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Neural Network Model for Cancer Tumor Growth with Minimizing the Error in Learning

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Abstract: Neural Network Learning is a process of exhibiting the original phenomena of any object in the network to simulate the desired output. Likewise, briefly processing the attributes of tumor identification from an ultrasound-screened image is a way to process it. A systematic approach for detecting malignant tumors is problematic approach. Given this fact, the data set used to classify the breast cancer tumor is less noisy. An ultrasound-screened image is a basic scanned image of a cancer tumor, which usually has the primary staging properties. Classification of malignant tumors in an ultrasound image is not as easy as possible for radiologists to predict the disease symptoms. Thus, automatic prediction is a challenging task for such images. Since it's a distribution of artificial intelligence, this ability applies to cancer prediction. Automatic classification of benign and malignant in ultrasound images is bounded within the neural network. The features in a tumor image are learned with machine learning algorithms like K-Means and back propagation. Increasing the learning rate is essential for feature learning. The Sigmoid activation function is used for optimization and minimizing the error for feature learning. The ultrasound-screened image is of low quality in nature, and learning about features is a task in predicting.

Keywords: Mammogram, Ultrasound Images, Segmentation, Neural Networks, Cancer Prediction.

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I. INTRODUCTION

Breast cancer is shared among all types of cancers occurring in females. Side effects of a breast tumor may include swelling in the bosom, a change in bosom nature, fat in the skin, fluid originating from the areola, or a red textured area on the skin. Breast cancer is shared among all types of cancers occurring in females. If not detected at the initial stage**,** it leads to very fatal results. The analysis purely depends on the image captured by using the acquisition devices. Image analysis plays a vital role in correctly predicting the different cancer stages.

Through mammogram analysis, radiologists have a detection rate of 76%-94%, which is considerably higher than the 57%-70% detection rate for a clinical breast examination. Many research studies have been conducted in the area of breast cancer detection and classification. Many universities, commercial institutions, and research centers are focused on this issue because breast cancer is becoming the most common form of cancer in today's female population. Cancer refers to a group of diseases marked by unchecked cell proliferation. Cancer harms the body when damaged cells divide uncontrollably to form lumps or masses of tissue called tumors. Cancer begins in cells and spreads to other parts of the body. The growth of supplemental cells develops a bulk of tissue known as a lump. So, early detection of cancer is more important. Mammography is an initial screening test to detect breast cancer. Breast cancer is the second most common cancer worldwide after lung cancer, the fifth most common cause of cancer death, and the major cause of cancer death in women. Breast cancer is the second most common cancer in women after skin cancer in the U.S. Both men and women can have breast cancer, but there are about 100 times more new cases of breast cancer in women than in men every year. Mammography is a well-known method used for the detection of breast cancer. Many researchers have worked in the area of breast cancer detection and have proposed segmentation methods.

We introduce a simple and easy approach for the detection of cancerous tissues in mammograms using Ultrasound images. This approach makes use of basic image processing methods like thresholding and averaging. There might be jaw torment, swollen lymph nodes, shortness of breath, or yellow skin. Ultrasound-screened images are a way step to process it. A systematic approach for detecting malignant tumors is problematic approach. The data set used to classify the breast cancer tumor is less noisy. An ultrasound-screened image is a basic scanned image of a cancer tumor, which usually has the primary staging properties [1, 2].

II. ANALYSIS OF EXISTING METHODS:

Existing methods include detection followed by segmentation of mammogram images based on simple image processing techniques, which provide good results in real time. This method consists of two main steps: detection and segmentation. In the detection phase, an averaging filter and thresholding operation are applied to the original input image, which outputs the malignant region area. To find the malignant tissues, we create a rectangular window around the output region and apply the Max-Mean and Least-Variance technique. In the segmentation phase, a tumor patch is found using a morphological closing operation and an image gradient technique to find the region boundary.

At another step of image processing, noise is removed from the image using Haar Wavelet Transform, and apply OTSU thresholding algorithm is applied. Convert RGB Channels into Grayscale images. Further classification is performed on that part after applying ROI. Extract the features like Contrast, Energy, Homogeneity, and Correlation are computed. Statistical features like Entropy and Mean intensity are also calculated. Color moments like Standard Deviation (SDR, SDG, and SDB) and Mean MR, MG, and MB of Red, Green & Blue Components, and SD Gray are manipulated. We are using back propagation NN here.

Another type of journal paper used 3D MRI and CT images. First step, we take the MRI image as the input image and pre-process the image, removing the noise by using the median filter image enhancement. Next step, we implement the segmentation, which matches the image with points. The Third step of our proposed method segments the images by using the Linde-Buzo-Gray algorithm (LBG) and the watershed algorithm. Fourth step, we detect and classify the normal or breast cancer region by using a knowledge-based breast detection technique that constructs the breast cancer location. In some papers, they used the KNN algorithm for segmenting the cancer tumor. And they used the Fuzzy algorithm to segment the detected area. Segmentation is the process of partitioning an image into several small segments. The main difficulties in image segmentation are noise, bias field, and partial volume effect (a voxel contributes to multiple tissue types).

The median filter is used to remove the unwanted noise in the image. After removing the unwanted. Removing unwanted data in the image is segmented by using the entropy method. The entropy-based segmentation approach is proposed to segment a gray-scale breast image [3-6]. The approach calculates the histogram of an image and also finds the entropy. Then, by calculating the thresholding value of an image, the segmented image is shown at the output. In some journals, an applied and enhanced double thresholding-based approach for mammogram image segmentation. An enhancement has been done to the segmentation approach by applying a morphological operation after double thresholding. Here, we used the same way of double thresholding segmentation applied in and for mammogram image segmentation [3, 4].

III. METHODOLOGIES OF PROPOSED WORK:

We propose introducing a simple and efficient approach to detect the cancer region in mammogram images. Our approach also segments the cancer region on input Ultrasound mammogram images. To classify breast cancer tumors using Neural Networks, to reduce the error in prediction.

(1) Pre-processing the raw ultrasound-screened breast cancer images.
(2) Segmenting the Benign and malignant tumors.
(3) Neural network backpropagation is used for learning the attributes for tumor classification.
(4) Reducing the error rate in learning parameters for optimizing cancer prediction.

1. IMAGE ACQUISITION:

Input the Ultrasound mammogram images of the cancer tumor in the breast. High-frequency sound waves are used in ultrasound imaging, also known as sonography, to observe the interior of the body. The real-time nature of ultrasound imaging allows it to display blood flowing via blood vessels as well as the movement of the body's internal organs.

Figure 1, 2: Ultrasound Scanner & image

Mammograms are X-ray images of the breast that can reveal early signs of breast cancer. A mammogram can be generated by one of two methods. Digital mammography produces digital pictures, whereas film-screen mammography produces a photographic film. This prevents the image from blurring and flattens the breast for a better image.

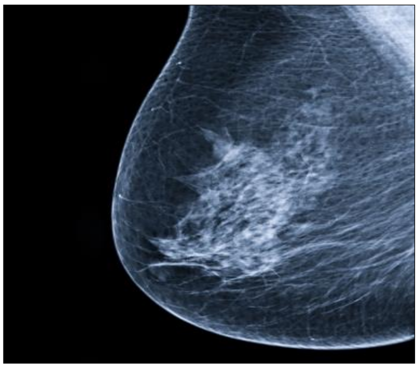

Figure 3: Ultrasound breast cancer image

Mammogram images are often noisy and have low levels of contrast. In breast mammography, bright regions represent cancer. Malignantand normal dense tissues can both be shown in some mammography images [5].

2. PREPROCESSING:

Pre-processing is a process of different operations with images at the lowest level of abstraction both input and output are intensity images. The aim of pre-processing is an improve the image data that suppresses unwanted distortions or enhances some image features important for further processing. The data set used to classify the breast cancer tumor is less and noisy, so here we remove the noise using a Gaussian filter, convert the original image into a Grayscale image by splitting the RGB Channels. A pixel's brightness level in a grayscale picture ranges from 0 to 255.

The conversion of a color image into a gray scale image involves converting the RGB values (24-bit) into grayscale values (8-bit). Various image processing techniques and software applications convert color images to grayscale images [6].

2.1 GRAY SCALE CONVERSION

This indicates that the effect of the red color must be reduced, the influence of the green color must be increased, and the influence of the blue color must be balanced. So the new equation that form is, **GS image = ((0.21*R) +(0.72 *G) +(0.07*B)).**

According to this equation, Red has contributed 30%, Green has contributed 59%, which is greater than all three colors and Blue has contributed 11% [7].

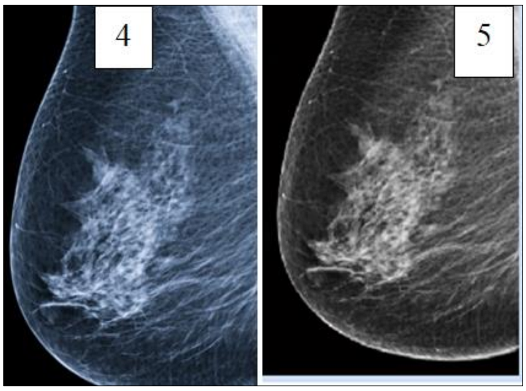

Figure 4, 5: Color Image & Grayscale image

2.2 GAUASSIAN FILTERING

For early filtering tests, Gaussian filters are an excellent option because only one parameter has to be adjusted for modifying their behavior.

The Gaussian filter function is defined as **G (x, y)=1/2πσe-(x2+y2)/2 σ^2.**

The value of the sigma (the variance) corresponds inversely to the amount of filtering; smaller values of sigma mean more frequencies are suppressed and vice versa [8].

3. SEGMENTATION

Image segmentation is the process of dividing a digital image into many segments, which are collections of pixels also known as super-pixels. Image segmentation yields either a collection of contours derived from the image or a collection of segments that together cover the entire image. Here, we segment the Benign and malignant tumors using the K-Means algorithm. The unsupervised K-means clustering algorithm is used to distinguish the interest area from the background. Algorithm steps include.

Step 1: *Initialize cluster centers.*

Step 2: *Step two: Assign observations to the closest cluster center.*

Step 3: *Revise cluster centers as a means of assigning observations.*

Step 4: *Continue performing steps 2 and 3 repeatedly until the process reaches convergence [9].*

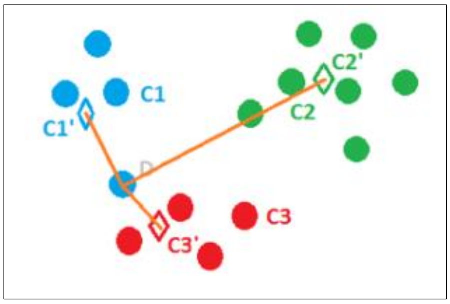

Figure 5: K-Means Segmentation

4. CLASSIFICATION

Neural Network Learning is a process of showing the original function of any object in the network to simulate the required output. The Neural network backpropagation is used for learning the attributes for tumor classification. Neural Networks (NN) are useful data mining techniques, that are often used for classification and clustering. It is an attempt to build a machine that will mimic brain activities and be able to learn. NN usually learns by example. If NN is supplied with enough examples, it should be able to perform classification and even discover new trends or patterns in data. Three layers make up a simple neural network: input, output, and hidden layer. Multiple nodes may be included in each layer, with the nodes in the input layer being linked to those in the hidden layer. Nodes from the hidden layer are connected to the nodes from the output layer. Those connections represent weights between nodes. This paper describes one of the most popular NN algorithms, the Back Propagation (BP) Algorithm. The aim is to show the logic behind this algorithm. The idea behind the BP algorithm is quite simple: the output of the NN is evaluated against the desired output. If the outcomes are not beneficial, the weights (connections) between layers are altered, and the procedure is performed repeatedly until the error is sufficiently minimal. A simple BP example is demonstrated in this paper, with NN architecture also covered. A new implementation of the BP algorithm is emerging, and there are a few parameters that could be changed to improve the performance of BP [10].

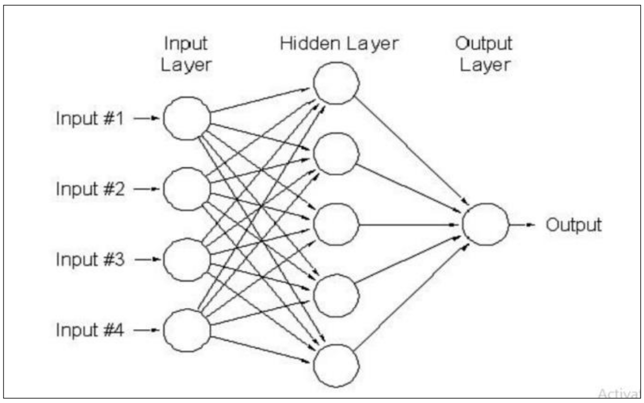

Figure 6: NN-Back Propagation

5. PREDICTION PERFORMANCE: True positive accuracy, reducing the error rate in learning parameters for optimizing cancer prediction [11].

III.FUNCTION BLOCKDIAGRAM

The **Function Block Diagram** (**FBD**) is a graphical language for programmable logic controller design that can describe the function between input variables and output variables. A function is represented using a series of basic blocks, with input and output variables linked to these blocks through connecting lines [12, 13].

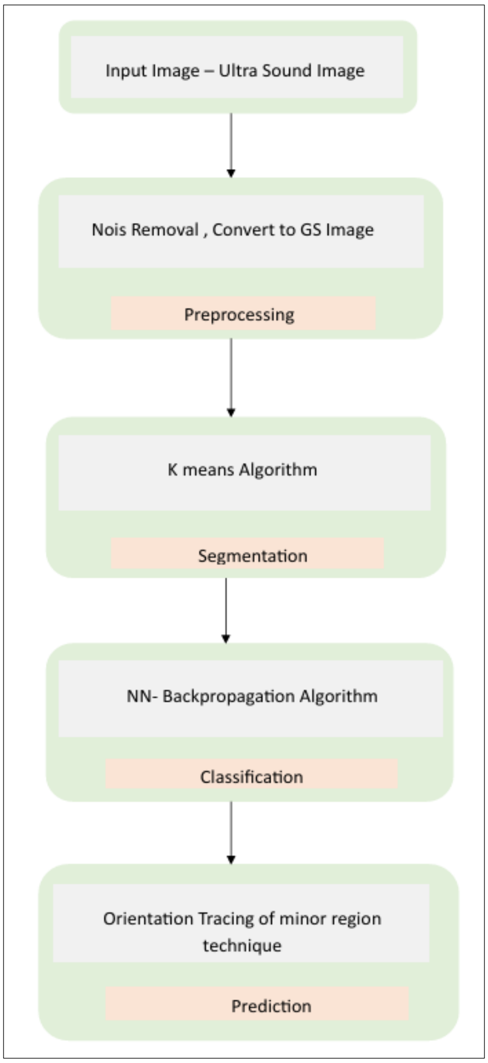

Figure 7: Flow Diagram

IV DISCUSSION

The neural model developed for classifying breast cancer tumors through ultrasound images demonstrates improved diagnostic precision and reduced learning errors. Using backpropagation, it adjusts internal weights over time, allowing for more accurate differentiation between benign and malignant tumors. The sigmoid activation function further supports effective binary classification by enabling steady convergence during training.

Preprocessing steps play a crucial role in boosting performance. Grayscale conversion using perceptually weighted formulas enhances important features, while Gaussian filtering minimizes noise, making tumor regions more distinct. These processes significantly impact the quality of segmentation and classification. Tumor areas are identified using K-Means clustering, which, despite being simple and effective, may struggle with image noise and overlapping tissues—indicating a need for more advanced or hybrid segmentation methods.

Reducing prediction errors is a key goal. Fine-tuning learning parameters improves accuracy, though the overall success depends heavily on the size and quality of the dataset. Current results are promising, but broader validation across diverse datasets is necessary for real-world implementation.

Potential future enhancements could include adaptive grayscale techniques, the use of deeper CNN architectures for automatic feature extraction, and integration of multiple imaging methods—such as combining MRI with ultrasound—to further strengthen diagnostic performance [14, 15].

CONCLUSION

The neural model efficiently classifies breast cancer tumors in ultrasound images through a combination of preprocessing, segmentation, and backpropagation methods. Techniques like grayscale conversion and Gaussian filtering improve image clarity, while K-Means clustering is used to isolate tumor regions. Backpropagation allows the system to accurately learn and distinguish between tumor types. Despite ongoing challenges such as image noise and overlapping tissue structures, the model demonstrates strong potential for enhancing diagnostic precision. Incorporating Convolutional Neural Network (CNNs and multimodal imaging in future work could further improve outcomes. With thorough validation, this approach may aid in early cancer detection and support clinical decision-making.

Author Contributions:
Heber Anandan contributed to this paper; Anandan H designed the overall concept and outline of the manuscript; Dhanisha JL and Vinitha Babuselvan contributed to the development, design, writing and editing of the manuscript; JoeRoseny. J and Tamilselvi Murugaraj contributed to the discussion and conclusion.

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