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Diabetic Retinopathy Classification using Transfer Learning Techniques

Bindhumol M
Department of Computer Sciences & Engineering
Amrita School of Engineering ,Bengaluru
Amrita Vishwa Vidyapeetham, Indiag
BL.EN.P2DSC21009@bl.students.amrita.edu

Tripty Singh
Department of Computer Sciences & Engineering
Amrita School of Engineering, Bengaluru
Amrita Vishwa Vidyapeetham, India
tripty_singh@blr.amrita.edu

Prakash Duraisamy
Computer Science Department
University of South Alabama, United States. Of America
prakashduraisamy@southalabama.edu

Abstract:
Neuralgia & anatomical anomalies to visual capillaries indicates Diabetic Retinopathy (DR). Although the role of the pathophysiology process causing retinopathy is still not fully known, it appears that exploratory diabetes in humans as well as persistent blood-glucose buildup with non-diabetic humans both recapitulate many aspects of the process. The most prevalent reason of emerging instances of blindness in persons between the ages of 20 and 74 is DR. Almost all Type-I diabetes victims & more than 60percent of Type-II diabetic victims developed retinopathy throughout the initial 2 decades of the illness.3.6 percent of Type-I diabetes victims with a adolescent start & 1.6 percent of Type-II diabetes victims with an elderly start got totally visionless in the Wisconsin Epidemiologic Research of DR. DR has been responsible for 86 percent of the vision-loss in the adolescent population. A third of total vision-loss incidences in the elderly category have been brought on by diabetic retinopathy, while various eye disorders was prevalent. Five DR categories are available: 0, 1, 2, 3, & 4. The source data in this study comprise patient's fundus eyeball pictures. This design had DR recognition accuracy of 96.11percent. The competing designs, EfficientNetB5 & ResNet50, are being evaluated in the conclusion.

Keywords: *Diabetic Retinopathy (DR), EfficientNetB5, ResNet50, Deep Learning,Transfer Learning*

Introduction:

Although DR is the most prominent result of persistent hyperglycemia, patients having diabetes may additionally have a number of various visual problems. Severe ischemic optical neuralgia, visual degradation as per the age group, ocular circulatory blockage, cataracts & glaucoma all contribute to eyesight impairment particularly in elderly diabetic's people. This paper offers a comprehensive review & an outline of the present understanding of the major retinal illnesses (with the exception of DR) & its correlation in diabetic people.

The set of data employed in this work was obtained via "Aravind Eye Hospital" which is accessible on Kaggle under the name "APTOS (Asia Pacific Tele Ophthalmology Society)". We contrast EfficientNetB5 & Resnet50, both being convolutional neural network (CNN) designs, then present the comparative findings of both these systems. Latest experiments & studies have shown that Deep Learning (DL) in AI models specifically provides the best appropriate results for uncovering buried layers across a variety of AI applications, notably in the area of healthcare picture evaluation. Using DL models to categorise illnesses, helps decision-making medically, & enhance enduring reasoning.

Literature Survey

The 2-Stage Classifier is an ensembles approach for categorization that integrates different machine learning (ML) techniques. In the study under consideration, the model is used to forecast DR, an optical condition which damages diabetes victims' retinas & eventually results in total vision-loss. The issue is that it takes a long duration to discover such condition, despite the reality that an initial recognition is necessary to prevent total impairment. To identify the presence of DR, we employ ML methods, then compared the accuracy of the utilised methods. In aspects of correctness as well as parallel processing, the 2-stage Classifier proves to be superior [1]. On a database for DR, they evaluated multiple methods. On the sample for DR, they employed a 2-stage algorithm & discovered that it performed better than the alternative ensemble methods. The amount of attributes in the phase 2 is limited to the amount of methods, while the 2-Stage predictor could operate in concurrent in the primary phase. The accuracy on the testing set equals 76.4 percent, whereas the efficiency on the trained set equals 79.50 percent. In comparison to various ML methods, two 2-stage predictor results are clearly superior [2]. Depending on 5 assessment measures, Youden's J indices, consistency, Somers' D statistics, & equitable accuracy—the suggested method is contrasted to the key methods. Based on the outcomes, the suggested method improved the scores for each assessment measure that was taken into consideration. Therefore, it is suggested that SVM featuring a Gaussian kernel being utilised to make predictions about DR [3]. The developed optimized-deep belief network (O-DBN) classifying system can measure picture characteristics up into multiple categories which offer the intensity ranges of DR condition after extracting features. Additionally, in light of sensitivities, selectivity, F1-measure, accuracy & prediction duration the suggested cloud-enabled DR predictive model employing the SNE extraction of features with O-DBN classifying system might surpass the current digital forecasting approaches [4]. Vast numbers of individuals could benefit from the recognition step's reduction, which is essential. CNN have been effectively used in a variety of related fields, as well as in the identification of DR. Nevertheless, the effectiveness of such algorithms is hampered by the costly expense of large labeled datasets as well as variation among clinicians. Using a mere snapshot of the person's fundus, we suggest in this study an automated DL—based approach in detecting the severity of DR. We also suggest the multiple stage transfer learning strategy that uses comparable samples by means of diverse labeling [5].

Machine learning vs. Transfer learning

The Transfer learning (TL) refers to the application of a formerly learnt concept to a novel challenge. Given that deep NNs may be trained using little to no information at the moment, it is notably well-liked in the field of DL.TL is a really effective method for addressing issues in the actual environment. It deals with a variety of commercial issues. TL allows users to acquire a satisfactory outcome using a small database, whereas DL often performs well if given larger amounts of trained set.

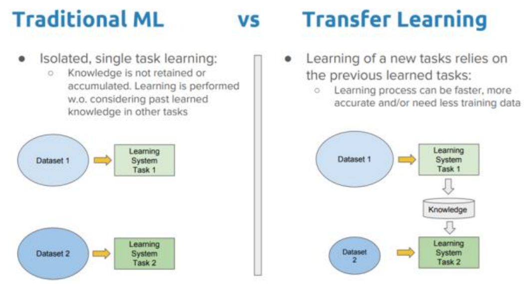


Fig.1: Machine Learning vs. Transfer Learning

ML vs. TL Fig.1 is shown; the appropriate training of ML methods intended in handling challenging works might consume a lot of effort. Companies will not have to build again from zero every occasion a comparable design is needed thanks to TL. An ML system's training efforts & duration might be spread among several scenarios.

Dataset: Consider having the ability to predict vision loss in advance. DR, the primary reason for vision-loss in young-working individuals, affecting masses of individuals. The Aravind Eye Hospital from India aims both in identifying & stopping the spread of serious illness across remote residents wherein healthcare monitoring becomes challenging to do. The clinic's capacity to find new victims would enhance thanks to the winning submissions in this challenge. Furthermore, the fourth Asia Pacific Tele-Ophthalmology Society (APTOS) Conference would disseminate the remedies among various eye-specialist doctors.

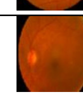
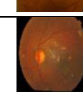
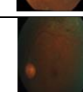
S.No	Class	Image Type	Image
1	0	No DR	
2	1	Mild	
3	2	Moderate	
4	3	Severe	
5	4	Proliferative DR	

Table.1: Dataset Sample Images

Presently, Aravind workers visit such remote places for taking pictures before relying upon incredibly skilled physicians who examine their pictures & offer a diagnostic. Its objective is to leverage technologies in also scaling their initiatives, giving them the power to instantly detect ailment through photos & offer details about the potential severity of the issue. Users are given access to a sizable collection of eyeball photographs that were captured utilizing fundus photos in a range of scanning scenarios. On a range from 0 to 4, a doctor has given every picture in Table a seriousness rating of DR. The objective of this project is to develop a photo classifying system that would examine photographs & categorize them in one to 5 categories (0,1,2,3,4) based on a single set sampling of pictures (0,1,2,3,4). This procedure for identifying vision-loss in sufferers could be sped up employing such picture classifying technique. Specialists presently evaluate every picture & assign it to one of five classifications. Testing set has 1928 pictures, whereas training set has 3662

Both the labeling as well as the photos might consist of disturbance, much like anyother actual information collection. Pictures could be focused less, photo shopped, lacking in detail, or include artifacts. The photos have been collected during a lengthy stretch of timeframe via many centers employing a range of lenses that would bring more diversity.

Methodology

EfficientNet

A CNN framework & leveling technique which uses a complex parameters to consistently expand every length, breadth, & pixel density parameters sums up a EfficientNet.

EfficientNet Architecture

The basic structure has a significant impact on how well designs scale. As a result, in order to significantly enhance efficiency, EfficientNetB5 structure is presented in Figure 2. We additionally have created a novel foundation structure via utilising the AutoML MNAS technology for undertaking a NNs structure evaluation that maximizes overall correctness & effectiveness (FLOPS). Because of a greater FLOP cost, the resultant structure employs mobility inversed bottleneck convolution (MBConv), which is comparable to MobileNetV2 & MnasNet. The basic system would then be scaled upwards to create the EfficientNets series of systems.

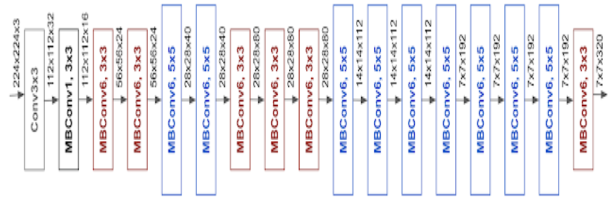


Fig.2: EfficientNet Architecture

EfficientNetB5

In Fig.3, the EfficientNetB5 Architecture is displayed. This procedure provides a Keras picture classifying system that may or may not include weight that has already been trained over ImageNet. Be careful to study the manual on TL & fine-tuning for application of TL.

Be aware that every Keras program anticipates a particular form of data preprocessing. Although inputs preparation is a Rescaling stage for Efficient Net, the method for keras applications. shows it to be Efficient Net. preprocess input is effectively an entry. Floating tuples of pixel containing values between [0-255] are what EfficientNet systems anticipate as input data.

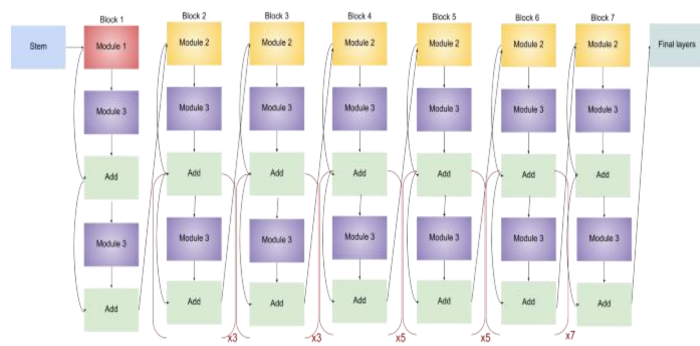


Fig.3: EfficientNetB5 Architecture

ResNet50

ResNet50 In Fig.4, the ResNet50 architecture is displayed. A ResNet prototype version called ResNet50 contains 48 Convolutional , 1 MaxPool & one Average Pool layerings. There are 3.8 x 10^9 decimal number functions available. Now it is a commonly employed ResNet framework, thus we have thoroughly examined the ResNet50 design.

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix}3\times3, 64\\ 3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 64\\ 3\times3, 64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\ 3\times3, 64\\ 1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\ 3\times3, 64\\ 1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\ 3\times3, 64\\ 1\times1, 256\end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix}3\times3, 128\\ 3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 128\\ 3\times3, 128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\ 3\times3, 128\\ 1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\ 3\times3, 128\\ 1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\ 3\times3, 128\\ 1\times1, 512\end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix}3\times3, 256\\ 3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 256\\ 3\times3, 256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\ 3\times3, 256\\ 1\times1, 1024\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\ 3\times3, 256\\ 1\times1, 1024\end{bmatrix}\times23$	$\begin{bmatrix}1\times1, 256\\ 3\times3, 256\\ 1\times1, 1024\end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix}3\times3, 512\\ 3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 512\\ 3\times3, 512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\ 3\times3, 512\\ 1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\ 3\times3, 512\\ 1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\ 3\times3, 512\\ 1\times1, 2048\end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Fig.4: ResNet50 Architecture

We will next explain the ResNet50 & its design of the 18 & 34 layers we mentioned before. For ease of use, ResNet is however provided residue mappings but is never displayed. For the ResNet50 & higher, there were a little alteration done; previously, the shortcuts links bypassed 2 levels, but currently they skipped 3 levels. Additionally, there were inserted 1 * 1 convolution layerings, which we will go over in more depth using the ResNet50 Structure.

The scholars introduced a deep residue learning approach to overcome this issue, and as a result, they also introduced shortcuts links which just carry out identification maps.

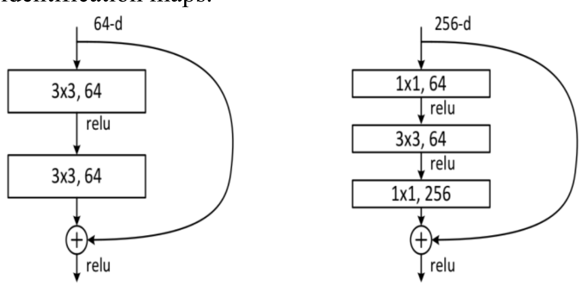


Fig.5: Layer fit

The initial mappings yields H(x):=F(x)+x as shown in Fig. 5. Researchers expressly allowed these levels to match a residual mappings and denoted such as H(x), while also allowed their non-linear levels to match additional mappings F(x):=H(x)x.

Our system did not require this acquisition of any new variables, while calculation duration remained retained under control thanks on such quick identification mappings.

Gaussian Blur

Gaussian ("gow-see-an") blurring was that process that applying some mathematics calculation to a picture through purpose effectively blurring it. It's also termed that following researcher Carl Friedrich Gauss (whose title rhyming of "grouse"). According of shooter Kenton Waltz, "this's similar layering a translucent substance such vellum upon over of actual picture."

Fig.6: Image Smoothing using Gaussian Blur

Pictures may include various sorts as distortion, just like many other information, particularly according to their origin (camera sensor). Distortion was reduced with aid of picture softening methods. Picture smoothness, commonly known as fading, can always be accomplished using OpenCV using wide variety of methods. Picture softening utilizing OpenCV Gaussian Blur is seen in Fig. 6.

Data Augmentation

In information mining, procedures called "data augmentation" were utilized that expand that quantity given information by providing small changes in versions of either available information or brand-new adjusted by bringing that is derived using previous information. It serves as just a smoothing filter & aids in reducing over fitting whenever a machine learning technique is being trained. Pictures that were enhanced with DR information are shown in Fig.7.

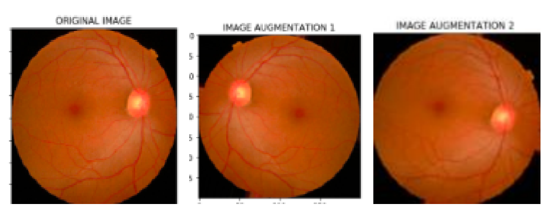


Fig.7: Data Augmentation Sample Images.

Proposed System

The proposed system is to classify Diabetic Retinopathy, using a retinopathy dataset, there are five different classes. Proposed system generated two classification models using transfer learning methods

EfficientnetB5 and ***Restnet50.***

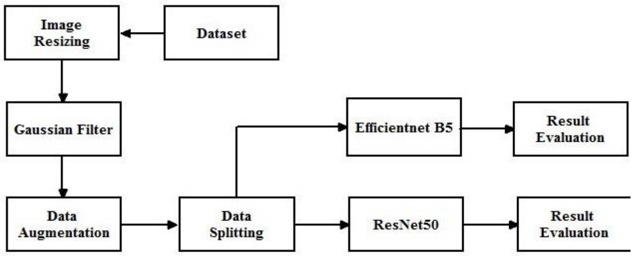


Fig.8: Proposed System Architecture

Data pre-processing techniques used in this system are image resizing, Gaussian blur flittering and data augmentation. After pre-processing, dataset is splitted into 80% and 20% ratio for training and testing for both the models.

Fig.9: Class Image Distribution Train Data

In this Fig.9 graph shows how images are used in train data in each class, in this graph x axis refers to diagnosis of DR classes & y axis refer to count images like classes and count.

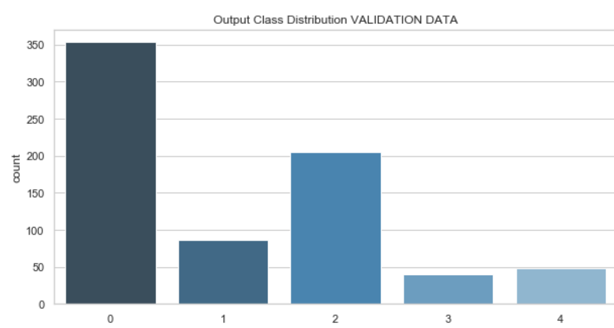


Fig.10: Class Image Distribution Validation Data

In this Fig.10 graph shows how images are used in validate data in each class, in this graph x axis refer to diagnosis of DR classes & y axis refer to count images like classes and count.

Result Analysis

Epoch expansions may improve precision according until a particular point, then after your models starts to become overfit

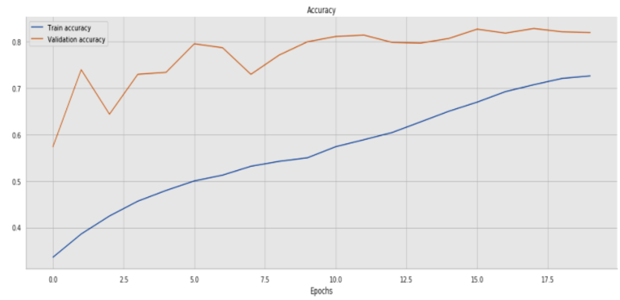


Fig.11: Epoch vs. Accuracy

Fig.11 illustrates that epoch affects precision. Underfitting would likewise arise from possessing a really small level. Watch that. Users may thus clearly determine whether you were overfitting your system by examining there at large contrast from epoch 99 & epoch 100.

```
 - 472s - loss: 0.5275 - acc: 0.5498 - val_loss: 0.2919 - val_acc: 0.7997
Epoch 11/20
 - 472s - loss: 0.4945 - acc: 0.5738 - val_loss: 0.3801 - val_acc: 0.8112
Epoch 12/20
 - 472s - loss: 0.4725 - acc: 0.5888 - val_loss: 0.3226 - val_acc: 0.8140
Epoch 13/20
 - 472s - loss: 0.4402 - acc: 0.6046 - val_loss: 0.3665 - val_acc: 0.7983
Epoch 14/20
 - 472s - loss: 0.4121 - acc: 0.6267 - val_loss: 0.2916 - val_acc: 0.7969
Epoch 15/20
 - 472s - loss: 0.3773 - acc: 0.6502 - val_loss: 0.3036 - val_acc: 0.8069
Epoch 16/20
 - 472s - loss: 0.3508 - acc: 0.6698 - val_loss: 0.2739 - val_acc: 0.8269
Epoch 17/20
 - 473s - loss: 0.3222 - acc: 0.6921 - val_loss: 0.2961 - val_acc: 0.8183
Epoch 18/20
 - 472s - loss: 0.2970 - acc: 0.7074 - val_loss: 0.2647 - val_acc: 0.8283
Epoch 19/20
 - 472s - loss: 0.2770 - acc: 0.7208 - val_loss: 0.2809 - val_acc: 0.8212
Epoch 20/20
 - 472s - loss: 0.2732 - acc: 0.7262 - val_loss: 0.2721 - val_acc: 0.8196
```

Fig.12: EfficientnetB5 Accuracy Progress

In this Fig.12, EfficientNetB5 architecture gave the training accuracy of 72.62% and validates accuracy of 81.96 to DR detection.

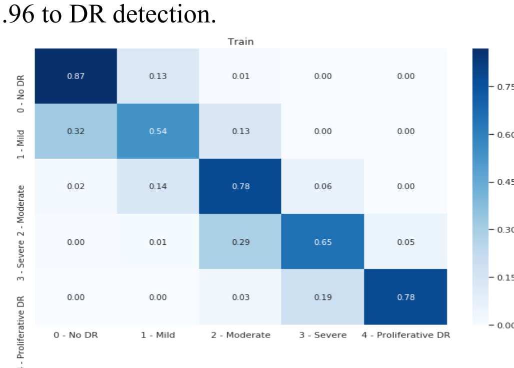


Fig.13: EfficientNetB5 Confusion Matrix

EfficientnetB5 confusion matrix is shown in Fig.13, would be a figure which indicates how well particular categorization technique performs. Its effectiveness of any categorization system is seen and summarised using the Efficientnet B5confusion matrix. Users made a good prediction, and so it came correct.

```
293/293 [==============================] - 248s 845ms/step - loss: 0.0259 - accuracy: 0.9920 - val_loss: 0.4038 - val_accuracy:
0.9199
Epoch 13/40
293/293 [==============================] - 247s 843ms/step - loss: 0.0225 - accuracy: 0.9938 - val_loss: 8.4704e-04 - val_accur
acy: 0.9414
Epoch 14/40
293/293 [==============================] - 247s 841ms/step - loss: 0.0175 - accuracy: 0.9942 - val_loss: 0.4052 - val_accuracy:
0.9331
Epoch 15/40
293/293 [==============================] - 247s 844ms/step - loss: 0.0140 - accuracy: 0.9951 - val_loss: 0.1702 - val_accuracy:
0.9355
Epoch 16/40
293/293 [==============================] - 248s 845ms/step - loss: 0.0134 - accuracy: 0.9952 - val_loss: 0.5615 - val_accuracy:
0.9321

Epoch 00016: ReduceLROnPlateau reducing learning rate to 1.249999968422344e-05.
Epoch 17/40
293/293 [==============================] - 247s 844ms/step - loss: 0.0132 - accuracy: 0.9955 - val_loss: 0.0080 - val_accuracy:
0.9314
Epoch 18/40
293/293 [==============================] - 248s 846ms/step - loss: 0.0115 - accuracy: 0.9963 - val_loss: 0.2255 - val_accuracy:
0.9321
Restoring model weights from the end of the best epoch
Epoch 00018: early stopping
```

Fig.14: ResNet50 Accuracy Progress

In this Fig.14 shows RestNet50 architecture gave a training accuracy of 99.63% and validate accuracy of 93.21 to DR detection.

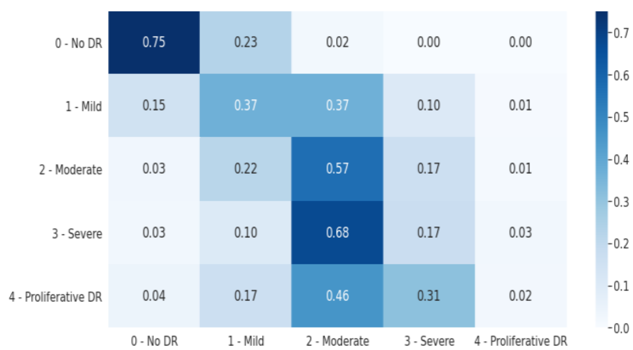


Fig.15: ResNet50 confusion matrix

This Fig.15 shows the ResNet50 confusion matrix. Its effectiveness that any categorization system was seen & summarised using its EfficientnetB5 confusion matrix. Your made a good prediction, & that came correct.

Conclusion

In his research work, the proposed system classifies the Diabetic Retinopathy images into 5 different classes such as 0,1,2,3,4. The proposed system employs the Transfer Learning algorithms such as EfficientNetB5 and ResNet50. Based on the classification & confusion matrix result obtained for both the models, the ResNet50 gave the best accuracy when compared to EfficientNetB5 in classifying the DR images. Here we have used the DR images from the Aravind Eye Hospital Dataset available on Kaggle.

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