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COMPUTER AIDED DETECTION OF MAMMOGRAPHIC LESIONS

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Abstract - *Breast cancer is the most common form of cancer among women and it has surpassed lung cancer as the most commonly diagnosed cancer, with an estimated 2.3 million new cases which is (11.7%) of all cancer cases by 2020. The rates of women suffering from breast cancer have been increasing at an alarming rate in recent years all around the globe. Probability out of 100, more than 30 women suffer from breast cancer once in a whole life. When trying to find the main reason behind this increasing rate, it was found that the majority of the women get to know about their Cancer is at the last stage due to lack of a system detecting the cancer at an early stage. We intend to develop a detection system to successfully identify the cancer at an early stage using the Mammographic Report. Computer Aided Detection Of Mammographic lessons is a result-based system which is created through the data of thousands of Breast Cancer Patients for detecting Cancer in new Patients. In this paper, we attempt to list down the different methodologies of profound discovering that were trailed by us, for example vgg16 model, mobilenet, RELU model, Softmax Activation Function, pre-trained weights of vgg16 model and a lot more which has assisted us with building up the model which had the option to give us promising precision and unequivocal outcomes. Test results show that our framework accomplishes an accuracy of 90%*

***Key Words*: Computer Aided Detection of Mammographic Lessons, vgg16 model, mobilenet, pretrained vgg16 weights, RELU model, Convolution Neural Networks, Deep learning.**

1. INTRODUCTION

Breast cancer emerges in the covering/ lining cells (epithelium) of the ducts (85%) or lobules (15%) in the glandular tissue of the breast. At first, the dangerous development is restricted to the duct or lobule ("in situ") where it for the most part causes no manifestations and has negligible potential for spread (metastasis).Over the long haul, these in situ (stage 0) cancers may advance and attack the encompassing breast tissue (invasive breast malignant growth) at that point spread to the close by lymph hubs (local metastasis) or to different organs in the body (far off metastasis). On the off chance that a lady kicks the bucket from bosom malignant growth, it is a direct result of far and wide metastasis. In 2020, there were 2.3 million women diagnosed with breast cancer and 685 000 deaths worldwide. As of the end of 2020, there were 7.8 million women alive who were diagnosed with breast cancer in the previous 5 years, making it the world's most predominant cancer. Breast cancer is one of the main malignancies among Indian women, with over 1.5 lakh new Breast cancer patients recorded in India in 2018. It represents 14% of all diseases among women. Today, one in each 28 ladies (1 of every 22 women in metropolitan Indian, 1 out of 60 women in rural India) is in danger of appearing Breast cancer in the course of her life. The gross number of patients in India are better contrasted with the numbers for developed nations like the US/UK is less where 1 out of 8 women are diagnosed every year. In India, the survival rates are very low because of high populace and low awareness proportion. Probably the most compelling reason for the high death rates is a late finding which is fundamentally because of absence of awareness and the shortfall of legitimate breast cancer screening programs, analysis at an advanced stage and inaccessibility of suitable clinical offices. Larger parts of breast cancers are analyzed at a generally progressed stage. Numerous patients in the metropolitan zones are analyzed at stage two when the lesions become palpable lumps, however much of the time from rural territories, these lesions are analyzed solely after they change to metastatic tumors. The primary focus of this paper is to detect the cancer in an early stage through the rigorously trained model with high accuracy.

2. RELATED WORK

This section tries to summarize review of relevant and significant work already performed from literature for COMPUTER AIDED DETECTION OF MAMMOGRAPHIC LESSONS.

Reference [1] Provides a solution by using a genetically weighted ensemble of convolutional neural networks. These networks were trained on raw images of cancer, benign and malign mammogram reports. On these three image sources, the model was trained and benchmarked an AlexNet network, an InceptionV3 network, a ResNet network having 64 layers and a VGG-16 network. A pretrained ImageNet model was used for the above-mentioned networks. Then, we used a generic algorithm, a weighted sum of all networked evaluated outputs, and got the final class distribution. This distribution which was

formulated by the weighted sum of all Softmax layers yielded an accuracy of 67 % using VGG-16 model and an accuracy of 79% by using Resnet50 but their proposed solution took a high computation time.

Reference [2] Provides a solution by which we focused on pre-processing. In this part, the region of interest was located by using multiple detectors and the area that were not useful were cropped out, thus obtaining the regions that would be the enabling main focus width and height of the region is increased by 35% i.e. 17.5% to left and 17.5% to the right, thus enabling us to detect lump, which otherwise would have been faded out. The third part is segmentation, which is primarily based on locating the area of the lump present in the pre-processed images. It was done by firstly converting the image into two different colour spaces namely, HSV and YCrCb. The last part was extraction of features Percentage of the Lump (PL) and Area of Lump (AL). PL was obtained by calculating skin pixels in two regions of the image whereas, AL was calculated using total area. The bottlenecks was used as a classifier in this approach. They received an accuracy of 86.33%.

Reference [3] Created their own dataset similar to the dataset for COMPUTER AIDED DETECTION OF MAMMOGRAPHIC LESIONS. They proposed a solution that consists of weighted convolutional neural networks. The proposed convolutional neural networks were trained on raw images. They used AlexNet Krizhevsky and an InceptionV3 Szegedy model on those three image sources. In the InceptionV3 network, they fine-tuned an already used ImageNet model (i.e. transfer learning) which was pretrained. Then, they final weighted sum of all networks' outputs yielding the final class distribution. The weights were evaluated using a genetic algorithm. The accuracy was 89%, the implementation of this system in real-time was a very complex and tedious task.

3. DATASET DESCRIPTION

First of all, it was a very tedious process to get data. We got the data from the University Of South Florida Digital Mammography dataset. They had 2620 cases in 43 volumes of each benign, malign and cancer patient. So, we picked 500 cases of each cluster. The dataset that we obtained was in Lossless Joint Photographic Experts Group (LJPEG) Format. So, we used a ruby script on it with an Encoded file that we got from the University of Southern Florida itself. We converted LJPEG data to PNM (Portable Any Map) file. On top of it we used a python script to convert PNM to PNG file. This dataset from University Of South Florida has 3 classes named benign, malign and normal as shown in images.

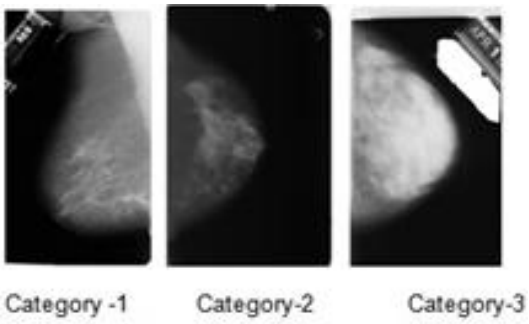

Fig -1: Categories of Cancer Detection.

Malign(category 1), Benign(category 2) and Normal (category 3) . In total, we have more than 10000 images for training and 4,500 images for testing. We have also used 4000+ images for validation and testing. Refer to the images provided above & below for reference.

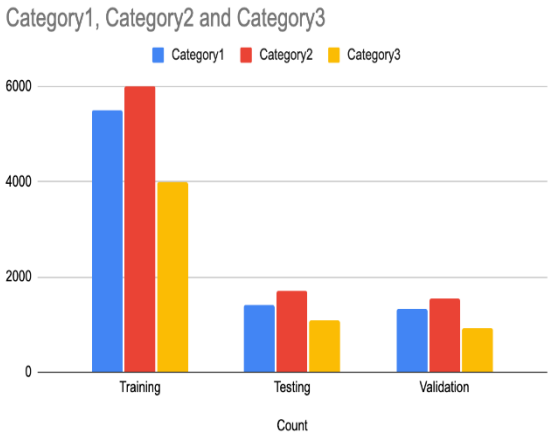

Chart -1: Number of Images for Process.

In total we have more than 10000 images for training and 4,500 images for testing. We have also used 4000+ images for validation and testing. Refer to the images provided above & below for reference.

4. IMPLEMENTATION

1. We referred to the first approach and we used a sequential model. For implementing a sequential model, we used keras. The model consists of a linear stack of layers. We can create a model of multiple layers. It has one disadvantage that it doesn't allow us to create models which can share layers or have many inputs or outputs. In our approach we had different sequential layers that were present in models such as Conv2d, max pooling with pool size of (2,2) and relu was used for activation with sigmoid. Flatten and dense was also used along with the mentioned layers. The optimiser used was rmsprop, with categorical_crossentropy and accuracy was used as a metric to evaluate the result. It was found that rmsprop optimiser had outperformed better than the ADAM optimiser as the learning curve of rmsprop had a better learning rate curve when compared with ADAM. The

overall accuracy of this method was only about 67%. The problem of this method was that it was not able to identify the needed accuracy as the accuracy was quite low. Then, we tried performing permutation & combination and probability, we figured it out by changing a few values at specified layers by the concept of loops. The results of these were plotted and the accuracy were improved. Surprisingly the result that we obtained increased only 12% and we got accuracy of 79%. It was not what we thought.

2. Then we moved to second by making use of Convolution Neural Network where we used convolution neural networks. CNN have performed impressively in object detection, action recognition, image classification, natural language processing and many more, since the last few years. The CNN architecture includes Convolutional filters/layers, Activation functions, Pooling layer and Fully Connected (FC) layer. CNN architectures that were readily available are AlexNet, ZFNet, VGGNet, GoogLeNet, ResNet. We are using GoogLeNet in our project to detect lump in patients as tensorflow for poets by google is using the concept of bottlenecks to correlate the classification. In total we used 4500+ images and out of which we used 4500+ images for testing/validation. GoogLeNet architecture uses 1 x 1 convolutions in the middle of architecture and global pooling. One can also use 5 x 5 convolution using 48-56 filters in the middle. We used 3X 3 convolutions with 36 filters in it. In the activation function we used RELU layer and SGD as optimiser. The accuracy we received was really awesome. We got around 85%. In this approach we had to use tensorflow version 2.0 and docker container classes as well. The computation time needed was quite high. Another issue that we got was in a few cases it was not able to understand between benign and malign lump.

3. The third approach we used was the Mobilenet model which is another CNN. Mobilenet is widely used for object detection, fine-grained classifications, face attributes, and localization. It is even lighter than GoogLeNet architecture. We also made a few changes over here, we used 18 layers which were normalized at particular intervals using batch normalization followed by relu. In this approach we also have added flatten and dense layers. The optimizer that we used was SGD. SGD took a large amount of time to process and there were issues with it involved so to overcome it we used a checkpoint method that helped us to get better accuracy and even obtaining micro level performance. It could be done using epochs. So, epochs we used were 60. It increases the learning accuracy to 92% but validation accuracy was about 90%. The result can be obtained at table 1 below. The fourth approach used by us was transfer learning i.e. solving one issue and using this stored knowledge on some other issues. The confusion matrix that we got and transfer learning both helped us to differentiate lump in benign and malign. Another advantage that we got was it saved lots of computing time. Instead of developing new models from scratch we used existing models to increase testing accuracy. We used the Mobilenet model for our approach. On this approach we just used 13 epochs and we are able to achieve a training accuracy of 91% which was a significant increase when compared to previous approaches. The model showed us exponential results and we got 91% of validation as well.

5. RESULTS & DISCUSSION

5.1. CASE 1:

The result of the first model used the sequential model as it was not upto the mark and accuracy of the model was not satisfactory. Table 1 below depicts the results of the vgg-16 mode.

Table -1:

Prediction Rate of Case 1			
COUNT	BENIGN	MALIGN	NORMAL
Total Sample	1300	2600	750
Correct Prediction	1027	2000	570
Incorrect Prediction	273	600	130
Accuracy	79	76	81

This model provided above increased a prediction rate substantially since normal accuracy was 81% and benign accuracy was 79% but we found malign accuracy to be 76% only.

5.2. CASE 2:

Table-2 represents GoogLeNet Model in which we saved the weights in the model. The accuracy of the model was satisfactory but there were few issues as it was not able to categorize malignant and benign images properly.

Table -2:

Prediction Rate of Case 2			
COUNT	BENIGN	MALIGN	NORMAL
Total Sample	1300	2600	700
Correct Prediction	1098	2200	600

Incorrect Prediction	202	400	100
Accuracy	85	85	86

This model provided above increased a prediction rate substantially since normal accuracy was 86% benign accuracy was 85% and found malign accuracy to be 85%.

5.3. CASE 3:

Table -3 represents transfer learning in which we saved the weights in the model. The accuracy of the model was satisfactory.

Table -3:

Prediction Rate of Case 3			
COUNT	BENIGN	MALIGN	NORMAL
Total Sample	1300	2600	700
Correct Prediction	1150	2400	640
Incorrect Prediction	150	200	60
Accuracy	88	91	91

This model provided above increased a prediction rate substantially since normal accuracy was 91%, benign accuracy was 88% but we found malign accuracy to be 91%.

6. CONCLUSIONS & FUTURE SCOPE

Breast Cancer is a very serious disease that women face so an effort is made to develop a detection system to successfully categorize mammographic reports to malign, benign and n It is always preferable to detect cancer at an early stage and advise the patient to treat it. Thus, an attempt to develop procedure and implement it using different methods and algorithms is done. Here, we present a robust Convolutional Neural Network based system to detect Breast Cancer. We used the various approaches of deep learning that were followed by us such as the GoogLeNet model, mobilenet, RELU model, pretrained weights of vgg16 model, Convolution Neural Network, Softmax activation function and many more which helped us to develop a Computer Aided Detection of Mammographic Lesions. Experimental results show that the model predicts the distracted drivers with an accuracy of 90%. As an extension of the work, in order to increase the project visibility we can use layers which will identify the stage of cancer also while on-going treatment.

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BIOGRAPHIES

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