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AI in Uveitis

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Abstract

Uveitis is a serious intraocular inflammation of the pigmentary vascular coat of the eyeball, which ranks fifth as the leading cause of worldwide blindness because of possible complications related to retinal ischemia, ocular hypertonia, post inflammatory scarring, glaucoma, and macular edema [1,2,3]. The incidence of uveitis is 17-52/100,000 people and its prevalence ranges form 38-284/100,000 people [3]. Since uveitis encompasses nearly 80 etiologies stemming from: distinct ophthalmological diseases, infectious disease, inflammatory disease, masquerade syndromes, drug induced, autoimmune disease, genetic factors (HLA-B27), and indeterminate causes, in 2005 and 2021, SUN, the Standardization of Uveitis Nomenclature group, developed classification criteria for uveitis [4,46].

Introduction

The Standardization of Uveitis Nomenclature, SUN, A Multimodal Machine Learning Model

From a databank of over 4,000 uveitis patients, for whom a consensus of expert clinicians previously made the diagnosis of uveitis, the patients were placed in a subclass of uveitis and divided into training and validation sets. Using Machine Learning, consisting of: (1) Multimodal data, (combining text, images or numerical measurements), (2) logistic regression, (an algorithm used to estimate "yes" or "no" probability of a categorical outcome), (3) data regularization, LASSO ("Least Absolute Shrinkage and Selection Operator" to add an absolute value to insure regularized output of the model), and [4] the expert uveitis group's standardized criteria for the diagnosis of uveitis, the SUN group developed the uveitis model. The SUN accuracy in the validation set of the uveitis subclasses was anterior uveitis, 95%, intermediate uveitis, 99.3%, posterior uveitis 98%, panuveitis, 94%, and infectious posterior uveitis/panuveitis 93.3% [4].

Methods

Since this is a small review of AI in uveitis diagnostics, the following topics were target searched for references in Doxgpt, Google Gemini, and Microsoft Copilot over the last decade in the following areas:

1. Review articles on diagnostic categories of uveitis and their classification
2. Expert review panels on classification criteria of uveitis with particular attention to SUN, Standardization of Nomenclature group, and ULISSE, Evaluating a Standardized Strategy for Uveitis Etiologic Diagnosis
3. Review articles on uveitis diagnostic work up
4. Review article on uveitis management

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5. Reviews on OCT imaging of Anterior Segment Uveitis with Expert panels included
6. Reviews on OCT imaging of Posterior Segment Uveitis with expert panels included
7. Papers with panels using AI to Assess Noninfectious Posterior Uveitis and achieve proper panel consensus as well as higher metric accuracy scores were favored for presentation.
8. Papers using neural networks with different architectures to examine vetted uveitis or uveitis/AMD/DME patient data sets with 70% accuracy or better were also favored for presentation.

Results

Algorithmic and AI Updates to encompass Uveitis Diagnostic Variables

The epidemiology of causative factors for uveitis varies in different countries. It may be affected by genetic and environmental factors, different types of exams, and variable anatomic locations. It may present with different clinical signs. These variables render uveitis a complex disease which may be difficult to diagnose [2,5,6]. Several investigators have addressed the most cogent diagnostic approaches to diagnosing uveitis [2,4,6, 7,8,9,12,44,45,46]. They offer valuable guidelines from the standpoints of internal medicine, ophthalmology, autoimmune disease, and rheumatology. de Parisot et al. [10] did a controlled study comparing a "standardized" minimal uveitis evaluation compared to an open strategy evaluation. The standardized group of 303 patients from 2010-2013 had complete blood count, erythrocyte sedimentation rate, C-reactive protein, TB skin test, syphilis serology and chest x-ray. The open group of 373 patients from 2010-2013 had whatever investigation the ophthalmologist ordered.

de Parisot, et al. found there was no significant difference in the etiologic diagnosis established. The etiologic diagnosis was established in 54.4% of the open group and 49.5% of the standard group. However, the open group had 5371 investigations, and the standard group only had 3759, P<.0001) [2,10,11]. Factors mitigating an algorithmic approach to uveitis diagnosis may be inexperienced clinicians and the large amount of uveitis data that needs to be aggregated and developed into algorithms. [2,5,13]. Although machine learning techniques in more recent reports have utilized Bayesian networks, multilayered rule based expert systems, decision trees to explore uveitis diagnosis with algorithms to encompass demographic, ophthalmological and extra-ophthalmological, complementary exams, and treatment response factors, these systems achieved the correct diagnosis in only 54-74% [2,14-20]. Also, these computer aided-systems may have limited number of etiologies with ophthalmic, demographic, clinical and ancillary tests not reliably incorporated into the algorithms' dataset. There may have been restricted, or missing data, or small patient numbers, and small training data bases. In others, uveitis study factors were made available later, after the diagnosis of uveitis was made. This has caused these algorithms to be of limited use [2, 19, 20]. If the two most probable etiologies underlying uveitis were queried, however, then the AI based system performed with a classification accuracy of 93-99% and a sensitivity of at least 80% [2,20,].

AI in AS OCT

AI applied to anterior segment, AS, OCT images compared to a clinical exam with a slit lamp showed a significant and independent correlation with SUN classification for quantifying AS inflammation [21-27]. Agarwal, et al. [21] using high speed OCT for inflammation detection, identified hyperreflective spots whose count was representative of AS inflammatory grade. Automated OCT count vs manual count of grades agreed on all grades except 4; in grade 4 the automated OCT measurement detected the greater number of cells, in eyes with corneal edema and central thickness from 702- 1020 microns.

Sorkhabi, et al. [22] using Anterior Image OCT Analyzer (AI-OCT version 1.0) analyzed anterior segment structures and did particle detection with a deep learning. After setting up a custom UNet architecture for image segmentation, it was trained on a database of 844 manually segmented AS-OCT scans. In addition, a separate deep learning particle segmentation algorithm was trained on a database of 1330 manually segmented AS-OCT scans. Only frames with marked particles were used. Training and validation sets were then selected for image and particle segmentation. Thus, a deep learning segmentation model for particle detection with a custom UNet CNN architecture was developed.

32 eyes of 19 patients with a diagnosis of anterior uveitis in at least one eye were assigned a SUN grade; all the control group eyes had a SUN grade of 0. No abnormal AC architectures were observed. Pearson linear correlation between manual and automatic AI based segmentation was p = 0.9948 for the number of particles in anterior chamber by AI software and manual segmentation. Goodness of fit, R^2 for linear regression fit was evaluated as 0.9897 [22]. Although the SUN group standard for quantification of vitreous inflammation is a clinical exam with an indirect ophthalmoscope compared to a set of standard photographs, several investigators have suggested that macular OCT scans offer greater accuracy and reliability for vitreous inflammatory intensity [28,29,30]. Passaglia, et al. [31] compared computer vitreous haze grade scores to those of clinicians using an image processing algorithm they designed. The agreement between the expert clinicians and the algorithm had a Kappa value of 0.61. (Cohen's Kappa coefficient is a measure of reliability of two observers agreeing, taking into consideration what might be purely by chance. 1.0 means perfect agreement and 0.0 means the agreement is random guessing. So, a 0.6 is a moderate agreement and acceptable, whereas 0.6-0.8 would be substantial.)

AI in Posterior Segment OCT

Posterior segment OCT to (1) quantify choroidal inflammation, [32] , (2) quantify choriocapillaris inflammation with automated swept source OCT [33], (3) detect choriocapillaris flow attenuation, [34], and (4) automate detection and quantification of macular edema for AMD and diabetic retinopathy, [35,36,37], (which

could be applied to measuring uveitc macula edema), have not as yet achieved widespread clinical use [20]. Employing non-imaging clinical data, the SUN group used AI to classify uveitis into 25 of the most common categories. [4,20] After they collected over 4000 cases of uveitis from centers on 5 continents with about 100-200 per clinical center, they used consensus to establish a ground truth for each. The cases were then split into training and testing, 85% and 15% respectively. Machine learning with multinomial logistic regression was used to then with each subclass classify each patient with uveitis. The accuracy ranged from 93% to 99% and worked well in clinical research. However, there are thus far no prospective or comparative studies showing how the SUN performs in clinical practice [20].

To develop imaging based measures to assess noninfectious posterior uveitis, an expert committee reviewed and extracted the consensus based imaging recommendations from the multimodal imaging in uveitis initiative, MUV. The primary objective was to distinguish active disease from inactive disease or equivocal disease by an independent expert committee [38]. For the most common noninfectious posterior uveitides, **NIPU, multiple evanescent white dot syndrome, MEWDS,** [39], **acute posterior multifocal placoid pigment epitheliopathy, AMPEE,** [40], **multifocal choroiditis and panuveitis (MFCPU), punctate inner choroidopathy (PIC),** [41], **serpiginous choroiditis (SC),** [42] **and birdshot chorioretinopathy (BSCR),** [43] an expert subcommittee was formed that prepared imaging guidelines which were listed in the previous MUV report "for assessment of disease activity and complications, e.g. choroidal neovascularization, CNV, for the NIPU entities" [38].

Given the above disease entities, the experts focused on the following diagnostic modalities: **FFA** (Fundus Fluorescein Angiography), **IGCA** (Indocyanine Green Angiogrphy), **OCT** (Optical Coherence tomography), **FAF** (Findus Autofluorescence), and **OCTA** (Optical Coherence Tomography Angiography). For each imaging modality, the experts compiled statements for each disease above to serve as outcome measures, categorizing them with features into "suggestive of active disease", or "inactive" disease and "advanced stage of healing" [38]. Study data was collected and managed using REDCap (Research Electronic Data Capture, hosted at Vanderbilt University Medical Center). It provided data capture, validation of data capture, automated export and statistical procedures and procedures for data integration locally and for export [38].

Briefly, largely extracted from the individual disease tables [38] and expert investigators [39-43]), mostly **OCT** image highlight findings are presented here:

MEWDS [39] had OCT with multifocal disruption, and hypo reflectivity of the ellipsoid zone, EZ, inner zone, IZ, and external limiting membrane, ELM, with 100% expert agreement.

AMPE [40] had early hypofluorescence and late hyperfluorescence on **FFA** and hyperreflectivity of EZ, ELM, ONL on OCT, with 96% expert agreement.

MFCPU/PIC [41] had OCT fluffy subretinal hyperreflective material with EZ disruption and focal choroidal thickening, 91-98% expert agreement.

SC [42] **OCT** had choriocapillaris thickening and loss of "dotted pattern" active disease, 93.9% agreement, but disruption of outer retina or RPE are equivocal features according to 100% of the experts.

BSCR [43] **OCT** had limited role except for CME and retinal membrane with it; ICGA was valuable, however, in BSCR, in assessing choroidal involvement, typically with early hypofluorescent white dots, but loss of large choroidal vessel contour and late-phase **ICGA** hyperfluorescent illustrating choroidal vascular inflammation, 93% expert agreement [38].

(Comprehensive tables are presented in the Disease Activity in Noninfectious Posterior Uveitis Taskforce, Report 10 [38] and they delve into the efficacy of each of the diagnostic modalities with respect to each of the non-infectious posterior uveitis [38]). Thus, the uveitis MUV taskforce in report 10 was able to coherently link the assessment of disease activity in noninfectious posterior uveitis entities with different multimodal diagnostic imaging techniques and with expert consensus. This suggested that classifying diagnostic criteria for individual uveitis disease activity, inactivity or temporarily compensated state, which had eluded general categorization previously, was now possible [38].

Jacquot, et al. 2024: the Neural Network to predict etiological diagnosis of uveitis

Looking at the heterogeneity of causes of uveitis, the large number of ophthalmological and extra-ophthalmological diagnostic features, Jacquot et al. developed a neural network to predict the etiological diagnosis of uveitis [2]. The cohort was comprised of 375 patients with uveitis of unknown etiology. One hundred and nine variables, including demographic, ophthalmic and clinical information associated with complimentary exams were analyzed. Twenty-five causes of uveitis were included. The neural network model was developed to predict the etiological diagnosis of uveitis. The model performance was compared to the consensus etiological diagnosis of two uveitis experts [2].

The neural network architecture type multilayer perceptron, NN-MLP, presented the best prediction of etiological diagnosis of uveitis. Its diagnosis of the most probable diagnosis matched the senior clinician diagnosis in 292 of 375 patients, in 77.8%. It had an accuracy of 93% when the two most probable diagnosis were considered. In diagnosing idiopathic uveitis. The multilayer perceptron had a sensitivity of 81% and specificity of 82%. For over three-quarters of the etiologies, the NN-MLP had a diagnostic sensitivity >70% and specificity > 80% [2]. These types of early modelling results suggest that developing AI models for the diagnosis of uveitis (with all its diagnostic complexity) may be valuable in the future [2].

A Brief view of Random Forest and NN-MLP CNNs; A possible role for additional AI work in Uveitis in the Future? Of interest, in Jacquot, et al [2] although NN-MLP was the best CNN network architecture performer at 93% accuracy (if the top two uveitis diagnosis were considered), Random Forest came in a close second at 92.3% [2]

Random Forest

Mahalakshmi and Justin [48] developed a new deep CNN architecture that can automatically detect early signs of AMD from public dataset of retinal OCT images. Combining VGG19 CNN architecture for deep image feature extraction with a Random Forest classifier to obtain a more accurate diagnosis, the model was combined with Global Average Pooling to lower the dimensionality of the features and then pool them into a single vector per image. This enabled accuracy in differentiating early, intermediate, and late AMD stages. The model achieved an accuracy of 99.3%, outperforming a standard CNN-based classifier.

Random Forest classifier improved image classification efficiency by being able to use a smaller labeled data set, (unlike CNNs that require datasets in the thousands to perform well). Since each decision tree within the random forest can independently use a data subset, the training process can occur in a parallel fashion across different CPU scores. Independent processing units in the computers central processing unit read and execute programs, faster than deep learning networks for larger Support Vector Machines, SVM [49]. SVM is a machine learning algorithm for classification; the algorithm finds the optimal decision boundary that separates different classes of data in multi-dimensional space. The SVM maximizes the margin of the closest data points in any class, which are known as support vectors. For small to medium datasets with fewer samples, but high feature dimensions, a CPU is then efficient in calculating the boundary line. (Google Gemini).

Although this example identifies specific features of Random Forest in conjunction with CNNs in classifying AMD in general, similar adaptation of Random Forest might be considered, for example, in classifying patients retinal OCTs who develop recurrent uveitis from e.g. athletic ocular trauma and already have mild AMD.

With macular scarring. Random Forest segmenting that data might be useful to learn if there is uveitis macular edema as well as mild AMD.

NN-MLP CNNs and other CNNs; Segmentation ability; Varied predictive outcomes

In this section, I would like to walk the reader through the bare basics of NN-MLP CNN from the Jacquot uveitis model and other CNN models of a similar nature [2, 50,51,52,53].

The first layer is called the **input** layer. It consists of the same number of neurons as the study factors, (109 demographic, ophthalmological, (according to SUN), anatomical type of uveitis, chronicity, laterality etc.). The second layer, called the **hidden** layer, transforms the neuron value from layer 1 with a weighted linear summation which allows the MLP layer, **Multi-layer Perception**, (also called the fully connected, FC, layer or dense layer) to model data with complex nonlinear relationships. Nonlinear relationships of study factors and their weights can lead to new insights into the data, that may not have been appreciated by the human perusal. The third layer or output MLP layer converts each neuron's output into a probability distribution, for each uveitis etiology, using a softmax function. (Softmax functions take the raw data called logits and transform every value so that it is between 0 and 1, and all values sum to 1; (for mathematical formula details see YouTube, Data MListic) Each output neuron is associated with a specific etiology related to patient study factors, such as age, gender, etiology factors. The MLP algorithm's parameters were optimized using a Bayesian optimization algorithm, which improved performance of the MLP algorithm [2, 47].

In the Jacquot model, [2] one of the significant problems with the algorithms' outcomes was calling "idiopathic uveitis" as "ocular sarcoidosis", n = 5 or "vitreoretinal lymphoma", n = 2; or ocular sarcoidosis and HLA-B27 mispredicted as idiopathic uveitis in 20 and 6 cases respectively [2]. Thus, algorithm adjustments were instituted [2]. Despite the need to consider two diagnoses for a higher CNN or Random Forest accuracy, and that the algorithm's predictive outcomes can confuse idiopathic uveitis with ocular sarcoid or HLA-B27 or vitreoretinal lymphoma, this type of early AI modelling of uveitis can be adjusted and improved and can be a valuable beginning for CNN upstaging in uveitis macula fluid and retinal layer diagnostics.

Given the enormous realm of diagnostic complexity in uveitis, the CNN multimodal model may become more accurate with slightly more nuanced neural network OCT image segmentations, similar to that which evolved in CNN segmentations in quantitating macular fluid volumes in AMD: e.g. see Schlegl, et al. [50] 2018, vs Schmidt-Erfurth, et al. [51] 2020. Schlegl, et al. did groundbreaking CNN quantitative volumetric OCT macular image fluid measurements; Schmidt-Erfurth et al achieved longitudinal CNN quantitative volumetric OCT macular images, which were used as a therapeutic marker of macular edema two years into macular edema with VEGF therapy. [50,51]. In a similar vein, Wilson, et al. 2021 [52] looked at model segmentations for intraretinal fluid, subretinal fluid and pigment epithelial detachment. Two senior ophthalmologists with more than 10 years' experience and Moorfields Reading Center OCT reader certification, in 107 AMD OCT scans and 66 DME scans from Topcon 3D OCT-2000, and Heidelberg Spectralis took a mean of 50 hours per scan set; The 3-D U-Net CNN model took only 10 seconds per scan. This CNN architecture translates OCT into a map with 15 classes of anatomical and pathological features [52].

However, the fact that OCT scans from 173 patients with AMD or DME with higher quantitative accuracy scores (on automated quantitated of macula fluid detection) did not reliably outperform the retinal experts suggests that there is certainly more to be learned in iterative world of CNN segmentation of retinal OCT images in AMD and DME. Wilson, et al. [52] suggested that qualitative as well as quantitative OCT segmentations may enhance model performance compared to the experts. In short, in comparing slight and moderate retinal OCT reading differences between CNN model and expert, the model was better or comparable to one expert in 149 of 173 scans, but worse in 24 of 173 scans [52].

Liefers, et al. [53], seeking to validate a deep learning model for segmentation of 13 features associated with neovascular and

atrophic AMD, found that on 11 of 13 features the model achieved a mean Dice score of 0.63, (Dice score measures the spatial overlap of two data sets, one, automated or AI predicted segmentation outcome, and two, a human annotated ground truth; 0.9-1.0 is excellent, 0.8 to 0.89 is good; 0.7 or less is less than fair or marginal); However, when the identification of the OCT pathological feature, (ellipsoid zone loss internal retinal fluid, pigment epithelial detachment, subretinal fluid, drusen etc.) were compared model to expert observers, the scores of identification with each were quite close [53].

Thus, with better feature representative datasets [53], (including rare disease representative datasets not illustrated here [2,5,6,8]), more algorithmic sensitivity to model weaknesses [52], additional detailed joint segmentation effects [52,53] for quantitative as well as qualitative OCT image characteristics [52], more effective train and test datasets can be used to gain additional insights into inflammatory, autoimmune, glaucomatic, systemic, pharmacologic and masquerade uveitis diseases in the future [1,2,3.4,5,6,7,8,50,51, 52,53].

Conclusion

This paper has endeavored to review a few of the recent major clinical tactical advances in understanding uveitis typology and diagnostics in the last few decades, such as SUN [4,46] and MUV [38]. The richness of the diagnostic etiologic terrain in conjunction with the complexity of multimodal analytic tools, such as OCT, are continually being chartered and bridged by expert investigators from ophthalmology to rheumatology to AI with CNN, to confront and overcome many of the diagnostic challenges. Data science and AI have stepped into many of the learning gaps, such as database weaknesses, consistency, variety and typology, algorithm adjustments for model improvement, and more diverse image segmentation for more nuanced feature analysis. It has also sought to bring order to ophthalmologic and general medical laboratory variations or deficiencies in different countries. With the continued deployment of deep learning particularly in CNN OCT retinal imaging, uveitis diagnosis and management will steadily improve patient care on the world stage.

Conflicts of Interest

None.

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References

1. Dick AD, Tundia N, Sorg R, Zhao C, Chao J, et al. (2016) Risk of ocular complications in patients with noninfectious intermediate uveitis, posterior uveitis, or panuveitis. Ophthalmology 123: 655-662.
2. Jacquot R, Ren L, Wang T, Mellahk I, Duclos A, et al. (2024) Neural networks for predicting etiological diagnosis of uveitis, Eye (Lond) 39(5): 992-1002.
3. Prete M, Dammacco R, Fatone M, Racanelli V (2016) Autoimmune uveitis: clinical, pathogenetic, and therapeutic features. Clin Exp Med 16: 125-136.
4. Heiligenhaus A, Rothaus K, Pleyer U (2021) Development of classification criteria for uveitis by the Standardization of Uveitis Nomenclature (SUN) working group. Ophthalmol Z Dtsch Ophthalmol Ges 118: 913-918.
5. Sève P, Cacoub P, Bodaghi B, Trad S, Sellam J, et al. (2017) Uveitis: diagnostic work-up. A literature review and recommendations from an expert committee. Autoimmun Rev 16: 1254-1264.
6. Abad S, Sève P, Dhote R, Brézin AP (2009) [Guidelines for the management of uveitis in internal medicine]. Rev Med Interne 30: 492-500.
7. Jabs DA, Busingye J (2013) Approach to the diagnosis of the uveitides. Am J Ophthalmol 156: 228-236.
8. Selmi C (2014) Diagnosis and classification of autoimmune uveitis. Autoimmun Rev 13: 591-594.
9. Smith JR, Rosenbaum JT (2002) Management of uveitis: a rheumatologic perspective. Arthritis Rheum 46:309-318.
10. de Parisot A, Kodjikian L, Errera MH, Sedira N, Heron E, Pérard L, et al. Randomized controlled trial evaluating a standardized strategy for uveitis etiologic diagnosis (ULISSE).
11. de Parisot A, Jamilloux Y, Kodjikian L, Errera MH, Sedira N, et al. (2020) Evaluating the cost-consequence of a standardized strategy for the etiological diagnosis of uveitis (ULISSE study). PLoS ONE. 2020;15: e0228918.
12. McCluskey PJ, Towler HM, Lightman S (2000) Management of chronic uveitis. BMJ 320: 555-558.
13. Rathinam SR, Babu M (2013) Algorithmic approach in the diagnosis of uveitis. Indian J Ophthalmol 61: 255-262.
14. Jamilloux Y, Romain Scelle N, Rabilloud M, Morel C, Kodjikian L, et al. (2021) Development and validation of a Bayesian network for supporting the etiological diagnosis of uveitis. J Clin Med 10: 3398.
15. González López JJ, García Aparicio ÁM, Sánchez Ponce D, Muñoz Sanz N, Fernandez Ledo, N et al. (2016) Development and validation of a Bayesian network for the differential diagnosis of anterior uveitis. Eye Lond Engl 30: 865-872.
16. Wiehler U, Schmidt R, Skonetzki S, Becker M (2006) Optimierung der differenzial diagnostischen Strategie bei Patienten mit sekundären Uveitis formen mit einem computer gestützten System. Ophthalmologe 103: 406-9.
17. Mutawa AM, Alzuwawi MA (2019) Multilayered rule-based expert system for diagnosing uveitis. Artif Intell Med 99: 101691.
18. de la Torre Díez I, Martínez Pérez B, López Coronado M, Díaz JR, López MM (2015) Decision support systems and applications in ophthalmology: literature and commercial review focused on mobile apps. J Med Syst 39: 174.
19. Gegundez Fernandez JA, Fernandez Vigo JI, Diaz Valle D, Mendez Fernandez R, Cuiña Sardiña R, et al. (2017) Uvemaster: a mobile app-based decision support system for the differential diagnosis of uveitis. Investig Ophthalmol Vis Sci 58: 3931-3939.
20. Jacquot R, Sève P, Jackson TL, Wang T, Duclos A, et al. (2023) Diagnosis, classification, and assessment of the underlying etiology of uveitis by artificial intelligence: a systematic review. J Clin Med 12: 3746.
21. Agarwal A, Ashokkumar D, Jacob S, Agarwal A, Saravanan Y (2009) High-speed Optical Coherence Tomography for Imaging Anterior Chamber Inflammatory Reaction in Uveitis: Clinical Correlation and Grading. Am J Ophthalmol 147: 413-416.e3.
22. Sorkhabi MA, Potapenko IO, Ilginis T, Alberti M, Cabrerizo J (2022) Assessment of Anterior Uveitis through Anterior-Segment Optical Coherence Tomography and Artificial Intelligence-Based Image Analyses. Transl Vis Sci Technol 11: 7.

23. Baghdasaryan E, Tepelus TC, Marion KM, Huang J, Huang P, et al. (2018) Analysis of ocular inflammation in anterior chamber-Involving uveitis using swept-source anterior segment OCT. Int Ophthalmol 39: 1793-1801.

24. Sharma S, Lowder CY, Vasanji A, Baynes K, Kaiser PK, et al. (2015) Automated Analysis of Anterior Chamber Inflammation by Spectral-Domain Optical Coherence Tomography. Ophthalmology 122: 1464-1470.

25. Invernizzi A, Marchi S, Aldigeri R, Mastrofilippo V, Viscogliosi F, et al. (2017) Objective Quantification of Anterior Chamber Inflammation: Measuring Cells and Flare by Anterior Segment Optical Coherence Tomography. Ophthalmology 124: 1670-1677.

26. Lu M, Wang X, Lei L, Deng Y, Yang T, et al. (2020) Quantitative Analysis of Anterior Chamber Inflammation Using the Novel CASIA2 Optical Coherence Tomography. Am J Ophthalmol 216: 59-68.

27. Kang TS, Lee Y, Lee S, Kim K, Lee WS, et al. (2021) Development of fully automated anterior chamber cell analysis based on image software. Sci Rep 11: 10670.

28. Keane PA, Karampelas M, Sim DA, Sadda SR, Tufail A et al. (2014) Objective measurement of vitreous inflammation using optical coherence tomography. Ophthalmology 121: 1706-1714.

29. Zarranz Ventura J, Keane PA, Sim DA, Llorens V, Tufail A, et al. (2016) Evaluation of Objective Vitritis Grading Method Using Optical Coherence Tomography: Influence of Phakic Status and Previous Vitrectomy. Am J Ophthalmol 161: 172-180: e4.

30. Terheyden JH, Ometto G, Montesano G, Wintergerst MWM, Langner M, et al. (2021) Automated quantification of posterior vitreous inflammation: Optical coherence tomography scan number requirements. Sci Rep 11: 327.

31. Passaglia CL, Arvaneh T, Greenberg E, Richards D, Madow B (2018) Automated Method of Grading Vitreous Haze in Patients with Uveitis for Clinical Trials. Transl Vis Sci Technol 7: 10.

32. Agrawal R, Salman M, Tan KA, Karampelas M, Sim DA, et al. (2016) Choroidal Vascularity Index (CVI)--A Novel Optical Coherence Tomography Parameter for Monitoring Patients with Panuveitis? PLoS ONE 2016, 11, e0146344.

33. McKay KM, Chu Z, Kim J B, Legocki A, Zhou X, et al. (2021) Automated Quantification of Choriocapillaris Lesion Area in Patients with Posterior Uveitis. Am J Ophthalmol 231: 179-193.

34. Chu Z, Weinstein JE, Wang RK, Pepple KL (2020) Quantitative Analysis of the Choriocapillaris in Uveitis Using En Face Swept-Source Optical Coherence Tomography Angiography. Am J Ophthalmol 218: 17-27.

35. De Fauw J, Ledsam JR, Romera Paredes B, Nikolov S, Tomasev N, et al. (2018) Clinically applicable deep learning for diagnosis and referral in retinal disease. Nat Med 24: 1342-1350.

36. Schmidt Erfurth U, Vogl WD, Jampol LM, Bogunović H (2020) Application of Automated Quantification of Fluid Volumes to Anti–VEGF Therapy of Neovascular Age-Related Macular Degeneration. Ophthalmology 127: 1211-1219.

37. Moraes G, Fu DJ, Wilson M, Khalid H, Wagner SK, et al. (2020) Quantitative Analysis of OCT for Neovascular Age-Related Macular Degeneration Using Deep Learning. Ophthalmology 128: 693-705.

38. Agarwal A, Ramtohul P, Invernizzi A, Sarraf D, Gupta V (2026) Imaging Measures for the Assessment of Disease Activity in Noninfectious Posterior Uveitis - Multimodal Imaging in Uveitis (MUV) Taskforce: Report 10. Am J Ophthalmology 287: 43-57.

39. Munk MR, Stillenmunkes R, Tillmann A (2025) Evidence and Consensus based imaging guidelines in multiple evanescent White Dot syndrome Multimodal Imaging in Uveitis (MUV) Taskforce Report 6. Am J Ophthalmol 278: 191-202.

40. Carreño E, Maghsoudlou P, Fonollosa A (2025) Evidence and consensus-based imaging guidelines in acute posterior multifocal placoid pigment epitheliopathy (APMPPE) - Multimodal Imaging in Uveitis (MUV), Taskforce Report 7. Am J Ophthalmol 278: 38-51

41. Gangaputra S, Agarwal A, Norel J (2025) Evidence and consensus-based imaging guidelines in multifocal choroiditis with panuveitis and punctate inner choroiditis-Multimodal Imaging in Uveitis (MUV) Taskforce Report 5. Am J Ophthalmol 276:272-285.

42. Agarwal A, Agarwal A, Goldstein D (2025) Evidence and consensus-based imaging guidelines in serpiginous choroiditis-Multimodal Imaging in Uveitis (MUV) Task Force Report 4. Am J Ophthalmol 278: 81-92.

43. Pichi F, Miserocchi E, Grewal D (2025) Evidence and consensus-based imaging guidelines in Birdshot chorioretinopathy: Multimodal Imaging in Uveitis (MUV) Taskforce Report 8. Am J Ophthalmol 278: 271-281.

44. de Parisot A, Kodjikian L, Errera MH, Sedira N, Heron E, et al. (2017) Randomized controlled trial evaluating a standardized strategy for uveitis etiologic diagnosis (ULISSE). Am J Ophthalmol 178: 176-185.

45. Jamillou x Y, Kodjiklan L, Errera M H (2020) Quality of life in patients with uveitis: data from the ULISSE study (Uveitis: cLInical and medico-economic evaluation of a Standardized Strategy for the Etiological diagnosis). British J Ophthalmol 105(7): bjophthalmol-2020-315862.

46. Jabs D, Nussenblatt R Rosenbaum (2005) Standardization of Uveitis Nomenclature (SUN) Working Group Standardization of Uveitis Nomenclature for reporting clinical data. Results of the First International Workshop. Am J Ophthalmol 140: 509-516.

47. Snoek J, Larochelle H, Adams RP (2012) Practical Bayesian optimization of machine learning algorithms. In: Advances in neural information processing system. NIPS.

48. Mahalakshmi D, Justin J (2025) A Deep Learning Model Using VGG19 and Random Forest for AMD Stage Classification on Retinal OCT Images. Conference: 2025 2nd International Conference on Computing and Data Science (ICCDS).

49. (2021) Science Direct, Computer Science, Core Processor, Shigeyuki Takano, Thinking Machines.

50. Schlegl T, Waldstein S, Bogunovic H, Gerendas B, Langs G (2018) Fully Automated Detection and Quantification of Macular Fluid in OCT Using Deep Learning. Ophthalmology 125(4)P: 549-558.

51. Schmidt Erfurth U, Vogl W D, Jampol L, Bogunovic H, (2020) Application of Automated Quantification of Fluid Volumes to Anti-VEGF Therapy of Neovascular Age-Related Macular Degeneration. Ophthalmology 127(9): 1211-1219.

52. Wilson M, Chopra R, Wilson M, Cooper C, MacWilliams P, et al, (2021) Validation and Clinical Applicability of Whole-Volume Automated Segmentation of Optical Coherence Tomography in Retinal Disease Using Deep Learning. JAMA Ophthalmol 139(9): 964-973.

53. Liefers B, Taylor P, Alsaedi A, Warwick A, Tufail A, et al,)2021) Quantification of Key Retinal Features in Early and Late Age-Related Macular Degeneration Using Deep Learning. Amer J Ophthal 226: P1-12.