Detection of Diabetic Retinopathy Using Convolutional Neural Network

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ABSTRACT: ***Images of the retina taken by a fundus camera are used to diagnose diabetic retinopathy which requires experienced optometrist to recognize the level of severity and significant features to reduce the time consumption and difficulty using complex grading. We suggest a convolutional neural network architecture in this paper to diagnose the diabetic retinopathy and accurately classify its severity by data augmentation which can recognize the characteristics like micro-aneurysm, hard exudates and haemorrhages. We train the data which is available on kaggle. We have a data set of 2755 images which is used in our proposed method to achieve an accuracy of 91.67% .***

KEYWORDS: ***convolutional neural networks, Image classification,Diabetic retinopathy,deep learning.***

1. INTRODUCTION

A disease of the retina known as diabetic retinopathy which can cause blurry vision and complete blindness. DR is a condition which can not be cured but treated at early stages. DR occurs with time and affects blood vessels in the retina.Due to increasing life-expectancy, modern lifestyle people become more prone to be diabetic.The diabetic person should get them tested once in a year which is costly. This is the reason behind proposing the CNN model through which DR patients do not need to visit the clinics.

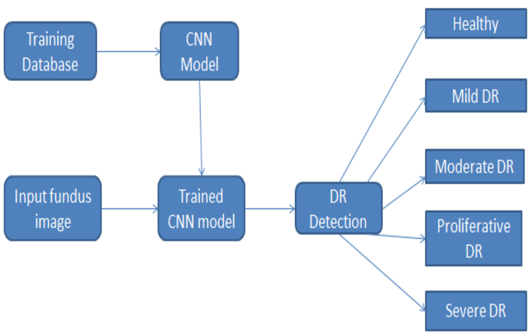
The reason behind recognizing the severity of DR as soon as possible is that it can not be cured. The classification of the numerous characteristics is a bit of a time taking process for technicians. Computers are able to achieve the classification of features much quickly.

Kth nearest neighbour classifiers and Support vector machine is being used extensively to identify the characteristics and determine the stage of DR. Most learning techniques for classification are two-class classifications for DR or no DR.

We propose a project in which there is a website for detecting DR.This website has the interface having a login page . After login, a user can choose a file or image of the fundus image. CNN is used as an algorithm for classifying the fundus images.A subset of deep learning known as convolutional neural networks (CNNs) has a notable track record for use in the medical stream for imaging..All the information about a user is collected as a database. MongoDB and NodeJS are used for back-end and front-end.

There are two main aims of achieving a desirable sensitivity and accuracy. This significantly classifies the problem into five classes which are
1. healthy
2.mild DR
3.moderate DR
4.proliferative DR
5. severe DR.
 Overfitting is also another concern for neural networks.Massive skewness is common in large datasets.

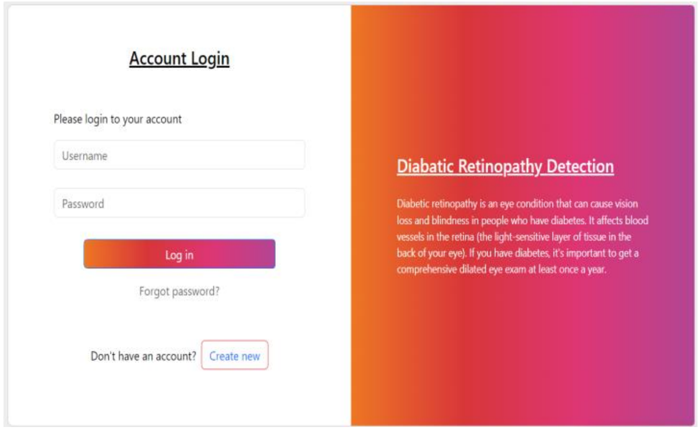
The evaluation of the model is done by confusion matrix and F_score.This model can classify the input image of retina into five classes.ANN can also be used for classification but accuracy came out lesser than CNN.

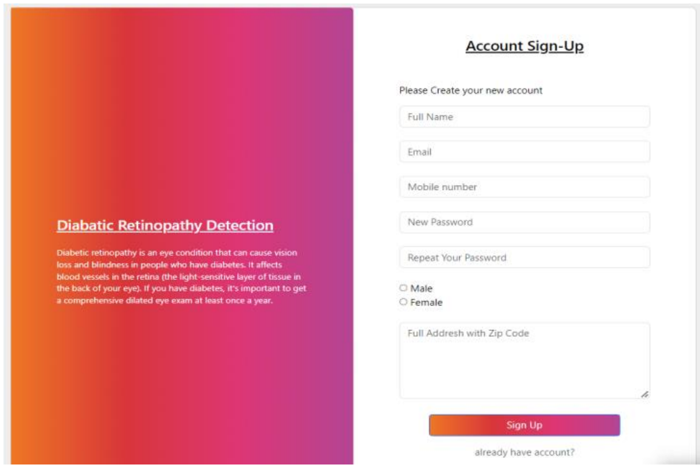


System Architecture

2. METHODOLOGY:

In this project, a user interface is provided to login and signup for those who already have an account. Pug template is used for front-end, Node.js and Express.js for backend and MongoDB is used for creating databases. Then merged the machine learning code and web development code using Node.js including Tensorflow.js.

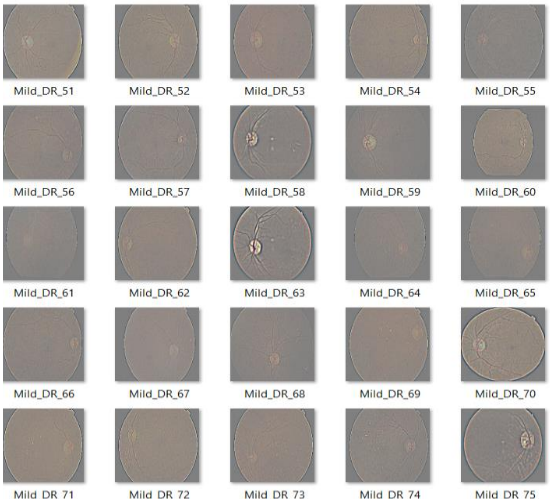




1.DATASET AND SOFTWARE: The dataset can be obtained from kaggle which is present all the time. Dataset is divided in five labels:

1. Healthy(1000 images of size 256 * 256).
2. Mild DR(370 images of size 256 * 256).
3. Moderate DR(900 images of size 256 * 256).
4. Proliferative DR(290 images of size 256 * 256).
5. Severe DR(190 images of size 256 * 256)

Keras is used with Tenserflow(https://www.tensorflow.org/install/pip) as back end. These two were picked because of their thorough documentation and speedy computation. The classification of an image takes about 0.04 seconds, making it possible to provide the patient with feedback in real time.



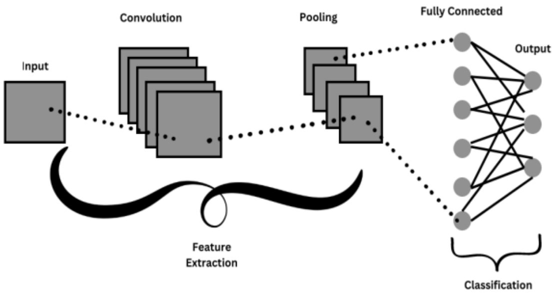
2. DATA EVALUATION: In this step, we are getting all the files by importing ‘os’. Then data is being evaluated by checking out the first five rows, finding the length, and doing some value counts.

3.DATA PRE-PROCESSING:The collection included pictures of patients in a range of age groups and lighting conditions. To normalise the size of each image and colour.The size of dataset of 2750 images are converted into an array of size 75*75*3. By importing labelEncoder from sk-learn we are getting the first five labels and then fit the model by using fit_transform. Then splitting of data is done by splitting train and test into 70% and 30% respectively.

```
        for f in file:
            img = cv2.imread(data_path+'/'+f)
            img = cv2.resize(img,(image_size,image_size))
            images.append(img)
            labels.append(i)

In [8]:  # Transform the image array to a numpy type

         images = np.array(images)
         images.shape
Out[8]:  (2750, 150, 150, 3)

In [9]:  images = images.astype('int64')/255.0

In [10]: images.shape
Out[10]: (2750, 150, 150, 3)

In [11]: from sklearn.preprocessing import LabelEncoder,OneHotEncoder

         y = fundus_df['dr_stage'].values
         print(y[:5])
         ['Healthy' 'Healthy' 'Healthy' 'Healthy' 'Healthy']

In [12]: # for y

         y_labelencoder = LabelEncoder()
         y = y_labelencoder.fit_transform(y)
         print(y)
         [0 0 0 ... 4 4 4]
```

4. CONVOLUTIONAL NEURAL NETWORK:

The network architecture known as a CNN is specifically utilised for picture classification and recognition. CNNs use different types of multi perceptrons layers to minimise preprocessing.. Convolutional networks' fundamental concept is derived from biological processes; it is comparable to the neuron network in the animal brain's visual cortex. Receptive field, a specific region of the visual field, is where single neurons respond. In the end, every single neuron's receptive field integrates to cover the entire visual field. Comparing CNN's preprocessing to other classification methods, it is quite minimal.. In contrast to traditional algorithms, which learn manually, the network learns the filters automatically. Convolutional layer, ReLu (Introducing NonLinearity) layer employing arctan or sigmoid function, Pooling layer, and fully linked layer make up the majority of its layers.

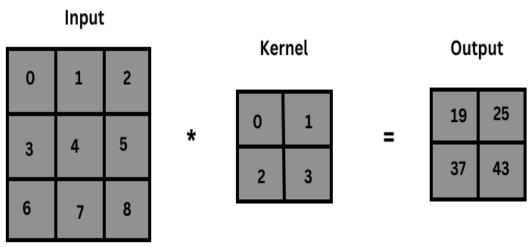


CNN Architecture

1.Convolutional Layer:

The main job of a CNN is to extricate characteristics from an image given by the user. It keeps the link between pixels while learning visual attributes using a tiny matrix known as strides of data given by user. The filter is moved over the input image to create a feature map. In contrast to filters, feature maps are provided separately for each input image.

 We are using Conv2D having filters of 32 , size of 5*5 ,activation of ‘relu’and input size of 75*75*3(same as array size).



Filter Matrix

2.Max Pooling Layer:

Max pooling process is mainly used to minimise the size of the image for retaining the most important features. Sub-sampling and down-sampling are other names for it.
Max, Average, Sum, and more types of pooling are available.The feature matrix's elements are replaced by their averages in average downsampling.
The feature matrix's elements are replaced by the maximum among them while using max down sampling. The elements of the feature matrix are replaced by the sum of the elements in sum down sampling. Max pooling typically produces the greatest results among the aforementioned pooling approaches in CNN, according to practical experience.It lessens the number of network parameters and calculations., which controls overfitting while also making the input depiction (feature dimension) smaller and easier to manage.

.

3. Fully Connected Layer:

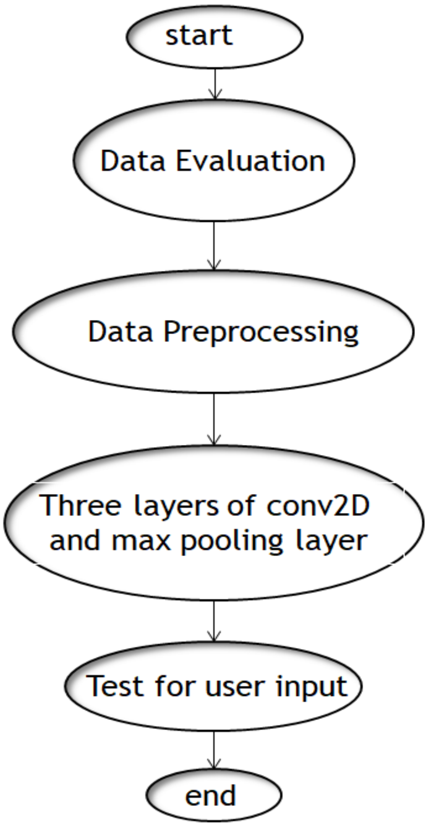
It’s primary duty is to classify the input image using the training dataset and these attributes. All of the output goals from this layer should total up to 1 when added together. The probabilistic classifier Softmax serves as the sigmoid function for the output layer. A vector of randomly generated real-value scores is compressed by the softmax function to a value between zero and one that adds up to 1.

This is done 3 times with different filters and only in the first layer we have to mention the input size.Densing is done by flattening and densing using activation softmax function.

```
In [4]:

cnn = keras.Sequential([

  layers.Conv2D(filters=32, kernel_size=(5,5), activation = 'relu' ,input_shape=(150,150
  layers.MaxPooling2D((2,2)),

  layers.Conv2D(filters=64, kernel_size=(5,5), activation = 'relu'),
  layers.MaxPooling2D((2,2)),

  layers.Conv2D(filters=128, kernel_size=(5,5), activation = 'relu'),
  layers.MaxPooling2D((2,2)),

  #dense

  layers.Flatten(),
  layers.Dense(128, activation = 'relu'),
  layers.Dense(10,activation = 'softmax')
])
```

5. EVALUATION AND TESTING: We are fitting the cnn model with epochs equal to 50 to increase the accuracy.

```
Epoch 41/50
83/83 [==============================] - 25s 296ms/step - loss: 0.4237 - accuracy: 0.8439
Epoch 42/50
83/83 [==============================] - 25s 301ms/step - loss: 0.3931 - accuracy: 0.8580
Epoch 43/50
83/83 [==============================] - 27s 321ms/step - loss: 0.3796 - accuracy: 0.8606
Epoch 44/50
83/83 [==============================] - 25s 296ms/step - loss: 0.3561 - accuracy: 0.8716
Epoch 45/50
83/83 [==============================] - 25s 298ms/step - loss: 0.3314 - accuracy: 0.8769
Epoch 46/50
83/83 [==============================] - 25s 296ms/step - loss: 0.3321 - accuracy: 0.8788
Epoch 47/50
83/83 [==============================] - 25s 298ms/step - loss: 0.2924 - accuracy: 0.9000
Epoch 48/50
83/83 [==============================] - 25s 298ms/step - loss: 0.3138 - accuracy: 0.8894
Epoch 49/50
83/83 [==============================] - 25s 299ms/step - loss: 0.2757 - accuracy: 0.9098
Epoch 50/50
83/83 [==============================] - 25s 302ms/step - loss: 0.2557 - accuracy: 0.9167

<tensorflow.python.keras.callbacks.History at 0x268ab27b7c0>
```



Flowchart of implementation

3. RESULTS:

The dataset has 2755 photos utilised for validation. According to the five-class problem,the accuracy is calculated by dividing the total number of true positive and true negative results by the total number of true positive, true negative, true positive, and false positive results

.The accurate classification of patients is how we determine accuracy. The trained network obtained 30% sensitivity and 91.67% accuracy. The network's classifications were denoted by the numbers 0 -healthy, 1 -mild DR, 2 -moderate DR, 3 -proliferative DR, and 4 -severe DR.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP}$$

4.COMPARATIVE ANALYSIS:

Name	Technique	Result	Type
Ratul Ghosh ,et. al.[1]	CNN using theano	85	DR/NO DR
Ratul Ghosh ,et. al.[1]	CNN using theano	95	5 CLASS
Xiaoliang Wang,et. al[2]	InceptionNet V3	63.23	5 CLASS
Yu Shang, et. al,[3]	CNN	91	DR/NO DR
Kwasigroch, et. al.[4]	CNN	51	5 CLASS
Kwasigroch, et. al.[4]	CNN	81	DR/NO DR
Li Xiaogang, et. al.[5]	CNN	92	DR/NO DR
Enrique Carrera,et. al.[9]	SVM	85	DR/NO DR
Arisha Roy, et. al.[10]	SVM	96.23	DR/NO DR
Ours	CNN	91.67	5 CLASS

5.FUTURE SCOPE:

1. Making a CNN model using image processing for extricating the attributes of the retina image. The resizing of the fundus images in the same dimensions as input to the CNN.Three layers of conv2D used to decrease the time and increase the accuracy.
2. Creating an interactive front end graphical user interface for the model using the free source Python package FLASK in order to improve human engagement for model deployment.
3. Raising the dimensions of the training data set and employing powerful GPUs to implement the model will increase accuracy.

6.CONCLUSION:

Using colour fundus pictures, a model is proposed for classifying DR stages according to severity. The effectiveness of CNN model is being evaluated using various indicators. The performance of the suggested model is satisfactory, accuracy comes out to be 91.67 percent for five class classification on the Kaggle dataset. The model retains the ability to be implemented as a user-interactive programme that can shorten the time needed for diagnosis from two weeks to one day.

REFERENCES

[1] Ghosh, Ratul, Kuntal Ghosh, and Sanjit Maitra. ”Automatic detection and classification of diabetic retinopathy stages using CNN.” 2017 4th International Conference on Signal Processing and Integrated Networks (SPIN). IEEE, 2017.

[2] Wang, Xiaoliang, et al. ”Diabetic Retinopathy Stage Classification Using Convolutional Neural Networks.” 2018 IEEE International Conference on Information Reuse and Integration (IRI). IEEE, 2018.

[3] Yu, Shuang, Di Xiao, and Yogesan Kanagasingam. ”Exudate detection for diabetic retinopathy with convolutional neural networks.” 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2017.

[4] Kwasigroch, Arkadiusz, Bartlomiej Jarzembinski, and Michal Grochowski. ”Deep CNN based decision support system for detection and assessing the stage of diabetic retinopathy.” 2018 International Interdisciplinary PhD Workshop (IP hDW). IEEE, 2018.

[5] Li, Xiaogang, et al. ”Convolutional neural networks based transfer learning for diabetic retinopathy fundus image classification.” 2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI). IEEE, 2017.

[6]https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/?fbclid=IwAR0S2Lw6ntGyl3KxyPYZQBnCQRHT5 0t5GQG6OV NEpy5MXcC0s11LYkDUzY.

[7] https://en.wikipedia.org/wiki/Rectifier(neuralnetworks).

[8] Zheng, Zejia, Zhu Li, and Abhishek Nagar. ”Compact Deep Neural Networks for Device-Based Image Classification.” Mobile Cloud Visual Media Computing. Springer, Cham, 2015. 201-217.

[9] Carrera, Enrique V., Andrs Gonzlez, and Ricardo Carrera. ”Automated detection of diabetic retinopathy using SVM.” 2017 IEEE XXIV International Conference on Electronics, Electrical Engineering and Computing (INTERCON). IEEE, 2017.

[10] Roy, Arisha, et al. ”Filter and fuzzy c means based feature extraction and classification of diabetic retinopathy using support vector machines.” 2017 International Conference on Communication and Signal Processing (ICCSP). IEEE, 2017.

[11]. Kocur, I., Resnikoff, S.. Visual impairment and blindness in europe and their prevention. Brit J Ophthalmol 2002;86(7):716–722.

[12]. Evans, J., Rooney, C., Ashwood, F., Dattani, N., Wormald, R.. Blindness and partial sight in England and Wales: April 1990-march 1991. Health Trends 1996;28(1):5–12.

[13]. Sector, S.P., et al. State of the nation 2012. Diabetes UK 2013;.

[14] . Sculpher, M., Buxton, M., Ferguson, B., Spiegelhalter, D., Kirby, A.. Screening for diabetic retinopathy: A relative cost-effectiveness analysis of alternative modalities and strategies. Health Econ 1992;1(1):39–51.

[15]. Benbassat, J., Polak, B.C.. Reliability of screening methods for diabetic retinopathy. Diabetic Med 2009;26(8):783–790.

[16]. Grading diabetic retinopathy from stereoscopic colour fundus photographs an extension of the modified air lie house classification: Etdrs report number 10. Ophthalmology 1991;98(5):786–806.

[17]. Philip, S., Fleming, A.D., Goatman, K.A., Fonseca, S., Mcnamee, P., Scotland, G.S., et al. The efficacy of automated disease/no disease grading for diabetic retinopathy in a systematic screening programme. Brit J Ophthalmol 2007;91(11):1512–1517.

[18]. Fleming, A.D., Philip, S., Goatman, K.A., Prescott, G.J., Sharp, P.F., Olson, J.A.. The evidence for automated grading in diabetic retinopathy screening. Current Diabetes Reviews 2011;7:246 – 252.

[19]. Mookiah, M.R.K., Acharya, U.R., Chua, C.K., Lim, C.M., Ng, E., Laude, A.. Computer-aided diagnosis of diabetic retinopathy: A review. Comput Biol Med 2013;43(12):2136–2155.

[20]. Fukushima, K.. Neocognitron: A self-organising neural network model for a mechanism of pattern recognition unaffected by shift in position. Biol Cybern 1980;36(4):193–202.
[21]. Cun, Y.L., Boser, B., Denker, J.S., Howard, R.E., Habbard, W., Jackal, L.D., et al. Advances in neural information processing systems 2. Citeseer. ISBN 1-55860-100-7; 1990, p. 396–404.
[22]. 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.
[23]. Nair, V., Hinton, G.E.. Rectified linear units improve restricted boltzmann machines. In: Proceedings of the 27th International Conference on Machine Learning (ICML-10). 2010, p. 807–814.
[24]. Ioffe, S., Szegedy, C.. Batch normalisation: Accelerating deep network training by reducing internal covariate shift. arXiv 2015;URL: arXiv:1502.03167.
[25]. He, K., Zhang, X., Ren, S., Sun, J.. Deep residual learning for image recognition. arXiv 2015;URL: arXiv:1512.03385.
[26]. Gardner, G., Keating, D., Williamson, T., Elliott, A.. Automatic detection of diabetic retinopathy using an artificial neural network: a screening tool. Brit J Ophthalmol 1996;80(11):940–944.
[27]. Nayak, J., Bhat, P.S., Acharya, R., Lim, C., Kagathi, M.. Automated identification of diabetic retinopathy stages using digital fundus images. J Med Syst 2008;32(2):107–115.
[28]. Acharya, R., Chua, C.K., Ng, E., Yu, W., Chee, C.. Application of higher order spectra for the identification of diabetes retinopathy stages. J Med Syst 2008;32(6):481–488.
[29]. Acharya, U., Lim, C., Ng, E., Chee, C., Tamura, T.. Computer-based detection of diabetes retinopathy stages using digital fundus images. P I Mech Eng H 2009;223(5):545–553.
[30]. Adarsh, P., Jeyakumari, D.. Multiclass svm-based automated diagnosis of diabetic retinopathy. In: Communications and Signal Processing (ICCSP), 2013 International Conference on. IEEE; 2013, p. 206–210.
[31]. Gurcan OF, Beyca OF, Dogan O. A Comprehensive Study of Machine Learning Methods on Diabetic Retinopathy Classification. Int J Comput Intell Syst. 2021;14(2):1132–1141. doi: 10.2991/ijcis.d.210316.001. [CrossRef] [Google Scholar]
[32]. Hattiya T, Dittakan K, Musikasuwan S. Diabetic Retinopathy Detection Using Convolutional Neural Network: A Comparative Study on Different Architectures. Mahasarakham Int J Eng Technol. 2021;7(1):50–60. doi: 10.14456/mijet.2021.8. [CrossRef] [Google Scholar]
[33]. He K, Zhang X, Ren S, Sun J (2016) Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp 770–778. 10.1109/CVPR.2016.90
[34]. Howard, AG, Zhu, M, Chen, B, Kalenichenko, D, Wang, W, Weyand, T, Andreetto, M, Adam, H (2017) MobileNets: efficient convolutional neural networks for mobile vision applications, arXiv:1704.04861v1 [cs.CV], pp 1–9. 10.48550/arXiv.1704.04861.
[35]. Huang G, Liu Z, Van Der Maaten L, Weinberger KQ (2017) Densely connected convolutional networks. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 4700–4708, arXiv:1608.06993v5 [cs.CV]. 10.48550/arXiv.1608.06993.
[36].. Das S, Kharbanda K, Suchetha M, Raman R, Edwin DD. Deep learning architecture based on segmented fundus image features for classification of diabetic retinopathy. Biomed Signal Process Control. 2021;68:1–10. doi: 10.1016/j.bspc.2021.102600. [CrossRef] [Google Scholar].
[37]. Das D, Biswas SK, Bandyopadhyay S. A critical review on diagnosis of diabetic retinopathy using machine learning and deep learning. Multimed Tools Appl. 2022;23:1–43. doi: 10.1007/s11042-022-12642-4. [PMC free article] [PubMed] [CrossRef] [Google Scholar]
[38]. Deepa V, Kumar CS, Cherian T (2021) Ensemble of multi-stage deep convolutional neural networks for automated grading of diabetic retinopathy using image patches, Journal of King Saud University –Computer and Information Sciences, pp 1–11 10.1016/j.jksuci.2021.05.009
[39]. Deepa, V, Kumar, SC, Cherian, T (2022) Automated grading of diabetic retinopathy using CNN with hierarchical clustering of image patches by siamese network, Physical and Engineering Sciences in Medicine, pp.1–13 10.1007/s13246-022-01129-z [PubMed]
[40]. Dong, B, Wang, X, Qiang, X, Du, F, Gao, L, Wu, Q, Cao, G, Dai, C (2022) A Multi-Branch Convolutional Neural Network for Screening and Staging of Diabetic Retinopathy Based on Wide-

Field Optical Coherence Tomography Angiography, IRBM, pp.1–7 10.1016/j.irbm.2022.04.004.
[41]. Ege BM, Hejlesen OK, Larsen OV, Møller K, Jennings B, Kerr D, Cavan DA. Screening for diabetic retinopathy using computer based image analysis and statistical classification, Comput. Methods Programs Biomed. 2000;62(3):165–175. doi: 10.1016/S0169-2607(00)00065-1. [PubMed] [CrossRef] [Google Scholar]
[42]. Fadzil, MHA, Ngah, NF, George, TM, Izhar, LI, Nugroho, H, Nugroho, HA (2010) Analysis of foveal avascular zone in colour fundus images for grading of diabetic retinopathy severity, 32nd Annual International Conference of the IEEE Engineering in Medicine and Biology, pp. 5632–5635, 10.1109/IEMBS.2010.5628041 [PubMed]
[43]. Fadzil MHA, Izhar LI, Nugroho H, Nugroho HA. Analysis of retinal fundus images for grading of diabetic retinopathy severity. Med Biol Eng Comput. 2011;49(6):693–700. doi: 10.1007/s11517-011-0734-2. [PubMed] [CrossRef] [Google Scholar]
[44]. Fan GF, Zhang LZ, Yu M, Hong WC, Dong SO. Applications of random forest in multivariable response surface for short-term load forecasting. Int J Electr Power Energy Syst. 2022;139:1–30. doi: 10.1016/j.ijepes.2022.108073. [CrossRef] [Google Scholar]
[45]. Fong DS, Aiello L, Gardner TW, King GL, Blankenship G, Cavallerano JD, Ferris FL, Klein R. Retinopathy in diabetes. Diabetes Care. 2004;27(1):84–87. doi: 10.2337/diacare.27.2007.S84. [PubMed] [CrossRef] [Google Scholar]
[50]. Goh JKH, Cheung CY, Sim SS, Tan PC, Tan GSW, Wong TY. Retinal imaging techniques for diabetic retinopathy screening. J Diabetes Sci Technol. 2016;10(2):282–294. doi: 10.1177/1932296816629491. [PMC free article] [PubMed] [CrossRef] [Google Scholar]
[51]. Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, Venugopalan S, Widner K, Madams T, Cuadros J, Kim R, Raman R, Nelson PC, Mega JL, Webster DR. Development and validation of a deep learning algorithm for detection of diabetic Retinopathy in retinal fundus photographs. JAMA. 2016;316(22):2402–2410. doi: 10.1001/jama.2016.17216. [PubMed] [CrossRef] [Google Scholar]