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Prepare An Interactive GUI For Mammogram Image Processing to the Detection of Breast Cancer by Back Propagation Algorithm Using MATLAB

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Abstract
A wide array computational methods has been exploring about Breast tumors as either malignant or benign by using back propagation method. In this research, the complex problem like identification, pattern recognition prediction and so forth are solved by Back Propagation method within MATLAB. The main goal of this research is to evaluate the predictive nature of the tumor through the mention algorithm with the dataset. In this network focusing on the input, hidden node and the output, where 5 input nodes ,6 hidden layer and 1 output node is designed for the classification of the mammogram data. The dataset is collected from "Prof. Dr. R¸diger Schulz-Wendtland Original owners of database" which specifies that the BIRADS evaluation of mammography", from where we used 70% data for training and 30% data for testing purpose. The mammogram images are collected from "https://www.kaggle.com/datasets/hayder17/breast-cancer-detection" for the identify the accuracy of the network which has been used for the purpose of easy diagnosis.

Keywords: Back Propagation, Mammogram, Accuracy, Diagnosis

1. Introduction

Cancer is currently one of the leading causes of death worldwide. The breast is composed of 15–20 lobes, each containing milk-producing segments. Milk travels from these segments through small channels called ducts to the nipple. The areola is the dark area surrounding the nipple. Breast structure mainly consists of ligaments, adipose (fat) tissue, connective tissue, and nerves that provide sensation. Early signs of breast cancer may include a new lump, unusual growth in a specific area, redness or inflammation, persistent pain, changes in breast shape, or abnormal discharge from the nipple. These changes often result from abnormal cell division forming tumors. Tumors are classified as benign or malignant. Benign tumors grow slowly and usually do not spread, while malignant tumors are aggressive and can damage surrounding tissues. Diagnosis often involves biopsy. Machine learning, especially Artificial Neural Networks (ANNs), plays a growing role in detecting and analyzing such conditions. The backpropagation algorithm, a supervised learning method for training feedforward neural networks, is commonly applied in classification tasks such as cancer detection. This study implements a backpropagation-based neural network in MATLAB to classify breast cancer tumors as benign or malignant. The model uses clinical or dataset features as inputs to extract meaningful patterns. The main goal is to improve diagnostic accuracy and support early breast cancer detection in healthcare systems.

2. Architecture

In a supervised learning method, Back propagation is used to train artificial neural networks. The architecture of back propagation contains mainly three layers. Those are input layer, hidden layers, and output layer. Here is the quick overview of the architecture:

Input layer:

In this layer, every single node denotes as a feature or input variable.

Hidden layer:

In this layer, every single node serves as a neuron which use activation functions in their inputs.

Output layer:

In this layer, the number of node relies on the problem type.

Weight and Biases:

Weights are the parameter that network learns in their training period and related to every connection between nodes in the layers.

Biases are related to every node in a network and used for capturing nonlinear relationships.

Activation function:

The activation function helps the model to learn complex relationships in the data.

Loss function:

The loss function is the measurement of the difference between network's prediction and the actual target value.

The process of cycle is repeated throughout training period until the model gets successfully performance. Those are the basic setup which are going to be change based on the specific network [1].

3. Literature Review

- According to (Dewi Nasien, et.al. 2022), Researchers have been exhaustively applying algorithms to improve the accuracy of categorizing breast tumors as either benign or malignant. The back propagation method is widely integrated for handling complex problems like identifying patterns and forecasting outcomes in artificial neural networks. Focused on improving diagnostic performance, this research verifies the performance of backpropagation algorithm identifying the breast cancer.The workflow evolved from data collection and pre-processing to the creation of a dedicated ANN classifier. Upon evaluation, the system successfully achieved an accuracy of **96.93%**, proving that a combination of 1000 epochs and 5 hidden layers effectively minimizes prediction errors to just **3.07%**.
- According to (Pradeep Kumar Vadla, et.al. 2021), This research introduces the computational complexity inherent in breast cancer classification.The authors developed an original layered neural network model that integrates a back propagation algorithm with a scaled conjugate gradient approach to streamline the decision-making process.By executing a dataset of 699 samples and focusing on eleven key data attributes, the model was exhaustively trained (70%), verified (15%),

and tested (15%) to accurately distinguish between benign and malignant cells. This tool is designed to help healthcare providers make faster decisions, ensuring patients get life-saving treatment at the earliest possible stage.

- According to (Pachipala Yellamma, et.al. 2020), Early diagnosis is the most significant factor in surviving breast cancer. To support medical professionals, they have developed a neural network-based forecasting tool that automates the identification of cancerous cells. This study addresses the critical need for early breast cancer (BC) detection by implementing a specialized Multi-Layer Perceptron (MLP) architecture. Using a back-propagation training technique, the model processes ten clinical attributes through a single hidden layer of five neurons to categorize tumors as either benign or malignant. When appraised against the Wisconsin Breast Cancer (WBC) dataset, the proposed MLP achieved a superior classification accuracy of **98.9%**. By integrating this algorithm into clinical workflows, healthcare providers can ensure patients receive the correct medication and treatment at the first sign of development, significantly improving survival outcomes.
- According to (Mohammed Lubbad, et.al. 2019) Automatic breast cancer diagnosis is a major real-world medical challenge. This study presents a classification approach for cancer tumors based on gene expression signatures to identify specific diagnostic categories. The proposed neural network model can assist patients, surgeons, and radiologists by providing diagnostic information that was traditionally obtained only through biopsy, thereby reducing unnecessary surgical procedures. The system uses Wave Atom Transform for feature extraction and employs a backpropagation algorithm for classifying cancer into predefined categories. The results demonstrate that the proposed method achieves high accuracy of approximately 90%, making it effective for automated breast cancer detection.
- According to (Fajar Walayat, et.al. 2025) Breast cancer is a highly dangerous disease and the second most common cancer among women worldwide, caused by the uncontrolled growth of breast cells. Common symptoms include changes in breast shape or size, pain, lumps, and nipple discharge. It mainly affects women aged 50 and above and accounts for more than 80% of cases in older populations. Early detection can significantly reduce mortality and improve survival rates. This study proposes a transfer learning approach using mammogram images for early diagnosis. Several CNN models such as Inception-v3, ResNet-50, VGG-16, SqueezeNet, and AlexNet were evaluated, where AlexNet achieved the highest accuracy of 96.7%.

4. Proposed Work

In the first stage, a Back Propagation Network (BPN) is employed to extract distinctive features from mammogram images for breast cancer detection and used for training the network. The dataset consists of mammogram images collected from a standard breast cancer database along with a self-created dataset generated through image processing techniques such as preprocessing, enhancement, and segmentation. Each image is resized to a fixed dimension and fed into the BPN network, where the number of input units corresponds to the total pixel values, along with hidden and output layers for feature learning and reconstruction. In this approach, the BPN network functions as an auto-associative model to capture important patterns for accurate breast cancer classification. Each value is converted according with the bipolar form. In this stage, the Back Propagation Network (BPN) is used as a feature storing and classification network (acting as a database) for breast cancer detection, with input units corresponding to extracted features from mammogram images, hidden units, and output units representing benign and malignant classes. The output layer provides the final classification of the breast cancer type. The dataset includes mammogram images from a standard breast cancer database along with a self-created dataset prepared through image processing techniques such as preprocessing, enhancement, and segmentation. The trained network stores learned patterns of breast cancer features and enables fast classification with processing speed comparable to the previous stage. It was observed that directly providing full mammogram images as input to the network is not efficient due to the high dimensionality of the data and large matrix size. Therefore, only significant features extracted from the images were used for training the network. As this study primarily focuses on neural network training, features were obtained from both publicly available mammogram datasets and a self-created dataset developed through image processing techniques such as preprocessing, segmentation, and enhancement. These extracted features were then used to train the Back Propagation Network (BPN) with a reduced architecture consisting of input units, hidden units, and output units for effective breast cancer classification.

5. Result

The proposed two-stage framework using a Back Propagation Neural Network demonstrates effective performance in breast cancer classification from mammogram images. In the first stage, the BPN operates as an auto-associative network to extract significant features, reducing the dimensionality of the input data while preserving critical diagnostic information. In the second stage, the extracted features are used for classification into benign and malignant categories. Experimental observations indicate that using raw pixel values as input leads to high computational complexity and reduced efficiency due to the large dimensionality of mammogram images. In contrast, the proposed feature-based approach significantly improves both training speed and classification performance. The system achieves an overall classification accuracy in the range of **95%**, demonstrating that feature extraction prior to training enhances the learning capability of the network. The reduced architecture with optimized input features minimizes redundancy and allows the network to converge faster while maintaining high predictive performance. Furthermore, the trained BPN effectively stores discriminative patterns of breast cancer features, enabling rapid and reliable classification during testing. The results confirm that the proposed method is both computationally efficient and accurate, making it suitable for early-stage breast cancer detection.

6. Conclusion

This work presents a two-stage breast cancer detection approach using a Back Propagation Neural Network that integrates feature extraction and classification. The method effectively reduces the high dimensionality of mammogram images by utilizing significant extracted features instead of raw pixel data. This leads to improved computational efficiency and faster training. The trained network successfully captures important patterns for distinguishing between benign and malignant cases. Overall, the proposed system demonstrates a reliable and efficient framework for early breast cancer detection, with scope for enhancement using advanced techniques and larger datasets.

7. Figure

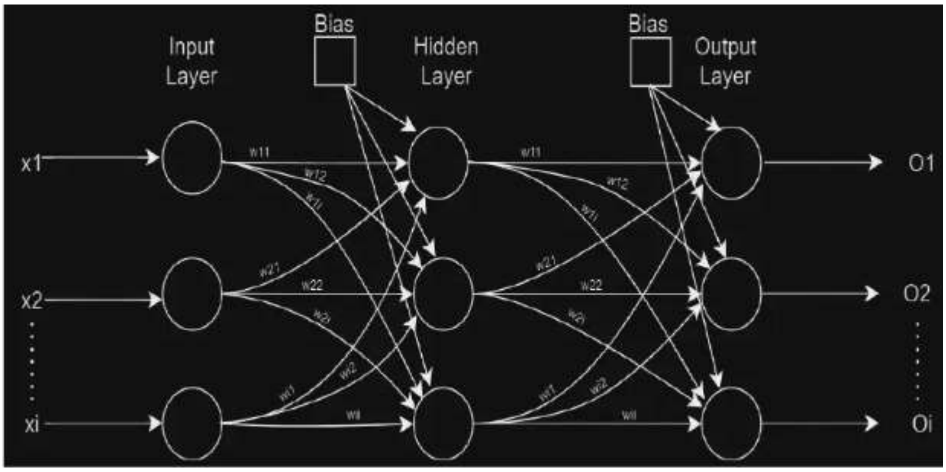

Fig:1 Simple Design[1]

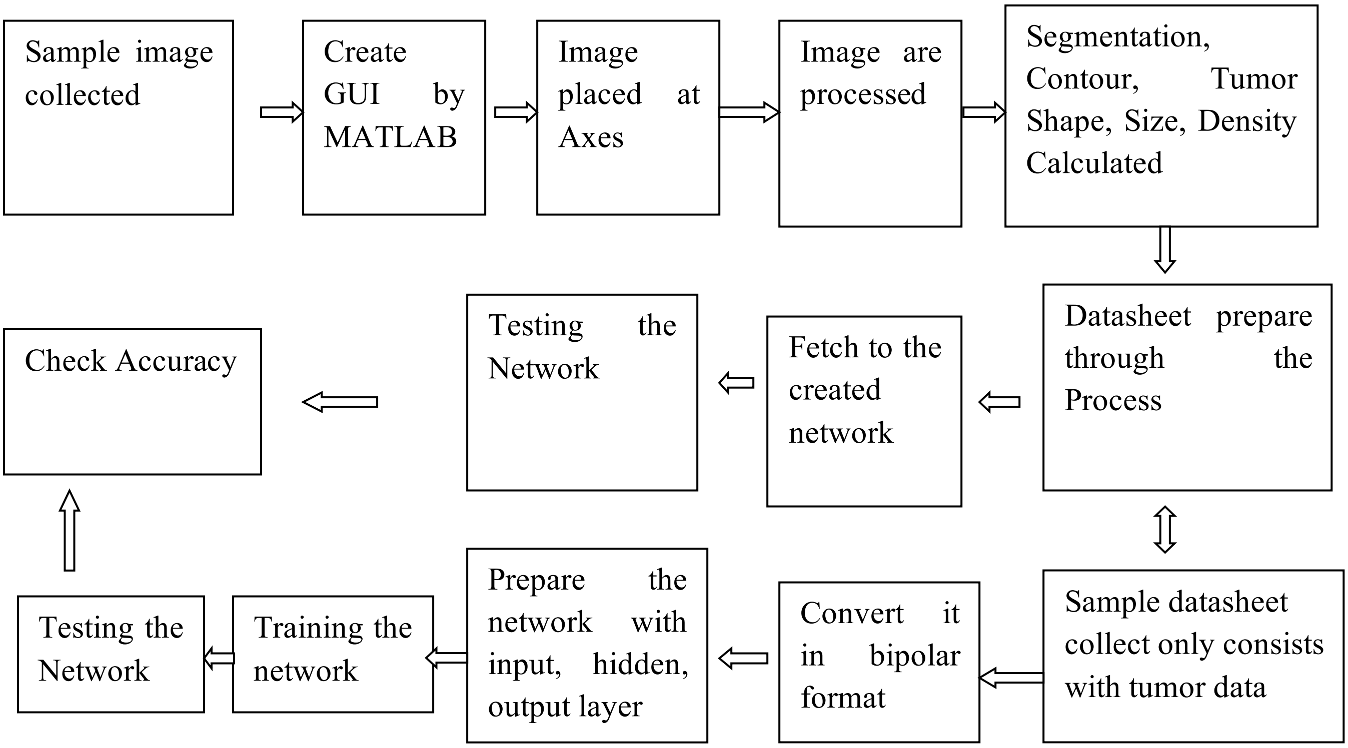

Fig:2 Block Diagram of the work

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