Automated Detection of Posterior Vitreous Detachment on Optical Coherence Tomography Using Computer Vision and Deep Learning Algorithms

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Abstract

**Objective:** To develop automated algorithms for the detection of posterior vitreous detachment (PVD) using optical coherence tomography (OCT) imaging.

**Design:** Evaluation of diagnostic test or technology.

**Subjects:** 42,385 consecutive OCT images (865 volumetric OCT scans) obtained with Heidelberg Spectralis from 865 eyes from 464 patients at an academic retina clinic between 10/2020 and 12/2021 were retrospectively reviewed.

**Methods:** We developed a customized computer vision algorithm based on image filtering and edge detection to detect the posterior vitreous cortex for determination of PVD status. A second deep learning (DL) image classification model based on convolutional neural networks and ResNet-50 architecture was also trained to identify PVD status from OCT images. The training dataset consisted of 674 OCT volume scans (33,026 OCT images), while the validation testing set consisted of 73 OCT volume scans (3,577 OCT images). 118 OCT volume scans (5,782 OCT images) were used as a separate external testing dataset.

**Main Outcome Measures:** Accuracy, sensitivity, specificity, F1-scores, and area under the receiver operator characteristic curves (AUROC) were measured to assess performance of the automated algorithms.

**Results:** Both the customized computer vision algorithm and DL model results were largely in agreement with the PVD status labeled by trained graders. The deep learning approach achieved an accuracy of 90.7% and F1-score of 0.932 with a sensitivity of 100% and a specificity of
74.5% for PVD detection from an OCT volume scan. The AUROC was 89% at the image level and 96% at the volume level for the DL model. The customized computer vision algorithm attained an accuracy of 89.5% and F1-score of 0.912 with a sensitivity of 91.9% and a specificity of 86.1% on the same task.

Conclusions: Both the computer vision algorithm and the DL model applied on OCT imaging enabled reliable detection of PVD status, demonstrating the potential for OCT-based automated PVD status classification to assist with vitreoretinal surgical planning.
The age-related process of vitreous separation occurs as a result of vitreous liquefaction, ultimately leading to a complete posterior vitreous detachment (PVD). Optical coherence tomography (OCT) is one of the most widely used imaging modalities in ophthalmology and is a critical tool in the analysis of the vitreoretinal interface. In particular, OCT is often utilized in the clinical setting to aid in the determination of a posterior vitreous detachment.

The accurate detection of PVD status is important for clinical prognostication and for pre-surgical planning for vitreoretinal surgeons. Patients with a recent diagnosis of acute PVD are at increased risk of retinal tears and detachments and should be followed closely by an ophthalmologist. Conversely, patients with floaters without a PVD are at a reduced concern for a retinal tear. PVD status also has been shown to have prognostic implications in regards to disease progression and in how patients respond to treatment in retinal diseases such as diabetic retinopathy, retinal vein occlusion, and age-related macular degeneration. In addition, knowing whether a patient has a partial or a complete PVD is important in guiding surgical planning. For example, if a patient does not have a complete PVD, a surgeon may be more inclined to choose scleral buckle as the procedure of choice for retinal detachment repair instead of pneumatic retinopexy or pars plana vitrectomy.

Enabled by increasing medical imaging data availability, deep learning (DL) and artificial intelligence (AI) have recently been applied to the field of ophthalmology, assisting clinicians in the diagnosis and management of ophthalmic diseases. Image-based DL models such as convolutional neural networks (CNNs) have shown promising results in the automated detection of retinal diseases such as diabetic retinopathy, epiretinal membrane, and age-related macular degeneration. Despite the wide application of computer-aided algorithms in the diagnosis of the above-mentioned retinal diseases, to our knowledge there is currently no reliable computer
vision algorithm or DL model that can localize the posterior vitreous cortex and detect PVD status on OCT images. Although there have been a few prior studies using DL approaches for diagnosing PVD, these models used ocular ultrasound images rather than OCT images, which are far more common in real-world clinical practice.\textsuperscript{19,20} The aim of this study is thus to enable and evaluate automated detection of PVD through OCT imaging to improve evaluation of the vitreoretinal interface.
Methods

Clinical Protocols and Dataset Annotation

This study adhered to the tenets set forth in the Declaration of Helsinki and the Health Insurance Portability and Accountability Act, and Institutional Review Board (IRB)/Ethics Committee approval was obtained at the University of California San Diego (UCSD). Waiver of written informed consent was granted. Patients that had undergone evaluation by a retina specialist with OCT imaging at the UCSD Department of Ophthalmology between October 2020 and December 2021 were reviewed. Adults and children encompassing a wide range of retinal pathologies were included. Exclusion criteria consisted of poor OCT image quality (i.e., scans with poor resolution due to anterior segment or vitreous opacity or due to motion artifact), and eyes with known history of having undergone prior pars plana vitrectomy.

Macular OCT scans were obtained using a spectral-domain system (Spectralis OCT, Heidelberg Engineering, Heidelberg, Germany) composed of a volume scan consisting of 49 horizontally-oriented B-scans covering a 6 mm x 6 mm area at a resolution of 512 x 496 pixels per B-scan (frame averaging over 16 frames), in addition to a 9 mm vertical and horizontal line scan that included the optic nerve at a resolution of 768 x 496 pixels (Spectralis High-Speed scan protocol with frame averaging over 100 frames). Four trained ophthalmologists reviewed the entire volume B-scans in addition to the horizontal and vertical raster scans of each patient for determination of PVD status. The definition of PVD in this study was a complete stage 4 PVD without any presence of the premacular bursa or posterior vitreous cortex on any scans of the OCT. In questionable cases, consensus grading was performed by an expert trained retina specialist (E.N.) for the final determination of PVD status. Patient information was anonymized and images were de-identified prior to transferring data for analysis.
Automated PVD Detection Algorithms

We approached the computer-aided, automated PVD detection task using two different methods (Figure 1): (1) developing a computer vision algorithm to detect the presence or absence of a PVD based on posterior vitreous cortex localization, and (2) training a deep convolutional neural network (CNN) model based on our OCT dataset for determination of PVD status.

Computer Vision Algorithm Based on Posterior Vitreous Cortex Localization

The customized PVD detection algorithm was designed and prototyped in Python 3 code. The algorithm evaluated PVD status by examining the posterior vitreous cortex in each raster of the OCT volume scan. If the premacular bursa or posterior vitreous cortex was detected in any part of the OCT image for more than one scan out of 49 OCT B-scans in the volume scan, the algorithm determined that the posterior vitreous cortex was attached, so there was an absence of a complete PVD. On the contrary, if the posterior vitreous cortex was not visualized for more than 47 scans out of 49 OCT B-scans (thresholding parameters applied to avoid false positives), the algorithm determined that a complete PVD (stage 4 PVD) was present.

For the automated detection of PVD status, the customized computer vision algorithm consisted of two parts (Figure 2): image preprocessing and posterior vitreous cortex localization. In the image preprocessing step, the OCT scans were normalized based on pixel intensity. A Gaussian blur (OpenCV-python library version 4.1.2) was then applied to the original OCT scan to reduce noise in the image. A kernel with a denoise level of 5x3 was used to suppress imaging noise present across the image and to facilitate detection of the internal limiting membrane (ILM). Instead of using a common square-shaped kernel, we chose this specific kernel size to be longer in the horizontal axis than the vertical axis, as the ILM spans more pixels horizontally in an image than vertically. Furthermore, less denoising power was applied in the vertical axis, as
keeping high resolution and high frequency signals on the vertical axis of the image was crucial to subsequent ILM and posterior vitreous cortex detection. Next, an edge detection-based algorithm was utilized to detect the ILM of the retina and to segment out the posterior vitreous cortex. The ILM segmentation algorithm first recognized candidate segments of the ILM on rectangular sliding windows of the image using a customized edge-detection function based on the intensity difference between the vitreoretinal interface and thresholding of continuity of the ILM. In this customized function, a sliding window of size 1x10 scanned through the image stepwise pixel by pixel to detect a difference in mean intensity values with a threshold greater than 100 to recognize potential ILM segments. The algorithm then removed outlier segments far away from the main ILM segments in terms of a vertical distance threshold of 20 pixels and further applied a spline fitting to the rest of potential ILM segments to outline the final ILM. Because only the area above the ILM was needed for posterior vitreous cortex localization, the retinal area below the ILM was masked out to save extra computations. Thus, after masking, only the vitreous area was retained for further processing.

In the posterior vitreous cortex localization step, another Gaussian blur filter with a 7x1 kernel was applied to further smooth the image of the vitreous and to remove horizontal noise. Similar to the kernel size selection in the image preprocessing step, we chose 1 pixel length in the vertical axis due to the need to retain higher resolution on the vertical axis of image since the posterior vitreous cortex also empirically spanned more pixels horizontally as compared to vertically in a B-scan. A customized function similar to the ILM detection method was crafted to localize the posterior vitreous cortex based on intensity thresholding using a 10x15 pixel-sized sliding window. After candidate segments of the posterior vitreous cortex were detected, the same outlier removal algorithm as used in ILM segmentation was then applied. Once a target
segment that satisfied the intensity threshold was detected, the total pixel length and a continuity metric defined by the vertical difference of the two adjacent candidate segments was calculated. When all the evaluation criteria for posterior vitreous cortex recognition was satisfied, the algorithm localized the detected line as the posterior vitreous cortex.

To develop and fine-tune this algorithm, 110 OCT volume scans (5,390 OCT images) were used. Among these scans, 10 eyes from 10 different patients were examined in detail to estimate the thresholding for visual features and relevant sliding window sizes used in the algorithm, including posterior vitreous cortex thickness threshold, intensity threshold, and line continuity metrics. These eyes were also used in the kernel size selections of Gaussian blur filters for visual examination of denoising outcomes. The remaining 100 OCT scans (4,900 images) were used to test-run prototypes of the algorithm and fine-tune the threshold values based on feedback from trained retina specialists.

Training DL Model for PVD Detection

To enable a DL approach to automatically detect a PVD, we implemented a DL pipeline in Pytorch 1.9.0 to train convolutional neural networks (CNNs) to determine the PVD status of an OCT image from the PVD status label of the volume scan. A ResNet-50 CNN model was trained on Google Colab with a Tesla P100-PCIE-16GB GPU to learn visual representations of images from an eye with complete PVD versus absence of complete PVD. We performed the training-validation dataset split on the volume (per eye) level to prevent data snooping so that the validation set would not contain any image from an eye that the model was trained on. A random shuffle was performed for the 9:1 training-validation dataset split to ensure that the data from the two classes were roughly balanced, following the same distribution of the entire dataset. The training set consisted of 674 OCT volume scans (33,026 OCT images), with 51.0% volume scans
from eyes with complete PVD and 49.0% scans from eyes without complete PVD. The validation set used for model selection and hyperparameter tuning consisted of 73 OCT volume scans (3,577 OCT images), with 41.6% volume scans from eyes with complete PVD and 58.4% scans from eyes without complete PVD. The ResNet-50 version 1.5 model used was pretrained on the ImageNet dataset to enable transfer learning of visual image representations.

To make image sizes compatible with the pretrained model, all OCT images were converted to RGB (red, green, and blue) images from greyscale images (PIL Image Python library version 7.1.2) and downsized to 256 x 256 pixels (torchvision Python library version 0.13.1) at runtime in the customized dataloader code. The loss function used in training was cross-entropy loss, and the optimizer used was Adam. The training process used a uniform learning rate of 5E-5, and batch size 128. We trained the model for 100 epochs and saved the model weights with the lowest validation loss during training as the best model to be used in testing and evaluation.

**Evaluation and Comparison of PVD Detection Algorithms**

In addition to evaluating the two methods on the validation dataset with 73 OCT volume scans, we additionally collected 118 OCT volume scans (containing 5,782 OCT images) as a separate external testing dataset for final evaluation of our automated PVD detection methods in December 2021. The test set included 63.2% volume scans from eyes with complete PVD and 36.8% scans from eyes without complete PVD. There was no overlap in OCT images used in the testing dataset and the dataset used for training and validation for either of the two algorithms. Patients that had undergone prior vitrectomy were included in this testing data set in order to better simulate real-world clinical practice with anticipated future application of the AI algorithm.
to all patients who present to retina clinic and undergo OCT imaging, regardless of prior surgical status. Baseline characteristics of the patients in each data set are provided in Table 1.

To evaluate and compare the computer vision approach and the DL model, we performed testing by running both algorithms on the same testing set of 118 OCT volume scans. For each eye in a volume scan, we recorded the predicted PVD status as either complete PVD or absence of complete PVD, and compared the results to ground truth labels to calculate the accuracy, sensitivity, specificity, precision, and F1-score of both algorithms. Receiver operating characteristics (ROC) curves were plotted by varying the probability output threshold of the deep learning model, and the area under the receiver operator characteristic curves (AUROC) were calculated (Scikit-learn Python library version 1.0.2) for both image-level and volume-level PVD status detection results. Since the two classes of PVD status were not perfectly balanced in the dataset, we also plotted the precision-recall curves to show the trade-off in precision as the decision threshold shifted to correctly recognize more complete PVD images. The average precision scores (AP) of the precision-recall curves, equivalent to the area under curve, were also calculated at the image level and volume level.
Results

Performance of Algorithms on Validation Dataset

Validation testing was performed on both automated algorithms on our dataset of 3,577 images and 73 OCT volume scans (Table 2). The DL algorithm achieved an accuracy of 81.4% with an 88.3% sensitivity, 76.6% specificity, and 0.795 F1-score at the image level. At the volume level, the DL algorithm achieved a 100.0% sensitivity and 80.8% specificity with an accuracy of 88.1% and F1-score of 0.866, while the customized algorithm attained an 82.1% sensitivity and 79.0% specificity with an accuracy of 80.3% and F1-score of 0.779.

Comparison of PVD Detection Algorithms with Testing Dataset

Both the customized algorithm and DL model detection results were largely in agreement with the PVD status labeled by trained graders with the testing dataset (Table 3). For the DL model, at the level of each individual OCT image, an accuracy of 83.0% and F1-score of 0.874 were attained with a sensitivity of 93.2% and a specificity of 65.6%. The AUROC was 89% and average precision was 86% at the image level (Figure 3). By encompassing the entire volume OCT scan and averaging the probabilities of complete PVD from each image, we achieved an accuracy of 90.7% and F1-score of 0.932 with a sensitivity of 100% and a specificity of 74.5%. At the volume level, the AUROC was 96% and average precision was 94% for the DL model (Figure 3). For the customized algorithm at the volume level, the accuracy was 89.5% and F1-score was 0.912, with a sensitivity of 91.9% and a specificity of 86.1%.
Discussion

Utilizing both traditional computer vision and deep learning approaches, we developed reliable algorithms for the automatic detection of PVD status from OCT images. The accurate detection of PVD status is a critical feature in the ophthalmological examination, as it is a clinically important entity for disease prognostication and pre-surgical planning for vitreoretinal surgeons. There are many different techniques for assessing PVD status, including slit lamp biomicroscopy, ultrasonography, and OCT imaging. The presence of a Weiss ring on clinical evaluation suggests a complete PVD; however, identification through biomicroscopy can be challenging at times and does not allow staging of PVD status.\textsuperscript{1,21} B-scan ultrasonography has shown utility in the detection of PVD status; however, it has limited anatomic resolution and is highly operator-dependent with lower inter-examiner agreement compared to OCT.\textsuperscript{1,21,22} The use of OCT to assist evaluation of PVD status has thus become increasingly important, as it is a clinically practical tool that ophthalmologists can use to efficiently and effectively identify the presence or absence of PVD.\textsuperscript{21–23} Kraker et al. found that 6-mm OCT scans detected complete PVD with 91% sensitivity and 99% specificity.\textsuperscript{24} Peri-papillary scan images can also improve the diagnostic ability of OCT, especially in cases in which vitreous separation occurs in the macula but the vitreous still remains attached at the optic nerve.\textsuperscript{22} In our study, we utilized both the 6 mm x 6 mm volume scans in addition to the 9 mm vertical and horizontal line scan that included the optic nerve for the determination of PVD status.

Often, the greatest challenge in PVD status determination is distinguishing between stage 0, in which there is a completely attached hyaloid and absence of PVD, and a stage 4 complete PVD.\textsuperscript{2,3} Some strategies to classifying an eye as stage 0 include attempting to visualize if the premacular bursa is visible but not the posterior vitreous cortex.\textsuperscript{3} Once the process of vitreous
separation occurs, identifying a partial PVD by visualizing the posterior vitreous cortex is easier and more apparent. However, there are cases in which vitreoretinal separation is difficult to discern on OCT for the human examiner. A computer algorithm trained to visualize the posterior vitreous cortex may be able to more accurately distinguish between stage 0 and early stage 1 partial PVD, and between stage 0 and stage 4 PVD. While developing our customized computer-vision based algorithm, we found that the algorithm detected the presence or absence of PVD more accurately in several instances after reviewing the OCT again in cases in which there was a discrepancy between the human and machine interpretation. In this way, computer-aided diagnosis (CAD) may be able to assist providers in more accurately delineating PVD staging for clinical prognostication. Furthermore, in a high-volume clinic in which reviewing OCT volume scans can be time-consuming, a reliable artificial intelligence algorithm for PVD status determination may allow for more efficient clinical decision-making.

Within ophthalmology, deep learning techniques have been applied to the diagnosis of many retinal diseases including age-related macular degeneration, diabetic retinopathy, and macular edema. Automatic segmentation of nine retinal layer boundaries has been successfully validated on eyes with non-exudative age-related macular degeneration using a novel framework based on convolutional neural networks (CNN) and graph search methods. While the majority of deep learning techniques have been applied to the retina, there are few reports of segmentation of the vitreous. To our knowledge, there are currently no deep learning methods that have been developed to automatically segment the posterior vitreous cortex for identification of posterior vitreous detachment on OCT. A deep learning segmentation algorithm was developed for automated eye compartment segmentation of the vitreous, retina, choroid, and sclera. In this model, the vitreous was defined above the demarcation line of the internal...
limiting membrane. Automated segmentation of vitreous hyperreflective foci (vHF), the vitreous, and retinal pigment epithelium (RPE) has also been developed using a deep-learning approach in patients with uveitis. In this methodology, the hyperreflective structure of the posterior vitreous cortex was manually removed by the clinician as a false-positive structure during the image-preprocessing step. A deep learning system to recognize vitreous detachment, retinal detachment, and vitreous hemorrhage on ophthalmic ultrasound was developed and achieved accuracies of 0.90, 0.94, and 0.92, respectively. To our knowledge, prior literature is scarce regarding automated algorithms to recognize PVD status utilizing OCT imaging, and we believe that our study presents an innovative development in artificial intelligence for automated PVD detection.

In our study, both automated algorithms demonstrated good reliability in PVD detection on OCT imaging volume scans, achieving accuracies of 89.5% and 90.7%, with sensitivities of 91.9% and 100%, and specificities of 86.1% and 74.5% for the traditional computer vision approach and deep-learning method, respectively. For the ResNet-50 deep learning model, AUROC analyses confirmed that PVD detection was more accurate when analyzing the entire OCT volume scan (96%) compared with at the image level (89%). This increase in accuracy and specificity was as expected because when all the scans from a volume were considered, averaging the probability of each image provided a higher confidence level.

The deep learning method using ResNet-50 CNN achieved better overall performance than the customized algorithm method, yet both algorithms have the potential to be further improved and refined to increase reliability in PVD detection. For the deep learning approach, the performance would likely improve with the adoption of a more advanced model architecture such as the vision transformers (ViT) model, which incorporates attention modules that
examine input images by smaller regions. Transformer-based architectures were originally
developed for natural language processing but in recent years applied to computer vision, and
ViT models were shown to be superior in performance in image recognition task benchmarks
compared to traditional CNN models. However, the performance advantage over ResNet models
only reveals itself when the number of training data set images surpasses a certain threshold.\textsuperscript{27}

Given the limited amount of OCT images in our study, a pretrained ResNet-50 model with fewer
model parameters was thus used for optimal convergence and less overfitting. If the training
dataset of OCT imaging for PVD detection grows substantially in the future, we envision ViT
models pretrained on image recognition benchmark datasets achieving better performance on this
task than the ResNet-50 model used in our study.

We developed the customized algorithm based on the idea of utilizing traditional image
analyses and heuristics in PVD diagnosis from OCT imaging. Traditional image analyses
typically involve manual development of techniques based on feature extraction and edge
detection.\textsuperscript{28} The customized algorithm applies automated image processing and calculations of
visual metrics to examine the presence of the posterior vitreous cortex in an OCT B-scan, a
feature that an ophthalmologist would also use to determine PVD status. In this sense, the
customized algorithm method can be seen as an automated version of exercising existing
knowledge about PVD diagnostics. This concept is similar to the clinical setting in which the
examiner typically scrolls through the OCT volume scan to detect if any posterior vitreous cortex
is visualized in any frame for final determination of PVD status. For our automated algorithms,
the parameters and threshold metrics were determined heuristically by running the PVD
detection algorithms on the training and validation data sets and then selecting the values which
resulted in best accuracy. The generalization capability of this method is thus dependent on the
set of OCT images that were used to determine the parameters. Since the number of parameters of this algorithm is orders of magnitude fewer than the deep learning model, the deep learning model was able to generalize features learned in the training dataset better than the thresholding-based customized algorithms. To further improve this automated algorithm method, more visual features used in clinical PVD detection can be taken into account, and the decision-making can be further fine-tuned to increase precision and complexity of the algorithms.

Other limitations of our study include that our models were trained on images obtained using the Spectralis OCT system at a single academic institution. Although we included real-world images from both eyes with and without pathology, additional future studies utilizing OCT images from different systems and from other institutions are needed to establish external validity and broader generalizability. We excluded OCT images of poor image resolution, and thus both of our methods were not developed to navigate around poor image quality or motion artifacts. A lack of a very large, robust training data set composed of thousands of images also may have limited the training of our deep learning model and usage of more sophisticated models with higher number of parameters.

In conclusion, we demonstrated a novel application of both traditional computer vision algorithms and deep learning methods for the automated detection of posterior vitreous detachment on OCT imaging. Future steps include performing external validation studies and optimizing the algorithms for efficient usage in the clinical setting to assist providers in clinical decision making. Digital analysis tools such as our algorithm offer promise in enhancing the evaluation of the vitreoretinal interface to help guide pre-surgical planning and clinical prognostication for improved patient care.
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Figure Legends

Figure 1. Flowchart summary for the two posterior vitreous detachment (PVD) automated detection methods implemented on optical coherence tomography (OCT) imaging: customized computer vision algorithm (upper); deep learning convolutional neural network (CNN) model (lower).

Figure 2. Stepwise image processing illustration for customized posterior vitreous cortex localization algorithm. A. Original optical coherence tomography (OCT) B-scan image of a patient without a complete posterior vitreous detachment (PVD). B. Gaussian blur filter from OpenCV is applied to the entire image (blue mask). C & D. The internal limiting membrane (ILM) is located using the customized algorithm (orange line). E. Retinal area below the ILM is masked out (orange mask) and only relevant areas are kept for further posterior vitreous cortex localization. F. Gaussian blur filter from OpenCV is applied to the vitreous area (blue mask). G & H. The posterior vitreous cortex (if present in the image) is detected and located. Customized distance metrics are calculated on the detected segments and compared against heuristic thresholds to determine if the posterior vitreous cortex is present in the image.

Figure 3. Receiving operator characteristic (ROC) curves and precision-recall (PR) curves at the optical coherence tomography (OCT) image level and volume level for the deep learning (DL) model for posterior vitreous detachment (PVD) detection. Area under the receiver operator characteristic curves (AUROC) and average precision (AP) are depicted in the diagram.
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<th>Training/Validation Data Set</th>
<th>Testing Data Set</th>
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<td>Number of OCT Images</td>
<td>33026/3577</td>
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<tr>
<td>Patients</td>
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<td>57(*6)</td>
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<td>Age (years), mean (SD)</td>
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<td>69.75 (16.5)</td>
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OCT – optical coherence tomography; SD – standard deviation

*Mandatory exclusion patients were excluded from demographics analysis
Table 2. Algorithms performance metrics comparison on validation dataset

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<th>Per Volume</th>
<th>Customized Algorithm</th>
<th>Deep Learning Model</th>
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<td>Sensitivity</td>
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<td>Specificity</td>
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<td>Precision</td>
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<table>
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<td>Sensitivity</td>
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<td>Specificity</td>
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Table 3. Algorithms performance metrics comparison on testing dataset

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<th>Sensitivity</th>
<th>Specificity</th>
<th>Precision</th>
<th>F1-score</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Per Volume</strong></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Customized Algorithm</td>
<td>89.5%</td>
<td>91.9%</td>
<td>86.1%</td>
<td>90.5%</td>
<td>0.912</td>
</tr>
<tr>
<td>Deep Learning Model</td>
<td>90.7%</td>
<td>100.0%</td>
<td>74.5%</td>
<td>87.2%</td>
<td>0.932</td>
</tr>
<tr>
<td><strong>Per Image</strong></td>
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</tr>
<tr>
<td>Deep Learning Model</td>
<td>83.0%</td>
<td>93.2%</td>
<td>65.6%</td>
<td>82.2%</td>
<td>0.874</td>
</tr>
</tbody>
</table>
We developed a customized computer vision algorithm and a deep learning classification model for the automated detection of posterior vitreous detachment using optical coherence tomography (OCT) imaging.
Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: