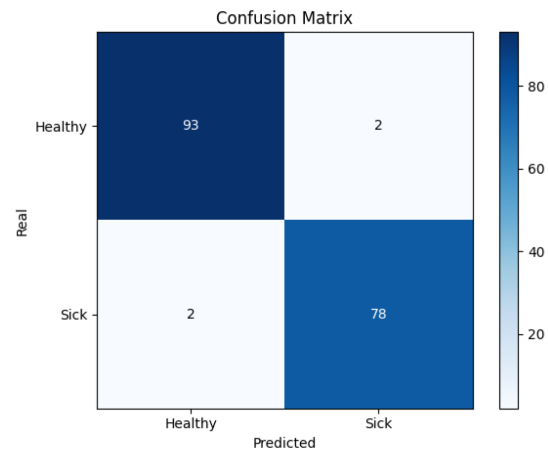


Fig. 6. Confusion matrix of the optimized SVM model

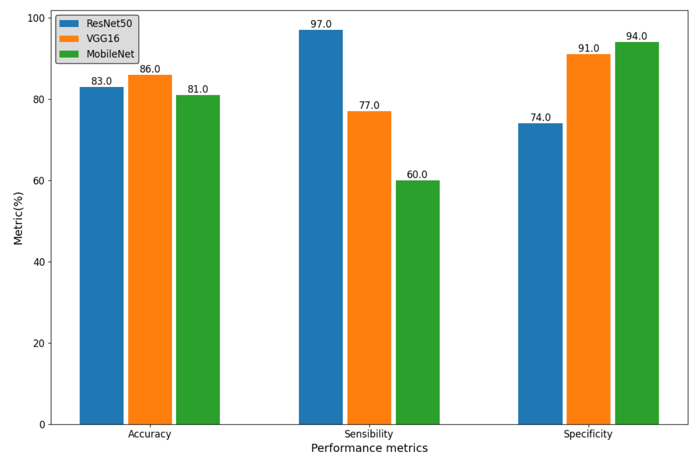


Fig. 7. Accuracy, sensitivity, and specificity for the pre-trainned networks ResNet50, VGG16 and MobileNet

of 97% and the best specificity of 91% was obtained with MobileNet. It is important to note that although VGG16 showed the highest accuracy, it is important to analyze the sensitivity together, because in the case of classifying cancer patients, it is very important that the sick ones are correctly classified. A failed diagnosis can compromise the possibility of the patient starting early treatment, increasing the chances of a cure. Therefore, ResNet50 presented the best set of metrics, with accuracy of 83%, sensitivity of 97% and specificity of 74%. Among the 23 sick patients, 22 were classified correctly and the model misclassified 9 among the 34 healthy patients.

## VI. CONCLUSION

The development of artificial intelligence algorithms combined with techniques for feature extraction from infrared images are an important tool to assist in the diagnosis of breast cancer. In this work, the results of two approaches were presented using the bidimensional discrete wavelet transform combined with classic machine learning algorithms and the feature extraction through convolutional layers of pre-trained

CNN with resizing of fully-connected layers for the binary classification problem. The best results were obtained using the first approach with the SVM algorithm, which presented an accuracy of 98%, sensitivity of 97%, and specificity of 98%, compared to the results of the second approach with ResNet50, which presented an accuracy of 83%, sensitivity of 97%, and specificity of 74%. This finding contradicts the common expectation that CNNs, especially those pre-trained on large datasets like ImageNet, always outperform more traditional machine learning methods. This difference in performance can be attributed to several factors. Firstly, the dataset size is a crucial aspect. CNNs are highly parametric models that require large amounts of data to avoid overfitting and to effectively extract relevant features from the images. When the dataset is limited, as in the present study, CNNs may not have enough data to generalize adequately, resulting in a loss of performance. In contrast, SVM, in combination with DWT, is less susceptible to overfitting due to its ability to work effectively with smaller datasets. Another point to consider is the specificity of the features extracted by DWT. DWT is a powerful tool for multiscale signal analysis, allowing the decomposition of images into components that capture both high and low-frequency information. This feature extraction approach can provide a more informative and compact representation of thermal images, facilitating the classification task for algorithms like SVM. The manual feature extraction with DWT may, therefore, offer an advantage when compared to the automatic approach of CNNs, which rely solely on their ability to learn these features from raw data. Furthermore, the use of transfer learning in CNNs, although widely adopted, may have limitations when applied to domains significantly different from those for which the network was originally trained. In the case of this study, the networks were pre-trained on natural images (ImageNet), which have very different visual characteristics from the thermal images used. This may have led to less effective extraction of relevant features for breast cancer detection, contributing to the inferior performance of CNNs. Finally, the intrinsic regularization of classical algorithms like SVM plays a crucial role in preventing overfitting and improving generalization ability, especially in scenarios with limited data. The careful optimization of SVM hyperparameters in this study demonstrates how these models can be effectively tuned to maximize performance, resulting in high accuracy, sensitivity, and specificity. In summary, although CNNs are powerful tools widely used in image processing applications, the results of this study highlight that, in situations with smaller datasets and specific characteristics, traditional methods such as the combination of DWT and SVM may still offer a more robust and effective solution.

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## Author Contributions

Antonio Marcio Crepaldi Júnior, Pablo Rodrigo de Souza, and Nelson Luciano da Silva Neto were responsible for the conceptualization, implementation of the model, analysis of results, and drafting of the manuscript. Dimas Augusto Mendes Lemes and José Guilherme Picolo contributed to the interpretation of results and review of the manuscript. Guilherme Ribeiro Sales, Valentino Corso, and Cides S. Bezerra contributed to the conceptualization, supervision, interpretation of results, and final revision of the manuscript.

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