Figure 2: Fundus pictures showing bone spicule pigmentation, waxy pale discs and attenuated vessels in a patient with retinitis pigmentosa

(BCVA) in 26 (30.2%) of all eyes studied was >6/18.

Conclusion: The prevalence of RP in this study was higher than previous figures ranging between 0.31% and 0.69% from similar studies from various parts of Nigeria.[3-7] A male preponderance was noted and this is similar to other studies but differed from a report from Cameroon.[9] The mean age was identical to what was obtained in a study in Onitsha[3] but lower than other recent multicenter studies in Nigeria.[5,7]Poor vison was the commonest presenting complaint akin to findings in Benin city.[6] Prevalence of visual impairment noted was similar to other local studies in Nigeria.[3,7] There was a high prevalence of cataracts and low rate of glaucoma comparable to findings in China but differing from other studies. [5,9,10] RP is a common inherited retinal disease in our populace. There is an increasing prevalence possibly attributable to increased patient awareness. Molecular and genetic studies are important tools in accurate diagnosis of these patients.

References
1. Hartong Dt, Berson E, Dryja TP. Retinitis pigmentosa. Lancet 2006. 368(9549):1795-809
2. Ferrari S, Di Iorio E, Barbaro V, Ponzin D, Sorrentino FS, Parmeggiani F. Retinitis pigmentosa: genes and disease mechanisms. Curr Genomics. 2011 Jun;12(4):238-49
3. Nwosu SNN, Ndulue CU, Ndulue OI, Uba-Obiano CU. Retinitis Pigmentosa in Onitsha, Nigeria. J West Afr Coll Surg. 2020 Apr-Jun;10(2):30-35
4. Ashaye AO. Presumed hereditary retinal degenerations: Ibadan experience. West Afr J Med. 2005 Jan-Mar;24(1):49-53
5. Nkanga D, Agweye CT, Akanbi T, Ovienra W, Adenuga O, Ibanga A et al. Visual Status of Patients with Retinitis Pigmentosa: A Multicenter Study. West Afr J Med. 202l. 38(11):1108-1113.
6. Ukponmwan CU, Atamah A. Retinitis pigmentosa in Benin, Nigeria. East Afr Med J 2004;81:254–257
7. Onakpoya O, Adeoti C, Oluleye T, Ajayi I, Majengbasan T, Olorundare O. Clinical presentation and visual status of retinitis pigmentosa patients: a multicenter study in southwestern Nigeria. Clin Ophthalmol. 2016;10:1579-1583
8. Babalola YO, Baiyeroju AM. Optic disc drusen and a constellation of other features of Retinitis pigmentosa: A case report. International Journal of Ophthalmology & Visual Science. Int Ophthal & Vis Sci 2021;(6) 1:63-166
9. Eballe AO, Koki G, Emche CB, Bella LA, Kouam JM, Melong J.Blindness and visual impairment in retinitis pigmentosa: A Cameroonian hospital-based study. Clin Ophthalmol 2010; 4:661-665
10. Tian L, Long Y, Li Z. Ocular abnormalities in a large Western China patient cohort with Retinitis Pigmentosa. BMC Ophthalmol 2021. 21:43

Advancing Health Access and Equity: Artificial Intelligence for Diabetic Retinopathy Grading in Nigeria

Mary-Brenda Akoda[1,2] and Dennis George Nkanga[3,4]

[1]Independent AI Researcher
[2]Computer Science Department (Machine Learning and Artificial Intelligence), University of London, United Kingdom.
[3]Department of Ophthalmology, University of Calabar, Calabar, Nigeria.

[4]*Department of Ophthalmology, University of Calabar Teaching Hospital, Calabar, Nigeria.*
Corresponding author: *Professor Dennis Nkanga. E-mail: zeraheyecenter@yahoo.com +2348036755700*

Introduction: Diabetic Retinopathy (DR) is the leading cause of vision loss in adults aged 20-79 years, significantly impacting the economically active age group and carrying profound socioeconomic implications.[1-3] Early detection of asymptomatic DR is crucial for timely treatment and preventing vision loss. Many low-and-middle-income countries (LMICs), including Nigeria, face limited and inequitable access to DR screening and grading services, often due to a shortage oftrained personnel.[4-7] This study sought to develop artificial intelligence (AI) for DR detection and explore the potentialof leveraging this automation to enhance equitable access to DR grading in Nigeria.

Methods: Six deep learning models were trained and evaluated using a public data set (APTOS 2019) comprising 3,662 retinal fundus images[8], and then externally validated using a Nigerian data set comprising 168 retinal fundus images from the University of Calabar Teaching Hospital. Data preprocessing techniques included contour detection and Contrast Limited Adaptive Histogram Equalization (CLAHE) (Figure 1).[9-10] To address class imbalance, the study employed stratified sampling, class weighting, and the Quadratic Weighted Kappa (QWK) loss function.[11] Evaluation metrics included QWK score, referable class sensitivity (the model's ability to correctly identify cases requiring referral to an eye specialist), and combined specificity for non-referable classes (the model's ability to correctly identify cases not requiring referral). Data augmentation and regularisation techniques were applied to enhance model generalisability. Notably, a stacked ensemble learning model out performed

individual models in early stages but was omitted in the regularisation stage due to its complexity and resource-intensive nature.[12]

Results: Each model's performance was evaluated on a single test set (Table 1). The top-performing model, EfficientNetV2S, achieved a 92.1% QWK score, 98.9% referable class sensitivity, and 93.0% combined specificity for non-referable classes. ResNet50V2 and VGG16 followed closely, excelling in different aspects of evaluation. However, external validation on a Nigerian data set showed a significant decline in model performance, with sensitivities dropping to 43.8% (VGG16), 68.8% (ResNet50V2), and 56.3% (EfficientNetV2S), and negative QWK scores, indicating worse than random agreement. Apart from domain shift, differences in retina pigmentation and a lack of image capture
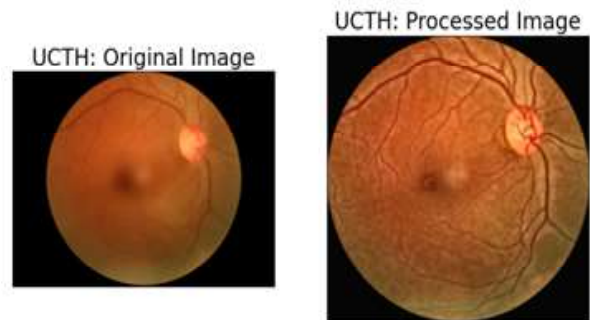

Figure 1: Results of Pre-processing Techniques applied to a Retinal Fundus Image from the UCTH dataset

specifications were identified as potential causes of misclassification in the Nigerian dataset.[13]

Discussion: Evidence suggeststhat this is the first AI study for DR detection in Nigeria and one of few such studies in LMICs.[14-15] While the study highlights AI's potential in DR detection, the performance decline during external validation

Table 1: Comparison of Model Performance on APTOS and UCTH datasets

Evaluation Metrics	APTOS 2019 Single Test Dataset			UCTH Dataset		
	VGG16	ResNet50V2	EfficientNetV2S	VGG16	ResNet50V2	EfficientNetV2S
QWK Score	88.3%	90.2%	92.1%	-15.2%	-5.4%	-10.2%
Sensitivity for Referable Class	96.1%	94.5%	98.9%	43.8%	68.8%	56.3%
Combined Specificity	91.9%	96.2%	93.0%	17.8%	3.3%	5.9%

underscores the importance of fine-tuning modelsbefore deployment innew populations.The study alsoemphasises the need for local training data and the adoption of specifications for image capture to ensure full coverage of critical DR diagnostic features.[5]

Conclusion: The study underscoresthe need for caution and rigorous validation before deploying AI models in new populations. It emphasises the significance of locally sourced data to ensure the effectiveness and reliability of AI models in their intended context. The research also supports the need for the establishment of a national DR screening programme in Nigeria and proposes a multicentre collaborative study that leverages diverse locally sourced data to refine AI models, ultimately enhancing their diagnostic accuracy and relevance in the Nigerian population.

References

1. Wong TY, Sabanayagam C. Strategies to Tackle the Global Burden of Diabetic Retinopathy: From Epidemiology to Artificial Intelligence. Ophthalmologica 2020; 243 (1): 9–20. https://doi.org/10.1159/000502387.

2. Agweye CT, Ibanga AA, Udoh MME, Enang OE, Nwajei AI, Nkanga DG. Pattern of diabetic retinopathy in a tertiary healthcare facility in Southern Nigeria. Niger J Med 2021;30:538-42.

3. Momoh ZD, Agweye CT, Oguntolu V, Nkanga D. Diabetic retinopathy screening in Calabar, Nigeria: Factors influencing referrals and uptake of screening service. Niger J Ophthalmol 2017; 25:118-22.

4. International Diabetes Federation. IDF Diabetes Atlas, 10th edition. Brussels, Belgium: International Diabetes Federation; 2021. https://www.diabetesatlas.org.

5. Federal Ministry of Health. National Guideline for Screening and Management of Diabetic Retinopathy. Private Communications.

6. Nkanga D, Adenuga O, Okonkwo O, et al. Profile, Visual Presentation and Burden of Retinal Diseases Seen in Ophthalmic Clinics in Sub-Saharan Africa. Clin Ophthalmol 2020;14:679-87.

7. Oteri O, Nkanga D, Faal H, Zondervan M, Bascaran C.Strengthening diabetic retinopathy services in Nigeria through DR-NET – from grass roots to national policy development. Eye News. Vol 30:2 August/September 2023.

8. Asia Pacific Tele-Ophthalmology Society (APTOS). APTOS 2019 Blindness Detection.Kaggle. https://www.kaggle.com/c/aptos2019-blindness-detection/. Published 2019.

9. Kumar Rai R, Gour P, Singh B. Underwater image segmentation using clahe enhancement and thresholding. International Journal of Emerging Technology and Advanced Engineering. 2012;2(1):118–23.

10. Hayati M, Muchtar K, Roslidar, *et al.* Impact of CLAHE-based image enhancement for diabetic retinopathy classification through deep learning. Procedia Comput Sci. 2023;216:57-66. doi:10.1016/j.procs.2022.12.111.

11. Torre J, Puig D, Valls A. Weighted kappa loss function for multi-class classification of ordinal data in deep learning. Pattern Recognition Letters. 2018;105:144-154. doi: 10.1016/j.patrec.2017.05.018.

12. Akoda M, inventor; Method and System for Diabetic Retinopathy Grading based on Stacked Ensemble Learning. Nigeria Patent F/PT/NC/2023/8907. August 31, 2023.

13. Gulshan V, Peng L, Coram M, *et al.* 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.

14. Bellemo V, Lim ZW, Lim G, *et al.* Artificial intelligence using deep learning to screen for referable and vision-threatening diabetic retinopathy in Africa: a clinical validation study. Lancet Digit Health. 2019;1(1):e35-e44. doi: 10.1016/S2589-7500(19)30004-4.

15. Cleland CR, Rwiza J, Evans JR, et al. Artificial intelligence for diabetic

retinopathy in low-income and middle-income countries: a scoping review. BMJ Open Diabetes Res Care. 2023; 11(4) : e003424. doi:10.1136/bmjdrc-2023-003424.

Bilateral exudative retinal detachment as an initial ocular presentationof metastatic breast cancer: A case report

Udoh, Martha-Mary[1], Ezeh, Ernest[1,2], Abatai, Mercy O[1], Etim, Bassey A[1,2], Nkanga, Elizabeth D[1,2], Nkanga, Dennis G.[1,2]

[1]Department of Ophthalmology, University of Calabar Teaching Hospital, Calabar, Cross River State, Nigeria.
[2]Department of Ophthalmology, University of Calabar, Calabar, Cross River State, Nigeria.
Corresponding Author: *Elizabeth Dennis Nkanga.* E-mail: bettienkanga@gmail.com; Phone: +234 8173692585.

Introduction: Exudative retinal detachment (ERD), an ocular emergency and cause of painless visual loss results from defective fluid clearance from the subretinal space or excessive exudation within this space.[1,2.3] Aetiologies include inflammatory, neoplastic or vascular diseases affecting the choroid, retinal pigment epithelium (RPE) or the retina. It can also arise from effusive systemic diseases such as chronic or end-stage renal disease.[3-10]

Generally, the eye is a rare site for metastatic disease due to the absence of well-developed lymphatic system. Thus, metastases to ocular structures occurs by haematogenous route. In adult females, the most common primary site is the breast, while the lung is the commonest primary site in males.[6-10] Notably, ocular involvement in breast carcinoma is under-reported, however, with the increasing survival rates following recent advances in systemic treatment options, and improved diagnostic modalities, there has been an increase in reports of cases of ocular involvement.[6-10] The presentation could also be part of ocular paraneoplastic syndrome.[10]

We report a case of metastatic breast carcinoma presenting initially as exudative retinal detachment.

Case presentation: A 41-year-old female presented with a 9-day history of sudden profound diminution in vision involving both eyes. It started as flashes or flickering in her left eye, with hemifield vision distortion but progressively within 6 days of onset deteriorated to involve the entire visual field and the right eye. It involved both near and distant vision, however, near vision was worse. There was no history of floaters, micropsia, macropsia or metamorphopsia. She had pregnancy induced hypertension about 3 years prior to presentation but had stopped the use of antihypertensives as her blood pressure had since been stable. There was a 3 weeks history of cough with associated dyspnoea on mild exertion. She also complained of right flank pain. The patient initially reported to be well, but on further questioning with regard to comorbidities she mentioned, though hesitantly, noticing a breast lump about 1 year earlier.There was no history of weight loss or any other systemic/bodily disorder. Her aunty died of breast cancer.

Examination revealed an anxious lady with presenting visual acuity of 6/60, N36 in both eyes, with normal anterior segments. Intraocular pressures at 11:35am were 11mmHg bilaterally. Dilated fundus evaluation showed pale, smooth detached temporal retina involving the macula, worse in the left eye, with no obvious retinal breaks. The optic disc was round, pink, with distinct margins and cup-disc ratio of 0.4 and 0.3 in right eye and left eye respectively.

The fundus photographs and optical coherence tomography scans of the macula are shown in Figures 1 and 2. Chest X-ray showed bilateral nodular lung metastases.

The patient was referred to the oncologist. Cytology and immunocytochemistry of the breast lump revealed invasive breast lesion HER2 Neu-positive.
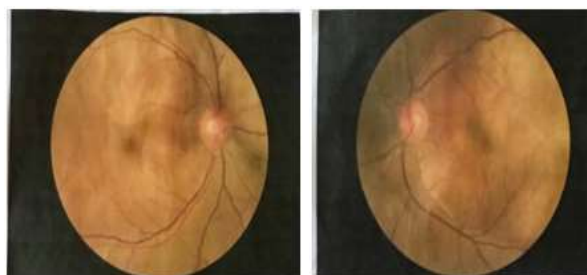

Figure 1: *Fundus photograph showing bulbous exudative retinal detachment, and no obvious tear. Right eye (a) & Left eye (b)*