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Classification of Retinal Diseases Using Transfer Learning Approach

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Abstract*—Retinal disease classification of Color Fundus Images using Computational Imaging has been widely accepted. This paper proposes a transfer learning approach for Retinal Disease Classification using Deep Learning. Deep learning methods are widely used due to higher performance and accuracy but at the cost of time. A large amount of time and processing power is required to train a dataset and achieve considerable accuracy. Transfer learning reduces a load of using huge data-sets, thereby reducing the time complexity of the training data. We have selected VGG19 model to fine-tune the network for the extraction of knowledge. The VGG19 model is fine-tuned with a retinal database. The results contain accuracy the network on changing various hyper-parameters like learning rate, number of epochs, optimizer algorithm to find a suitable set of parameters for higher accuracy. The motivation for using Deep Neural network is the fact that it has multi-fold benefits like better performance compared to traditional machine learning techniques, higher accuracy, automated feature extraction and easier to design and process.

Keywords*— Cognitive Intelligence, Deep Neural Networks, Eye, Knowledge Transfer, Medical Imaging

I. INTRODUCTION

Retina is the photosensitive portion of our eyes which is delicate, crucial and responsible for the vision. Even minor damage to these tissues can result in symptoms like distorted vision, blurry vision and even loss of sight. These symptoms if left unattended can result in serious diseases like vision impairment or even temporary or permanent loss of sight. Hence it is very crucial to detect and attend to these diseases to the earliest. There are various different diseases that can be caused due to effects in the retina like Glaucoma, Diabetic Retinopathy, Retinal Tear, Retinal Detachment, Macular Degeneration etc., The rectification of these diseases is necessary as early as possible. In order to rectify the disease, it is necessary to figure out the type of disease. This paper provides a solution to this problem by detecting the disease through transfer learning, a deep learning method. Deep Learning requires a lot of data to train and it may require a lot of time and memory as well but this is an efficient method once the neural network model is trained of the data set completely. It effectively detects the retinal disease and even classifies them, making it easier to cure. The issue that usually occurs in traditional machine learning models and the neural network is the time and processing power which is required to compute the output. In order to improve the accuracy, new data should be fed to the system, but in case the system has a huge dataset, high processing power, and time commitment is required to get decent accuracy. In this paper we propose a system that transfers its knowledge from a relatively pre-trained model and implements this on our dataset, to update the weights and biases. This knowledge transfer between machine learning algorithms is known as Transfer Learning. The profit of using this methodology is it retains most of the neural architecture of the pre-trained model and tunes the architecture to minimize the loss for the un-trained model. Hence it requires less computing and is much faster as compared to the traditional CNN and Machine Learning algorithms.

II. LITERATURE REVIEW

In a very few decades, biomedical imaging and retinal image computing have gathered the attention of various researcher as the output of the computation system is considered better than verbal dictation of the system or other traditional methodologies. Prior works in this field are done by [1], [2] have used machine learning methods to generate an accuracy of 81-86%, [3] compared popular algorithms to produce and increase the accuracy in classification, while [4] uses simple image processing for detection of defects. This paper uses transfer learning as it is suitable for small scale data set [5]. The motivation of the proposed system was from [6], according to which VGG19 [7] model showed a decent accuracy as compared to other models.

III. SYSTEM SPECIFICATION AND OVERVIEW

A. Hardware Specification

When designing a prototype, the performance always depends upon the hardware specifications, the better the hardware, the less is the execution time and higher is the processing power there by increasing the overall performance. This section of the paper provides a detailed outline of the hardware specifications that we used to get to the result of this paper. The neural net model was designed and deployed on a system with the following specifications.

TABLE 1: HARDWARE SPECIFICATIONS

Sl. No.	Specifications	
	Name	***Value***
1.	Processor	Intel Core i5-8300H Processor
2.	RAM	8 GB DDR4 2666MHz
3.	GPU	NVIDIA GEFORCE GTX 1050 Ti (4GB GDDR5)

B. Software Specifications

PyTorch is a python based neural network computing frame work. We have used PyTorch to design and execute the neural network model. PyTorch is completely python based and hence it is preferred by us as it is very friendly with the native python based packages like Numpy, Scipy, Python Imaging Library (PIL) etc., VGG-19 is a pre-trained deep neural model which is 19 layers deep. We have preferred this model for fine-tuning our custom dataset and to transfer knowledge as it is faster and more efficient [8].

TABLE 2: SOFTWARE SPECIFICATIONS

Sl. No.	Specifications	
	Name	***Value***
1.	Language	Python 2.7
2.	Frame Work	Pytorch
3.	GPU	Cuda 9.0
4.	Pre-trained Model	VGG-19

The GPU used (Refer table 1) supports Cuda 9.0, which increases efficiency of the model [9].

C. Pre-trained Model – VGG19

VGG network was designed in [10], which proposed simple and effective network architecture for efficient accuracy and was trained on a million images.

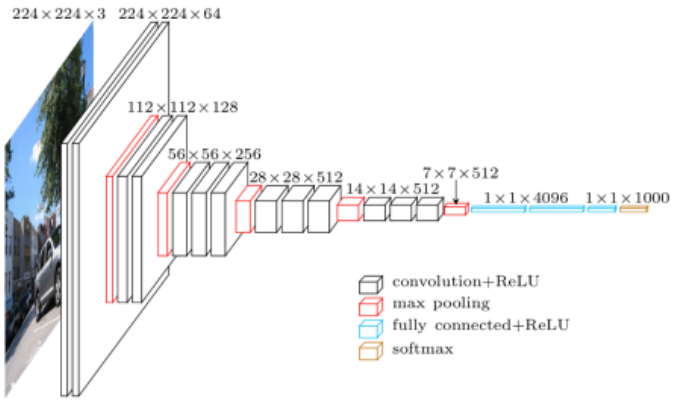


Fig.1. VGG Architecture

Source : (https://www.cs.toronto.edu/~frossard/post/vgg16/)

The proposed system involves 3x3 convolution layers planted one above another in respect of the increasing depth followed by two fully connected layers with 4096 nodes in each layer and one fully connected layer with 1000 nodes which is again followed by a soft-max layer for image classification.

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Fig.2. VGG Configuration (https://qph.fs.quoracdn.net/main-qimg-30abbdf1982c8cb049ac65f3cf9d5640)

IV. METHODOLOGY

This section of the paper explains the architecture of the proposed system and the method incorporated to reach to the conclusion.

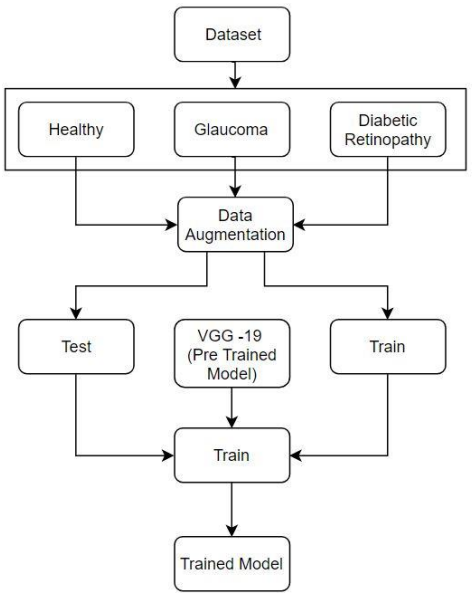


Fig.3. Model Representation

The dataset contains three types of images, healthy, glaucoma and diabetic (Refer to Fig. 5). These images are segregated into different folders. Here VGG network (Visual Geometric Group) [11] is used. First we go through preprocessing followed by extraction of features and then finally identification of images.

A. Preprocessing of images

Since the dataset [12] has less number of images, more images needs to be created because this helps in increasing accuracy of the model. We went through the process of data augmentation for this purpose. The process of data augmentation involves rotation, flipping and cropping of images. This helps in creating more number of images [13]. Not only does it just increase the number of images but also it increases the overall robustness of the model there by making it more accurate.

B. Extraction of features from image

This step involves extracting specific features from the images which later will be used in identifying and segregating the images into healthy, glaucoma and diabetic. For this processes VGG-19 [14] network is used, it was created by Oxford. VGG can contain 11-19 layers but here all 19 layers are used. This convolution network is built using layers having size of 3*3. The diagram below gives the description of layers in VGG [11].

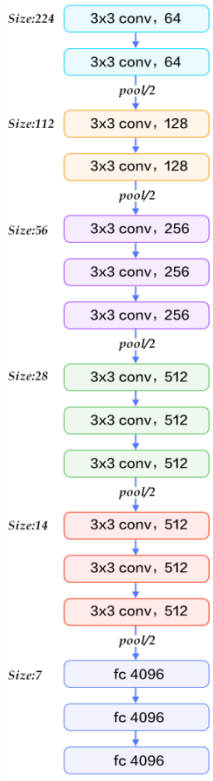


Fig.4 Layers of VGG (https://qph.fs.quoracdn.net/main-qimg-e657c195fc2696c7d5fc0b1e3682fde6)

C. Identifying the images

After getting the desired accuracy, we have saved the trained model into a dictionary format which we use for inference on the required data. In order to predict, we pass the retinal color fundus image through the model which identifies the features from the image and predicts the retinal disease. The results for the experimentations are discussed in the next section.

V. RESULTS AND DISCUSSION

In order to figure out the best preferred hyper parameters, or the optimum hyper parameters, we have used a brute force approach by plotting the epoch vs. accuracy curve at different frequently used learning rates. The accuracy of the model is changed by changing the number of epochs keeping a constant learning rate. It is observed that greater than 90% (Refer to Table 3) of the accuracy is reached in most cases. The model successfully classifies the images into healthy, glaucoma and diabetic (Refer to Fig.8).

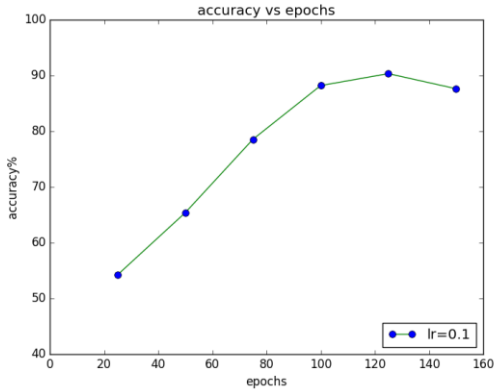
TABLE 3: SOFTWARE SPECIFICATIONS

Epochs	Learning Rate	Accuracy (%)	Loss (%)
25	0.1	54.24	20.8
50	0.1	65.39	13
75	0.1	78.56	8
100	0.1	88.20	7
125	0.1	90.34	6.8
150	0.1	87.64	6.66

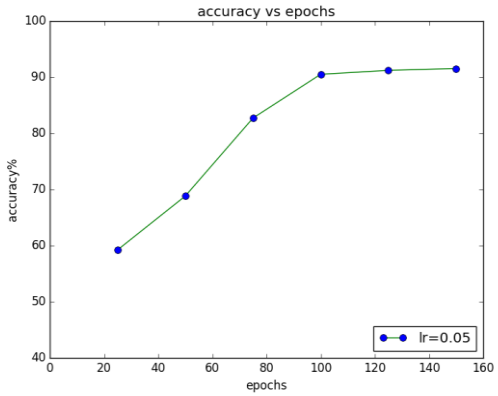
Epochs	Learning Rate	Accuracy (%)	Loss (%)
25	0.01	59.24	24.80
50	0.01	68.83	8
75	0.01	82.72	7.2
100	0.01	90.52	7.2
125	0.01	91.23	6.7
150	0.01	91.56	6.5

Epochs	Learning Rate	Accuracy (%)	Loss (%)
25	0.05	62.94	14.8
50	0.05	81.30	10
75	0.05	86.00	9
100	0.05	91.40	7
125	0.05	91.88	6.5
150	0.05	92.13	6.2

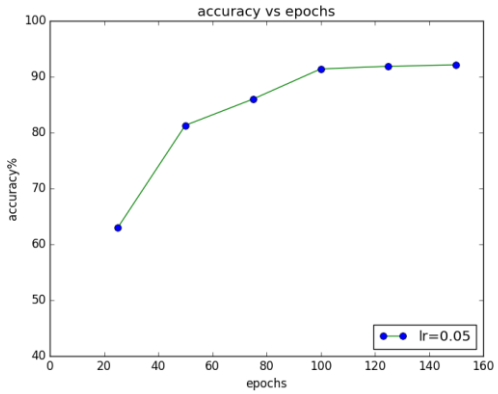
Epochs	Learning Rate	Accuracy (%)	Loss (%)
25	0.001	66.54	20.8
50	0.001	71.23	13
75	0.001	88.92	8
100	0.001	93.20	7
125	0.001	93.35	6.3
150	0.001	93.58	6.2



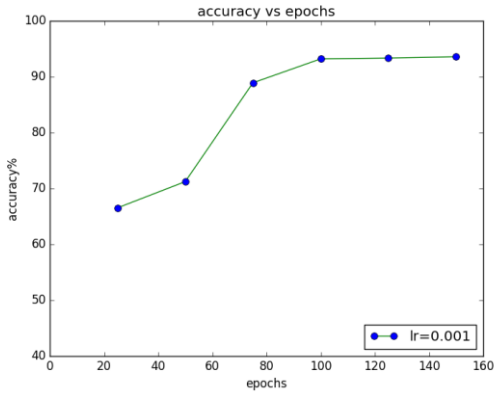
(a) Learning rate: 0.1



(b) Learning rate: 0.05



(c) Learning rate: 0.05



(d) Learning rate: 0.001

Fig . 5. Graphs depicting accuracy vs. epoch of various learning rates.

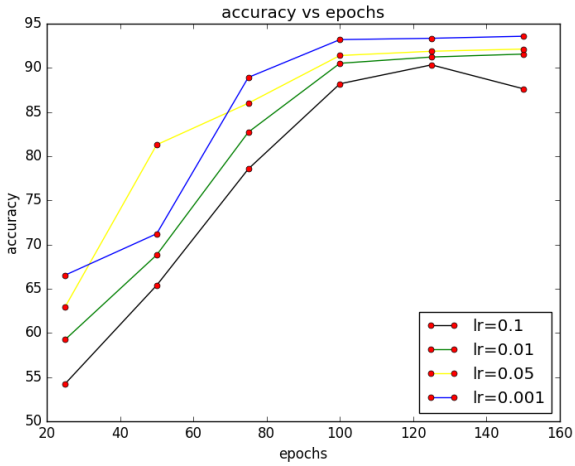


Fig. 6. Comparison Graph depicting the accuracy vs. epoch of experimented learning rates

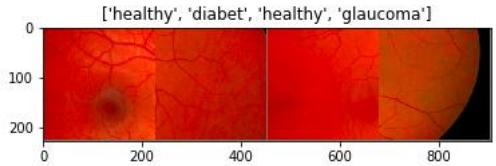


Fig.7 Training Set

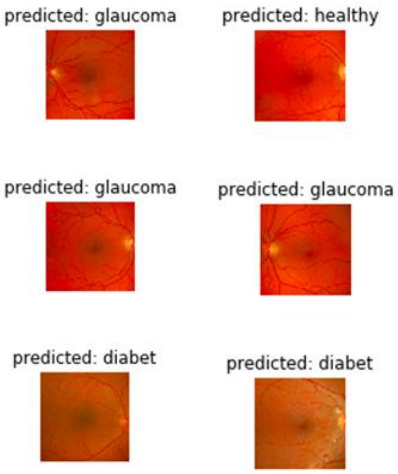


Fig.8 Classified retinal images

VI. CONCLUSION AND FUTURE SCOPE

It can be concluded that this method can be used for classifying and identifying various diseases in eyes and can prove to be helpful in medical purposes. The proposed method is accurate and can be used for mobile and early detection of retinal diseases. The number of classes used for this network is 3 (Healthy, Glaucoma, Diabetic) but number of retinal conditions can be included and a more accurate and variable network model can be created for better identification of retinal diseases using the proposed method.

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