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A lightweight CNN model for early detection of Glaucoma

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Glaucoma, Google Net, CNN model, dropout layers.

ABSTRACT

Glaucoma is rapidly increasing in middle-aged population in India and worldwide. High intra-ocular pressure damages the optic nerve and progresses towards loss of vision an irreversible process. Hence, early detection of the disease can save people from losing their faculty of vision. Various techniques in the literature, such as threshold-based segmentation of optic disc (OD) and optic cup (OC), super pixel approaches, deep Convolutional generative adversarial networks, optical coherence tomography (OCT), and high- resolution tomography (HRT), are either computationally complex or time-consuming. This study proposes a lightweight Convolutional Neural Network (CNN) implemented in MATLAB, achieving the highest accuracy on popular glaucoma datasets. A peak accuracy of 99.8% has been achieved with the proposed lightweight CNN model

1. INTRODUCTION

With ageing population, India is expected to become the second-largest source of glaucoma disease by 2020. In India, it is estimated that 11.9 million people suffer from glaucoma. Glaucoma prevalence in India varies by location, with rates ranging from 2.3 to 4.7 percent across various demographics and groupings[1].

Glaucoma is an eye disease that develops in the optic nerve as a result of intra-ocular pressure buildup in the retina. When the front part of the eye fills with a transparent fluid called aqueous humor, it causes pressure. This fluid initially maintains a constant flow, resulting in a constant pressure. When this fluid does not flow or has obstructions, the pressure in the eye gradually rises, resulting in glaucoma. No symptoms or lack of early symptoms makes detection of Glaucoma a very difficult task that causes sudden vision loss. Lack of early symptoms makes the detection difficult. Ophthalmologists employ different conventional methods to measure intra-ocular pressure in the eye using tonometry, pachymetry etc., which are time consuming and labor-intensive methods and need to be performed under the supervision of an expert. Computer aided Diagnostic (CAD) Systems have been built for detection of Glaucoma in the recent past. Dissimilarity in the patient eye size, texture, and variable cup to disc ratio makes the detection process difficult. Machine and deep learning models have gained popularity in solving complex and ill defined problems. Machine learning methods employ calculation of various features followed by feature optimization and then classification. Choosing the right kind of features solves makes the model simple. Some of the features like Harlick features Color features, geometrical features and Local Binary patterns have been widely used for classification tasks. Deep learning is a sub branch of Machine learning that employs various deep neural network architectures for classifications tasks. Automatic feature extraction and feature optimization is carried out by the hidden layers of the network. Various deep learning architectures such as GoogLENet, RESNet, Shuffle net have demonstrated good classification accuracy[2]-[8],[21]. Since these networks are very deep and have many layers, the time to train the networks is large. Two lightweight Convolution neural network models have been built that demonstrate good classification accuracy on various Glaucoma Datasets such as Dataset from Kaggle, DRISHTI 64x64 and DRISHTI GS. The Performance metrics have been evaluated on various pre-trained models and lightweight models.

2. RELATED WORK

Ahn et al. [9] employed deep learning algorithms on Fundus pictures to differentiate between normal and glaucoma patients. Logistic classification is used to categorize people with advanced glaucoma. However, enhanced glaucoma detection necessitates the use of sophisticated technology.

The Deep Learning architecture developed by Chen et al. [10] consists of six learnt layers: four Convolutional layers and two fully-connected layers.
Dropout and data augmentation are

techniques used to improve glaucoma diagnosis. datasets. The AUC of the receiver operating characteristic curve in glaucoma detection was 0.831 and 0.887 in the two datasets, ORIGA and SCES, respectively.

Fu et al. [12] developed a unique Disc-aware Ensemble Network (DENet) for automated glaucoma screening directly from fundus pictures. Experiments on two glaucoma datasets, SCES and new SINDI, show superior performance when compared to other state-of-the-art methods.

Li et al. [13] employed the Inception-v3 architecture, a convolutional neural network made up of 11 inception modules. For training, a minibatch gradient descent of size 32 was utilised, with an Adam optimizer learning rate of 0.002 for improved convergence.

M.Christoper et al. [14] employed a large database of fundus pictures (n = 14,822) from a racially and ethnically varied group of people (nearly 33% of whom were of African heritage) that were examined by professional reviewers and categorized as glaucomatous optic neuropathy or healthy. Several deep learning architectures were studied, as well as the influence of transfer learning. In differentiating glaucomatous optic neuropathy eyes from healthy eyes, the highest performing model scored an overall area under receiver operating characteristic (AUC) of 0.91.

Shibata et al. [15] employed a training dataset that included 1,364 colour fundus pictures with glaucoma symptoms and 1,768 colour fundus photographs without glaucoma symptoms. A testing dataset includes 60 glaucoma participants' eyes and 50 normal participants' eyes. For classification, a deep Resnet architecture has been used, and the resultant area under the curve is 96.5.

Sungheetha et al. [16] extracted characteristics using Convolutional neural networks. On moderate DR pictures, the micro aneurysm may be observed in the early phases of the transition from normal to ill state. The suggested CNN architecture enabled the early diagnosis of the diabetes state by detecting Hard exaduates in an eye's blood vessel.

By adapting U-Net CNNs, Sevastopol sky et al [17] presented a technique for automated optic disc and cup segmentation. On several datasets such as RIM-ONE v.3, DRISHTI-GS, and others, they obtained considerable reductions in prediction time.

Based on three-dimensional optical coherence tomography (OCT) data and colour fundus scans, R. Asaoka et. al [19], developed a machine learning-based system for glaucoma diagnosis in patients with open- angle glaucoma. Convolutional neural network (CNN) with transfer learning was utilized. A random forest (RF) classifier was built to differentiate between healthy and glaucomatous disc Fundus pictures.

Chakravarty et al. [20] employed a CNN that uses a mix of image appearance data and structural characteristics from the Optic Disk and Optic Cup segmentation for Glaucoma classification.

Chen et al. [21] carried out experiments on ORIGA and SCES datasets. The results show that AUC of the receiver operating characteristic curve in glaucoma detection at 0.838 and 0.898 respectively.

3. PROPOSED APPROACH

A. Structure of CNN

A Convolutional Neural Network (CNN) is a powerful deep learning technique, trained on large datasets. CNNs can learn rich features for a wide range of images from these large collections. Features extracted from CNN outperform hand-crafted features like HOG, LBP, or SURF. The basic Block diagram of CNN is shown in Fig 3.1. The convolution operation generates a feature map as the convolution kernel slides along the input matrix for the layer, which then contributes to the input of the next layer. Other layers such as pooling layers, fully connected layers, and normalization layers are then added. Pooling Layers reduce the dimensions of data by combining output from a group of neurons in the previous layer to a neuron in the present layer. Fully connected layer is a multi-layer perceptron neural network which takes the flattened input and produces the classified output image.

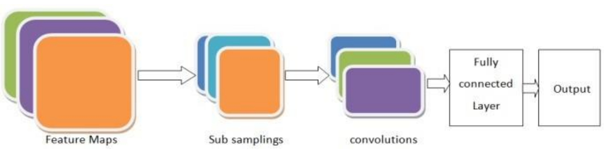

Fig 3.1. Basic structure of a Convolutional neural network

B. Datasets

The Kaggle Glaucoma Dataset contains 1022 images divided into 2 groups: contains 511 glaucoma negative fundus images and 511 Glaucoma Positive fundus images. Drishti-GS is a dataset meant for validation of segmenting OD, cup and detecting notching. The images in the Drishti-GS[14] dataset have been collected and annotated by Aravind Eye hospital, Madurai, India. This dataset is of a single population as all subjects whose eye images are part of this dataset are Indians. The dataset is divided into two: a training set and a testing set of images. Training images (50) are provided with ground truths for OD and Cup segmentation and notching information. The Drishti Dataset [18] contains 101 Fundus images of which 70 belong to Glaucoma and 31 belong to non Glaucoma.

C. Methodology

The efficiency of the model greatly depends on the quality and amount of image data available. Since the number of images in the dataset are small, pre- processing i.e data augmentation has been carried out. Angular rotation, Shear to the right and shear to left are applied on the images. Various pre-trained models such as Resnet-50, Resnet-101, Squeeze Net, MobilenetV2, Shufflenet, Googlenet, and Densenet have been used for classification. After preprocessing the data has been divided into testing set and training set and 5 fold cross validation has been applied on various pre trained networks as well as lightweight CNN model 1 and CNN model 2 with 9 layers and 11 layers respectively. The performance of these networks are evaluated with respect to accuracy, misclassification rate, True positive rate, False positive rate, sensitivity, precision, specificity and F Score. The working methodology is demonstrated in Fig. 3.2

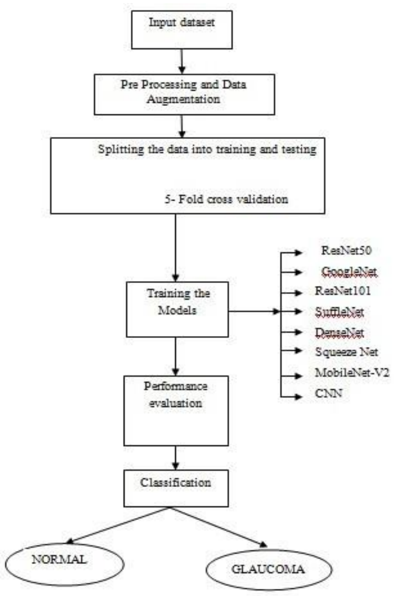

Fig 3.2. Flow Diagram for detection of Glaucoma

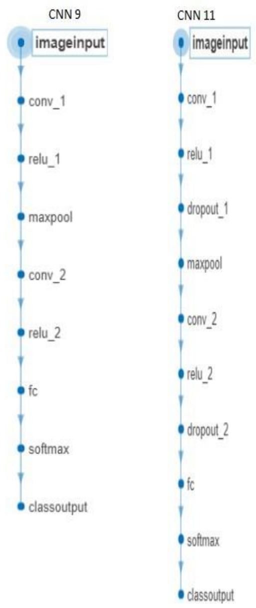

Fig 3.3: Light Weight CNN Models

D. Pre-Trained Deep neural Networks

ResNet-50 is a deep residual network with 50 layers. The vanishing gradient problem plagues deep networks. As the model back propagates, the gradient becomes very small. Smaller and smaller gradients can make learning difficult. The skip connection enables the network to learn by allowing it to skip through layers that are less relevant in training.

GoogLENet architecture consisting 22 layers. Over fitting is another issue with deep neural networks, solved by using the GoogLENet.Convolution operation is performed on inputs with three filter sizes: (1 1), (3 3), and (5 5), which are max-pooled before being sent to the next inception module. Because neural networks are time-consuming and expensive to train, the number of input channels are limited by adding an extra (1 1) convolution to reduce the network's dimensions and perform faster computations.

SqueezeNet is an 18-layer deep convolutional neural network with a small network size that achieves performance comparable to AlexNet. Smaller DNNs are easier to deploy on FPGAs and other memory-constrained hardware. The ReLU activation is applied to all squeeze and expand layers. Dropout layers are used to reduce over fitting and the network do not use fully connected layers.

ResNet is a powerful backbone model that is widely used in computer vision tasks. ResNet-101 is a 101- layer deep. To reduce the vanishing gradient problem, ResNet employs skip connections to add the output from an earlier layer to a later layer.

MobileNetV2 is an architecture for convolutional neural networks that works well on mobile devices. It is based on a residual structure that has been inverted. As a source of non-linearity, ~~the intermediate~~ expansion layer filters features using lightweight depth wise convolutions. The initial fully convolution layer with 32 filters in MobileNetV2 is followed by 19 residual bottleneck layers.

AlexNet has a much greater depth than LeNet5, which has five Convolutional layers, two fully-connected hidden layers, and one fully-connected output layer. AlexNet's activation function is ReLU rather than the sigmoid. The other critical steps in achieving excellent performance in computer vision tasks were dropout, ReLU, and pre-processing.

DenseNet is a type of Convolutional neural network that uses dense connections between layers via Dense Blocks, which connect all layers directly. Each layer receives additional input from all preceding layers and passes its own feature-maps to all following layers.

E. Light weight CNN

In setup one, a nine layer CNN network consisting of input layer, two convolution layers, two ReLU layers, one max pooling layer, one fully connected layer, one softmax layer followed by one output layer has been used to classify the Fundus images. In setup 2 additional dropout layers has been added in addition to the layers described in setup one. The two light weight CNN models are depicted in Fig 3.3.

4. RESULTS AND DISCUSSION

Transfer Learning approach has been applied on various pre-trained models discussed in section III D. The models are trained on DRISHTI 64X64 Dataset and metrics such as Accuracy, Misclassification, Sensitivity, Precision and F-score have been evaluated.

Accuracy is defined as defined as the number of correct predictions divided by the total number of predictions, multiplied by 100. It indicates how often the given classifier is correct.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} * 100 \ldots\ldots\ldots\ldots(1)$$

Misclassification rate represents how often the classifier is wrong defined as

$$\text{Misclassification} = \frac{FP + FN}{TP + TN + FP + FN} * 100 \ldots\ldots(2)$$

Precision represents the possibly correct classification if the classifier predicts the class as Yes and is defined as the ratio between the total no. of correctly classified inputs to total no. of predicted inputs.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (3)$$

Sensitivity is a measure of the proportion of actual positive cases that got predicted as positive (or true positive). Sensitivity is also termed as Recall defined as the ratio between the total numbers of correctly classified inputs to the total number of correctly predicted inputs.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad \ldots\ldots(4)$$

Specificity is defined as the proportion of actual negatives, which got predicted as the negative

$$\text{Specificity} = \frac{TN}{TN+FP} \quad \ldots\ldots(5)$$

F-score is the measure of test accuracy which is the harmonic mean of the precision and recall.

$$\text{Fscore} = \frac{2 * \text{Sensitivity} * \text{Precision}}{(\text{Sensitivity} + \text{Precision})} \quad \ldots\ldots(6)$$

TP =True positive, TN=True negative, FP=False positive, FN=False negative

Table 4.1: Performance of pre-trained Networks

Parameter	ResNET 50	Goog-LeNet	ResNET 101	Squeeze Net	Mobile Net V2	Shuffle Net	Dense Net
% Accuracy	78.2	70.3	74.3	69.3	72.3	75.2	71.3
%Misclassification	21.7	29.7	25.7	30.7	27.7	24.8	28.7

Sensitivity	0.65	0.842	0.828	0.9	0.81	0.84	0.75
Specificity	0.83	0.387	0.548	0.225	0.51	0.54	0.61
Precision	0.61	0.756	0.805	0.724	0.79	0.80	0.81
F-score	0.36	0.796	0.816	0.802	0.80	0.82	0.78

Table 4.2: Performance of pre-trained Networks on single CPU

Parameter	ResNET 50	GoogLeNet	ResNET 101	SqueezeNet	MobileNet V2	ShuffleNet	DenseNet
% Accuracy	68.3	74	82	53.3	66.3	64.4	78
% Misclassi-fication	31.7	26	18	46.5	33.7	35.6	22
Sensitivity	0.65	0.9	0.97	0.87	0.914	0.728	0.71
Specificity	0.83	0.48	0.74	0.19	0.548	0.580	0.33
Precision	0.61	0.74	0.89	0.70	0.820	0.707	0.71
F-score	0.63	0.84	0.93	0.78	0.864	0.460	0.71

Table 4.3 Classification results using lightweight CNN

Parameter	CNN-9	CNN-11
% Accuracy	99.8	98.8
% Misclassification	0.0019	0.012
Sensitivity	0.5	0.495
Specificity	0.5	0.9166
Precision	0.9980	0.9980
Fscore	0.6664	0.3309

optimizer, MaxEpochs=30, MiniBatchSize=8 and and an initial learning rate as 0.0001.

Two light weight CNN models CNN-9 and CNN-11 are trained on Kaggle Glaucoma datasets and the results of Accuracy are promising. Table 4.1 describes the results obtained for Glaucoma disease classification using different pre-trained networks using transfer learning approach on a GPU, while Table 4.2 describes the parameters of classification for different pre-trained networks using single CPU with 2 GHz i3 processor with 4 GB RAM . The accuracy of classification is small in case of the machine trained on single CPU. Since the deep neural networks like ResNET,GoogLeNET, SqueezeNet, Mobilenet, ShuffleNet and DenseNet consume the computational resources in a large scale, two simple lightweight CNNs CNN-9 and CNN-11 are built and the parameters of classification have been evaluated as depicted in Table 4.3. These lightweight CNNs can be deployed on to the embedded hardware for building a standalone system.

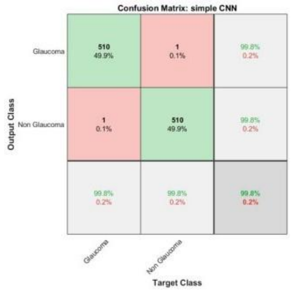

Fig 4.1: Confusion Matrix for CNN -9

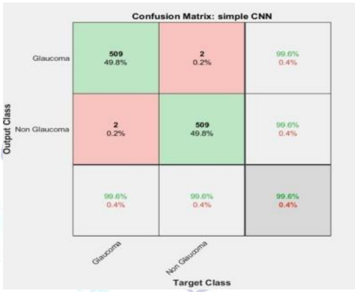

Fig 4.2: Confusion Matrix for CNN -11

A lightweight CNN-9 performs well with an accuracy of 98.8 %. It demonstrates less misclassification rate and high precision and F-score in comparison to CNN- 11 and other pre-trained models. Since the network is lightweight, it can be deployed on to the edge hardware to make it a complete standalone system.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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