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Article

Deep Learning-Based Automated Detection of Diabetic Retinopathy: A Review of Recent Developments

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Abstract: Diabetes mellitus can cause diabetic retinopathy (DR), a fatal ailment of the eyes that, may lead to blindness and optical loss if untreated. The increased occurrence of diabetes has made early detection of DR a vital public health issue. This study explores the topic of eye disorders, with a focus on DR because of its important influence on visual health. It examines the body of research on DR, emphasizing the signs and symptoms, course, and necessity of prompt treatment. The study also examines different approaches to deep learning detection, with a particular emphasis on their use in deep learning systems. In medical imaging and diagnostics, deep learning—a subset of artificial intelligence—has demonstrated amazing promise. Deep learning models are able to recognize patterns and anomalies by utilizing big datasets and sophisticated algorithms. The research compares the efficacy and performance of several deep learning models in identifying DR at various phases by presenting the findings of those models. The study ends with suggestions and future approaches, highlighting the necessity of ongoing study and advancement in deep learning methods for DR detection. It also emphasizes how crucial it is to incorporate these advanced methods into clinical practice in order to improve patient outcomes, increase early identification, and eventually lessen the impact of diabetic retinopathy on public health.

Keywords: diabetic retinopathy, deep learning, early detection, medical imaging, and public health.

INTRODUCTION

The human eye is a remarkably complex organ, essential for interpreting the world around us. It converts light into electrical signals, which the brain processes to form images, enabling vision. However, due to its intricate structure and function, the eye is susceptible to a variety of diseases and disorders. These conditions can range from common, easily treatable issues to severe, vision-threatening illnesses that can significantly impact quality of life. Following are some of the major eye complications:

Cataracts: A disorder where the lens of the eye turns clouded, resulting in blurry vision and blindness if left untreated. Although age is the main cause of cataracts, other factors that may contribute include diabetes, trauma, or extended exposure to UV radiation (World Health Organisation,2019).

Glaucoma: This group of eye disorders occurs when there is excessive intraocular pressure resulting into optic nerve injury. It can result in irreversible visual loss if treatment is not received (Tham et al., 2014).
Age-Related Macular Degeneration (AMD): Affected

areas of the retina include the macula, which is in charge of central vision. It can significantly affect the vision in elderly people and results in loss of sharp, central vision, which is required for tasks like reading and driving (Mitchell et al., 2018).

Diabetic Retinopathy (DR): The condition has an impact on the retinal blood vessels and is a consequence of diabetes. It develops gradually and, if left untreated, can result in blindness or severe visual loss. Regular ocular examinations are essential for early detection (Cheung et al., 2010).

Dry Eye Syndrome: Inflammation and pain result from dry eye syndrome, which is caused by either insufficient production of tears or excessive vaporization of tears. It may be brought on by ageing, certain medications, or environmental factors (Craig et al., 2017).

Conjunctivitis: The conjunctiva is a clear membrane that lines the eyelid and covers the white portion of the eye. Conjunctivitis aka pink eye, occurs when this membrane becomes inflamed or infected.

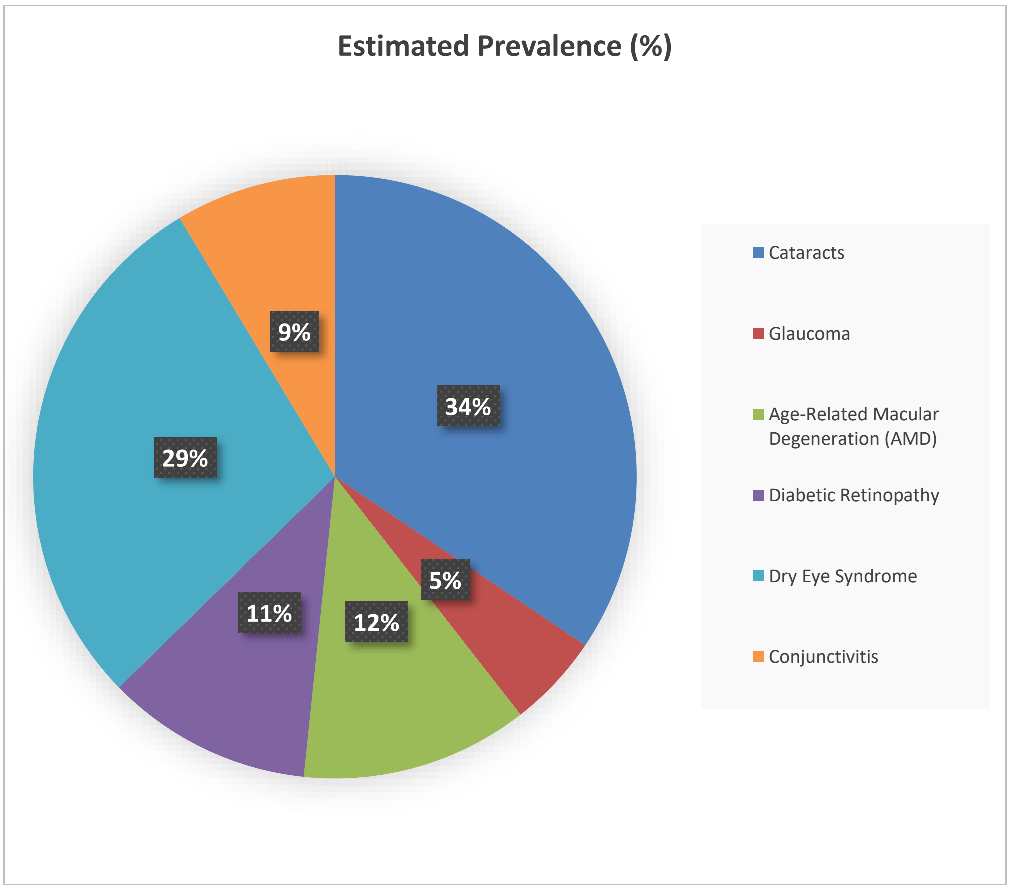

Figure 1: Prevalence of Eye Diseases

Among these, DR is the most hazardous medical conditions associated with diabetes mellitus. Retinal blood vessel injuries, which results in progressive vision loss and blindness, is the main feature of DR. As diabetes rates soar globally, the incidence of DR is expected to rise, underscoring the need for effective screening and detection methods.

Prevalence of Diabetic Retinopathy by Region

Global Prevalence: Approximately one-third of the estimated half a billion diabetic adults will be effected by DR to some extent, according to the Diabetes Atlas, 9th edition (2019) (International Diabetes Federation, 2019).

United States: (Centers for Disease Control and Prevention, 2010) reported, the number of DR affected Americans is estimated to rise to 14.6 million by 2050 from 7.7 million in 2010 to.

Europe: In the EURODIAB study, the prevalence of DR was found to be about 35% in diabetic patients of type 1 and type 2 (Stamler et al., 1993).

China: According to a 2017 meta-analysis, 18.45% of Chinese people have diabetic retinopathy (DR) (Song et al., 2018).

India: Studies report a prevalence of DR in India ranging from 17% to 28% (Raman et al., 2019; Rema et al., 2005).

Africa: Diabetic patients in sub-Saharan Africa are being affected with DR in range of 16.2% to 47% (Rheeder, 2018).

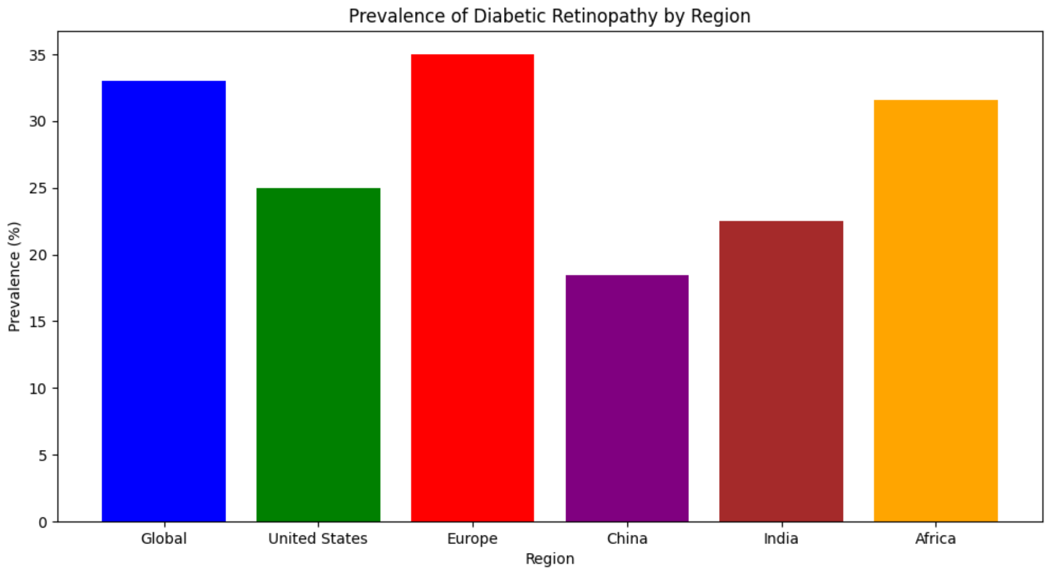

Figure 2: Diabetic Retinopathy (Region wise

LITERATURE REVIEW:

Epidemiology and Impact: Adult-onset visual loss is primarily caused by diabetic retinopathy. About one-third of diabetics worldwide suffer from DR, a prevalence that rises with the length of diabetes (Yau et al., 2012). Early stages of DR often present no symptoms, making regular screening crucial for timely intervention.

Pathophysiology: Figure 3 shows stages of DR including normal retinal image and Figure 4 shows the percentage of stages of DR (Wilkinson et al., 2003). The initial stages involve microaneurysms and retinal hemorrhages, while advanced stages are marked by neovascularization and the formation of fibrous tissue, which ultimately leads to vision loss.

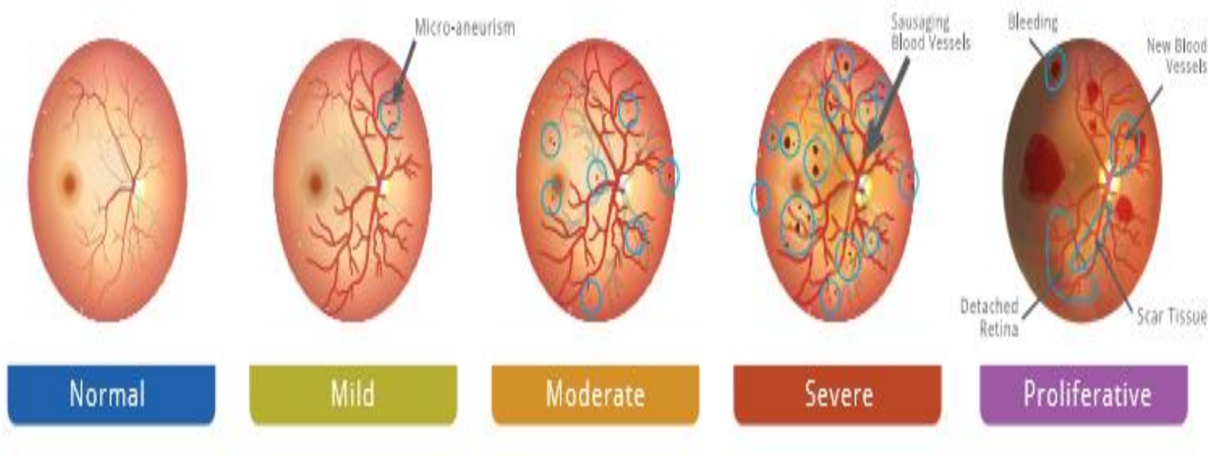

Figure 3:Normal Fundus image and stages of Diabetic Retinopathy

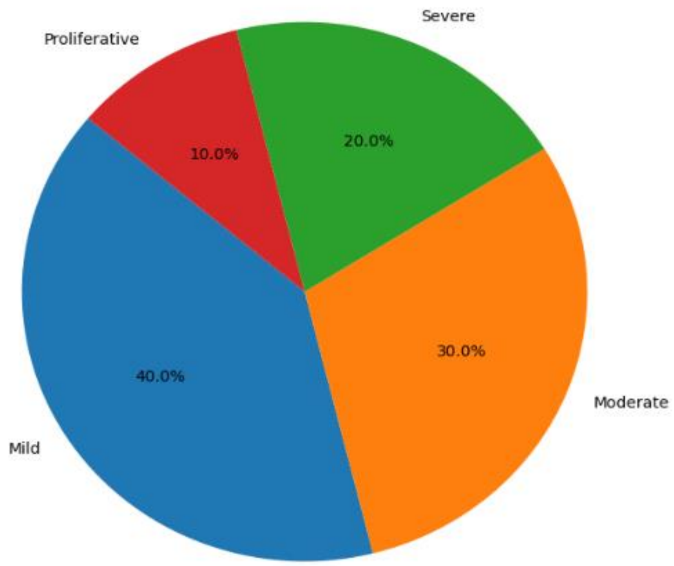

Figure 4: Diabetic Retinopathy in percentage (Wilkinson et al., 2003)

Stage	Description	Symptoms
Mild Non-proliferative Retinopathy	little patches of balloon-like retinal blood vessel enlargement.	Often asymptomatic; vision typically remains unaffected.
Moderate Non-proliferative Retinopathy	Retinal oedema is caused by clogged blood arteries that nourishes the retina.	Vision may start to become blurry; increased risk of more severe complications.
Severe Non-proliferative Retinopathy	Numerous other blood vessels are obstructed, denying blood flow to multiple regions of the retina and initiating signals for the formation of new blood vessels.	Significant risk of vision loss; more noticeable vision changes.
Proliferative Diabetic Retinopathy (PDR)	New, abnormal blood vessels begin to grow in the retina and into the vitreous, the gel-like fluid inside the eye.	Severe vision loss or blindness due to bleeding into the vitreous; may cause retinal detachment or glaucoma.

Table 1:Symptoms of various stages of Diabetic Retinopathy

Current Detection Methods: Fundus photography, fluorescein angiography, and ophthalmoscopy are examples of conventional techniques for DR detection. These methods, while effective, are time-consuming and require skilled personnel. The development of automated detection systems aims to overcome these limitations, providing quicker and more accessible DR screening (Abràmoff et al., 2010).

Advances in Deep Learning for DR Detection

Early Efforts and Milestones: In early attempts, random forests and support vector machines (SVMs) accompanied with traditional image processing methods were used for detecting DR. These methods were both time-consuming and less accurate due to manual feature extraction process.

Convolutional Neural Networks (CNNs): The advent of CNNs revolutionized the field of DR detection. Using images of the retinal fundus, Gulshan et al. (2016) created a CNN-based model that successfully identified DR with high sensitivity and specificity. Their model showed that deep learning could match the performance of human specialists in DR detection, having been trained on an extensive dataset of retinal images.

Transfer Learning and Pre-Trained Models: Transfer learning has been particularly beneficial in DR detection, allowing models pre-trained on large general datasets like ImageNet to be fine-tuned on medical imaging datasets. For instance, Pratt et al. (2016) utilized a pre-trained CNN model and achieved significant improvements in DR detection performance by fine-tuning it on the EyePACS dataset.

Ensemble Methods: Combining predictions from multiple models, have shown to improve DR detection accuracy. Voets et al. (2019) demonstrated that an ensemble of ResNet, DenseNet, and InceptionV3 models outperformed individual models, achieving higher accuracy and AUC-ROC scores.

Methodology of DR Detection Using Deep Learning

The creation of algorithms that can learn from and make conclusions based on massive datasets has been made possible by deep learning, which has completely changed the area of medical imaging. CNNs are more effective in image analysis, making them ideal for the detecting and classifying eye diseases from retinal images (LeCun et al., 2015).

Dataset Preparation: High-quality datasets are essential for deep learning model training. Commonly used datasets include the EyePACS dataset and the Diabetic Retinopathy Detection dataset from Kaggle, both of which are publicly available. These datasets (Kaggle, n.d.; EyePACS, n.d.) contain labelled retinal pictures, which are crucial for model training and validation.

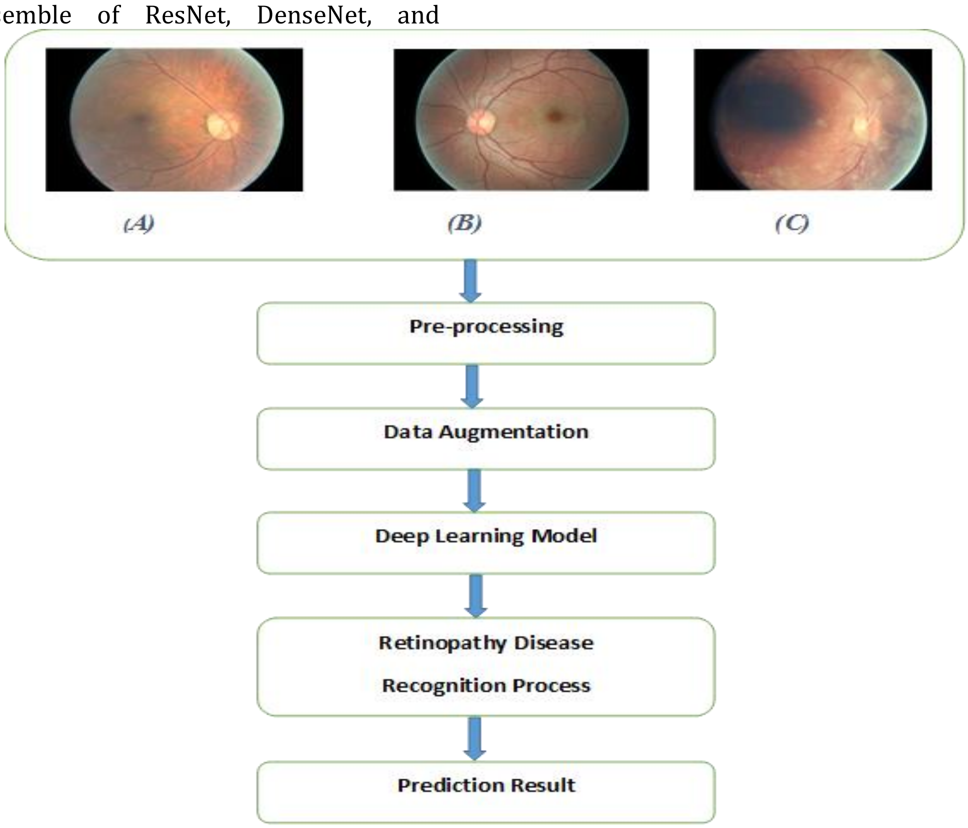

Figure 5: Methodology for DR detection and classification

Model Architecture: CNNs are the primary architecture used for detecting DR. A typical CNN model for detecting DR involves multiple layers of convolutions, pooling, and fully connected layers. Advanced architectures such as ResNet, DenseNet, and InceptionV3 have shown high accuracy in DR classification tasks (He et al., 2016; Huang et al., 2017; Szegedy et al., 2016).

Training and Validation: The training process involves feeding the dataset into the model, allowing it to learn features indicative of DR. The performance of the model is confirmed using an alternative validation set to ensure that it functions properly when applied to new, untested data. To improve model performance, methods like hyperparameter tuning, transfer learning, and data augmentation are used (Shorten & Khoshgoftaar, 2019; Pan & Yang, 2010).

Performance Metrics: The effectiveness of deep learning models is evaluated using a variety of metrics, such as accuracy, sensitivity, specificity, precision, recall, and the area under the receiver operating characteristic curve (AUC-ROC). These measures shed light on how well the model detects different stages of DR (Saito & Rehmsmeier, 2015).

RESULTS, ANALYSIS, AND FINDINGS

ResNet: ResNet (Residual Networks) has been widely used in DR detection due to its ability to train deeper networks effectively. Studies have reported high accuracy rates, with some models achieving over 90% accuracy in detecting various stages of DR. For instance, a ResNet-50 model trained on the EyePACS dataset achieved an AUC-ROC of 0.95, indicating excellent performance in distinguishing between different stages of DR (Gulshan et al., 2016).

DenseNet: DenseNet (Densely Connected Convolutional Networks) models have also shown promising results in DR detection. DenseNet-121, for example, has been employed to classify DR images with an accuracy of around 88%. Its dense connections help in better feature propagation and reduce the risk of vanishing gradients, contributing to its robustness in image classification tasks (Li et al., 2019).

InceptionV3: InceptionV3 is another popular architecture used for DR detection. This model leverages convolutional layers of varying sizes, enabling it to capture fine-grained details in retinal images. In one study, the efficacy of the InceptionV3 model in classifying diabetic retinopathy was demonstrated by its 87% accuracy and 0.93 AUC-ROC on the Kaggle Diabetic Retinopathy dataset (Gulshan et al., 2016).

Ensemble Models: Combining multiple models into an ensemble has been shown to improve performance further. For instance, on EyePACS dataset, 92% of accuracy is achieved by an ensemble of ResNet, DenseNet, and InceptionV3 models and 0.97 of AUC-ROC. Ensemble models benefit from the strengths of individual models, resulting in more robust and accurate predictions (Voets et al., 2019).

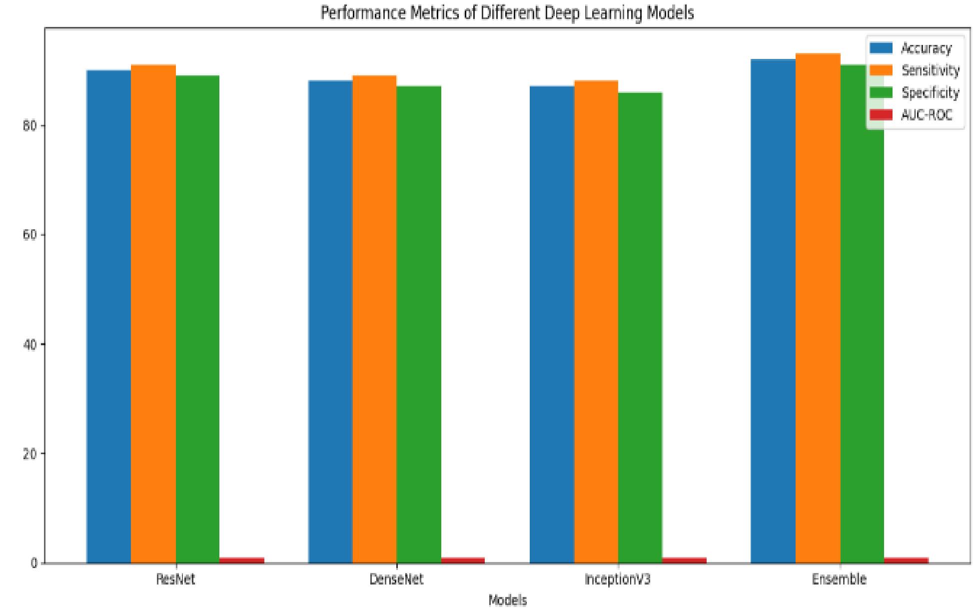

Figure 6: Performance Metrics of Different Deep Learning Models (In Percentage)

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CONCLUSION

The use of deep learning to identify and classify diabetic retinopathy has shown immense promise, offering potential for more efficient and accurate screening methods. While current models achieve high accuracy, challenges remain in terms of data variability, model interpretability, and integration into clinical practice. Future research should focus on improving model robustness, addressing ethical considerations, and ensuring widespread accessibility to these advanced diagnostic tools.

REFERENCES

1. Cheung, N., Mitchell, P., & Wong, T. Y. (2010). Diabetic retinopathy. The Lancet, 376(9735), 124-136. https://doi.org/10.1016/S0140-

6736(09)62124-3
2. Craig, J. P., Nichols, K. K., Akpek, E. K., Caffery, B., Dua, H. S., Joo, C. K., ... & Stapleton, F. (2017). TFOS DEWS II definition and classification report. The Ocular Surface, 15(3), 276-283. https://doi.org/10.1016/j.jtos.2017.05.008
3. Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., ... & Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA, 316(22), 2402-2410. https://doi.org/10.1001/jama.2016.17216
4. Mitchell, P., Liew, G., Gopinath, B., & Wong, T. Y. (2018). Age-related macular degeneration. The Lancet, 392(10153), 1147-1159. https://doi.org/10.1016/S0140-6736(18)31550-2
5. Tham, Y. C., Li, X., Wong, T. Y., Quigley, H. A., Aung, T., & Cheng, C. Y. (2014). Global prevalence of glaucoma and projections of glaucoma burden through 2040: A systematic review and meta-analysis. Ophthalmology, 121(11), 2081-2090. https://doi.org/10.1016/j.ophtha.2014.05.013
6. World Health Organization. (2019). World report on vision. Retrieved from https://www.who.int/publications/i/item/world-report-on-vision
7. Abràmoff, M. D., Niemeijer, M., Russell, S. R., Folk, J. C., Ginneken, B. V., & Sonka, M. (2010). Automated detection of diabetic retinopathy: No human intervention required. Investigative Ophthalmology & Visual Science, 51(11), 5846-5852. https://doi.org/10.1167/iovs.10-5880
8. EyePACS. (n.d.). EyePACS: Eye Picture Archiving Communication System. Retrieved from https://www.eyepacs.com
9. Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A., ... & Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA, 316(22), 2402-2410. https://doi.org/10.1001/jama.2016.17216
10. 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 (pp. 770-778). https://doi.org/10.1109/CVPR.2016.90
11. Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4700-4708). https://doi.org/10.1109/CVPR.2017.243
12. Kaggle. (n.d.). Diabetic Retinopathy Detection. Retrieved from https://www.kaggle.com/c/diabetic-retinopathy-detection
13. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444. https://doi.org/10.1038/nature14539
14. Li, T., Gao, Y., Wang, K., Guo, S., Liu, H., & Kang, H. (2019). Diagnostic assessment of deep learning algorithms for diabetic retinopathy screening. Information Sciences, 501, 511-522. https://doi.org/10.1016/j.ins.2019.05.003
15. Pan, S. J., & Yang, Q. (2010). A survey on transfer learning. IEEE Transactions on Knowledge and Data Engineering, 22(10), 1345-1359. https://doi.org/10.1109/TKDE.2009.191
16. Pratt, H., Coenen, F., Broadbent, D. M., Harding, S. P., & Zheng, Y. (2016). Convolutional neural networks for diabetic retinopathy. Procedia Computer Science, 90, 200-205. https://doi.org/10.1016/j.procs.2016.07.014
17. Saito, T., & Rehmsmeier, M. (2015). The precision-recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets. PLoS ONE, 10(3), e0118432. https://doi.org/10.1371/journal.pone.0118432
18. Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. Journal of Big Data, 6(1), 60. https://doi.org/10.1186/s40537-019-0197-0
19. Voets, M., Møllersen, K., & Bongo, L. A. (2019). Reproduction study: Development and validation of deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. PLOS ONE, 14(6), e0217541. https://doi.org/10.1371/journal.pone.0217541
20. Wilkinson, C. P., Ferris, F. L., Klein, R. E., Lee, P. P., Agardh, C. D., Davis, M., ... & Global Diabetic Retinopathy Project Group. (2003). Proposed international clinical diabetic retinopathy and diabetic macular edema disease severity scales. Ophthalmology, 110(9), 1677-1682. https://doi.org/10.1016/S0161-6420(03)00475-5
21. Yau, J. W., Rogers, S. L., Kawasaki, R., Lamoureux, E. L., Kowalski, J. W., Bek, T., ... & Wong, T. Y. (2012). Global prevalence and major risk factors of diabetic retinopathy. Diabetes Care, 35(3), 556-564. https://doi.org/10.2337/dc11-1909
22. Centers for Disease Control and Prevention. (2010). The state of vision, aging, and public health in America. Retrieved from https://www.cdc.gov/visionhealth/resources/publications/vision_and_aging.htm
23. International Diabetes Federation. (2019). IDF Diabetes Atlas (9th ed.). Retrieved from

https://diabetesatlas.org/
24. Raman, R., Gella, L., Srinivasan, S., & Sharma, T. (2019). Diabetic retinopathy: An epidemic at home and around the world. Indian Journal of Ophthalmology, 67(6), 785-793. https://doi.org/10.4103/ijo.IJO_144_19
25. Rema, M., Premkumar, S., Anitha, B., Deepa, R., Pradeepa, R., & Mohan, V. (2005). Prevalence of diabetic retinopathy in urban India: The Chennai Urban Rural Epidemiology Study (CURES) Eye Study, I. Investigative Ophthalmology & Visual Science, 46(7), 2328-2333. https://doi.org/10.1167/iovs.05-0019
26. Rheeder, P. (2018). The prevalence of diabetic retinopathy in sub-Saharan Africa: A systematic review and meta-analysis. Diabetes Research and Clinical Practice, 139, 234-243. https://doi.org/10.1016/j.diabres.2018.03.028
27. Song, P., Yu, J., Chan, K. Y., Theodoratou, E., Rudan, I., & Chan, L. (2018). Prevalence, risk factors and burden of diabetic retinopathy in China: A systematic review and meta-analysis. Journal of Global Health, 8(1), 010803. https://doi.org/10.7189/jogh.08.010803
28. Stamler, J., Vaccaro, O., Neaton, J. D., & Wentworth, D. (1993). Diabetes, other risk factors, and 12-yr cardiovascular mortality for men screened in the Multiple Risk Factor Intervention Trial. Diabetes Care, 16(2), 434-444. https://doi.org/10.2337/diacare.16.2.434