Significantly accurate system for Breast Cancer malignancy or benign classification

MAJOR PROJECT1 REPORT

DELHI TECHNOLOGICAL UNIVERSITY

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

SUBMITTED BY:

SAMAN SAADIZADEH (M.TECH S.P.D.D)

ROLL No. : 2K19/SPD/24

CANDIDATE'S DECLARATION

I hereby certify that the work for project "**Significantly accurate system for Breast Cancer malignancy or benign classification"** submitted to the Department of Electronics & Communication Engineering of Delhi Technological University, is an authentic record of my own work. The matter represented in this report has not been submitted by me for award of any other degree for this or any other institute/university.

Date: 14/01/2021

SAMAN SAADIZADEH
M.Tech S.P.D.D. (Third Semester)
ROLL No. : 2K19/SPD/24

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ABSTRACT

Breast cancer happens to one out of eight females worldwide. It is the most elevated reason for cancer malignancy deadliness among ladies. It is identified by finding the cancerous cells in breast tissue. Novel techniques in medical image processing utilized histopathology dataset images taken by an advanced microscope, and then disintegrate the images by applying various algorithms and techniques. Artificial Intelligence methods are presently being applied for processing pathological imagery and tools. Here in the project work, we concentrate on building up the capability of computer-aided diagnosis (CAD) to anticipate the severity of cancerous cells. Common cancerous cell detecting is a tedious process and involves the fault of physicians, to this end we can use computer-aided detection (CAD) system to reduce the fault and obtain the more acceptable outcome in comparison to a common pathological detection system. Here we are comparing, our framework with the other three machine learning frameworks in breast image segmentation and classification on a well-known dataset (BreakHis) trial arrangement. Classification in deep neural network mainly utilize feature extraction by the means of convolutional neural network and then by embedding a fully connected network, the result would be an acceptable output. Deep learning has a vast amount of functionality in medical image processing without any need for supervision of any professional person during the process and the procedure can be done automatically. Here in our project we train a bunch of histopathology images through a convolutional neural network and obtain accuracy in prediction more than 92%.

Keywords: Histopathology image , BreakHis Dataset , Medical image processing ,Convolutional neural network, Breast cancer classification

Introduction

Among all kinds of cancer in women, breast cancer has the highest rate to occur. Breast cancer is the second-highest deadliness rate after Lung & Bronchial cancer, and about 30% of recently found cases are of breast cancer only. Progressing the fight toward cancer necessitates early-stage detection which can only be possible with a suitable detection system. Techniques have been developed to detect breast cancer, including medical image processing and digital pathology. Images are acquired by histopathology, which generally includes biopsy of the concerned tissue. Tissues containing the tumor are extracted by the pathologist and stained by H&E, which is the mixture of histological stains called hematoxylin and eosin, hence it is examined under a microscope for cancerous cells by searching for malignant features in cellular structures such as nuclei. These microscopic images can be compiled and try for developing computer-aided detection systems. Manual detection is a tedious, time consuming task and most likely to comprise human fault, as most portion in a cell has commonly consist of an irregular random and arbitrary perceptible part. The main target is to classify the cell and predict the malignant or non-malignant cell in the validation set, as malignant tumors tend to grow fast, and treatment should be started instantaneously to prevent more complications. Image is a binary classification problem and can be resolved by diverse machine learning techniques. In a recent investigation it has been found that by using machine learning, our algorithm outperformed in comparison to the human pathologist. A majority of scholars have found that medical image processing using machine learning provides highly accurate results in comparison to the objective diagnosis given by a pathologist. A study in Europe depicted that in which a set of algorithms along with breast images provided more accurate detection. This investigation is also evidence that utilizing high-resolution images and different algorithms can make better proficiency and accuracy toward detecting cancer. The remainder of this report has been described below: We explain the preprocessing steps and architecture of the convolutional neural network which has been utilized in the experiment followed by neural network classification. We are using BreakHis Dataset. Results and experiment are represented in this report. In the end , we complete our project by introducing a few hints for future research that are going to be done in the fourth semester as my research project.

Dataset Used

There are many various datasets which are available for histopathological stained images for example Breast Cancer for breast (WDBC) cancer Wisconsin Original Data Set (UC Irvine Machine Learning Repository), MITOS ATYPIA 14, and BreakHis . We have chosen the BreakHis database, which has been compiled from the result of a survey by P&D Lab, Brazil. Breast tissues are taken as a specimen by the procedure of surgical (open) biopsy (SOB). Samples are stained by hematoxylin and eosin and conducted by a standard paraffin process in which specimen infiltration and embedment are done in paraffin. Images have been taken by a Samsung high-resolution device (SCC 131AN) which has coupled with an Olympus BX 50 microscopic system that has been equipped by a relay lens and the magnification of the system is 3.3x. The mentioned histopathology images consist of TrueColor(8bits per color channel) and three-channel color (which is RGB) coding arrangement. This The BreakHis database consists of a total amount of 7009 images with 700x460 pixel resolution, The histopathological images have been taken in four various levels of magnification. The allotment of images is categorized below in Table 1.

Table 1

Amount of labeled images in dataset

magnification	malignant	benign	total
40x	652	1370	1995
100x	644	1437	2081
200x	623	1390	2013
400x	588	1232	1820
total	**2480**	**5429**	**7909**

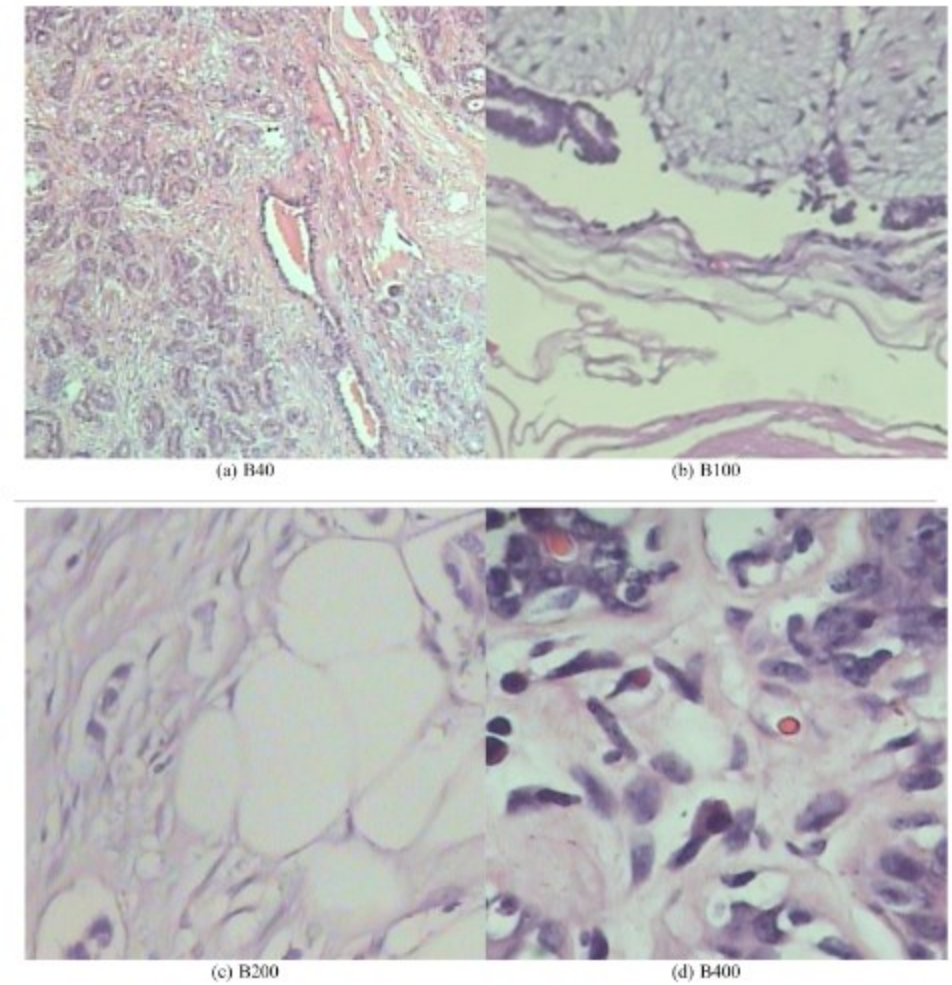

Figure1.Random Benign Testing image

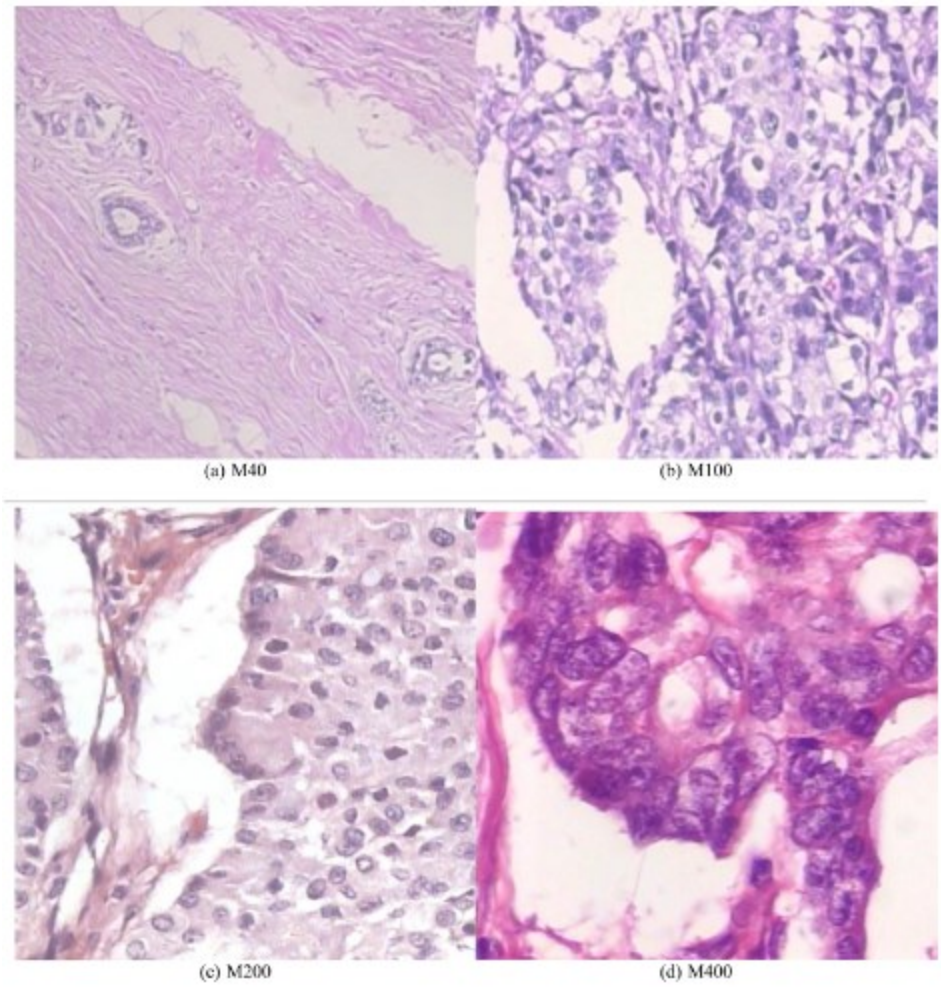

Figure2.Random malignant testing image

Convolutional neural network

In Machine learning, convolutional neural network emerges by modifying the vast variety of deep neural network which relies on the relationship between nearest pixels(neighborhood). It uses incidentally defined patches for input at the start, and alter them in the training process. Once training is finished, the network uses these correctly changed patches to predict and validate the result in the testing and validation process. CNN already has shown many breakthroughs in classifying the images, , also the defined nature of CNN matches the data point distribution in the image. Thereupon, many image processing tasks modify CNN for automatic feature extraction. CNN is frequently utilized for image segmentation and also medical image processing.

The CNN architecture has two main kinds of transformation. The first step in this procedure is convolution, in which pixels have convolved a filter or kernel. Here, This step provides the dot product between image patch and kernel. The width and height of filters will be set according to the network, and the depth of the filter will be equal to the depth of the input. A second arrogant transformation is subsampling, which is categorized in many types (max pooling, min pooling, and average pooling) and used as per necessities. The size of the pooling filter can be set by the user and is generally chosen in odd numbers. The pooling layer is capable for lower the dimensionality of the data and is quite functional to reduce overfitting. After using a mixture of convolution and pooling layers, the output is transmitted to the next layer which is a fully-connected layer for the further process which is the classification. See the architecture of the complete process is presented in Fig. 3.

Apart from the architecture of CNN, there is an additional key point, for instance, the simplicity to the subscriber is beneficial through the development part, as CNN requires an enormous amount of data to train them. It also consumes more time for training by comparing it with other supervised and unsupervised training approaches.

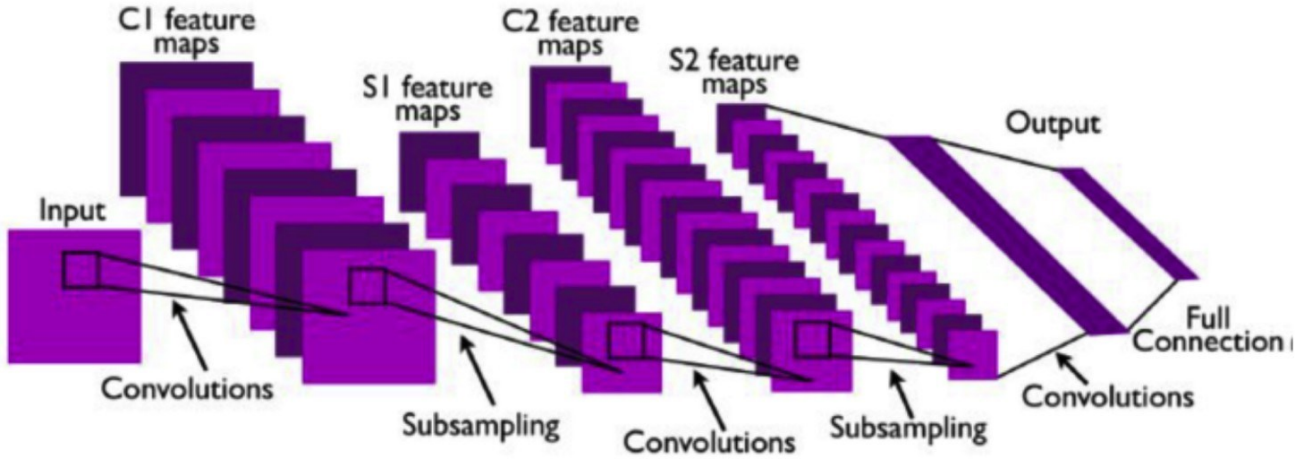

Figure3.CNN architecture

Methodology

This report describes and implements new neural network machine learning structure to detect the cancerous cell in breast with unsupervised learning and automatically which consists of basics of both image classification and deep learning methods. We have introduced Convolutional Neural Networks which adapted to image data . The input images transmitted to the CNN architecture as a raw binary pixels and then the CNN extract the important parts of visual figure, in the next step the mentioned important parts is used to discriminate that weather the tissue is cancerous or not, working much the same as digital coloring , in which it highlights the important part of image for diagnostic decision making, by using a classifier network. The Convolutional neural network has been trained utilizing 2480 benign images and 5429 malignant tumor image kinds which was in three channel (Red, Green, Blue). Therefore, the system depicted in fig.4 provides a very proficient classifier to classify the breast tissue images and predict weather it is benign or malignant in validation set.

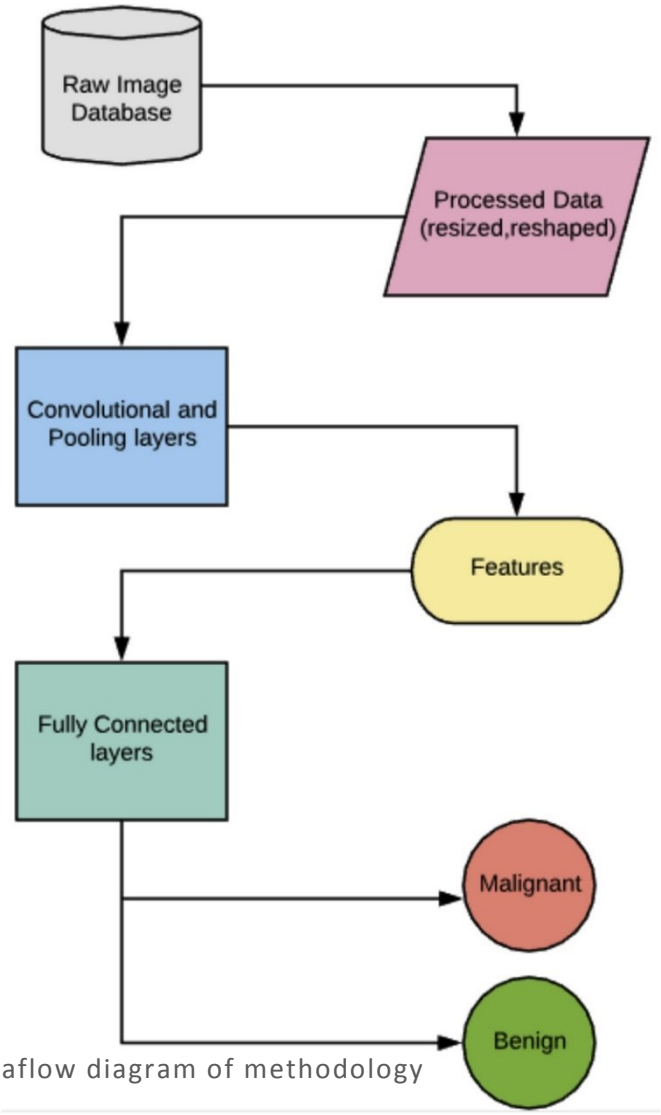

Figure4.Dataflow diagram of methodology

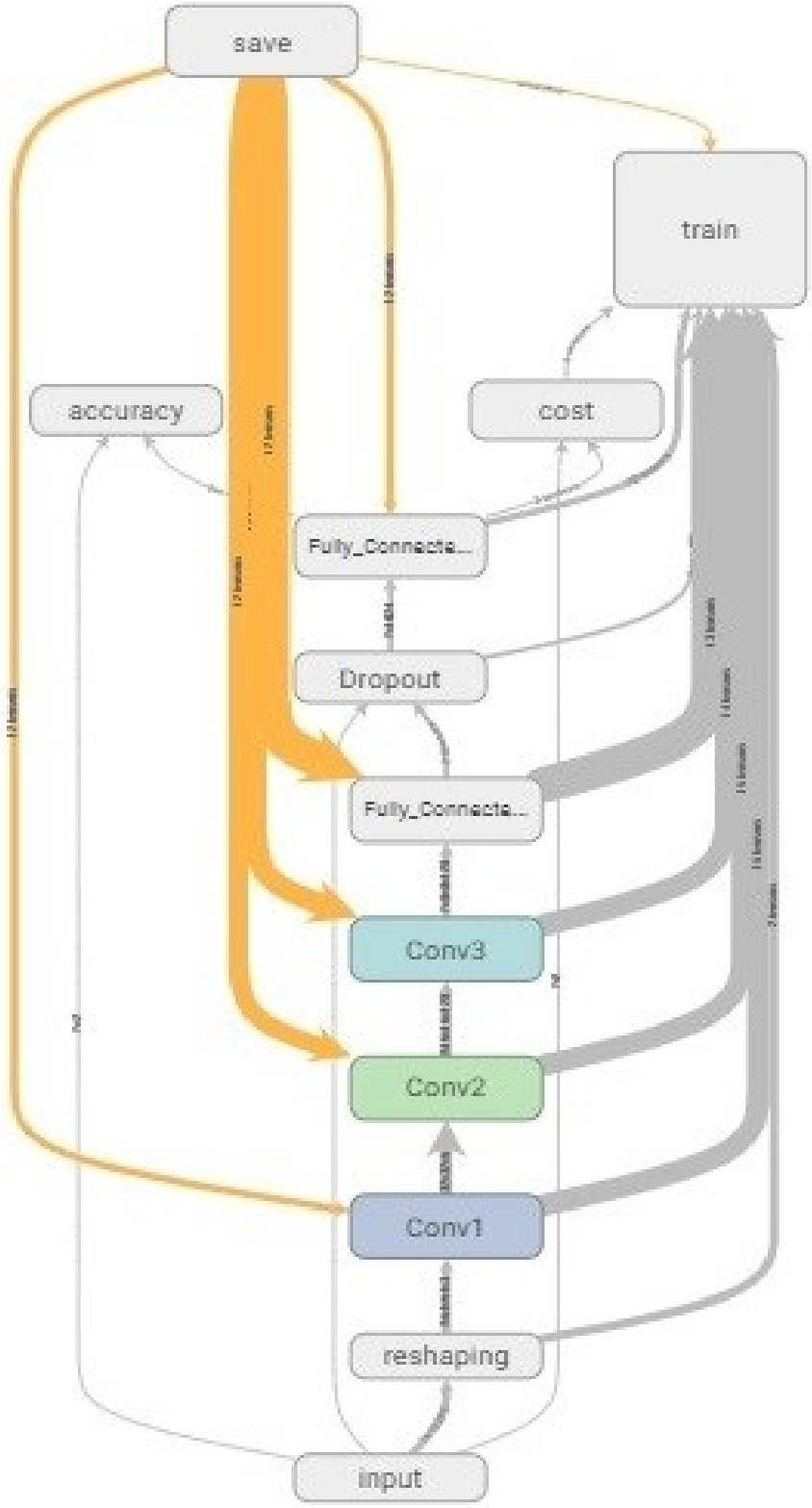

Figure5. Graph of classifier architecture

Dropout

In artificial intelligence and machine learning, Deep neural network along with the nodes and layers and other fundamentals are extremely powerful tools. A considerable issue in the neural network is overfitting. More layers in neural networks will lead the process to decrease in speed, so it would be more inconvenient to deal with overfitting by using the prediction set from a vast amount of neural network during validation. A solution to this problem is using a technique so-called dropout. The main procedure of the Dropout technique is incidentally cut off the node units with their corresponding weight while it is training in the neural network. Dropout will impede co-adapting which used to happen between nodes frequently. In the training process, by the dropout the random layer we make a less layered neural network which will result in a better test setting. During validation, evaluation of the fewer layers in the neural network is more convenient and it is easier to investigate the averaging the prediction, we can pursue it just with the help of a solo full layered net which has fewer weight values. This efficiently decreases the problem of overfitting, it will bring breakthrough achievements in comparison to various techniques for regularization as well.

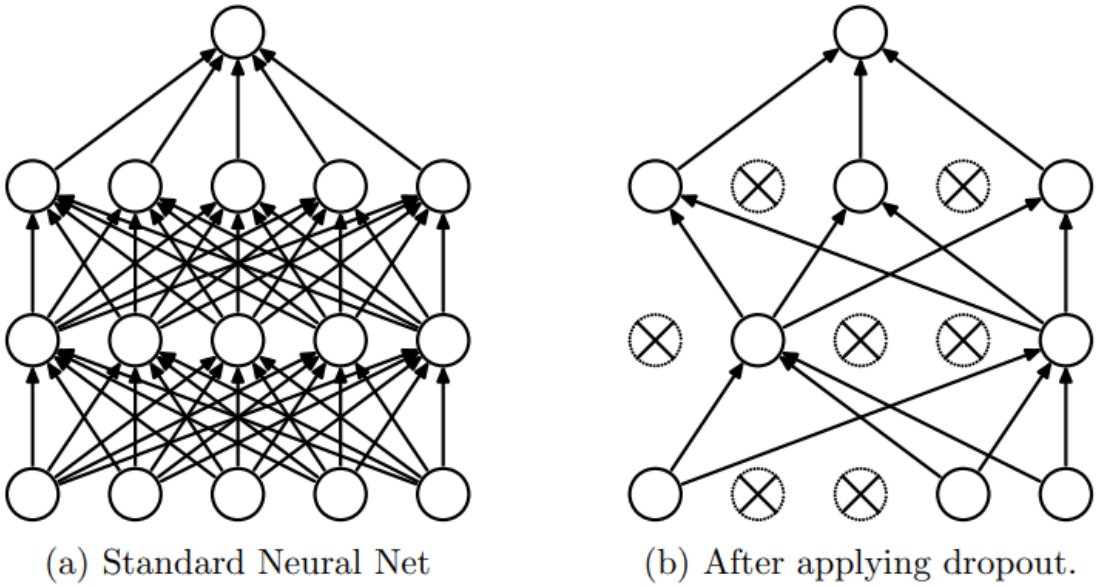

Figure6.Dropout

Image preprocessing

Most of the pixels in the image are irrelevant and do not contribute substantially to the intrinsic information of an image. While working with AI networks, it is required to put out them to avoid

unnecessary computational load overhead. This can be complete by compression techniques. We start the implementation of our deep net by processing the images in the dataset. This will be achieved with the utilizing of the OpenCV library in Python. There are plenty of modules that capable to be used in this step e.g. MATLAB or other image processing libraries or software like python which is our platform to implement. This is necessary to omit irrelevant data that are transmitting the input of the neural network as the redundant data only causes to make more evaluation complexity in the system and does not have any useful information for the output.

Feature extraction

- Feature learning is a very important step in the classification process for both human and machine algorithms. A study depicted that the human brain is sensitive to shapes, while computers are quite more sensitive to patterns and texture. Hence, feature learning is completely different for manual versus machine. In the visual context, malignant tumors are willing to have large and irregular nuclei or multiple nuclear structures. The cytoplasm also gone through changes, furthermore, new structures appear, or normal structures get vanish. Malignant cells consist of a small cytoplasmic amount, frequently with vacuoles. In this scenario, the ratio of cytoplasm to the nucleus is reduced. All of these features have been tested by experts, our algorithms are modified to quantify these features to automate detection. This approach is hard and imprecise as selection and quantification consist of various unknown errors that are difficult to address. In the case of supervised learning in the deep neural network, there is no need to provide these features explicitly. Here the images are used in architecture like CNN, along with their class as a label which is categorized as Benign or Malignant. From the automatic update of filter values in the training step of the project, CNN can extract the computational features. To the end, for a given architecture of CNN filters and their weights, are features that are utilized at the time of testing for model evaluating. In this work, CNN takes raw pixels of an image and gives the output as learned filter weights. These weights serve as input to the dense architecture of the deep neural network for final prediction. In our graph architecture Fig.5, the convolutional neural network is made up of two types of layers:
- Convolutional Layer
- Pooling Layer

The details of the network are shown in Table 2, pursuing its visual representation in Fig.3 The convolution process will increase the depth of the input layerby the number of filter that has given in CNN and turned input to a thicker output with the same size. On the other hand in pooling activation , the output layer's depth remains the same like the input but size is decreased. Visual representation of Table 2 is shown in Fig. 7 convX@YxY shows convolution with X number of filters of size Y x Y, and pool@ZxZ represents max pooling with a kernel size of ZxZ.

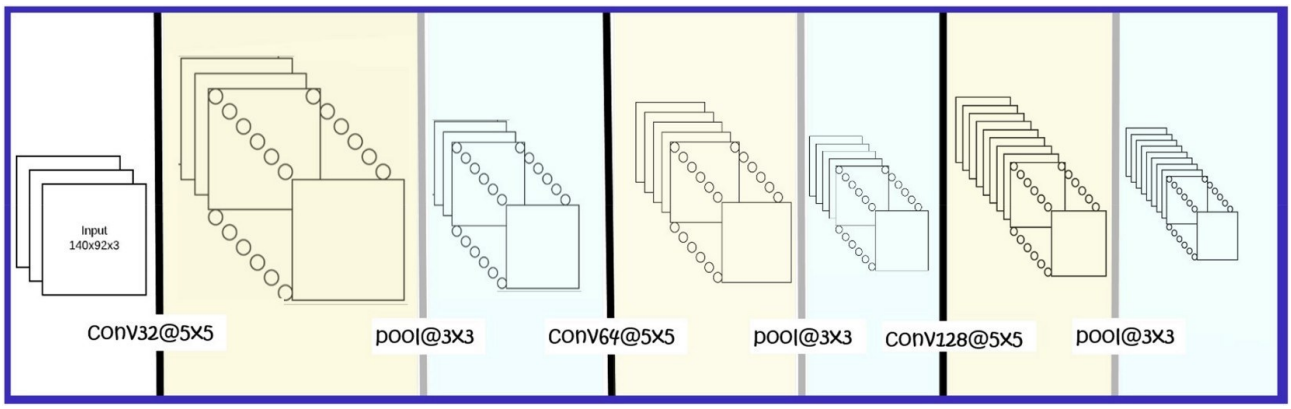

Fig. 7. Visual representation of layers in the convolution process

Table2

Parameters of the CNN architecture.

Layer attribute	L1	L2	L3	L4	L5	L6
Type	conv	pool	conv	pool	conv	pool
Channel	32	–	64	–	128	–
Filter Size	5 x5	–	5 x5	–	5 x5	–
Conv. stride	1x1	–	1x1	–	1x1	–
Pooling size	–	3X3	–	3X3	–	3X3
Pooling stride	–	1 x1	–	1 x1	–	1 x1
Padding size	same	none	–	none	–	none
Activation	ReLu	–	ReLu	–	ReLu	–

Learnable Parameters

In unsupervised machine learning, we need learnable parameters to modify our results and obtain better accuracy. **Weights** and **biases** are two learnable parameters that we can use for our aim in the neural network.

Nodes are the fundamentals of deep learning. Every node in an artificial neural network represents a unit layer. While inputs are being transferred, the weights and biases of the specific node will be transfer along with the input value.

$$\boldsymbol{Y = \Sigma(weight * inputs + bias)}$$

Weights penalized the input to select input. More weight will increase the strength of the input feature. In another point of view, a weight controls the influence of input.

Biases, the value of biases are generally constant, so as to map input features to the output. It has a unity value. Values of biases do not influence by any prior nodes and weights, so they are not connected to former input layers but they manipulate the activation function of the output connection with their corresponding weights, It will have the model to best fit. With bias value, we have the concept of in case the entire nodes have the zero value also there is some activation value with some bias**.**

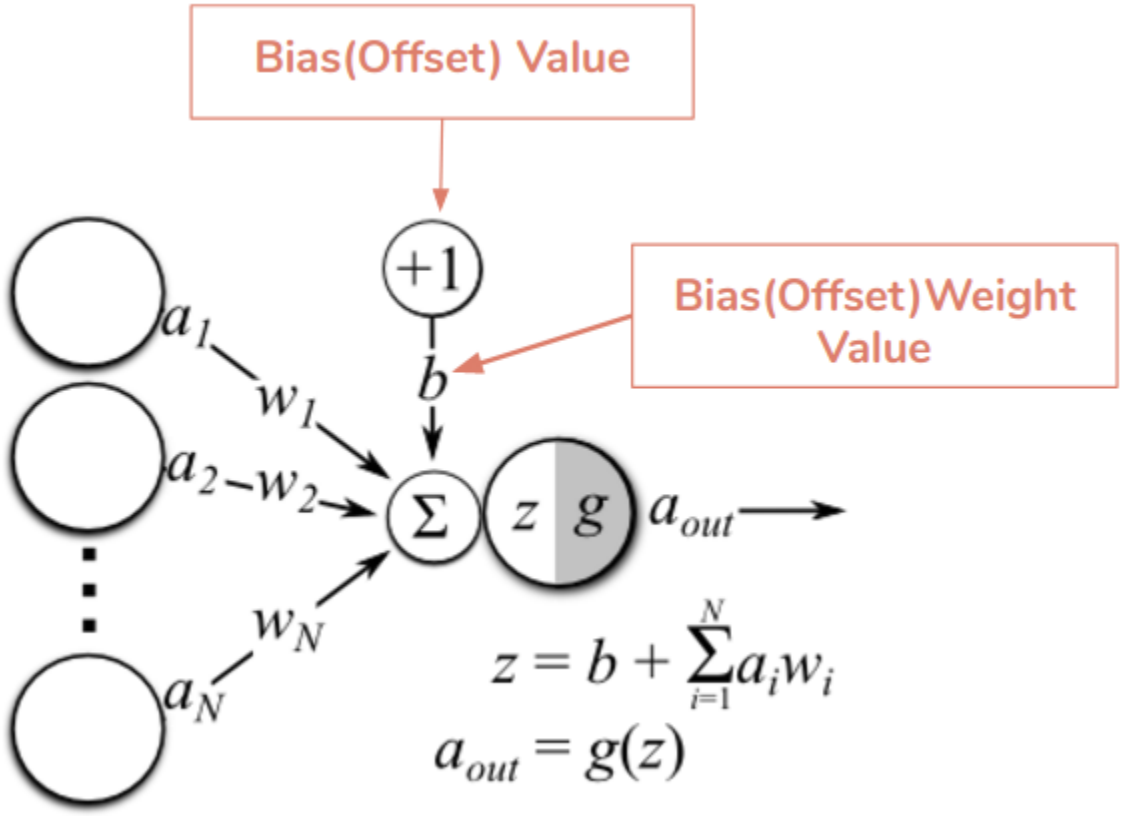

Figure8. Weights and Biases in neural network

Classification

The procedure of classification has been done by taking the flattened weighted feature map obtained from the final pooling layer and has been utilized for input then transmit towards a fully connected network, Where the loss function updates weights of underlying in hidden layer orderly. The parameters of these layers have been demonstrated in Table 3. These layers are stacked after preprocessing is finished. The output of the last layer has been chosen as the final output as usual.

Table3

Details of fully connected network

Layer Attribute	FC-1	FC-2	FC-3
No. Of Nodes	62	62	2
Activation used	ReLu	ReLu	Softmax

Experimental result

By considering the previously discussed setup we have obtained a training accuracy of 92.86% with a test train difference of 0.2. Loss and accuracy curves of training and validation achieved during the training process are shown in Fig. 10 and Fig. 11, in order. As expected from a network, both losses shown in Fig. 11 start with a high value and reduced while training procedure. This performance is similar to the standard training procedure for deep learning. The contrast between the two loss saturation level in training and validation is so small and negligible (0.2) , which is accept the permissible amount for a network to avoid underfitting or overfitting. The graphical plot of accuracy distribution is shown in Fig. 10. Accuracy starts to increase with the number of epochs, and ultimately saturates, which shows that the training on the dataset is done and completed for the designed network. Moreover, an important conclusion from this graph is that the network is trained without having characteristics of underfitting and overfitting, as validation accuracy and training accuracy curves are same in distribution.

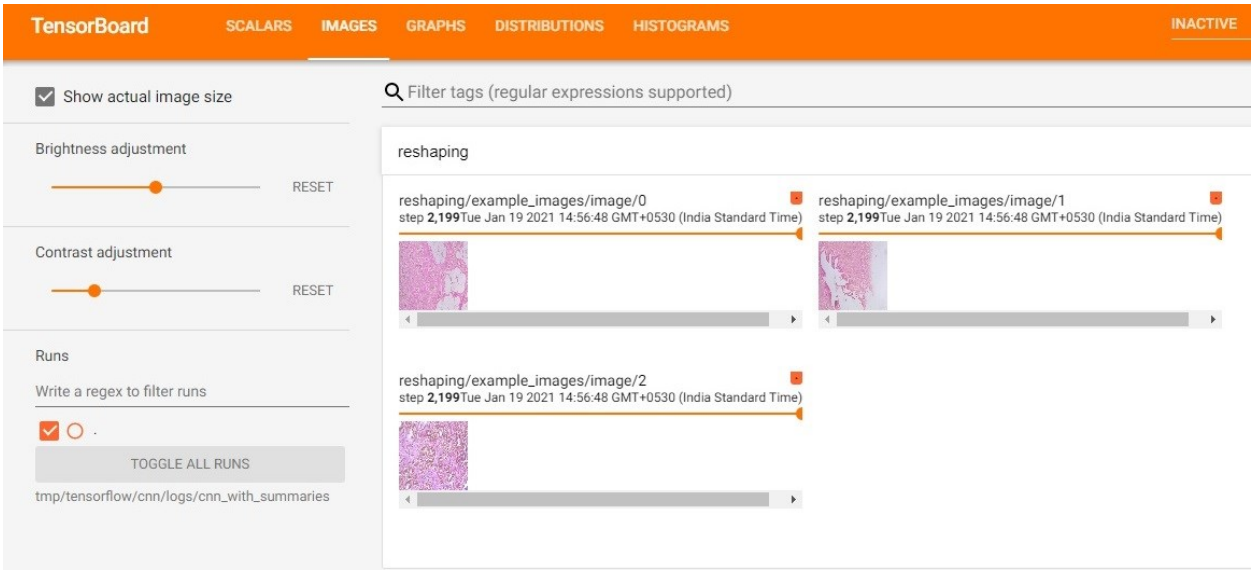

Figure9. reshaping and extracting features

Table 4

Details of sample images from test set.

Label	Resolution	Image name in Dataset
B40	40X	SOB_B_A-14-29960CD-40-015.png
B100	100X	SOB_B_PT-14-22704-100-018.png
B200	200X	SOB_B_TA-14-19854C-200-016.png
B400	400X	SOB_B_TA-14-13200-400-008.png
M40	40X	SOB_M_LC-14-12204-40-001.png
M100	100X	SOB_M_LC-14-12204-100-049.png
M200	200X	SOB_M_MC-14-13418DE-200-012.png
M400	400X	SOB_M_PC-14-12465-400-013.png

Table5

Prediction result.

Label	Actual Class	Predicted Accuracy	Predicted Class
B40	Benign	100%	Benign
B100	Benign	99.99%	Benign
B200	Benign	99.99%	Benign
B400	Benign	99.99%	Benign
M40	Malignant	100%	Malignant
M100	Malignant	99.99%	Malignant
M200	Malignant	99.99%	Malignant
M400	Malignant	99.99%	Malignant

Accuracy

As demonstrated in graph with the proposed CNN classification of images to the malignant and benign method accuracy reaches up to 94% for training set (blue color)and 92% for testing set(orange Color).

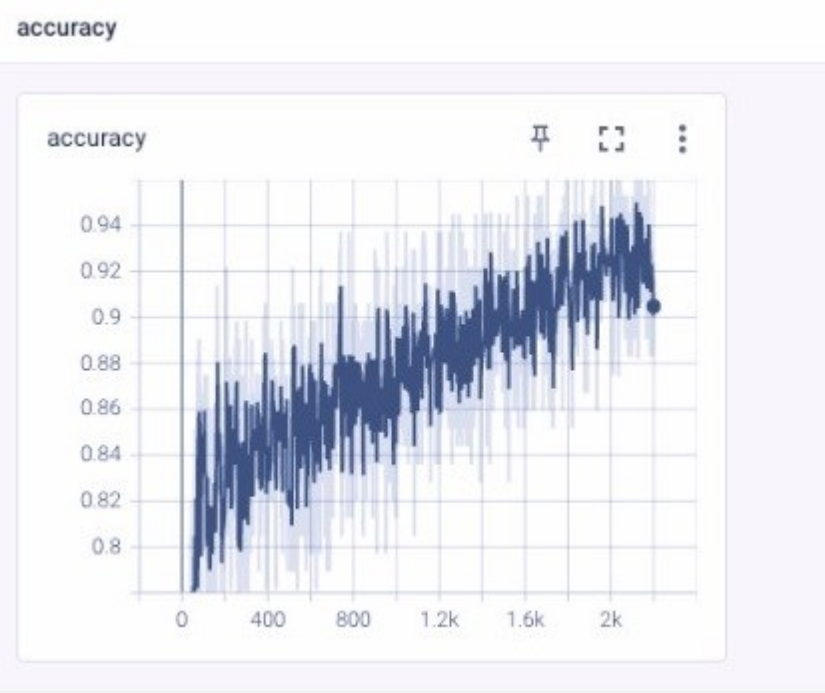

Figure10-a.Acuracy for training

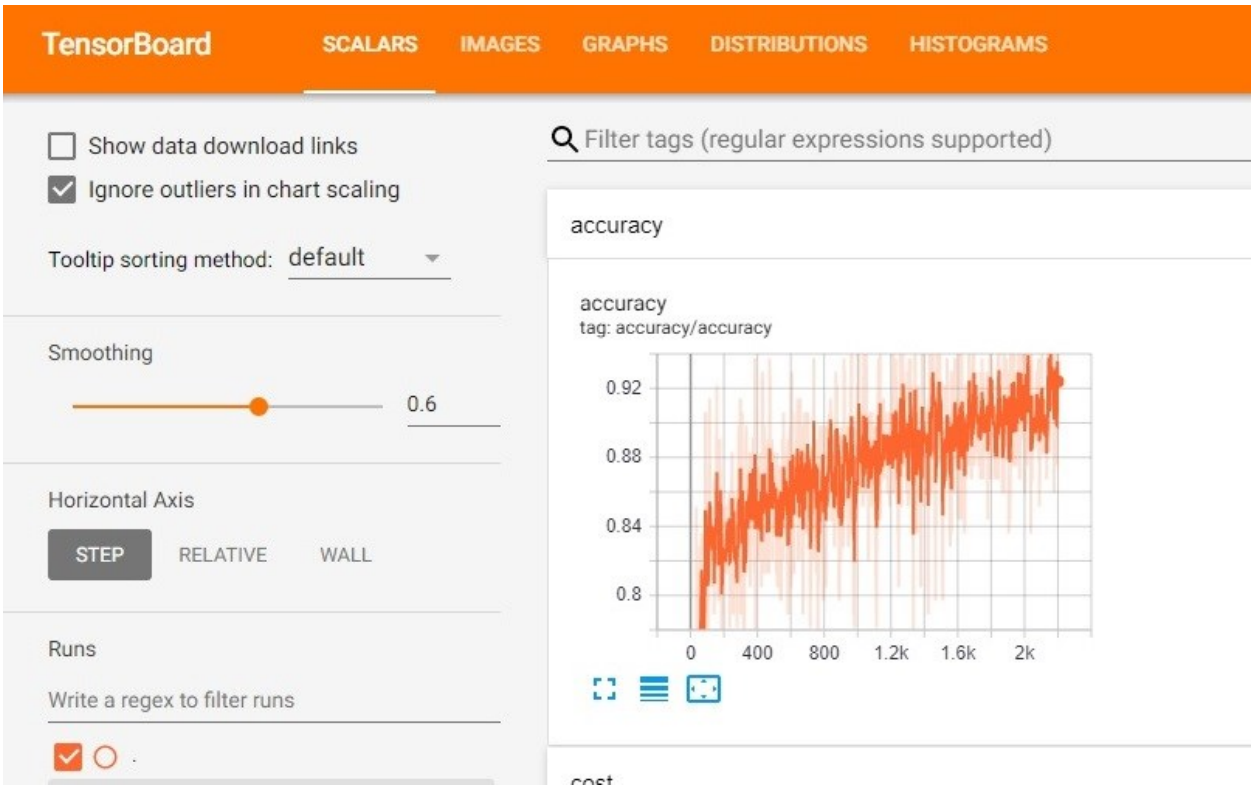

Figure10-b.Acuracy for Prediction

Cost Function

Cost Function evaluates the proficiency of our model in artificial intelligence from a specified chosen database. It is another learning fundamental in the deep neural network, used for evaluation of error obtain from the difference between prediction and expectation value and map this difference on a diagram with the numeric values. Cost function will let the neural network learn that a model is correctly predicted or it needs modification as well as change the behavior to reduce the mistakes. It will evaluate in what terms, the model is being wrong and what kinds of capability it has to change the wrong model. minimizing the error is the main target of this function.

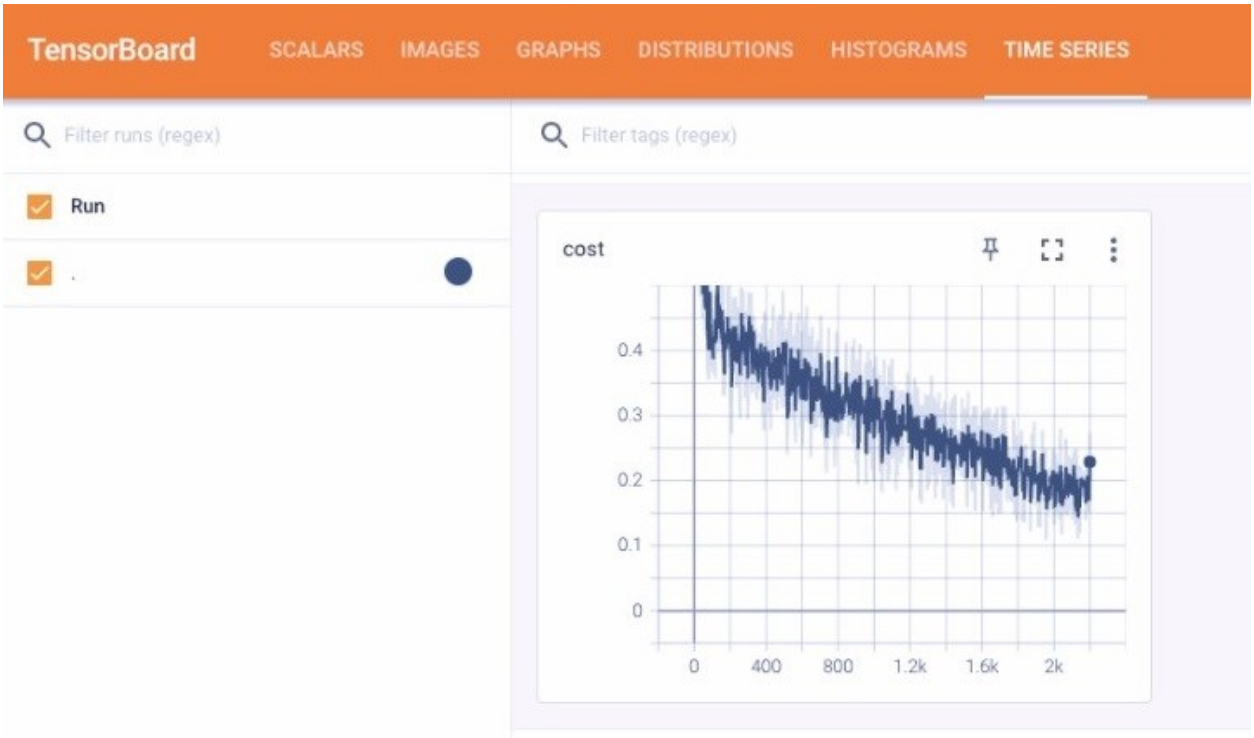

Figure11-a.Cost function for training

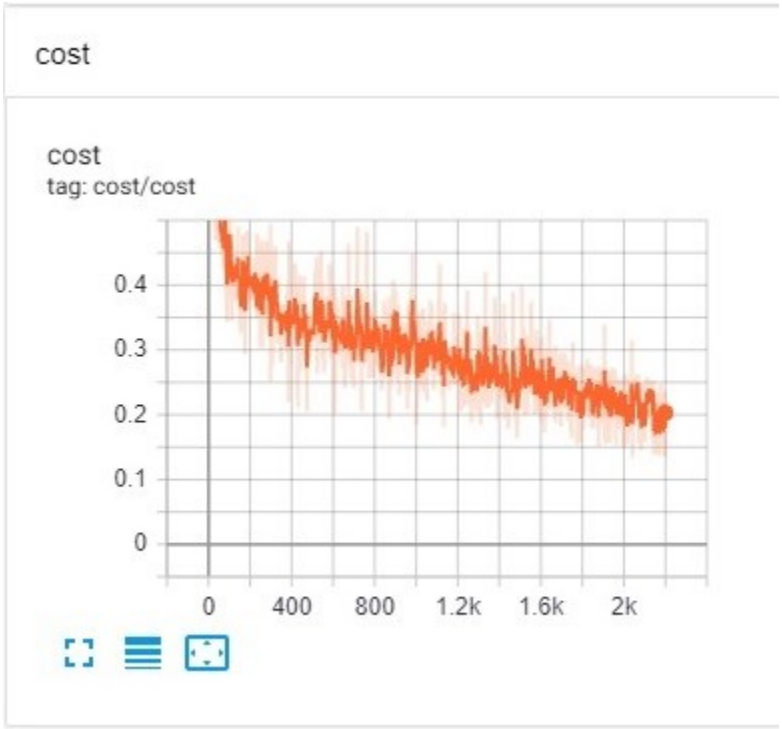

Figure11-b.Cost function for prediction

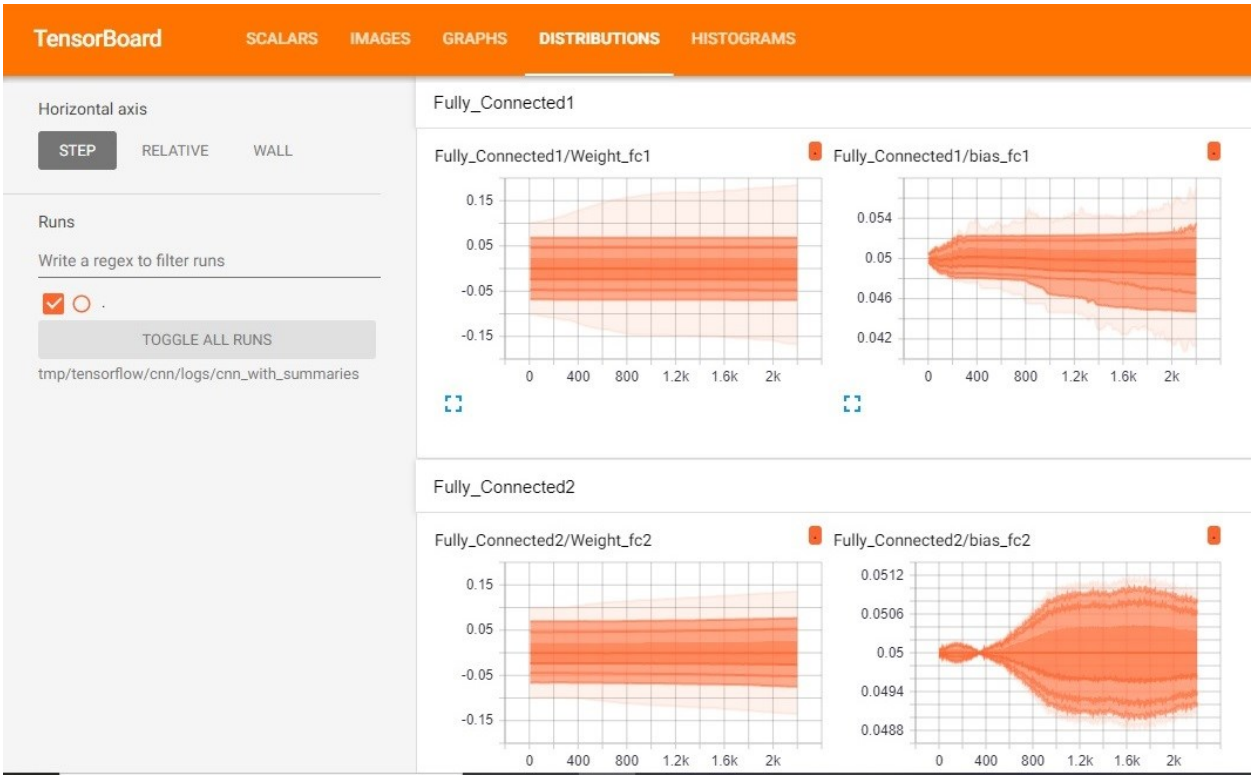

Figure12. Distribution of weights and bias in different epoch

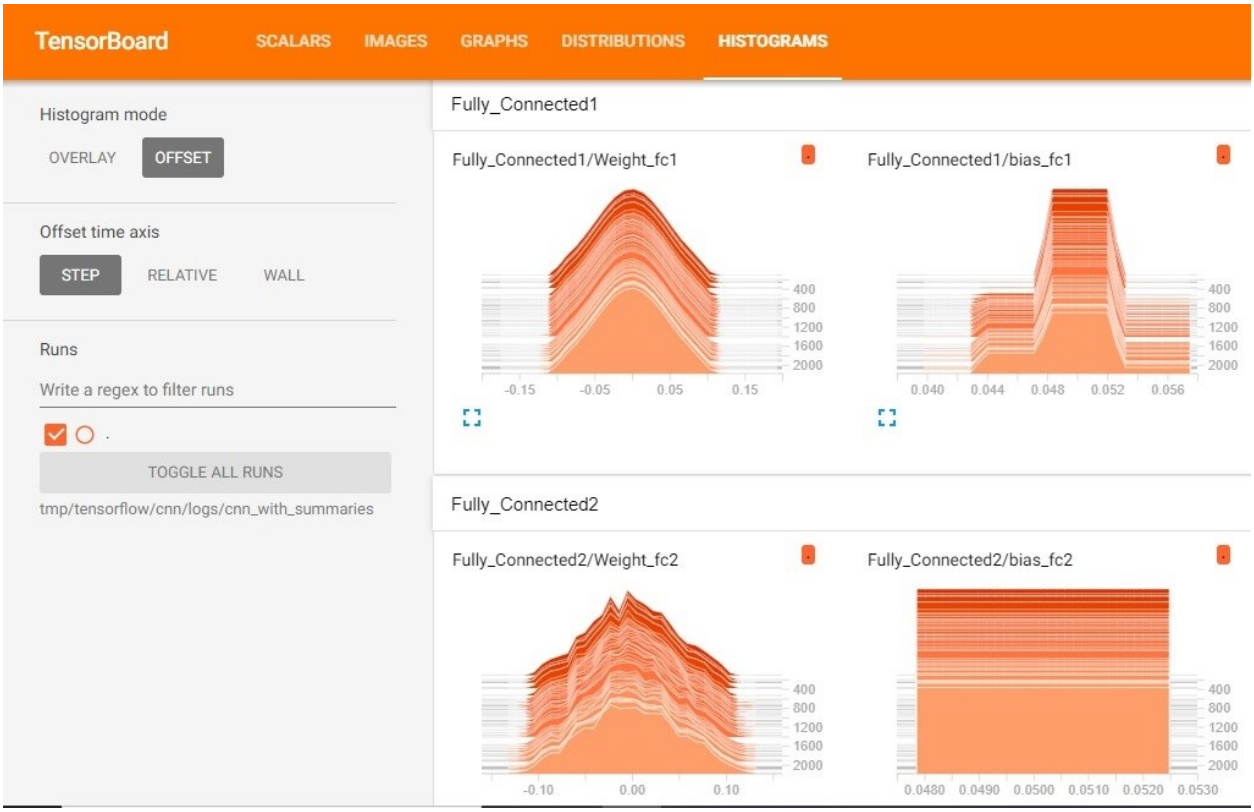

Figure13.Histogram of distribution of W&B in epochs

```
WARNING:tensorflow:From C:\Users\LENVO\Downloads\classifying-cancer-master\cnn_image_classifier\cnn_model.py:284:
ith dimension is deprecated and will be removed in a future version.
Instructions for updating:
Use the `axis` argument instead
Prediction: This is a malignant cell.
Validation: It was a malignant cell
```

Figure14. prediction and validation of a random image from BreakHis in python

For comparison, we have compared our result which has 94% validation accuracy from the test set with several published studies in Table 7. The model has been tested with the various resolution of histopathology images and the results have been relatively insensitive to resolution (refer to Table 6). By utilizing this automated procedure there is a possibility of low cost detection of cancer in the early stages, which can ultimately boost up survival rate among breast cancer patients.

Table7 Existing methods and respective Accuracy

Method Used	Validation Accuracy Range(in %)	Error Rate

K-Nearest Neighbor	83 to 86	19.28
Pre-Trained Networks	80 to 89	4.74
Feature Extracted Using CNN	83 to 90	4.28
Deep Convolution Neural Network	91.54	8.34

Future Work

Breast cancer detection by using digital histopathology images is a significant concern in the field of medical pathology. It has also emerged advanced opportunities in the field of research as there are many brand new areas that can be investigated by the means of neural network and machine learning model in artificial intelligence. We may obtain improved results by replacing the network design and parameters. As an improvement to this method, one can implement an autoencoder instead of manually decreasing image size by reshaping . It can compress data without losing the important features, because autoencoders can recreate up to 90% of the original image From the point of method improvement, we can merge spectral imaging. Spectral imaging has been utilized to achieve images with different wavelengths, which is different from the negligible three channel RGB image. Furthermore , we may add different types of advanced technologies together for example MRI, CT Scan, ultrasound, and mammographic imaging, and evaluate their total outputs . This technique has been called as multimodel fusion. Issues explained above will be solved by deep learning, and has been utilized for a high quality performance research which will lead us to even better results.

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