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Diabetic Retinopathy Detection Using Machine Learning

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Abstract: It is a disease of the retina initiated through poorly controlled diabetes. In addition to damaging the retina, Diabetic Retinopathy causes irreversible damage to the human eye. It must be detected early to prevent permanent vision loss. In this work, we consider the five stages of diabetic retinopathy, also including a healthy retina. We use APTOS 2019 Blindness Detection Diabetic Retinopathy to train our model. We implement multiple approaches for forecasting machine-learning models in five stages. This proposed model predicts the stage of diabetic retinopathy: This model best works for South Asian people because there is some variation in the retinal image of different e geographical locations of the people. This proposed system only identifies diabetic retinopathy. And not applicable to other retinal diseases. This project aims to classify the diabetic retinopathy stage using images of any size of the patient's retinal fundus. The patient provides the retinal fundus image, and this program converts the image into the required size and predicts the stage of diabetic retinopathy. Also, other researchers can see the predictions of different models used in this project.

Keywords: APTOS 2019; Convolutional Neural Networks (CNNs); Diabetic Retinopathy Detection; Deep Learning.

1. Introduction

The backlight at the back of each eye is lined with the light-sensitive sphere-shaped structure called the retina. Images are captured by retinas, transforming them into electric signals and sending the macula to the retina's central black spherical part. The region at the macula's center is also called the fovea [1].

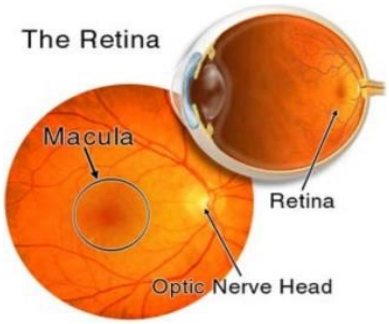

Figure 1. Image of human eye retina [2]

Also, the blood supply should flow normally to maintain the blood sugar level. Blood vessels all over the body are affected by diabetes' high blood sugar levels,which also harm the body's essential organs. Diabetic retinopathy, neuropathy, and nephropathy are the results of diabetes's harm to the eye, brain, and kidney. Diabetic retinopathy signs and symptoms include:

Redness or discomfort in the eye, Cloudy vision, Vision problems. A dark or vacant area in the line of

sight, Trouble seeing in dim light.

Blindness is the worst outcome of diabetic retinopathy, which happens when abnormalities in the retina are brought on by diabetes. These anomalies result in weak retinal blood vessels bulging, which causes micro aneurysms.

It is possible to view micro aneurysms as theessential component of diabetic retinopathy(DR). Micro aneurysms are tiny and practically round. There are six forms of micro aneurysms. They include irregular, pedunculated, mixed saccular/fusiform, focal bulk, saccular, fusiform, and fusiform.

Figure 2 shows these images in the fundus with different types of micro aneurysms (MA).

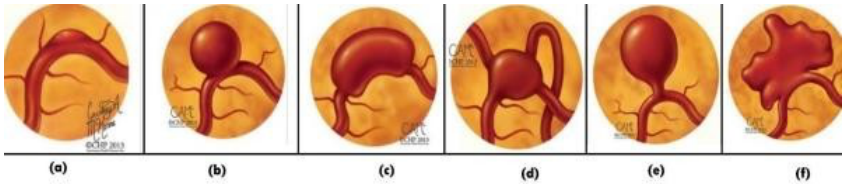

Figure 2. These images show different MA. (a) Focal Bulge (b) Saccular (c) Fusiform (d) Mixed Saccular/ Fusiform (e) Pedunculated (f) Irregular [3]

Later, the abnormal retinal blood vessels form microvascular networks by producing new,tiny blood vessels. Retinal neovascularization is the name of this microvascular network. Cotton wool patches, hard and soft exudates, and hemorrhages are additional abnormalities in diabetic retinopathy. Moreover,these anomalies cause vision loss and irreversibleblindness. The size of the blot or dot created by the leakage of blood from the weak retinal bloodvessels is more important than its width. Hemorrhages (HA) are the term for these dots [4].There are two types of hemorrhages. These are hemorrhages in the form of blots and flames. Fig 1.3 shows Different types of Hemorrhage.

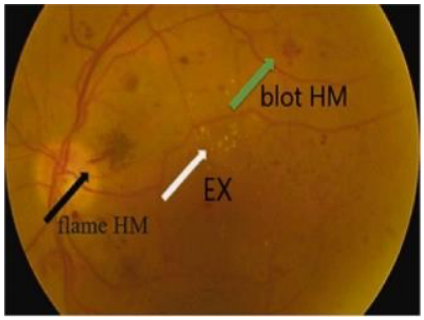

Figure 3. Different types of Hemorrhage [5]

Serious eyesight issues may result from bleeding.These eyesight issues are typically transient. They may, however, occasionally be long-lastingand dangerous to one's vision. They damage the retina's tiny blood vessels because of insufficient blood flow. If the patient has no new symptoms, they typically go away and pose no threat to the vision.(Chronic the hard exudate is the result of vascular leakage.) When abnormal retinal capillaries leak extracellular fluids, hard exudatesform. Hard exudates surround the retinal micro aneurysms or edema in the posterior pole of the eye. They can also be distinguished in the retina as distinct yellow flecks and occasionally as yellow-white dots. Hard exudatesare severe conditions that can impair vision.

Thereare many diabetic patients. The patient can have no symptoms at all or few symptoms. Weak blood arteries may allow fluid to flow into the retina in NPDR, leading to macula oedema, an impairment in a diabetic person. Patients with NPDR may also experience macula ischemia. In this disease, the macula cannot receive blood, which impairs vision.

Proliferative diabetic retinopathy is more severe and killing, a stage of diabetic retinopathy that may result in permanent vision loss. In the case of PDR, the retina starts to grow new blood vessels. Due to the fragility of these blood vessels, the blood that can fill the vitreous may leak. Retinal detachment brought onby the development of scar tissue and glaucoma eye disease are two more PDR side effects. Glaucoma may result in

increasing harmto the nerve of the eye. With PDR, fresh blood vessels drain the eye's fluid. By drastically raising eye pressure, this fluid harms the optic nerve. PDR can result in irreversible blindness and significant vision loss if left untreated.

The Reset model variant is ResNet50. This model contains forty-eight (48) convolution layers, one Mapoon, and one Average Pool layer. It is the most widely used Reset model [7].

Figure 4 shows different Symptoms of Diabetic Retinopathy.

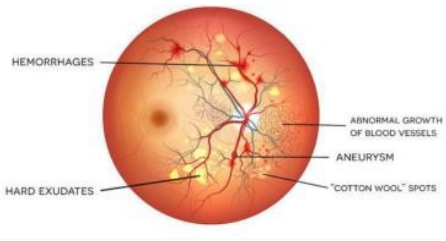

Figure 4. Different Symptoms of Diabetic Retinopathy [6]

ResNet101 is an improved version of ResNet50. It achieves more accuracy than the ResNet50 model. ResNet101 uses ninety-nine (99) convolution layers. It's one (1) Max pool and one (1) average pool are the same as those used in ResNet50 [8].

ResNet152 is an improved version of ResNet50 and ResNet101. It has a depth of 152 layers and achieves more accuracy than the ResNet50 and ResNet101 models. ResNet152 uses one hundred fifty (150) convolution layers. One (1) Max pool and one (1) Average pool are the same as the layers used in ResNet50 and ResNet101 [8].

VGG, [9] also known as the Vignette, stands for visual Geometry group. The VGG is a standard deep Convolution neural network having multiple layers. The word "deep" is due to the layer VGG has, which is 16 or 19 convolution layers. VGG is still one of the best architectures that surpass the baseline on many image datasets.

The VGG19 is more profound than the VGG16 because it supports three more layers. Nineteen convolution layers are in VGG19. We imported the model from the Keras library and then implemented it [10].

Inception v3 learns and classifies image data. This image-learning model is made up of symmetric and asymmetric blocks. We trained our model using Inception V3 [11]. We imported the Inspection V3 library with some other vital libraries from Keras and implemented this model.

Using a compound coefficient, efficient net B0 scales the image data dimensions (with/height/depth). This model scales the image data to achieve better performance [12].

Diabetic patients are increasing daily. This increase is a challenge because patients suffering from Diabetic Retinopathy may lose their eyesight partially or wholly. Sometimes, this vision loss is irreversible if Diabetic Retinopathy is not diagnosed and treated on time. Various methods have been developed for early detection of Diabetic Retinopathy.

2. Literature Review

Zineb et al. [13] suggested a technique of randomly modified visibility graphs. They employed contrast-limited adaptive histogram averaging (CLAHE). A random transformation was used to convert a 2D image into a 1D image. After that, a visibility graph was created, and the ECOC was used to categorize the evaluation of diabetic retinopathy. They producedresults with a 97.92% accuracy.

Romany [14] proposed a deep learning-based algorithm for detecting DR. They proposed an LDA-based feature selection Alex Net DNN-based model. They produce with a precision of 97.93%.

Hybrid feature extraction algorithm M.R.K. They were proposed by. Maliyah, U. Rajendran Acharya and others. [15] Differentiate the two stages of diabetic retinopathy from ordinary. Their average accuracy, sensitivity, and specificity were 96.15%, 96.27%, and 96.08%, respectively.

Baling Natal and Andres Hindu [16] have proposed a feature extraction technique for classifying diseased

vs. normal retinas and implemented it using various machine learning algorithms. They achieved a specificity of 91%, a sensitivity of 90%, and an accuracy of 90%.

Farrah Alamo et al. [17] suggested a system for the grading of the severity of diabetic retinopathy using fractal analysis and random forest on the MESSIDOR dataset. Their system determined fractal dimensions as features after image segmentation was performed. They could not differentiate between mild and severe diabetic retinopathy.

Mariah et al. [18] presented an automated algorithm for classifying retinal images into impaired and normal categories based on the proposed Concurrent CNN & SVM approach. According to the author, the proposed work would be divided into two sections: the first heading towards feature extraction should be obtained using neural networks, and classification would be processed finally using SVM with better classification ability. Typical characteristics include exudates, haemorrhages, and microaneurysms. Deep learning is the most appropriate and powerful way to address the five stages of diabetic retinopathy identification and classification. Deep automatic methods for identifying diabetic retinopathy are proposed by Kwasigroch et al. A criterion class code is embedded when training the CNN in this approach. Experiments to test the effectiveness of the proposed technique are conducted on 88,000 fundus pictures from the retinal dataset. The model's performance is authenticated by deploying the calculated quadratic weighted kappa score between the dataset and the predicted score.

For an active investigation of diabetic retinopathy by deep hybrid learning, the work of Seth and Agarwal [19] is noteworthy. This methodology uses digital fundus images, where the degree of severity of diabetic retinopathy is ascertained. During the training stage, a heterogeneous dataset, EyePACS, was built and used with a support vector machine (SVM). Though the dataset varied, the model developed showed good sensitivity and specificity. The model struggles to use big heterogeneous datasets to get good precision and recall scores.

Sisodia et al. [20] used feature extraction and preprocessing techniques to recognise diabetic retinopathy. They took the raw retinal data and extracted the information using a preprocessing strategy that included scaling, augmentation, histogram equalisation, and green channel approaches. After removing the fourteen features from the fundus images, they do a quantitative analysis. The training and validation are done using the Kaggle dataset. Their model divides the fundus images into severe, mild, and regular categories. Diabetic Retinopathy Diabetic retinopathy detection from SD-OCT images using an automated technique was presented by ElTanboly et al. They divide their work into three stages: segmenting the twelve layers of the retina; getting features-descriptor reflectance, tortuosity, thickness, and foveal angle-from the OCT images; and doing statistical analysis to find the differences among these layers.

Diabetic retinopathy detection using convolutional neural networks along with proposed data augmentation has been proposed by Pratt et al. [21]. Their proposed model achieved an accuracy of 75% on the training dataset consisting of 80,000 photos.

Gondal et al. [22] proposed a region of interest-oriented CNN supervised learning-based method for diabetic retinal damage detection in fundus images. The data-set utilized for this experiment was DiaretDB1. They achieve 95.4 percent accuracy.

Farrikh Alzami et al. [23] proposed a fractal analysis and random forest-based diabetic retinopathy grade classification system using the MESSIDOR dataset. Their system computed fractal dimensions as features after it had segmented the pictures. They could not differentiate between severe and moderate diabetic retinopathy.

Qomariah et al. [24] Presented an automated approach using CNN and a support vector machine for classification of normal and diseased retinal images. The author divided the suggested system into two sections: the first was the use of a support vector machine that classified, and the second was the feature extraction section through neural networks.

3. Methodology

We will identify one of the five stages of diabetic retinopathy. The symptoms are minor initially and do not manifest on theretina until they become more serious. This makes the diagnosis of diabetic retinopathy

difficult. In this study, we experimented withsequential convolutional neural networks (CNN), as well as ResNet-50, ResNet-101, ResNet-152, VGG16, and VGG19 convolutional neural network architectures, as well as EfficientNet-B0 (base model) and Inception V3. We compare the output of eachmodel after training our model using these approaches to determine which model performs the best.

We use Python 3.9.12 as the programming language to create and train the model. Many libraries must be added to access the various Python features. We run code Using Jupyter Notebook, an integrated function of Anaconda Navigator. In addition, Anaconda Navigator 4.12.0 is installed to provide rapid access to many functionalities.

3.1. Data Set

We must offer a sufficient amount of image data to train our model. We downloaded a total of 3662 photos forthis project. APTOS 2019 Blindness Detection Diabetic Retinopathy is the name of the dataset [25]. This dataset is publicly available and has undergoneexpert medical scrutiny. The Arvind Eye Hospital in India, which gathered fundus photographs from several regions of India, donated this dataset. The image ID and accompanying label were included in a CSV file attached to the data file. The total number of images was divided into 1805 with no diabetic retinopathy, 370 with mild diabetic retinopathy (DR), 999 with moderate diabetic retinopathy (DR), 193 with severe diabetic retinopathy (DR), and 295 with proliferative diabetic retinopathy (DR).

Class Name	Class Label	Total Data	Train Data	Test Data
No-Dr	0	1805	1264	541
Mild-Dr	1	370	259	111
Moderate-DR	2	999	699	300
Severe-DR	3	193	135	58
proliferative-DR	4	295	207	88

Figure 5. Shows the Statistical data of APTOS 2019 Blindness Detection Diabetic Retinopathy.

Images in the dataset come in different sizes. To efficiently model all photos, each one must have a distinct shape. All pictures were scaled to224*224 pixels for this. We transform the imageinput into a NumPy array and then insert it into the model. Afterwards, each class underwent multiple labelling. This is only true if the image is from phase 4, which includes all of the earlier phases, as proliferative retinopathy requires mild, moderate, and severe stages. For training and testing purposes, we split 70% of the data as training data and 30% as testing data.

3.2. Image Data Augmentation

The ImageDataGenerator [26] software is employed to increase the size of the training dataset. We used Keras' built-in Image Data Generator package to accomplish this. In this project, the images were zoomed by 10%, enabling the horizontal and vertical flip accurate options and setting the zoom range to 10%. This magnification allows the machine to see more details, essential for the optimum outcome.

The entire training process is broken down into numerous more miniature stages to construct the model correctly. Fig 3.2 Shows the Proposed Methodology.

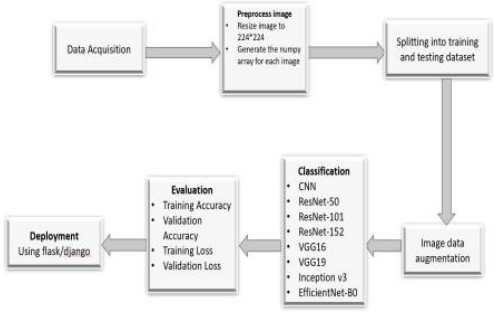

Figure 6. Show Proposed Methodology

3.3. Conceptual Models

Selecting a model that will produce the best results is challenging. Some algorithms perform better than

others. Again, a variety of factors affect accuracy. Thus, it makes sense to test a few algorithms and choose the one with the highest accuracy to create the best model. We are using convolutional neural networks (CNN) [27S]. Several convolutional neural network architectures, including ResNet-50, ResNet-101, ResNet-152, VGG16, VGG19, EfficientNet-B0 (base model), and Inception V3, will also be tested. Next, we will assess each model's performance to determine which is best for our project.

4. Results

We implement different models to predict the five stages of Diabetic retinopathy. All models are trained on the APTOS 2019 Blindness Detection Diabetic Retinopathy dataset. We use 549 fundus images for validation, thirty per cent of the total data.

The table illustrates the sequential convolution neural network and other CNN architecture we used in this project. Table 4.1 below describes the parameters, depth, training accuracy, and training loss, testing accuracy, and testing loss the models experienced during the training phase.

Table 1. Shows the performance of all implement mod

Model	Parameter	Train Accuracy	Train Loss	Val. Accuracy	Val. Loss
ResNet50	22,089,577	0.9840	0.5311	0.78778	8.6556
ResNet101	43,159,941	0.9809	0.4453	0.8078	10.223
ResNet152	58,872.709	0.9809	0.5714	0.7960	9.0762
VGG16	14.840,133	0.9717	0.6221	0.7978	6.7228
VGG19	20,149.829	0.9758	0.5919	0.7823	6.8811
Inception V3	22,058,789	0.8842	4.3899	0.7250	21.0217
EfficientNet-B0	4,363,176	0.9744	0.3127	0.7984	3.3907
Sequential	5,718,501	0.9918	0.0271	0.7404	1.5270

4.1. Sequential Model

This model has a total parameter of 5,718,501—Based on trainable 5,718,501 parameters, 0 non-trainable parameters 0. During training, this model uses Adam's Optimizer with the learning rate of or=1e-5 (0.00005). This learning rate is prolonged. Due to this, we run 800 total epochs step by step. Figure a shows the highest training accuracy of 77 per cent run on 100 epochs. The model improves accuracy in Figures B and c. Figure d shows the highest training accuracy of 99.18 per cent and the highest validation accuracy of 74.04 per cent.

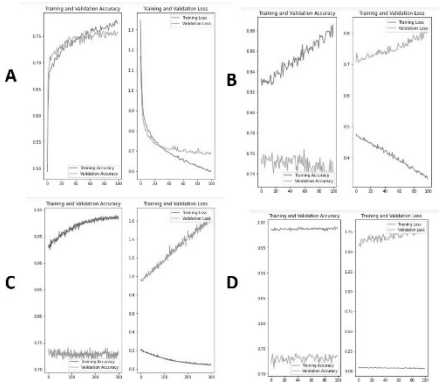

Figure 7. Shows the training and testing

4.2. ResNet-50

This model has a total parameter of 24,089,577. Based on trainable parameters 501, 7065, non-trainable parameters 23,567,712, and 25 epochs, ResNet-50 generates the highest training accuracy (left) of 98.40 per cent and highest validation accuracy (left) of 78 per cent. This model generates the average training loss (right) of 0.5311 and the average validation loss (right) of 8.6556.

Figure 8. (left) shows the training and testing accuracy of model a (right) shows the training and testing loss of the model

4.3. ResNet-101

This model has a total parameter of 43,159,941. Based on trainable parameters 501,765, non-trainable parameters 42,658,176, and 20 epochs, ResNet-101 generates the highest training accuracy (left) of 98.09 per cent and the highest validation accuracy (left) of 80.78 per cent. This model generates the average training loss (right) of 0.4453 and the average validation loss (right) of 10.223.

Figure 9. (left) shows the training and testing accuracy of the model, and (right) shows the training and testing loss of the model.

4.4. ResNet-152

This model has a total parameter of 58,872,709. Based on trainable parameters 501,765, non-trainable parameters 58,370,994, and 20 epochs, ResNet-152 generates the highest training accuracy (left) of 98.09 per cent and the highest validation accuracy (left) of 79.60 per cent. This model generates the average training loss (right) of 0.5714 and the average validation loss (right) of 9.0762.

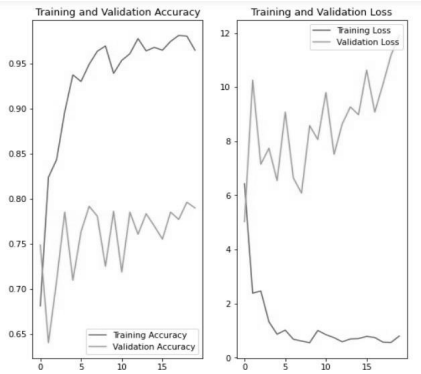

Figure 10. (left) shows the training and testing accuracy of the model, and (right) shows the training and testing loss of the model.

4.5. VGG16

This model has a total parameter of 14,840,133. Based on trainable parameters 125,445, non-trainable parameters 14,714,688, and 15 epochs, VGG16 generates the highest training accuracy (left) of 97.17 per cent and the highest validation accuracy (left) of 79.78 per cent. This model generates the average training loss (right) of 0.6221 and the average validation loss (right) of 6.7228.

Figure 11. Shows (left) the training and testing accuracy of the model, and (right) shows the training and testing loss of the model.

4.6. VGG19

This model has a total parameter of 20,149,829. Based on trainable parameters, 125,445 non-trainable parameters, 20,024,284, and 15 epochs, this model generates the highest training accuracy (left) of 97.58 per cent and the highest validation accuracy (left) of 78.23 per cent. This model generates the average training loss (right) of 0.5919 and the average validation loss (right) of 6.8811.

Figure 12. (left) shows the training and testing accuracy of the model, and (right) shows the training and testing loss of the model.

4.7. EfficientNet-B0

This model has a total parameter of 4,363,176. Based on trainable parameters 313,605, non-trainable parameters 4,049,571, and 50 epochs, ResNet-101 generates the highest training accuracy (left) of 97.44 per cent and the highest validation accuracy (left) of 79.84 per cent. This model generates the average training loss (right) of 0.3127 and the average validation loss (right) of 3.3907.

4.8. Inception V3

This model has a total parameter of 22,058,789. Based on trainable parameters 256,005, non-trainable parameters 21,802,784 and 30 epoch inception, V3 generates the highest training accuracy (left) of 88.42 per cent and the highest validation accuracy (left) of 72.50 per cent. This model generates the average training loss (right) of 4.3899 and the average validation loss (right) of 21.0217.

Figure 13. Displays the model's training with testing accuracy on the left and tested loss on the opposite side.

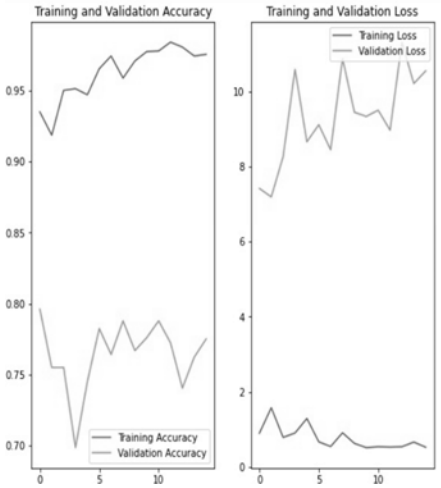

Figure 14. Shows (left) shows the training and testing accuracy of the model a (right) shows the training and testing loss of the model

5. Conclusions

The dataset used in this project was gathered from various parts. This project is specifically made to predict the more accurate stage of Diabetic Retinopathy in South Asians. Hence, this dataset contains 3662 fundus images categorized into five classes. We have trained our model on this dataset and predicted the stage of Diabetic Retinopathy. All the transfer learning models and sequential convolutional neural networks were trained on this dataset and performed very well while maintaining appreciable accuracy. However, the model that gave the highest test accuracy among them is our proposed model: Sequential Convolution Neural Network. This model has a test accuracy of 99% and a validation accuracy of this model of 74%. We would focus on implementing this project in a web application and further try to launch the Android and the IOS applications so that people could more easily detect diabetic retinopathy. Other retinal diseases we will try to predict from the retinal fundus are Retinal detachment, Macular whole, Macular degeneration, and Retinal tear.

References

1. Uzair Ishtiaq, Sameem Abdul Kareem, Erma Rahayu Mohd Faizal Abdul- lah, Ghulam Mujtaba, Rashid Jahangir, and Hafiz Yasir Ghafoor. Diabetic retinopathy detection through artificial intelligent techniques: a review and open issues. Multimedia Tools and Applications, 79(21):15209–15252, 2020.
2. Muhammad Imran Iqbal, Abiodun Musa Aibinu, Nagendra Srinivas Gubbal, and Asim Khan. Automatic diagnosis of diabetic retinopathy using fundus images, 2006.
3. Wejdan L Alyoubi, Wafaa M Shalash, and Maysoon F Abulkhair. Diabetic retinopathy detection through deep learning techniques: A review. Informat- ics in Medicine Unlocked, 20:100377, 2020.
4. Ankita Gupta and Rita Chhikara. Diabetic retinopathy: Present and past. Procedia computer science, 132:1432–1440, 2018.
5. Francesco Bandello, Marco Attilio Zarbin, Rosangela Lattanzio, and Ilaria Zucchiatti. Clinical strategies in the management of diabetic retinopathy. Springer, 2016.
6. MA Fayemiwo, SA Akinboro, and OA Adepegba. Identification and classi- fication of diabetic retinopathy using machine learning. Adeleke University Journal of Engineering and Technology, 1(1):245–259, 2018.
7. Understanding resnet50 architecture https://iq.opengenus.org/resnet50architecture/#:~:text=ResNet50%20is%20a%20variant%20of, explored%20ResNet50%20architecture%20in%20depth.(Accessed on 09/26/2022).
8. Understanding and visualising resent — by Pablo Ruiz — towards data science. https://towardsdatascience.com/understanding-and-visualizing-resnets-442284831be8. (Accessed on 09/26/2022).
9. Komal Damodara and Anita Thakur. Deep learning based method for multi- class classification of diabetic retinopathy. Journal of Informatics Electrical and Electronics Engineering (JIEEE), 2(2):1–5, 2021.
10. Vgg-19 convolutional neural network - mat lab vgg19 - math works United Kingdom. https://uk.mathworks.com/help/deeplearning/ref/vgg19.html; jsessionid=634e3b7cad180b21ef308196ace7. (Accessed on 09/26/2022).
11. T Vijaya, M Sangeeta, and B Kartika. Efficient analysis of diabetic retinopathy on retinal fundus images using deep learning techniques with inception v3 architecture. Journal of Green Engineering, 10(10):9615–9625, 2020.
12. Keras Team. Keras documentation: Efficient Net B0 to B7 — keras.io. https: //keras.io/ape/applications/efficient net/. [Accessed 25-Sep-2022].
13. Zineb Mohammadpoory, Mahda Nasrolahzadeh, Anthem Mahmood Ian, and Java Haddadnia. Automatic identification of diabetic retinopathy stages using fundus images and visibility graph method. Measurement, 140:133–141, 2019.
14. Romany F Mansour. Deep-learning-based automatic computer-aided diagno- sis system for diabetic retinopathy. Biomedical engineering letters, 8(1):41–57, 2018.
15. Moth Rama Krishnan Mookie, U Rajendran Acharya, Roshan Joy Marti's, Chua Kuang Chua, Choo Min Lim, EYK Ng, and Augustin's Laude. Eva- evolutionary algorithm based classifier parameter tuning for automatic diabetic retinopathy grading: A hybrid feature extraction approach. Knowledge-based systems, 39:9–22, 2013.
16. Baling Natal and Andhra's Hindu. An ensemble-based system for automatic screening of diabetic retinopathy. Knowledge-based systems, 60:20–27, 2014.
17. Farrah Alamo, Rama Arya Megan Tara, Ahmad Zainap Fanny, et al. Diabetic retinopathy grade classification based on fractal analysis and random forest. In 2019 International Seminar on Application for Technology of Information and Communication (semantic), pages 272–276. IEEE, 2019.
18. Denial Umami Knurl Mariah, Handyman Tjandrasa, and Chastise Fatichah. Classification of diabetic retinopathy and typical retinal images using CNN and SVM. In 2019 12th International Conference on Information & Communication Technology and Systems (ICTS), pages 152–157. IEEE, 2019.
19. Shikhar Seth and Basant Agarwal. A hybrid deep learning model for de- tecting diabetic retinopathy. Journal of Statistics and Management Systems, 21(4):569–574, 2018
20. Dilip Singh Sisodia, Shruti Nair, and Pooja Khobragade. Diabetic retinal fundus images: Preprocessing and feature extraction for early detection of diabetic retinopathy. Biomedical and Pharmacology Journal, 10(2):615–626, 2017.
21. Harry Pratt, Frans Coenen, Deborah M Broadbent, Simon P Harding, and Yalin Zheng. Convolutional neural networks for diabetic retinopathy. Procedia computer science, 90:200–205, 2016.

22. Waleed M Gondal, Jan M K¨ohler, Ren´e Grzeszick, Gernot A Fink, and Michael Hirsch. Weakly-supervised localization of diabetic retinopathy le- sions in retinal fundus images. In 2017 IEEE international conference on image processing (ICIP), pages 2069–2073. IEEE, 2017.
23. Farrikh Alzami, Rama Arya Megantara, Ahmad Zainul Fanani, et al. Diabetic retinopathy grade classification based on fractal analysis and random forest. In 2019 International Seminar on Application for Technology of Information and Communication (iSemantic), pages 272–276. IEEE, 2019.
24. Dinial Utami Nurul Qomariah, Handayani Tjandrasa, and Chastine Fatichah. Classification of diabetic retinopathy and normal retinal images using cnn and svm. In 2019 12th International Conference on Information & Communica- tion Technology and System (ICTS), pages 152–157. IEEE, 2019.
25. Aptos 2019 blindness detection.
26. Ramaprasad Pooja, Roma Raina, and Amit Kumar Mondale. Effect of data-augmentation on fine-tuned CNN model performance. IAES International Journal of Artificial Intelligence, 10(1):84, 2021.
27. Leith Alzubaidi, Jingling Zhang, Amjad J Humaidi, Ayad Al-Dujaili, Ye Duan, Omran Al-Shamma, Jos´e Santamar´ıa, Mohammed A Fadhel, Muthana Al-Amidie, and Laith Farhan. Review of deep learning: Concepts, cnn architectures, challenges, applications, future directions. Journal of Big Data, 8(1):1– 74, 2021