Comparative Study of Pre-Trained Neural Network Models in Detection of Glaucoma

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Abstract - *Glaucoma is one of the major causes of blindness in people all over the globe. If detected quickly, its progression can be slowed, stopped & even permanent blindness can be prevented [1,2]. Several automated methods have come up for the early detection of glaucoma using various artificial neural networking models. In this paper, we present a comparative study of various pre-trained neural network models for the early detection of glaucoma. Six pre-trained models were built and analyzed with the help of several parameters for their comparison.*

Key Words: **Glaucoma, Neural Network, Convolutional Neural Network, Transfer Learning, Deep Learning, Pre-Trained Model.**

1.INTRODUCTION

Glaucoma is considered one of the leading causes of blindness all over the globe. According to a study by WHO (World Health Organisation), more than 65 million people have been affected by glaucoma throughout the globe. The characteristic feature of glaucoma is a damaged optic nerve due to a rise in intraocular pressure. It is an irreversible neurodegenerative disease. However, its early detection can help in treatment to slow or stop its progression [3].

Glaucoma is generally detected by an ophthalmologist using a set of eye-test known as comprehensive eye test which includes – Tonometry, Pachymetry, Perimetry, Dilated Eye Test, and Gonioscopy. These tests must be done on a regular basis & can be tedious for the ophthalmologist conducting it. A skilled ophthalmologist usually takes an average of about 8 minutes for conducting the test & therefore a computer-aided system is a necessity. Various automated techniques are being developed nowadays for quick & accurate examinations which use neural networking models for the identification of the disease. Fundus scans of an eye can be used to feed the neural network model to detect whether the eye under consideration is glaucomatous or non-glaucomatous.

As there are many neural network models for image classification, it may be difficult to compare each one and choose the better one for glaucoma detection. In this paper, we have classified six pre-trained neural networking models viz. Inception, Xception, ResNet50, MobileNetV3, DenseNet121, and DenseNet169. The Accuracy and Loss Graph of each model was analyzed and along with several other parameters obtained with the help of confusion matrix values were used for the classification of models.

2. Requirements

A labelled database that contains 9690 fundus images from both eyes classified into two classes namely glaucomatous(3422 images) and non-glaucomatous(6268 images), Google Cloud Platform (GCP) – for Cloud Computing, Jupyter notebook - Interactive Python Notebook, Tensorflow – Open source machine learning library for creating and training the models, Keras – Deep learning API for the artificial neural network which runs on top of Tensorflow, NumPy – Python library for high-level mathematical calculations on arrays, Pandas - tool for data manipulation and analysis, Matplotlib – python library that can create animated, static and interactive data visualizations, Seaborn – library for Data Visualization.

3. METHODOLOGY

The steps for building the classification model are mentioned below.

1.1 Data Pre-Processing

The initial setup is the localization of the optic nerve head (ONH) including locating other anatomical structures like blood vessels, tracking, and registering changes within the optic disc region, etc. The input images were first pre-processed for the removal of outliners. Initially, the unnecessary part of the image was cropped. Then several filters were applied to the cropped image to extract useful information [4].

A given dataset may contain images of different dimensions and parameters which may hamper the performance of the neural networking model. Hence, an image data generator which is a library of Keras is used to remove the differences between the individual images in a dataset. It sets the dimensions of images to the given value so that the differences are removed. We have set the resolution to 224 x 224 which is generally used for pre-trained models as they can be memory intensive. Also, batch size can be set according to the hardware used. We kept the batch size of 32 images which was optimum according to the pre-trained model used.

Data Augmentation is the way of creating new data by performing several operations such as flipping, rotating, etc on the original dataset. Dataset size have a huge impact on the accuracy of the neural network model and hence data augmentation is a powerful method for the same. In our study, we have implemented data augmentation by performing zooming, shearing, horizontal flip, vertical flip, and validation split on the training dataset. Data Augmentation plays a major role in balancing the 2 classes of datasets [5] viz. Glaucomatous and Non-Glaucomatous. The total number of data points in a dataset gets increased with the help of augmentation.

1.2 Model Creation

A neural network model is a collection of various nodes or neurons, and each node consists of a set of inputs, weights, and a biased value. Whenever input data enters the node, the weight is multiplied by the input and the output generated is either feed to the next layer or is observed. We have set the weight to ImageNet as it is able to categorize the images into 22,000 categories based on a defined set of parameters. The top layer is set to False as we must classify the dataset into 2 classes.

The pooling layer helps to reduce the resolution of the features. The features obtained are then robust against noise and distortions. We have used Global Average Pooling 2D for building the model. The Global Average Pooling 2D layer makes the model more robust to spatial translations in an image as it sums out the spatial information in the image [6]. Further, the dense layer is created by setting the activation function as SoftMax and keeping the number of training classes as 2.

Dense layer along with the pooling layer of the specified model is used to predict the output by giving them as the second parameter to the Model function. The input to the Model function is provided by the base class of the specified model such as ResNet50, VGG 16, DenseNet 169, etc [7]. In this way, we have built a transferred learning model using 6 pre-trained ImageNet models [8].

1.3 Model Implementation

Once the model is built, it is compiled using Adam optimizing algorithm and the loss is set to categorical crossentropy. The categorical crossentropy measures the model's performance and generates results whose output is a biased value between 0 or 1. The metric to measure the model's performance is accuracy as it is generally used in all the models. Finally, the model is run for 20 epoch cycles and the validation dataset is used to validate the trained model by comparing the results.

4. RESULTS

After completing all 20 epoch cycles, the accuracy and loss of all the models were found. To show the basic CNN performance, the accuracy graph and loss graph were plotted with the accuracy graph having epoch cycles along the x-axis and accuracy value on the y-axis and the loss graph having epoch cycles and loss value on the x-axis and y-axis respectively. The Matplotlib and NumPy libraries were used to plot the graph. An example of a graph is shown in Chart 1.

Calculating accuracy alone can sometimes be misleading when you have an unequal number of observation classes. So, we decided to plot a confusion matrix that shows the statistical classification of the algorithm's performance. The test data was tested with all the models and the confusion matrix showing Actual Class Vs Predicted Class was plotted. You can see the confusion matrix of the DenseNet169 model in Fig 1 which shows True Positive, True Negative, False Positive, and False Negative images from the test results [9].

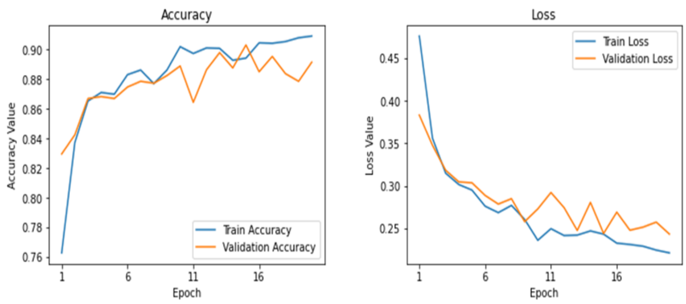

Chart -1: Accuracy and Loss Graph for DenseNet169

The confusion matrix was plotted with the help of Seaborn and Pandas library. With the help of the confusion matrix, several parameters can be compared such as Precision, Recall, Specificity, F1 Score, etc.

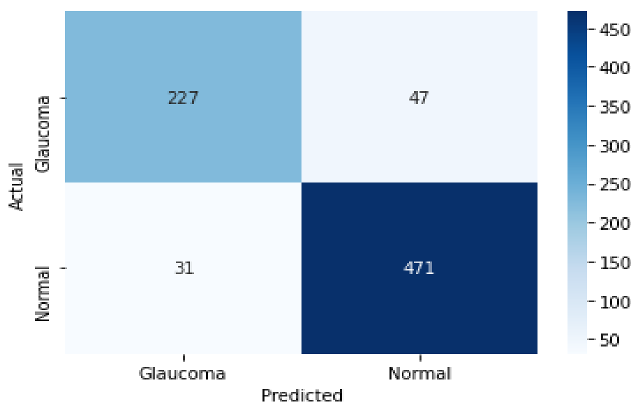

Fig -1: Confusion Matrix of DenseNet169 Model

The parameters are calculated based on the values acquired from the confusion matrix with the help of the formulae mentioned below.

Precision = TP / (TP+ FP)

Recall = TP / (TP+ FN)

F1 Score = (2 × Precision × Accuracy) / (Precision+ Accuracy)

Accuracy = (TP+TN) / (TP+TN+ FP+FN)

Specificity = TN / (TN+ FP)

Using the mentioned formulae, all the parameters for each model was calculated [10]. A detailed analysis of all the models can be done more accurately by including more parameters.

Table -1: Parameter Values for Pre-Trained Models

Parameter	Pre-Trained Models					
	Incep -tion	Xcept -ion	ResN-et50	Mobil -eNet V2	Dense -Net 121	Dense -Net 169
Precision	0.794	0.867	0.910	0.785	0.875	0.880
Accuracy	0.827	0.889	0.918	0.869	0.879	0.900
F1 Score	0.738	0.838	0.879	0.823	0.817	0.853
Recall	0.690	0.810	0.850	0.865	0.766	0.829
Specificity	0.902	0.932	0.954	0.871	0.940	0.938

5. CONCLUSIONS

Based on the parameter's table for 20 epoch cycles, the model's performance can be concluded for each of them. ResNet50 gives the most promising results with the highest value in Precision i.e., 0.910, Accuracy i.e., 0.918, F1 Score i.e., 0.879 & Specificity i.e., 0.954 as compared to other models. DenseNet169 can also be taken into consideration after ResNet50 as its Precision, Accuracy & F1 Score are better than the other pre-trained models excluding ResNet50. Xception & DenseNet121 models give average results and must be fine-tuned if we want to use them for classification. MobileNetV2 & Inception give the least promising results among all the models. MobileNetV2 has the highest Recall value however when comparing other parameters, it lags almost every model. This classification also proves that the pre-Trained model can be used for classification with almost perfect accuracy, much less time and limited resources compared to the conventional neural networking models. This study was done on a preliminary basis and the models can be fine-tuned for better results. Also, the epoch cycles were kept 20 due to hardware limitations but can be increased along with an increase in the size of the dataset for making a much more robust model.

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