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Detection of Diabetic Retinopathy Using Clahe Based Transfer Learning

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Abstract: Diabetic Retinopathy(DR) has been a noticeable increase in the number of people diagnosed as blind in today's day and age. Many of the individuals who were diagnosed as blind had long- term diabetes. As a result, persons who have had diabetes for a long time may develop diabetic retinopathy, an eye disease. This usually happens when high blood sugar levels damage the retina's blood vessels. These blood vessels have the potential to enlarge and leak. All of these variables have the potential to cause blindness. Diabetic Retinopathy affects roughly 117.12 million people, according to WHO (World Health Organization) figures from 2021 [Global Prevalence of DR and Projection of burden through 2045].Diabetic retinopathy is divided into four categories: no DR, moderate Nonproliferative (NP), Moderate NPDR, severe NPDR, and Proliferative DR. Early detection of DR can prevent blindness caused by long-term diabetes, which can be accomplished if DR is detected early. We employ a preprocessing approach called Contrast Limited Adaptive Histogram Equalization (CLAHE) and CNN algorithms like Alex net, Resnet, and Train net to classify eyeballs in this research. Normal eyes are classified as mild np, moderate np, and severe np based on the accuracy predicted. The evaluation results reveal that the suggested pre-processing algorithm CLAHE is effective in removing noise and redundant features from an input image, and when fed into the Efficient network, this system achieves a 96 percent accuracy.

Keywords: Image preprocessing CLAHE algorithm, Transfer learning CNN.

I. INTRODUCTION

Diabetes has always been a very common condition. High blood sugar is the cause. Diabetic Retinopathy is an eye condition that develops in people who have had diabetes for a long time. This occurs when sugar obstructs the retina's small blood veins, causing them to leak fluid. The number of adults affected by diabetic retinopathy in2021 is expected to reach 117.12 million, accordingto the article Global Prevalence of Diabetic Retinopathy and Projection of Burden through 2045. Diabetic Retinopathy might result in blindness in severe cases. As a result, it has become one of the most common causes of blindness. The likelihood of getting diabetic retinopathy isproportional to the length of the condition. It isclassified into 4 types: mild NP, moderate NP,severe NP, Proliferative Diabetic retinopathy eye(PDR).In today's world, there has been anoteworthy increase in the number of people diagnosed as blind. Many of the individuals whowere diagnosed as blind had long-term diabetes. Asa result, persons with long-term diabetes maydevelop diabetic retinopathy, an eye condition.This usually happens when high blood sugar levelsdamage the retina's blood vessels. These bloodvessels have the potential to enlarge and leak. Allof these variables have the potential to causeblindness. DR is thought to have afflicted 93million people worldwide. In those with long-termdiabetes, DR affects about 40% of the population. Diabetic retinopathy can be divided into four categories: (no DR, mild, non-proliferative DR and proliferative DR).The blindness caused due toprolonged diabetes can be stopped by earlydetection of DR, this can be achieved if we detect DR at an early stage hence, we require technologies to be available free of cost and be present everywhere. Asra momeni et al.,[21] (2020) proposed a new diabetic retinopathy monitoring model by using the Contrast Limited Adaptive Histogram Equalization method to improve theimage quality and equalize intensities uniformly asthe pre-processing step. Then, EfficientNet-B5 architecture is used for the classification step.Yitian Zhao et al.,[11] (2019) proposed a useful technique called CLAHE that is presented for the amplification of the vessels in retinal fundus images as the pre-processing step. Therefore, by increasing the contrast, the important information inside the images is improved.The efficiency ofthis network is in uniform scaling all dimensions ofthe network.

II. RELATED WOKS

Lei Zhang et al.,[1] (2020) work on DiabeticRetinopathy Detection competition that was heldon Kaggle Platform. The images that were derived were basically classified into 5 categories namely No DR, Mild DR, Moderate DR, Severe DR and Proliferative DR. It uses the Migration LearningApproach which is one of the new machinelearning approaches. There are four different approaches to implement this method: they haveused Feature based Transfer Learning.

The pre- training model they used is based on ImageNet. Since there was a requirement of data augmentation which involved the usage of image

Data Generator which is a class present in Keras. . They used the pre-training model for feature extraction that was required to develop a final model to detect DR. The accuracy that was obtained using ResNet50 was 0.50. This paper adopts the method of migration learning, using Keras built-in pre-training model to fine-tune the new dataset to achieve the classification based on the degree of diabetic retinopathy.

Idowu paul okuwobi et al.,[2] (2017)mentionedthat the database used was borrowed from thedataset provided by Kaggle during the competition to detect Diabetic Retinopathy Detection. Theybasically followed a two-step process whichincludes data pre-processing and augmentation and convolution layer. The convolutional layer was further divided into a 5-step process which involved convolutional layer, The basic buildingblock of Convolutional neural extracting weights, Pooling Layer, connecting layer and logisticclassifier (the values it output represent theprobability of each class). The accuracy that was obtained was 74%.

Lama seoud et al.,[3] (2015) proposed the Prognosis of Microaneurysm and early diagnostics system for non-proliferative diabetic retinopathy (PMNPDR) capable of effectively creating DCNNsfor the semantic segmentation of fundus imageswhich can improve NPDR detection efficiency and accuracy. A sparse Principal Component Analysis based unregulated classification approach for detecting microaneurysm was developed. Oncea model that represents MA has been developed, any deviating from the standard MA is detected by statistical monitoring, a scarce Principal Component Analysis is employed to find the latent structure of microaneurysm data.

Shan shan zhe et al.,[4] (2017) proposed EyeFundusScopeNEO, a Tele- Ophthalmology system that supports opportunistic and planned screening of Diabetic Retinopathy in primary care. Preliminarytests show the device is safe, that clinicians canacquire images quickly after reduced training, andthat the non-mydriatic system focuses appropriatelyon eyes with different dioptres. The characteristicsof the system address long-standing issues ofcurrent screening programmes, are expected to beable to increase the reach of screenings once the system is implemented.

Keerthi ram et al.,[5] (2019) described the association between the tortuosity with type 2 diabetes and DR severity was investigated based ona Chinese population-based cohort. Higher contrast retinal photographs taken by a confocal scanning laser ophthalmoscope were used to extract retinal arteriolar and venular tortuosity from both mainand branching vessels, thus this study is with higher reliability. Arteriolar and venular tortuosity increased with increasing DR severity, and diabeticpatients with more tortuous venules weremore likely to suffer from moderate NPDR, severe NPDR, and PDR, whereas those with more tortuous arterioles were more likely to suffer from severe NPDR and PDR, which indicates that retinalvascular tortuosity might be an 6 remarkable indicator of the retinopathy. Harihar narishma iyer et al.,[6] (2018) emphasizedthe necessity for an automated technique for NPDRretinal image classification. Moreover, this road map reminds us that the evaluation of the Skeletoncould in principle be a promising approach to getmany fractal features like, for instance, informationand correlation dimensions in order to have goodideas concerning the existence of gaps and thebifurcation point as well.

Romany F.Mansour et al.,[7] (2020) proposed model has a Siamese-like architecture which accepts binocular fundus images as inputs and predicts the possibility of RDR for each eye byutilizing the physiological and pathological correlation of both eyes. The evaluation result shows that proposed binocular model achieves high performance with an AUC of 0.951 and a sensitivity of 82.2% on the high specificityoperating point and a specificity of 70.7% on the high sensitivity operating point, which outperforms that of existing monocular model based onInceptionV3 network. These results also demonstrate that the proposed model has greatpotential to assist ophthalmologists to diagnoseRDRmore efficiently and improve the screeningrate of RDR.

Maziyar M.khansari et al.,[8] (2019) proposed a data augmentation scheme to compensate for the lack of PDR cases in DR-labeled datasets. It builds upon a heuristic-based algorithm for the generation of neovessel-like structures which relies on the general knowledge of common location and shape of these structures. NVs which present an unusual shape or that are too slight are still beingmissed by the model, likely due to its lack ofrepresentation in the generated dataset. This studyshows the potential of introducing NVs in retinal images for improving the detection of these proliferative DR signs, thus allowing to improvethe performance of computer-aided DR gradingmethods and easing their clinical.

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Yizhou et al.,[9] (2014) focused on classifying allthe stages of DR, and proposed a CNN ensemble-based framework to detect and classify the DR's different stages in color fundus images. Resultsshow that the proposed ensemble model performsbetter than other state-of-the-art methods and isalso able to detect all the stages of DR. In future inorder to further increase the accuracy of early- stage, they plan to train specific models for specific stages and then ensemble the outcome in order toincrease the accuracy of early stages.

Juan Wang et al.,[10] (2018) proposed modelredesigns the network structure of the traditionalLeNet model, adding BN layer to obtain a newmodel BNCNN, effectively preventing the gradient diffusion, accelerating the training speed andimproving the accuracy of the model.This papersolves the problem of how one-dimensionalirrelevant data is convolution, breaks the traditional specificity of CNN in the field of image, and also obtains a good prediction result. This studyprovides a basis for the early diagnosis of diabetic complicated retinopathy and the optimization of diagnostic procedures. It combines deep learning with electronic medical record information andachieves good results.

Yitian Zhao et al.,[11] (2019) proposed a usefultechnique called CLAHE that is presented for theamplification of the vessels in retinal fundus images as the pre-processing step. Therefore, byincreasing the contrast, the important informationinside the images is improved. Also, the new EfficientNet-B5 architecture is employed for the classification step. The efficiency of this network isin uniform scaling all dimensions of the network.

Jianwu Wang et al.,[12] (2016) delineated the largest publicly available datasets of eye fundus images (EyePACS and APTOS datasets) were used to train and evaluate the developed model. Limitations of the developed approach 8 which is commonly encountered in deep learning models is the comprehensiveness of the datasets used and the training time associated with using a very large number of images. However,once the model is trained, it classifies a test orunknown image in a short time (<0.5 s). A possible future extension of this work includes the real-time implementation of this model as a smartphone app so that it can easily be deployed in clinical environments for diabetic retinopathy eye examination.

Doshi D et al.,[13] (2018) proposed that when multi-scale shallow CNNs combined with performance integration is introduced to the early detection of Diabetic Retinopathy through theclassification of retinal images. Owing to the feature sensing under various vision-related receptive fields by different base learners and the repeatable dataset sampling, it can do imageclassification well when there are not enough high- quality labeled samples. Moreover, the proposed approach also performs well on small datasets when considering both classification effect and efficiency compared with other approaches.

Pratt H et al.,[14] (2019) mentioned that Naturalimages in ImageNet have structures different fromthose of fundus images; they adapted the hierarchical structure of a pre-trained CNN model to the fundus images by reinitializing the filters of its CONV1 layer using the lesion ROIs extracted from the annotated E-ophtha dataset and then fine-tuned it using the ROIs. For tuning them to high-level features, reduce the model complexity, andavoid overfitting, they replaced the FC layers with a PCA layer learned using ROIs and used.

Jude hemanth.D et al.,[15] (2019) proposed theemployment of image processing with histogram equalization, and the contrast limited adaptive histogram equalization techniques. Next, thediagnosis is performed by the classification of a convolutional neural network. The method was validated using 400 retinal fundus images within the MESSIDOR database, and average 8 values for different performance evaluationparameters were obtained as accuracy 97%, sensitivity (recall) 94%, specificity 98%, precision 94%, FScore 94%, and GMean 95%.

Yi wei chen et al.,[16] (2018) They propose a recognition pipeline based of cnn deep convolutional neural networks. In our pipeline, they design lightweight networks called SI2DRNet-v along with six methods to further boost the detection performance. Without any fine-tuning, their recognition pipeline outperforms state of the art on the Messidor dataset along with 5.26x fewer in total parameters and 2.48x fewer in total floatingoperations.

Uzair Ishtiaq et al.,[17] (2020) proposed a system that developed image preprocessing techniques, contrast enhancement combined with green channel extraction contributed the most in classification accuracy. In features, shape- based, texture-based and statistical features were reported as the most discriminative inDR detection. The Artificial Neural Network was a proven classifier compared to other machine learning classifiers. In deep learning, Convolutional Neural Network outperformed compared to other deep learning networks. Finally, to measure the classification performance, accuracy, sensitivity, and specificity metrics were mostly employed.

Sairaj burewar et al.,[18] (2018) proposed at atdetecting the various stages of Diabetic Retinopathy by using U-Net segmentation withregion merging & Convolutional Neural Network(CNN) to automatically diagnose and thereby classify high-resolution retinal fundusimages into 5 stages of the disease based onseverity. A major difficulty of fundus imageclassification is high variability especially in thecase of Proliferative diabetic retinopathy where there exists retinal proliferation of new blood vessels and retinal detachment. Hence, The properanalysis of the retinal vessel is required to get theprecise result, which can be done by RetinalSegmentation. Retinal Segmentation is the 10 process of automatic detection of boundaries ofblood vessels. The features lost during segmentation are retained during region merging & passed through the image classifier, with the accuracy up to 93.33%.

Navoneel Chakrabarty et al.,[19] (2019) they proposed a method to automatically classify patients having diabetic retinopathy and not having the same, given any High-Resolution Fundus Image of the Retina. For that an initial image processing has been done on the images which includes mainly, conversion of coloured (RGB) images into perfect greyscale and resizing it. Then, a Deep Learning Approach is applied in which the processed image is fed into a Convolutional Neural Network to predict whether the patient is diabetic or not. This methodology is applied on a dataset of 30 High Resolution Fundus Images of the retina. The results obtained are a 100 % predictive accuracy and a Sensitivity of 100 % .

Abhishek samanta et al.,[20] (2020) proposed a transfer learning based CNN architecture on color fundus photography that performs relatively well on a much smaller dataset of skewed classes of 3050 training images and 419 validation images in recognizing classes of Diabetic Retinopathy from hard exudates, blood vessels and texture. This model is extremely robust and lightweight, garnering a potential to work considerably well in small real time applications with limited computingpower to speed up the screening process. The dataset was trained on Google Colab. We trained our model on 4 classes - I)No DR ii)Mild DR iii)Moderate DR iv)Proliferative DR, and achieved a Cohen's Kappa score of 0.8836 on the validation set along with 0.9809 on the training set.

Asra momeni et al.,[21] (2020) proposed a new diabetic retinopathy monitoring model by using the Contrast Limited Adaptive Histogram Equalization method to improve the image quality and equalize intensities uniformly as the pre-processing step. Then, EfficientNet-B5 architecture is used for the classification step. The efficiency of this network isin uniformly scaling all dimensions of the network.

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The final model is trained once on a mixture of twodatasets, Messidor-2 and IDRiD, and evaluated on the Messidor dataset. The area under the curve (AUC) is enhanced from 0.936, which is the highest value in all recent works, to 0.945. Also, once again, to further evaluate the performance of the model, it is trained on a mixture of two datasets, Messidor-2 and Messidor, and evaluated on the IDRiD dataset. In this case, the AUC isenhanced from 0.796, which is the highest value in all recent works, to 0.932. In comparison to other studies, our proposed model improves the AUC.

III. PROPOSED SYSTEM

The current technologies for detecting DR are time-consuming and labor-intensive. Some existing systems have used image Data Generator, which is featured in Keras, for augmentation and have leveraged technologies like Migration learningmethod. Some systems used the binocular model and achieved an accuracy of 0.85%, while others used the Lenet model to avoid gradient diffusion and boost speed. The current technique necessitatesthe examination and evaluation of the fundus picture of the retina by skilled medical staff. As a result, there are delays in the results, which leads to miscommunication and treatment delays. Only the appearance of lesions as well as vascular anomaliesinduced by the disease allow clinicians to diagnose DR. Although this approach is effective, it has a significant drawback in terms of resource demands being high.The skills and resources needed to detect DR are frequently low in certain places, particularly when the number of diabetic patients ishigher. As the number of people suffering from diabetes rises, infrastructure must be enhanced, andtechniques must be modernized and accurate.

A. System Architecture

The main idea of this project is to change the wayof detecting Diabetic Retinopathy so that each person who wants their eyes to be analyzed neednot wait and his/her eye can be analyzed accurately. Here the main requirement for the detection of Diabetic Retinopathy is the FundusImage. Here we are using Kaggle dataset which hasthe fundus images of eyes. It has over 8000 images The fundus image is hence then undergoing thepre-processing stage using CLAHE algorithm where the unnecessary features like noise are removed. Then the preprocessed image is fed into transfer learning techniques like Alex net, Efficient net and Resnet. Transfer learning can take the accurate models produced from large trainingdatasets and help apply it to smaller sets of images. The CLAHE algorithm is used for improving the quality of the image. This method is applied inbackground and foreground to limit the noise and enhance the contrast.

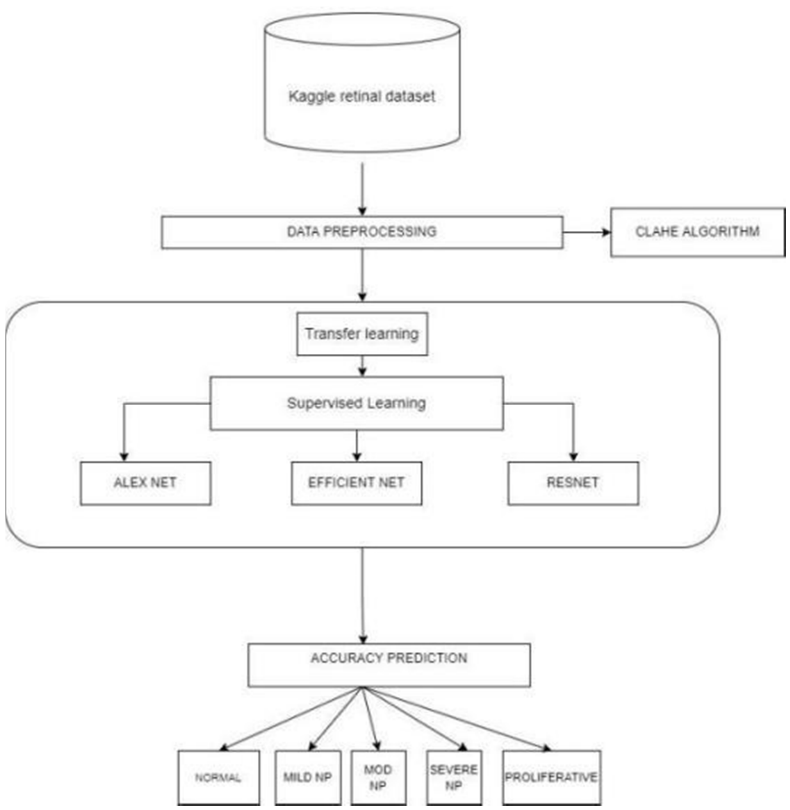

Figure 1: System Architecture

B. Architectural Description

The Retinal image dataset of an eye is presented as input in this figure 1 architectural diagram of diabetic retinopathy identification. The CLAHE algorithm is then used to pre-process the image. During pre-processing, unwanted elements such as noise, edges, and picture contrast are removed, and the image is shrunk. The pre-processed image is then fed into the CNN classifier algorithm. To extract features, various filters convolve an image. To minimize the size of feature maps, the pooling layer is usually applied after the CONV layer. There are other pooling strategies, but the mostcommon are average pooling and maximum pooling. FC layers are a little feature that can be used to characterize the entire input image. The most commonly utilized classification function is the SoftMax activation function. The most commonly utilized classification function is the SoftMax activation function. The accuracy predicted is used to classify the pictures and retinal images. As an output, the eye images are categorized as Normal eye, Mild NP, Moderate NP, Severe NP, and Proliferative eye. The architectural description of diabetic retinopathy is given in fig 1, and the flow of this system begins when a retinal image dataset is fed into a pre-processing algorithmcalled clahe, which removes the noise and redundant features present in the backdrop of the picture for greater accuracy. Thus, transfer learningtechniques alexnet, efficient net, and resnet are used to classify the pre-processed images. The aforementioned classification will result in photos being produced into five categories: normal, mild np, moderate np dr, severe np dr, and proliferative.

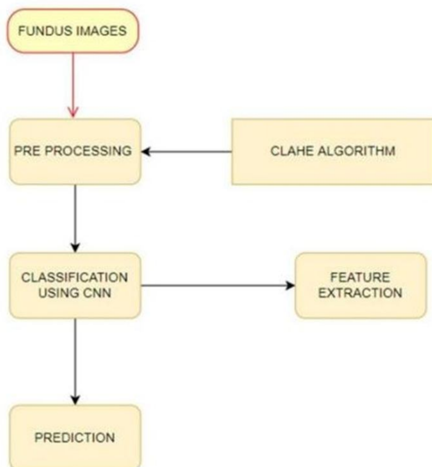

Figure 2: Flow Diagram

C. Preprocessing Module

The flow of this system begins when a retinal image dataset is supplied into a pre-processing algorithm called clahe, which removes the noise and redundant characteristics present in the picture's backdrop for improved accuracy. To classify the pre-processed photos, transfer learning cnn employ alexnet, efficient net, and resnet is utilized. Normal, mild np, moderate np dr, severe np dr, and proliferative are the five groups that will be formed as a result of the aforementioned classification. Clip Limit and TileGridSize are the two key parameters of the CLAHE Algorithm. The image is separated into little tiles, each of which is histogram equalized as normal. As a result, Histogram would be confined to a small area in a small space. Noise will be intensified if it exists. If any histogram bin exceeds the specified clip limit, the pixels are clipped and evenly distributed to other bins. Bilinear interpolation is used after equalization to remove artifacts in the tile boundaries.

1) CLAHE Algorithm

a) Input: The input given to the system is Image.

b) Output

- *After Pre-processing*

- *After Classification*

Classification of the given image and categorizes as no dr, mild dr, moderate np dr, proliferative.

- *Step 1:* Divide the original intensity of the image into a non overlapping contextual region. Number of image tiles is equal to A*B
- *Step 2:* Calculate the histogram of each contextual region based on gray level in image.
- *Step 3:* Calculate the contrast limited histogram for each contextual region by CL value

*Bavg = (BrX*BrY)/Bgray* Bavg is average number of pixel,Bgray is number of gray levels,

BrX and BrY are number of pixels in X and Ydimension

Actual CL is *BCL = Bclip*Bavg*

where BCL is actual CL,Bclip is normalized CL in range of [0,1]

If number of pixel is greater than BCL the pixels are clipped.The total number of clipped pixel isBsclip,Then average of pixel to distribute to each gray level is

Bavggray=Bsclip/Bgray

The histogram clipping rule is

Step 3.1:If Hreg(i) > BCL thenHreg_clip(i) = BCL

Step 3.2:Else if (Hreg(i)+Bavggray) > BCL thenHreg_clip(i) = NCL

Step 3.3:Else

Hreg_clip(i) = Hreg(i)+BCL

Where Hreg and Hreg_clip are the originalhistogram and clipped histogram.

- *Step 4:* Redistribute the remain pixels until theother pixels are distributed D=Bgray/Bremain where Bremain is remaining of clipped pixels D isthe positive integer at least 1
- *Step 5:* Enhancing intensity values in each region by rayleigh transform.The clipped histogram is transformed to cumulative probability.
- *Step 6:* Calculate the new gray level assignment of pixels within the contextual region by interpolation

D. Model of Supervised Learning

Convolution Neural Network (CNN) is a deep learning system that can take an image and give relevance (learnable weights and biases) to various aspects/objects in the image, allowing it to distinguish between them. A convolutional layer, a pooling layer, and a fully connected layer are the three layers of a CNN. The image or data associated with the problem is identified and entered into the algorithm. The hidden weights of the output layer would then manifest themselves in a variety of ways. We employed widely used architecture such as construct net, Resnet, and Efficient net in this project.

1) *Resnet:* Following multiple deep CNN advances in image classification, ResNet, a deep neural network including residual connections, has been proposed. ResNet solves the problem of vanishing gradients (training deep networks incorporates backpropagation of error gradients which gets reduced as it passes in backward direction). They were able to overcome the vanishing gradient by using ResNet and its variants for picturecategorization and skip connections. We chose ResNet50 as one of their variations since its learning representations from the unlabeled image were good.

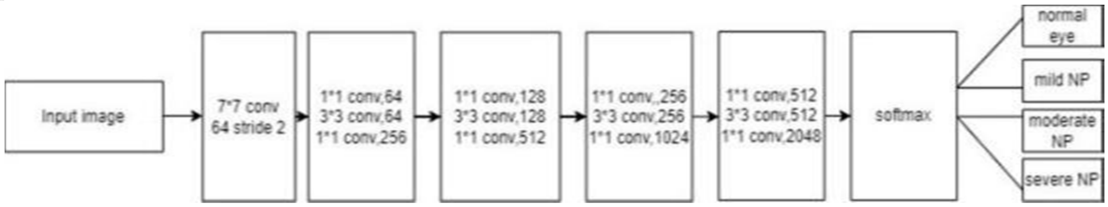

Figure 3 Architecture diagram of Resnet.

2) Efficient Net

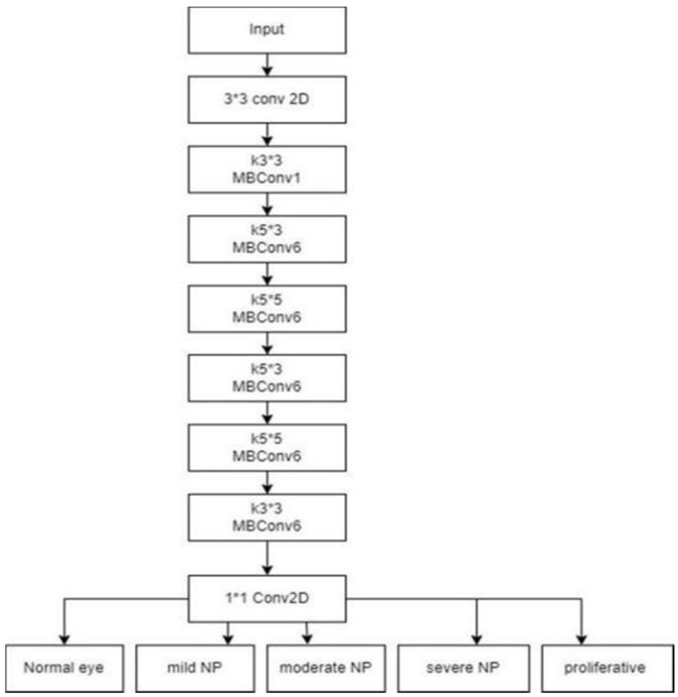

Figure 4 Architecture Diagram of Efficient net

The retinopathy dataset in figure 4 includes both infected and non-infected images. The tainted data is sorted into four categories and listed in that order. These datasets are used to train the model, which is then applied to finding fresh photo sets. The input layer gathers and pre-processes all of the image datasets. The second layer is 3*3 conv 3d. By convolving the layer input with a convolution kernel, this layer yields a tensor of outputs. The photographs are then processed using several custom layers, with the output layer providing the final result.

3) Alexnet

Alex Net is a deep convolutional network that was created to accommodate large coloured images (224x224x3). It had over 62 million trainable parameters in total. There are 11 layers in all, including 5 convolutional layers, 3 maximum pooling layers, and three fully linked layers. The convolutional layer uses kernels to conduct a convolution operation on a pre-processed picture. Then there's the max pooling layer, which uses the first layer's output as an input. Similarly, the previous layer's output is used as the input for the next layer. The output tensor is produced by the fully connected layer, which then passes through the softmax activation function. The network prediction is contained in the softmax activationfunction's output.

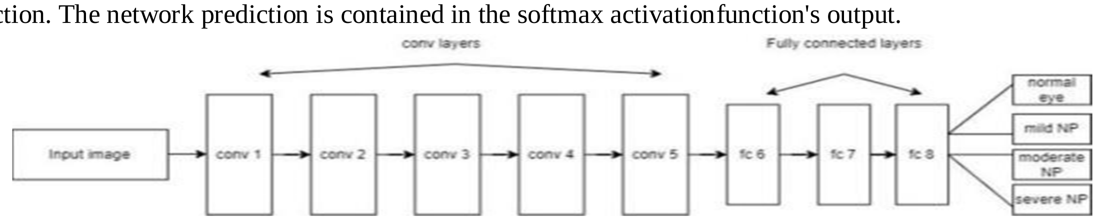

Figure 5 Architecture Diagram of Alexnet

E. Accuracy Prediction

Finally, using the methodologies described above, the accuracy of the retinal picture is anticipated, and the eye is classified as normal, mild NP, moderate NP, severe NP, and proliferative eye as 0,1,2,3,4. This ultimate accuracy is based on how many retinopathy features we took into account.

IV. EXPERIMENT RESULTS

The Pre-processed image is provided as input, andit is pre-processed using the CLAHE algorithm.The pre-processed image is then classed, and accuracy is projected using the CNN classifier algorithm. The fundus picture is then characterized as normal, mild, moderate, severe, or proliferative dr.

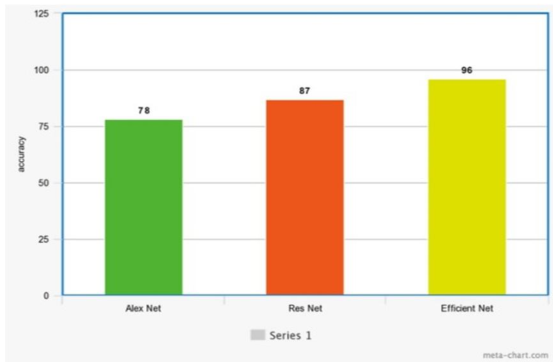

Figure 4.1 Comparison graph between networks

The above figure 4.1 is plotted against several networks we have implemented and the accuracy that has been obtained while implementing the networks. In this project we have achieved the accuracy of 60% for Train net,78% for Alex net,96%for Efficient net and 87% for Resnet.

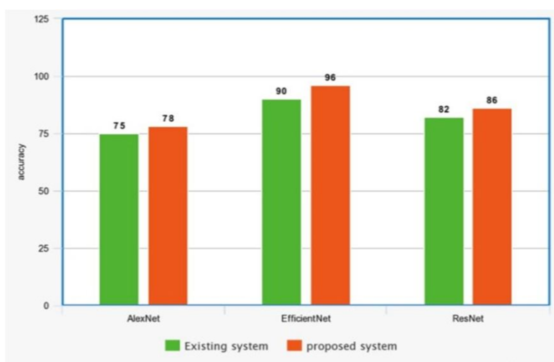

Figure 4.2 Comparison graph between existing andproposed system

We compared current publications to our study in Figure 4.2 and achieved the above accuracy. The CLAHE technique was not implemented in most prior publications' pre-processing modules, allowing our approach to attain superior accuracy.

Table 4.3 Performance of proposed system

CLASS	EXISTING SYSTEM	PROPOSED SYSTEM
Accuracy	93.2%	96.3%
Sensitivity	93%	97%

A. Existing Paper Reference

Automatic Detection and Monitoring of Diabetic Retinopathy using Efficient Convolutional Neural Networks and Contrast Limited Adaptive Histogram Equalization. [Mohammad Nasajpour, Mahmut Karakaya, Seyedamin Pouriyeh, Reza M. Parizi, "Federated Transfer Learning For Diabetic Retinopathy Detection Using CNN Architectures", SoutheastCon 2022, pp.655-660, 2022.]

V. CONCLUSION AND FUTURE SCOPE

The proposed method is a revolutionary technique for Diabetic Retinopathy detection. Diabeticretinopathy can be detected early and treated tohelp patients recover. The project's output, which is produced from a fundus image, indicates if the eye is normal, mild, moderate, proliferative, or non proliferative. Sensitivity, specificity, accuracy, precision, recall, and F1 score metrics are used to evaluate the suggested system. And we got 87 percent accuracy for Resnet, 96 percent accuracy for Efficient net, 60 percent accuracy for Train net, and 78 percent accuracy for Alex net. The sensitivity of this system was 97 percent.The suggested technology detects disease with great accuracy and precision. We can still add services in the future, such as online consultations based on the accuracy anticipated by the proposed system, toassist patients.

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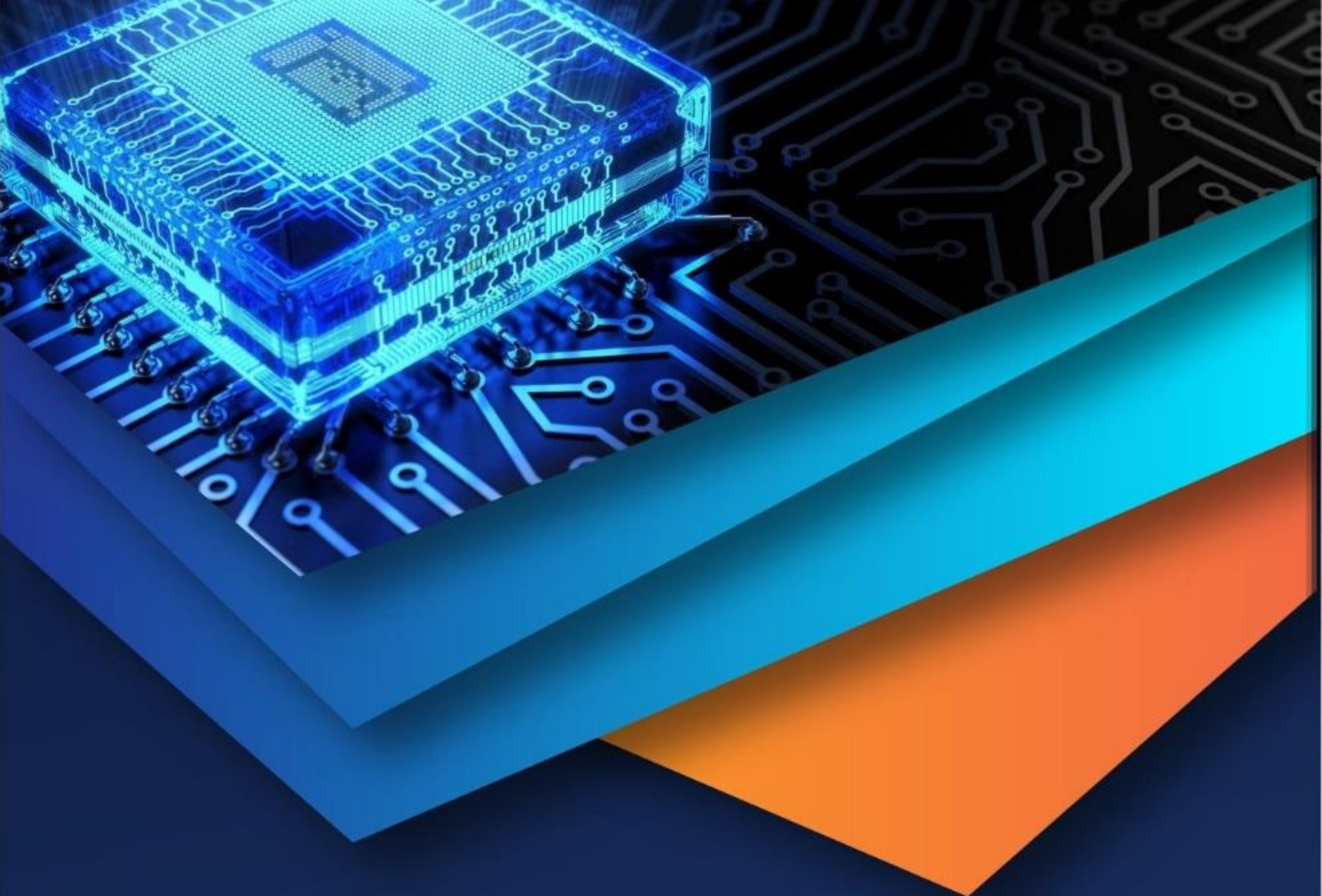

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