Automatic Detection and stage classification of Diabetic Retinopathy Using Convolutional neural network with densenet120

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Abstract. Diabetic retinopathy (DR) is a leading eye disease which damages the blood vessels in the retina. Initially DR is asymptomatic and eventually ends up with severe or complete vision loss. The main reason of the DR is diabetic mellitus (DM) which is a type of diabetic where the pancreases fail to produce enough amount of insulin in the blood to maintain the blood sugar and glucose. Due to lack of insulin production the sugar and glucose levels are unmanageable. The person with DM is always at a higher rate of acquiring DR. the prevalence DM diabetes affects the retinal blood vessels which lead to complete blindness. According to the recent statistics of The International Diabetes Federation (IDF) around 463 million people are affected with diabetes mellitus worldwide [1]. The early detection of Diabetic Retinopathy which can postpone the progression of the blindness hence in this research work we put forwards the convolutional neural network (CNN) deep learning model to identify the different stages of diabetic retinopathy using fundus images from the kaggle database. The proposed CNN model trained with two different networks resnet 50 and densenet120 respectively. The proposed CNN model outperforms compare with the previous work reported on the deep learning methodology and yields maximum accuracy of 82.58% in multiclass classification.

Keywords: Fundus, Diabetic Retina, Convolutional neural network, Densenet 120, Resnet 50 confusion matrix.

1 Introduction

Diabetic retinopathy is a condition which causes eye complications and leads to blindness. The main cause of diabetic retinopathy is diabetes. Both type 1 and type 2 diabetes leads to diabetic retinopathy. The eye is made up of tiny blood vessels called the micro vessels, which supplies blood and nutrients to the interior structures of the eye. When sugar level in the blood increases, the sugar molecules blocks the vessels causes blood blockages in the eye resulting in micro aneurysm[2][7]. When the blood vessels are blocked there is insufficient supply of blood to the retina and other structures in the eye. In order to receive the required supplements, retina releases a protein called vascular epithelial growth factor (VEGF)[12]. This VEGF protein has the ability to generate blood vessels. Thus new blood vessels are grown to supplement the retina. But the newly grown blood vessels are very fragile which causes leakage of the fluids and blood in the retina causing hard exudates and soft exudates. Hard exudates are made of extracellular lipid that leaks in the anomalous retinal

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capillaries. Soft exudates are often called “cotton wool” region is a yellow white lesion in the superficial retina. When the leakage in the eye increases it leads to retinal detachment. DR which stimulates the abnormal blood vessels to grow the scar tissue that pulls out retina from the back of the eye which leads to partial vision blurring. Due to progression and tissue growth the vision may affected severely. Recently for diagnosing the stages DR significant interest have been considered on machine learning and deep learning algorithms. The machine learning approach is needed with manual feature extraction. If there is any misidentification in the feature extraction which may lead the misprediction in the diagnosis of DR stages hence the proposed approach focused on deep learning algorithms where the hidden biomarkers or features are identified by the hidden layer automatically [11]. For deeplearning assessment the different stages of diabetic fundus retinal images are used. The fig 1.1 and 1.2 shows the healthy and fundus of Diabetic Retinopathy images respectively.

Fig 1.1 Healthy retinal image

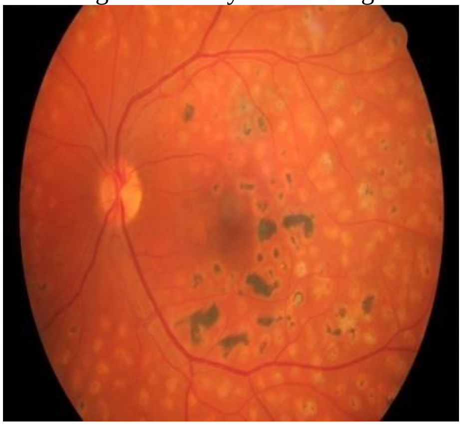
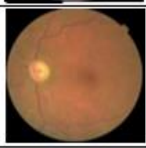


Fig 1.2 Diabetic Retinal image

Table1: Different Stages of DR images from kaggle

0 - No DR	
1 - Mild	
2 – Moderate	
3 - Severe	
4 - Proliferative DR	

The fundus images of the eye is done using fundus photography which is acquired based on the principles of indirect monocular ophthalmoscopy. No early symptoms are observed in diabetic retinopathy which makes it difficult to diagnose at initial stages. Diagnosing the stages of diabetic retinopathy often takes long time. The defects caused by diabetic retinopathy are irreversible. Once left unnoticed causes permanent damage. In this study we focued on early detection of DR which can assist the clinicians to make decision to stop the progression or helping in medication. The proposed approach utilizes the CNN model of two different network achieve the better results. The resnet 50 and densenet 120 models have been utilized to diagnose the different stages of DR using the fundus images of the eye. The resnet 50 is a subset of CNN model consists of 50 layers which can handle large number of input images and pretrained the networks very faster for large volume of data. The resnet 50 allows only the input image size of 224 x224 hence the image augmentation is done before training the model. The densenet 120 getting the additional input from the preceding layers which can helps in fastening the process and diagnose the stages effectively.

2 Literature review

Gazala Mushtaq and Farheen Siddiqui proposed the identification of diabetic retinopathy using CNN deep learning model for multiclass stage classification of DR. they compared the deep learning and regression model for the stage prediction. The level of blindness is performed using the densenet-196 model CNN architecture. ZahraHeidari et all performed the type 2 diabetes mellitus for diagnose the retinopathy multivariate logical regression model is used to predict the cholesterol and FGF21 concentration associated with the diabetic retinopathy different FGF21 considered and assesses to predict the diseases. Even though they yield the maximum accuracy of 93.5 %, the proposed analysis is limited to binary model. They failed to report the multiclass classification [3].AmartyaHatua et all proposed the hadoop framework for diagnosing DR which can identify the early signs of diabetics. The automatic medical diagnosing system helps the clinicians for interventions of the different stages of DR. The DR explores the haemorrhages, microaneurysms and neovascularisation events effectively which plays a significant role in finding the different stages [4].VíctorVives-Boix et all performed the CNN based DR detection with synaptic metaplasticity. The Synaptic metaplasticity back propagation CNN model directly influencing in the learning and memory allocation which fasten the process. The growth of the new cells in the retinal region is identified by the scar in the blood vessels. The metaplasticity model enhances the process and increases the accuracy. In the same direction we put forward the automatic identification of stage classification of diabetic retinopathy using convolutional neural network with resnet 50 and densenet 120 models. The experiment performed using the fundus images of the retina downloaded from the Asian Pacific Tele-Ophtalphmology Society 2019[5][8]. The different stages are classified as (0-4) healthy, mild, medium, severe and Proliferative DR. It is a coherent due to the lack of secretion of insulin in the body which leads the sugar content in the blood. The increasing blood and glucose components cause the retinal retinopathy which eventually ends up with blindness. The main objectives of this research work are to develop a novel method to diagnose diabetic retinopathy faster and more accurately, to automate the diagnosis of diabetic retinopathy and classify the different stages of retinopathy.

3 Proposed Methodology

The fundus images are collected from the kaggle database; the collected images are categorized into 5 different stages as well as splitting into training and testing image inputs. The image size is not fit for the two different networks namely densenet 120 and resnet 50 hence it is resized into 224x224 pixels. the prepared images are feed to the input of CNN model the cnn network assigns input layer for each images the input layer and weigh metrics are convolved and produce the activation function. This activation function is feedback to the pooling layer to down sample the activation layer which is again feed to the input layer of the CNN model. Hyper parameter tuning helps to enhance the model accuracy. From the confusion matrix the performance metrics are calculated to identify the different stage accuracy.

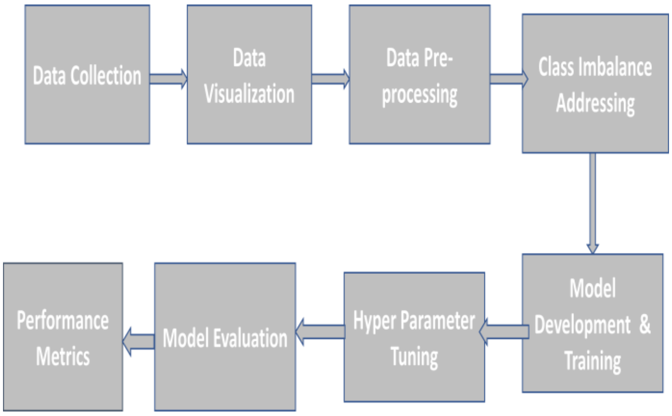


Fig2: Proposed block diagram of CNN model for stage classification of DR

4 Data preprocessing

The actual retinal image sizes are 576 x 576, the resnet 50 network considers only the image size of 224 x 224 the image should be resized. The offline augmentation techniques are implemented to resize the images of different classes[10]. For this analysis we have considered 34316 fundus images to diagnose the DR. Fig 3 shows the augmented images of different class.

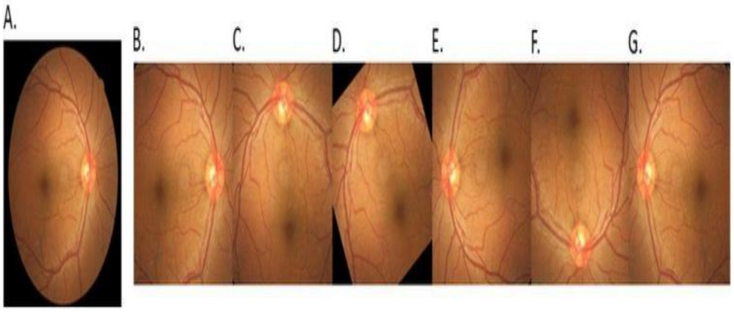


Fig 3: Image augmentation

5 Results and discussion

The experiment is performed in tensor flow backend. The l2 regularization techniques are employed to dimensionality reduction. The input layers are scaled with the weight parameters and it increases the length of the data when the layers are identifying the hidden biomarkers. Hence the L2 regularization technique helps to discard the insignificant features that can avoid the data overfitting. L2 regularisation shrinks or normalize the linear coefficient learnt from the hidden layers and avoid the linear incremental of the input data. CNN input layer is convolved with the convolutional layer and generate the input matrix which are given to the max pooling layer. The max pooling layer assigns the next input layer with the highest value obtained from the previous layer. 4x4 max pooling layer is used in the dimensionality reduction. The same operation is performed for 5 iterations to predict the hidden biomarkers from the input data. After finding the significant features from the different stages the fully connected layer is fixed to convert the matrix in a single column vector. The fully connected layer is connected with the softmax layer which finds the probability function of each class and map with the corresponding stage of the DR. Initially for training the network it is spitted in to training and testing images. 80 % for training and 20 percentages for testing data are utilized for classification of stages. Totally 34316 have been considered for this study. The total images for this study are given in the fig 4. The CNN model convolves the images and produces the highest accuracy of 83 % for multiclass classification of densenet 120 and yields the second highest accuracy of 82% for resnet 50.

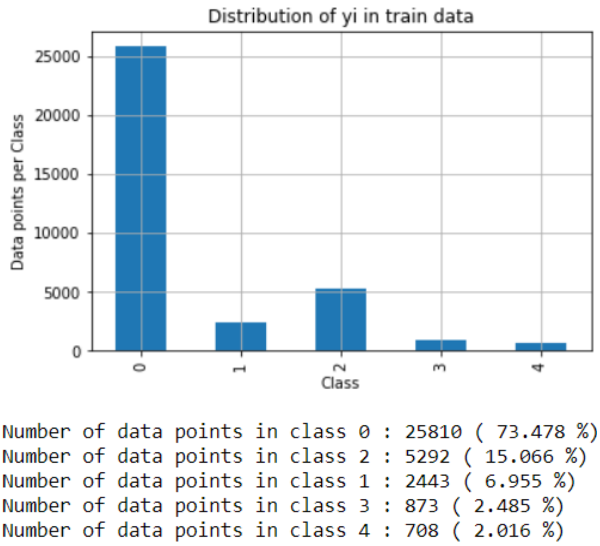


Fig 4 Confusion matrix of the densenet 120

Fig 4 shows the confusion matrix of the densenet 120. It is evident that each class is classified and shows the true positive (TP), true negative (TN), false positive (FP) and false negative (FN) values. These values are used for finding the performance metrics such as accuracy sensitivity and specificity.

The confusion matrix is plotted between the predicted class vs original class. All the five classes have been classified. The diagonal elements show the true positive values of each class which helps to find the performance metrics of each class. CNN model predicts the stage 0 (no DR) data accurately and yields the maximum accuracy and specificity of 84.1, 97.15% respectively. The stage of severe (3) has an accuracy and specificity of 97.44 and 98.27 % respectively in the densenet 120 model. The fig 5(b) shows the confusion matrix of resnet 50 model which explores the correct prediction of input images in the diagonal value. The resnet model produces the cumulative accuracy of 80% and mild stage accuracy and specificity as 98%, 99% respectively.

Table2: Performance metrics measures:

Metrics	Formula
Accuracy	$\frac{TN + TP}{TN + TP + FN + FP} * 100$
Sensitivity	$\frac{TN}{TP + FN} * 100$
Specificity	$\frac{TN}{TN + FP} * 100$

Fig 5(a): Confusion Matrix obtained from DenseNet-121 model

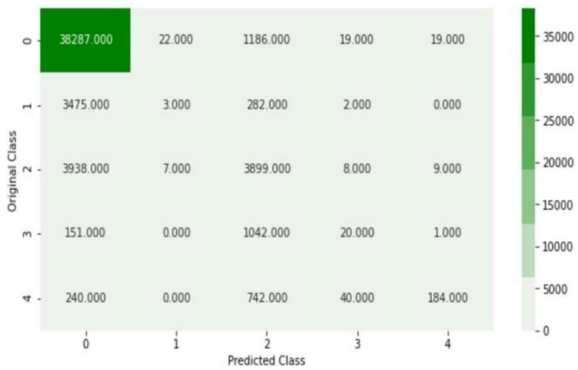


Fig 5(b): Confusion Matrix for Resnet-50 model

Fig 6(b) shows the loss plot of the resnet 120, it has a training loss of 18 % and validation loss of 23 % for the 30 iterations. Fig6 (a) depicts the loss plot of densenet 120 which has a training loss of 18% and validation loss of 21 %. There is slight improvement in the densenet120 model compare with resnet 50.

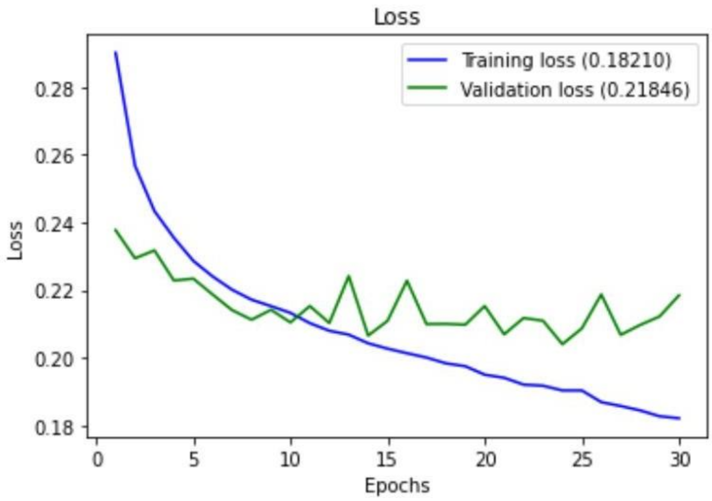


Fig 6(a) Training loss Vs Validation loss of DenseNet121

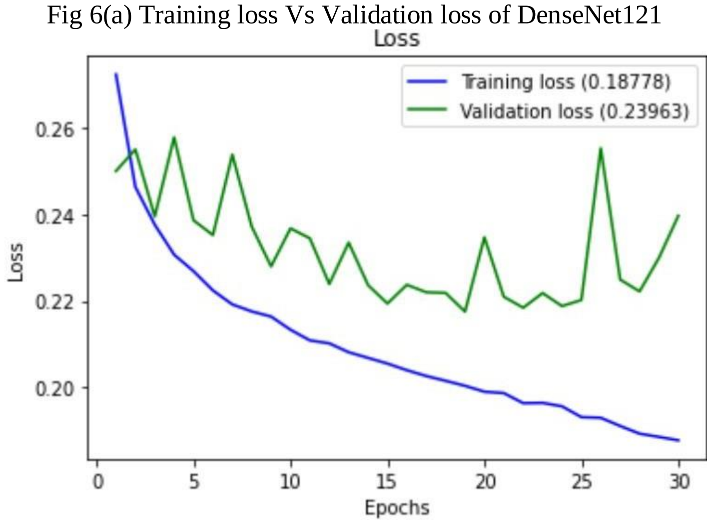


Fig 6(b) Training loss Vs Validation loss of Resnet50 model

Fig 7 (a) and (b) illustrates the accuracy plot of densenet 120 and resnet 50.the accuracy plot is plot between correct predictions between the number prediction values. The densenet 120 model yields an accuracy of 83 % and the resnet model acuuracy is 80%.

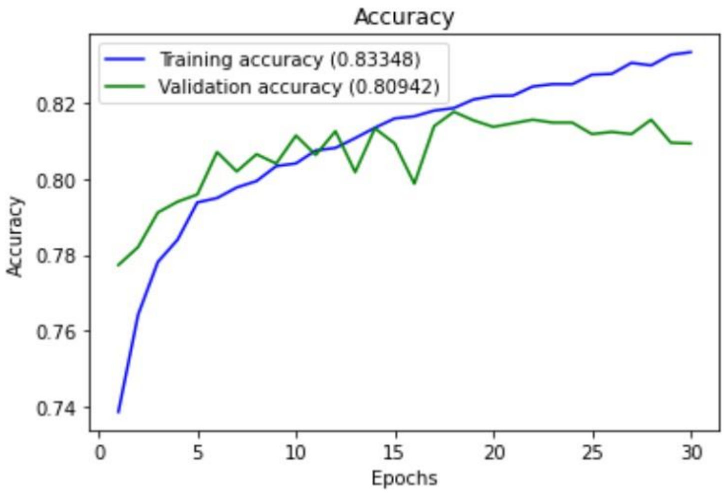


Fig 7 (a) Training and validation
Accuracy of DenseNet-121 model

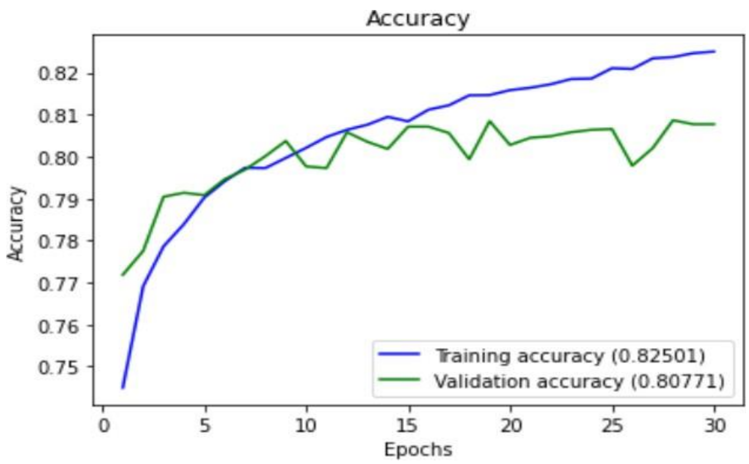


Fig 7(b) Training and validation
Accuracy of Resnet50

Table 3 Cumulative performance:

Model	Training Accuracy in %	Training loss in %	Validation accuracy in %	Validation loss in %
DenseNet-121	83	18.2	80.9	21.3
Resnet 50	82	18.7	80.7	23.9

Table 4 CNN Performance metrics:

Model	Stage	TN	TP	FN	FP	Acc	Sen	Spe
Densenet 120	No DR	6679	38409	1124	7364	84.1	97	47.6
	Mild	49799	178	3761	15	92.9	26	99.6
	Moderate	43668	3803	4058	2047	88.6	48.3	95.5
	Severe	51748	457	757	614	97.4	37.6	98.8
	Proliferative	52026	522	684	344	98.4	43.2	99.3
Resnet 50	No DR	6239	38387	1246	7804	83.1	96.8	44.4
	Mild	49785	323	3759	29	92.9	79	99.9
	Moderate	42463	3899	3962	3252	86.3	49.5	92.8
	Severe	52293	20	1194	69	97.6	16.4	99.8
	Proliferative	52341	184	1022	29	98.0	15.2	99.9

Conclusion

The person with DM is always at a higher rate of acquiring DR. the prevalence DM diabetes affects the retinal blood vessels which lead to complete blindness. The early detection of DR helps the clinicians to treat the subjects on time and helps to stop the progression. In this research work we explored the deeplearning model to find the early stages of DR from the fundus images. Also the proposed network yields the maximum accuracy of 89% and 80% for Densenet 120 and resnet 50 models.l2 regularization techniques is used to avoid data overfitting and dimensionality reduction. Future work some of the new optimizer and hybrid model of CNN+LSTM architecture can be implemented to enhance the prediction accuracy.

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