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ORIGINAL ARTICLE

Efficiency of web-based code-free artificial intelligence platform in classification of vitreomacular interface diseases

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Abstract

Purpose: The aim of this study is to evaluate the effectiveness of Teachable Machine (TM), a code-free web-based artificial intelligence (AI) platform, in the detection and classification of vitreomacular interface diseases (VMIDs) in optical coherence tomography (OCT) images.

Methods: A dataset of 445 cross-sectional OCT images from patients with VMID, along with 200 images from healthy individuals, was retrospectively prepared at a tertiary health-care institution. The OCT images were categorized into three groups: Epiretinal membrane (ERM), macular hole (MH), and vitreomacular traction (VMT). Subsequently, a deep learning (DL) model for VMID classification was developed using TM, a code-free web-based AI platform. The model underwent training on 160 ERM, 96 MH, 100 VMT, and 160 normal images, followed by testing on 40 ERM, 25 VMT, 24 MH, and 40 normal images. Sensitivity, specificity, and receiver operating characteristic curve were calculated to evaluate the effectiveness of the developed model.

Results: The DL model showed 100% sensitivity and specificity in detecting any VMID compared to normal eyes. For detecting VMT, TM had 100% sensitivity, 98.08% specificity, and an AUC of 0.99. In ERM detection, sensitivity and specificity were both 100%, with an AUC of 1.00. MH detection had 91.67% sensitivity, 100% specificity, and AUC of 0.958.

Conclusion: This study demonstrates that TM can be used with high efficiency in detecting and classifying VMID. TM application, which performs image classification with DL, can be considered an effective alternative, especially for physicians who do not have coding knowledge to develop AI models.

Keywords: Artificial intelligence; deep learning; epiretinal membrane; macular hole; teachable machine; vitreomacular interface disorders; vitreomacular traction.

The group of diseases known as vitreomacular interface disorders (VMIDs) occurs as a result of incomplete separation of the posterior vitreous, leading to pathologies such as vitreomacular adhesion (VMA), vitreomacular traction (VMT), macular hole (MH), or epiretinal membrane (ERM). Depending on the degree of involvement of the foveal region and the duration of the disease, various levels of visual loss or complaints such as metamorphopsia may occur.[1] At present, optical coherence tomography (OCT) is commonly used for the diagnosis of these diseases. The development of OCT has been highly effective in diagnosing macular diseases and evaluating the necessity and efficacy of treatments.[2] In addition to this, an ophthalmologist is still required to make definitive retinal diagnoses based on OCT findings.

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Artificial intelligence (AI) involves the ability of computer systems to simulate human intelligence processes, including tasks such as learning and problem-solving, to a level commonly associated with human capabilities.[3] Deep learning (DL) is a subfield of AI that relies on multilayer artificial neural networks (convolutional neural networks [CNN]) to achieve advanced functions such as computer vision, speech recognition, and natural language processing.[4] Recently, several AI models have been developed for the diagnosis of ophthalmology-specific pathologies, as in other medical disciplines.[4-8] AI models using retinal imaging techniques such as OCT and color fundus photographs have shown high accuracy comparable to experts in diagnosing various retinal diseases.[9-11] Especially, DL-based models have been popular in recent years for analyzing and classifying various retinal diseases.[4,5,9,12] While the application of AI techniques such as DL often requires coding knowledge, there has been an increasing inclination toward code-free machine learning classification models finally, facilitated by AI platforms such as Google's Teachable Machine (TM).[13] To the best of our knowledge, there is no study evaluating the effectiveness of code-free AI applications in the classification of VMID.

The aim of our study is to evaluate the effectiveness of the code-free TM application in the identification and classification of VMID using spectral domain (SD) – OCT images.

Materials and Methods

Preparation of the Dataset

Between January 2018 and May 2021, cross-sectional horizontal single-line fovea-centered retinal SD-OCT images of patients diagnosed with VMID at the tertiary ophthalmology center were retrospectively reviewed. The images were classified into three main groups based on the presence of ERM, MH, and VMT by two retinal specialists (H.Ö. and A.K.), and images with a quality index <25 were excluded. As a result, a dataset of 445 retinal OCT images from 362 patients was saved in .jpeg format for use in the developed DL model. Among the total of 445 OCT images, 200 had ERM, 125 had VMT, and 120 had MH. In addition, a control group of 200 macular-centered cross-sectional SD-OCT images was recorded from 100 healthy individuals without any retinal pathology (Fig. 1).

All images were cropped to 224 × 224 pixels to be fovea-centered while ensuring the removal of any patient and device information present in the images. Subsequently, the available images from each group were subjected to random division, allocating 80% to the training set and the remaining 20% to the test set. Each image class was methodically categorized and organized for utilization in both the training and test sets.

The study protocol was approved by the institutional non-interventional research ethics committee (No: 2022/68). Informed consent was obtained from all participants. All principles of the Helsinki Declaration were followed.

TM Platform and Model Training

TM (version 2.0) was released by Google in 2017. This platform utilizes the pre-trained with transfer learning MobileNet-V2 CNN for image classification. CNN is a powerful DL technique widely employed in image recognition software, known for its remarkable success.[13,14] The TM application is a free, web-based tool available to the public for image classification. Users can simply upload their preferred images to the TM platform and simply develop their own AI models.

To develop the model, the online TM platform, which utilizes the TensorFlow online DL library without requiring coding, was utilized. The study was conducted through

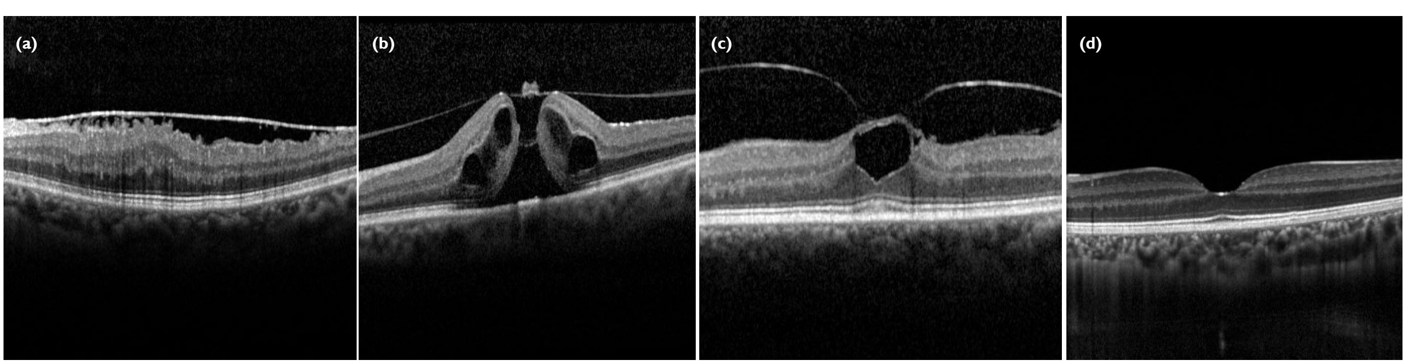

Fig. 1. Spectral domain-optical coherence tomography images for each group. **(a)** Epiretinal membrane, **(b)** Macular hole, **(c)** Vitreomacular traction, **(d)** Normal.

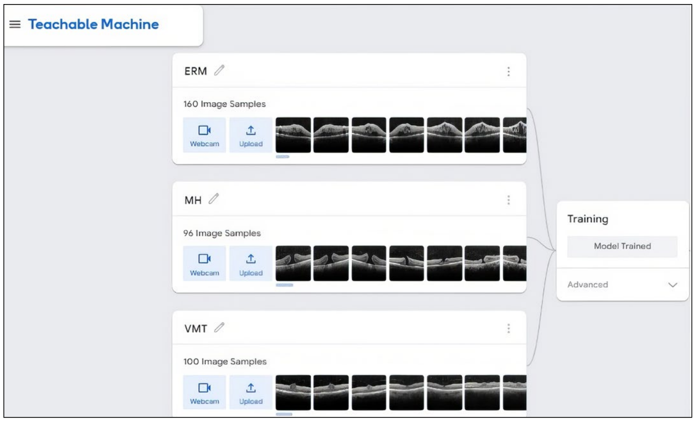

Fig. 2. The user interface of the Teachable Machine platform used to develop the deep learning model.

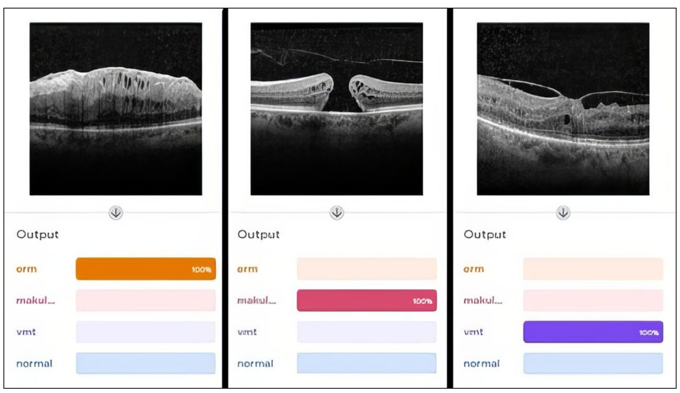

Fig. 3. Predictions of the developed model on sample test images

the website https://teachablemachine.withgoogle.com/. For VMID classification, four image classes were created in the program, namely ERM, VMT, MH, and normal. To train the model, 160 ERM, 96 MH, 100 VMT, and 160 normal images were uploaded to the program in their respective image classes (Fig. 2). The OCT images used for model training were "trained" using the following default setting parameters (Epochs 50, batch size 16, and learning rate 0.001).

Model Testing

The developed DL model was tested using a test set consisting of 40 ERM, 25 VMT, 24 MD, and 40 normal images, which were randomly separated from each image class at a ratio of 20%. The test images were input into the model by selecting the "file" option in the "input" section, allowing the model to be tested with ERM, MH, VMT, and normal images, respectively (Fig. 3).

Statistical analysis was conducted using SPSS (Version: 22.0, SPSS Inc., IBM, Chicago, IL, USA). The sensitivity and specificity rates of the developed model in detecting any VMID class and each VMID class were calculated. In addition, the effectiveness of the model in image classification was determined by performing a receiver operating characteristic (ROC) curve analysis and calculating the area under the ROC curve (AUC). The calculated AUC values were considered follows: 0.5 indicates no discrimination, 0.5–0.7 indicates inadequate discrimination, 0.7–0.8 indicates acceptable, 0.8–0.9 indicates excellent, 0.9–1.0 indicates outstanding, and 1.0 indicates full agreement.

Results

The mean age of the 462 participants included in the study was 67.2±11.25, with 57.79% being females. In this study, a total of 129 SD-OCT images were utilized to test the model, comprising 40 images with ERM, 25 images with VMT, 24

Table 1. Comparison of the model predictions with reference labels

	Ground truth			
	ERM	VMT	MH	Normal
TM				
ERM				
Image, n	40	0	0	0
%	100.0%	0.0%	0.0%	0.0%
VMT				
Image, n	0	25	2	0
%	0.0%	92.6%	7.4%	0.0%
MH				
Image, n	0	0	22	0
%	0.0%	0.0%	100.0%	0.0%
Normal				
Image, n	0	0	0	40
%	0.0%	0.0%	0.0%	100.0%

TM: Teachable Machine; ERM: Epiretinal membrane; VMT: Vitreomacular traction; MH: Macular hole.

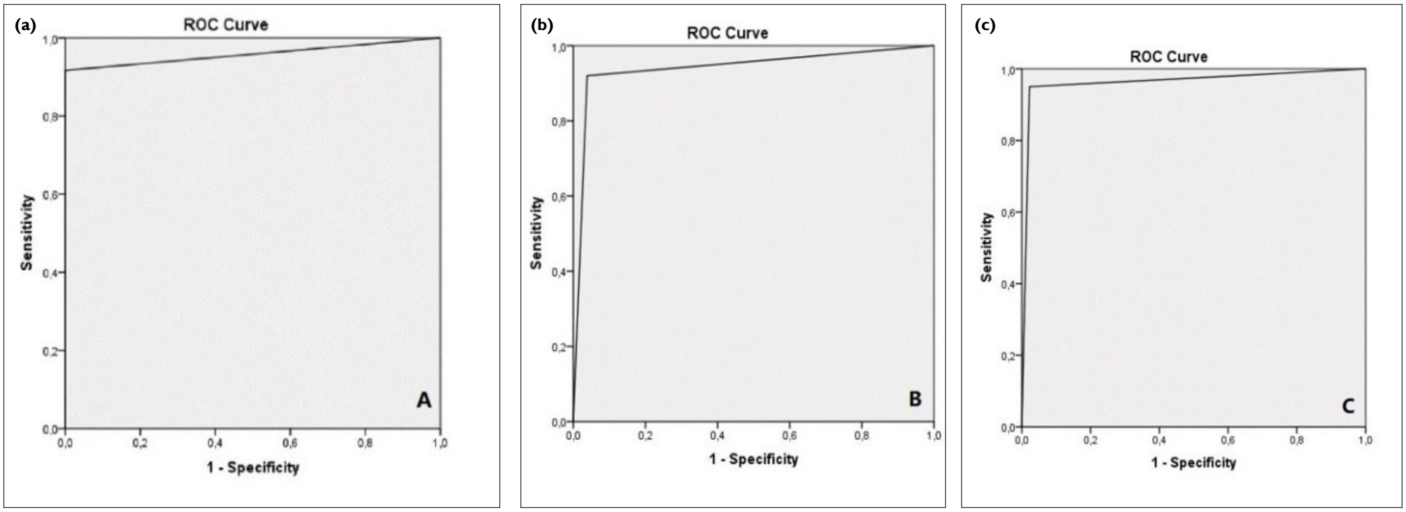

Fig. 4. ROC curve analysis. **(a)** Macular hole, **(b)** Vitreomacular traction, **(c)** Epiretinal membrane.

images with MH, and 40 normal images. The distribution of these test images and the comparison of the model's detected results with the reference classes were performed to identify VMID classes and normal images from the cross-sectional OCT images. The summarized findings are presented in Table 1.

The developed model demonstrated 100% sensitivity and specificity in detecting VMID regardless of the specific class. When analyzing VMID classes individually, the sensitivity and specificity for VMT detection were 100% and 98.08%, respectively, with an AUC of 0.99. For ERM detection, both sensitivity and specificity were 100%, resulting in an AUC of 1.00. In MH detection, the sensitivity was 91.67% and the specificity was 100%, with an AUC of 0.958. The ROC curves illustrating the developed model's performance in detecting VMID classes are presented in Figure 4.

Discussion

This study found that the developed model using the code-free internet-based AI platform, TM application, can be effectively utilized for the classification of VMID. In the field of ophthalmology, various DL models have already demonstrated successful use in diagnosing and classifying diseases such as diabetic retinopathy and age-related macular degeneration, glaucoma, and retinopathy of pre-maturity.[4,8,10,11,15-20] However, to the best of our knowledge, there is no AI-based study that detects and classifies VMID diseases with a code-free approach. The results of this study demonstrate the promising potential of AI-based approaches for the accurate detection and classification of VMID disorders and contribute to the literature on the role of code-free AI platforms in ophthalmologic research and clinical practice.

Various AI models developed for VMID have been described in recent years. Previous studies have demonstrated the utility of DL models in ERM detection, segmentation, and post-operative prognosis estimation. Lo et al. achieved successful ERM detection with 98.7% sensitivity and 98% specificity using OCT images.[12] In addition, Sonobe et al. demonstrated that their DL model, utilizing 3D-OCT images, outperformed the classical machine learning approach, support vector machine, in ERM detection.[9] Similarly, various AI-assisted studies, such as the computation of MH detection volume, have been reported in the literature. Lu et al. developed a DL-based system to automatically classify serous macular detachment, cystoid macular edema, MH, and ERM pathologies in OCT images. The model achieved accuracies of 0.957 for ERM detection and 0.978 for MH detection, demonstrating comparability with the physicians.[21] Compared to other VMID conditions, there are relatively fewer studies focusing on VMT pathologies.

DL models typically entail intricate processes that demand coding and programming proficiency. In recent years, studies investigating the applicability of DL algorithms for medical image classification without the need for coding have been published. The obtained results demonstrate the success of this novel approach. This highlights the potential of using AI in medical imaging without the requirement of coding and suggests that it could lead to significant advancements in medical diagnosis and research. Recent studies have shown that TM, a code-free DL platform, can also be successfully used to analyze medical images.[22-24]

Previous studies reported classification accuracy rates above 90% when transfer learning was used to train relatively large datasets. Despite the high accuracy levels of DL-based models in many ophthalmic diseases, there are still several clinical and technical challenges to their real-time application in clinical practice. The algorithm learns from the presented data. If the training image set provided to the model is small or does not represent the real patient population, the software cannot produce accurate results. More evidence is needed to obtain high-quality ground truth labels for different imaging tools. Our study has a relatively small sample size in our sample groups and needs to be supported with more images. Nevertheless, it has shown a high success rate with a small amount of data. One of the most important factors here is the use of transfer learning models, which can achieve high accuracy rates with a small amount of data.[25]

The model we have developed can help expedite the diagnostic process for these diseases and reduce the cost of VMID disease diagnosis. It is particularly useful for regions where access to retinal specialists is limited due to various reasons, such as economic issues or medical resource allocation. Individuals detected with abnormalities by the DL model can be referred to a retinal specialist for further examination and timely treatment allocation. In our study, the DL model did not exhibit any deficiencies when compared with ophthalmologists. This supports the potential use of DL in OCT interpretation. In addition, the fact that the study was conducted with a code-free application provides ease of use. The availability of the application for free access can also be considered an advantage. The exportability feature of the trained model also enables its utilization by other users.

The limitations of this study should be taken into consideration. First, VMAH is more prevalent in older age groups and often coexists with pathologies that can affect the clarity of OCT imaging, such as cataracts. In our study, only clear OCT images were used. In addition, the OCT images were collected only from one imaging center. Device settings, camera systems, and population characteristics can influence OCT images and the system's performance. To further validate this system, future studies will require data sets from different eye centers and larger patient groups. Furthermore, in complex OCT images with multiple abnormalities (such as choroidal neovascular membrane, serous macular detachment, and diabetic macular edema), it is of great importance to identify each pathology separately. Due to the limited number of images, our study used a very small number of OCT images with multiple abnormalities. To validate and optimize our system and to make it an efficient AI tool for clinical cases, larger datasets consisting of complex OCT images will be required.

Our study has the potential to increase diagnostic efficiency, facilitate easier access to expert knowledge, simplify therapeutic decision-making, and reduce overall health-care costs. In addition, when the automatic DL model is integrated with clinical workflows, it can help clinicians prevent medical errors and misdiagnoses. Therefore, the derived model can potentially serve as a clinical decision support system to promote patient safety. The DL-based automated model can assist clinicians in reducing their workload and preventing health-care worker burnout.

Conclusion

Our study demonstrates that the code-free AI application, TM, is an effective tool for the detection and classification of VMID. The developed DL model exhibited high sensitivity and specificity in detecting various VMID pathologies, including ERM, VMT, and MH. The code-free approach offered by TM allows for ease of use and accessibility, making it a valuable asset in ophthalmology, particularly for clinicians without coding knowledge. With its promising performance in VMID classification, TM has the potential to enhance diagnostic accuracy and streamline the evaluation of retinal OCT images. The results of this study highlight the utility of code-free AI applications in ophthalmic diagnosis and pave the way for further advancements in the integration of AI technologies into clinical practice for improving patient care and outcomes.

Ethics Committee Approval: This study was approved by Bezmialem Vakif University Ethics Committee (26.04.2022 date; number E-54022451-050.05.04-60613).

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