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SEQUENTIAL CONVOLUTIONAL NEURAL NETWORK FOR AUTOMATIC BREAST CANCER IMAGE CLASSIFICATION USING HISTOPATHOLOGICAL IMAGES

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ABSTRACT: Breast cancer is the major cause of death among the women in all over the world and detection of breast cancer at early or initial stage can increase the survival rate of the patient. Malignancy of the cells of breast tissue is detected for diagnosing the breast cancer. Now days various image processing techniques are used to analyze the histopathological images for diagnosing the cancer. Manual detection of these cells is very time consuming and the result will depend upon the experience of the pathologist. So computer aided techniques are used for fast processing and accurate result of the diagnosis. The Deep learning model uses the Convolutional neural network (CNN) that automatically extracts the features and classify the image using fully connected network. In this paper, we have trained a Sequential convolutional neural network and obtained the highest prediction accuracy for detection of breast cancer up to 99.61%.

KEYWORD: CNN, Histopathological Image, medical image processing, Breast cancer, deep Learning.

I. INTRODUCTION:

Now a day's cancer is the major public health issue in all over the world. According to report of WHO (World Health Organization), GBD (Global Burden of Disease Cancer Collaboration) and IARC (International Agency for Research on Cancer) , between 2006 to 2016 cancer cases are increased by 28% and by the 2030 2.7 million new cancer cases will appear [1-2]. In all types of cancers breast cancer is the most common type of cancer in the women (1.7 million incident cases, 535,000 deaths, and 14.9 million disability-adjusted life years)[2]. So the Detection and diagnosis of breast cancer is very important at early stage so that the survival rate of the patient can be increased. Different types of medical imaging techniques are used for diagnosing of breast cancer like X-ray, CT scan, MRI and ultrasound. Biopsy is also the very important

technique for diagnosing the breast cancer. Normal biopsy techniques contain vacuum-assisted biopsy, surgical biopsy and fine-needle aspiration. In the process of biopsy samples or tissues of cells are collected, fix them on the microscope slide, and then mark them for the further process [3]. After the marking the images are diagnosed by the pathologist to detect the cancer lumps [4].

Figure 1(a) Normal Breast.)

Figure 1 (b) Left breast malignant mass

(Ref: Collected from PARAM MRI center Gwalior (M.P.)

Though, the manual detection of these histopathological images for detection of breast cancer is very time consuming and difficult task and the result can be affected by the knowledge or the experience of the pathologist. So the automatic analysis of histopathological images [5] plays an important role for the detection & diagnosis of breast cancer at the early level. Although the development of tool for automatic detection and analysis of breast cancer impeded by the various challenges. First, the histopathologival images of breast cancer is high resolution and fine grained images that have very complex structure. Second, the large storage is required for processing of these histopathological images. Other challenges are selection of appropriate algorithms & models for feature selection, Data mugging and privacy etc. The major challenge in using computer aided system for lumps detection in breast mammograms is the high false positive rates (FPR). False positives result can cause anxiety in patient, needless exposure of radiations, increased health care costs etc. [6].

Recent research in computational technologies and Artificial intelligence shows important progress in image processing and Deep learning techniques, and occurrence of digital mammograms images provides an opportunity to address the challenging issue of early detection of breast cancer using deep learning (DL) methods [7–10].

Deep learning has the powerful feature extraction and the various challenges for analysis of histopathological images for breast cancer; this paper analyzes histopathological images of breast cancer using deep learning techniques. Deep learning method especially convolutional neural network of deep learning (CNN or known as ConvNets) have achieved lot of consideration for analyzing the mammograms as they overcome the limitations of CAD systems [11]. A recent research studies shows that to use deep learning model for breast cancer detection reduced human error rate by 85% [12]. Currently CNN are designed to detect breast cancer at initial level by detecting small lesions so that radiologist can prepare current diagnosis for further treatment planning [13-15].

II. BACKGROUND STUDY & RELATED WORK:

Literature survey

Dhungel, N et. al. [16] presented the use of multi scale belief network for detecting the masses in breast mammograms. Using the INbreast and DDSM-BCRP datasets, the sensitivity achieved in this paper was 85%–90% respectively. The main drawback of this paper was the use of limited size training set that were 39 and 40 cases respectively.

Deep convolution neural network and support vector machine is used by **Wichakam I. et. al.** for detection of breast cancer [17] . In this paper the sensitivity achieved was 98.44% using the INbreast dataset.

Bayramoglu, N et. al. Presented a method to classify breast cancer images using Convolutional neural network. In this paper the author proposed two different architectures; first the single task CNN is used to expect malignancy and the second multitask CNN is used to imagine both levels simultaneously that are malignancy and image magnification. The experiments are performed on BreakHis dataset and the result shows the improvement as compared to the traditional machine learning approach [18].

For the categorization of hematoxylin and eosin stained breast biopsy images **Araújo et al.[19]** presented used the dataset of 269 images using CNN model that is categorized into four classes (i) normal tissue (ii) benign lesion (iii) *in situ* carcinoma and (iv) invasive carcinoma and in two classes (i) carcinoma and (ii) non-carcinoma. In this paper SVM is trained using the features extracted by the CNN. Accuracy achieved using SVM for four classes is 77.8% and for two classes is 83.3%.

For providing an accurate and reliable solution for multi-class classification of Breast cancer **Han et al. [20] presented** a class structure-based deep convolutional network using hierarchical feature representation. In this paper authors achieved 95.9 % accuracy for multiclass classification of breast cancer.

Jiang et. al. [21] used a new dataset named BCDR-F03 (Film Mammography dataset number 3) for the conditions of the area under the receiver operating characteristic curves (AUC). In this paper to classify the breast lesion the authors used GoogLeNet and the AlexNet architecture with an AUC of 0.88 and 0.83, respectively.

To predict the subclass of the tumors a DenseNet based model for multi-class breast cancer classification is presented by **Nawaz et al. [22].** In this paper the BreakHis dataset used and the experimental result shows the accuracy of 95.4%.

Motlagh et al. [23] used the breast cancer images of BreakHis dataset and the pre trained model of ResNet_V1_152 **[24]** for the diagnosis of benign and malignant tumor as well as for the finding that are based on multi-class classification of different subsets of histopathological images. In this paper the experimental result shows the accuracy of 98.7% and 96.4% for binary classification and multi-class classification, respectively.

Mehdi Habibzadeh Motlagh et. al. [25] presented the fine tuned pre- trained deep neural network for breast cancer detection and classification using histopathological images. In this paper different cancer types using 6,402 tissue micro-arrays (TMAs) training samples are classified for the testing approach. The authors implemented framework using ResNet V1 50 pre-trained model for the four different types of cancers that are including breast, bladder, lung and lymphoma and achieved average accuracy of 99.8%. After that BreakHis dataset of 7,909 images is used for the classification of breast cancer sub types. For classification benign and malignant breast cancers ResNet V1 152 model achieved the accuracy of 98.7%.

Recent study shows that for early detection of breast cancer thermographic procedure is very promising tool that can increase the cure rate of the breast cancer patient. **J. H. de Vasconcelos et.al. [26]** presented the analysis of different methods for classification of digital images that includes thermographic or infrared (IR) images. The objective of authors for analyzing these digital images was to explore the feasibility of infrared or thermographic images for classification of breast cancer. In this paper the IR images are acquired and processed and then the characteristics extraction was performed from the thermograms using feasible temperature ranges. For the binary classification (Cancerous or non- cancerous), the authors successfully achieved 93.42% accuracy, 94.73% sensitivity and 92.10% specificity and for the multiclass classification ((Malignant, Benign, Cyst and Normal) the authors achieved 63.46% accuracy, 80.77% sensitivity and 86.54% specificity.

Xie, J. et. al. [27] presented the deep convolutional neural network for analyzing the histopathological images of breast cancer images using supervised and unsupervised learning. For the binary and multiclass classification of breast histopathological images the authors used Inception_V3 and Inception_ResNet_V2 architectures by transfer learning techniques. In this paper the experimental result shows that the classification of breast cancer using supervised histopathological image and the comparison with the results from existing studies reveal that Inception_V3 and Inception_ResNet_V2 architecture is finer for breast cancer image classification then the existing methods. Studies in this paper shows that for diagnosis og breast cancer histopathological images Inception_ResNet_V2 network is the best deep learning architecture. So the authors used the Inception_ResNet_V2 network for unsupervised analysis also.

Dabeer, S et.al used the convolutional neural network for classification of breast cancer using BreakHis dataset. The experimental result in this paper shows the prediction accuracy of up to 99.86% [28].

For extracting the useful visual features using deep learning model with convolutional layer for classification of breast cancer is presented by **Duc My Vo** et. al [29]. In this paper the experimental result shows the accuracy of 96.4% and 99.5% for four and two class classification tasks, respectively. For breast cancer diagnosis **Fung Fung Ting et.al. [30],** presented Convolutional Neural Network Improvement for Breast Cancer Classification algorithm. This algorithm can assist radiologist or oncologist to classify the mammographic medical images in three categories that are (i) benign (ii) Malignant and (iii) Healthy patient without prior information presence of cancer lesion. The presented model in this paper achieved 90.50% accuracy.

Reddy, A et.al. [31] presented a new method called Deep Neural Network with Support Value (DNNS) for breast cancer detection. The presented method is based on the support value on the deep network. In this paper the normalization process is used for better performance, efficiency and quality of images in medical image analysis.

The deep learning based convolutional neural network model called BreastNet is presented by **Toğaçar, M et.al. [32].** the structure of the BreastNet is a residual architecture that is built on attention modules. The BreastNet architecture in this paper uses the augmentation technique to generate the artificial training data before giving any input to the model. For the experimental purpose the BreakHis dataset is used and achieved better performance in comparison of AlexNet, VGG-16 and VGG-19 models.

Dataset:

There are various histopathological images datasets are available for breast cancer like breast (WDBC) cancer

Wisconsin Original Data Set (UC Irvine Machine Learning Repository) **[33]** **,** MITOS- ATYPIA- 14 **[34]** and BreakHis **[35].** We have used BreakHis database which contains total 7009 images with resolution of 700*460 pixels. For the BreakHis dataset images are captured using four different magnification labels that are 40x, 100x, 200x and 400x.All of these labels are classified into benign and malignant tumors images and both benign and malignant is having various subsets. Benign tumor is classified into 4 subsets that are Adenosis (AD), Fibroadenoma (FI), Phyllodes Tumor (PT) and Tubular Adenoma(TA). A malignant tumor is having Ductal Carcinoma (DC), Lobular Carcinoma (LC), Mucinous Carcinoma (MC), and Papillary Carcinoma (PC). The division & description of dataset is given in table-1.

Label	**Benign**				**Malignant**				**Total**
	AD	**FI**	**PT**	**TA**	**DC**	**LC**	**MC**	**PC**	
40x	114	253	109	149	864	156	205	145	**1995**
100x	113	260	121	150	903	170	222	142	**2081**
200x	111	264	108	140	896	163	196	135	**2013**
400x	106	237	115	130	788	137	169	138	**1820**
Total	**444**	**1014**	**453**	**569**	**3451**	**626**	**792**	**560**	**7909**

Table 1: BreakHis dataset classification

Convolutional neural Network (CNN)

The convolutional neural network is the types of deep learning algorithms that are mainly used for image classification, features extractions, object detection, face recognition etc. The CNN use the randomly defined weights to the input at the starting and modifies these weights after every layer. When the training of the model is done than CNN will used these weights to predict the result in the validation and testing process. Recently CNN is frequently using for image segmentation and medical image processing also [36-39]. CNN model automatically learns features from back-propagation using multiple layers such as Convolution, pooling, and fully connected layers. The architecture of CNN has mainly two steps. In first step pixels are convolved with kernel or filter and provide the convolution (dot product) of image square

and the kernel. The depth of the filter will be same as the depth of the input and the height & width can be kept according to the size of the network. A second most important step is the pooling or sub-sampling that can be of many types such as max_pooling, min_pooling and average_pooling. The pooling layer in CNN is used to reduce the over fitting and to reduce the dimensionality of the data. The user decides the size of the filter in pooling layer and it generally takes odd no filters for pooling operation.

III. PROPOSED METHOD

This paper introduces the automatic detection of breast cancer lesion using deep learning methodology. We have used CNN architecture for image classification. Using the BreakHis dataset we are using input images which are labeled as benign and malignant. In this work CNN was trained using RGB color model with 2480 benign and 5429 malignant samples of breast . The proposed architecture to distinguish between benign and malignant tumor is shown in figure 1.

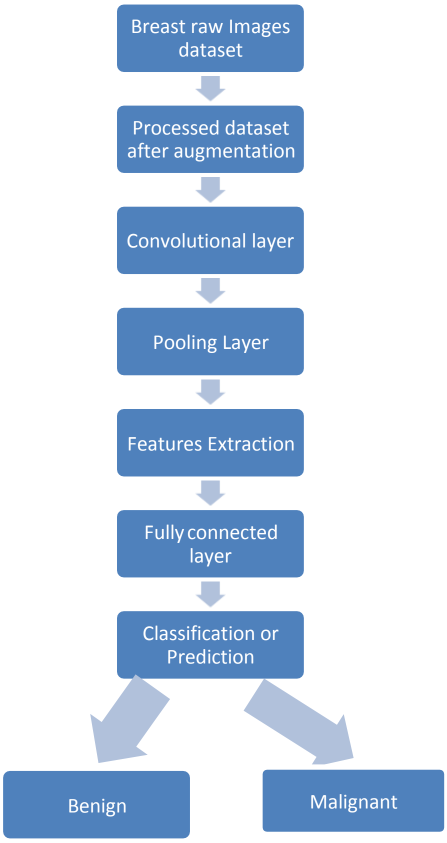

Figure 3 : Model Process Flow

Image Preprocessing:

An image contains number of redundant pixels that are not used to describe any information regarding image [40]. In the artificial intelligence these pixels can be removed using the compression techniques. In implementation of our model for preprocessing of images we have used OpenCV library of python. This preprocessing is needed to reduce the computational complexity and overhead of the network so that we can get better result.

Feature Extraction

Feature extraction is the important step for the classification of images. Previous studies shows that computers or machines are very sensitive to pattern as compare to the human brain that is sensitive to shape [41]. So automatic feature learning will be different from the manual learning. In the visual representation of breast images malignant tumors have large lesions and the irregular nuclear structure. We have used CNN model to process the images with the labeled class such as benign and malignant. From the automatic weight updation in the training process CNN will be able to extract the features of the image. In our proposed architecture CNN model is having 2 layers.

(i) Convolutional layer

(ii) Pooling Layer

After the convolutional process the number of filters are used to increase the depth of the input and after that pooling layer is used that remains the same depth with reduced size.

Classification

In the classification process, flattened weighted feature map are used that are acquired from the final pooling layer and it will be used as an input to the fully connected layer that calculates the loss and accuracy and according to the result weights of the internal nodes will be modified automatically to improve the result.

After the preprocessing is done these layers are stacked .The output of the last layer is taken as the final output as usual.

Convolutional neural network for Automatic identification of Breast tumor as Benign or Malignant:

Model Creation

Here we are discussing the process to identify whether the person is suffering from breast cancer or not by diagnosing the histopathological images. For the implementation of same we have used BreakHis dataset that is having data in 2 classes (i) Benign (ii) Malignant. Total numbers of images used from the BreakHis dataset in this model are 1000 .The dataset is split into 90% training and 10 % testing samples.

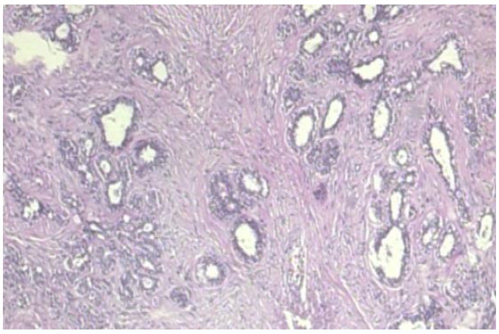

Figure 4 (a) Benign Brest Image

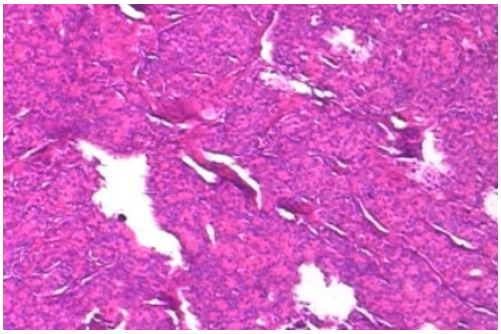

Figure 4 (b) Malignant Brest Image

Ref: BreakHis Dataset (35)

This model is developed in Python language by using the deep learning libraries: numpy, opencv and Keras. We used a batch size of 32 which is the very important hyper-parameter to adjust in DL. We use a medium batch size to train our models as we are using small dataset of breast images. Some data augmentation is also used to artificially create training set from the existing dataset. We have created an image generator object which performs random rotations, shifts, flips, crops, and sheers on our image dataset. This allows us to use a smaller dataset and still achieve high results. In the model Our **CONV** layer has 32 filters with a 3 x 3 kernel and **RELU** activation (Rectified Linear Unit) , pooling layer of size 3x3 and dense layer with ReLu and Softmax activation function.. After that we have applied 25% (0.25) dropout, batch normalization and max pooling. Visualization is done after every layer and adam optimizer is used with epoch of 09.

IV. RESULTS AND DISCUSSION

After the successful implementation of our CNN model with convolutional and pooling layer we have taken the sample images from the training dataset and visualize the output after every layer.

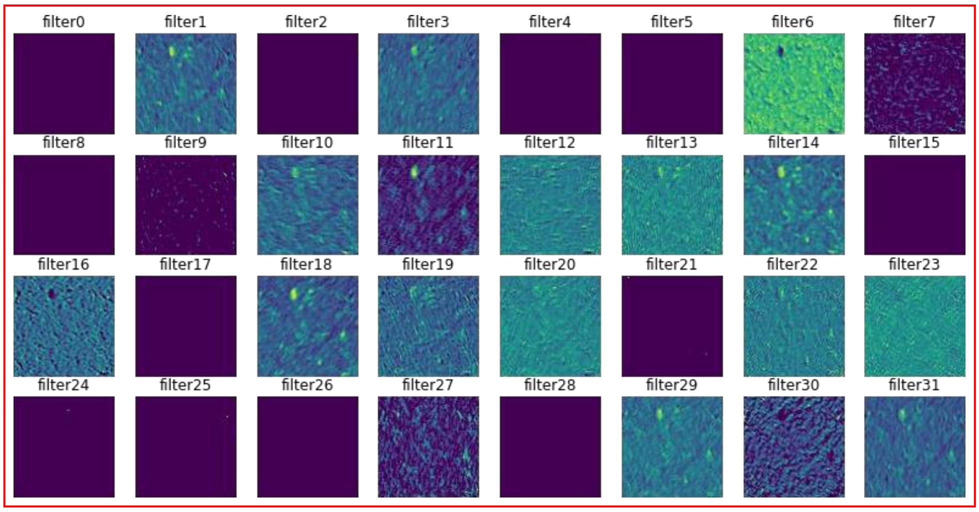

Figure 5 (a) Visualization of layers (conv2d_1)

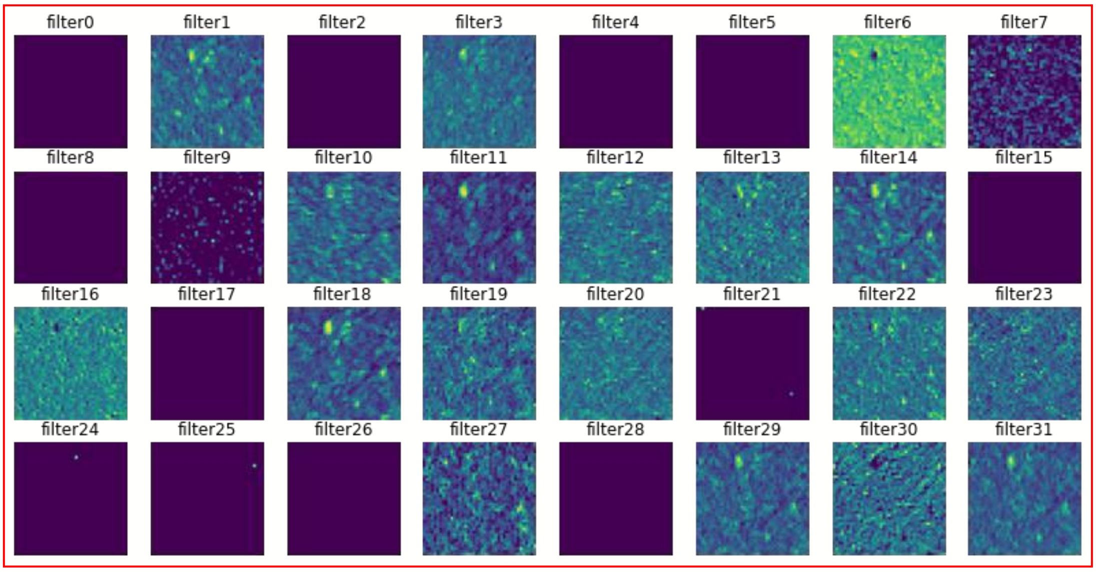

Figure 5 (b) Visualization of layers (max_pooling2d_1)

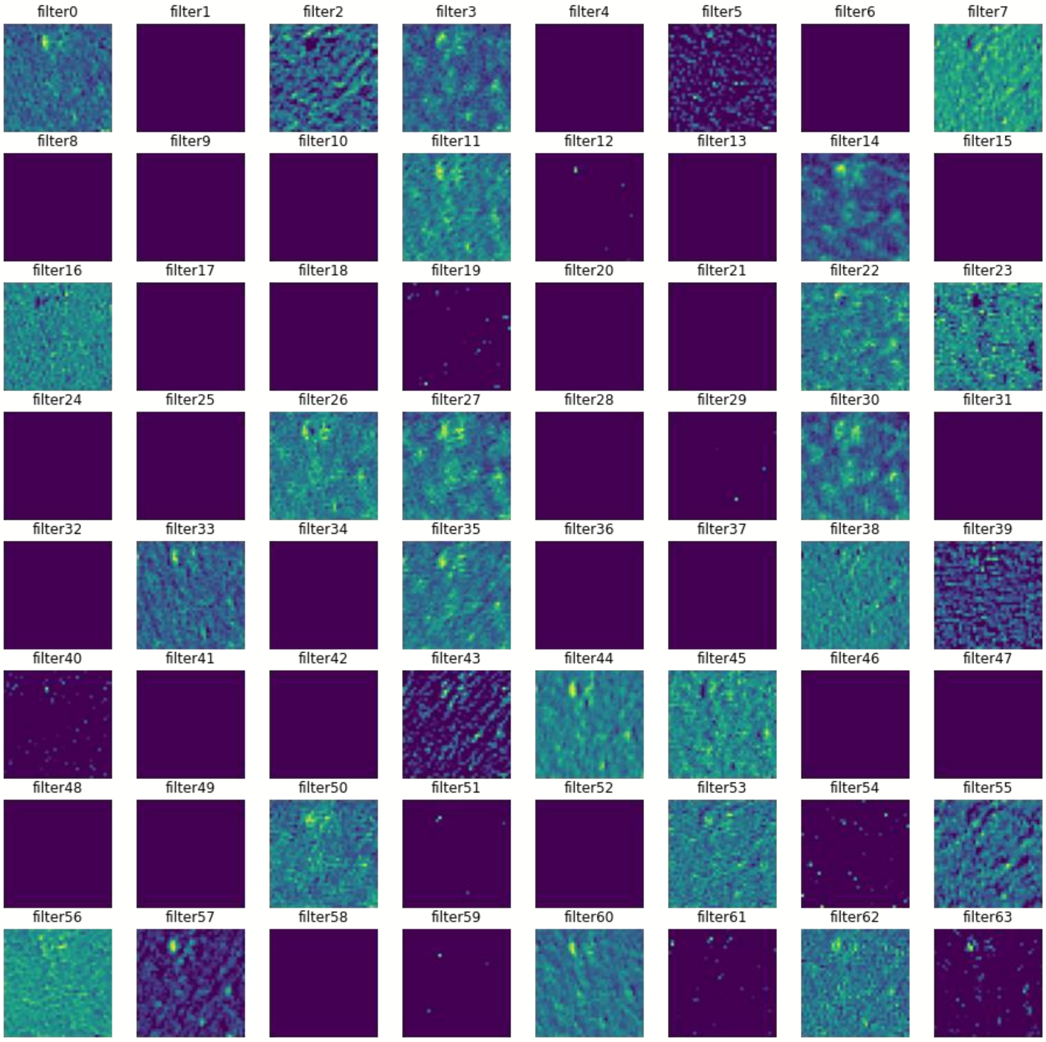

Figure 5 (c) Visualization of layers (conv2d_2)

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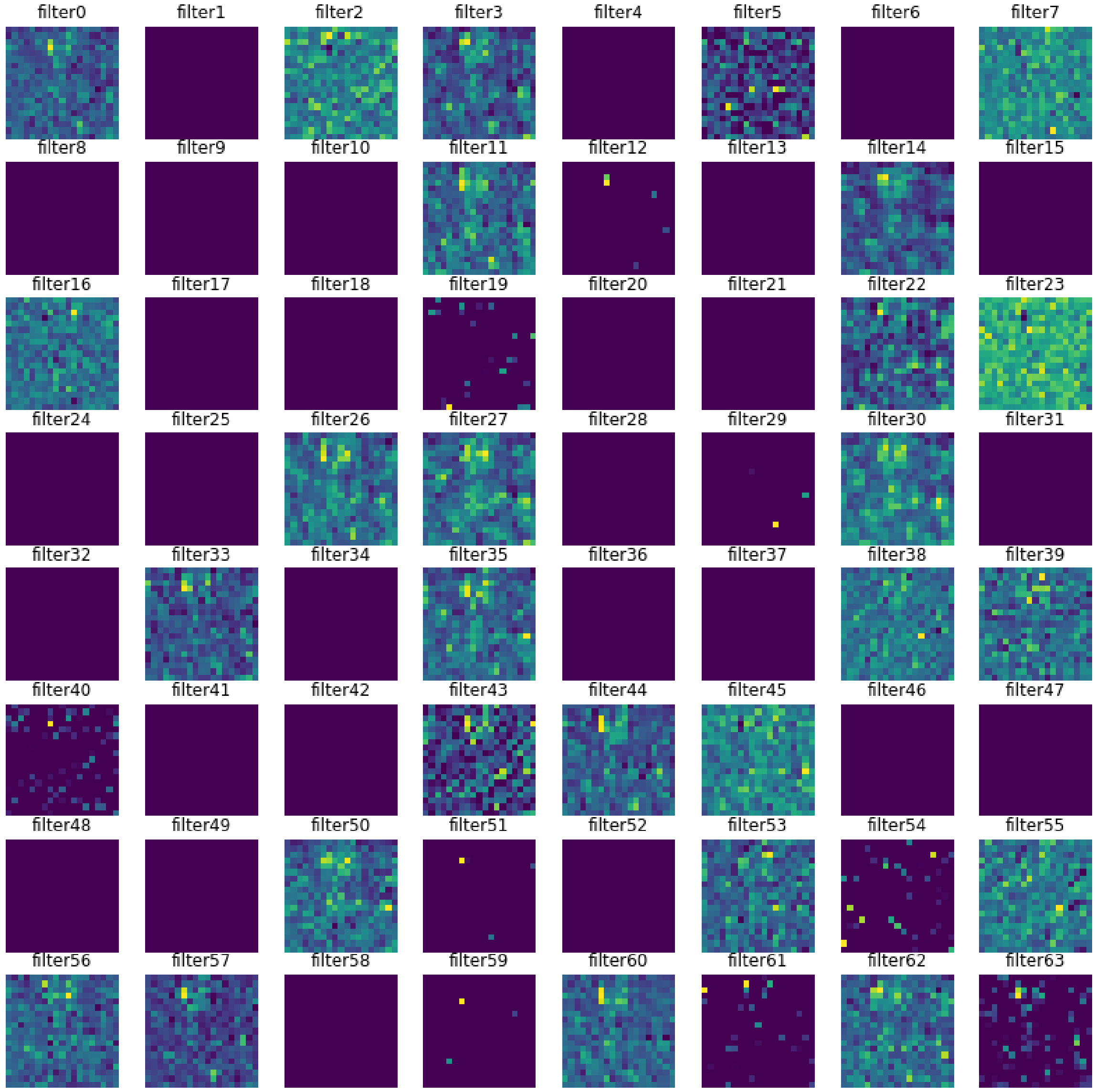

Figure 5 (d) Visualization of layers (max_pooling2d)

After that we have presented the graph for training & validation loss and training & validation accuracy using Matplotlib. In these graphs losses are decreasing and accuracy is increasing that shows that our model is trained in a better way.

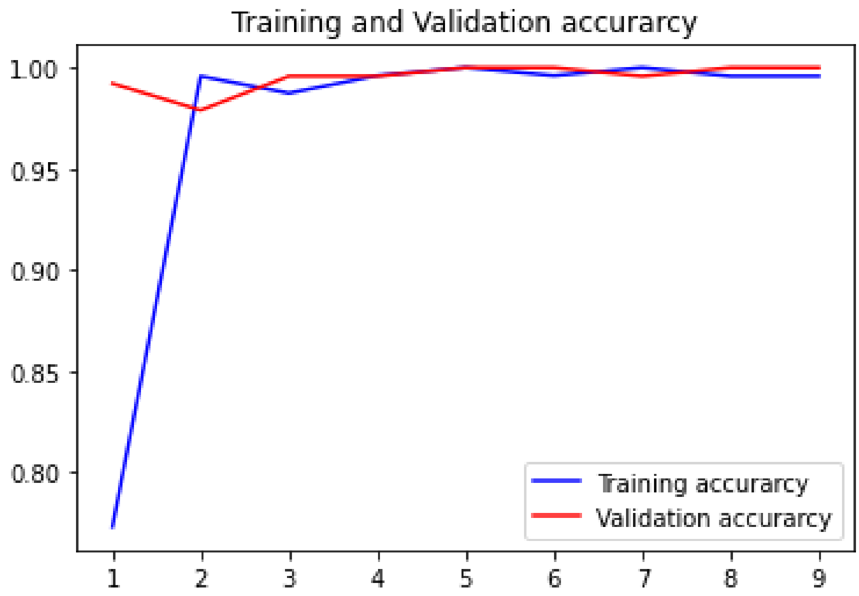

Figure 6 Training & Validation Accuracy

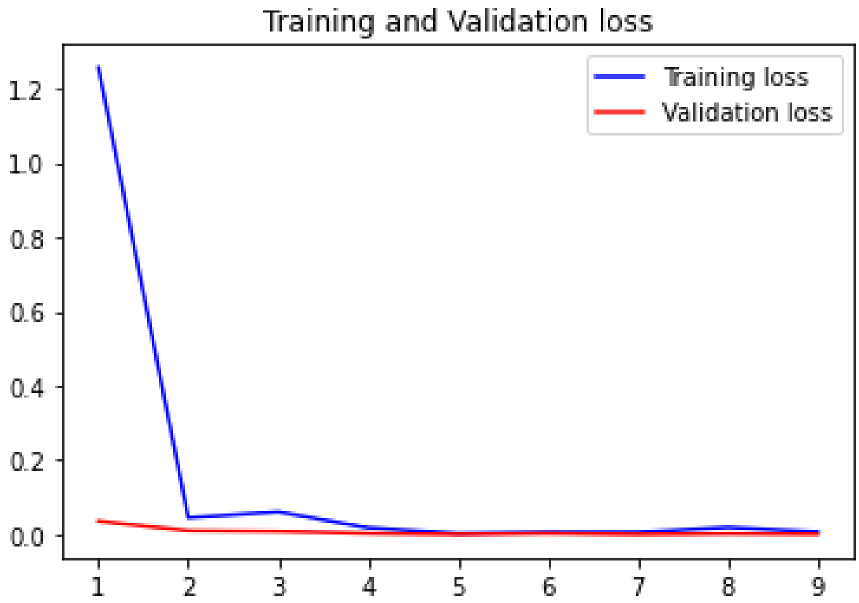

Figure 7 Training & Validation Loss

After the successful implementation has done for prediction to classify the image as benign or malignant so we have done preprocessing of our image to pass in a model to predict. Following prediction output is generated.

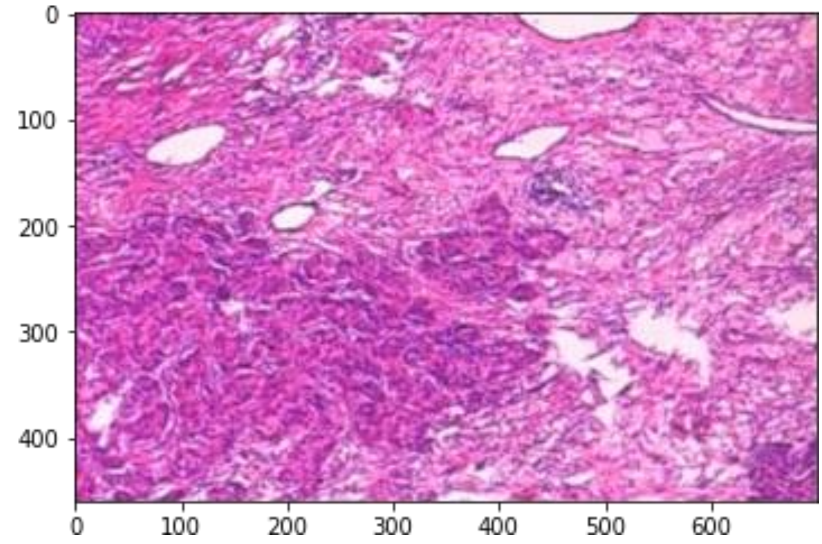

Figure 8 Malignant Image

V. CONCLUSION:

Breast cancer detection in deep learning by using histopathology images is a sign in the field of medical pathology. It has provided the new opportunities for research as there are many undiscovered areas that can be exposed by techniques and tools of machine learning and deep learning. We may obtain improved results by altering the network design and parameters. As an improvement to the proposed method, in future one can implement an autoencoder instead of manually reducing image size. It can compress data without losing the important features, because autoencoders can regenerate up to 90% of the original images.

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