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Wavelet-Convolutional Neural Network: An Improved Deep Learning Model for Breast Cancer Detection from Histopathology Images

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ABSTRACT

Background: Invasive ductal carcinoma (IDC) is a prevalent type of breast cancer with significant mortality rates. Early detection is crucial for effective treatment options. Deep learning techniques have shown promise in medical image analysis, but further improvements are needed.

Methods: A Wavelet-Convolutional Neural Network (WCNN) is proposed, incorporating wavelet filters and convolutional filters in each layer to capture both frequency and spatial domain features. The processed images resulting from both types of filters were combined and passed through a MaxPooling layer to extract salient features. Four such hybrid layers were considered for extracting effective features. This novel approach allowed the model to effectively learn multi-scale representations, leading to improved performance in breast cancer classification tasks. The model was trained and evaluated on a publicly available breast histopathology image dataset.

Results: The proposed WCNN achieved a classification accuracy of 98.4% for breast cancer detection, outperforming existing state-of-the-art models.

Conclusion: The WCNN framework demonstrated the potential of combining wavelet and convolutional filters for improved breast cancer detection, offering a promising approach for early diagnosis and better patient outcomes.

INTRODUCTION

The ongoing process of digitizing pathology aims to automatically detect and diagnose numerous medical conditions. This process requires continual development due to the increasing amount of data acquired from patients. Invasive ductal carcinoma is the predominant form of breast cancer, accounting for 80% of all cases in this category. Prompt identification and diagnosis of such illness are crucial for the patient's life. Several techniques are being utilized to acquire breast cancer images, such as Magnetic Resonance Imaging (MRI). Ultrasound (US), mammography, and histopathological imaging techniques. Histopathology images offer a comprehensive depiction of tissue structure, enabling thorough investigation at the level of the nucleus to identify any developing abnormalities. Traditional diagnostic methods, such as mammograms and biopsies, can be invasive and may not always be accurate. Therefore, there is a need for more accurate and non-invasive methods for early detection of breast cancer.

Understanding the causes of breast cancer before assessing the diagnosis procedure is crucial. Genetic disorders associated with family history account for 10-15% of breast cancer cases. BRCA1 carriers have an 80% probability of developing breast cancer before 50 or after 80. Both endogenous and exogenous hormones affect breast cancer. Lifestyle and food consumption matter, especially for heavy

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drinkers and smokers. [1,2] Exposure to chemicals, electromagnetic fields, and ionizing radiation causes breast cancer. [3] Breast cancer is also linked to underarm cosmetics. Current breast cancer conditions affect treatment. Some tumors are smaller but grow faster, while others are larger at diagnosis but develop slower. Most cancer experts recommend surgery initially for patient survival. [4-6] Other therapies include chemotherapy, targeted therapy, hormonal therapy, and radiation therapy. Invasive ductal carcinoma, invasive lobular carcinoma, Paget's disease of the nipple, inflammatory breast cancer, phyllodes tumors, locally progressed, and metastatic breast cancer are all types of breast cancer.

The potential contributions of this work are mentioned in the following points:

- Novel Deep Learning Architecture: We propose a novel deep learning architecture, Wavelet-Convolutional Neural Network (WCNN), which integrates wavelet filters directly into the convolutional layers. This innovative approach allows the model to capture both frequency and spatial domain features more effectively.
- Enhanced Feature Extraction: By incorporating wavelet filters, the WCNN model can extract more comprehensive and discriminative features from histopathology images, leading to improved classification performance.
- State-of-the-Art Performance: Our proposed WCNN model achieves state-of-the-art performance on a publicly available breast histopathology image dataset, demonstrating its effectiveness in breast cancer detection.
- Practical Implications: This research contributes to the development of more accurate and reliable computer-aided diagnosis systems for breast cancer, which can aid in early detection and improve patient outcomes.

The novelty, the hypothesis, the dataset and the results of this work are described as follows:

- This work uses wavelet transformation as a part of the CNN model instead of using wavelet transformation as a pre-processing step like other works.
- The following hypothesis is considered for this work: Integrating wavelet filters into the convolutional layers of a deep learning model will enhance feature extraction from histopathology images, leading to improved accuracy in breast cancer detection compared to traditional CNN models.
- The improved architecture is used for breast cancer detection from a histopathology image dataset that is publicly available in Kaggle.
- The proposed Wavelet-Convolutional Neural Network (WCNN) model demonstrated superior performance in breast cancer detection compared to traditional CNN models. By integrating wavelet filters into the convolutional layers, the model was able to extract more comprehensive and discriminative features from histopathology images, leading to improved classification accuracy and robustness.

The rest of the manuscript is structured as follows. Section 2 discusses the recent developments in breast cancer detection. Section 3 lays out the specific procedures followed to build the suggested approach; Section 4 is devoted to the outcomes of this methodology and comparisons in different formats; the method and results are discussed in Section 5. Section 6 provides a summary of the entire work and an outlook for its future.

Related Works

In recent decades, numerous works have been developed for the automated detection of cancer from image inputs, a few of which are discussed in this section.

Small and large mitotic counts in breast histopathology images indicate the severity of invasive breast cancer and tumor progression. Counting little mitosis is difficult for the human eye. [7] Some researchers have employed an atrous fully connected convolutional network (A-FCN) and a multi-scale faster regional convolutional neural network. [8] Radial-Based Function Kernel Extreme Learning Machine method has been used which adjusts parameters using differential evolution. A-FCN was utilized to generate the bounding box for large and small mitosis in breast histopathology images, and MS-RCNN was used to detect them. A single convolutional neural network (CNN) model can extract picture information, but two models create and classify bounding boxes, making the process complicated. This method's F scores on ICPR-12, ICPR-14, and AMIDA-13—0.902, 0.495, and 0.644—need to be improved for biomedical image processing. [9] For multi-class classification, Liu *et al.* presented a collaborative transfer network (CTransNet) with a transfer learning backbone that could extract and predict from the optimum fused features with an accuracy of 98.29%. [10] Deep learning-based models like ResNet, DenseNet, VGG-16, scale-invariant feature transform (SIFT), Global Image Structure Tensor (GIST), Histogram of oriented gradients (HOG), and local binary pattern (LBP) extract features, which are then processed using RCA (refinement, correlation, and adaptation). The final classification is done using a Gradient-boosted decision trees (GBDT) classifier. Despite complicated feature selection, classification accuracy must be improved. [11] Machine learning model has been combined with Principal Component Analysis (PCA), Multi-Layer Perceptron (MLP), and Support Vector Machine (SVM) to identify breast cancer. PCA reduces feature size, and then MLP uses the results. The final categorization is done by deleting the last MLP layer and connecting MLP to SVM. Their transfer learning-based classification of the Breast Cancer Coimbra Dataset (BCCD) yielded an accuracy of 86.975. This method needs to improve its accuracy to compete with deep learning. [12] Vijayarajeswari *et al.* retrieved mammography characteristics using two-dimensional Hough transform and classified data using SVM. [13] For training, 152 patients were imaged and stained with ER, PR, and Ki-67. For validation, 366 samples from 98 strangers were gathered. VGG-16 CNN model was pre-trained with ImageNet. Two skilled pathologists confirmed the results. The accuracy of this approach (88%) needs to be improved to compete with state-of-the-art approaches. [14] Wu and Hicks used retrieved attributes at different threshold levels to classify breast cancer as triple negative or non-triple negative. The classification was done using NB, KNN, DT, and SVM models. The SVM classifier outperformed other ML models in accuracy, sensitivity, and specificity.[15]

A deep learning-based breast cancer detection model uses AdaBoost for classification improvement. Deep learning uses CNN-based ensemble learning and a Sparse Autoencoder (SAE). Some researchers verified this method using MRI, ultrasound, and mammography images and achieved 97.2% accuracy. Mammography has also been used to detect breast cancer. [16] Alzubaidi *et al.* explored the use of transfer learning for classifying biopsy images into four categories. They experimented with two approaches: 1) training on a related dataset followed by fine-tuning on the target dataset, and 2) training on a dissimilar dataset followed by fine-tuning. Their method demonstrated impressive results, achieving an image classification accuracy of 97.4%.[17] Other studies employed deep learning with minimal pooling modifications to interpret mammography breast pictures differently. Cancerous breast tissue was segmented using global and region-based pooling. Method validation was done using CBIS-DDSM and InBreast datasets. The accuracy was 0.93 for the InBreast dataset but 0.76 for the CBIS-DDSM dataset, which needs to be improved for biomedical image processing that concerns life risk.[18] 3-dimensional CNN architecture has been used in automated breast ultrasound (ABUS) for cancer detection. The threshold loss is indicated for classifying non-cancer and cancer breast pictures. The proposed approach was tested on ABUS. In this strategy, the authors achieved 95% sensitivity and 0.61 F1-score. Therefore, biomedical image classification with this finding needs more analysis and performance improvement.[19]

A deep CNN model and multi-instance-based learning have been used to detect breast cancer in histopathology images. The authors divided histopathological slide images into patches and trained CNN architecture on them, with multi-instance pooling added to the CNN model. The authors tested the model on the BreakHis dataset and found 93.06% accuracy, with the accuracy of the IUPHL dataset being 96.63%, and that of the UCSB dataset being 95.83%. Thus, classification accuracy needs to be enhanced with simple design for easy implementation. [20] Transfer learning-based residual CNN model has been proposed for histopathology image analysis by Gour *et al.* for cancer detection. Data augmentation techniques such as stain normalization, image patch generation, and affine transformation were applied before the deep learning model application. This method provided 92.52% accuracy that needs to be improved. [21] Some studies have proposed CNN for breast histology image processing to classify invasive ductal carcinoma from healthy breast pictures, classifying lymphoma subtypes using the same technique. For example, one study used the residual CNN model from FusionNet architecture, an autoencoder to verify the model on the [22] dataset available for download and achieved 87.67% IDC detection accuracy, 81.54% F1 score, and 97.67% lymphoma classification accuracy. The researchers concluded that IDC detection findings for early-stage breast cancer diagnosis must be improved.[23]

Classifying Multilayer Perceptron and Light GBM classifiers have been used in one study to analyze histopathology images for breast cancer detection. Multilayer Perceptron model was used for feature extraction whereas Light GBM was applied to classify the features and that model provided 98.28% detection accuracy. [24] Sampath and Srinath proposed a new technique, called Hybrid CNN, which combined the Sine Cosine Algorithm (SCA) with transfer learning (TL). It was proposed that this framework leverage TL to pre-train the VGG16 network on ImageNet, while the final three convolutional layers were fine-tuned using TL. SCA was employed to optimize hyperparameters. [25] Shallu and Sumit proposed a hybrid model using Xception as a feature extractor and SVM with RBF kernel as the classifier. Different magnification values , i.e., 40X, 100X, 200X, and 400X were also applied to observe the variation in performance. In that way, authors were able to achieve 96.25% accuracy with 40X and 100X magnification, 95.74% with 200X and 94.11% with 400X magnification. [26] In another work, ten different pre-trained CNNs were used for extracting features from breast cancer histopathology images. A linear support vector machine was employed to develop classification models for the various feature sets generated by those pre-trained CNNs. The features extracted using ResNet50 and the classification using SVM provided 92.40% accuracy that was the highest among all other combinations. [27] In another work, Aldakhil *et al.* used augmentation for class balancing as pre-processing step prior to classification using a modified deep learning model named as ECSAnet. In this work, stain normalization was used, achieving 94.2% accuracy. [28] Transfer learning-based deep neural network (DNN) model and XGBoost have been combinedly used for cancer detection. The method utilized the strengths of deep neural networks and XGBoost, but the complexity of the model increased due to the considered steps. That model provided 93.6% accuracy in detecting cancers from histopathology images. [29] Wavelet transformation has been used as a pre-processing step prior to training by CNN model, with a good accuracy of 98.08% in breast cancer detection.

The advantages and disadvantages of discussed recent works are summarized in Table 1.

Table 1. Advantages and disadvantages of the related works

Ref.	Method	Advantages	Disadvantages
[7]	A-FCN for segmentation and MS-RCNN for classification	Combination of A-FCN and MS-RCNN effectively improves the detection accuracy	Increased computational complexity due to series actions of the steps considered.
[8]	RBF-KELM	The optimization of RBF-KELM parameters using DE can improve the model's classification accuracy	RBF-KELM relies on fixed kernel functions, which may limit its ability to capture complex patterns in the data.
[9]	CTransNet	CTransNet architecture effectively combines transfer learning and residual learning	The large-scale DenseNet model used in this work can be computationally expensive to train and deploy.
[10]	ResNet, DenseNet, VGG-16, SIFT, GIST, HOG, and LBP features and RCA classifier	The model's ability to handle limited data through feature selection helps mitigate the overfitting problem	The feature selection and classification processes can be computationally expensive
[11]	PCA + MLP + SVM	PCA effectively reduces the dimensionality of the data, potentially enhancing model performance.	The combination of PCA, MLP, and SVM can increase the complexity of the model,
[12]	Hough Transform + SVM	Hough Transform is a robust technique for detecting specific shapes in images, making it suitable for identifying circular or elliptical masses	SVM classifiers can be prone to overfitting, especially when dealing with large datasets.
[13]	Pre-trained CNN	The deep learning-based digital mask automates the process of identifying epithelial cells.	The model's performance may be affected by staining inconsistencies.
[14]	SVM	The use of feature selection techniques helps identify the most relevant genes for classification.	Use of SVM with large dataset is not a good choice.
[15]	CNN + LSTM for feature engineering and DLA-EABA for classification	Use of deep learning techniques, such as CNNs and LSTM, allows for the extraction of complex features from medical images.	Increased computational complexity due to series actions of the steps considered.

[16]	Hybrid CNN	Improved features	Increased computational complexity due to series actions of the steps considered.
[17]	CNN with special pooling structures	Reduced annotation effort, End-to-End learning by using deep learning model.	Mammograms can be affected by noise and artifacts.
[18]	ABUS	Provides 3D views of the whole breast, Low false positives.	It is a time-consuming image review process. Also there is a potential for errors by oversight during review.
[19]	CNN	The MIL-based approach effectively handles the large size of WSI images.	The quality of the extracted patches can significantly impact the model's performance.
[20]	Residual Learning CNN	Application of data augmentation techniques helps to improve the model's generalization ability and reduces overfitting.	Stain normalization, image patch generation, and affine transformation increase methodological complexity.
[21]	CNN + Autoencoder	It effectively combines the strengths of convolutional neural networks and autoencoders	Increased computational complexity due to series actions of the steps considered.
[23]	MLP + LightGBM	Improved features	Increased computational complexity due to series actions of the steps considered.
[24]	SCA + CNN	Improved features	Increased computational complexity due to series actions of the steps considered.
[25]	Xception + SVM	Improved features and analyzing the effect of magnification of images	Increased computational complexity due to series actions of the steps considered.
[26]	ResNet 50 + SVM	Improved features. Analysing the performance of SVM trained with Deep features	Increased computational complexity due to series actions of the steps considered.
[27]	Data Augmentation + Stain Normalization + ECSAnet	Class imbalance is addressed and stain normalization is done	Increased computational complexity due to series actions of the steps considered.
[28]	Transfer Learning-based DNN features + XGBoost classifier	Combines the strengths of deep neural networks and XGBoost	Increased computational complexity due to series actions of the steps considered.
[29]	(EWT+DWT) features + CNN classifier	Good feature engineering is done	Increased computational complexity due to series actions of the steps considered.

From the above study, it is clear that convolutional neural networks are utilised for extracting only the spatial features. Wavelet transformation has been used as pre-processing steps; however, its application along with convolutional layer is not yet tested. This work focuses on designing a novel deep learning model by integrating convolutional layers with wavelet filters in a single model, not one after another, but in parallel.

METHODS

Proposed Model

The proposed method includes both wavelet features and convolutional features in the same WCNN model. The workflow diagram of the proposed method is shown in Figure 1.

The suggested method is uniquely designed to enhance the task of cancer detection. In most of the work, it is observed that wavelet features are extracted once prior to training by any deep learning-based model. In this work, the effectiveness of wavelet features is enhanced in the CNN model itself by applying wavelet transform along with each convolutional layer followed by a MaxPooling layer. Each part of the proposed method is described in the next subsections.

Dataset Description

The validity of the proposed model is confirmed by utilizing breast histopathology [30] images that include both NonIDC and IDC images. The initial collection comprises 162 whole-mount slide photographs that were scanned at a magnification of 40x. The IDC and Non-IDC patches are recovered from the images with a size of 50x50. These patches are labelled with the patient ID, the coordinates of the pixels from which the patches are cropped in the x and y directions, and the appropriate class. The class value 0 corresponds to NonIDC, while the class value 1 corresponds to IDC. Once the dataset was gathered, we proceeded to rename the dataset photos using straightforward labels. For instance, we used "NonIDC" to denote healthy breast histopathology images and "IDC" to indicate images that include cancer cells.

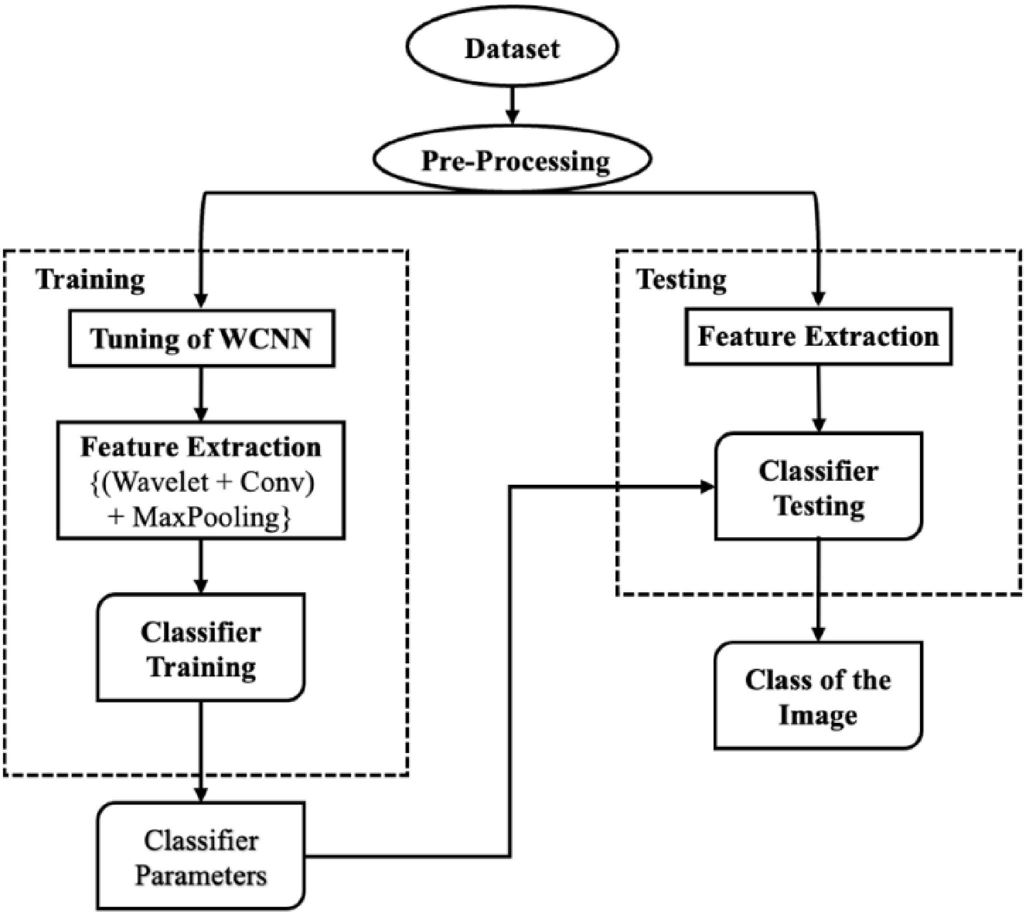

Figure 1. Flow chart of the proposed method

Figure 2 displays a representative selection from each category of images. One can distinguish between a healthy breast tissue and a breast tissue with cancer cells by carefully examining histopathological images and inspecting the ductal cells. In the case of IDC, the presence of anomalous proliferations is observed within the lactiferous duct, with the potential for local tissue infiltration. In healthy breast conditions, the milk ducts are devoid of any anomalous growths. The growths can manifest as tubules, nuclear pleomorphism, or a high mitotic count, but visually identifying them manually is a time-consuming process. Hence, employing deep learning algorithms is the optimal decision for automated and expedited analysis.

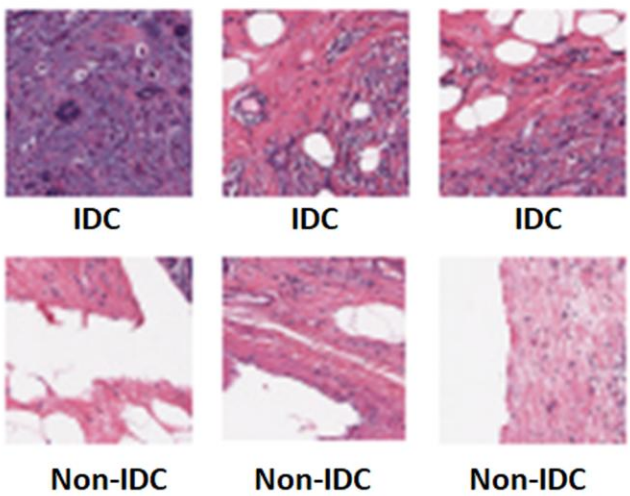

Figure 2. The breast histopathology image dataset, including several samples

Preprocessing

Converting breast histopathology images from their native RGB (Red, Green, Blue) color scheme to grayscale is typically the first step in the process of preparing these images for further analysis. This transformation is essential for a number of different reasons. Initially, grayscale images minimize the dimensionality of the data, which simplifies later processing chores and has the potential to improve computational efficiency. Second, grayscale images avoid the possibility of color biases or artifacts that could be caused by variances in lighting circumstances or staining processes. In grayscale photographs, the emphasis is placed on intensity values rather than color information, which allows for the underlying structural characteristics of the tissue to be brought to the forefront. These characteristics include cellular morphology and architectural patterns.

This simplification has the potential to improve the capability of machine learning algorithms to accurately classify or segment various sections of the breast tissue. A preparatory step that must be completed before performing 2D wavelet transformation is the conversion to grayscale. This integrated technique has the potential to produce a multitude of traits that can be utilized for a variety of tasks, including the classification of breast cancer.

Wavelet Transform

Using a mathematical technique known as the wavelet transform, an image can be broken down into a collection of basic functions that are referred to as wavelets. Due to the fact that these wavelets are localized in both time (or space) and frequency, they are ideally suited for the analysis of signals that have transitory characteristics.[31]

The 2D wavelet transform's translated and scaled basis elements were provided earlier. The multiresolution representation of the scaling functions, $\varphi(x, y)$ and wavelet function $\psi^i(x, y)$ for the 2D is given below. The two-dimensional wavelets are used in image modification.

$$\varphi_{j,m,n}(x, y) = 2^{j/2}\varphi(2^j x - m, 2^j y - n)$$

$$(\psi^i_{j,m,n}(x, y) = 2^{j/2}\psi^i(2^j x - m, 2^j y - n)$$

Where $i = \{\mathrm{H}, \mathrm{V}, \mathrm{D}\}$ and H, V, D refer to the horizontal, vertical and diagonal directions. $j \geq j_0$, where j_0 is an arbitrary starting scale, x and y are the spatial coordinates of the image pixels, and m and n are the indices that determine the scale and position of the wavelet basis functions.

An important benefit of wavelet transform is its capacity to extract characteristics on various scales. This is accomplished by employing wavelets of varying sizes and orientations. Approximation coefficients scale low frequency components with no change in orientation and extracts overall image structure. The approximation function of the wavelet representation is given as

$$W_\varphi(j_o, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\varphi_{j_o,m,n}(x, y)$$

Where M and N represents the dimension of the image. Horizontal coefficients scale higher frequency components with horizontal orientation and extracts horizontal edges and textures. The horizontal sub-band is represented as

$$W^H_\psi(j, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\psi^H_{j,m,n}(x, y)$$

Vertical coefficients scale higher frequency components with vertical orientation and extract vertical edges and textures. The vertical sub-band is represented as

$$W^V_\psi(j, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\psi^V_{j,m,n}(x, y)$$

Diagonal coefficients scale higher frequency components with diagonal orientation and extract diagonal edges and textures. The diagonal sub-band is represented as

$$W^D_\psi(j, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\psi^D_{j,m,n}(x, y)$$

The above expressions are utilized to extract wavelet features. Samples of such wavelet coefficients are shown in the results section.

Convolutional and MaxPooling Layer

Convolutional layers utilize filters to process the input image, extracting distinct features at various positions. These filters have the capability to identify edges, corners, textures, and various other patterns. Convolutional layers achieve weight sharing across spatial dimensions, resulting in parameter reduction and improved model efficiency. Convolutional layers exhibit spatial invariance, rendering them well-suited for tasks such as object recognition and detection. In this work, four convolutional layers are taken with 256, 128, 64 and 32 neurons, respectively.

The processing of input data (x) in a convolutional neural network is as follows:

$$y = f(x) = \sigma(W * x + b)$$

The symbol σ denotes the activation function, W represents the weights, and b indicates the bias used in the training process. In our work, we employ the Rectified Linear Unit (ReLU) activation function for the convolution layers. The error evaluation is conducted with binary cross-entropy (BCE), which is expressed mathematically as:

$$BCE(y_{real}, y_{pred}) = -\sum_{l=1}^{2} y_{real} \log y_{pred}$$

Where, y_{real} and y_{pred} represent the actual or real label of the data and predicted labels respectively.

MaxPooling layers decrease the spatial dimensions of the feature maps, enhancing the computational efficiency of the model. This layer identifies and prioritizes the most significant features within a specific area, hence directing the model's attention to the most relevant information. In this work, MaxPooling is used after convolutional layer, but it is somehow different from regular CNN models. The details of this improved technique are presented in the next subsection.

Wavelet-Convolutional Neural Network (WCNN)

In this work, a unique architecture is created by implementing wavelet transformation in every convolutional layer. In Fig.3, the addition sign denotes a cross-product operation of images from two different sets. Each image of a convolutional layer is added to each image of wavelet features set. The aggregated characteristics are next sent into a MaxPooling layer to extract valuable features, as described in the preceding subsection. This phase is repeated four times in a sequential way in the proposed model. A flatten layer followed by two dense layers is taken at the last stage of the WCNN model. The last dense layer has two neurons activated with SoftMax activation function for the final classification of images as either IDC or Non-IDC.

The structural parameters of the proposed WCNN model are given in Table 2.

While there is no strict mathematical formula to determine the optimal number of neurons in a CNN layer, values that are the powers of 2 are chosen as it is a common practice. However, the number of layers is determined by looking into the size of input images, i.e., 50x50 in this work.

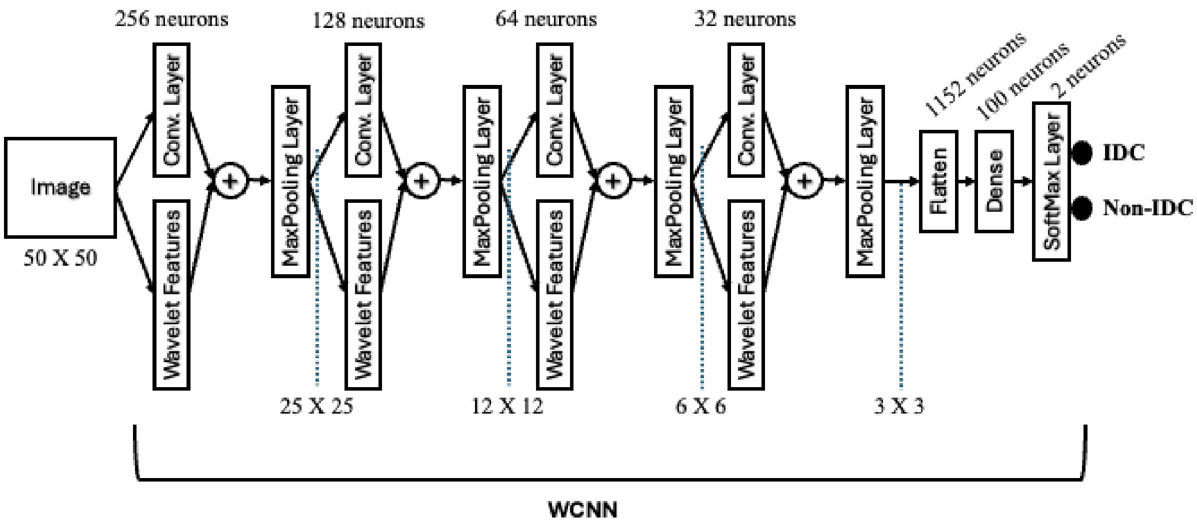

Figure 3. Architecture of the proposed WCNN model

Table 2. Parameters of the Proposed WCNN Architecture

Layer (type)	Output Shape
Conv2D	(None, 50, 50, 256)
Wavelet2D	(None, 50, 50, 4)
MaxPooling2D	(None, 25, 25, 1024)
Conv2D	(None, 25, 25, 128)
Wavelet2D	(None, 25, 25, 4)
MaxPooling2	(None, 12, 12, 512)
Conv2D	(None, 12, 12, 64)
Wavelet2D	(None, 12, 12, 4)
MaxPooling2	(None, 6, 6, 256)
Conv2D	(None, 6, 6, 32)
Wavelet2D	(None, 6, 6, 4)
MaxPooling2	(None, 3,3, 512)
Flatten	(None, 1152)
Dense	(None, 100)
Dense	(None, 2)

RESULTS

System Specification

Python version 3.7 was used in the Google Colaboratory platform with an online GPU on a computer equipped with an Intel Core i3 processor and 8 gigabytes of random access memory (RAM) to test the applicability of the suggested model. Through the utilization of an 80:20 ratio, the dataset was partitioned into the training set and the validation set

Wavelet Features

2D wavelet transform is applied on the preprocessed grayscale images. A sample of the resulting images is given in Figure 4.

Just like convolutional features, four different features are generated by applying wavelet transform on each image. These images are later added with convolutional features to pass through the MaxPooling layer.

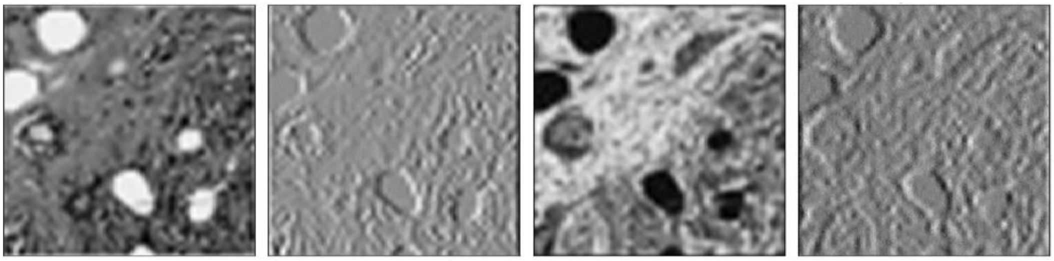

Figure 4. Wavelet features with for a sample image

Model Evaluation

At the initial stage, a simple CNN model is trained directly with histopathology dataset images for performance verification. The classification accuracy obtained in that case was 91.06% that was not up to the satisfaction level. Performance was again checked by training the same CNN model with wavelet features. In this case, wavelet transformation was used as a preprocessing step. The classification results increased and obtained a classification accuracy of 94.31%. This increase in performance motivated the integration of wavelet features as the part of CNN model, leading to the development of the proposed WCNN model. The WCNN model provided classification accuracy of 98.39% that represents improved and highly accurate cancer detection. The performance of all the considered models is shown in Figure 5.

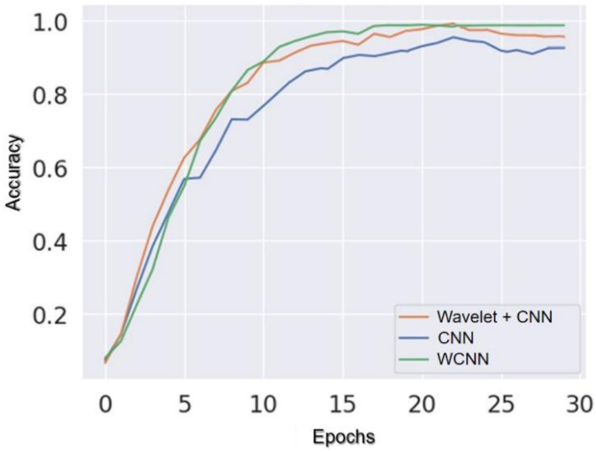

Figure 5. Classification accuracy comparison of the considered models

In Figure 4, Wavelet + CNN represent the method where wavelet transformation is used as a preprocessing step and the extracted coefficients are used to train CNN. The predictions done by the proposed model on the test set with 2000 images is shown in terms of the confusion matrix in Figure 6.

The observed values are the true values whereas the predicted labels are the predictions made by the proposed model. The confusion matrix shows that the model predicted 990 numbers of images as IDC and 978 images as Non-IDC that are the correct predictions.

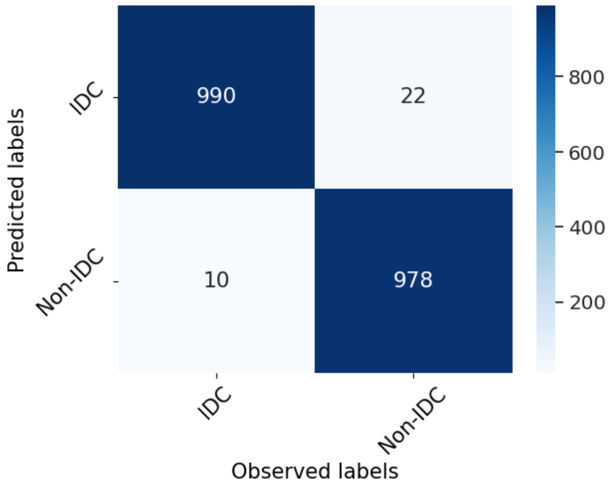

Figure 6. Confusion matrix obtained using test set

The number of wrong predictions is there, but this count is very low and does not represent the effectiveness of the proposed model. Classification accuracy comparison with state-of-the-art model is given in Table. 3. The accuracy, F1 score, precision, recall, sensitivity, and specificity are calculated from the confusion matrices for the proposed model using equations (9-14).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100$$

$$Precision = \frac{TP}{TP+FP} \times 100$$

$$Recall = \frac{TP}{TP+FN} \times 100$$

$$F1\ Score = 2 \times \frac{Recall \times Precision}{Recall + Precision}$$

$$Sensitivity = \frac{TP}{TP+FN}$$

$$Specificity = \frac{TN}{TN+FP}$$

DISCUSSION

The study introduces a novel Wavelet-Convolutional Neural Network (WCNN) architecture for breast cancer detection. By integrating wavelet and convolutional filters, the WCNN effectively extracts both frequency and spatial domain features, leading to superior classification accuracy compared to existing methods. The wavelet component enables multi-scale analysis, capturing both fine-grained details and coarser structures, while the convolutional layers focus on local patterns. This combined approach enhances feature representation and improves the model's ability to detect subtle patterns and textures.

Table 3. Performance comparison with state-of-the-art methods

Work	Accuracy(%)	F1-Score	Recall	Precision	Sensitivity	Specificity
[7]	-	0.902	0.893	0.912	-	-
[8]	91.13	0.9283	-	-	91.01	91.34
[9]	98.29	-	-	-	-	-
[10]	93.3	-	-	-	-	-
[11]	86.97	-	-	-	-	-
[12]	94					
[13]	88	-	-	-	0.82	0.88
[14]	86	0.53	0.75	0.41	-	0.81
[15]	97.2	-	-	-	0.983	0.965
[16]	96.1	-	-	-	-	-
[17]	92.2	-	-	-	-	-
[18]	-	0.61	-	0.50	0.95	-
[19]	96.63	0.9528	0.9609			0.9584
[20]	92.52	93.45	-	-	-	-
[21]	89.57	0.8154		0.7945	0.8375	0.9177
[23]	98.28	-	-	-	-	-
[24]	96.9	-	-	-	-	-
[25]	96.25	0.96	0.96	0.96	-	-
[26]	92.40	0.8588	0.8644	0.8547	-	-
[27]	94.2	94	-	95	94	98.23
[28]	93.6	-	-	-	-	-
[29]	98.08	0.978	0.9920	0.9841	0.9920	0.9355
Proposed model	98.4	0.98	0.9950	0.985	0.9782	0.9898

While adding the Wavelet transformation along with convolutional layer, it adds more complexity in comparison to traditional CNN models. The proposed model took more time for training in comparison to the model without wavelet as a part of it, but the test samples were evaluated within fractions of a second.

The proposed deep learning model, incorporating parallel wavelet and convolutional layers, presents a complex architecture that demands significant computational resources. The parallel processing of wavelet and convolutional features, while enhancing feature extraction, increases the model's parameter count and computational complexity. Consequently, training and inference times are expected to be higher compared to simpler architectures. However, the potential for improved feature representation and classification accuracy may justify the increased computational cost, especially when dealing with the intricate patterns present in the HAM10000 dataset.

The model's reliance on a public dataset with potential limitations and the lack of clinical validation necessitate further research to ensure its practical applicability in clinical settings. Additionally, improving the model's interpretability would enhance its clinical acceptance and trust. The real-time implementation will enhance the model's robustness through ongoing training and continual performance updates.

CONCLUSION

This study showed that CNNs and wavelet processing work well together to detect breast cancer in histopathology images. The suggested model combined the strengths of the two methods, using wavelet transform for multi-scale feature extraction and CNNs for robust learning. By using wavelet transform, the model was able to improve its class discrimination by capturing both global and local data in the input images. In contrast, the model was able to autonomously extract pertinent features for the classification job since the convolutional layers learnt hierarchical data representations. By surpassing both conventional and alternative deep learning architectures, the suggested model attained a remarkable 98.4 % classification accuracy. This finding demonstrates the promise of wavelet transform with CNNs for various image analysis tasks. Future work on expanding the method's applicability may involve exploring fusion with other modalities. In addition, we intend to create a system that can analyze histopathology pictures and other data to determine the cancer stage.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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DATA AVAILABILITY

All data relevant to the study are included in the article.

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