iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 10 **Issue:** VII **Month of publication:** July 2022

DOI: https://doi.org/10.22214/ijraset.2022.45939

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue VII July 2022- Available at www.ijraset.com

Diabetic Retinopathy Disease Classification Using Deep Neural Network and Retina Images

Syed Efath Hamid Andrabi[1], Mr. Ankur Gupta[2]
[1]*M. Tech Scholar, Department of Computer Science and Engineering, RIMT University, Mandi Gobingarh, Punjab, India*
[2]*Assistant Professor, Department of Computer Science and Engineering, RIMT University, Mandi Gobingarh, Punjab, India*

Abstract: ***The diabetes disease known as diabetic retinopathy damages the retinal blood vessels, which has an impact on the eyes. It may initially show no symptoms or cause cyclical vision problems. Both eyes are affected as the illness becomes worse, which can lead to partial or complete vision loss. When the blood sugar level is out of control, it often occurs. A person with diabetes mellitus is therefore always at risk of developing the disease. If early discovery is done, the potential of total and permanent blindness can be averted. Therefore, a reliable screening technique is needed. The current study examines a deep learning technique that can be utilized to identify diabetic retinopathy early, particularly a Densely Connected Convolutional Network (DenseNet-201). There are four categories it uses to categorize fundus images: No DR, Mild, Moderate, Severe, and Proliferative DR. Both of the datasets utilized in this study—Aptos 2019 Blindness Detection and Diabetic Retinopathy Detection 2015—were acquired from Kaggle. The proposed method entails several processes, including data collecting, preprocessing, augmenting, and modeling. Our recommended model was able to achieve an accuracy rate of 90%. Regression modeling was also applied, and the accuracy rate was 78%. The main objective of this research is to offer a trustworthy way for identifying different DR.***

Keywords: Diabetic Retinopathy. Visual defects, Densenet

I. INTRODUCTION

Diabetes is one of the most common diseases, and it is becoming more common everywhere. As a result of improper metabolic processes and difficulties including cardiovascular disease, renal failure, neurological disorders, and diabetic retinopathy (vision loss), among others, it is mostly associated with the body's production of insulin and high blood sugar levels [1]. A dangerous eye condition called diabetic retinopathy results in permanent visual loss that cannot be prevented or treated. People who have had diabetes before are more likely to obtain it; whether a person has type 1 or type 2 diabetes, their chance of getting the disease rises with age [2]. According to the WHO, DR is a serious eye condition that requires rapid response on a global scale. According to a study, 60 million diabetics in India receive visual care from about 12,000 ophthalmologists. The fact that so many individuals lack awareness of their disease is the main factor contributing to the huge number of sufferers. They exhibit a lack of awareness and prudence when it comes to this illness as well. Around 18% of diabetics have DR, and a diabetic is 25 times more likely to develop DR than a healthy individual [3]. . Due to its asymptomatic nature or its mild symptoms, which can leave a person in the dark and progressively impair their eyesight, it is challenging to identify this ailment early on. As a result, preventing the disorder's complexity requires early detection of DR. Experts and professionals that encourage advancements in improving the prognosis of this problem must employ highly effective technology and methods to diagnose this condition..

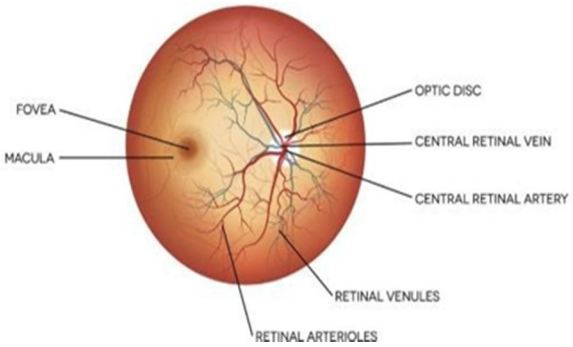


Figure 1. Original Retina

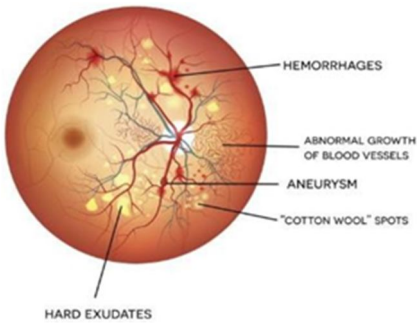


Figure 2 Diabetic Retinopathy

Images of a normal retina and a retina affected by diabetic retinopathy, respectively, are shown in Figures 1 and 2 [4]. The severity degree of DR must be classified and avoided, hence a reliable automatic detection method is necessary. Prior to the difficulty of manual feature extraction, the majority of DR research relied on feature extraction using machine learning approaches. This led researchers to resort to deep learning. A spate of computer-aided technologies, including data mining, image processing, machine learning, and deep learning, were made possible by more medical research. . On the other hand, deep learning has become more popular recently in fields including sentiment analysis, handwriting recognition, stock market prediction, and medical image analysis, among others. CNN in deep learning often produces effective results for categorizing images. The architecture of CNN and its many layers are shown in Figure 3[5].

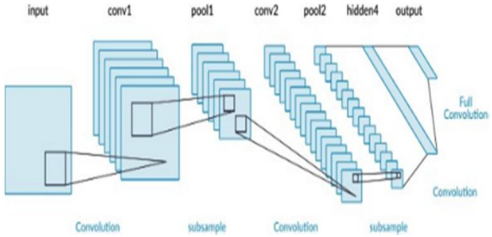


Figure 1 CNN Architecture

The current work use deep learning technology, namely CNN variant DenseNet 201, which extracts segmentation results instead of manually, to categorize fundus (eye) photographs depending on severity degree. Kaggle's "Diabetic Retinopathy Detection" 2015 data set and Kaggle's "Aptos 2019 Blindness Detection" data set were merged for this investigation.

II. OBJECTIVES

The goal of our thesis is to identify diabetic retinopathy and determine the severity level. The thesis has the following specific objectives:

1) Process color fundus retinal pictures for Diabetic Retinopathy identification.
2) From the pre-processed photos, extract essential characteristics.
3) Find out whether you have Diabetic Retinopathy.
4) Determine if the Diabetic Retinopathy exists and whether it is moderate or severe.

III. LITERATURE REVIEW

One of the first to suggest neural networks for DR detection was Gardner et al. (1996) [42], who used them to recognize minute patches of the original image. After an ophthalmologist classified the patches' properties, the information was fed into the SVM. In 2000, Ege et al. [43] proposed utilizing k-nearest neighbors and Bayesian classifiers to identify DR..

In order to calculate the size of locations with specific DR symptoms such haemorrhages, micro-aneurysms, oedema, and blood vessels, Acharya et al. (2008) [44] and Adarsh et al. (2013) [45] employed SVM.

Roychowdhury et al. (2014) [46] used a two-level model using a Gaussian mixture model (GMM), kNN, and support vector machine. (SVM). These methods, on the other hand, have the disadvantage of only using a small number of properties. The attention has shifted to convolutional neural networks as a result of Alex Krizhevsky et alhugevictory .'s in the ImageNet Large Scale Visual Recognition Challenge in 2012 [47]. (CNNs)

IV. METHODOLOGY

A. *Diabetes mellitus*

1) *Pathogenesis*

The main energy source in the human body is glucose. It is necessary for all immune cells, muscles, and organs, and the body's metabolism may transform it into more intricate structures.

A healthy adult employs a variety of control mechanisms during routine activity to maintain blood glucose levels between 4 and 5 mmol/l. After eating, the levels can increase to 10 mmol/l, and they can decrease to around 3 mmol/l after exercise or hunger...

One of the most crucial mechanisms for controlling blood glucose is the insulin mechanism. The pancreatic islets of Langerhans' beta cells produce the protein known as insulin. Blood glucose levels fall when glucose is released into the circulation and reaches the cells. The body's primary energy supply, glucose, is exhausted when the islets of Langerhans are disrupted, and catabolic processes take over. These processes can result in acid-base imbalance, dehydration, and hyperglycemia (shift of pH out of the normal range) A long-term metabolic disorder called diabetes mellitus is characterized by hyperglycemia brought on by insulin production and cognitive issues. According to predictions, the number of people with diabetes mellitus will increase from 382 million in 2013 to 592 million by 2035 [1]. Diabetes can have several negative effects, including microvascular (retinopathy, neuropathy, and nephropathy) and macrovascular (stroke, infarction) vascular problems [2].

2) *Classification*

Beta cell loss is a distinctive feature of type 1 diabetes, which causes complete insulin insufficiency and a lifetime need on insulin injection. When the pancreas is unable to produce any insulin, glucose is still present in the bloodstream. An autoimmune response, which commonly results in the death of beta cells in genetically susceptible individuals, is triggered by a viral infection (such as influenza, rubella, or herpes) [3]..

Type 2 is the most typical. The most prevalent sign is insulin resistance, however it can also be accompanied with a partial decrease in beta-cell insulin production. Glucose remains in the blood because body cells are unable to respond to insulin properly. Type 2 diabetes is mostly brought on by consuming too many calories, eating poorly, engaging in little to no physical activity, being stressed out, and smoking. The onset of type 2 diabetes often happens around the age of 40, and it advances slowly without manifesting any symptoms. The use of prescription insulin may or may not be necessary for patients [3], [4].

B. *The eye*

The human eye is a sophisticated organ that allows our view. It has a circumference between 69 and 85 mm and a diameter between 22 and 27 mm [5]. The organ is protected by the orbits. The eye, the optical nerve, the ocular muscles, and the lacrimal apparatus are all protected by a pair of structures in the skull called the orbits (tear production). Each orbit contains seven bones. [6]. Three intrinsic muscles aid in concentration, whereas six extraocular muscles aid in eye movement. Blood is supplied through a branch of the internal carotid artery [5]. The three levels of the eye anatomy are depicted in Figure 2.1.

1) *Outer layer: protective function*

- *Sclera* - It is a non-transparent white protective outer layer made up of collagen fibers [6]..

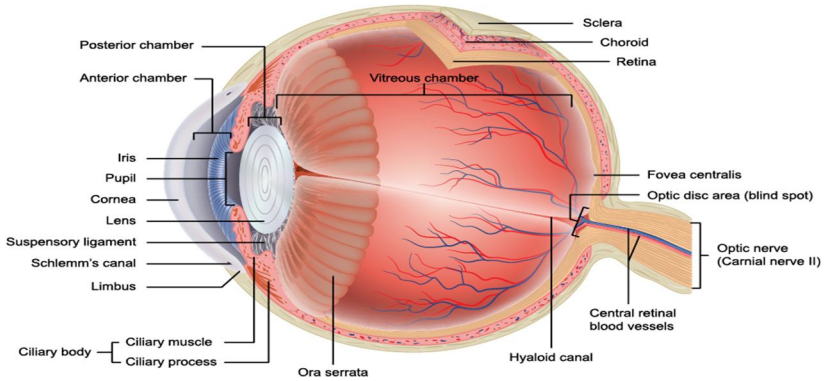


Figure 4 Eye anatomy, source [7].

- *Cornea* - The cornea is a transparent, intricate, and very thin structure. The lens' primary function is to refract light [6], and along with the lens, they produce a diminished, inverted image [8].

2) Medium Layer: Nutrient Function

- *Iris* - The iris, the colorful part of the eye, controls how much light enters the eye by controlling the pupil's size and, if there is too much light, by shutting it [9].
- *Ciliary body* - The ciliary muscle, which controls the lens directly, is found here..
- *Lens* - The lens is a clear optical device that permits light to be focused onto the retina. The choroid is a thin layer that houses the majority of the arteries in the eye.

3) Inner layer: .

- *Vitreous Humour* - The clear, gelatinous fluid that fills the eye cavity is known as vitreous humour [9].
- *Optic Nerve* - A bundle of over a million nerve fibers that allows neurological impulses to be sent from the retina to the brain [9]. Regarding the sensory function of the retina

4) Retina

The retina is a thin, translucent structure thatmain purpose is to provide photosensitive receptors. It has 10 layers [6] that range in thickness from 0.1 to 0.5 mm. It is attached to by the choroid and retinal pigment epithelium on the inner eyewall [10].
Two kinds of photosensitive receptors are distinguished.

- *Cone Cells* - There are around 6 million of them and they need a lot of light to function properly [11]. There are 92 million rod cells, which are 100 times more sensitive to a single photon than cones and are better at recognizing contrasts in low light [12]. The following characteristics may be visible [6] when looking through the retina with an ophthalmoscope (Figure 2.2):
- *Optic Disc* - A bright spot, where the arteries enter, and veins and nerves leave the retina.
- *Macular Area with Fovea and Foveola*- The supporting vision cells (bipolar cells and ganglion cells) are redirected in the high-acuity zone, letting light to directly reach the cone cells, producing incredibly sharp and focused vision [8]. the nasal and temporal blood vessel arcades The veins are wider while the arteries are thinner.

5) Diabetic Eye Diseases

Diabetic ophthalmopathy is a term used to describe a number of ocular problems that can be brought on by diabetes mellitus [13]. As a result, people with diabetes may develop diabetic retinopathy, diabetic maculopathy, iris rubeosis, secondary glaucoma, complicated cataracts, diabetic neuropathy of the cerebral nerves supporting the ocular muscles, and diabetic neuropathy of the optic nerves. The most devastating of the aforementioned diseases is diabetic retinopathy [13].

C. Diabetic retinopathy

The most prevalent microvascular consequence of diabetes is diabetic retinopathy (DR) [14].

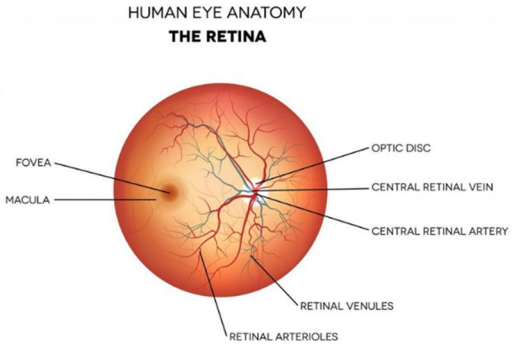


Figure 5 Schematic sight through the opthalmoscope, source [?].

It is a common chronic progressive microvascular diabetes complication and the main reason for blindness in working-age individuals in industrialized nations [6]. Retinal cells undergo morphological and functional changes as a result of long-term hyperglycemia in the small retinal arteries and capillaries [15].

1) Epidemiology

The number of patients with diabetes is rising [6]. More than 858 thousand individuals in the Czech Republic had diabetes mellitus as of 2016 [16], including 95 100 people who had diabetic retinopathy and 2 267 people who had lost their sight as a result of the condition. Around 4.2 million people worldwide are affected by it. In the US, there will be 16.0 million people with DR by 2050, 3.4 million of whom would have diabetic retinopathy that might impair their eyesight. DR is a major public health issue that costs $492 million USD in direct medical bills each year, as well as $492 million USD in lost productivity and income [8].

2) Symptoms

Patients who have DR describe varied degrees of symptoms. This is because until the macula is compromised, the patient might not experience any subjective symptoms. The most typical signs [16] are as follows:

. blurry or distorted vision that makes it challenging to read or watch television. challenges with balancing

increased sensitivity to light

being unable to see in the dark

3) Clinical signs

Clinical indications (seen in Figure 2.3) comprise:

microaneurysms: Early signs of DR include small, circular red lesions in the retina that are not optically concerning and often go away in three to four months.

Retinal hemorrhages: In distinct retinal layers, hemorrhages can be of varied sizes and shapes.

Lipid and protein depositions appear as yellow, irregularly shaped lesions with sharp edges (hard (lipid) exudates). This is an indication of diabetic macular edema, which often affects the macula, when it is coupled with retinal thickness. Clinical indications (seen in Figure 2.3) comprise:

microaneurysms: Early signs of DR include small, circular red lesions in the retina that are not optically concerning and often go away in three to four months.

Retinal hemorrhages: In distinct retinal layers, hemorrhages can be of varied sizes and shapes.

Lipid and protein depositions appear as yellow, irregularly shaped lesions with sharp edges (hard (lipid) exudates). This is an indication of diabetic macular edema, which often affects the macula, when it is coupled with retinal thickness. .

- *Cotton-wool Spots (Soft Exudates):* A nerve fiber layer infarct, which is a sign of retinal ischemia, is indicated by white lesions with receding edges that frequently surround the optic disc [8].
- *Intraretinal Microvascular Abnormalities (IRMA):* Existing blood vessels may branch or enlarge abnormally as a result of the development of new blood vessels or the remodeling of existing ones [17].
- *Macular edema:* Plasma spills into the retinal tissue when the blood-retinal barrier is broken, resulting in edema. It can result in retinal wall detachment and can happen at any stage of DR [8].
- *Venous Beading:* Dilated, erratic, and twisted veins are a general sign of retinal ischemia. Neovascularization is the term used to describe an abnormal proliferation of new blood vessels. The vitreous cavity may get infiltrated by these veins, obscuring vision and perhaps leading to hemorrhages. A complete retinal detachment may result from irreversible changes to the retinal structure [6]. Changes in retinal strain and fibrosis: A complete lesion can result from severe abnormalities in the retinal structure.

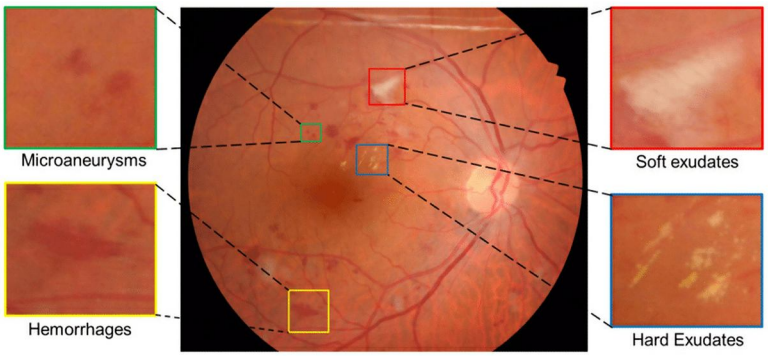


Figure 6 Some clinical signs of DR, source [19]. . vitreous haemorrhage: Bleeding into the vitreous cavity [18].

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue VII July 2022- Available at www.ijraset.com

V. SYSTEM ARCHITECTURE

The creation of a trustworthy and noise-tolerant approach for identifying diabetic retinopathy is the main objective of this study. Based on the severity level, diabetic retinopathy is diagnosed in this study using deep learning technology (No DR, Mild, Moderate, Severe and Proliferative DR). The photographs through a variety of processes before being shared to the network. In this work, we trained two models—our proposed model and the regression model—and compared the accuracy of the two models' predictions. Despite the fact that the regression model performed better than our proposed strategy. Figure 4 shows the suggested approach..

Figure 7 Proposed Methodology

A. *Data Source*

This study's data originates from the kaggle projects Diabetic Retinopathy Detection 2015[21] and APTOS 2019 Blindness Detection [22]. Each database contains hundreds of retinal images taken in diverse settings. Each participant will receive photographs of both eyes, left and right. due to the fact that the photos come from several sources, including various cameras and camera brands. It requires a number of preprocessing steps because it has a lot of noise that has to be removed. The diabetic retinopathy linked to each image was rated on a scale of 0 to 4 as follows:

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

Figure 5 depicts retinal pictures with severity levels ranging from 0 to 1.

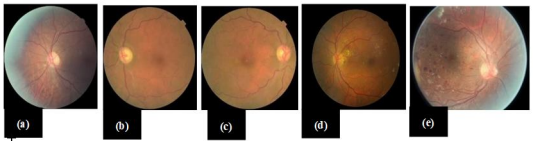


Figure 8 Image samples based on severity from dataset: (a) is level ‘0’, (b) is level ‘1’, (c) is level ‘2’, (d) is level ‘3’, (e) is level ‘4’.

B. *Data Preprocessing*

We need to preprocess the photos in the dataset to convert them to the conventional format since they include a lot of pollution, such as out-of-focus images, images with a lot of exposure, images with extra lighting, images with a dark background, etc. The following activities are finished in the preparatory step::

- *Cutting the black border:* The black background around the images has been eliminated because it doesn't offer any information to the fundus image and is therefore superfluous.
- *Remove the black corner:* Because the fundus picture is circular, there are still some dark corners after eliminating the black border. The image's black edges are eliminated in this stage.
- *Resizing image:* The photos have been reduced in size to 256*256 pixels (width*height).
- *Applying the Gaussian Blur:* The photos are given a Gaussian blur by setting the kernel size to 256/6. This technique aids in the removal of Gaussian noise.

Figure 6 shows the images obtained after preprocessing was carried out.

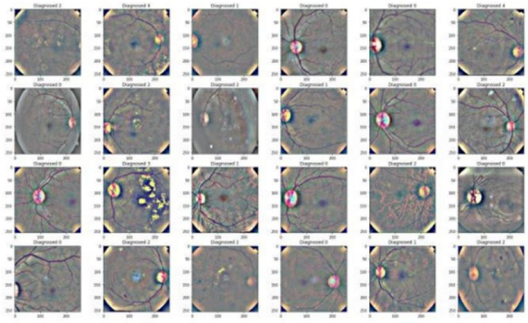


Figure 9 Preprocessing images

C. Data Augmentation

After evaluating the data, we discovered that as seen in figure 7, there is a substantial amount of data imbalance within the classifications of diabetic retinopathy severity, which suggests that data augmentation is likely.

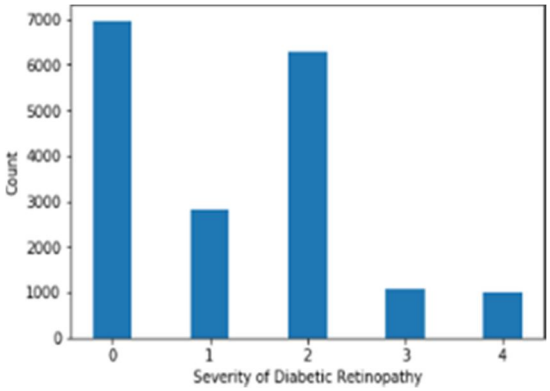


Figure 10 Highly unbalanced data before augmentation

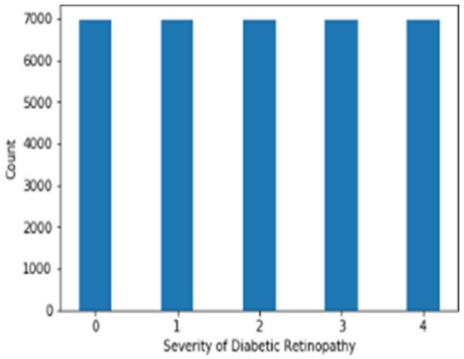


Figure 11 Balanced data after augmentation

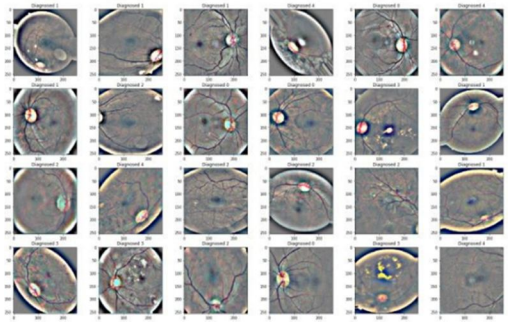


Figure 12 Images Obtained after Data Augmentation

D. Modelling

We used a Simple regression and a DenseNet-201 (Densely connected CNN model) for training. In DenseNet-201, weights are communicated to the brain without the need of a top or final layer. When first simulating the network, there is no final layer. With Global Average Pooling 2D, a Dropout layer set to 0.5, and a five-node output for each class, we built this layer. Global Average Pooling 2D operates similarly to 2D pooling, with the exception that it uses the whole input block size as the pool size. A multilayer perceptron deals with overfitting. The Adam optimization method is used to optimize the weights for training this model. Using a sequential modeling approach, convolutional, dropout, dense, optimizer, and other layers are added and altered..

1) *Convolution Layer:* To go through the fundus pictures and generate a dot product, it uses numerous kernels or filters. This layer's kernels and filters each draw different picture features.
2) *Pooling Layer:* By lowering the spatial dimension, it gives an abstract representation of convolved features. It's comparable to the convolution layer but depending on the type of pooling from kernel-overlapped input, it uses the max or min region.
3) *Dropout Layer:* To govern neural networks and avoid over-fitting, the dropout method has been applied.
4) *Flatten Layer:* In a one-dimensional series, flattening converts the data to the next layer. [23].

The deep DenseNet-201 model is depicted in figure 10 [24], which has three Dense blocks and three transition layers, including a pooling and convolution layer.

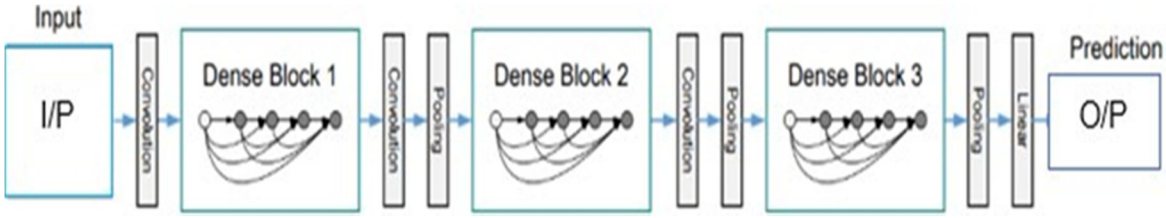


Figure 13 DenseNet-201 model with three dense blocks

5) *Implementation:* The implementation was done in Python utilizing a variety of libraries for image processing and learning about the convolutional neural network generation technologies, such as DenseNet-201. The library utilized for image management (such rotation and scaling) and preprocessing was OpenCV [25]. The mathematical operations required for the implementation were carried out using NumPy [26]. Additionally, Scikit-learn [28] and TensorFlow [27] were used for quick deep learning model building and model maintenance. The model's implementation uses a GPU-capable device to benefit from easier and quicker processing.

VI. SIMULATION AND RESULTS

We used a combination of kaggle datasets from Diabetic Retinopathy Detection 2015[21] and APTOS 2019 blindness detection [22] to train our proposed model using DenseNet-201. Pre-processing was necessary because the dataset provided a lot of noisy images. To make the fundus picture the primary emphasis, the black borders and corners of the photos were removed during pre-processing. The images were also resized to a common size of 256*256 pixels in both width and height. To remove the Gaussian noise, the images were finally blurred using a Gaussian blur.

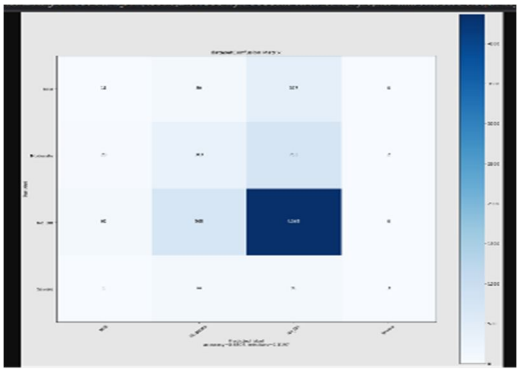


Figure 14 Confusion matrix after 1 epoch

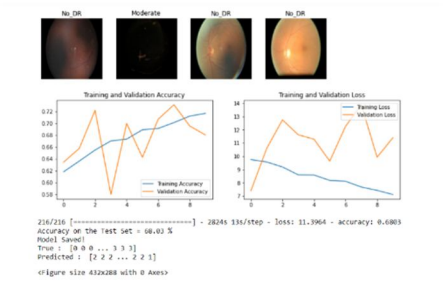


Figure 15 Loss and accuracy plot after 1 epochs

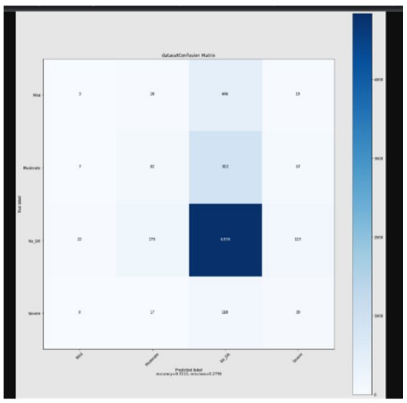


Figure 16 Confusion matrix after 10 epochs

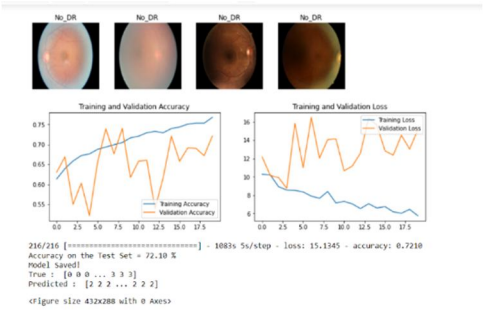


Figure 17 Accuracy and loss plots after 10 epochs

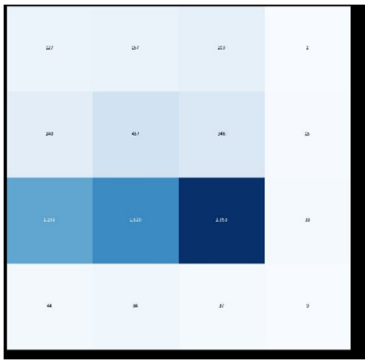


Figure 18 Confusion matrix after 20 epochs

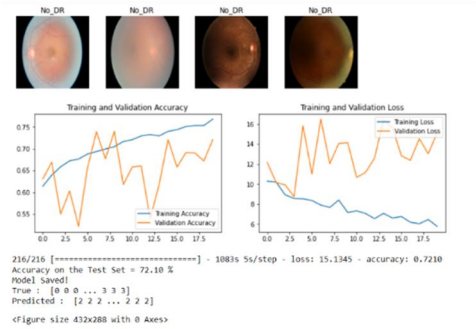


Figure 19 Accuracy and loss plots after 20 epochs

After pre-processing, we found that the distribution of the data across the severity classes was noticeably unequal, with the majority of the data falling into class "0," i.e., no DR. We used data augmentation to address this issue, which gave us 7000 images from each severity class and balanced the data. After pre-processing and image augmentation, data were sent to the DenseNet-201 to train the model. We were able to get a training accuracy of 0.953 and a validation accuracy of 0.9034 after evaluating our model.

VII. CONCLUSION

Numerous research have been done to automate the detection process using machine learning and deep learning techniques because the conventional approach for detecting DR is time-consuming, challenging, and expensive. In this research, we reviewed all existing methods for automatically detecting diabetic retinopathy and tried to provide our own deep learning solution for retinal early diagnosis using a DenseNet-201 model (which is a new CNN architecture, having many deep layers). The kaggle datasets were used for this inquiry. The 2015 and 2019 versions of APTOS were integrated to identify diabetic retinopathy. There was a lot of pre-processing and augmentation done in order to organize the data in a desirable way and eliminate the undesirable noise. To compare the outcomes, we used a regression model in addition to the DenseNet-201 classifier. The proposed approach was also contrasted with machine learning classifiers including SVM, DT, and KNN. The proposed model classifies the images into a broader variety of categories and has the highest accuracy of all. The regression model fared worse than our advised model, only achieving a 78 percent accuracy compared to our suggested model's 90 percent accuracy.

A. Future Scope

Techniques that not only retain all the little vital details while also enabling for successful pre-processing should be employed since there are several photographs acquired under various situations that need to go through a lot of pre-processing and augmentation. Additionally, many photos should be provided for each patient rather than just two, since this will increase the likelihood that the images will be correctly classified because more data can be gathered. The capacity to tweak hyper-parameters is continuously improving with the introduction of new neural networks and enhanced pooling techniques. Future study should look into these techniques to determine if there are any methods to boost performance in this area.

REFERENCES

[1] International Diabetes Federation—Facts & Figures. Available online: https://www.idf.org/aboutdiabetes/what-is-diabetes/ facts-figures.html (accessed on 13 November 2020).
[2] Diabetes. Available online: https://www.who.int/news-room/fact-sheets/detail/diabetes (accessed on 13 November 2020)
[3] Diabetes Treatment: Using Insulin to Manage Blood Sugar—Mayo Clinic. Available online: https://www.mayoclinic.org/ diseases-conditions/diabetes/in-depth/diabetes-treatment/art-20044084 (accessed on 13 November 2020)
[4] Diabetic Retinopathy Data and Statistics | National Eye Institute. Available online: https://www.nei.nih.gov/learn-about-eye- health/resources-for-health-educators/eye-health-data-and-statistics/diabetic-retinopathy-data-and-statistics (accessed on 13 November 2020)
[5] Diabetes and You: Healthy Eyes Matter! 2014. Available online: https://www.cdc.gov/diabetes/ndep/pdfs/149-healthy-eyes- matter.pdf (accessed on 13 November 2020)
[6] National Diabetes Statistics Report, 2020 | CDC. Available online: https://www.cdc.gov/diabetes/data/statistics-report/index. html (accessed on 13 November 2020).
[7] Key Facts About Diabetic Retinopathy [Infographic] | Welch Allyn. Available online: https://www.welchallyn.com/en/ education-and-research/research-articles/key-facts-about-diabetic-retinopathy-infographic.html (accessed on 5 March 2021)

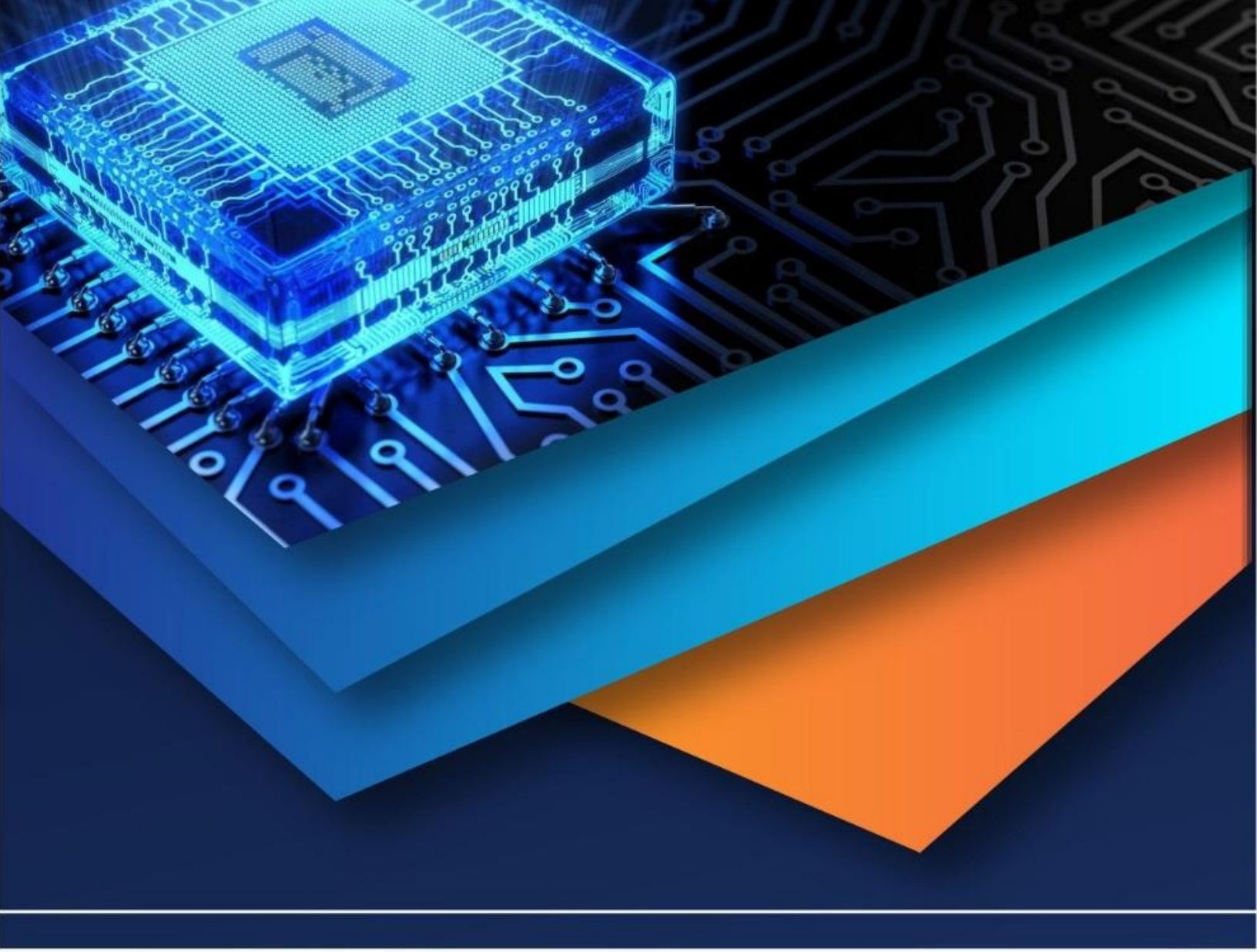
[8] Islam, M.M.; Yang, H.-C.; Poly, T.N.; Jian, W.-S.; Li, Y.-C. Deep Learning Algorithms for Detection of Diabetic Retinopathy in Retinal Fundus Photographs: A Systematic Review and Meta-Analysis. Comput. Methods Programs Biomed. 2020, 191, 105320. [CrossRef

[9] Hemanth, D.J.; Deperlioglu, O.; Kose, U. An enhanced diabetic retinopathy detection and classification approach using deep convolutional neural network. Neural Comput. Appl. 2020, 32, 707–721. [CrossRef]

[10] Shankar, K.; Sait, A.R.W.; Gupta, D.; Lakshmanaprabu, S.K.; Khanna, A.; Pandey, H.M. Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning model. Pattern Recognit. Lett. 2020, 133, 210–216. [CrossRef

[11] Gayathri, S.; Gopi, V.P.; Palanisamy, P. A lightweight CNN for Diabetic Retinopathy classification from fundus images. Biomed. Signal Process. Control 2020, 62, 102115. [CrossRef]

[12] Liu, H.; Yue, K.; Cheng, S.; Pan, C.; Sun, J.; Li, W. Hybrid model structure for diabetic retinopathy classification. J. Healthc. Eng. 2020, 2020, 8840174. [CrossRef]



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY