ORIGINAL RESEARCH ORİJİNAL ARAŞTIRMA

DOI: 10.5336/ophthal.2023-96253

Determination of Optimum Hyperparameters in Diagnosis of Strabismus Using Artificial Intelligence Model: Cross-Sectional Study

Yapay Zekâ Modeli ile Şaşılığın Saptanmasında Optimum Hiperparametrelerin Belirlenmesi: Kesitsel Araştırma

Ersin AKBULUT[a], Furkan KIRIK[b], Havvanur BAYRAKTAR[c], Ayşe Rümeysa MOHAMMED[d], Betül TUĞCU[b]

[a]Clinic of Ophthalmology, Sultanbeyli State Hospital, İstanbul, Türkiye
[b]Department of Ophthalmology, Bezmiâlem Vakıf University Faculty of Medicine, İstanbul, Türkiye
[c]Clinic of Ophthalmology, Diyarbakır Gazi Yaşargil Training and Research Hospital, Diyarbakır, Türkiye
[d]Distributed and Collaborative Virtual Environments Research Lab, University of Ottawa, Ottawa, Canada

This study was presented as an oral presentation at Turkish Ophthalmological Association 55th National Congress, November 3-7, 2021, Antalya, Türkiye.

ABSTRACT Objective: This study aims to analyze the effectiveness of the internet-based, free Teachable Machine (TM) platform, which does not entail code knowledge, in detecting the presence and types of strabismus in the optimum hyperparameters. **Material and Methods:** The images obtained from the patients who presented to our clinic with the complaint of ocular deviation were analyzed, and 523 [176 esotropia (ET), 195 exotropia (XT), and 152 orthophoria (ORTHO)] images were included in this study. After the images were uploaded to the TM platform, 6 different batch sizes and 9 different learning rates were tested using the grid search method, with the number of epochs fixed at 4,000 to determine the optimum hyperparameter. **Results:** The highest overall test accuracy was 0.887, and the hyperparameters from which this accuracy was obtained were 200 for the number of epochs, 256 for the batch size, and 0.0005 for the learning rate. In the TM model trained with these parameters, accuracy values of ET: 0.96, ORTHO: 0.78 and XT: 0.9 were obtained in the subgroups, respectively. **Conclusion:** To achieve optimal accuracy at the stage of development of the artificial intelligence model, users should determine the appropriate hyperparameter values depending on the size of the available dataset and the complexity of the data. The results we obtained by determining the optimum hyperparameters have revealed that the presence of strabismus can be detected with high accuracy using TM, an internet-based, free deep learning platform that does not entail having code knowledge.

Keywords: Strabismus; artificial intelligence; deep learning; machine learning

ÖZET Amaç: Bu çalışmada kod bilgisi gerektirmeyen, internet tabanlı, ücretsiz "Teachable Machine" (TM) platformunun optimum hiperparametrelerde şaşılık varlığı ve tiplerini saptamadaki etkinliğinin değerlendirilmesi amaçlanmaktadır. **Gereç ve Yöntemler:** Kliniğimize gözde kayma şikâyeti ile başvuran hastalardan elde edilen görüntüler analiz edilmiş olup, çalışma kriterlerine uygun olan 523 [176 ezotropya (ET), 195 ekzotropya (XT), 152 ortoforik (ORTO)] görüntü çalışmaya dâhil edilmiştir. Görüntüler TM platformuna yüklendikten sonra optimum hiperparametrelerin belirlenmesi için döngü sayısı 4.000'e sabitlenerek 6 farklı küme boyutu ve 9 farklı öğrenme oranı ızgara arama metodu ile test edildi. Test edilen hiperparametrelerde elde edilen doğruluk ve hata değerleri kaydedildi. **Bulgular:** En yüksek genel test doğruluğu 0,887 olarak saptanmış olup bu doğruluğun elde edildiği hiperparametreler döngü sayısı için 200, küme boyutu için 256 ve öğrenme oranı için 0,0005 olarak tespit edilmiştir. Bu parametrelerle eğitilen TM modelinde alt gruplarda sırasıyla ET: 0,96, ORTO: 0,78 ve XT: 0,9 doğruluk elde edilmiştir. **Sonuç:** Yapay zekâ modelinin geliştirilmesi aşamasında optimum doğruluğu elde edebilmek için mevcut veri setinin büyüklüğü ve verilerin karmaşıklığına bağlı olarak kullanıcılar uygun hiperparametre değerlerini belirlemelidir. Optimum hiperparametreler belirlenerek elde ettiğimiz sonuçlar şaşılık varlığının kod bilgisi gerektirmeyen, internet tabanlı, ücretsiz derin öğrenme platformu olan TM ile yüksek doğrulukta saptanabileceğini göstermektedir.

Anahtar Kelimeler: Şaşılık; yapay zekâ; derin öğrenme; makine öğrenmesi

Correspondence: Ersin AKBULUT
Clinic of Ophthalmology, Sultanbeyli State Hospital, İstanbul, Türkiye
E-mail: ersinakbulut93@gmail.com

Peer review under responsibility of Turkiye Klinikleri Journal of Ophthalmology.

Received: 21 Feb 2023 ***Received in revised form:*** 06 May 2023 ***Accepted:*** 09 May 2023 ***Available online:*** 16 May 2023

Strabismus is a prevalent health problem affecting approximately 2% (1.64-2.21) of the population.[1-3] Strabismus is an eye disorder that may cause amblyopia and binocular vision loss, as well as psychosocial problems, especially in children.[4] Although it is well-documented that these undesirable conditions can be prevented with orthoptic, medical, or surgical treatments after the diagnosis of strabismus, the crucial point here is the correct and early detection of the disease.[5,6] However, strabismus can be detected with a thorough examination that takes time and requires specialization. It is noticed that an effective and low-cost screening program is needed for this disease where early diagnosis and treatment are of great importance. Given the number of ophthalmologists and the available resources, it seems to be a good alternative to carry out this screening program through artificial intelligence (AI).

AI is promising in many domains of medicine regarding diagnosis and treatment facilities. Ophthalmology, where imaging is widely used, is the most important one of them.[7] In the literature, studies have been published suggesting that AI models can be successfully used in disorders, such as diabetic retinopathy, age-related macular degeneration, glaucoma, and strabismus, which are common in ophthalmology practice. However, in the studies, coding, special hardware, or paid platforms were often used.[7,8] Hence, the use of AI models by ophthalmologists without coding knowledge has been limited. Currently, many internet-based AI applications that do not require coding have been made available to clinicians and other researchers who do not have coding experience. On the other hand, studies on the effectiveness of these platforms in the diagnosis of diseases are limited.[9] The Teachable Machine (TM) application, made available by Google (California, United States), is also one of the internet-based, code-free, free AI platforms. The TM platform, which can be used for image classification purposes, allows the user to determine various hyperparameters that may affect performance during the development of the model.[10] This opportunity can be considered an advantage for obtaining successful results in data sets such as strabismus with external imaging and broad range of variables.[11,12]

The present study aims to determine the optimal hyperparameters to be used to determine the presence and type of strabismus with the TM platform. We also aim to assessment of the effectiveness of the free TM platform, which does not require coding in these optimal hyperparameters, in diagnosing strabismus.

MATERIAL AND METHODS

TM

The TM application (version 2.0) was made available by Google in 2017. The TM platform enables image classification using the MobileNet-V2 convolutional neural network (CNN).[10,13] CNN is a deep learning technique that is widely used in image recognition software studies and gives very successful results.[14,15] The CNN we use here is a pre-trained neural network. The use of a pre-trained neural network allows the AI-based learning model to yield successful results even with very few samples.[9,13,16]

The TM application is offered as an internet-based, free, and publicly available image classification tool (Figure 1). Users who want to create their own AI model using the TM platform can pass directly to the training phase after uploading the images they want to work with, or they can select the hyperparameter settings that may affect the success of the AI models from the advanced settings section and train their models in this way. After the training, the TM platform presented the accuracy values and error values of the model established to the user graphically, using the internal test data that it parsed by 15% from each group (Figure 2).

HYPERPARAMETER

Hyperparameters are variables that determine the structure of the artificial neural network and how it will be trained.[12,17] Minor changes in hyperparameters can lead to major changes in the training of our AI model.[18] Artificial neural networks contain many filters that are used to extract features from the processed image. Each of these filters has coefficients representing its weight in artificial neural networks. The AI updates these filter coefficients reversely and obtains the most accurate coefficients, considering the erroneous results in the training process of the

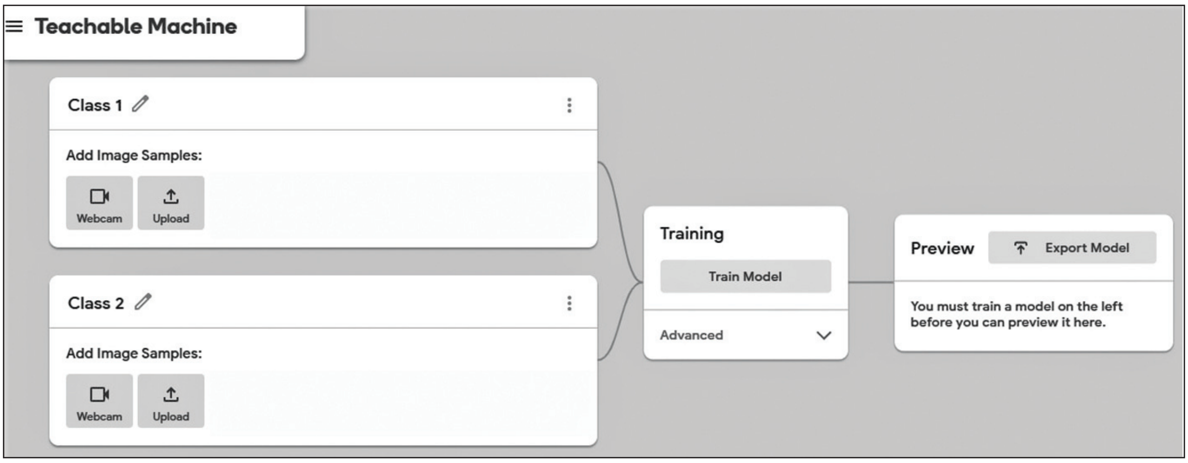

FIGURE 1: The interface of the Teachable Machine application.

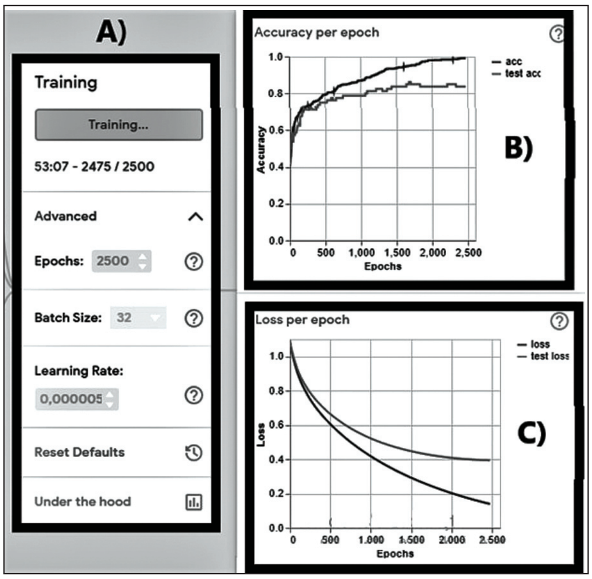

FIGURE 2: An image of an artificial intelligence model taken at the training phase. Predetermined hyperparameters (A), accuracy (B) and error values of the model (C) are seen.

model. Each of these training loops is called an epoch. This update process backward in each loop is termed backpropagation. As the number of epochs increases, the success of the model increases at the beginning, but after a certain number of epochs, the model shows excessive fit with the training data (overfitting). In this case, the success of the AI model in the tested new data decreases. Therefore, the number of epochs should be kept within the ideal range.[19-21] In each training cycle, the weights of the filters with backpropagation change depending on the learning rate. The learning rate controls the rate at which the artificial neural network trains itself during each training cycle. A small learning rate requires a lot of training cycles, hence time, to achieve optimal results. A large learning rate achieves results in a shorter time, but the result is usually suboptimal.[12,22] Instead of processing and learning all the data at the same time, the artificial neuronal network divides it into small groups, and the size of these groups is called the batch size.[12,18,21] The TM platform contains three hyperparameters that the user can modify. These are the number of epochs the batch size, and the learning rate.

DATA SET

The images of the patients who presented to the ophthalmology clinic of Bezmiâlem Vakıf University Faculty of Medicine between 2014 and 2020 with the complaint of ocular deviation were analyzed retrospectively. The photographs of the patients were divided into three groups namely exotropia (XT), esotropia (ET), and orthophoria (ORTHO). Images in which corneal light reflection was not apparent or with pathology that prevented clear selection of the reflex were excluded. Also, patients with head position or vertical shifts were excluded from this study.

To minimize the effects of variables, such as eyebrow, hair, skin color, and ear on the model performance, all images were created with the help of the clipping function of the Fiji ImageJ (ImageJ, 1.53f; National Institute of Health, Bethesda, MD, USA), the outer margin was arranged as the zygomatic arch and the lower margin as the nasal dorsum (Figure 3).

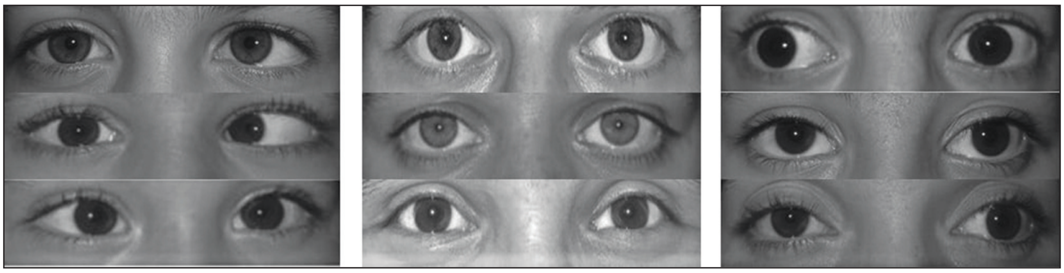

FIGURE 3: Sample data sets used in this study; esotropia on the left, orthophoria in the middle and exotropia on the right.

A total of 523 (176 ET, 195 XT, and 152 ORTHO) images that met the criteria of this study were identified and data sets were created. To determine the results with optimum accuracy, the number of epochs was fixed to 4,000, and six different batch sizes and nine different learning rates were tested with the grid search method. The training phase was stopped when overfitting tendency was detected (the test curve in the loss graph started to rise again after falling). The accuracy and error values obtained with the tested hyperparameters were noted down.

The data processed in the TM application is not available to other users and is not shared with third parties. The study protocol was approved by the institutional Ethics Committee of Bezmiâlem Vakıf University (date: May 17, 2022, no: 2022/66). Informed consent was obtained from all individual participants or their legal guardians. The study was conducted in accordance with the Declaration of Helsinki.

RESULTS

The demographic and clinical characteristics of the participants included in the study are summarized in Table 1. The accuracy value of the model in each predetermined group of hyperparameters in general and subgroups is summarized in Table 2, along with the number of epochs in which the training phase was terminated. According to the results obtained, the highest overall test accuracy was 0.887, and the hyperparameters from which this accuracy was obtained were 200 for the number of epochs, and 256 for the batch size, and 0.0005 for the learning rate. In the TM model trained with these parameters, accuracy values of ET: 0.96, ORTHO: 0.78 and XT: 0.9 were obtained in the subgroups, respectively. The results closest to this accuracy value were obtained with 621 for the number of the epoch, 32 for the batch size, and 0.00005 for the learning rate, and the overall test accuracy was 0.875. The highest overall test accuracy rate was obtained with 32 for the batch size, with an average of 0.809 at different learning rates. The highest overall test accuracy rate was obtained at the learning rate 0.005, with an average of 0.829. When the results are examined, it is noticed that the number of epochs increased with the decrease in the learning rate. In turn, it was observed that the time required for the training phase of the AI model increased.

TABLE 1: Demographic and clinical characteristics of the participants.

	Esotropia	Exotropia	Orthophoria
n (%)	176 (33.7)	195 (37.3)	152 (29.1)
Age ($\bar{X}$±SD)	13.51±10.28	14.95±11.40	16.09±10.16
(minimum-maximum)	(3-61)	(4-66)	(3-58)
PD ($\bar{X}$±SD)	25.34±6.84	25.72±6.81	
(minimum-maximum)	(15-48)	(15-46)	

SD: Standard deviation; PD: Prism dioptre.

DISCUSSION

Sufficient time and expertise are required for the accurate evaluation of strabismus. It is reasonable to have diverse searches for diagnosis in such a disease where early diagnosis and treatment are of critical importance. AI provides novel opportunities in all areas of life, as well as in the field of medicine. CNN, which operates with AI, allows us to make a diagnosis through image recognition and classification. This artificial neural network is a deep learning technique

TABLE 2: The accuracy values of the artificial intelligence model tested with six different batch sizes and nine different learning rates.

	16-0.01	16-0.005	16-0.001	16-0.0005	16-0.0001	16-0.00005	16-0.00001	16-0.000005	16-0.000001
ET accuracy	0.78	0.89	0.81	0.74	0.78	0.93	0.85	0.78	0.89
ORTHO accuracy	0.61	0.83	0.48	0.65	0.74	0.7	0.65	0.7	0.39
XT accuracy	0.8	0.8	0.9	0.93	0.8	0.83	0.93	0.9	0.77
Test accuracy	0.737	0.825	0.75	0.787	0.775	0.825	0.825	0.8	0.7
Test loss	1.680	0.683	0.602	0.537	0.726	0.491	0.537	0.46	0.697
Epochs	168	111	29	38	126	224	780	2,110	1,671
	32-0.01	32-0.005	32-0.001	32-0.0005	32-0.0001	32-0.00005	32-0.00001	32-0.000005	32-0.000001
ET accuracy	0.81	0.89	0.93	0.78	0.81	0.93	0.85	0.74	0.7
ORTHO accuracy	0.65	0.7	0.7	0.74	0.78	0.87	0.74	0.87	0.61
XT accuracy	0.87	0.83	0.9	0.7	0.83	0.83	0.87	0.93	0.83
Test accuracy	0.8	0.81	0.85	0.737	0.812	0.875	0.825	0.85	0.725
Test loss	0.978	0.77	0.455	0.638	0.39	0.35	0.438	0.394	0.65
Epochs	118	110	76	79	200	621	1,541	>4,000	>4,000
	64-0.01	64-0.005	64-0.001	64-0.0005	64-0.0001	64-0.00005	64-0.00001	64-0.000005	64-0.000001
ET accuracy	0.85	0.93	0.89	0.93	0.85	0.85	0.93	0.89	0.67
ORTHO accuracy	0.74	0.78	0.65	0.7	0.61	0.74	0.65	0.78	0.7
XT accuracy	0.83	0.8	0.83	0.83	0.93	0.7	0.77	0.9	0.83
Test accuracy	0.813	0.838	0.8	0.825	0.813	0.775	0.788	0.863	0.738
Test loss	0.617	0.577	0.623	0.505	0.585	0.684	0.503	0.413	0.767
Epochs	65	59	38	80	200	503	3,312	>4,000	>4,000
	128-0.01	128-0.005	128-0.001	128-0.0005	128-0.0001	128-0.00005	128-0.00001	128-0.000005	128-0.000001
ET accuracy	0.89	1	0.89	0.89	0.89	0.81	0.78	0.89	0.85
ORTHO accuracy	0.87	0.7	0.78	0.74	0.7	0.74	0.7	0.48	0.52
XT accuracy	0.77	0.8	0.83	0.83	0.73	0.83	0.8	0.67	0.8
Test accuracy	0.818	0.838	0.838	0.825	0.762	0.8	0.763	0.688	0.738
Test loss	0.516	0.527	0.533	0.507	0.515	0.579	0.569	0.655	0.723
Epochs	172	88	103	110	200	759	2,886	>4,000	>4,000
	256-0.01	256-0.005	256-0.001	256-0.0005	256-0.0001	256-0.00005	256-0.00001	256-0.000005	256-0.000001
ET accuracy	0.89	0.81	0.81	0.96	0.74	0.85	0.93	0.89	0.74
ORTHO accuracy	0.65	0.83	0.74	0.78	0.52	0.78	0.57	0.61	0.48
XT accuracy	0.73	0.83	0.93	0.9	0.73	0.9	0.83	0.8	0.8
Test accuracy	0.763	0.825	0.838	0.887	0.675	0.85	0.788	0.775	0.688
Test loss	0.55	0.634	0.504	0.319	0.655	0.477	0.568	0.293	0.83
Epochs	87	84	134	200	200	979	2,185	>4,000	>4,000
	512-0.01	512-0.005	512-0.001	512-0.0005	512-0.0001	512-0.00005	512-0.00001	512-0.000005	512-0.000001
ET accuracy	0.85	0.85	0.93	0.85	0.89	0.81	0.93	0.85	0.7
ORTHO accuracy	0.57	0.91	0.61	0.74	0.7	0.61	0.57	0.52	0.22
XT accuracy	0.77	0.77	0.77	0.9	0.93	0.77	0.77	0.83	0.8
Test accuracy	0.726	0.838	0.776	0.838	0.85	0.738	0.763	0.75	0.6
Test loss	0.616	0.562	0.628	0.363	0.415	0.578	0.572	0.597	0.913
Epochs	140	115	130	200	500	1,279	3,482	>4,000	>4,000

ET: Esotropia; ORTHO: Orthophoria; XT: Exotropia.

that is frequently used in fields other than ophthalmology and gives very successful results.[7,23] Although these neural networks, which require deep learning, give very successful results, they can be included in the routine use or research of clinicians in a limited way since they are not free or require coding and software knowledge. In recent years, many technology companies have established platforms that operate using deep learning that does not entail coding. Thus, clinicians without coding software experience had the opportunity to experience deep learning. In a study by Korot et al. in 2021, the performance of these non-coding-required platforms was evaluated using optical coherence tomography (OCT) and color fundus photography. Ultimately, the mean F1 scores were 93.9 (5.4) for Amazon (Washington, United States), 72.0 (13.6) for Apple (California, United States), 74.2 (7.1) for Clarifai (Delaware, United States), 92.0 (5.4) for Google, and 90.7 (9.6) for MedicMind (Otago, New Zealand), and 88.6 (5.3) for Microsoft (Washington, United States).[9] This result, presented by Korot et al., shows that these platforms, which do not require coding, can successfully classify retinal images with OCT and color fundus photography.[9]

When the literature is examined, it is seen that there are studies conducted using deep learning on the diagnosis of strabismus.[7,24-27] Zheng et al. aimed to detect horizontal shifts using deep learning in their study with photographs taken in the primary gaze position of 5,793 patients. As a result of the study, the accuracy rate of AI was 0.95. When the same patients were evaluated by three resident ophthalmologists with at least three years of strabismus experience over the same images, the accuracy rate was in the range of 0.81-0.85.[27] In addition, in the study of de Figueiredo et al. with CNN, published in 2021, classified the eye versions into nine positions of gaze through images. In the study conducted with 110 patients, the accuracy rates were in the range of 0.42-0.92.[25]

In another study, Chen et al. recorded eye movements of 42 participants (25 healthy controls, 17 strabismus patients) while looking at fixation points on the screen, using a gaze tracking system installed on a laptop computer. Images were tested with different CNNs and had the highest success rate of 95.2%.[26] In light of all these studies, the success rates suggest that AI is promisingly successful in detecting strabismus. The accuracy values obtained in our study (ET: 0.96, ORTHO: 0.78, and XT: 0.9) also were consistent with the values of previous studies. High accuracy values in detecting sick individuals suggest that AI can be used successfully, notably in strabismus screening. Unlike deep learning studies in the literature, a free platform that does not require coding was used in our study. It is noticed that we have achieved similar results compared to the success rates in diagnosing strabismus of other artificial neural networks that require coding software knowledge or special hardware.

In the literature, there are many studies using AI in other fields of ophthalmology besides strabismus, such as diabetic retinopathy, age-related macular degeneration, and glaucoma.[7] OCT images were used as data in these studies. The advantage of this is that OCT can take multiple sections and provide them non-invasively on a fixed background at high resolution. In strabismus, meanwhile, the images uploaded to the AI are mostly photographs and contain factors that may affect the results, such as different backgrounds, noses, and eyebrows. This situation might adversely affect the diagnostic success of the AI model we have established. Hence, we are of the opinion that it is crucial to specify the optimum parameters by changing the hyperparameters that determine the structure of the artificial neural network and how to train it before performing image classification with strabismus photographs. To create an AI model suitable for the data set we use, the success of our model could be increased with minor changes in hyperparameters. There are a wide variety of studies on optimizating hyperparameters outside the field of medicine, whereas there are limited studies in the literature in the field of medicine.[12,18,28,29] The study of Jeong in the field of oral and dental health in 2020 can be listed among these. The researchers sought to identify tongues with teeth marks, which are vital for oral health, by evaluating 1,250 tongue images using the TM platform we used in our study. In the study conducted with 1,250 images (704 tooth-marked tongues and 546 healthy tongues), the accuracy rate in detecting tooth-marked tongues was 92.1% after specifying the optimum hyperparameters.[11] Moreover, in another study conducted to detect tongues with dental marks, the mean accuracy rate obtained by establishing a deep learning model that required coding software and hardware was 72.7%.[30] Based on this, we can suggest that when the optimum hyperparameters are determined using TM, a free platform that does not require coding, higher success rates could be achieved than artificial neural networks that require coding software knowledge or additional hardware.

For our AI model, which we developed for the scanning program, to process images with a high success rate, we can state the necessity of centralizing the images and applying the clipping process to them as the weakness of our model. Due to the nature of deep learning models, the more data are inserted for training, the more successful a model will be built.[9,12,16] Thus, the number of images is considered to be the limitation of our study with 523 photographs. However, as the TM platform is a pre-trained deep learning model, it has shown high success in the diagnosis of strabismus with our relatively scarce visual data.

CONCLUSION

To our knowledge, this study is the first to evaluate the effectiveness of free deep learning platforms that do not require coding in detecting the presence of strabismus and determining strabismus types in the literature. The results obtained by determining the optimal hyperparameters indicate that the presence of strabismus can be detected with high accuracy with an Internet-based, free TM platform that does not require coding knowledge.

Source of Finance

During this study, no financial or spiritual support was received neither from any pharmaceutical company that has a direct connection with the research subject, nor from a company that provides or produces medical instruments and materials which may negatively affect the evaluation process of this study.

Conflict of Interest

No conflicts of interest between the authors and / or family members of the scientific and medical committee members or members of the potential conflicts of interest, counseling, expertise, working conditions, share holding and similar situations in any firm.

Authorship Contributions

***Idea/Concept:** Ersin Akbulut, Furkan Kırık, Ayşe Rümeysa Mohammed; **Design:** Ersin Akbulut, Furkan Kırık, Ayşe Rümeysa Mohammed; **Control/Supervision:** Furkan Kırık, Brtül Tuğcu; **Data Collection and/or Processing:** Ersin Akbulut, Furkan Kırık; **Analysis and/or Interpretation:** Ersin Akbulut, Betül Tuğcu; **Literature Review:** Ersin Akbulut, Havvanur Bayraktar; **Writing the Article:** Ersin Akbulut, Furkan Kırık, Havvanur Bayraktar; **Critical Review:** Furkan Kırık, Havvanur Bayraktar, Betül Tuğcu.*

REFERENCES

1. Hashemi H, Pakzad R, Heydarian S, Yekta A, Aghamirsalim M, Shokrollahzadeh F, et al. Global and regional prevalence of strabismus: a comprehensive systematic review and meta-analysis. Strabismus. 2019;27(2):54-65. [Crossref] [PubMed]
2. Friedman DS, Repka MX, Katz J, Giordano L, Ibironke J, Hawse P, et al. Prevalence of amblyopia and strabismus in white and African American children aged 6 through 71 months the Baltimore Pediatric Eye Disease Study. Ophthalmology. 2009;116(11):2128-34.e1-2. [Crossref] [PubMed] [PMC]
3. McKean-Cowdin R, Cotter SA, Tarczy-Hornoch K, Wen G, Kim J, Borchert M, et al; Multi-Ethnic Pediatric Eye Disease Study Group. Prevalence of amblyopia or strabismus in asian and non-Hispanic white preschool children: multi-ethnic pediatric eye disease study. Ophthalmology. 2013;120(10):2117-24. [Crossref] [PubMed] [PMC]
4. Nelson BA, Gunton KB, Lasker JN, Nelson LB, Drohan LA. The psychosocial aspects of strabismus in teenagers and adults and the impact of surgical correction. J AAPOS. 2008;12(1):72-6.e1. [Crossref] [PubMed]
5. Vaegan, Taylor D. Critical period for deprivation amblyopia in children. Trans Ophthalmol Soc U K (1962). 1979;99(3):432-9. [PubMed]
6. Mruthyunjaya P, Simon JW, Pickering JD, Lininger LL. Subjective and objective outcomes of strabismus surgery in children. J Pediatr Ophthalmol Strabismus. 1996;33(3):167-70. [Crossref] [PubMed]
7. Du XL, Li WB, Hu BJ. Application of artificial intelligence in ophthalmology. Int J Ophthalmol. 2018;11(9):1555-61. [PubMed] [PMC]
8. Ong J, Hariprasad SM, Chhablani J. A guide to accessible artificial intelligence and machine learning for the 21st century retina specialist. Ophthalmic Surg Lasers Imaging Retina. 2021;52(7):361-5. [Crossref] [PubMed]
9. Korot E, Guan Z, Ferraz D, Wagner SK, Zhang G, Liu X, et al. Code-free deep learning for multi-modality medical image classification. Nature Machine Intelligence. 2021;3(4):288-98. [Crossref]
10. Carney M, Webster B, Alvarado I, Phillips K, Howell N, Griffith J, et al. Teachable Machine: Approachable Web-Based Tool for Exploring Machine Learning Classification. Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems; 2020; Honolulu, HI, USA. [Crossref]
11. Jeong H. Feasibility study of Google's teachable machine in diagnosis of tooth-marked tongue. Journal of Dental Hygiene Science. 2020;20(4):206-12. [Crossref]
12. Gülcü A, Zeki K. Konvolüsyonel sinir ağlarında hiper-parametre optimizasyonu yöntemlerinin incelenmesi [A survey of hyper-parameter optimization methods in convolutional neural networks]. Gazi Üniversitesi Fen Bilimleri Dergisi Part C: Tasarım ve Teknoloji. 2019;7(2):503-22. [Crossref]
13. Howard A, Zhu M, Chen B, Kalenichenko D, Wang W, Weyand T, et al. MobileNets: efficient convolutional neural networks for mobile vision applications. arXiv. 2017. [Link]
14. Abdelhafiz D, Bi J, Ammar R, Yang C, Nabavi S. Convolutional neural network for automated mass segmentation in mammography. BMC Bioinformatics. 2020;21(Suppl 1):192. [Crossref] [PubMed] [PMC]

15. Jurczak M, Kołodziej M, Majkowski A. Implementation of a convolutional neural network for eye blink artifacts removal from the electroencephalography signal. Front Neurosci. 2022;16:782367. [Crossref] [PubMed] [PMC]

16. Zhang YC, Kagen AC. Machine learning interface for medical image analysis. J Digit Imaging. 2017;30(5):615-21. [Crossref] [PubMed] [PMC]

17. Eddelbuettel D. Parallel computing with R: a brief review. arXiv. 2021;13(2): e1515. [Link]

18. Feurer M, Hutter F. Hyperparameter optimization. In: Hutter F, Kotthoff L, Vanschoren J, eds. Automated Machine Learning: Methods, Systems, Challenges. 1st ed. Cham: Springer International Publishing; 2019. p.3-33. [Crossref]

19. Lawrence S, Giles CL. Overfitting and neural networks: conjugate gradient and backpropagation. Proceedings of the IEEE-INNS-ENNS International Joint Conference on Neural Networks. IJCNN 2000. Neural Computing: New Challenges and Perspectives for the New Millennium. 2000:1-6. [Crossref] [PubMed]

20. Ying X. An overview of overfitting and its solutions. Journal of Physics: Conference Series. 2019;1168(2):022022. [Crossref]

21. Chicco D. Ten quick tips for machine learning in computational biology. BioData Min. 2017;10:35. [Crossref] [PubMed] [PMC]

22. Na GS. Efficient learning rate adaptation based on hierarchical optimization approach. Neural Netw. 2022;150:326-35. [Crossref] [PubMed]

23. Doi K. Computer-aided diagnosis in medical imaging: historical review, current status and future potential. Comput Med Imaging Graph. 2007;31(4-5):198-211. [Crossref] [PubMed] [PMC]

24. Mao K, Yang Y, Guo C, Zhu Y, Chen C, Chen J, et al. An artificial intelligence platform for the diagnosis and surgical planning of strabismus using corneal light-reflection photos. Ann Transl Med. 2021;9(5):374. [Crossref] [PubMed] [PMC]

25. de Figueiredo LA, Dias JVP, Polati M, Carricondo PC, Debert I. Strabismus and artificial intelligence app: optimizing diagnostic and accuracy. Transl Vis Sci Technol. 2021;10(7):22. [Crossref] [PubMed] [PMC]

26. Chen Z, Fu H, Lo WL, Chi Z. Strabismus recognition using eye-tracking data and convolutional neural networks. J Healthc Eng. 2018;2018:7692198. [Crossref] [PubMed] [PMC]

27. Zheng C, Yao Q, Lu J, Xie X, Lin S, Wang Z, et al. Detection of referable horizontal strabismus in children's primary gaze photographs using deep learning. Transl Vis Sci Technol. 2021;10(1):33. [Crossref] [PubMed] [PMC]

28. Zhang F, Petersen M, Johnson L, Hall J, O'Bryant SE. Accelerating hyperparameter tuning in machine learning for Alzheimer's disease with high performance computing. Front Artif Intell. 2021;4:798962. [Crossref] [PubMed] [PMC]

29. Radzi SFM, Karim MKA, Saripan MI, Rahman MAA, Isa INC, Ibahim MJ. Hyperparameter Tuning and pipeline optimization via grid search method and tree-based AutoML in breast cancer prediction. J Pers Med. 2021;11(10):978. [Crossref] [PubMed] [PMC]

30. Li X, Zhang Y, Cui Q, Yi X, Zhang Y. Tooth-marked tongue recognition using multiple instance learning and CNN features. IEEE Trans Cybern. 2019;49(2): 380-7. [Crossref] [PubMed]