xIlkogretim Online - Elementary Education Online,2021; Vol 20 (Issue 1): pp.2327-2334
http://ilkogretim-online.org
doi: 10.17051/ilkonline.2021.01.259

An Effective Approach For Detection & Evaluation Of Breast Cancer Using Artificial Neural Network

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Abstract- Identification of breast cancer in early stage is the need of the hour. Precautions have to be taken to minimize false positive and false negative results. Malignant growth in breast can be recognized by a biopsy where tissue is evacuated and concentrated under magnifying instrument. The conclusion depends on the capability of the histopathology's, which will search for abnormal cells. Be that as it may, if the histopathology's isn't very much prepared, this may prompt wrong determination. With the ongoing advances in image handling and AI, there is an enthusiasm for endeavouring to build up a dependable example, acknowledgment based frameworks to improve the nature of analysis. The proposed framework distinguishes Breast cancer utilizing programmed order of Breast malignant growth histology images into generous and threatening, this can be accomplished with the aid of efficient net and Faster. We have decided to use Efficient Net because it is 6% more accurate than any existing model and it is open source published by google. The test study shows that convolution neural network accomplishes high exactness on arrangement when compared to earlier architecture.

Keywords: Fastai, Efficient Net, Data bunch, creating a model using CNN, Image Net

I. Introduction

Breast tumour, malignant growth is the most well-known obtrusive disease in ladies and the subsequent primary driver of malignant growth demise in ladies, after lung disease. International Agency for Research on Cancer (IARC), which is also a part of the World Health Organization (WHO), said the numbers of deaths caused by cancer in the year of 2012 alone came to around 8.2 million. In the year 2018 around 6.27lakhs women died because of breast cancer. The quantity of new cases is relied upon to increment to beyond what 27 million by 2030.Breast disease can be analyzed utilizing clinical pictures testing, similar to histology and radiology pictures. The radiology pictures investigation can assist with distinguishing the territories where the variation from the norm is found. [1] They however cannot be used to determine if the area is cancerous. The biopsy, where a tissue is taken and concentrated under a magnifying instrument to check whether malignancy is available, is the main approach to recognize if a territory is carcinogenic. In the wake of finishing the biopsy, the conclusion will be founded on the capability of the histopathologists, who will analyze the tissue under a magnifying lens, searching for strange or malignant cells. The histology pictures permit us to recognize the cell cores types and their engineering as per a particular example. We will be using Efficient Net which is the latest prêt rain CNN model, is more accurate and efficient compare to other model. For training the model we will be using fast.ai since it is fast and the training loss is pretty low.

II. Literature Survey

A. *[2*] A Dataset for Breast Cancer Histopathological Image Classification

The author used a dataset of 7909 breast cancer histopathology images acquired on 82 patients. The dataset includes both noncancerous and cancerous images. [3] The errand related with this dataset is the robotized arrangement of these pictures in two classes, which would be an important PC supported conclusion apparatus for the clinician. The author achieved accuracy ranges from 80% to 85%. By giving this dataset and an institutionalized assessment convention to mainstream researchers, they accumulated specialists in both the clinical and the AI field to progress toward this clinical application.

B. [4] A Deep Feature Based Framework for Breast Masses Classification

The author designed a deep feature based framework for breast mass classification task. It for the most part contains a convolution neural system (CNN) and a choice component. Consolidating power data and profound highlights naturally extricated by the prepared CNN from the first picture, proposed strategy could more readily recreate the symptomatic technique worked by specialists and accomplished condition of-workmanship execution. Right now, worldwide and nearby impressions left by mass pictures were spoken to by profound highlights separated from two distinct layers called significant level and center level highlights. In the interim, the first pictures were viewed as point by point depictions of the Breast mass. At that point, classifiers dependent on highlights above were utilized in blend to foresee classes of test pictures. What's more, results of classifiers dependent on various highlights were broke down together to decide the kinds of test pictures [5].

III. ARCHITECTURE

The first stage called stem and the final layer is common in all Efficient Net model in figure 1. The intermediate layer is quite different. Each model has 7 blocks and has various sub-blocks which will increase as we move from B0-B7.

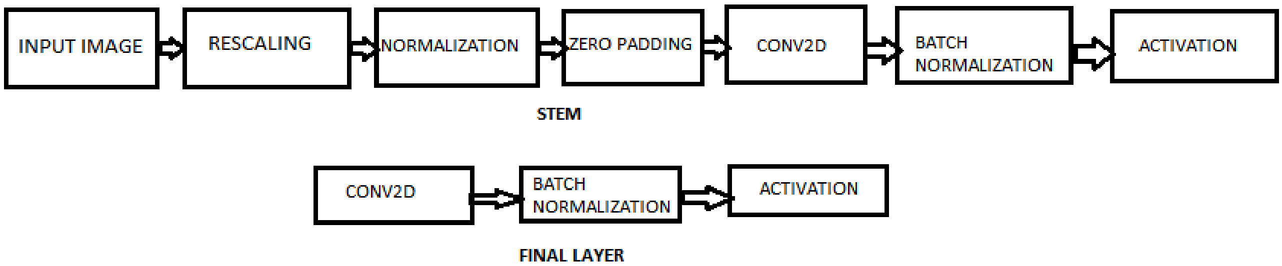

Figure 1. Stem and final layer of Efficient Net

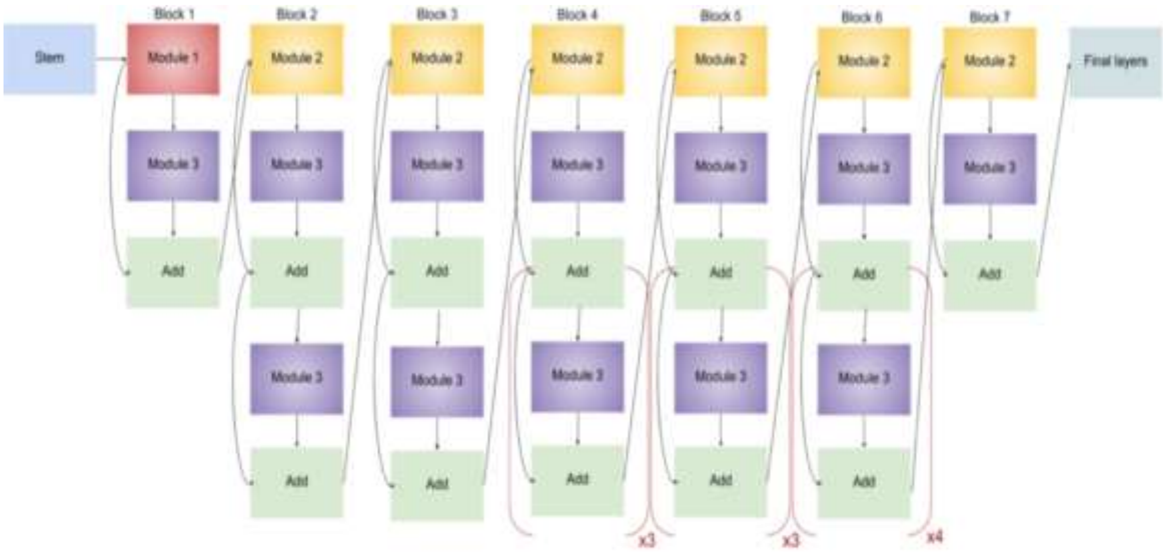

Figure 2. Architecture of EfficientNet-B3 (x3 means that modules inside the bracket are repeated thrice and x4 –module is repeated 4 times)
Proposed system

IV. PROPOSED SYSTEM

As shown in Figure 2 in this paper we are using Efficient Net and Fastai which make the model more efficient, fast and accurate. Overall system consists of 4 stages. In first stage, we have uploaded the data into data bunch, before uploading we have performed data augmentation which will solve problem of inadequate amount of data. Once the data is uploaded we have created the model using CNN, in this paper we are not creating the model from scratch, we used pre-train model which is efficientNet-B3, it is latest CNN model which is published by Google in 2019, It is 6% efficient than other CNN model. Once the model is created, we trained the model with the image present in data bunch. To train the model, two parameters are required - epoch and learning rate. So in fastai we can directly find the best learning rate with low loss. Now we will train the model using fastai learner method.

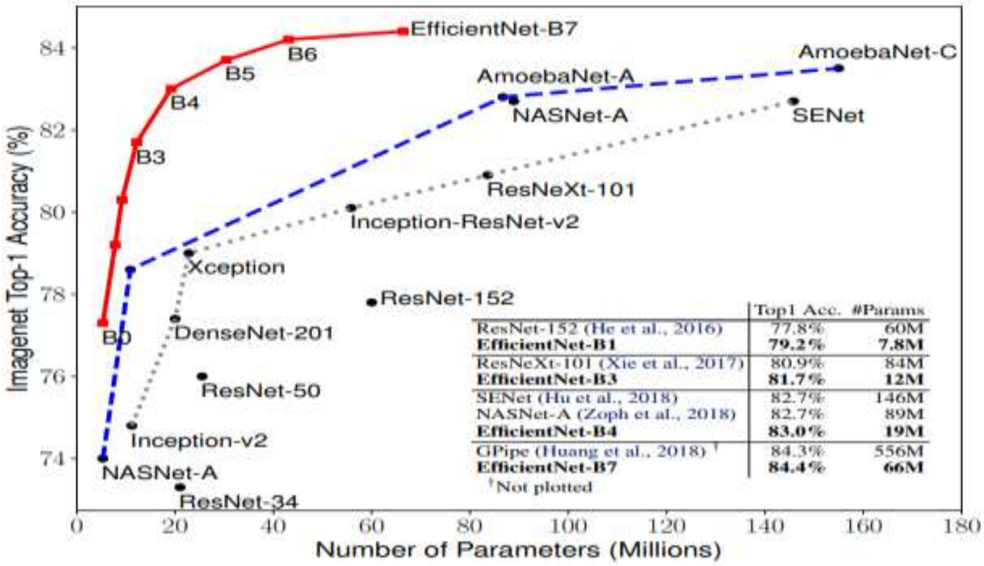

Figure 3. Model Size vs. Image Net Accuracy (1)

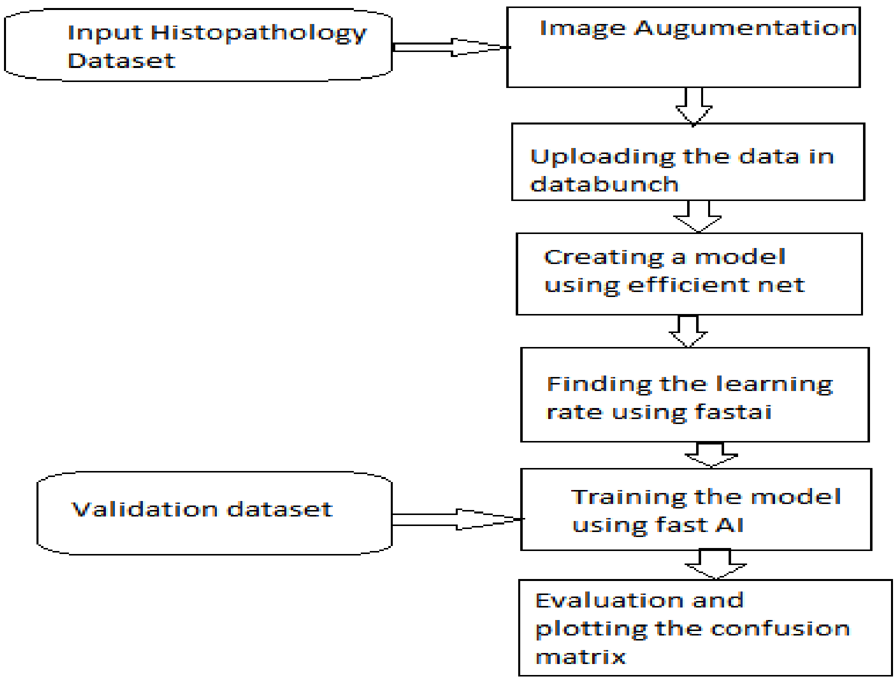

Figure 4. Block diagram of process.

A. Data set

We downloaded our data set from Kaggle. This data set is around 6 GB (storage size).It consists of two folders –Train and Test. In Train folder, we have 220025 images in (.tif) format and size (92x92). In the Test folder we have 57458 images in (.tif) format and size (92x92). We are given histopathology images, all of which are associated with a Boolean value. It demonstrates whether picture contains malignant growth cells or not. Genuine qualities are mapped to 1, bogus qualities to 0. We will regard those qualities as classes for our order. The figure 3 in Model Size vs. Image Net Accuracy.

B. Data Augmentation

We utilized this strategy to lessen information necessities. It permits to adjust model information sources and basically made new pictures during preparing so as to viably expand information size. There are numerous sorts of information enlargement, for example, turn, flip, cushioning, viewpoint twisting, and so forth. This is very simple and powerful tool for problems related to the area of PC vision. Since for this problem image orientation should not have any influence on the predicted class, we allow images to be flipped in both axes. Further, we determine how lot of pictures can be pivoted, zoomed and distorted. At long last, we had additionally indicated parameters for changing the brilliance of created pictures. Loading Input Data into data bunch and, the figure 4 in block diagram of process.

Data for deep learning models is stored in an object called Data Bunch. It contains:

1. training set - data the model is learning with
2. validation set - data that model does not look at when training, used to calculate and print metrics
3. (optionally) test set - data without labels
4. data loader - used by learner to load data into the memory

As the Data Bunch item will be utilized by the profound learning model, we have to pass two progressively significant parameters. First is information size - pictures utilized by our model will be squares of given size. Second one is bunch size - this parameter is utilized for load and procedure pictures (Number of pictures is prepared by GPU immediately). Those two parameters ought to be changed with deference to each other and, thus, they impact how quick our model is learning. At last, we pass parameters for changes utilized for information enlargement in changes object. We need to normalize the image so that model does not get instable and accuracy gets better.

C. Creating a model using CNN

For this problem we are using pre-train model of convolution neural network. We have created our classifier using one of the convolution neural network's extensions called Efficient Net. This cycle on neural system engineering makes it generously more profound, increasingly precise and proficient to prepare. Associations between layers near both info and yield layers are a lot shorter. Thanks to that Efficient Net offers many advantages over standard CNN (Convolution Neural Network), few of which are strengthened feature propagation or reduced number of parameters. We are using efficientnet-b3 from Efficient Net, Which has top accuracy around 95%.There are other model which perform are better than efficientNet-b3 but the quality of image is does full fill the requirement of higher model [6].

D. Finding Learning rate using fast. AI

Training takes place in iterations called epochs. During every age our model gets an opportunity to take a gander at all of information pictures precisely once. In view of that it refreshes its parameters. There are two significant parameters for preparing which are number of ages and learning rate. First one defines how many times we show each image to our model; second one defines how fast we move through solution space that is how rapidly the model updates its parameters .Both parameters, in conjunction, influence how quickly our model is learning. One caveat is that those parameters have to be chosen experimentally, as there's no automatic way to find a good learning rate or number of epochs. We have to ensure that both of those parameters are sufficiently high with the goal that we can prepare the model in limited time and sufficiently low so we abstain from over fitting or model disparity. Fastai conveys helpful strategies for deciding those parameters. [7] For learning rate we will utilize lr_find, which plots model misfortune as for learning rate. As a dependable guideline, we ought to pick a rate, where the estimation of the capacity diminishes the quickest with negligible variety. These guarantee models parameters refresh are merged and moderately quick. As far as number of ages, we have to focus on train loss and validation loss measurements (loss function calculated against training and validation sets). Here we ought to take a stab at keeping those qualities close to each other, both consistently diminishing, with validation loss marginally higher than train loss.

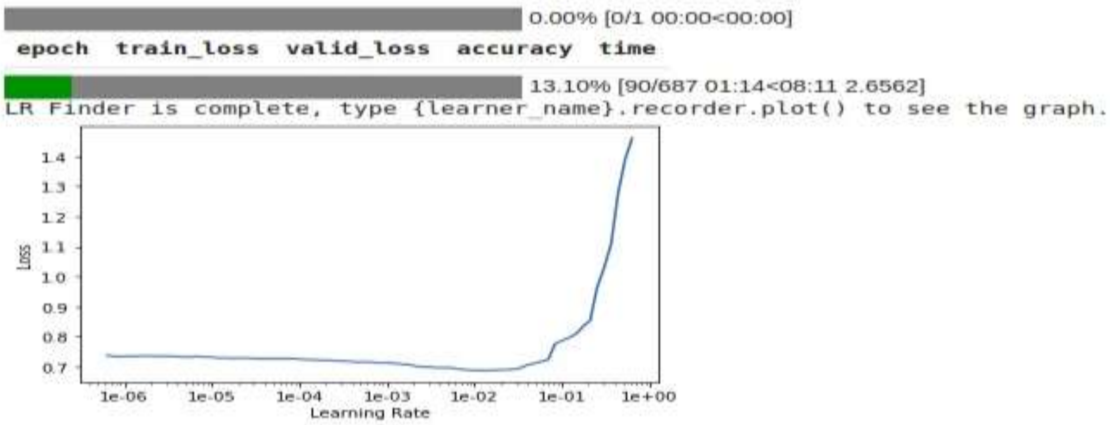

Figure 5. Graph showing the learning rate Vs Loss

As shown in Figure 5 graph, we can find that the learning rate is smooth at 1e-03 and loss is small at that point. So the best learning rate would be 1e-03.

E. Training the model using fast.AI

It has a similar interface (number of ages and learning rate), however treats learning rates slightly in an unexpected way. It utilizes expanding learning rates toward the start of every age to ensure our model moves the correct way and help investigate the whole arrangement space [8]. Towards the end is a fuse, strategy called learning rate toughening, which means learning rate diminishes at the end, forestalling the model to diverge.

F. Fine tuning

As we said previously, our model comes as of now pre-trained. What it implies, for the underlying ages, we are not refreshing the absolute first layers however just the last ones. Right now it can bear to move quicker (update parameters faster), since our model has a strong base. In order to further improve the model we used unfreezes function, which allows all model parameters to be updated during training. Having that as a top priority, we should be progressively cautious with the pace of preparing and diminishing learning rates. We utilized discriminative learning rates. This implies that as opposed to indicating one learning rate esteems, we can give a learning rate go between two qualities. First worth will be applied to introductory layers, last to conclusive layers and the rest similar appropriated. As shown in table 1 the train-loss, valid-loss, accuracy (metric) and time of every epoch.

Table 1. show the train-loss, valid-loss, accuracy (metric) and time of every epoch

epoch	train_loss	valid_loss	accuracy	time
0	0.536126	0.504494	0.755687	08:03
1	0.433435	0.408089	0.818202	07:51
2	0.381219	0.372425	0.835655	07:42
3	0.347615	0.329085	0.857539	07:36
4	0.336712	0.317223	0.862334	07:20
5	0.338056	0.314435	0.864197	07:33

G. Over fitting

We have already used transfer learning method, when we trained our model on top of an existing model pre-trained on Image Net dataset. Now, we have a model that is relatively good at recognizing cancer in 32x32 histopathology images. In order to avoid over fitting, we can reuse the data set, but scaling images to 64x64. This will appear as a totally new dataset for our model. This is the part where we used transfer learning again - we take a model that we have, previously trained on 32x32 sized images, and train it a new dataset of 64x64 sized images. The table 2 in status after training with 64x64 sized image
We will follow the same training scheme as above.

Table 2. Status after training with 64x64 sized image

epoch	train_loss	valid_loss	accuracy	time
0	0.273358	0.250631	0.897443	09:24
1	0.237019	0.222352	0.909351	09:30
2	0.225804	0.204614	0.917373	09:26

V. FINDINGS AND RESULTS

A. ROC

Entries are assessed on ROC (Receiver/operating Characteristics Curve) bend between the anticipated likelihood and the watched target. Until this point we have been utilizing exactness as a measurement, which gave great knowledge into how our model was performing and whether it showed improvement of not. We have used ROC outscore metric from sklearn. In Figure 6. It runs from 0 to 1 (binary classifier system) which says about true and false positive rate. If the value is '1', it indicates the model prediction is accurate and '0' indicates the model prediction is false.

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Final accuracy of the model: 92.05772399902344 %.
Final AUC of the model: 0.9733268618583679.
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Figure 6. ROC and accuracy using sklearn

B. Confusion matrix

The Figure 7 in Confusion matrix gives information about how many your model assigned certain class with regard to what class they actually belong to. This is especially important for this case - the biggest problem is when histopathology image contains cancer cells, while our model predicts that it does not.

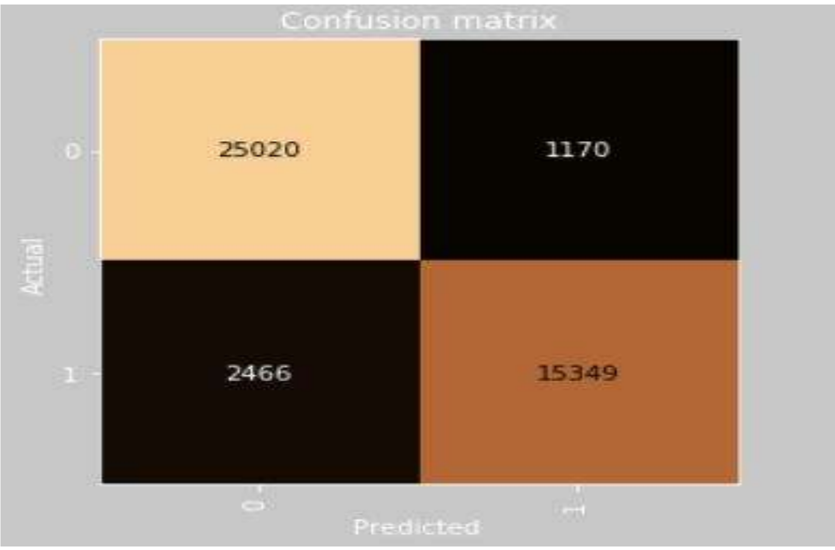

Figure 7. Confusion matrix

“0 represent as non-cancer and 1 represent as cancer”. In the above matrix it shows that out 27486 non-cancer image it predict 25020 as non-cancer while wrongly predict 2466 as cancer. Similarly, it also shows that out of 16519 cancer image it predict 15349 as cancer and 1170 as non-cancer. The figure 8 shows the result of classification of test set images from data set which predicts the cancerous and non-cancerous images.

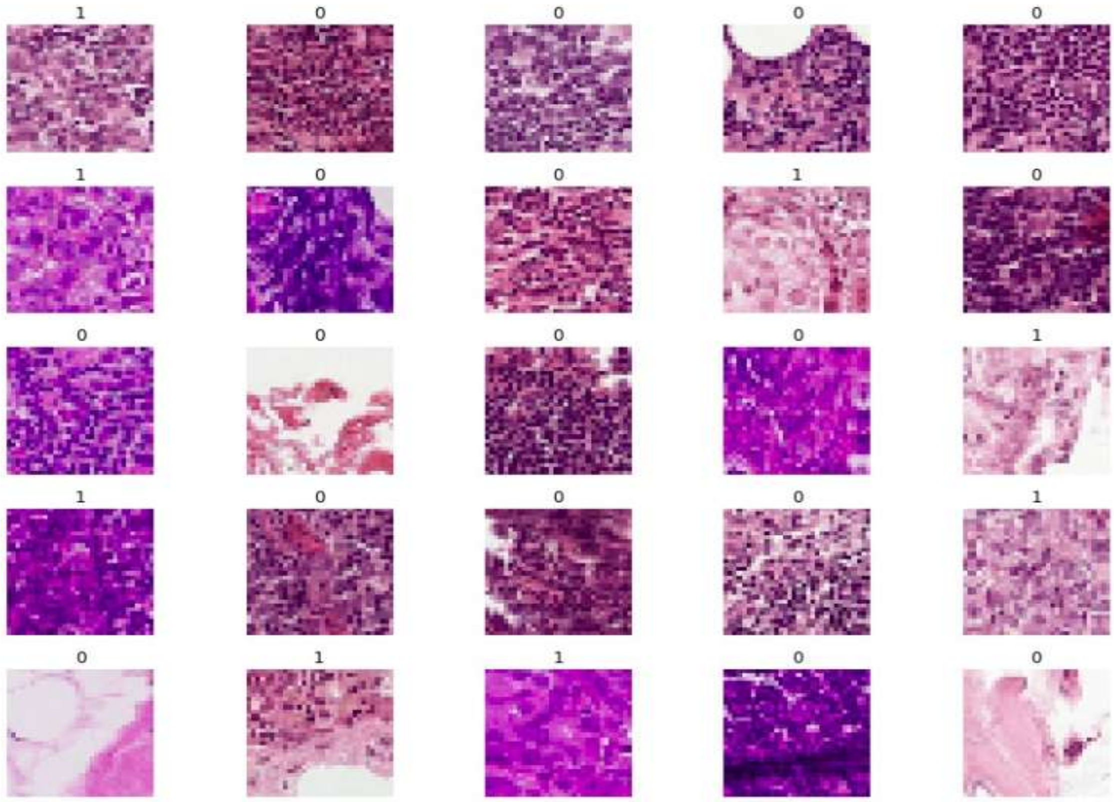

Figure 8. Results of Classification of test images (0-Benign, 1-Malignant)

C. *Comparison of few Previous works*

Reference paper	Accuracy	Architecture	Dataset
[2]	92%	MIL(Multiple Instance Learning) CNN	Private 7909 images 82 patients

[7]	90%	RF SVM	Private 228
[8]	82%	SVM	Private

VI. CONCLUSION

In this paper, with the assistance of deep learning technique and Convolution Neural Network Architecture the features of an image were extracted and have classified the image into cancerous (1) and non-cancerous (0) tumor. It is seen that the accuracy to classify solely relies on how the Convolution Neural Network extracts and learns the features in different layers with the variation in parameter. In the proposed system, efficiency is pretty good. The efficiency of our model can be improved if the quality of training image can be improved.

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