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International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 11, Issue 2 | Pages 609-615 | e-ISSN: 2347-470X

A Diabetic Retinopathy Detection Using Customized Convolutional Neural Network

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ABSTRAC- The disease, Diabetic Retinopathy (DR) causes due to damage to retinal blood vessels in diabetic patients. DR occurs if you have type 1 or 2 diabetes along with high blood sugar. When the retinal blood vessels are damaged, they can become clogged, some of which can block the blood supply to the retina leading to blood loss, these new blood vessels may leak, and the creation of scar tissue can lead to loss of vision. It takes a lot of time and effort to examine and analyse fundus images the old-fashioned way to find differences in how the eyes are shaped. In this modern era, technology has evolved so fleet which has the solution to every problem. In this paper, we have proposed a Customized Convolutional Neural Network (CCNN) deep learning technique for Diabetic Retinopathy Detection. We have clung to traditional strategies mainly containing input Data retrieval, pre-processing of data, segmentation, trait measurement, feature extraction, model creation, model training, model testing, consequence, and interpretation of the model. Performance evaluation is done on standard MESSIDOR Dataset in which 560 images for training phase whereas 163 images for testing phase. The experiment results achieved the highest test accuracy of 97.24% which is effectively higher than that of existing algorithms.

General Terms: Diabetic Retinopathy, Customized Convolutional Neural Network (CCNN), Deep Learning
Keywords: SCSA, BP, Photo plethysmography, CNN, Non-invasive, Cuff-less.

ARTICLE INFORMATION

Author(s): Deepak Mane, Sunil Sangve, Prashant Kumbharkar, Snehal Ratnaparkhi, Gopal Upadhye and Santosh Borde;
Received: 19/02/2023; **Accepted**: 13/06/2023; **Published**: 30/06/2023;
e-ISSN: 2347-470X;
Paper Id: IJEER-2023_149;
Citation: 10.37391/IJEER.110250
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-11/ijeer-110250.html

This article belongs to the Special Issue on **Mobile Computing assisted by Artificial Intelligent for 5G/ 6G/ Radio Communication**

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1. INTRODUCTION

According to studies, there is no cure for diabetic retinopathy. The simpler it is to develop a treatment, however, the sooner the sickness is discovered. High blood pressure and a high blood sugar level in the body both have an impact on diabetic retinopathy [1]. The majority of individuals have diabetic retinopathy (DR). DR testing are still performed manually, which results in laborious, time-consuming procedures, delayed findings, and insensitive treatment of patients [2]. About 80% of individuals have diabetes and have had it for more than ten years. It may have repercussions for a number of problems, including diabetes, poor management, and early pregnancy in women [3]. DR includes two main denominations as Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). NPDR is segregated into three types, called moderate DR, severe DR, and mild DR [8]. Due to DR retina's blood vessels can get damage and which later leads to vision loss [12]. In the early stage, Diabetic Retinopathy is asymptotic, so most people are unaware of the symptoms unless they reached the unusual limitations in their eyesight. Therefore, using image processing and pattern recognition, this initiative seeks to provide an automated, pertinent, and advanced method, which leads to early identification of the Diabetic Retinopathy symptoms of a patient. The main objectives of proposed CCNN are;

- Developing CCNN model for detection and classification of diabetic retinopathy
- To build an efficient and customized CNN deep learning model which will reduce the tedious task of detecting diabetic retinopathy manually

The summary of a paper is presented as: The overview of relevant research in the area of diabetic retinopathy was discussed in *Section 2*. The methodology utilised for the study was described in *Section 3*. *Section 4* displays the difficulties encountered while working, while *section 5* explains the conclusion and the future scope.

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2. RELATED WORK

Many researchers did their research in the field of DR detection. Authors [1] presented co-learning is a machine learning (ML) model, to ensure an integrated approach. In the first instance, they were trying to simulate a database with the use of traditional ML techniques including Logic Regression, KNN, LDA, Random Forest, SVM, decision tree, and Naive Bayes Algorithm. Out of the five CNN layers in the ML model, 80% of the sounds were accurately predicted. specifically, the Relu, the first softmax, and the four layers. For speedy and efficient results, the model is trained with the assistance of an optimizer called Adam, who has a learning rate of 0.001. The maximum accuracy of up to 80% have been achieved, which is equipped with a total of 5 CNN layers (for four with a ReLU activation, and 1 with a Softmax activation), the training you can add to the Adam optimizer, which started with the aid of the model, the learning rate of 10-3 for fast convergence of the results.

In 2020, Akhilesh et al. [2] it has been suggested that a hybrid-ResNet-v2 is a framework for DR detection in the patient by examining the pictures in the color of the fundus. The previously trained Early-ResNetV2 and a CNN block were employed in the proposed model. They have made use of the Kaggle-available data sets Messidor and ATPOS. They had a 72 % accuracy rate, which was greater than Google Net's 6.3 %. The method may be used to capture large volumes of data using a generative network matrix. Morgan, et al. [3] underlined the importance of deep learning ensemble learning approaches in 2020. The programme, which sourced its data from the OCTA data set and co-registered structural images, was utilised to distinguish diabetic retinopathy (DR) from the coloured fundus images. The Ensemble network was developed using calibrated VGG19 pre-trained models for the main stacking techniques, with 92 percent accuracy and 90 percent. The neural network was constructed using a single kind of data and pre-trained using ImageNet's pre-defined weights using the ResNet, DenseNet, and VGG19 architectures.

The Ensemble learning approach improves CNN's parameters and performance for categorising the OCTA Data set for the Diabetic Retinopathy use case. A pre-trained Keras model that is incorporated into the training process was found in 2019 by Yuchen Wu, et al. [4]. They began by going through the specifics of data augmentation, such as data expansion and contrast adjustment. InceptionV3, VGG19, and Resnet50 were employed in addition to the previously trained models, and finally, all of the images were divided into 50 classes. This system's accuracy was measured at 61 percent of the InceptionV3 model. The ConvNet-based approach Mamta, A. et al. [5] presented in 2019 may be used to distinguish the coloured fundus pictures. In order to solve the issue of the identification of diabetic retinopathy, they also indicated the viability of a Deep CNN technique. In order to categorise each picture into one of five distinct groups, they have developed a deep learning model that is based on the vibrant vector representations of the fundus. A trained model is based on an image of the fundus, and they had a 74% accuracy rate. In their model, it is tested on the basis of the model, learning rate, and the time that would take place in order for the model to train. According to their later use, they can try to use a pre-defined model, which is the higher performance and reliability of the results of the two models. In 2018, Asti H. et al. [6] suggested the peculiarities for DR apprehension and managing a combination of neural network architecture and swarm optimization. Their combined neural network (NN) and particular swarm optimization (PSO) model has a 76.11 % efficiency, compared to the neural network method's 71.76 %.

The results of all the studies indicate a 4.35 % improvement in the accuracy of the Symantec network model employing a range of Particular Swarm Optimization feature systems coupled to the Neural Network standard. The data accuracy attained using the traditional ML algorithms in this form of categorization are quite poor, according to the aforementioned findings. By using various kinds of algorithms, deep learning models may provide results with great accuracy According to the analysis of earlier works, CNN is among the most effective methods for solving picture categorization issues in the medical industry [18][19][20]. In 2022, Yang, B et al. [23] proposed adaptive feature map and GENet which got 95.6 % accuracy for retinopathy detection. Recently, in 2023, S., Sudha, et al. Used different signal processing, image processing approaches applied to detect retinopathy [24].

3. SYSTEM ARCHITECTURE

Till date many researchers are tried to apply many machine learning techniques on DR detection. However according to the previous results, the highest accuracy for diabetic retinopathy detection of existing papers was 80% [1]. We have increased the accuracy rate by using a customized convolutional neural network (CCNN) algorithm which achieved 97.24% accuracy. Our paper is purely dependent on the Deep learning CNN applications in case scenario of detection of diabetic retinopathy. We are aware that automatic feature extraction and quick and effective mathematical computation are the key characteristics of every CNN model. Different parameters of convolutional layers, pooling layers adjusted in such a way that it produces the better results so convolutional neural network provided us a seamless and efficient approach to pursue this in this paper. CCNN system architecture is represented in *figure 1*. We have approached many previous papers. All the papers had used traditional methods for implementation of Diabetic retinopathy. But we have built custom model which consists of callback methods like Reduce LR on Plateau and Early Stopping.

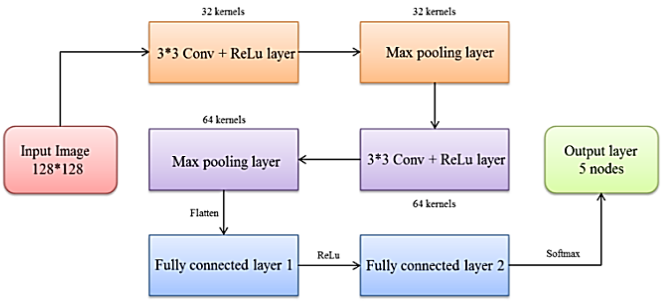

Figure 1: CCNN System Architecture

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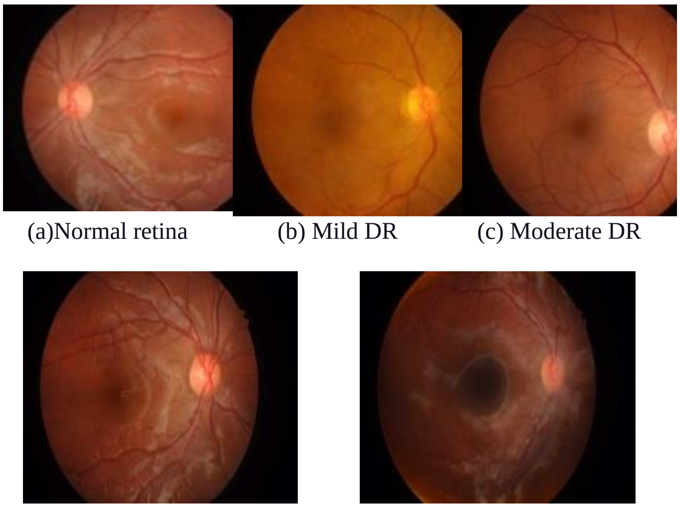
CNN is the Convolutional neural network layer which helps in the work of image matrix convolution, concerning that there are pooling layers and activation layers in different combinations and multiple Combinations and state of stacks. In the CNN, we pass data as input which is pre-processed and convolved with various filters in various stages of CNN. These filters are traditional image processing filters. In the case of CNN, filters are learned and created automatically instead of manually creating a new one. As per the model training, we have analyzed for two configurations as 80: 20 and 70: 30. We chose Approximately 187 images randomly to validate our model. Customized Convolutional layer is used to extract hidden features from retinopathy input image and max pooling layer used to reduce the burden of overfitting model.

3.1 Pre-processing of Images

A MESSIDOR dataset was taken into consideration for practicing and examination of model. This dataset contains a set of fundus images. Samples of Diabetic and Non-diabetic retinopathy stages images are represented in *figure 2*. Initially, we did some analysis on the dataset. There is a large number of images in category 0 concerning another division. The amount of non-DR images were more as compared to DR images. Hence, we look after to create a model based on an equal amount of data. There were a lot of obstacles. The quality of images was not clear in the dataset, almost 20 to 30 per cent of images were un-useful. We decided to take a maximum of 150 images that have good lighting and which are not blurred. Apart from that, we removed black images which might lead to unwanted learning of the model. The data segregation and data cleaning process took place.

We obtained a dataset containing 723 images. The bifurcation of the dataset images are 151 images for 0 stage (No DR), 139 images for stage 1 (Mild DR), 136 images for stage 2 (Moderate DR), 151 images for stage 3 (Severe DR), and 146 images for stage 4 (Proliferative DR), which is also shown in *figure 3*.



(a)Normal retina (b) Mild DR (c) Moderate DR

(d) Severe DR (e) Proliferative DR

Figure 2: Samples of Diabetic and Non-diabetic retinopathy stages: (a) Normal retina, (b) Mild DR, (c) Moderate DR, (d) Severe DR and (e) Proliferative DR

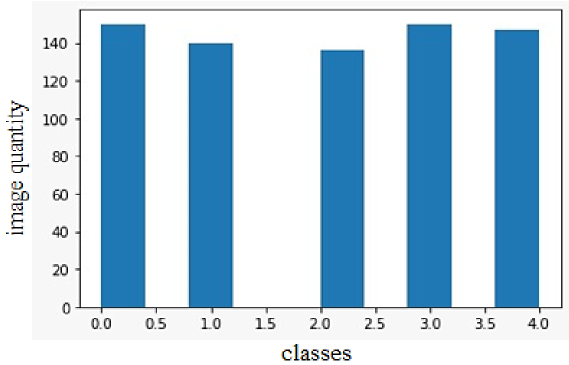


Figure 3: Image Segregation

Images from the dataset are read using the OpenCV library used for image pre-processing purposes, as it contains rich built-in libraries for fast, effective, and efficient image processing. These pre-processed input images were just a matrix of pixels to an algorithm. This matrix has its height, width, and channels. Each cell shows a value of the pixel along with the channel referring to RGB color. Images in the dataset demand too much RAM usage for pre-processing and further computations, which results in slower computation. Hence, we downsized the image pixel in 128*128 sizes. As current hardware is not suitable for large image sizes so we have taken images size as 128*128. After all processing on data finally, we divided data into training and testing statistics of 80: 20. This capacity of data is used to analyses execution of model.

3.2 Data Augmentation for model training

Deep learning models always perform best whenever they have a good amount and good quality of data with different features and set of random data. So, in deep learning, we always do a data augmentation before model training. Also, this helps to expand data so that model can predict better results. For data augmentation, we use a library i.e. Image augmenter which generates more data without collecting more no of actual data. Keras library has an inbuilt library that provides the functionality of data argumentation. As per the techniques discussed above in this paper, we mainly used features like Brightness adjustment, rescaling, zoom, channel shift and resizing. The further section is discussing the methodologies we used in designing of deep learning model.

3.3 CCNN Learning Algorithm

Parameter tuning is applied to traditional CNN models, like using different regularization approaches, different kernels, and filter sizes, different activation functions, etc. Different parameters of convolutional layers and pooling layers are adjusted in such a way that it produces better results, so CCNN provided us with a seamless and efficient approach to pursue this in this paper

Learning steps for Customised Convolutional neural network Algorithm are:

Input for Algorithm –Number of Filters, Previous Layer's Parameters, Learning rate.

Algorithm is as follows:

// At start, Weight ranges from (0, 1)

// At start, Bias ranges from (0, 1)

```
// starting with Convolution neural network Layer
Begin
//Forward Propaganda
Uh=long ((Ih - Fs)/St)+1    // Ih-Height of Image
Uw=long ((Iw - Fs)/St)+1  // Iw-Width of Image, Fs-Size of filter
For Ht=1 upto Uh do // Uh-Height (In unit)
        For Wt=1 upto Uw do // Uw-Width (In unit)
                For Cl=1 uptoNc do // Ihe-Image's horizontal end
                        L_s=pre_layer[Ivs:Ive,Ihs:Ihe,:]
                        Outcome=add(L_s*Wt)+Bs
                Close For // Ivs-Image's vertical start
        Close For // Ive-Image's vertical end
Close For    // Ihs-Image's horizontal start
Outcome [outcome<=0]=0 //ReLu layer
// Max Pool
For Ht=1 upto Uh do
        For Wt=1 upto Uw do
                For Cl=1 upto Nc do   // Nc-Channel's number
                    L_s=pre_layer[Ivs:Ive,Ihs:Ihe,:]
                     outcome=max(L_s) // L_s-Slice of layer
                Close For
        Close For
Close For
// Backward Propaganda
 For Ht=1 upto Uh do   // Ht-Height
        For Wt=1 upto Uw do   // Wt-Weight
                For Cl=1 uptoNc do // Cl-Channel
                        L_s=pre_layer[Ivs:Ive,Ihs:Ihe,:]
                 //The derivation would be
                        dWt+ = L_s – outcome[Ht,Wt,Cl]
                        dBs+ = Outcome[Ht,Wt,Cl]
                Close For
          Close For
Close For
//Output Weight and Bias
Wt= β * dWt
Bs= β * dBs
Terminate
```

CNN is a set of mathematical operations which generally used to extract features from images like borders, shapes, outlines, spots, etc. The Convolutional layer is the first and main step in model creation as it enables the image to transform to learn features from images. The convolution operation is performed in image *figure 4*. This operation is resulting in a lowering or same dimension matrix which is purely based on the padding provided in each layer of the model. In Deep neural network model filters is the parameters or tools that are learned by the suitable back-propagation algorithm

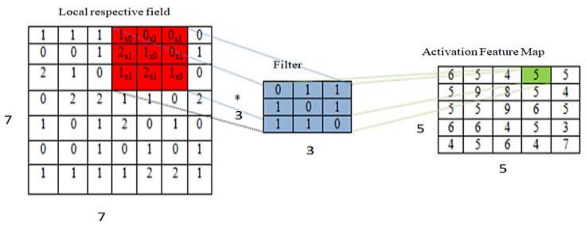


Figure 4: Convolution Method

Convolution is frequently indicated by '*' sign(dot product). The image is displayed as I and a filter denoted by f, then the expression will be:

$$Z = I * f + Bias \tag{1}$$

Stride is a one of the important parameters of the neural network's filter which modifies the quantity of movement of filters over the image. After this CNN layer pooling layers subsequently decrease the dimensionality of data as represented in *figure 5*. Conventionally in major project max pooling or average pooling are used most. They can help to achieve great features from images as well as handle overfitting

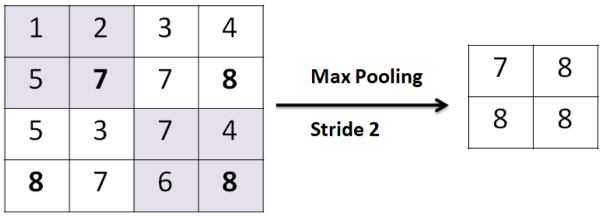


Figure 5: Max-Pooling

The activation layer is one of the most important layers in the model which provides a function of non-linear function mapping to learn complex features from images efficiently and effectively. The activation layer activates those neurons which having high value or which can be taken as a feature from images. Some of the activation functions are ReLU, it is one of the best activation function which triggers next neuron i.e. sets the output value as 1 if they provide value is greater than 0 if it is less than or equal to 0 then it keep it as 0 and not triggers the neuron, next is Sigmoid, this activation function is always kept in the last layer of the model as it provides output in form of probabilities so it is useful to rectify the results, and the last one is SeLu (Scaled Exponential Linear Units).Here are a few activation functions that we often apply to the model. Typically, Softmax is used in the last layer that produces a multiclass predicted label. The dropout layer is playing one of an important role in deep learning model training as it randomly sets the value as 0 to layers which help in avoiding the over fitting of a model. A dropout layer is introduced in the model architecture, as it randomly removes neurons during training. Deep learning model consists of several stacks which are generally created by using these mentioned layers. Each stack layer in the model provided its output for every input. Output from each stack is provided to the next stack for further processing. At last, after all, stack there is flattening layer which takes input from the last stack and converts it into straight one dimension array which further passed to the neural network. After layers are constructed the weights to each layer of the model and bias of every neuron are initialized randomly so that after model training these weights and biases are used for model-data predictions. To assess the inaccuracy in the model's prediction, a relevant loss function, such as categorical Cross-Entropy, was created. Compilation optimizers allow for the learning of a parameter that minimises costs and determines the rate and accuracy of learning. In this paper, an SGD optimizer is used

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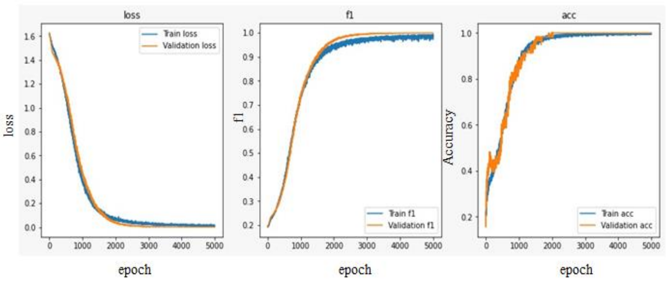
which is preferred over Group Gradient Descent for optimizing a training algorithm.

3.4 Hyper-Parameter Tuning and Selection of parameters for CCNN model

In proposed Customized CNN architecture, we made the different modifications rather than the traditional CNN architectures. Here, we decided to use 3 layers i.e. stacks of 3 CNN blocks which consist of the CNN layer, max-pooling layer, and at last dropout layer. Initial kernel size for CNN layer we took as (3,3), No of filters as 32, padding as same, activation function as ReLu, image size as (128,128,3) which is an RGB image. In the $2^{nd}$and 3^{rd}layers, we increased no of filters to 64. In the last layer, we used the softmax activation function which provides a class for an input image. This parameter we decided after many trials and much model training with different combinations and with different parameters.

4. EXPERIMENTAL RESULTS

We have used the MESSIDOR Dataset [24]; 560 images for DR-Training whereas 163 images for DR-Testing. As per the model training, we have analysed for two configurations as 80: 20 and 70: 30. The hardware we used for implementation was HP pavilion, Intel core i5, and 8th generation with NVDIA G-force_GTX graphics card. Now, the model is ready to be used for the prediction of unseen data that is testing data, If the model is set for training-on-training data with the best accuracy. Model accuracy goes up to 99.79 % for training while for testing it goes up to 97.24 % which is pretty awesome. During the training phase, the datasets were passed to the model in the batch of 32 images every iteration. The testing was performed on the test dataset and accuracy was used as the performance evaluation metrics. In the following figures, *figure 6(a)* represents the loss of the model. We can see that, there is gradually decrease in loss as epochs are decreasing. *Figure 6(b)* represents that, as F1 score is increased gradually as epochs are increased. Both training f1 and validation f1 scores are shown in graphs. *Figure 6(c)* represents the model accuracy, here epochs of the model are increasing in both train and validation.



(a) (b) (c)

Figure 6: Graph of Loss, F1 and Accuracy (a) Loss train vs validation(b) Train-f1 vs Valiadtion-f1(c) Training accuracy vs Validation Accuracy

The confusion matrix can be envisioned using the heatmap function. It is used to analyze the quality of the output on the dataset. We are provided with 600 eye images and their corresponding intensity scale [0,1,2,3,4]. (Here 0- No DR, 1- Mild DR, 2- Moderate DR, 3- Severe DR, 4- Proliferative DR). This data to be used for model training and prediction should be made from test data. Normalized Confusion Matrix obtained from Test Data is shown in *figure 7*. This figure shows that the color of the diagonal line is dark and has higher values, indicating that many predictions are correct.

Usually, everyone prefers using traditional algorithms for the detection purpose, but we have used custom convolutional neural network of 3 layers, these layers are again bifurcated into different layers. The ratio of non-diabetic retinopathy images was more with the comparison of diabetic retinopathy images; hence there were a lot of obstacles in predicting the accuracy more precisely.

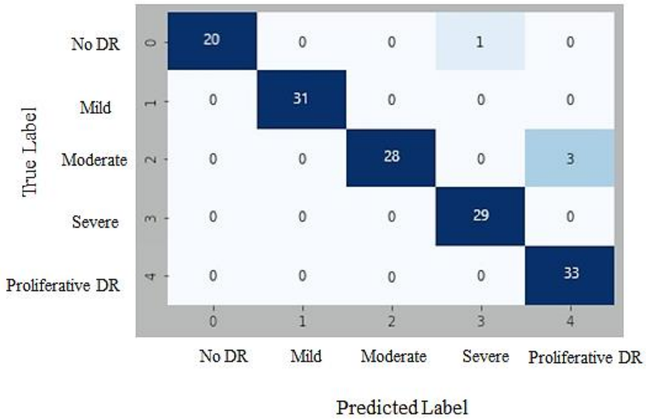


Figure 7: Confusion Matrix

Table 2 shows, accuracy classification report of experiment results

Table 2: Classification report

	precision	recall	f1-score	support
class 0 (NO DR)	1.00	0.95	0.97	21
class 1 (MILD DR)	1.00	1.00	1.00	31
class 2 (MODERATE DR)	1.00	0.90	0.95	31
class 3 (SEVERE DR)	0.97	1.00	0.98	29
class 4 (PROFERATIVE DR)	0.92	1.00	0.96	33
accuracy			0.97	145
macro avg	0.98	0.97	0.97	145
weighted avg	0.98	0.97	0.96	145

A large amount of data that is a course that leads to the overfitting of images in a single class, with a bit of a problem when you operate on a fundus image. For detecting the highest accuracy, we had to use a customized deep neural learning model. These customized models are pretty extended. Hence, for operating on large models, you have to use a high graphic card system. Though the dataset contains images in large numbers, the image quality was not clear used for training and testing purposes. Pre-processing of data was essential. As shown in *table 3*, the proposed result is compared with the method used in existing systems. The accuracy of the proposed system is more than the existing system.

Table 3: Comparative performance evaluation with existing approaches

Year & Ref.	Method	Accuracy
2019 [4]	ResNet50	61%
2020 [2]	Hybrid inception ResNet-v2	72%
2018 [6]	Particle swarn optimization	76%
2020 [1]	Convolutional neural network	80%
2019 [16]	Random forest classifier	80%
2020 [8]	DBN(Deep belief network)	82%
2020 [3]	DenseNet	87%
2017 [10]	Grey level co-occurrence matrix	90%
2017 [7]	Convolutional neural network	91%
2018 [13]	Linear Support vector machine	92%
2019 [5]	Deep Neural Network	93%
2017 [17]	Support vector machine	94%
2022[21]	CNN, VGG 16	90.6%
2022[22]	CNN & Transfer Learning	96%
Proposed Model	**CCNN**	**97.24%**

5. CONCLUSION

According to the experiment results acquired, it is concluded that Deep learning models are successful in such a case scenario of Diabetic Retinopathy detection. We tried 13 different varieties of configurations for a model and achieved the best accuracy of 97.24% for Deep learning algorithm. The main focus of our solutions is the trade-off between data volume and performance with a lightweight deep learning model. The novelty of our approach is the development of a lightweight Deep Convolution neural network architecture with less than 6 layers, and the appropriate hyperparameter settings for the efficient use of the MESSIDOR dataset. While, working on the MESSIDOR dataset, the amount of Non-Diabetic Retinopathy images was more as compared with Diabetic retinopathy images. So, while pre-processing the data we reduced the blur and unclear images. Our future scope will be to use all the data provided in the dataset rather than using only clear and transparent images.

REFERENCES

[1] Thiagarajan, Aswin Shriram et al.: Diabetic Retinopathy Detection using Deep Learning Techniques. Journal of Computer Science, vol. 16, pp. 305-313(2020).

[2] Akhilesh Kumar Gangwar and Vadlamani Ravi: Diabetic Retinopathy Detection Using Transfer Learning and Deep Learning. Evolution in Computational Intelligence, Advances in Intelligent Systems and Computing 1176, (2020).

[3] Heisler, Morgan et al.: Ensemble Deep Learning for Diabetic Retinopathy Detection Using Optical Coherence Tomography Angiography. Translational Vision Science & Technology, vol. 9, no.2 (2020).

[4] Wu, Yu-chen and Ze Hu: Recognition of Diabetic Retinopathy Basedon Transfer Learning. In: IEEE 4th International Conference on Cloud Computing and Big Data Analysis (ICCCBDA), pp. 398-401(2019).

[5] Arora, Mamta and MrinalPandey: Deep Neural Network for Diabetic Retinopathy Detection. In: International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon). Pp. 189-193(2019).

[6] Herliana, Asti et al.: Feature Selection of Diabetic Retinopathy Disease Using Particle Swarm Optimization and Neural Network. In: 6th International Conference on Cyber and IT Service Management (CITSM), pp. 1-4 (2018).

[7] Yu, Shuang et al.: Exudate detection for diabetic retinopathy with convolutional neural networks. In: 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 1744-1747(2017).

[8] Jadhav, A. et al.: Optimal feature selection-based diabetic retinopathy detection using improved rider optimization algorithm enabled with deep learning. Evolutionary Intelligence, pp.1-18 (2020).

[9] Shankar, K. et al.: Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning model. Pattern Recognition Letters, vol. 133, pp. 210-216 (2020).

[10] Roychowdhury, Sohini et al.: Automated detection of neovascularization for proliferative diabetic retinopathy screening. In: 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 1300-1303(2016).

[11] GeethaRamani, R. et al.: Automatic Diabetic Retinopathy Detection Through Ensemble Classification Techniques Automated Diabetic Retionapthy Classification. In: IEEE International Conference on Computational Intelligence and Computing Research, pp. 1-4 (2017).

[12] Kumar, S. and B. Kumar: Diabetic Retinopathy Detection by Extracting Area and Number of Microaneurysm from Colour Fundus Image. In 5th International Conference on Signal Processing and Integrated Networks (SPIN), pp. 359-364 (2018).

[13] Roy, Arisha et al.: Filter and fuzzy c means based feature extraction and classification of diabetic retinopathy using support vector machines. In: International Conference on Communication and Signal Processing (ICCSP), pp. 1844-1848 (2016).

[14] Chetoui, Mohamed and M. Akhloufi: Explainable Diabetic Retinopathy using EfficientNET*. In: 42nd International Conference of the IEEE Engineering in Medicine & Biology Society, pp. 1966-1969 (2020).

[15] Alzami, F. et al.: Diabetic Retinopathy Grade Classification based on Fractal Analysis and Random Forest. In: International Seminar on Application for Technology of Information and Communication (iSemantic) pp. 272-276(2019).

[16] Mane, D.T., Tapdiya, R. &Shinde, S.V. Handwritten Marathi numeral recognition using stacked ensemble neural network. Int. j. inf. tecnol. 13, 1993–1999 (2021). https://doi.org/10.1007/s41870-021-00723-w

[17] Mane, D. T. & Kulkarni, U. V. (2020). A Survey on Supervised Convolutional Neural Network and Its Major Applications. In I. Management Association (Ed.), Deep Learning and Neural Networks: Concepts, Methodologies, Tools, and Applications (pp. 1058-1071). IGI Global. https://doi.org/10.4018/978-1-7998-0414-7.ch059

[18] Dr. J. S. Awati, Prof. S.S. Patil and Dr. M.S. Kumbhar (2021), Smart Heart Disease Detection using Particle Swarm Optimization and Support Vector Machine. IJEER 9(4), 120-124. DOI: 10.37391/IJEER.090405.

[19] Menaouer, B., Dermane, Z., El HoudaKebir, N., &Matta, N. (2022). Diabetic Retinopathy Classification Using Hybrid Deep Learning Approach. SN Computer Science, Vol.3, Issue-367, 2022.

[20] Yasashvini, R. et. al. 2022). Diabetic Retinopathy Classification Using CNN and Hybrid Deep Convolutional Neural Networks. Symmetry, Vol. 14, 1932, pp-1-13.

[21] Yang, B., Li, T., Xie, H., Liao, Y., & Chen, Y.P. (2022). Classification of Diabetic Retinopathy Severity Based on GCA Attention Mechanism. IEEE Access, vol. 10, pp. 2729-2739.

[22] S., Sudha, et al. (2023). Detection and Classification of Diabetic Retinopathy Using Image Processing Algorithms, Convolutional Neural Network, and Signal Processing Techniques. Handbook of Research on Computer Vision and Image Processing in the Deep Learning Era, IGI Global, 2023, pp. 270-280.

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 11, Issue 2 | Pages 609-615 | e-ISSN: 2347-470X

[23] Messidor dataset: https://www.kaggle.com/competitions/diabetic-retinopathy-detection/data