



e-ISSN: 2319-8753 | p-ISSN: 2320-6710

# IJRSET

International Journal of Innovative Research in  
**SCIENCE | ENGINEERING | TECHNOLOGY**

# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 10, Issue 7, July 2021

**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA

Impact Factor: 7.569

9940 572 462

6381 907 438

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# Using a Convolutional Neural Network, Developing and Demonstrating Diabetic Retinopathy Diagnosis System based on Fundus Photography Images

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**ABSTRACT:** Diabetic retinopathy (DR) is the leading cause of disability from across world. In the formative development of DR, meanwhile, it can also be difficult to determine, and sometimes even seasoned specialists may find the process difficult. As a conclusion, a computer-assisted diagnostics methodology development of deep learning techniques is developed for evaluating multi-coloured retinal images to evaluate pertaining diabetes mellitus (RDR). A prototype Deep neural networks model with Siamese-like topology is now being developed while using gradient descent method. Diabetes Mellitus is a syndrome for which the arrangement of its red blood cells in the eye is affected. As a function, evaluating different diseases, including retinopathy, involves vascular removal. One of the demands which might arise is retinopathy.

**KEYWORDS:** CNN model, Deep learning, fundus images, diabetic Retinopathy prediction, Kaggle datasets.

## I. INTRODUCTION

Diabetic Retinopathy (DR) is one among leading common diabetic symptom that can also be developed by long-term diabetes mellitus and comprises retinal vascular damage. According to the survey, DR is rising to become the most of the world's leading increasing case for blindness and vision loss, responsible for 0.4 percent of the million cases of vision loss and 2.6 percent of million cases of severe stage of cases in 2015. In actuality, DR-related visual impairment may be managed or prevented if it is detected and treated swiftly sufficient. Because there are no Similar cases or indicators in the prior stages of the eye diabetes, many patients miss the best time to begin research indicate that if the eyes were treated and collect and process data and vigilantly, at least 90% of new cases might be eliminated. Diabetic retinopathy is more probable to create in individuals with diabetes who have had it for a long period. According to the International Diabetes Federation, 366 billion people around the globe had diabetes by 2011, with similar number anticipated to increase to 552% million of cases will increase by 2030. The number of populations suffering from type 2 diabetes has increased in every country. In low- and middle-income countries, diabetes affects 80% of the populace. India is in first place with a score of 195 percent. Diabetes mellitus (DM) is also one thought which frequently caused case among some Indian urban area people. research indicate that if the eyes were treated and collect and process data and vigilantly, at least 90% of new cases might be eliminated. Diabetic retinopathy is more probable to create in individuals with diabetes who have had it for a long period.

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affected by, diabetes by 80% of the populace. India is in first place with a score of 195 percent once thought to frequent among some Indian people from urban area.

As the condition in advances to moderate stage of NPDR, other DR symptoms may emerge, by including as abnormalities and the intraretinally and the microvascular cases of abnormalities. In severity and spread of the lesions worsens with severe stage in NPDR, and in the retinal blood will supply and becomes progressively decreased. The evolution of PDR lacking retinopathy would take 20 years or more, and through this slow rate, the DR can all be caught and detected early.

The duration and control of the diabetes are linked for the development and for progression of DR. And frequently asymptomatic in its previous stages of diabetes, but it may be cured soon. Both are shown that laser photographic can be reducing the risk factor of PDR related eye loss by more than half.

## II. RELATED WORK

A supervised classification is based about using labelled classes to characterize the test picture dataset from the training data. In general, class of classification which was handled by extracting the selected features from images and then determining classified classes using training data with labelled classes. The collected data were next used for classifying the severity of the diabetic retinopathy disorders. Diabetic retinopathy is formed and divided into five groups based on derived feature values, ranging from NPDR to PDR.

X. Zeng, H. Chen, Y, et.al.,[1], Here author uses the Transfer learning method to train a new deep learning model with Siamese kind of architecture is addressed. Unlike previous research, the proposed method takes binocular colour fundus images using as input and learns with their association to aid prediction. Again, author mentioned some pre-processing steps where in Image-pre-processing with Augmentation method used further. And performed between 2 eyes. He also done Randomly Flipping of the images of an eye of left and eye of right horizontally. Since because human eyes are structurally symmetrically mirror image. So, author used 3D formation of an image which is flipped horizontally and then exchanged for feeding into the network. When this model is resized and feeder into architecture called Siamese-like architecture. The system requires 2 fundus images from the left side eye for input and provides information from both eyes, either with or without DR. To even further assessed the effectiveness of the binocular design, a binocular model with five-class DR detection is trained and analysed on a 10% classification model. The accuracy of the model is 0.829, which is higher than that of current non-ensemble models.

Yadav, M. Sharma, et.al.,[2], Here in this paper author attempts to address This difficulty may be resolved by leveraging image recognition to not only detect the condition, but also to simplify the process by implementing a neural network to deliver results for a high number of patients in a short period. Here author used Exudates and other is Dot Haemorrhages are the two main components of the DR that are detected. To begin, we'll pre-process in the following ways:

1. Optic Disk Extraction.
2. Blood Vessel Extraction.
3. Exudates Detection.
4. Dot haemorrhage detection.

Here the author he uses only training images and are divided into four categories as Regular, Dot haemorrhages, Exudates, and Both. According to the author, this paper presents a method for detecting the DR by using computer vision and neural networks. It is a completely automated solution that will be applied in the future using open-source software such as OPENCV and TENSORFLOW to improve accuracy. For trainable datasets, the author achieved a 75 percent accuracy with this approach.

K. A. Anant, et.al.,[3], In this research paper author proposed the model with the technique for detecting texture and wavelet features using image pre-processing and by using data mining. The results were obtained for an image from the DIARETDB1 which is the standard database and further analysed using sensitivity, specificity, and accuracy parameters. Here author used pre-processing stage consists of the following stages: Image resizing, image sharpening, Laplace Edge Detection, and histogram thresholding are all options. DWT Transform and GLCM methodologies used. And he used KNN classifier which uses the Euclidean distance between images to determine whether they are normal or abnormal. The wavelet features are extracted from the binaries image using DWT. The features of the GLCM are



derived from the picture above. The texture features that were extracted for further classification are shown below. The method has a 97.75 percent accuracy rate, which can aid in the detection and prevention of diabetes.

M.Chetoui,et.al.,[4], In this paper the author used early symptoms of DR include haemorrhages, which are hard exudates, and also micro-aneurysms (HEM) which are detected in the eye. Which is important to diagnose HEM early in order to avoid blindness. And the Texture features like LBP have been commonly used in task for DR detection process. The author presented the use of various features with respect to DR in this paper, primarily Local Ternary Pattern and Local Energy-based Shape Histogram. They outperform LBP extracted features, as demonstrated for the classification of the derived histogram, Support Vector Machines are used.

Further for feature representation, a histogram-binning scheme is proposed and also the SVM is fed the LTP and LESH function vectors in order to analyse the patterns that better reflect the retinal fundus photographs of a normal eyes and an eye with symptoms of DR from the extracted vectors. Later, the trained DR models is used to classify images into DR and Non-DR categories. And finally, he acquired the result using LESH and LTP which performed well in detecting the case of DR in experimental experiments using the MESSIDOR database. Overall, using SVM with RBF kernels, LESH performed best, with an Accuracy of 93%.

Iyyanar p et.al.,[5], Here author designs his model and collects the involvement of microaneurysms, exudates, neovascularization, and haemorrhages increase the severity of diabetic retinopathy (DR). Diabetic retinopathy patients are divided into five stages: regular, mild, moderate, and extreme Non-proliferative or Proliferative diabetic retinopathy patients. He again used spatial analysis, as proposed deep learning method such as CNN provides high precision in the classification of these diseases. CNN is a dynamic architecture that is based on human visual perceptions. And suggested solution, among the other algorithms/frameworks involved, is to find a simpler and more optimised way to identify the image with minimal pre-processing techniques. The model was created using Google Net CNN architecture and image pre-processing techniques on a fundus data set from Eye PACS. He achieved a validation accuracy of 92% for 500 Eye PACS fundus images with a validation accuracy of No DR, Mild Severe NPDR, and PDR for a four-grade classification.

### III. METHODOLOGY

Convolutional neural networks (Classifier) are genetic algorithms with one or more convolutional layers that are also used for image processing and classification. Adding a magnitude measurement of weights to the loss function is a traditional procedure of smoothing. CNNs use a different approach to boundary conditions: they use the hierarchical structure in data to piece together again complex behavior from smaller, simpler patterns. As a result, CNNs stand towards to lowest of the interconnections and richness spectra. Individual cortical cell only sends signals in the spatial domain, a tiny percentage of the visual system. The antennae of hidden units require involvement, helping them to fill the whole visual system. Convolutional neural networks (Conv Nets or CNNs) are a subtype of neural network that is commonly used to detect and describe images.

As shown in the fig 1, The proposed model for predicting disease risk. It is obtained via the features of the two data types. The data types are included in the proposed model. The hospital dataset is made up of real-world data and is held in a data centre. The text data is primarily described in the in-patient portion. Unlike previous research, the proposed method takes binocular fundus pictures from as input and also learns their association to aid the prediction. The data collection, network design, and training method are the most critical components of a deep learning model.

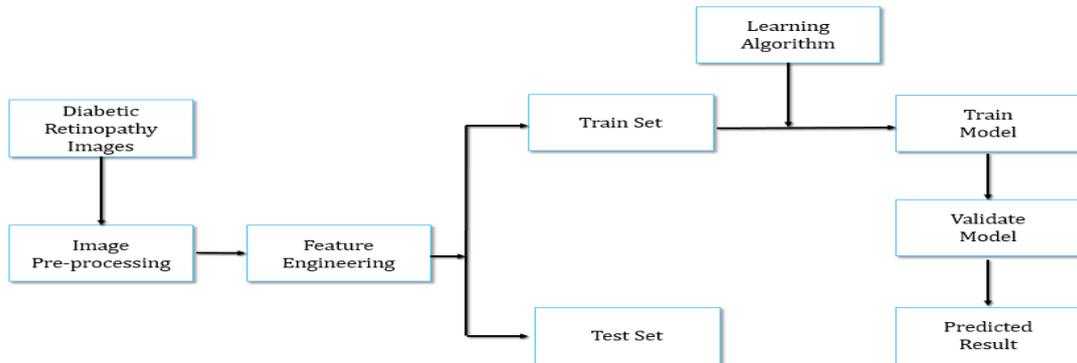


Figure 1: System Architecture

Convolutional neural networks (Conv Nets or CNNs) are a subtype of neural network that is commonly used to detect and describe images.

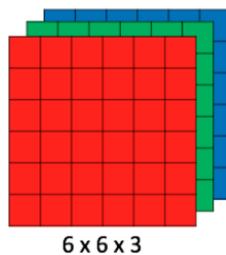


Figure 2 Array of RGB Matrix

As required to practice as well as test deep trying to learn CNN models, each input picture will be routed through a series of convolution stages using filters known as a host Pooling, data augmentation (FC), and the SoftMax function to identify an entity with statistical values between 0 and 1. To identify an element with probabilistic values between 0 and 1, combine connected layers (FC) and the SoftMax equation. The graphic below depicts the flow of CNN interpreting a feature map and exhibited characteristics based on values.

**CNN layers:**

Convnets involve significantly little from before the comparable to other image detection algorithms. This implies that the state will learn the filters that were traditionally hand-engineered in existing approaches. In order to create a Deep Neural Network topology, common layers are often used (DCNN). These CNN layers are further divided into sublayers as: *Convolutional Layer, Pooling Layer, ReLU Layer, Dropout layer, fully connected Layer, Classification Layer.*

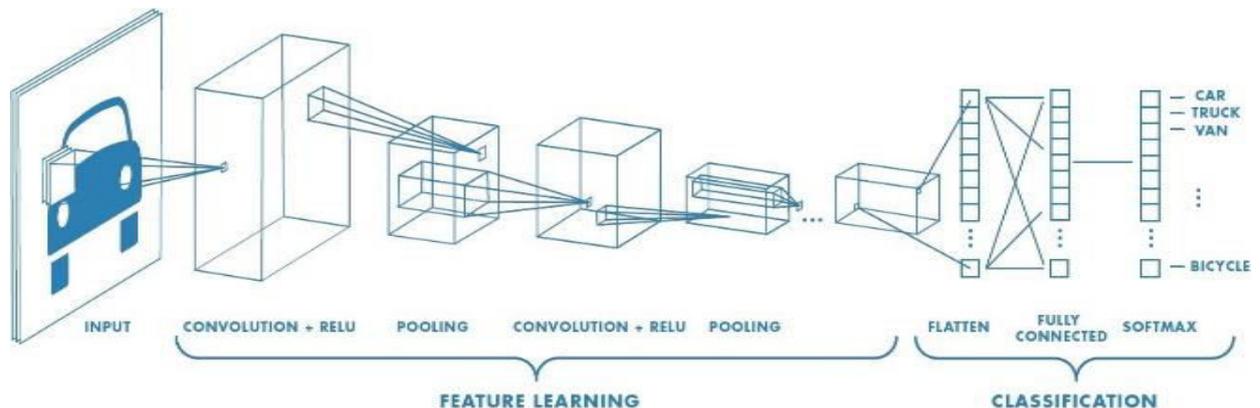


Figure 3 Convolution layers



**CONVOLUTIONAL LAYER :** This is the second and most fundamental layer, which is successfully applied after the input visual to be classed. For machine vision, deep convolution networks are being substantially built. The first design layer, convolutional, extracts main characteristics from a feature vector. Convolution teaches algorithms employing the actually imply item of input data to retain the work relationship between pixels. It's a two-input mathematical function that takes an image matrix in input and performs a filter or filter on it.

**POOLING LAYER:** Anything inhibits over-fitting by limiting the program's assumptions and calculations, which is one of the most common indicators and symptoms. When the images are too enormous, the pooled layering efficacy the parameters. Contains the number, also referred as reduction or down filtering, shrinks the file size while preserving valuable data.

**ReLU LAYER:** Is also known as Rectified Linear Unit used for layer is an activation function the model Architecture.

$$f(x) = \max(0, x)$$

- x – the neuron's input, as well as a ramp function
- The analytic function is a smooth approximation to a rectifier.

**DROPOUT LAYER:** The processing of the parameters generated according to each stacked layer is a key aspect of the deep neural networks. This might produce in over-fitting. To minimize future issues, certain neurons were discarded in the layer and effectively cascaded to the next layer.

**FULLY CONNECTED LAYER:** After the cumulates layer and max/average pooling layers, there is a completely integrated network. This layer even does high-level argumentation during categorization. A going into detail layer connects every neuron it incorporates to all transistors in the surrounding matrix from the max-pooling layer. We smoothed our sequencing into a vector and transmitted it to a completely integrated, analogous to a neural network, at the Convolution layers.

Which is shown in the chart below, the feature map matrix will be transformed into such a vector (x1, x2, x3...) Using the input images, we integrated these properties to create a picture.

**CLASSIFICATION LAYER:** The bottom layer after the multilayered or deep or several layers is a SoftMax which is the last layer that is piled at the end for describing the eyefundus picture, followed by the Convolutional layers output. Here, we will be having to choose between a single-class and then a multiclass grouping.

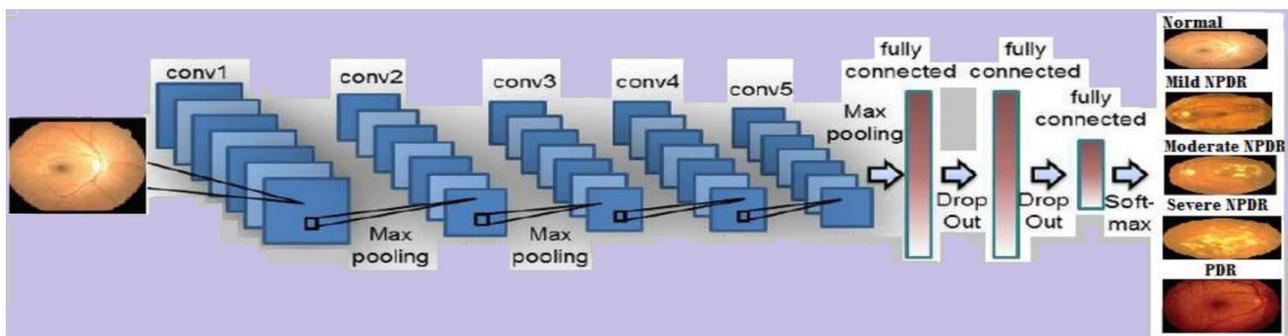


Figure 4 Classification of Diabetic Retinopathy

**Modules Description**

A module description contains specific information about the module and its supporting components that may be accessed in a variety of ways. we may read the supplied description directly, generate a brief html-description, or run an environment check for supporting components to see if all required types and services are present in the environment where they will be implemented.

- Image Acquisition and the Pre-processing steps
- Data Preparation and the Model construction

- Model training step
- Model testing and evaluation step

### Image Acquisition and Pre-processing steps

We will obtain data from an internet source in this module. We'll also resize the image for later usage. Picture resizing, also known as image scaling, is a geometric picture transformation that changes the size of an image using an image interpolation process. This image scaling procedure adjusts the absolute size of picture data by increasing or decreasing the resolution of a target picture. The image will be transformed to grayscale, and the computer will give a value to each pixel depending on its level of darkness.

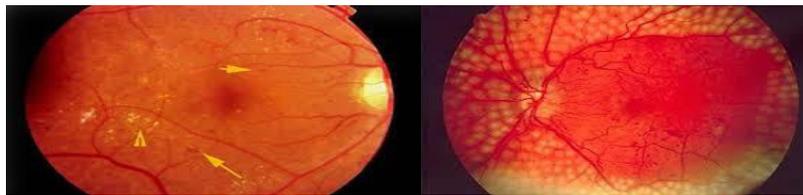


Figure 5 Image Acquisition and Pre-processing

### Data Preparation and Model construction.

Many times, individuals divide their dataset into two parts: train and test. They then set aside the Test set and pick X percent of their Train dataset as the true Train set and the remaining (100-X) percent as the Validation set at random. The strategy was once trained and checked on most of these distinct sets in turn, where X is a fixed value (say, 80%). As an end, we'll prepare data again for training and test using the same process. We can start building our neural network now that we've finished pre-processing. Also, because input of batch normalization layers should be two dimensional and the output of the convolution layer is four dimensional, we necessitate a flattening layer is between them and the output of the convolution layer.

### Model Training step

It's way to practice the model now that it's been created. We were able to create an artificial deep neural network enabling picture comprehension. The collection should then be divided in two sections: training sets and testing sets. Finally, we'll design and train the mode through using training samples.

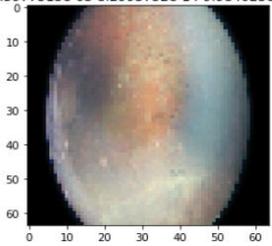
### Model Testing and Evaluation step

Model testing is available once the model has been trained and tested. A testing dataset of data are loaded at this step. Because the model has never encountered this data set, its genuine correctness will be confirmed. Finally, the model that has been saved may be utilized in the actual world. Model evaluation is the name of this step. This implies that the model can be applied to fresh data.

## IV. EXPERIMENTAL RESULTS

The performance evaluation aids in the prediction of human behaviour in screenshot images of the model. In the worst-case detection and best-case detection, the development of the model is demonstrated. Although this model is much faster to train and predict. It still requires a set of proposed regions for each input images.

```
In [64]: plt.imshow(img)
plt.title(single_result)
plt.show()

[5.2439959e-17 1.5977513e-03 8.2993752e-14 9.9840230e-01 1.5988252e-13]


In [65]: most_likely_class_index = int(np.argmax(single_result))
class_likelihood = single_result[most_likely_class_index]

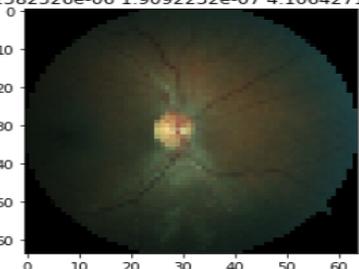
In [66]: most_likely_class_index
Out[66]: 3

In [67]: class_label = class_names[most_likely_class_index]

In [68]: print("Predicted class is {} - Confidence Score: {:.2f}".format(class_label, class_likelihood))
Predicted class is Proliferative_DR - Confidence Score: 0.998402
```

Figure 6 Test Results for Proliferative\_DR Class

```
In [158]: plt.imshow(img)
plt.title(single_result)
plt.show()

[4.4197681e-05 2.2582526e-06 1.9092232e-07 4.1064271e-03 9.9584693e-01]


In [159]: most_likely_class_index = int(np.argmax(single_result))
class_likelihood = single_result[most_likely_class_index]

In [160]: most_likely_class_index
Out[160]: 4

In [150]: class_label = class_names[most_likely_class_index]

In [126]: print("Predicted class is {} - Confidence Score: {:.2f}".format(class_label, class_likelihood))
Predicted class is Mild - Confidence Score: 1.000000
```

Figure 7 Test Results for Mild Class



	precision	recall	f1-score	support
0	0.72	1.00	0.84	264
1	0.76	1.00	0.86	551
2	1.00	0.43	0.60	495
3	0.95	1.00	0.97	78
4	0.95	0.99	0.97	85
accuracy			0.81	1473
macro avg	0.88	0.88	0.85	1473
weighted avg	0.86	0.81	0.78	1473

Figure 8 Classification Report for DR Classes

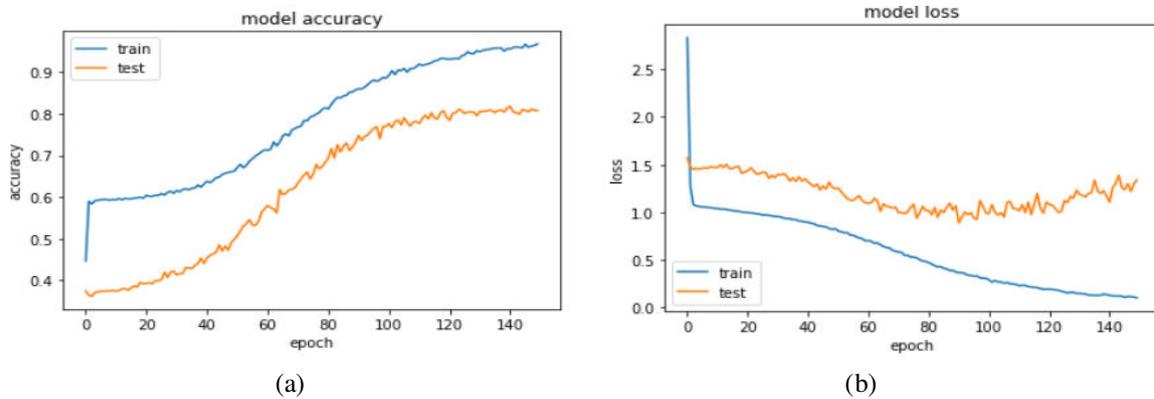


Figure 9 Represents the total accuracy and the loss of the model (a) Performance graph for model Accuracy and (b) Performance graph for model loss

V. CONCLUSION

In this work CNN is Based on multilayer prediction Algorithm which Consist for more image of Datasets fed into the CNN Network. Compared to Several typical prediction the CNN Algorithm predicts with good Accuracy as 97% in my project and value loss as 0.08%. The model trained by giving 400 images at a time for Pre-processing Model. When compared to the old system, the Multimodal prediction method is more accurate. Data properties are used in a convolutional neural network-based method. Determine the accuracy of each algorithm's forecast and use the multimodal disease risk prediction for the area. To increase the accurate performance of algorithms, use more relevant element selection approaches. In the future, this prediction performance model may be used for a larger range of multilayer detection models and approaches. It may also be utilized for a more relevant feature selection technique based on Algorithm to increase accuracy performance. This makes the CNN results outstanding, but we have plans to tailor our network to this specific purpose in the future.

REFERENCES

1. X. Zeng, H. Chen, Y. Luo and W. Ye, "Automated Diabetic Retinopathy Detection Based on Binocular Siamese-Like Convolutional Neural Network," in IEEE Access, vol. 7, pp. 30744-30753, 2019, doi: 10.1109/ACCESS.2019.2903171.
2. Yadav, M. Sharma and V. Saxena, "Diabetic retinopathy detection using feedforward neural network," 2017 Tenth International Conference on Contemporary Computing (IC3), 2017, pp. 1-3, doi: 10.1109/IC3.2017.8284350.
3. K. A. Anant, T. Ghorpade and V. Jethani, "Diabetic retinopathy detection through image mining for type 2 diabetes," 2017 International Conference on Computer Communication and Informatics (ICCCI), 2017, pp. 1-5, doi: 10.1109/ICCCI.2017.8117738.
4. M. Chetoui, M. A. Akhloufi and M. Kardouchi, "Diabetic Retinopathy Detection Using Machine Learning and



- Texture Features," 2018 IEEE Canadian Conference on Electrical & Computer Engineering (CCECE), 2018, pp. 1-4, doi: 10.1109/CCECE.2018.8447809.
5. Iyyanar p, parthasarathy j2, "DIABETIC RETINOPATHY CLASSIFICATION USING DEEP LEARNING FRAMEWORK" journal of critical reviews, ISSN- 2394-5125 vol 7, Issue 14, 2020
  6. Cun, Y.L., Boser, B., Denker, J.S., Howard, R.E., Habbard, W., Jackel, L.D., et al. Advances in neural information processing systems 2. Citeseer. ISBN 1-55860-100-7; 1990, p. 396-404.
  7. Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., Salakhutdinov, R.. Dropout: A simple way to prevent neural networks from overfitting. J Mach Learn Res 2014;15(1):1929-1958.
  8. Qummar, S., Khan, F. G., Shah, S., Khan, A., Shamshirband, S., Rehman, Z. U., ... Jadoon, W. (2019). A Deep Learning Ensemble Approach for Diabetic Retinopathy Detection. IEEE Access, 1-1. doi:10.1109 /access.2019.2947484
  9. S.Wang, et al, "Hierarchical retinal blood vessel segmentation based on feature and ensemble learning", Neurocomputing, International Journal of Computer Applications(0975-8887), Volume 121 – No.6,(2018)
  10. S.Giraddi, J Pujari, S.Seeri, "Identifying Abnormalities in the Retinal Images using SVM Classifiers", International Journal of Computer Applications(0975-8887), Volume 111 – No.6,(2017)
  11. Walter, T., Klein, J., Massin, P., & Erginay, A. (2016). "A contribution of image processing to the diagnosis of diabetic retinopathy-detection of exudates in color fundus images of the human retina". IEEE Transactions on Medical Imaging, 21(10), 1236-1243. doi:10.1109/tmi.2002.806290
  12. Akara sopharak, Bunny arit, uyyanonvara and sarah Barman [2017] "Automatic Exudate Detection from Non-dilated Diabetic Retinopathy Retinal Images Using Fuzzy C-means Clustering" sensors (Basel) 2017; 9(3): IEEE 2148-2161. Published online 2017 March 24. PMID: 22574005



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