Detection of Diabetic Retinopathy Using Integrated Deep Learning with Image Processing Technique

Preenon Bagchi*, Rushikesh Jagtap, Shivprasad Ravate, Shivali Harke

Department of Bioinformatics, Institute of Biosciences & Technology, MGM University Chh. Sambhajinagar
*Corresponding author, E-mail: pbagchi@mgmu.ac.in

Abstract

This study aims to diagnose diabetic retinopathy from retinal fundus images using a hybrid solution method. To be more specific, the hybrid approach relies on combining deep learning and image processing to achieve better outcomes. Reliable diabetic retinopathy (DR) detection from digital fundus images is considered an open problem in medical image processing, requiring the development of alternative solutions. Blindness and visual loss can result from DR. This study employs a radial basis function (RBF) neural network classifier to identify retinal images as either disease-related or non-drug-related automatically. Diabetic retinopathy (DR), which causes vision-impairing retinal lesions, is commonly associated with diabetes mellitus. If it is not detected in time, it may result in blindness. Early diagnosis and treatment of DR can help prevent vision loss. Deep learning has emerged as one of the most popular methods recently, showing improved performance across a wide range of applications, particularly in the analysis and classification of medical images. Due to their great effectiveness, convolutional neural networks are increasingly utilized as a deep learning technique in medical image analysis. Image processing is used in the study's suggested solution approach. A convolutional neural network is then classified to carry out the diagnosis. The EYEPACS database's 33000 retinal fundus images were used to validate the technique. Model for deep learning a thorough approach was used to train and assess model AlexNet for the detection of diabetic retinopathy. The model accuracy is 0.7349, and the results demonstrate noteworthy performance metrics and successful accurate classification.

Keywords**:** *Image processing, Fundus imaging, Diabetic retinopathy, Radial basis function, Deep learning, Machine learning, Convolutional neural network, EYEPACS, AlexNet*

1. Introduction

Approximately 93 million people worldwide are estimated to have diabetic retinopathy, making it the largest cause of blindness among working-age adults globally (Yau et al., 2012, International Diabetes Federation). Currently impacting 463 million people globally, diabetes mellitus is expected to affect 700 million by 2045, making it a major public health concern. Diabetic retinopathy (DR) is the most common type of diabetes-related eye illness, affecting at least one-third of people with diabetes. The two primary categories of diabetic retinopathy (DR) are non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). The advanced form of retinal disease is known as PDR. The early stage retinopathy is called PDR. Blood vessels, micro- aneurysms (MA), exudates, and hemorrhages are clinical signs of DR (Mookiah et al., 2013). Even though the early phases of diabetic retinopathy are mainly asymptomatic, during this time neuronal retinal damage and clinically undetectable micro vascular alterations occur. Therefore, patients with diabetes require routine eye screenings since prompt identification and treatments of the problem are crucial. Patients with diabetes, therefore, need to get regular eye exams because it is critical to diagnose and treat the condition as soon as possible. In order to determine who needs to be sent to an ophthalmologist for additional testing, automated screening helps alleviate this lack of access. The majority of current techniques, however, concentrate on recognizing retinal lesions, either singularly or in

combination, typically by taking advantage of extremely particular visual features. While most existing approaches concentrate on using handcrafted feature engineering to identify retinal lesions, more recent methods that use deep learning try to capture collective discriminative patterns of lesions in order to simplify the diagnosis process. Certain characteristics of diabetic retinopathy lesions, like brightness, size, and form, are searched for by those features. Modern techniques that capture collective discriminative patterns of lesions simplify such complexity (Einstein, Podolsky, & Rosen, 1935).

The fundamental idea behind hierarchical approaches, sometimes referred to as "lesion-first, referral-later," is that referability cannot be determined without first detecting lesions. However, the efficiency of existing deep learning systems is questionable, especially when it comes to their reliance on direct pixel inference for decision-making based on images. The difficulty of early DR detection is further compounded by global differences in the availability of ophthalmologists, with fewer specialists accessible in underprivileged locations. A study conducted before claimed that six countries—China, the United States, Russia, Japan, Brazil, and India—accounted for half of the world's 205,000 ophthalmologists. Less than one ophthalmologist is found in 23 countries, fewer than four in 30 countries, fewer than 25 in 48 countries, and more than 100 in 18 countries per million inhabitants, according to earlier studies (Rosas-Romero, Martínez-Carballido, Hernández-Capistrán, & Uribe-Valencia, 2015).

During the early stages of diabetic retinal dilation (DR), pericyte loss and degeneration cause visible micro aneurysms on the retina. Intraregional haemorrhages, soft and hard exudates, intraregional microvascular abnormalities (IRMA), venous beading, and venous loops or reduplication are additional diseases associated with non-papilledema retina (NPDR). Lastly, the presence of neovascularization—, the development of new retina vessels to existent ones due to ischemia—is the basis for differentiating between non-proliferative and proliferative diabetic retinopathy (Logue, 2010).

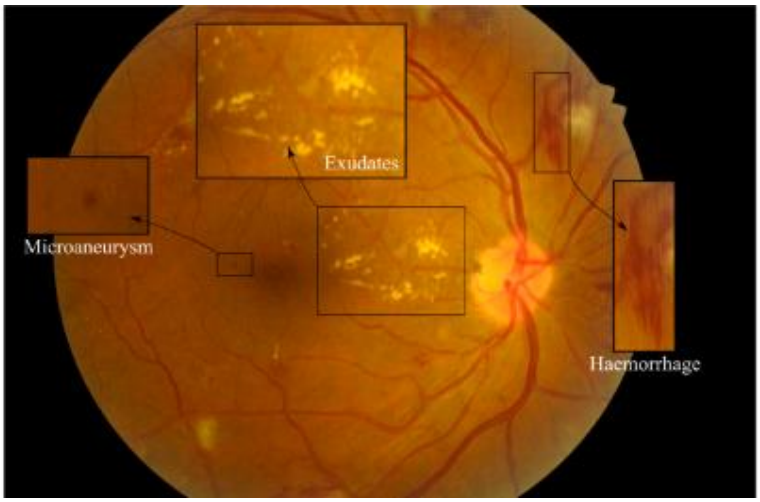


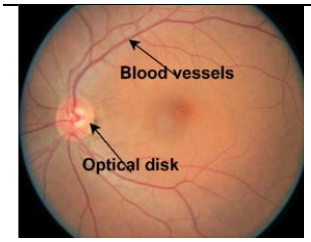
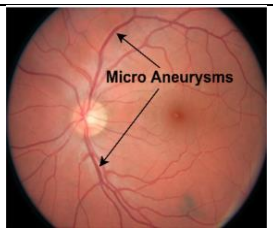
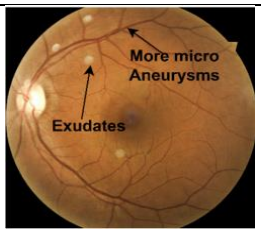
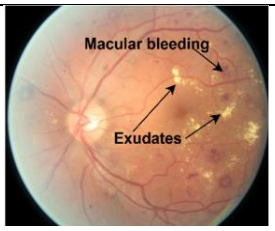
Figure 1 Indicative diabetic retinopathy lesions on a fundus image

A representative fundus picture of a retina is shown with several lesions in the above Fig.1 Diabetic macular edema (DME) is the most prevalent cause of blindness and can occur at any stage of diabetic retinopathy. Abnormalities such as exudates within one disc diameter of the fovea center, exudates within the macula, retinal thickening within one disc diameter of the fovea center, and micro-aneurysms or hemorrhages within one disc diameter of the fovea center are associated with the presence of edema (Lois, McCarter, O'Neill, Medina, & Stitt, 2014).

The following stages are where the suggested method helps: preprocessing, picture augmentation, extraction of ROI, and ophthalmic characteristics as given in Fig. 2. (Blood vessels, exudates, and micro-aneurysms). Following the identification of ocular characteristics, the method evaluated if the fundus image

was DR or not(Mookiah et al., 2013). Table 1 shows how the NPDR is categorized as mild, moderate and severe when certain ocular characteristics are present.

Table 1: NPDR classification and their features

Normal	Mild	Moderate	Severe
			
No Disease Found	Localized swelling of the small blood vessels in the retina (microaneurysms)	Mild NPDR plus small bleeds (dot and blot hemorrhages) leaks (hard exudates).	Moderate NPDR plus further damage to blood vessels (interetinal hemorrhages, venous beading).

2. Objectives

1) To enhance quality, contrast variations, and standardize image sizes.
2) To develop integrated deep learning model architecture that combines image processing techniques with deep neural networks.
3) To train the model on the preprocessed retinal image datasets to classify images into normal and diabetic retinopathy classes.
4) To translate the developed model into a practical tool for diabetic retinopathy screening in clinical settings.

3. Materials and Methods

3.1 Dataset: The 33,000 retinal fundus photos in the EYEPACS database were used to validate the method. Specifically, AlexNet, a deep learning model, was trained and evaluated on these images in order to identify diabetic retinopathy. This method guaranteed a comprehensive assessment of the model's functionality and its capacity to recognize diabetic retinopathy lesions in retinal pictures. These images showcase a variety of conditions related to diabetic retinopathy, ranging from normal to severe stages of the disease. The existence and severity of diabetic retinopathy are indicated by labels in the dataset. This dataset was utilized by us for this research. Therefore, the careful selection of this dataset aims to facilitate the development of advanced machine learning algorithms for early identification and detection of diabetic retinopathy. Researchers seeking to enhance automated methods for early detection will find immense value in the Diabetic Retinopathy Detection Dataset on Kaggle at https://www.kaggle.com/c/diabetic-retinopathy-detection/data. This dataset has been carefully selected to aid in the creation of cutting-edge machine learning algorithms for the early identification and detection of diabetic retinopathy. Researchers looking to enhance automated methods for the early identification and detection of diabetic retinopathy will find great value in the Diabetic Retinopathy Detection Dataset on Kaggle.

3.2 Python Libraries: Several Python libraries were essential to our study, which examined diabetic retinopathy detection. These included necessary libraries like pathlib for path management; random and datetime for randomization and timestamping; cv2 for image processing; NumPy for numerical operations;

and matplotlib. pyplot and matplotlib.image for visualization. Other libraries included OS and Shutil for file handling and operating system interactions. Seaborn also offered statistical insights, and signal processing was made easier by scipy.signal. Notably, TensorFlow—which includes Keras for model building, tensorflow_hub for pre-trained models, and various modules for configuring neural networks—was a major component of our research. We added ImageDataGenerator for data augmentation and sklearn.metrics for model development to our toolkit to ensure smooth data handling, image manipulation, and advanced machine learning model development and assessment for diabetic retinopathy detection.

3.3 Jupyter Platform: Throughout our research, the Jupyter Platform became a key tool because it provides an interactive computing environment that makes it easy to integrate code, graphics, and documentation. By enabling the seamless execution of Python scripts and the investigation of data-driven discoveries, the use of Jupyter Notebooks promoted collaborative and repeatable research.

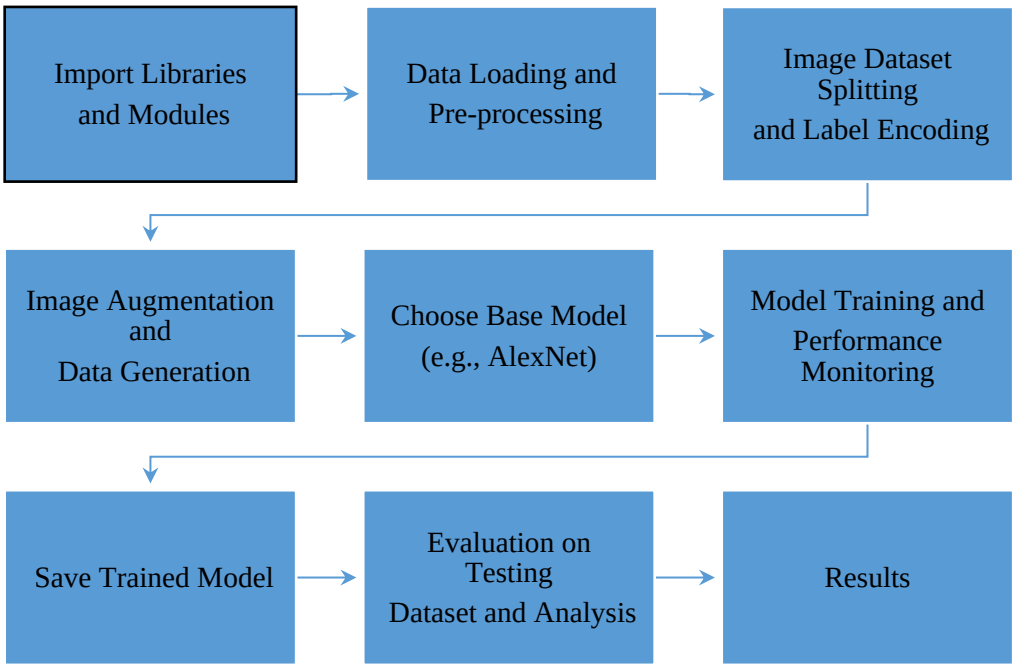


Figure 2 CNN step followed for detection

4. Results and Discussion

4.1 A thorough methodology was used to train and assess the deep learning models, especially AlexNet as suggested by LeCun et al. (2015), for the identification of diabetic retinopathy. With the model's stated accuracy of 0.7349, the results showed a notable degree of success in accurate classification.

One retinal image that has been pre-processed using the dataset's image pre-processing function is a crucial component of the output that is displayed. The resulting grayscale picture, shown in Fig. 3, has better contrast and makes fine details in the retinal structure more visible. The illustration shows how pre-processing methods can improve image quality and draw attention to important details, which may help with the severity classification and analysis of diabetic retinopathy in later stages. This particular example shows how the preprocessing stage can improve image quality and highlight important details. It is apparent that these improvements have the potential to be useful, and that they will have a favorable effect on the later phases of the diabetic retinopathy severity classification and analysis.

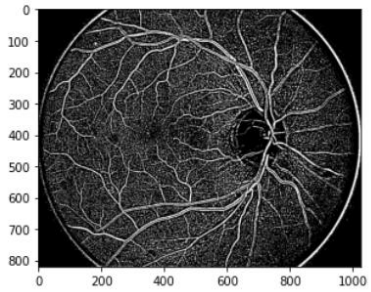


Figure 3 Preprocessing stage of grayscale image

The research underscores the critical impact of meticulous data pre-processing, including label conversion, and image enhancement techniques such as the Wiener filter and CLAHE. Additionally, the use of image augmentation through data generators contributed to enhanced model generalization and performance.

After Contrast Limited Adaptive Histogram Equalization (CLAHE) processing, a portion of the image dataset is displayed in the visualizations that are given. The grid-formatted figures show fifty randomly chosen retinal images that were all processed in Fig. 4 using the CLAHE method. Critical features in the images are better visible and have more contrast, owing to the grayscale representations (Pires et.al., 2014).

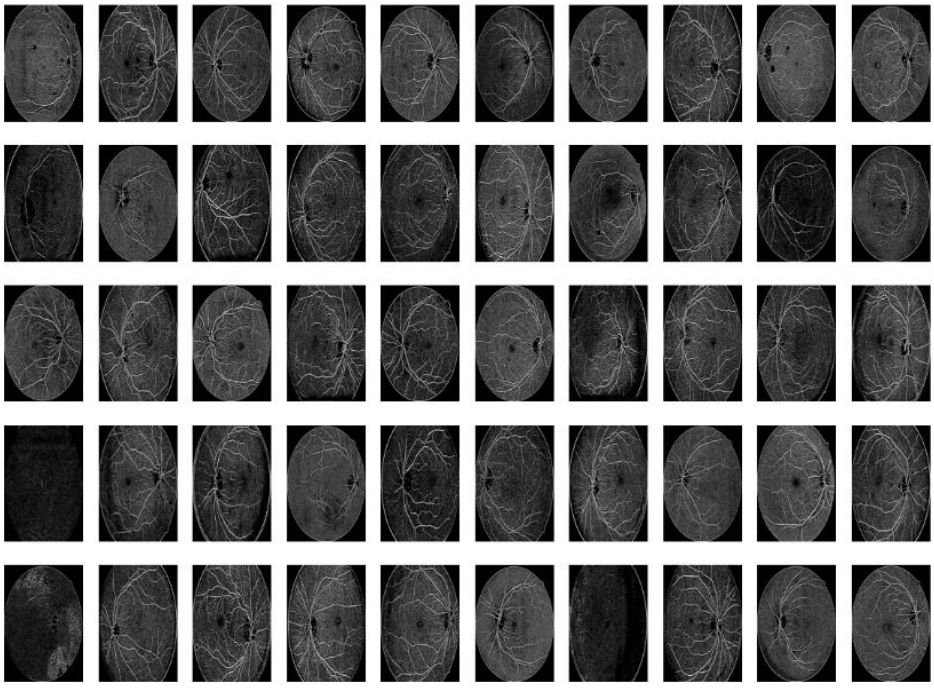


Figure 4 Image dataset from CLAHE processed image.

Retinal images from five different classes—No_DR (no diabetic retinopathy), Mild, Moderate, Severe, and Proliferate_DR—make up the dataset used in this study. Preprocessing was used to improve the images for the classification of diabetic retinopathy. This involved the use of Contrast Limited Adaptive Histogram Equalization (CLAHE), which raises the contrast and makes subtle features more visible, and Wiener filtering, which sharpens images and lowers noise as seen in Fig. 5. In order to guarantee that the machine learning models that came after would have access to high-quality input data, these pre-processing stages highlighted relevant image features. This will enable a more precise and reliable classification of the severity levels of diabetic retinopathy.

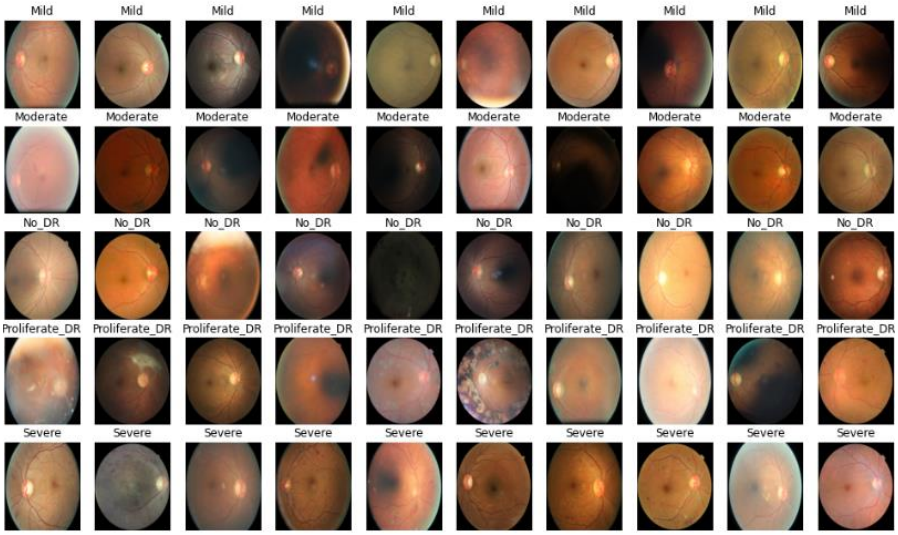


Figure 5 Image dataset randomly selected from the dataset

The model summary summates the complex architecture of the AlexNet, including the layer configuration, the output shapes of each layer, and the total number of trainable parameters. An informative synopsis of AlexNet model's architecture and parameters can be found in its summary. A sequence of convolutional, max-pooling, and fully connected layers make up the model. The performance metrics that are displayed for the AlexNet model offer a significant understanding of the model's training and validation process as given in Fig. 6.

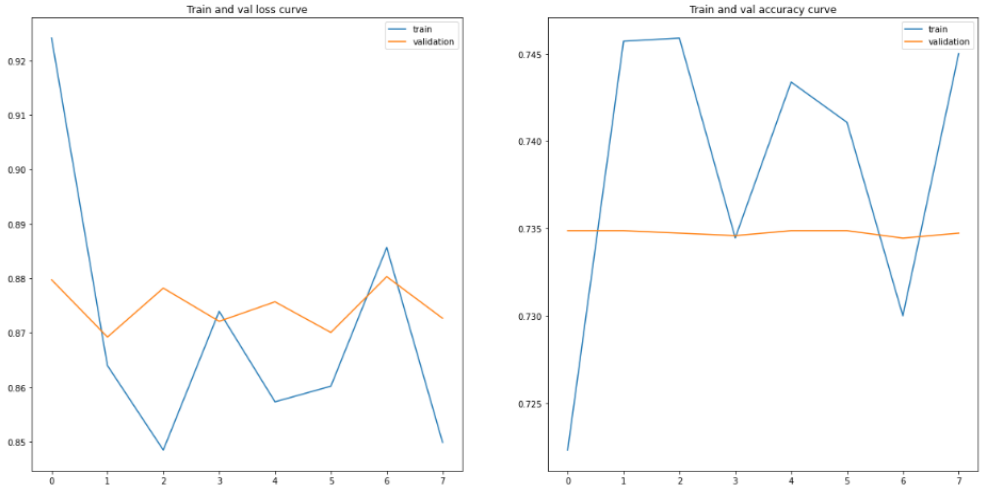


Figure 6 Confusion Matrix: Evaluation of Alex Net Model Performance

The loss and accuracy curves over the course of multiple epochs are plotted in the accompanying plots, providing a visual depiction of the learning dynamics of the model. A downward trend in the loss curve denotes better convergence since it shows declining training and validation losses.

Discussion

Deep learning techniques were used in all of the investigations that are discussed in this paper to adjust the diabetic retinopathy screening system. The growing number of individuals with diabetes has made the necessity for accurate diabetic retinopathy screening methods a pressing concern. DL solves the issue of choosing trustworthy features for machine learning (ML) in DR detection and classification, but it requires a large amount of data for training (Tsiknakis et. al., 2021). To counteract overfitting during the training phase and enhance the quantity of images, the majority of research employed data augmentation. In order to address the issue of data size and assess the DL approaches across a variety of datasets, the research discussed in the current study combined two or more public datasets (Sarker, 2021). Since deep learning takes a lot of data, one of the drawbacks of using it with medical field faces is the scale of the datasets required to train in the DL systems. The amount of training data is just as important to the performance of deep learning systems as its quality and class balance. Therefore, the sizes of the existing public datasets must be enlarged, and large datasets like the public Kaggle dataset must be improved to get rid of low-quality and miss-labeled data. The research that are described here use various DL approaches. There are tiny differences in the number of research that constructed their own CNN structure and those that chose to employ pre-existing structures with transfer learning, like VGG, ResNet, or AlexNet. It takes a lot of work and time to create a new CNN architecture from scratch, but organizing and creating new architecture is considerably faster and easier when transfer learning is used. However, it is noteworthy that the system that created its own CNN structure had a greater accuracy rate than the ones that used the pre-existing structures. Researchers should concentrate on this issue and carry out additional research to make an informed decision between the two tendencies. While some research classified input into one or more stages, the majority of the studies presented here solely classified the fundus input image as DR or non-DR (Alyoubi, Abulkhair, & Shalash, 2021). Conversely, a majority of the existing investigations failed to identify the afflicted lesions, whereas a majority of them did. Only 6% of the studies were able to identify the type of impacted lesion on the retained image and classify the photos. Neverthelss, it is noteworthy that an efficient follow-up strategy for DR patients prevents the risk of blindness by identifying various types of lesions and DR stages through the use of a dependable DR screening system (Alyoubi et al., 2021, Safi, et al., 2018). The system availability that could identify DR lesions and assess the five DR stages with high accuracy was the gap that needed to be filled. It is possible to view this point as the present research challenge for investigators. The Deep DR system achieved high sensitivity and specificity in DR grading. Rather than just generating a DR grading, it offers visual hints that help users identify the presence and location of different lesion types. (Dai, Wu and Li, 2021)

5. Conclusion

This work demonstrates that automated screening systems reduce ophthalmologist's time and money by drastically cutting down on the amount of time needed to diagnose patients. This allows patients to receive treatment on time. Early DR detection is facilitated by the use of automated DR detection systems. The types of lesions that manifest on the retina determine the DR phases. The most recent deep learning-based automated methods for the identification and categorization of diabetic retinopathy have been discussed in this article. We have presented the publicly accessible common fundus DR Datasets and provided a quick overview of deep learning methodologies. Because of its effectiveness, the majority of researchers have employed CNN for both DR image identification and classification. Additionally, this analysis has covered the helpful methods that can be utilized to detect and classify DR using DL.

6. Acknowledgements

We acknowledge the lab support provided by our department.

7. References

Alyoubi, W. L., Abulkhair, M. F., & Shalash, W. M. (2021). Diabetic retinopathy fundus image classification and lesions localization system using deep learning. *Sensors*, *21*(11), Article 3704. https://doi.org/10.3390/s21113704

Dai, L., Wu, L., Li, H. *et al.* A deep learning system for detecting diabetic retinopathy across the disease spectrum. *Nat Commun* **12**, 3242 (2021). https://doi.org/10.1038/s41467-021-23458-5

Einstein, A., Podolsky, B., & Rosen, N. (1935). Can quantum-mechanical description of physical reality be considered complete?. *Physical review*, *47*(10), 777-780. https://doi.org/10.1103/PhysRev.47.777

International Diabetes Federation. International diabetes federation diabetes atlas. (n.d.) ninth ed. Retrieved from https://www.diabetesatlas.org/en/

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436-444. https://doi.org/10.1038/nature14539

Logue, J. (2010). *Management of obesity: a National clinical guideline*. NHS Quality Improvement Scotland

Lois, N., McCarter, R. V., O'Neill, C., Medina, R. J., & Stitt, A. W. (2014). Endothelial progenitor cells in diabetic retinopathy. *Frontiers in endocrinology*, *5*, Article 44. https://doi.org/10.3389/fendo.2014.00044

Mookiah, M. R. K., Acharya, U. R., Chua, C. K., Lim, C. M., Ng, E. Y. K., & Laude, A. (2013). Computer-aided diagnosis of diabetic retinopathy: A review. *Computers in biology and medicine*, *43*(12), 2136-2155. https://doi.org/10.1016/j.compbiomed.2013.10.007

Pires, R., Jelinek, H. F., Wainer, J., Valle, E., & Rocha, A. (2014). Advancing bag-of-visual-words representations for lesion classification in retinal images. *PloS one*, *9*(6), e96814. https://doi.org/10.1371/journal.pone.0096814

Rosas-Romero, R., Martínez-Carballido, J., Hernández-Capistrán, J., & Uribe-Valencia, L. J. (2015). A method to assist in the diagnosis of early diabetic retinopathy: Image processing applied to detection of microaneurysms in fundus images. *Computerized medical imaging and graphics*, *44*, 41-53. https://doi.org/10.1016/j.compmedimag.2015.07.001

Safi, H., Safi, S., Hafezi-Moghadam, A., & Ahmadieh, H. (2018). Early detection of diabetic retinopathy. *Survey of ophthalmology*, *63*(5), 601-608. https://doi.org/10.1016/j.survophthal.2018.04.003

Sarker, I. H. (2021). Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions. *SN Computer Science*, *2*(6), Article 420. https://doi.org/10.1007/s42979-021-00815-1

Tsiknakis, N., Theodoropoulos, D., Manikis, G., Ktistakis, E., Boutsora, O., Berto, A., ... & Marias, K. (2021). Deep learning for diabetic retinopathy detection and classification based on fundus images: A review. *Computers in biology and medicine*, *135*, Article 104599. https://doi.org/10.1016/j.compbiomed.2021.104599

Yau, J. W., Rogers, S. L., Kawasaki, R., Lamoureux, E. L., Kowalski, J. W., Bek, T., ... & Mitchell, P. (2012). Wong TY; Meta-Analysis for Eye Disease (META-EYE) Study Group. Global prevalence and major risk factors of diabetic retinopathy. *Diabetes Care*, *35*(3), 556-564.