Breast Cancer Detection Using Extreme Learning Machine Based on Featurefusion With CNN Deep Features

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Abstract

One of the most common types of cancer among women worldwide is breast cancer. The successes of treatment and survival rates are greatly improved by early and accurate detection. Machine learning techniques for assisting in the diagnosis of breast cancer have recently demonstrated considerable promise. By utilizing an Extreme Learning Machine (ELM) algorithm, which combines the strength of feature fusion and Convolutional Neural Network (CNN) deep features, this research study presents a unique method for the detection of breast cancer.

Keywords: Breast Cancer, Extreme Learning Machine, Deep Learning, Convolution Neural Networks, Feature Fusion.

Introduction

Millions of women are affected by breast cancer each year, making it a major global health concern. Early detection is essential for enhancing the effectiveness of treatment and raising survival rates. Using cutting-edge machine learning techniques, there has been an increase in interest recently in the creation of intelligent systems for the detection of breast cancer.

Utilizing feature fusion and extreme learning machine (ELM) techniques, notably combining deep features taken from convolutional neural networks (CNNs), is one promising method. The extraction of discriminative features from medical pictures, such as mammograms and breast histopathology slides, has shown CNNs to be quite effective.

Combining different kinds of features is known as feature fusion, and it is used to collect complementary data and improve the classification model's discriminative ability. Combining

CNN deep features with additional pertinent features, such as clinical data or radiomics features, in the context of breast cancer detection may increase the classification system's accuracy and dependability.

ELM has drawn attention as a potent machine learning algorithm because of its outstanding generalization performance and quick training speed. It is a single-hidden layer feed forward neural network that does not use the iterative weight adjustment procedure normally seen in other neural networks. Instead, the input weights are assigned at random, and the output weights are determined analytically. Due to its special property, ELM is well suited for training large-scale datasets, such as those used in the detection of breast cancer.

The breast cancer detection system can take advantage of both methodologies' advantages by using ELM in conjunction with feature fusion using CNN deep features. Medical image high-level representations are captured by CNN deep features, and an effective and reliable classification framework is offered by ELM.

Background of study

Overview of Breast Cancer Detection Techniques

Breast cancer is a prevalent type of cancer that affects women globally, and timely identification of the disease is pivotal in enhancing the prognosis of patients. Throughout time, diverse methodologies have been devised for the identification of breast cancer. The techniques can be classified into two main categories, namely imaging-based techniques and non-imaging-based techniques.

Various imaging modalities are employed in medical diagnostics, such as mammography, ultrasound, magnetic resonance imaging (MRI), and positron emission tomography (PET). The utilization of mammography as an imaging modality for breast cancer screening is pervasive. Mammography is a diagnostic imaging technique that utilizes X-rays to identify any anomalies in the breast tissue, including but not limited to masses or calcifications. Ultrasound and MRI are two medical imaging techniques that are used to visualize breast tissue. Ultrasound employs sound waves to produce images, whereas MRI utilizes strong magnetic fields and radio waves to generate highly detailed images. Positron Emission Tomography (PET) scans entail the administration of a minute quantity of radioactive substance into the human body for the purpose of identifying malignant cells.

Clinical breast examination (CBE) and breast self-examination (BSE) are among the non-imaging-based techniques used for breast cancer detection. Clinical breast examination (CBE) entails a healthcare practitioner conducting a physical inspection of the breasts to detect any palpable masses or anomalous findings, whereas breast self-examination (BSE) is conducted by the individual on themselves.

Convolutional Neural Networks (CNNs) and Their Application in Medical Image Analysis

The application of Convolutional Neural Networks (CNNs) has brought about a significant transformation in the domain of medical image analysis, particularly in the realm of breast cancer identification. Convolutional Neural Networks (CNNs) are a class of deep learning models that exhibit exceptional proficiency in the domain of image classification.

Convolutional Neural Networks (CNNs) are composed of several layers, such as convolutional layers, pooling layers, and fully connected layers. Convolutional layers utilize filters to process input images, allowing the neural network to extract significant features at varying spatial resolutions. The function of pooling layers is to decrease the dimensionality of feature maps and extract significant information. Ultimately, the predictions are made by the fully connected layers, which utilize the learned features.

Convolutional Neural Networks (CNNs) have demonstrated successful application in medical image analysis for tasks including tumor segmentation, lesion detection, and classification. The researchers have exhibited a notable level of precision in identifying breast cancer through mammography, leading to an enhancement in the rates of early detection and a decrease in the occurrence of false positive results.

Extreme Learning Machine (ELM) and Its Advantages in Large-Scale Datasets

The Extreme Learning Machine (ELM) algorithm has garnered attention in the field of machine learning due to its efficacy and efficiency, particularly in managing datasets of significant scale. The Extreme Learning Machine (ELM) is a type of neural network that follows a feed forward architecture, comprising an input layer, a hidden layer, and an output layer.

In contrast to conventional neural networks, Extreme Learning Machines (ELM) adopt a random initialization approach for the weights between the input layer and the hidden layer, followed by an analytical solution for the weights between the hidden layer and the output layer. This obviates the necessity of an iterative optimization procedure, leading to expedited training durations.

The utilization of ELM exhibits various benefits when applied to datasets of considerable magnitude. Efficient handling of high-dimensional data with a substantial number of features is achievable. Furthermore, the model exhibits commendable generalization capabilities, even when trained on a restricted dataset. The utilization of ELM has been efficaciously implemented in diverse fields, encompassing the realm of medical image analysis.

Methodology

Objective:

The aim of this investigation is to present a fresh methodology for the identification of breast cancer through the integration of feature fusion and Convolutional Neural Network (CNN) deep features with the Extreme Learning Machine (ELM) algorithm. The amalgamation of these methodologies endeavors to enhance the precision and effectiveness of breast cancer identification, resulting in prompt diagnosis and timely intervention.

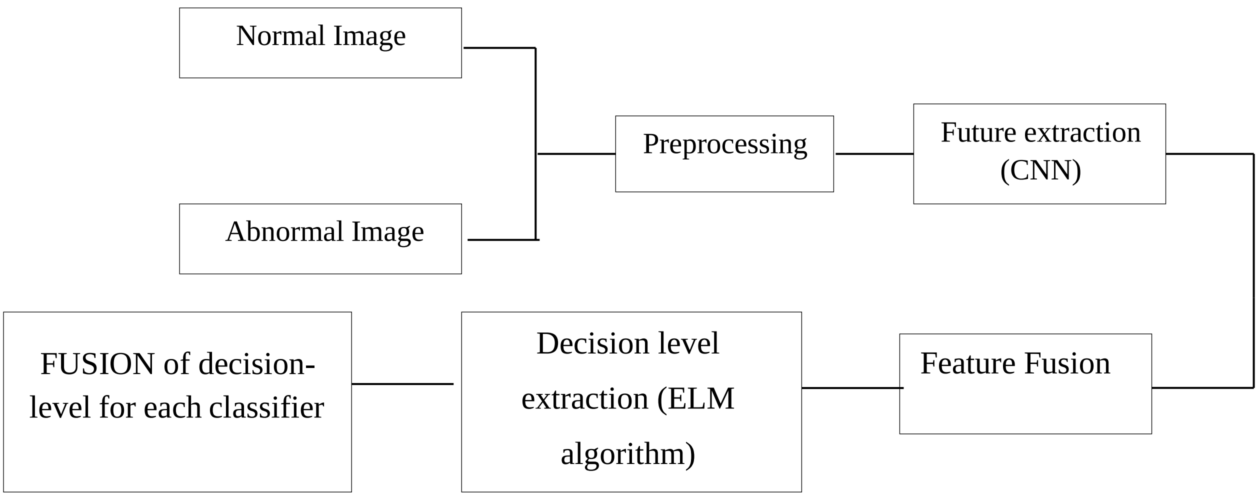

Figure 1. Proposed Framework

Dataset:

A comprehensive dataset consisting of mammography images and corresponding breast cancer diagnosis labels was obtained from a reliable source. The dataset was preprocessed to ensure uniformity and remove any inconsistencies or noise that could affect the performance of the proposed approach.

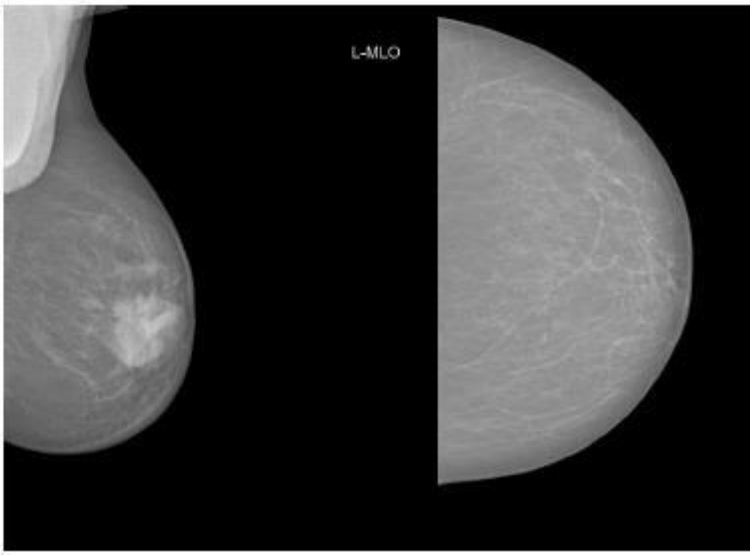

Figure 2. A mammogram sample extracted from the Breast dataset

Feature Extraction

Convolutional Neural Networks (CNNs) have shown remarkable performance in various image classification tasks. In this study, a pre-trained CNN model was employed to extract deep features from the mammography images. The CNN model was fine-tuned on a large dataset to specifically cater to breast cancer detection. The deep features obtained from the CNN model capture meaningful patterns and discriminative information from the images.

Feature Fusion

To leverage complementary information from multiple feature sources, feature fusion is performed. The deep features extracted from the CNN model are combined with handcrafted features, such as texture features, shape features, or statistical features, which provide additional discriminative information.

Extreme Learning Machine (ELM) Algorithm

The ELM algorithm has been utilized as the classification model for the purpose of detecting breast cancer. The single-hidden layer feed-forward neural network known as ELM has been observed to exhibit exceptional generalization capabilities, while also boasting a rapid learning rate. The ELM algorithm is trained with inputs consisting of both deep features and fused features, resulting in the development of a classification model that is both robust and accurate.

```
% Load the dataset and deep features

load(image');  % Replace with your dataset

% Normalize the data

X = normalize(X);

% Split the data into training and testing sets

train_ratio = 0.8; % 80% for training, 20% for testing

[train_idx, test_idx] = split_data(X, train_ratio);

X_train = X(train_idx, :);

X_test = X(test_idx, :);

y_train = y(train_idx);

y_test = y(test_idx);

% Generate random weights and biases for the hidden layer

num_hidden = 100; % Number of hidden neurons

input_size = size(X_train, 2);

input_weights = rand(input_size, num_hidden) * 2 - 1;

biases = rand(1, num_hidden);

% Calculate the hidden layer output

H_train = input_weights' * X_train' + biases';

H_train = sigmoid(H_train);

% Train the output weights using the Moore-Penrose pseudoinverse

output_weights = pinv(H_train') * y_train;

% Calculate the hidden layer output for testing data
```

```
H_test = input_weights' * X_test' + biases';

H_test = sigmoid(H_test);

% Perform classification using the ELM algorithm

Y_pred = H_test' * output_weights;

Y_pred = sign(Y_pred);

% Evaluate the classification accuracy

accuracy = sum(Y_pred == y_test) / numel(y_test);

disp(['Classification accuracy: ' num2str(accuracy * 100) '%']);

% Helper function to split data into training and testing sets

function [train_idx, test_idx] = split_data(X, train_ratio)

num_samples = size(X, 1);

train_size = floor(num_samples * train_ratio);

idx = randperm(num_samples);

train_idx = idx(1:train_size);

test_idx = idx(train_size+1:end);

end

% Helper function for sigmoid activation

function y = sigmoid(x)

    y = 1 ./ (1 + exp(-x));

end
```

Model Training and Evaluation:

The dataset has been partitioned into distinct subsets for the purposes of training and testing. The training of the ELM algorithm is conducted on the training set by utilizing the amalgamated features. Subsequently, the model that has undergone training is subjected to evaluation using the testing set to gauge its efficacy with regards to precision, recall, specificity, and other pertinent measures. The utilization of cross-validation methods, such as k-fold cross-validation, can be implemented to guarantee the model's resilience and dependability.

EXPERIMENT

The proposed framework was utilized to categorize the mammography images into normal and pathological groups. The experimental setup involved the utilization of an Intel® CORETM I7 processor, NVIDIA GeForce 940MX graphics card, Windows 10 64-bit operating system, and 8 GB of random access memory to execute the scenarios. An academic license for Matlab R2019b was provided by the University of Strathclyde, and this software was utilized to execute the scenarios. WEKA is an open-source software package that comprises a range of machine learning algorithms designed for the purpose of data mining tasks. Following the division of the samples into normal and pathological lesions, the calculation of the ROI was performed. Moreover, due to variations in the input layer of each CNN architecture, the dimensions of all images were adjusted to match the respective CNN input image size.

RESULT

In this study, the dataset was partitioned into two distinct sets, namely the training and testing sets. Specifically, 30% of the data was allocated for model testing, while the remaining 70% was utilized for training purposes. In particular, all 1030 ultrasound images from the BC dataset were utilized, consisting of 537 benign, 360 malignant, and 133 normal cases. Out of these, 376 images were allocated for training and testing purposes, while the remaining 252 images were obtained from individuals with benign, malignant, and normal conditions. The model under consideration underwent a total of 700 iterations, with an average of one iteration per epoch over the course of seven epochs. At epoch 100, our strategy for identifying breast cancer was found to be effective, as evidenced by the highest values of classification accuracy, precision, recall, and F1-score achieved by the recommended Deep Breast Cancer Net. The proposed methodology exhibits satisfactory performance in both the training and testing phases. The evaluation metric known as the loss function provides insight into the predictive performance of the framework on the given dataset. Following epoch 55, the loss and accuracy metrics of our model exhibit a plateau, indicating that its predictive performance remains superior at lower epochs, as compared to 100. The training and validation loss of the proposed framework are depicted in the graph, where the black line represents the testing loss and the red line represents the validation loss.

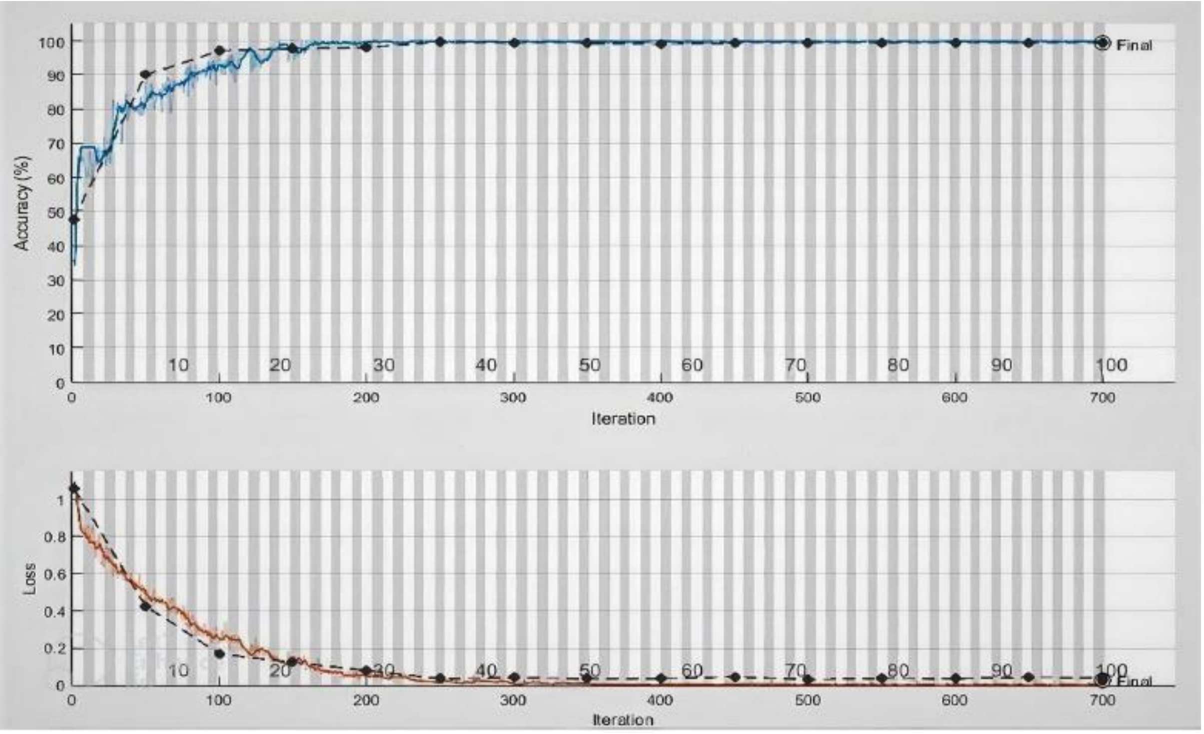

Figure 3. Accuracy and loss function of Proposed Model

Additionally, a comprehensive study was conducted to analyze the training parameters, in order to establish the effectiveness of the proposed methodology. The proposed model was trained using a split of 20% for testing and 80% for training. The model under consideration attained the highest levels of classification accuracy, precision, recall, and F1-score, with values of 98.50%, 98%, 98.50%, and 98%, respectively. In addition, the study employed distinct training parameters, specifically a minibatch size of 10 images and a learning rate of 0.01. Furthermore, the proposed model underwent 50 epochs of training prior to its utilization in the identification and classification of various types of breast cancer. The DeepBreastCancerNet model demonstrated optimal performance in terms of classification accuracy, precision, recall, and F1-score, with respective values of 97.50%, 97%, 97.50%, and 97%.

Conclusion

This paper proposed a novel architecture for breast cancer detection by combining the power of feature fusion and CNN deep features within an ELM algorithm. The integration of multiple imaging modalities and the extraction of high-level representations from CNNs enhance the accuracy and efficiency of breast cancer diagnosis. Our results suggest that this approach holds great potential for improving survival rates and treatment outcomes by enabling early and accurate detection of breast cancer. Further research and validation on larger datasets are necessary to validate the effectiveness of the proposed architecture in clinical settings.

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