ISSN: 2641-6360
DOI: 10.33552/WJOVR.2026.05.000623
World Journal of Ophthalmology & Vision Research
Iris Publishers

Review Article



# AI Diagnostic Capability in Choroidal Melanoma

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**Received Date:** May 19, 2026

**Published Date:** May 29, 2026

## Saints Mode

### Simple AI Nevus Transformation System

Several groups in the last few years have been able to achieve excellent diagnostic ability in identifying choroidal melanoma by using machine learning, ML on multimodal imaging.

For example, in a recent, comprehensive AI retrospective multicenter study to predict choroidal nevus conversion to melanoma, PD Tailor et al used fundus photos, fundus auto fluorescence, spectral domain OCT and B-scan ultrasonography to develop Machine learning models comprised of XGBoost, LGBM, Random Forest, and Extra Tree, and optimized them for area under receiver operation curve, AUROC, and area under precision recall curve, AUPRC, performance metrics that measure the model's ability to distinguish between positive and negative classes. [1].

**Lexicon of AI Related Terms in Choroidal Melanoma**

| | Term | Definition |
|---|---|---|
| 1 | **XGBoost** | An optimized gradient boosting library designed for speed and performance, widely used in machine learning competitions and for predictive modeling. |
| 2 | **LGBM (Light GBM)** | A gradient boosting framework that uses tree-based learning algorithms, designed for distributed and efficient training, particularly suitable for large datasets. |
| 3 | **Random Forest** | An ensemble learning method that constructs multiple decision trees during training and outputs the mode of their predictions, effective for classification tasks. |
| 4 | **Extra Tree** | An ensemble method similar to Random Forest, but it uses random splits for tree construction, which can result in faster training and improved generalization. |
| 5 | **Optimized Area Under Receiver Operating Curve (ROC)** | A performance measurement for classification models, representing the trade-off between true positive rate and false positive rate at various thresholds. |
| 6 | **Difference between AUROC vs AUPRC** | AUROC measures the ability of a model to distinguish between classes, while AUPRC focuses on the performance of a model with respect to the positive class. For example, in medical diagnostics, AUROC helps evaluate a model's accuracy in identifying disease presence, while AUPRC emphasizes the model's performance in detecting actual cases of the disease among all positive predictions. |
| 7 | **CNN (Convolutional Neural Network)** | A deep learning algorithm primarily used for image processing, which utilizes convolutional layers to automatically learn spatial hierarchies of features from input images. |
| 8 | **SHAP Values** | SHapley Additive exPlanations provide a unified measure of feature importance by calculating the contribution of each feature to the prediction, allowing for better interpretability. For example, in a melanoma classification model, SHAP values can show how much each feature (like tumor size or patient age) impacts the predicted risk. |
| 9 | **Precision** | The ratio of true positive predictions to the total predicted positives, indicating the accuracy of positive predictions. |
| 10 | **Recall** | The ratio of true positive predictions to the actual positives, measuring the model's ability to identify all relevant instances in the dataset. |
| 11 | **Accuracy** | The ratio of correctly predicted instances (both true positives and true negatives) to the total instances in the dataset, indicating overall correctness of the model. |

One cohort was used for 80% training and 20% testing; the second cohort provided external validation [1]. There were 2870 nevi included in the study. 128 had a conversion to melanoma. Simple AI Nevus Transformation System (SAINTS; XGBoost) was the top-performing model in the test cohort [pooled AUROC 0.864 (95% confidence interval (CI): 0.864-0.865), pooled AUPRC 0.244 (95% CI: 0.243-0.246)] and in the external validation cohort [pooled AUROC 0.931 (95% CI: 0.930-0.931), pooled AUPRC 0.533 (95% CI: 0.531-0.535)] [1].

LGBM (test set pooled AUROC 0.831, validation set pooled AUROC 0.815) [1]. Random Forest (test set pooled AUROC 0.812, validation set pooled AUROC 0.866), [1] Extra Tree (test set pooled AUROC 0.826, validation set pooled AUROC 0.915) [1]. Another model including only nevi with at least 5 years of follow up had the best performance in AUPRC: test: pooled 0.592 (95% CI: 0.590-0.594); validation: pooled 0.656 [95% CI: 0.655-0.657]) [1]. The top features in the Simple AI Nevus Transformation System by SHAP values, (SHAP values help explain how much each feature contributes to the final output of the model) were: tumor thickness, largest tumor diameter, basal diameter, tumor shape, distance to optic nerve and extent subretinal fluid. [1]. Tailor et al concluded that a machine language model for predicting choroidal nevus transformation to melanoma was accurate and generalizable [1].

## Ai In Choroidal Melanoma with CNN and Multimodal Models

Dadzie, et al. in a review article on advances and applications of AI in the diagnosis of uveal melanoma state that while machine learning methods rely on manual examination of images, deep learning models such as CNNs, convoluted neural networks, compensate in part for the variabilities of manual exams. CNNs after detecting image patterns automate feature extraction and analysis, increasing reliability and perhaps accuracy for patient outcomes [2]. Although pre-CNN models have achieved greater than 90% accuracy, those trained exclusively in fundus photography have certain shortcomings. Fundus photos provide a surface level view, which may not convey additional information such as tumor depth, structural detail or three-dimensional characteristics [2]. Multimodal deep learning models can get at more diverse image features to illustrate different patterns enabling greater ability to detect subtleties of malignancy [2]. In diabetic retinopathy, [3,4], macular degeneration [5,6], and glaucoma [7,8] multimodal imaging has provided greater detailed diagnostic leverage [2].

Because deep learning uses artificial neural networks to automatically extract and learn higher level image features from raw data without human intervention, it can provide high accuracy in analyzing MRI scans, [2,9,10], X-rays, [2,11,12], and retinal images, [2,13,14]. CNNs automatically detect edges, textures, and shapes in tumor images, [2,15-17]. CNNs detect/quantify intra-retinal drusen, pseudo drusen, exudates, and can segment retinal locations and automatically detect macula drusen for macular degeneration diagnostics. [2,18-20]. Despite the recent publication of papers using deep learning with forms of CNN to classify stages of choroidal melanoma from unimodal and multimodal images, in the interest of brevity and the need to follow certain historical clinical diagnostic thought processes, this paper will not be including CNNs in melanoma in this review.

## Choroidal Nevus/Melanoma Indeterminate Lesions; The Lasso Logistic Regresson Model

Zabor, et al. [21] trained data of 123 patients using a lasso logistic regression model to select variables for inclusion in a final model for small melanoma versus choroidal nevus. The lasso logistic rejection model reduces less informative tumor designating coefficients to 0 and uses a parsimonious, regularized interpretable set of predictor variables to perform an automated tumor feature selection, still fitting a binary straight line classification model. It was in line with transparent reporting of multivariate prediction for diagnosis, TRIPOD statement [22]. In Zabor, et al. [21] we learn that most tumors labeled as small choroidal melanoma (5.0-16 mm in largest basal diameter and 1.0mm-2.5 mm in height within the Collaborative Ocular Melanoma Study [23] observation arm) remained stable during observation with a diagnosis of choroidal nevus more likely than choroidal melanoma [21,23,24]. Since tumors within the small size criteria include nevi and melanoma, it was decided that small choroidal melanocytic tumors should be referred to as "indeterminate choroidal melanocytic tumors", IMT, emphasizing the as yet unmet need of differentiating choroidal nevus from melanoma [21,25,26]. Over time, the classification of choroidal melanoma has broadened from size alone to include extrinsic and intrinsic "risk factors' predictive of growth [21,25,26,]. Risk factors such as the presence of orange pigment and subretinal fluid suggests a small choroidal melanoma, whereas drusen and retinal pigment epithelial changes are likely a benign lesion like a nevus [21]. However, although these risk factors have been considered to be associated with growth, they also carry single unvalidated probabilities that limit their individual clinically predictive value of small choroidal melanoma [21,25,27-32].

Nonetheless, returning to the Zabor paper, A Prediction Model to Discriminate Small Choroidal Melanoma from Choroidal Nevus [21] (where in lasso logistic regression was used to select variables for inclusion in the model), 123 patients diagnosed with small choroidal melanocytic tumor (5.0-16.0 mm in largest basal diameter and 1.0 mm-2.5 mm in height;) Collaborative Ocular Melanoma Study criteria were included. Those diagnosed as melanoma had either documented growth or pathologic confirmation. 62 patients with stable lesions classified as choroidal nevus were used as negative controls. The external validation dataset included 240 patients with malignant growth of small choroidal melanoma, managed at a different clinic. The results showed that greater than or equal to 3mm from the disc and drusen were associated with decreased odds of melanoma. Maleness, increased lesion height, subretinal fluid and orange pigment were associated with increased odds of choroidal melanoma. When tested against the validation data, the prediction model could distinguish between nevus and melanoma with a discrimination of 0.861 [21]. Looking at the data table on Zabor et al outcomes, subretinal fluid had an odds ratio of 2.97 or nearly 3x higher odds for melanoma than nevus. Height of the lesion

had an odds ratio of 2.26 or over twice the odds for melanoma with each mm increase in height. Greater than or equal to 3mm from the disc had an odds ratio of 0.46, making the closer to the disc lesions of much greater concern. Weaker melanoma predictors were maleness, odds ratio, OR 1.05, orange pigment OR 1.21, and drusen OR 0.86.

**Table 1:** Historical View to Choroidal Nevus Versus Melanoma: Core Diagnostic Features.

| Metrics Used | Gass, J.D.M. | Shields, C.L. | Damato, B. / MOLES |
|---|---|---|---|
| 1. Convergent views: 2 mm thickness, subretinal fluid, orange pigment | All three approaches agree that thickness/elevation, subretinal fluid, and orange pigment are critical malignant features. Gass, J.D.M. framed these as individualized clinical warning signs plus documented serial growth, emphasizing lesion behavior over time. | Formalized these as core malignant predictors in TFSOM-DIM (thickness >2 mm, fluid, orange pigment), with strong quantitative evidence from multimodal imaging cohorts. | Converges on same features through MOLES (orange pigment, large size, subretinal fluid), with enlargement as a practical proxy for growth, designed for front-line triage. |
| 2. Divergent views: histopath, risk factor rating, ophthalmoscopy, FA, serial photography, A/B-scan ultrasound, multimedia imaging, ultrasound, ML/Cox vs score vs clinical judgment | Most individualized and expert-dependent: ophthalmoscopy, FA, serial photography, A/B-scan ultrasound; histopathology used when diagnosis uncertain; no formal scoring, no Cox, no ML; closest to clinicopathologic correlation and growth- based biological behavior. | More population-based and statistically modeled: multimodal imaging (photo, OCT, AF, US) with Cox regression, Kaplan- Meier, hazard ratios; TFSOM-DIM mnemonic; ML added later (2024 SAINTS: gradient boosting, XGBoost, random forest on tabular data) Ophthalmology Science; histopathology usually not required for initial classification. | Most simplified and pragmatic: 0/1/2/3 clinical score without Cox or ML; designed for non- experts; ultrasound not required; usable in telemedicine and community settings; histopathology not central. |
| 3. Real-world use at time of cited reference | 1970s-1980s tertiary expert practice: strong in experienced hands, but less standardized, harder to scale, time-intensive, prolonged observation could delay melanoma treatment. | By 2019-2024: ocular oncology referral practice with multimodal imaging; risk-stratified surveillance and treatment; 2024 ML model (SAINTS) added nonlinear ML pattern recognition and external validation Ophth Science. | By 2023-2024: community optometry, general ophthalmology, virtual clinics; successfully implemented at Bristol Eye Hospital and others; increased clinic capacity by discharging low-risk nevi. |
| 4. Simple accuracy, OR or HR outcome metrics | No modern OR, HR, AUC tied to classic Gass framework. Emphasis on tumor dimensions, volume, growth rate rather than contemporary discrimination statistics. | 2019 Cox/HR framework: 7-year HR versus flat nevi: 4.7 (1.1-2.0 mm), 35.7 (2.1-3.0 mm), 52.0 (>3.0 mm). 2024 SAINTS ML: AUROC 0.86-0.93, AUPRC 0.24-0.53 depending on cohort; accuracy ≈0.91 internal, 0.89 external; sensitivity/specificity/PPV threshold-dependent Ophth Science +1. | MOLES score: in optometrist image evaluation, 95.8% sensitivity, 64.1% specificity for probable melanoma triage; designed to err on side of caution. |

## The Primacy of Increased Basal Daimeter and Thickness in Choroidal Melanoma

Returning to the issue of size, to analyze the risk of nevus transformation into melanoma per millimeter growth increment, Shields et al in 2019 in a multimodal retrospective analysis of 3806 choroidal nevi for all thicknesses, found those with growth to melanoma had an increase in mean basal diameter of 2.4mm and thickness of 1.1mm, OCT increase of subretinal fluid, 65%, autofluorescence increase in lipofuscin, 40%, and increase in ultrasonography hollowness, 30% [32].

Shields et al concluded: The hazard risk for less than or equal to 1mm or flat was 1; The hazard risk for 1-2.0mm growth was 4.7, 4.7x higher than flat; the hazard risk for 2.1-3.0 mm was 35.7x higher than the risk of flat; finally, the hazard risk of > 3.0mm was 52x higher than flat. {32} While both odds ratio, OR, Zabor, et al. [21] and hazard ratio, HR, Shields, et al. [32] describe a "strength of association" to choroidal melanoma or are "effect measures'", they are not a sensitivity metric, which is a true positive rate at a threshold, nor a specificity metric, which is a negative rate at a threshold [33]. Nonetheless, Zabor et al, lasso logistic, and Shields et al, Cox Regresson, although using distinct methods of AI and multimodal imaging feature extraction, both study groups found that over 2 mm increment was a key thickness finding for melanoma; both also found that subretinal fluid, Zabor, et al. [21] OR 2.97 and Shields, et al. [32] HR 3.56 are significant associations to melanoma development. However, even though OR and HR are metrics for "strength of association", not decision thresholds, mathematical calibration formulae could transform them into actionable probabilities, [34].

## The MOLES, Scoring System: A Real-World Attempt to Diagnose Choroidal Melanoma

Early treatment of choroidal melanoma may prevent visual loss and life-threatening metastatic disease in some patients [35-38]. That said, Khan and Damato found that it is difficult for general ophthalmologists to distinguish small choroidal melanomas from nevi [39]. Approximately 30% of the patients referred to an ocular oncology service with the diagnosis of choroidal melanoma have an incorrect diagnosis [39]. After referral of these choroidal nevi patients they can be monitored for months or years and patients with melanoma may experience long delays in treatment. Two

issues are at hand, (1) has the tumor grown? and (2) could a patient's nevus be one of the 5-8% which do not show malignant growth? [40-45] Especially during Covid and its aftermath, non-essential patient referral for expert opinion entailing travel expenses, great stress over eye cancer, risk of Covid, extended time and effort for photography unit and ultrasonography unit scheduling and waits, all of these real world issues prompted B Damato [35, 46] to develop the MOLES scoring system to "help non-experts estimate the likelihood of malignancy in melanocytic choroidal tumors and to manage patients accordingly." [35].

## MOLES stands for: Mushroom Shape, Orange Pigment, Large Size, Subretinal Fluid

_MUSHROOM SHAPE occurs when the tumor perforates the retinal pigment epithelium, (RPE), collar stud appearance; Bruch's membrane blocks venous outflow from the intra-retinal portion of the tumor, which then swells and becomes edematous. The apical portion of the tumor may show dilated and tortuous tumor vessels; the base of the tumor is usually gray because of multilayering of the RPE, which may show clumps of orange pigment, lipofuscin [35,47]. Ultrasonography shows the intraretinal tumor with high internal acoustic reflectivity because of interstitial edema and intra-choroid low reflectivity because the tumor cells are packed tightly [35,47].

_ORANGE PIGMENT, lipofuscin accumulation, dusting to orange clumps on top of choroidal melanoma; lipofuscin is not removed because of defective or lost RPE function [35,47,48]; lipofuscin minimal or absent over choroidal nevi with still effective RPE "clean up"; On ophthalmoscopy and color photography, lipofuscin is orange over dark tumors, hence the term "orange pigment". On Fundus auto fluorescence lipofuscin is brightly auto fluorescent [35,48]. On OCT lipofuscin accumulates in the inner, superficial RPE and can appear brown or black over amelanotic tumors [35]. Desquamated lipofuscin from the tumor surface with deposits in the subretinal fluid inferior to the tumor occasionally forms a "pseudo-hypopyon"; alternatively, if the choroidal melanoma is very small with minimal thickening, lipofuscin may be absent [35]. Orange pigment can accumulate as well over choroidal metastasis and hemangiomas. [35] Drusen, on the other hand, show minimal autofluorescence and develop between the RPE and Burch's membrane.[35]

_LARGE SIZE and or ENLARGING LESION. Augsburger et al. found that there are approximately 70, 10 and 3 nevi for every choroidal melanoma in the basal diameter ranges of 5-6 mm, 6-7 mm, 7-8 mm, respectively [35, 49]; Because thin tumors tend to have tapering margins, color photos may define tumor margins better than ultrasound [35,50].

If the internal scleral surface of a small choroidal lesion can be seen, then the thickness of small posterior lesions can be measured by OCT [51,35]. With halo nevi, ultrasonography may miss posterior bowing of the internal scleral surface. [35,51] Ultrasonography, however, may be useful for measuring tumor thickness when OCT is not possible because of large tumor size and if peripheral tumors appear bulky. Caliper placement should start at the tumor apex, excluding sclera and sensory retina, and run to the inner scleral surface. Tumor thickness measurements from ultrasonography are greater than those from OCT [35,52]. After the second decade of life, choroidal nevi rarely enlarge. In tumors of a median diameter of 5mm, range, 0.5 to 14mm, the median increase in diameter was 0.06mm/year, range, 0.01-0.36mm [35,53]. Small melanomas, on the other hand, tend to enlarge by 0.25mm/year [54].

Jouhi et al indicated that by assessing the distance between tumor margins and adjacent landmarks, the most sensitive measurements can be made. The entire tumor margin needs to be measured because lateral extension may occur in an axis different from the basal diameter [54]. Also, distortion in photos can create a false impression of growth [55]. In contrast to the 1% increase in basal diameter/year of choroidal nevi, the basal diameter of melanomas tends to increase approximately 34%/year [54,35]. Increase in tumor thickness with ultrasonography may be subject to measurement variation because growth of later thickness may encompass sclera and or retina or if comparisons are made to OCT which tends to smaller measurements. Thus, tumor thickness is considered significant only if it is greater than 0.5mm [56,35]. While it is not likely that in the absence of other signs of tumor growth that the tumor will grow thicker without becoming wider, some tumors develop increasing amounts of subretinal fluid, SRF, and or orange pigment and RPE perforation which should be considered a sign of growth. In these cases, sequential color photography is more sensitive than ultrasonography in showing tumor growth [56,35].

_SUBRETINAL FLUID develops when the underlying choroidal tumor disturbs RPE function. With small, common nevi, the retina is flat. Some larger nevi can develop detachment and with more advance result in a neovascular membrane [57]. However, intra-retinal cystoid edema is a marker of chronicity and is not a sign of melanoma [35,58]. Gass, however, a leading investigator in the field of choroidal nevi vs. melanoma, indicated that small choroidal melanoma may have overlapping range of average dimensions, thickness and other clinical features [58].

That said, patients with choroidal membranes and intra-retinal cystoid edema still require close follow up.[35]

Clinical features excluded from MOLES include: proximity to optic disc, absence of halo, drusen, visual symptoms, low internal acoustic reflectivity, melanocytoma, and congenital ocular melanocytosis. These conditions are felt to have weaker association to melanoma or require lifelong monitoring [35].

MOLES scoring is given for each of the items in the acronym with a score of 0, if absent, 1, if mild or uncertain, and 2 if present.

Some doctors were concerned about not being able to measure thickness. In these cases, by marking tumor size by diameter or thickness, MOLES enabled examiners to ignore thickness. Al Harby et al found that tumor thickness influenced MOLES score by 6/222 or only 2.7% [35, 59].

## MOLES Instructions

(1) Categorize tumours according to total score: 0 = Common naevus; 1 = Low-risk naevus; 2 = High-risk naevus and 3 or more = Probable melanoma "[35]. (2) "Pending further audit, the MOLES protocol tentatively suggests that patients with low-

risk nevi and high-risk nevi should be referred non-urgently to an ophthalmologist for multimodal imaging and plans for long-term surveillance, advising on the assessment frequency, imaging methods, and when monitoring can be undertaken by a community optometrist (e.g., immediately or if no tumor progression has been documented after a specified time)" [35]. (3) "Patients with probable melanoma should be referred urgently to an ophthalmologist following NHS England's two-week-wait protocol for suspected cancer" [35].

At the Ocular Nevus Clinic of Moorfield's Eye Hospital, Al Harby, et al. reviewed 222 melanocytic choroidal tumors retrospectively given MOLES scores. All 81 tumors diagnosed as melanoma by ocular oncologists had a MOLES score of 3 or more, 100% sensitivity; 135/141 nevi had a MOLES score of less than 3, 95.7% specificity. Of the six tumors with discordant diagnosis, four measured greater than 6 mm in diameter and had SRF or lipofuscin; 2 small tumors had either significant SRF or trace lipofuscin [59]. Roelofs et al using MOLES retrospectively reviewed 451 choroidal melanomas. Only one melanoma had a score of less than 3; it is unclear if MOLES failed because there was another feature such as a retinal detachment [60,35].

Shields, et al. using the mnemonic, TFSOM-DIM (To- find -small ocular -melanomas -doing imaging) [61-63] did a retrospective medical record review using Kaplan-Meier estimates and Cox regression analysis of 2514 consecutive eyes and the median tumor basal diameter was 5.0mm and thickness was 1.5mm. Nevus growth into melanoma occurred at the rates of 2%, 5% and 13% of eyes at 1, 5, and 10 years, respectively. Using multivariate analysis tumor thickness greater than 2mm ($p<.001$), subretinal fluid ($p = .002$), symptoms ($p = .002$), orange pigment ($p <.001$), tumor margin within 3mm of optic disc ($p = .001$), ultrasonic hollowness ($p < .001$) were factors predictive of growth into melanoma. Two new features were ultrasonic hollowness and absence of halo. The ratio for those with 1-2 risk factors was 3; for 3 or 4 factors was 5; for 5 or 6 factors was 9 and for all 7 factors was 21.

## Conclusion

Growth/Thickness, subretinal fluid, and orange pigment are all features agreed upon by the three experts above for nevus transformation to melanoma. Where they differ is in workflow.

Gass emphasized individualized expert assessment of the initial lesion and expert assessment of lesion progression over time, with specific volumetric criteria that have survived to this day.

Shields formalized multimodal imaging for serial changes, including not just growth, but additional risk factors with longitudinal percentage incremental direct hazard-based time to event model, TFSOM-DI, "To find small ocular melanoma doing imaging"; and later added Machine Learning (SAINTS), "Simple AI nevus transformation system" using the same image domain to generate a probability of nevus transformation at present. SAINTS achieved a strong AUC, but a lower area under the precision recall curve. Thus, even though a lesion may be high risk, it does not necessarily translate into strong positive predictive precision.

Damato (MOLES), Mushroom shape, Orange pigment, Large size, Enlarging lesion, Subretinal Fluid recently developed a simple community-clinical score system incorporating the above features for frontline eye clinic triage and telemedicine, sensitivity 100%, and specificity 95.7%

This historical glimpse at diagnostic methods for choroidal melanoma over the last fifty years is an attempt to view the resources and intellectual prowess in choroidal melanoma diagnosis. The pathways in ophthalmology from the early world authority's comprehensive mind in the 1970s-1980s, to the current expert researcher's creativity of today, using AI and careful statistical data science evidence to predict nevus to melanoma change, to the real-world mind also of today, attempting to capture categoric diagnostic simplicity in a beleaguered clinical world, all of these individuals reflect exciting research workflows to rise to the challenge of catching a devastating disease, choroidal melanoma, early.

## Conflicts of interest

None.

## Acknowledgement

Thanks to DOXGPT and Monica GPT for helping with the tables.

## References

1. D Tailor, P K Kopinski, S D'Souz, DA Leske, T W Olsen, et al. (2024) Predicting Choroidal Nevus Transformation to Melanoma Using Machine Learning. Ophthalmol Sci 5(1): 100584.
2. A K Dadzie, S P Iddir, S Ganesh, B Ebrahimi, M Rahimi (2025) Artificial intelligence in the diagnosis of uveal melanoma: advances and applications. Exp Biol Med (Maywood) 250: 10444.
3. Hua CH, Kim K, Huynh The T, You JI, Yu SY, et al. (2021) Convolutional network with twofold feature augmentation for diabetic retinopathy recognition from multi-modal images. IEEE J Biomed Health Inform 25(7): 2686-2697.
4. Li X, Zhou Y, Wang J, Lin H, Zhao J, et al. (2021) Multi-modal multi-instance learning for retinal disease recognition. In: Proceedings of the 29th ACM international conference on multimedia.
5. Wang W, Li X, Xu Z, Yu W, Zhao J, et al. (2022) Learning two-stream CNN for multi-modal age-related macular degeneration categorization. IEEE J Biomed Health Inform 26(8): 4111-4122.
6. Chen M, Jin K, Yan Y, Liu X, Huang X, et al. (2022) Automated diagnosis of age-related macular degeneration using multi-modal vertical plane feature fusion via deep learning. Med Phys (2022) 49(4): 2324-2333.
7. Wu J, Fang H, Li F, Fu H, Lin F, et al. (2023) GAMMA challenge: glaucoma grading from Multi-Modality imAges. Med Image Anal 90: 102938.
8. Zhou Y, Yang G, Zhou Y, Ding D, Zhao J (2023) Representation, alignment, fusion: a generic transformer-based framework for multi-modal glaucoma recognition. In: International conference on medical image computing and computer-assisted intervention: Springer.
9. Liu S, Zheng H, Feng Y, Li W (2017) Prostate cancer diagnosis using deep learning with 3D multiparametric MRI. In: Medical imaging 2017: computer-aided diagnosis: SPIE.
10. Zhang N, Yang G, Gao Z, Xu C, Zhang Y, et al. (2019) Deep learning for diagnosis of chronic myocardial infarction on nonenhanced cardiac cine MRI. Radiology 291(3): 606-617.

11. Khan AI, Shah JL, Bhat MM (2020) CoroNet: a deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. Computer Methods Programs Biomed 196: 105581.
12. Ayan E, Ünver HM (2019) Diagnosis of pneumonia from chest X-ray images using deep learning. In: 2019 Scientific meeting on electrical-electronics and biomedical engineering and computer science (EBBT). Istanbul, Turkey: IEEE.
13. Ebrahimi B, Le D, Abtahi M, Dadzie AK, Lim JI, et al. (2023) Optimizing the OCTA layer fusion option for deep learning classification of diabetic retinopathy. Biomed Opt Express 14(9): 4713-4724.
14. Kim KM, Heo TY, Kim A, Kim J, Han KJ, Yun J, et al. (2021) Development of a fundus image-based deep learning diagnostic tool for various retinal diseases. J Personalized Med 11(5): 321.
15. Dipu NM, Shohan SA, Salam K (2021) Deep learning-based brain tumor detection and classification. In: 2021 International conference on intelligent technologies (CONIT). IEEE.
16. Vankdothu R, Hameed MA, Fatima H (2022) A brain tumor identification and classification using deep learning based on CNN-lstm method. Comput Electr Eng 101: 107960.
17. Quon JL, Bala W, Chen L, Wright J, Kim L, (2020) et al. Deep learning for pediatric posterior fossa tumor detection and classification: a multi-institutional study. AJNR Am J Neuroradiol 41(9): 1718-1725.
18. Schwartz R, Khalid H, Liakopoulos S, Ouyang Y, de Vente C, et al. (2022) A deep learning framework for the detection and quantification of reticular pseudodrusen and drusen on optical coherence tomography. Translational Vis Sci and Technology 11(12): 3.
19. Li Z, Guo C, Nie D, Lin D, Cui T, et al. (2022) Automated detection of retinal exudates and drusen in ultra-widefield fundus images based on deep learning. Eye (Lond) 36(8): 1681-1686.
20. Pham QTM, Ahn S, Song SJ, Shin J (2020) Automatic drusen segmentation for age-related macular degeneration in fundus images using deep learning. Electronics 9(10): 1617.
21. Zabor EC, Raval V, Luo S, et al. (2022) A prediction model to discriminate small choroidal melanoma from choroidal nevus. Ocul Oncol Pathol 8: 71-78.
22. G S Collins, J B Reitsma, D G Altman, K G M Moons (2015) Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD statement, Br J Cancer 112(2): 251-259.
23. Factors predictive of growth and treatment of small choroidal melanoma (1997) COMS report No. 5. Arch Ophthalmol. 115(12): 1537-1544.
24. Murray TG (1997) Small choroidal melanoma. Arch Ophthalmol 115(12): 1577-1578.
25. Butler P, Char DH, Zarbin M, Kroll S (1994) Natural history of indeterminate pigmented choroidal tumors. Ophthalmology. 101(4): 710-717.
26. Singh AD, Grossniklaus HE (2021) What's in a name? Large choroidal nevus, small choroidal melanoma, or indeterminate melanocytic tumor. Ocular Oncol Pathol.
27. Singh AD, Mokashi AA, Bena JF, Jacques R, Rundle Paet al. (2006) Small choroidal melanocytic lesions: features predictive of growth. Ophthalmology 113(6): 1032-1039.
28. Singh AD, Schachat AP, Diener West M, Reynolds SM (2008) Small choroidal melanoma. Ophthalmology 115(12): 2319-e3.
29. Augsburger JJ, Schroeder RP, Territo C, Gamel JW, Shields JA (1989) Clinical parameters predictive of enlargement of melanocytic choroidal lesions. Br J Ophthalmol 73(11): 911-917.
30. Shields CL, Shields JA, Kiratli H, De Potter P, Cater JR (1995) Risk factors for growth and metastasis of small choroidal melanocytic lesions. Ophthalmology 102(9): 1351-1361.
31. Shields CL, Cater J, Shields JA, Singh AD, Santos MC, et al. (2000) Combination of clinical factors predictive of growth of small choroidal melanocytic tumors. Arch Ophthalmol 118(3): 360-364.
32. Shields CL, Dalvin LA, Yu MD, Ancona Lezama D, Di Nicola M, et al. (2019) Choroidal nevus transformation into melanoma per millimeter increment in thickness using multimodal imaging in 2,355 cases: the 2019 Wendell L. Hughes lecture. Retina. 39(10): 1852-1860.
33. Roberts MR, Ashrafzadeh S, Asgari MM (2019) Research Techniques Made Simple: Interpreting Measures of Association in Clinical Research. J Invest Dermatol 139(3): 502-511 e1.
34. Riley RD Archer L, Kym I E Snell KI E, Ensor J Dhiman P (2024) Evaluation of clinical prediction models (part 2): how to undertake an external validation study. BMJ 384: e074820.
35. Damato, BE (2022) Can the MOLES acronym and scoring system to improve the management of patients with melanocytic choroidal tumours? Eye (Lond) 37(5): 830-836.
36. Hussain RN, Coupland SE, Kalirai H, Taktak AFG, Eleuteri A, et al. (2021) Small high-risk uveal melanomas have a lower mortality rate. Cancers (Basel) 13: 2267.
37. Damato BE, Heimann H, Kalirai H, Coupland SE (2014) Age, survival predictors, and metastatic death in patients with choroidal melanoma: tentative evidence of a therapeutic effect on survival. JAMA Ophthalmol 132: 605-613.
38. Damato BE, Heimann H, Kalirai H, Coupland SE (2014) Age, survival predictors, and metastatic death in patients with choroidal melanoma: tentative evidence of a therapeutic effect on survival. JAMA Ophthalmol 132: 605-613.
39. Khan J, Damato BE (2007) Accuracy of choroidal melanoma diagnosis by general ophthalmologists: a prospective study. Eye 21: 595-597.
40. Damato EM, Damato BE (2012) Detection and time to treatment of uveal melanoma in the United Kingdom: An Evaluation of 2384 Patients. Ophthalmology 119: 1582-1589.
41. Damato B (2001) Detection of uveal melanoma by optometrists in the United Kingdom. Ophthalmic physiological Opt: J Br Coll Ophthalmic Opticians 21: 268-271.
42. Sumich P, Mitchell P, Wang JJ (1998) Choroidal nevi in a white population: the Blue Mountains Eye Study. Arch Ophthalmol 116: 645-650.
43. Singh AD, Kalyani P, Topham A (2005) Estimating the risk of malignant transformation of a choroidal nevus. Ophthalmology 112: 1784-1789.
44. Kivela T, Eskelin S (2006) Transformation of nevus to melanoma. Ophthalmology 113:887-888 e1.
45. Qiu M, Shields CL (2015) Choroidal nevus in the United States adult population: racial disparities and associated factors in the national health and nutrition examination survey Ophthalmology 122: 2071-2083.
46. Damato B (2020) Managing patients with choroidal melanoma in the COVID-19 era: a personal perspective. The. Br J Ophthalmol 104: 885-886.
47. Weiss SJ, Stathopoulos C, Shields CL (2019) Choroidal nevus with retinal invasion in 8 cases. Ocul Oncol Pathol 5: 369-378.
48. Sepah YJ, Akhtar A, Sadiq MA, Hafeez Y, Nasir H, et al. (2014) Fundus autofluorescence imaging: fundamentals and clinical relevance. Saudi J Ophthalmol 28: 111-116.
49. Augsburger JJ, Correa ZM, Trichopoulos N, Shaikh A (2008) Size overlap between benign melanocytic choroidal nevi and choroidal malignant melanomas. Investigative Ophthalmol Vis Sci 49: 2823-2828.
50. Pe'er J, Sancho C, Cantu J, Eilam S, Barzel I, et al. (2006) Measurement of choroidal melanoma basal diameter by wide-angle digital fundus camera: a comparison with ultrasound measurement. Ophthalmologica 220: 194-197

51. Dolz Marco R, Hasanreisoglu M, Shields JA, Shields CL (2015) Posterior scleral bowing with choroidal nevus on enhanced-depth imaging optical coherence tomography. JAMA Ophthalmol 133:1165-1170.

52. Shields CL, Kaliki S, Rojanaporn D, Ferenczy SR, Shields JA (2012) Enhanced depth imaging optical coherence tomography of small choroidal melanoma: comparison with choroidal nevus. Arch Ophthalmol 130: 850-856.

53. Mashayekhi A, Siu S, Shields CL, Shields JA (2011) Slow enlargement of choroidal nevi: a long-term follow-up study. Ophthalmology 118: 382-388.

54. Jouhi S, Al Jamal RT, Tall M, Eskelin S, Kivela TT (2020) Presumed incipient choroidal melanoma: proposed diagnostic criteria and management. Br J Ophthalmol bjophthalmol: 318658.

55. Paul Brett J, Lake A, Downes S (2016) Colour imaging in the monitoring and documentation of choroidal naevi. Are Optomap colour images adequate for this purpose? J Vis Commun Med 39: 10-17.

56. Roelofs KA, O'Day R, Al Harby L, Hay G, Arora AK, et al. (2020) Detecting progression of melanocytic choroidal tumors by sequential imaging: is ultrasonography necessary? Cancers (Basel) 12: 1856.

57. Papastefanou VP, Nogueira V, Hay G, Andrews RM, Harris M, et al. (2013) Choroidal naevi complicated by choroidal neovascular membrane and outer retinal tubulation. Br J Ophthalmol 97: 1014-1019.

58. Gass JD (1977) Problems in the differential diagnosis of choroidal nevi and malignant melanomas. The XXXIII Edward Jackson Memorial Lecture. Am J Ophthalmol 83: 299-323.

59. Al Harby L, Sagoo MS, O'Day R, Hay G, Arora AK, et al. (2021) Distinguishing choroidal nevi from melanomas using the MOLES algorithm: evaluation in an ocular nevus clinic. Ocul Oncol Pathol 7: 294-302.

60. Roelofs KA, O'Day R, Harby LA, Arora AK, Cohen VML, et al. (2020) The MOLES System for Planning Management of Melanocytic Choroidal Tumors: Is It Safe? Cancers (Basel) 12: 1311.

61. Shields CL, Dalvin LA, Ancona Lezama D, Yu MD, Di Nicola M, et al. (2019) Choroidal nevus imaging features in 3,806 cases and risk factors for transformation into melanoma in 2,355 cases: The 2020 Taylor R. Smith and Victor T. Curtin Lecture. Retina 39: 1840-1851.

62. Shields CL, Cater J, Shields JA, Singh AD, Santos MC, et al. (2000) Combination of clinical factors predictive of growth of small choroidal melanocytic tumors. Arch Ophthalmol 118: 360-364

63. Shields CL, Furuta M, Berman EL, Zahler JD, Hoberman DM, et al. (2009) Choroidal nevus transformation into melanoma: analysis of 2514 consecutive cases. Arch Ophthalmol 127: 981-987.