



Mammogram image classification using deep learning

CLASSIFICATION OF BREAST CANCER AND MONITORING SYSTEM USING IoT

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Abstract : Early diagnosis of breast cancer is proved to reduce the risk of death by providing a better chance of identifying a suitable treatment. Among various diagnostic techniques, such as X-ray, MRI, breast ultrasound and digital mammograms are the most reliable and inexpensive to detect the symptoms of breast cancer at an early stage and can disclose a lot of information about these abnormalities like masses, micro calcifications, architectural distortion, and bilateral asymmetry. Digital mammography is one of the most efficient techniques to detect cancer at an earlier stage. There is a special detector that converts X-ray energy into a digital image. It helps people to reduce the mortality rate. It detects abnormalities easily. It is recommended that all women should do regular screening tests at the age of 35 to prevent this disease. There are many advantages to digital mammography, such as the patient spending less time for screening, the radiologist quickly transmitting the images to another physician, and they can be easily manipulated. Data mining is the process of discovering hidden patterns in a database. There are many techniques available, such as neural networks, association rule mining, classification, clustering, and so on. We've used Convolution Neural Networks.

IndexTerms -Convolution Neural Networks.

I. INTRODUCTION

Breast cancer constitutes a significant threat to women's health and is considered the second leading cause of death in women. Breast cancer is a result of abnormal behaviour in the functionality of normal breast cells. Therefore, breast cells tend to grow. Deep learning makes use of mathematical and statistical models to learn from data. Deep learning finds an important role in biomedical applications in which accuracy of measurements is a crucial factor. Subsequently, Deep learning algorithms can help diagnose breast cancer at its early stages. Deep learning tools can determine the most predicative features from complex and noisy data sets. As a result, false negative and false positive decisions could be significantly reduced, which yields better classification accuracy. Early Breast cancer detection is done using Deep learning approach to make the system detect the tumor cells automatically using advanced image processing techniques. It has four stages, Image is preprocessed by studying various parameters extractions such as color conversion, re-sizing and filtering is carried out by segmentation algorithms. This helps to identify the amount of lesions scattered over the body. Feature extraction is by Max Pooling and finally, mammogram image classified using Deep Convolution Network algorithm. Finally the results will be uploaded in IoT, whether it is normal, benign or malignant.

II. EXISTING SYSTEM

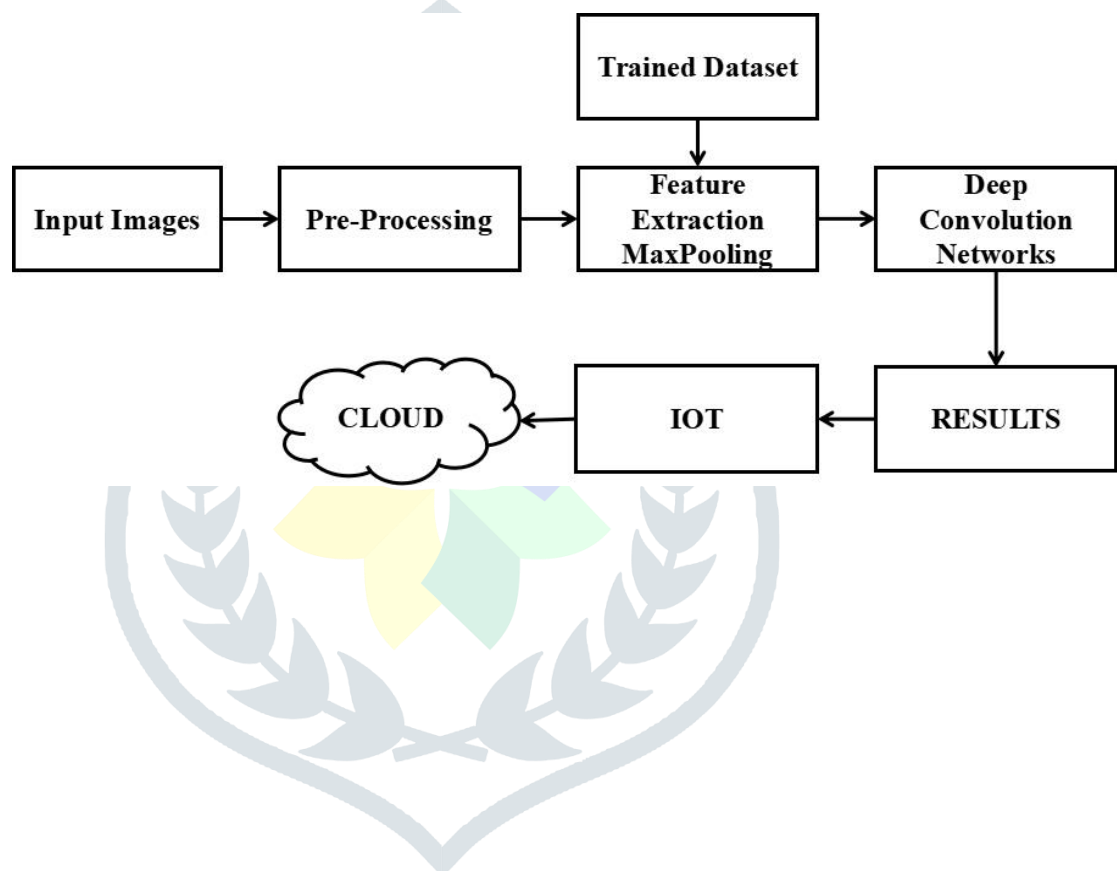
In the existing system, design of Critical and Early Breast cancer detection is done using machine learning approach to make the system detect the tumor cells automatically using advanced image processing techniques. It has four stages, Image is pre processed

by studying various parameter extractions such as color conversion, re-sizing and filtering. K-means algorithm is carried out by segmentation algorithms. This helps to identify the amount of lesions scattered over the body. Feature extraction is by GLCM and finally, mammogram image classified using LDA algorithm. Finally the message box will be displayed whether it is normal, benign or malignant

III. PROPOSED SYSTEM

In the proposed system, design of Critical and Early Breast cancer detection is done using deep learning approach to make the system detect the tumor cells automatically using advanced image processing techniques. It has four stages, Image is preprocessed by studying various parameters extractions such as color conversion, re-sizing and filtering is carried out by segmentation algorithms. This helps to identify the amount of lesions scattered over the body. Feature extraction is by Max Pooling and finally, mammogram image classified using Deep Convolution Network algorithm. Finally the results will be uploaded in IoT, whether it is normal, benign or malignant.

IV. BLOCK DIAGRAM OF PROPOSED SYSTEM



V. TECHNOLOGY AND DESIGN

Step 1: Data collection:

The images Mammography Image Analysis Society (MIAS) database used in the form of PGM (Portable Gray Map) format. In this research, 240 mammogram images were used to determine the various stages. Out of 240 images, 108 are for normal, 108 are for benign, 24 are for malignant.

Step 2:

After acquiring the image, we do pre-processing to resize the images to 500x500x3

Step 3:

The pooling layers gradually reduce the size of the image, keeping only the most important information. For example, for each group of 4 pixels, the pixel having the maximum value is retained (this is called max pooling), or only the average is retained (average pooling).

Pooling layers help control over fitting by reducing the number of calculations and parameters in the network.

After several iterations of convolution and pooling layers (in some deep convolutional neural network architectures this may happen thousands of times), at the end of the network there is a traditional multi layer perceptron or “fully connected” neural network.

Step 4:

Here the train set and test set are compared using the DCN algorithm. The strength of DCNNs is in their layering. A DCNN uses a three-dimensional neural network to process the Red, Green, and Blue elements of the image at the same time. This considerably reduces the number of artificial neurons required to process an image, compared to traditional feed forward neural networks.

Deep convolutional neural networks receive images as an input and use them to train a classifier. The network employs a special mathematical operation called a “convolution” instead of matrix multiplication.

The architecture of a convolution network typically consists of four types of layers: convolution, pooling, activation, and fully connected.

VI. DEEP LEARNING:

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VI.1. Convolution Layer

Applies a convolution filter to the image to detect features of the image. Here is how this process works:

A convolution—takes a set of weights and multiplies them with inputs from the neural network.

Kernels or filters—during the multiplication process, a kernel (applied for 2D arrays of weights) or a filter (applied for 3D structures) passes over an image multiple times.

Dot or scalar product—a mathematical process performed during the convolution. Each filter multiplies the weights with different input values. The total inputs are summed, providing a unique value for each filter position.

VI.2.ReLU Activation Layer

The convolution maps are passed through a non linear activation layer, such as Rectified Linear Unit (ReLU), which replaces negative numbers of the filtered images with zeros

VI.3.Pooling Layer

The pooling layers gradually reduce the size of the image, keeping only the most important information. For example, for each group of 4 pixels, the pixel having the maximum value is retained (this is called max pooling), or only the average is retained (average pooling).

Pooling layers help control overfitting by reducing the number of calculations and parameters in the network.

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VI.4.Fully Connected Layer

In many CNN architectures, there are multiple fully connected layers, with activation and pooling layers in between them. Fully connected layers receive an input vector containing the flattened pixels of the image, which have been filtered, corrected and reduced by convolution and pooling layers. The softmax function is applied at the end to the outputs of the fully connected layers, giving the probability of a class the image belongs to – for example, is it a car, a boat or an airplane.

VII. SOFTWARE IMPLEMENTATION

VII.1.SYSTEM REQUIREMENTS

Windows 10 Personal Computer

MATLAB

With Simulink, 4 GB is required

With Polyspace, 4 GB per core is recommended

VII.2.Algorithm:

There are four layers in CNN,

1. Image Input Layer of size ([500 500 3]) is a resized image size.
2. Image Filtering is performed by the function “ layer = convolution2dLayer(filterSize,numFilters,Name, Value)” creates a 2-D convolutional layer and sets the FilterSize and NumFilters properties.

Here we have used a filter size of [5 5]
The Number of filters we have used are four different sizes.
[8 8] , [16 16] , [32 32] , [128 128].
Padding is used with the same value.

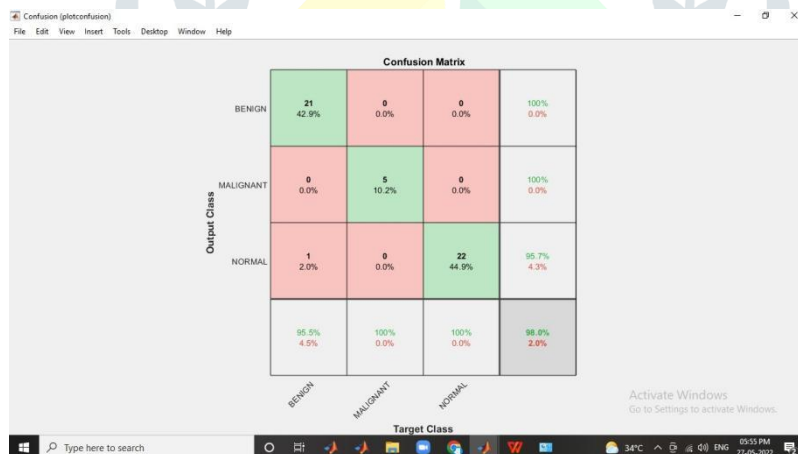
3. Rectified Linear Feature map is obtained by the function “reluLayer”
4. Max pooling is done using the function “layer = maxPooling2dLayer(poolSize,Name,Value)”
Pool Size of [2 2] is used
With a stride of value 2

VIII. HARDWARE DESCRIPTION

ESP 8266 MODULE

The ESP8266 is a low-cost Wi-Fi microchip, with a full TCP/IP stack and microcontroller capability, produced by Espressif Systems[1] in Shanghai, China. The chip first came to the attention of Western makers in August 2014 with the ESP-01 module, made by a third-party manufacturer Ai-Thinker. This small module allows microcontrollers to connect to a Wi-Fi network and make simple TCP/IP connections using Hayes-style commands. However, at first there was almost no English-language documentation on the chip and the commands it accepted. The very low price and the fact that there were very few external components on the module, which suggested that it could eventually be very inexpensive in volume, attracted many hackers to explore the module, the chip, and the software on it, as well as to translate the Chinese documentation. The ESP8285 is an ESP8266 with 1 MiB of built-in flash, allowing the building of single-chip devices capable of connecting to Wi-Fi. These microcontroller chips have been succeeded by the ESP32 family of devices, including the pin-compatible ESP32-C3.

IX. RESULTS AND OUTPUT:



X. CONCLUSION AND FUTURE WORK

Breast cancer is a disease of premenopausal women as a whole, but it's also affecting younger ages due to underlying risk factors of life style changes and more exposure to man-made chemicals that has become a part of our life. The most cause of the cancer may be due to risk factors of age, family history, and environmental factors. Mammogram images are used from MIAS database. We have used image processing techniques such as median filtering, Max Pooling, DCNN classifier. Our work focus on classification of normal, benign and malignant into five stage of breast cancer using image processing techniques and data mining technique is used to classify the stage of breast cancer and the performance of classifier is evaluated. In our future work focus on decision pre-classifier algorithm based image classification for detecting the breast cancer.

XI.ACKNOWLEDGMENT

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