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DIABETIC RETINOPATHY DETECTION: RAPID SCREENING AND EARLY DIAGNOSIS OF DISEASE RETINOPATHY USING SCANNED RETINAL IMAGES AND UNDERLYING DEEP LEARNING MODELS

By

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Abstract - Diabetic Retinopathy (DR) is a common complication of diabetes mellitus, which causes lesions on the retina that effect vision. If it is not detected early, it can lead to blindness. Unfortunately, DR is not a reversible process, and treatment only sustains vision. DR early detection and treatment can significantly reduce the risk of vision loss. The manual diagnosis process of DR retina fundus images by ophthalmologists is time-, effort-, and cost-consuming and prone to misdiagnosis unlike computer-aided diagnosis systems. Recently, deep learning has become one of the most common techniques that has achieved better performance in many areas, especially in medical image analysis and classification. Convolutional neural networks are more widely used as a deep learning method in medical image analysis, and they are highly effective. For this article, the recent state-of-the-art methods of DR color fundus images detection and classification using deep learning techniques have been reviewed and analyzed. Furthermore, the DR available datasets for the color fundus retina have been reviewed. Difference challenging issues that require more investigation are also discussed.

INTRODUCTION

We have seen the advancement of deep learning in solving complex business problems in Banking, E-commerce, and Autonomous Transportation. But have you ever imagined that an AI model can diagnose a disease without a doctor? Yes! It's actually happening in **Sankara Eye Hospital,** Bengaluru. Let's get dive deep into solving this case study using **Deep Learning**.

What is Diabetic Retinopathy?

Diabetic retinopathy is the most common form of diabetic eye disease and usually affects people who have diabetes for a significant number of years. The risk of diabetic eye is for aged people especially working persons in rural and slum areas. It increases with age as well as with less well controlled blood sugar and blood pressure level and occurs when the damaged blood vessels leak blood and other fluids into your retina, causing swelling and blurry vision. The blood vessels can become blocked, scar tissue can develop, and retinal detachment can eventually occur. Retinopathy can affect all diabetics and becomes particularly dangerous by increasing the risk of blindness if it is left untreated. The condition is easiest to treat in the early stages, which is why it is important to undergo routine eye exams before it becomes too late for treatment.

Problem Statement:

Technicians of Aravind Eye Hospital have collected a large number of scanned retinal images of diabetic persons by traveling through rural areas and hosted the problem in Kaggle as a competition where the best solutions will be spread to other ophthalmologists through APTOS. They want us to build a system where it takes the retinal image of a patient and tells us the severity of diabetic retinopathy.

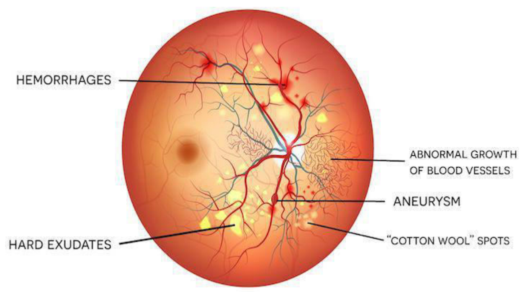
Why we need an automation system?

We have scanned images, then why can't we use trained doctors to diagnosis the disease instead of using the black box system? Is there a need for automation here? Yes! There are a couple of advantages here like below.

- It helps the patient especially to those who can't afford a doctor.
- It reduces human efforts especially when the number of doctors is less.
- Useful for people in rural areas where medical screening is difficult to conduct.
- It saves the time involved in diagnosing a disease.

Key Words:
Diabetic Retinopathy(DR), Deep learning

How Do we know patient has retinopathy?



Signs and Symptoms:

Diabetics should seek treatment right away if they experience:

- Blurry, cloudy vision
- Floaters or dark spots in their field of vision
- Trouble driving or seeing at night
- Fluctuating vision
- Loss of central vision, especially when reading and driving

- Compromised color vision
- Vision loss

Diabetic retinopathy grading and classification:

Mild	Moderate	Severe	Proliferative
• Microaneurysms ONLY.	• More than just microaneurysms. • With or without cotton-wool spots. • Venous beading, or intraretinal microvascular abnormality (IRMA).	• 20 or more intraretinal hemorrhages (dot blot hemorrhages) in each of all four quadrant. • Definite venous beading in 2 or more quadrants. • IRMA in 1 or more quadrants.	• Either: Definite neovascularization • Or: Preretinal or vitreous hemorrhage.

Microaneurysms are the earliest clinically visible changes of diabetic retinopathy. They are localized capillary dilatations which are usually saccular (round). They appear as small red dots which are often in clusters, but may occur in isolation

Hemorrhages may be 'dot' or' blot' shaped (termed 'dot/blot hemorrhages') or flame shaped depending upon their depth within the retina. The capillary network in the posterior retina is found in two layers; a superficial one in the nerve fiber layer and a deeper on within the inner nuclear layer.

Hard exudates are distinct yellow-white intra-retinal deposits which can vary from small specks to larger patches. Hard exudates are largely made up of extracellular lipid which has leaked from abnormal retinal capillaries, hence there is often associated retinal edema (which is not visible using direct ophthalmoscopy). The underlying problem is often apparent as the exudates will form a ring or 'circinate' pattern around the leaking vessels (which may be seen as a cluster of microaneurysms). Hard exudates are found principally in the macular region and as the lipids coalesce and extend into the central macula, vision can be severely compromised.

Cotton-wool spots are greyish-white patches of discoloration in the nerve fiber layer which have indistinct (fluffy) edges. They are the result of local ischaemia which leads to disruption of axoplasmic flow. Cotton-wool spots are common and one or two do not require intervention. However, multiple cotton wool spots (more than 6 in one eye) indicate generalized retinal ischaemia and this is regarded as a pre-proliferative state.

Venous dilatation, beading and duplication occur as retinal ischaemia progresses. Beading is a useful sign of diffuse retinal ischaemia. Venous dilatation is seen early in diabetic retinopathy but is a rather subjective diagnosis.

Typically, preproliferative retinopathy will consist of multiple cotton wool spots, multiple dot and blot hemorrhages, venous changes and intra-retinal microvascular abnormalities.

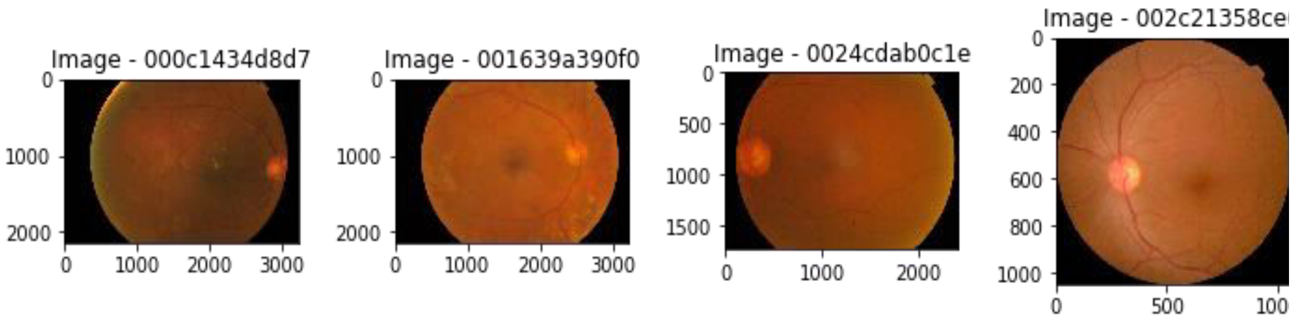
Image Preprocessing:

Open CV Library

We utilize the OpenCV (Open Source Computer Vision) library to manipulate the pictures in order to extract some useful information from them. We can reduce noises as well as control the brightness and color contrast. OpenCV is an open source computer vision and machine learning software library. OpenCV was built to provide a common infrastructure for computer vision applications and to accelerate the use of machine perception in commercial products.

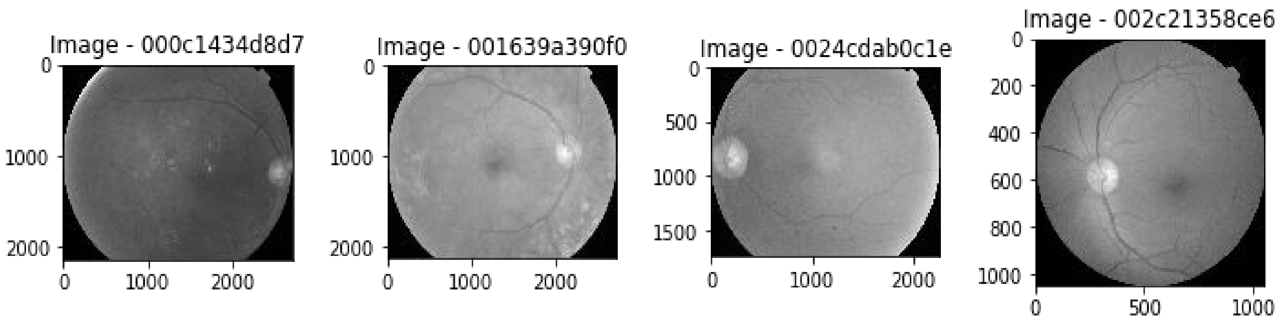
Color

Images come with many different lighting conditions; some images are very dark and difficult to visualize. We decided to convert the images to grayscale for better visualization. A grayscale is simple. It represents images and morphologies by the intensity of black and white, which means it has only one channel. To see images in grayscale, we need to convert the color mode into gray.



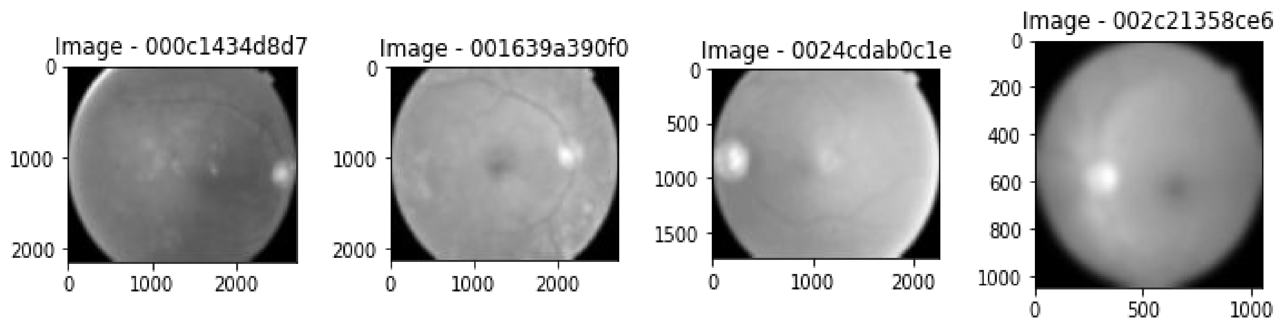
Cropping

Many images have unnecessary and uninformative black areas/borders. We decided to remove these areas with cropping. We keep only rows and columns which contain at least one pixel with a brightness value exceeding our predefined tolerance value of 7.



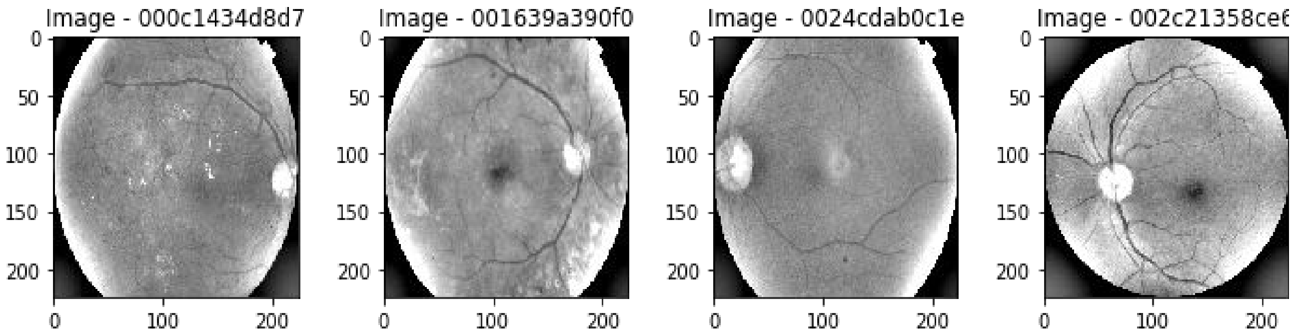
Blurring and Masking

We know that by smoothing an image we suppress most of the high-frequency components. Blurring is one technique we can use for this purpose. Ideally, we need to find an adequate amount of blurring without losing desirable edges. Gaussian filtering is highly effective in removing Gaussian noise from the image.



We then use this blurred image to create a "mask". Since the blurring technique suppressed most of the high frequency components, when we subtract the blurred image from the original image, the result is what we call a mask. This mask will have most of the high-frequency components that were blocked by the smoothing filter. Adding the mask back to the original image will enhance the high frequency components. OpenCV has a function which uses a weighted average of the original image and the blurred image that allows us to accomplish this task.

Finally, since our images come in many sizes, we make things consistent by resizing each image to 224 X 224 pixels.

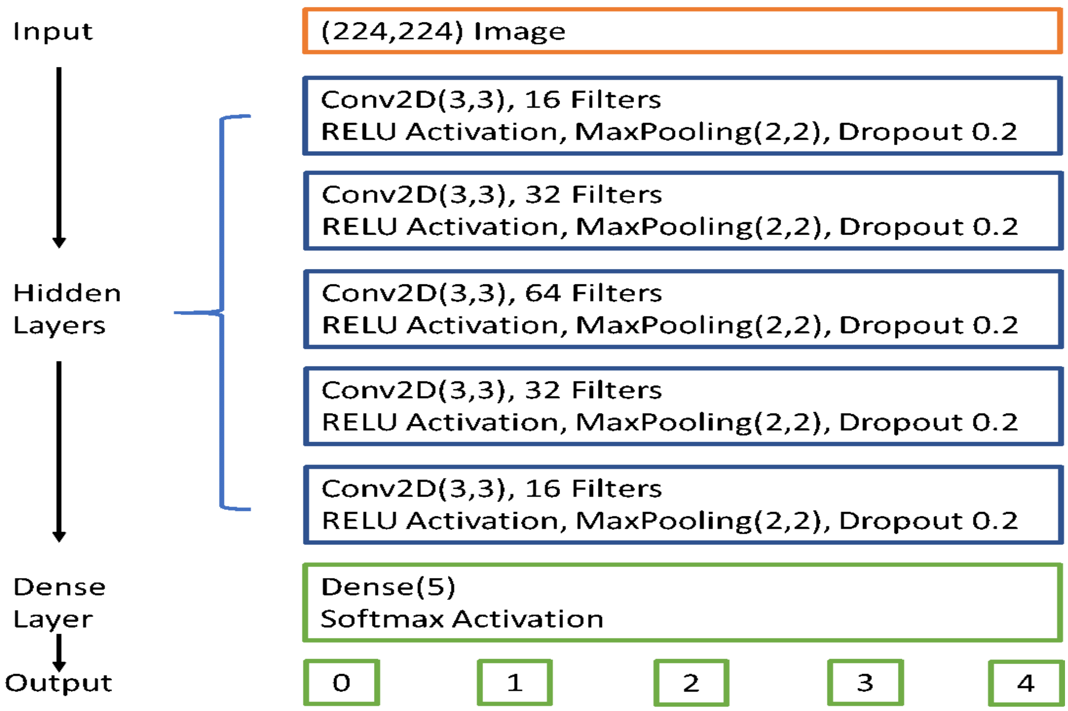


Convolutional Neural Networks

We use a convolutional neural network (CNN) for the classification of retina images into 5 categories. CNN is one of the most popular algorithms for deep learning, a type of machine learning in which a model learns to perform classification tasks directly from images, video, text, or sound. CNNs are particularly useful for finding patterns in images to recognize objects, faces, and scenes. They learn directly from image data, using patterns to classify images and eliminating the need for manual feature extraction. Applications that call for object recognition and computer vision — such as self-driving vehicles and face-recognition applications — rely heavily on CNNs.

Model Structure

Our model consists of an input layer, 5 hidden layers and a dense layer. The figure below shows the structure of the model, a more detailed diagram of the model can be found here. Often the hidden layers in a CNN consist of 3 operations; Convolution, Activation and Pooling. Due to overfitting issues we also added Dropout to each hidden layer of our model.



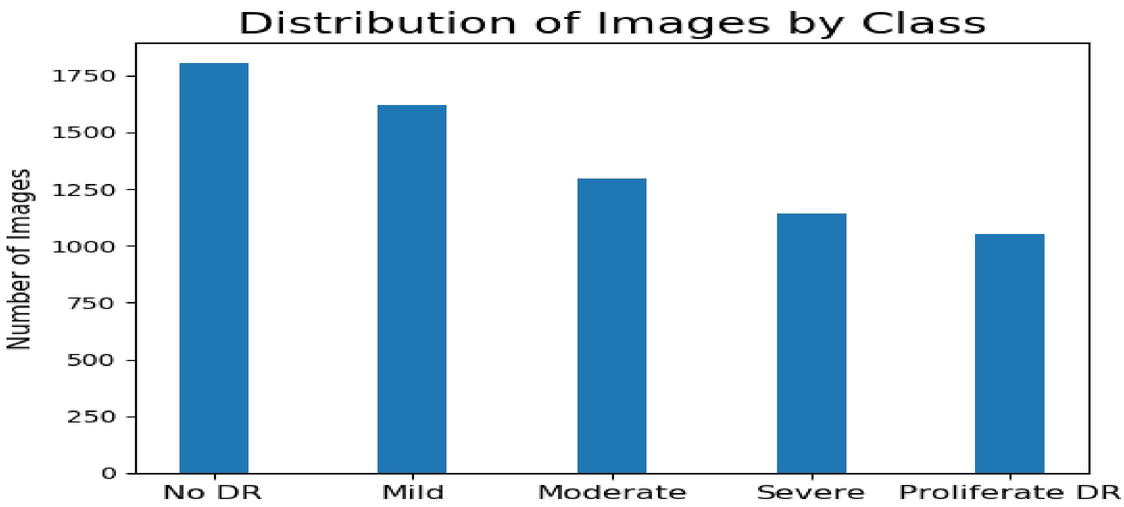
- Convolution: Convolution is the dot product between a filter array and a portion of input the image. The operation is repeated until all elements of the input image have been acted on by the filter. A filter is a set 'weights' to be apply on the input image. The weights determine the features extracted from the image, see examples.
- Activation: We use a RELU activation after each convolution. RELU function keeps the positive elements of an array and substitutes the negative elements with 0s, only the activated features are carried forward into the next layer.

- Pooling: Pooling simplifies the output by performing downsampling, reducing the number of parameters that the network needs to learn. Our model uses Max pooling, which looks at a region of an input array and keeps the maximum value within that region.
- Dropout: A technique used to reduce overfitting. During the training process the contribution of random elements of the network are temporarily ignored.

Data & Training

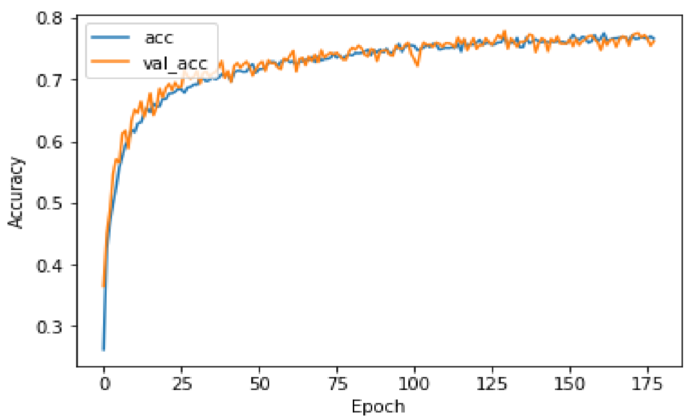
Our data set consisted of a total of 6,917 images obtained from 2 kaggle competitions and the Indian Diabetic Retinopathy Image Dataset (IDRiD):

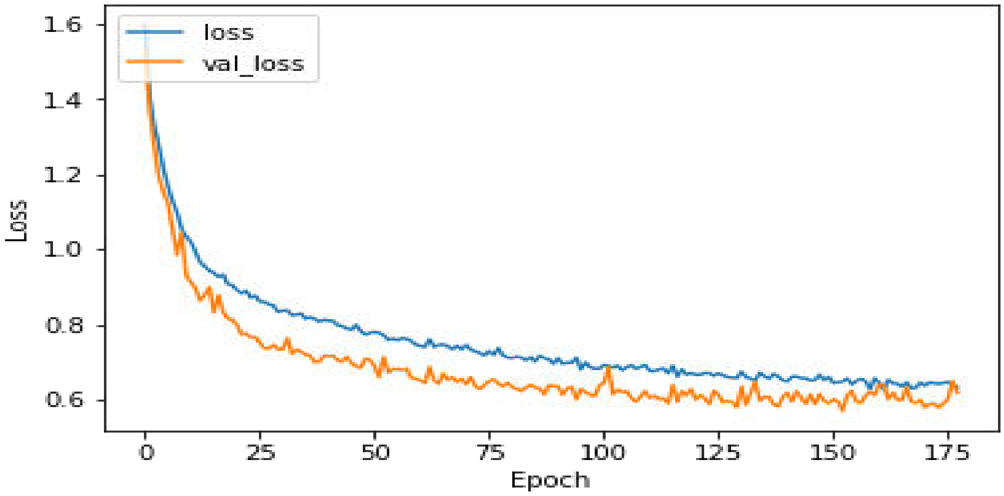
- APTOS 2019 Blindness Detection
- Diabetic Retinopathy Detection
- IDRiD

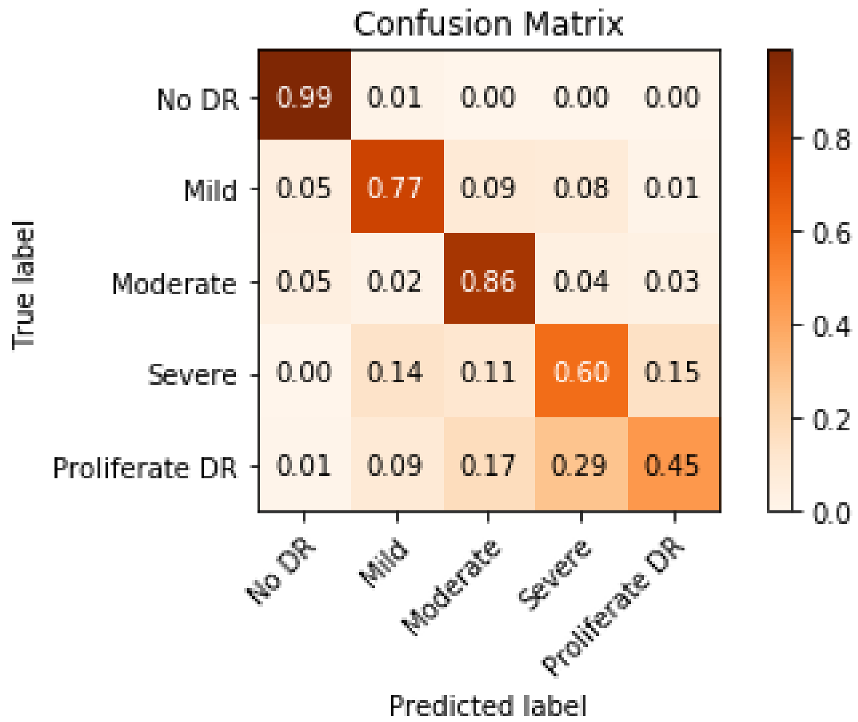


- We used sklearn to calculate a class weights for each of the five categories, since the number of images in the data set was different for each category.
- We used 85% of the images for training and 15% testing.
- We used image augmentation during the training process. Some of the training images were randomly flipped either horizontaly or verticaly, therefore the set of training images between two epochs was never the same. Image augmentation was implemented using ImageDataGenerator library from Keras.
- We implemeted an early stopping condition that would stop the model if the training loss did not improve after a specified number of epochs.
- To cut down on processing time training was performed in Google Colab. Colab allowed us to use up 22GB of memory and it also allowed us to enable a GPU.

Results







Metric Summary

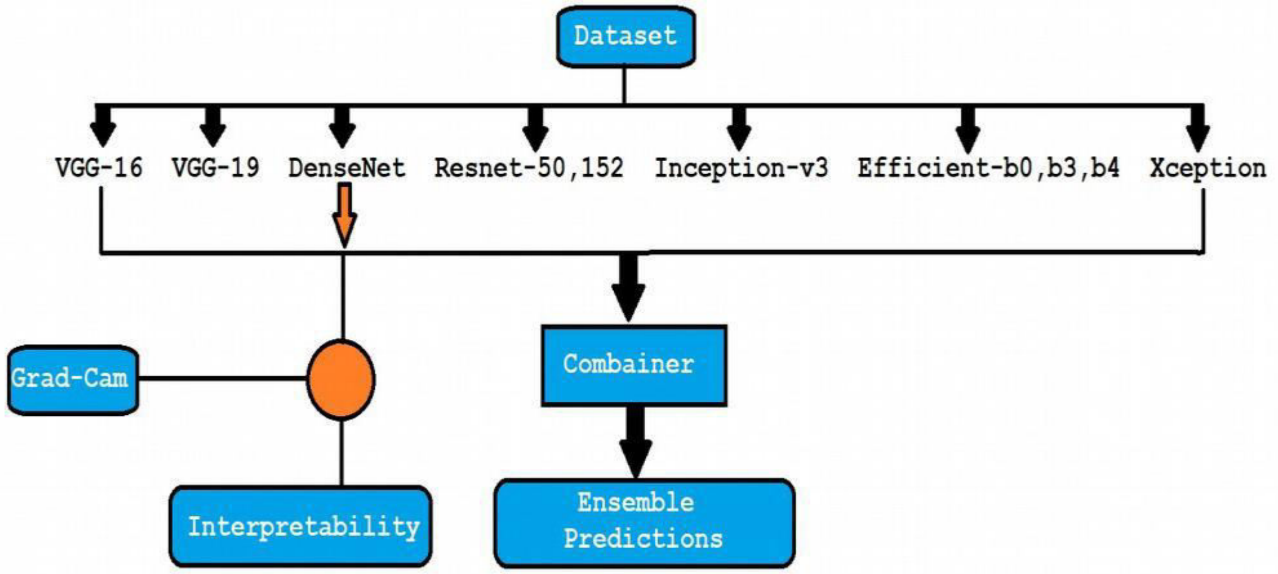
- Accuracy: 0.766
- Loss: 0.575
- Precision: 0.763
- Recall: 0.766
- F1 score: 0.760
- Kappa: 0.840

Conclusions: The final solution to our problem statement:

- After applying a couple of pretrained models, Ensembling those models has given a top score of **0.9314.**
- But here our goal is not only to give the best score but to provide a system that makes a prediction with an explanation.
- Here I have chosen DenseNet which has given the next best score of **0.923** val kappa score for model interpretability and ensemble of all pretrained models for final model prediction.

About Model Training

- Encoding class labels using ordinal regression.
- Adding class weight to balance the dataset.
- Binary cross entropy as loss function with Adam optimizer.
- Used Densenet architecture which is pretrained on the imagenet dataset. After running the model for 30 epochs, the model has given a score of 0.923 on the validation dataset which will be taken for model interpretability
- Ensembling for final model prediction.



Overall Observations of the case study:

- We can see their is high rate of misclassification among class-2 an class-3.
- More sample data on training can improve the performance on these classes.
- More preprocessing and with different sigmax (low than the actual) can be useful in predictions.
- Their is high chance of data shrinkage on square crop images. Hence we need to come up with different approach (manual cropping is best).
- Drawing circle on the images has made all the samples to be equal and also helped in interpretation of model prediction
- Partially Resolved the problem of over expose and under expose.
- Ensembles has worked best in our case. But it loses the property of interpretability.
- Advanced pretrained models on complex datasets especially trained on medical(eye) can fairly improve our model.
- Need to come up with different augmentation techniques to increase the size of the data set.

Future Work:

- Deep learning is the task of experimenting with multiple parameters. Hence I want to hyperparameter with more possible values.
- Using different augmentation techniques to increase the size of the dataset.
- Making use of 2015 data(the similar problem of binary classification) in Kaggle.
- Want to make a web API so that every ophthalmologist can access my work.

- I want to experiment by adding more convolutional layers in each model architecture.
- Making use of Super-resolution GANS to increase the resolution of images.

References:

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