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Original Article

Developing a compact machine learning–based predictor for detecting above-mild ocular surface disease index scores

Nur Shazwani Mohd Gharib [1], Mohd Zulfaezal Bin Che Azemin [1] , Noor Ezailina Badarudin [2] , Muhammad Afzam Shah Abdul Rahim [1] , Sharon Viola Shanthini [2] and Mohammed Aljarousha [2]

[1] *Department of Optometry and Visual Sciences, Kulliyyah of Allied Health Sciences, International Islamic University Malaysia, Bandar Indera Mahkota 25200 Pahang, Malaysia*

[2] *Department of Optometry and Vision Science, Rehabilitation and Well-being, Faculty of Health and Life Sciences, Management and Science University, Shah Alam, Malaysia*

ABSTRACT

Background: The 12-item Ocular Surface Disease Index (OSDI) is widely used to assess dry eye disease (DED) severity; however, its length may reduce patient compliance and clinical efficiency. Given the expanding role of machine learning in ophthalmology, we aimed to develop and validate a compact OSDI predictor using supervised machine learning techniques to improve the efficiency and accuracy of DED assessment.

Methods: This retrospective study analyzed a dataset of complete 12-item OSDI questionnaires obtained from adult residents of the Gaza Strip. OSDI scores were recalculated using the standard scoring formula, with “not applicable” responses treated as missing and excluded from the denominator. Participants were categorized as having moderate-to-severe dry eye (OSDI > 22) or not. Three supervised machine learning models (decision tree, support vector machine, and logistic regression) were developed using Python. Binary feature-importance analysis was initially performed using the full 12-item OSDI, after which each model was retrained using only questionnaire items with a binary feature-importance value of 1. Model performance was evaluated using accuracy, sensitivity, specificity, and precision.

Results: Among 452 participants (mean [standard deviation] age, 32.0 [11.8] years; 52.9% male), 252 (55.8%) were classified as having moderate-to-severe dry eye, 200 (44.2%) were not. In the reduced-feature testing models, support vector machine model demonstrated the best overall performance, achieving 94.5% accuracy, 98.0% sensitivity, 90.0% specificity, and 92.6% precision. Logistic regression also showed strong performance, with 93.4% accuracy, 98.0% sensitivity, 87.5% specificity, and 90.9% precision. The decision tree model yielded lower testing accuracy (78.0%) and sensitivity (70.6%) but maintained relatively high specificity (87.5%) and precision (87.8%). Feature-importance analysis identified sensitivity to light, gritty sensation, computer or bank machine use, windy conditions, low-humidity environments, and air-conditioned places as informative predictors in the decision tree model. Both support vector machine and logistic regression models identified gritty sensation, painful or sore eyes, blurred vision, reading, watching television, and air-conditioned places as key predictors.

Conclusions: Supervised machine learning models, particularly support vector machine and logistic regression models, effectively classified moderate-to-severe dry eye using recalculated standard OSDI scores and reduced feature sets. The identified predictors underscore the importance of ocular discomfort, visual disturbance, sustained visual activities, and environmental triggers in DED symptom severity. These findings support the potential utility of machine learning-assisted tools for symptom-based DED screening and severity assessment. Further validation in independent clinical populations and integration with objective diagnostic measures are warranted.

KEYWORDS

dry eye disease, questionnaire, ocular surface disease index, OSDI-6, machine learning, AI (artificial intelligence), learning, deep, learning, machine, vision, sciences, optometrist

Correspondences: Mohammed Aljarousha, Department of Optometry and Vision Science, Rehabilitation and Well-being, Faculty of Health and Life Sciences, Management and Science University, Shah Alam, Malaysia. Email: mohammed_aljarousha@msu.edu.my; aljaroosha@gmail.com. ORCID iD: https://orcid.org/0000-0001-9383-0561.

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INTRODUCTION

Dry eye disease (DED) is a prevalent condition worldwide, affecting 5–50% of the population [1]. DED can negatively impact patients' physical and mental wellbeing, reducing their quality of life [2]. Patients with moderate-to-severe DED rank the loss of utility similarly to conditions like hip fractures and angina [3]. Diagnosing DED can be challenging because its signs and symptoms do not always align, and other conditions with similar presentations need to be ruled out. DED is typically determined through patient history and multiple clinical diagnostics, such as symptom questionnaires, ocular surface staining, lipid layer analysis, tear film breakup time (TBUT), tear osmolarity, tear production, inflammatory markers, meibography, and eyelid health examination [4]. Appropriate identification of DED and selection of therapeutic strategies are also important in both primary care and specialist settings [5].

The Ocular Surface Disease Index (OSDI) is a widely used tool to assess the symptoms and effects of DED [6]. The OSDI is a 12-item questionnaire designed to evaluate ocular symptoms, visual function, and environmental triggers affecting patients over the past week [6, 7]. Questionnaire design and appropriate use are important considerations when assessing DED symptoms and their effect on daily function [8]. The 12-item OSDI is a standardized patient-reported instrument that quantifies DED severity and distinguishes normal, mild-to-moderate, and severe disease. Higher scores indicate greater visual and functional impairment. By capturing patients' perspectives on symptoms and daily activities, the 12-item OSDI complements objective clinical tests and provides reliable, comparable data for practice and research [9, 10].

Growing evidence supports the diagnostic utility of the 12-item OSDI. A significant inverse correlation has been found between 12-item OSDI scores and TBUT, a common objective test for DED. This correlation implies that higher 12-item OSDI scores, which indicate worse symptoms, are associated with shorter TBUT, a hallmark of DED [11]. The 12-item OSDI has likewise displayed good specificity in correctly identifying individuals without DED and moderate sensitivity in identifying those with the condition [12]. These findings highlight dependability and utility of the 12-item OSDI in both diagnosing and assessing DED severity.

Despite its widespread use, the 12-item OSDI may be burdensome for patients and clinicians because some items assess overlapping symptoms or environmental triggers, potentially complicating interpretation. A shorter, simplified version could improve clinical usability and screening efficiency. Supporting this approach, the OSDI-6 demonstrates stronger repeatability than the original 12-item OSDI and 5-item Dry Eye Questionnaire, highlighting its potential utility in clinical practice [13]. These simplified versions aim to provide a quicker and easier assessment while retaining diagnostic accuracy. One study conducted in China assessing the validity of the Chinese translation version of the OSDI-6 (C-OSDI-6) found a high level of reliability. Rasch analysis showed that reducing the scale from 12 to 6 items had no effect on the C-OSDI-6 questionnaire's psychometric properties in a clinical population [14]. A separate study evaluated and compared the psychometric properties of the Italian versions of the 12-item OSDI, OSDI-6, and Standard Patient Evaluation of Eye Dryness (SPEED). The findings indicated that while the OSDI-6 can be a practical alternative, it does not fully replicate the diagnostic scope of the original 12-item OSDI. Specifically, the OSDI-6 lacks one factor measured by the 12-item OSDI and revealed slightly lower internal consistency, partly due to the reduced number of items [15]. Although this shorter form simplifies scoring and cuts administration time, it assesses fewer underlying aspects of DED and therefore cannot be considered a true one-to-one replacement. The Italian version of the OSDI-6 shows lower repeatability [15] compared to the results reported by Pult and Wolffsohn [13], prompting the authors to recommend a cutoff score of 5 points rather than the originally proposed 4. Despite these limitations, the OSDI-6 remains a valuable screening tool in clinical settings, particularly when time efficiency is essential [15].

Artificial intelligence and machine learning have become revolutionary technologies in healthcare, enhancing diagnosis and treatment planning, particularly in diagnostic imaging [16]. Among the techniques comprising machine learning, deep learning is particularly promising. Deep learning algorithms can be trained on vast datasets of retinal scans and optical coherence tomography images. These algorithms can then detect subtle abnormalities associated with conditions such as diabetic retinopathy, glaucoma, and age-related macular degeneration, often with high accuracy [17]. Machine learning shows promise in ophthalmology, with one study evidencing automated detection of referable diabetic retinopathy from retinal images at performance levels comparable to those of ophthalmologists [18]. Similarly, a study developing predictive models for diabetic retinopathy in patients with type 2 diabetes mellitus using data-mining techniques reported that support vector machines outperformed decision trees, logistic regression, and artificial neural networks, achieving an accuracy of 79.5% and an area under curve of 0.839 [19].

Although the 12-item OSDI is widely used for DED screening, its length may enhance patient burden and reduce clinical efficiency [14, 20]. Despite growing applications of machine learning in ophthalmology and optometry [21–23], its use in identifying optimal 12-item OSDI subsets for predicting DED severity remains limited. Therefore, this study aimed to develop and validate a compact OSDI predictor using machine learning techniques. By identifying the most informative questionnaire items, this approach may reduce assessment burden, streamline clinical workflow, and improve prediction of DED severity. A validated compact OSDI predictor could facilitate faster clinical decision-making, enhance early intervention and patient outcomes, and ultimately improve DED diagnosis and care.

METHODS

This retrospective data analysis utilized a secondary dataset originally collected by Aljarousha et al. [24, 25], comprising responses from Palestinian residents of the Gaza Strip who completed the 12-item OSDI questionnaire. Ethical approval was obtained from the International Islamic University Malaysia (IIUM) Research Ethics Committee (IREC 2024-KAHS/DOVS10).

Participants were recruited from four provinces: Gaza City, Mid-Zone, North Gaza Strip, and South Gaza Strip. Inclusion criteria were age ≥ 18 years, residency in the Gaza Strip, and proficiency in Arabic and English. Records with incomplete responses, duplicate entries, non-resident data, or data collected more than five years before analysis were excluded.

For machine learning modeling and data preprocessing, the dataset comprised responses to the 12-item OSDI questionnaire, in which each questionnaire item served as an input attribute and the 12-item OSDI severity category served as the classification label. Responses were recorded on a 5-point Likert scale (0–4), and 12-item OSDI scores were binarized, with scores > 22 classified as moderate-to-severe dry eye. Feature weighting was applied to identify the most informative predictors, where a value of 1 indicated high predictive relevance and a value of 0 indicated low relevance. Prior to analysis, the dataset was preprocessed to remove incomplete and duplicate entries to ensure data consistency and quality.

Decision tree analysis is a supervised learning approach that recursively partitions the dataset into subsets based on attribute values, forming a tree-like structure for classification decisions [26–28]. The decision tree algorithm was applied to evaluate all 12 items of the OSDI questionnaire and identify the most informative splits distinguishing participants with moderate-to-severe dry eye (12-item OSDI score > 22) from those without.

The support vector machine algorithm was applied to construct a classification model by identifying the optimal hyperplane [27] that maximally separated the dataset into the two predefined OSDI score classes. Support vector machine maps input data into a high-dimensional feature space and identify the hyperplane that maximizes the margin between classes [26]. Logistic regression, a supervised learning algorithm for binary classification [27], was used to model the probability of moderate-to-severe dry eye using a logistic (sigmoid) function. Unlike linear regression, logistic regression estimates probabilities ranging from 0 to 1 [26]. The model estimated the probability of moderate-to-severe dry eye (12-item OSDI score > 22).

The dataset was randomly partitioned into two independent subsets: 80% (361 samples) for training and 20% (91 samples) for testing. This hold-out validation approach minimizes partitioning bias by training each algorithm exclusively on the training dataset and evaluating predictive performance on the unseen test dataset, thereby providing an unbiased estimate of generalization accuracy [26, 27]. Model performance was evaluated using accuracy, sensitivity, specificity, and precision, based on true-positive, true-negative, false-positive, and false-negative classifications [26, 29].

Exploratory data analysis was performed to characterize the study dataset [27]. Data from participants with completed 12-item OSDI questionnaires were entered into Microsoft Excel 2019 (Microsoft Corporation, Redmond, WA, USA) and analyzed using IBM SPSS Statistics version 26.0 (IBM Corp., Armonk, NY, USA). Continuous variables were assessed for normality and summarized as mean (standard deviation [SD]), categorical variables were presented as frequency and percentage. Machine learning analyses were conducted using Python version 3.10.11 and three supervised learning algorithms: decision tree, support vector machine, and logistic regression [27].

RESULTS

A total of 452 completed 12-item OSDI questionnaires met the inclusion criteria. Mean (SD) age of participants was 32.0 (11.8) years; 239 (52.9%) males and 213 (47.1%) females. Mean (SD) age was 36.3 (12.6) years in males and 27.1 (8.7) years in females. Based on standard 12-item OSDI scoring, 252 (55.8%) participants were classified as having moderate-to-severe dry eye, 200 (44.2%) were not.

Using binary feature-importance analysis based on the recalculated standard 12-item OSDI score, the decision tree model identified item 1 ("eyes that are sensitive to light"), item 2 ("eyes that feel gritty"), item 8 ("working with a computer or bank machine [ATM]"), item 10 ("windy conditions"), item 11 ("places or areas with low humidity [very dry conditions]"), and item 12 ("areas that are air-conditioned") as informative predictors of moderate-to-severe dry eye. These attributes were assigned a binary importance value of 1, the remaining questionnaire items were assigned a value of 0 (Table 1).

Using binary feature-importance analysis based on the recalculated standard 12-item OSDI score, the support vector machine model identified item 2 ("eyes that feel gritty"), item 3 ("painful or sore eyes"), item 4 ("blurred vision"), item 6 ("reading"), item 9 ("watching TV"), and item 12 ("areas that are air-conditioned") as informative predictors of moderate-to-severe dry eye. These attributes were assigned a binary importance value of 1, the remaining questionnaire items were assigned a value of 0 (Table 2).

Using binary feature-importance analysis based on the recalculated standard 12-item OSDI score, the logistic regression model identified item 2 ("eyes that feel gritty"), item 3 ("painful or sore eyes"), item 4 ("blurred vision"), item 6 ("reading"), item 9 ("watching TV"), and item 12 ("areas that are air-conditioned") as informative predictors of moderate-to-severe dry eye. These attributes were assigned a binary importance value of 1, the remaining questionnaire items were assigned a value of 0 (Table 3).

Model-performance results for the training and testing datasets are summarized in Tables 4 and 5, respectively. As shown in Table 4, after retraining each model using only its respective selected features with a binary importance value of 1, the decision tree model achieved the highest training accuracy (97.2%), specificity (99.4%), and precision (99.5%). The support vector machine model demonstrated the second-highest training accuracy (94.7%), followed by logistic regression (93.9%). Logistic regression and support vector machine models showed identical training sensitivity (95.0%), with the decision tree model showing slightly higher sensitivity (95.5%) (Table 4).

As seen in Table 5, the support vector machine model showed the best overall testing performance for predicting moderate-to-severe dry eye, defined as a recalculated standard 12-item OSDI score > 22, achieving the highest testing accuracy (94.5%) and specificity (90.0%). Logistic regression also evidenced strong testing performance, with 93.4% accuracy, 98.0% sensitivity, 87.5% specificity, and 90.9% precision. Both logistic regression and support vector machine models achieved identical testing sensitivity (98.0%), though the support vector machine model demonstrated higher precision (92.6%) than logistic regression (90.9%). In contrast, the decision tree model showed lower testing accuracy (78.0%) and sensitivity (70.6%) while maintaining relatively high specificity (87.5%) and precision (87.8%) (Table 5).

These findings indicate that, when model-specific reduced feature sets are applied, the support vector machine model demonstrates the strongest overall testing performance, followed closely by logistic regression, whereas the decision tree model shows evidence of overfitting.

Table 1. Attributes and binary feature importance of decision tree

Attribute	Binary Feature Importance
1. Eyes that are sensitive to light	1
2. Eyes that feel gritty	1
3. Painful or sore eyes	0
4. Blurred vision	0
5. Poor vision	0
6. Reading	0
7. Driving at night	0
8. Working with a computer or bank machine (ATM)	1
9. Watching TV	0
10. Windy conditions	1
11. Places or areas with low humidity (very dry)	1
12. Areas that are air conditioned	1

Note: A value of 1 indicates that the attribute was selected by the model as an informative predictor of moderate-to-severe dry eye, while 0 indicates that the attribute was not selected.

Table 2. Attributes and binary feature importance of support vector machine

Attribute	Binary Feature Importance
1. Eyes that are sensitive to light	0
2. Eyes that feel gritty	1
3. Painful or sore eyes	1
4. Blurred vision	1
5. Poor vision	0
6. Reading	1
7. Driving at night	0
8. Working with a computer or bank machine (ATM)	0
9. Watching TV	1
10. Windy conditions	0
11. Places or areas with low humidity (very dry)	0
12. Areas that are air conditioned	1

Note: A value of 1 indicates that the attribute was selected by the model as an informative predictor of moderate-to-severe dry eye, while 0 indicates that the attribute was not selected.

Table 3. Attributes and binary feature importance of logistic regression

Attribute	Binary Feature Importance
1. Eyes that are sensitive to light	0
2. Eyes that feel gritty	1
3. Painful or sore eyes	1
4. Blurred vision	1
5. Poor vision	0
6. Reading	1
7. Driving at night	0
8. Working with a computer or bank machine (ATM)	0
9. Watching TV	1
10. Windy conditions	0
11. Places or areas with low humidity (very dry)	0
12. Areas that are air conditioned	1

Note: A value of 1 indicates that the attribute was selected by the model as an informative predictor of moderate-to-severe dry eye, while 0 indicates that the attribute was not selected.

Table 4. Performance of classification models on the training dataset (n = 361)

Models	Number of Selected Features	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
Decision tree	6	97.2	95.5	99.4	99.5
Support vector machine	6	94.7	95.0	94.4	95.5
Logistic regression	6	93.9	95.0	92.5	94.1

Note: Performance metrics are reported for reduced-feature models.

Table 5. Performance of classification models on the testing dataset (n = 91)

Models	Number of Selected Features	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
Decision tree	6	78.0	70.6	87.5	87.8
Support vector machine	6	94.5	98.0	90.0	92.6
Logistic regression	6	93.4	98.0	87.5	90.9

Note: Performance metrics are reported for reduced-feature models.

DISSCUSSION

This study explored the predictive capability of three supervised machine learning algorithms (decision tree, support vector machine, and logistic regression) [27] for classifying moderate-to-severe dry eye, defined as a recalculated standard 12-item OSDI score > 22 [30], and for identifying the most informative questionnaire items associated with higher symptom severity. In this updated analysis, the 12-item OSDI score was recalculated using the standard 12-item OSDI formula [12], in which "not applicable" responses were excluded from the denominator rather than scored as zero [31, 32]. This approach provides a more methodologically appropriate estimate of symptom severity and improves the validity of the classification outcome. After binary feature selection, each model was retrained using only the questionnaire items assigned a binary feature-importance value of 1 by that specific model.

Growing evidence supports the application of artificial intelligence and machine learning in ophthalmology and optometry, with studies demonstrating strong performance in disease detection, risk-factor identification, and image-based characterization of DED using clinical and meibography data [21–23, 33–38]. In the present study, reduced-feature machine learning models also demonstrated strong classification performance for moderate-to-severe dry eye. In the reduced-feature training set, the decision tree model achieved the highest training accuracy (97.2%), specificity (99.4%), and precision (99.5%). The support vector machine model had the next-highest training accuracy (94.7%), followed by logistic regression (93.9%). Logistic regression and support vector machine models showed identical training sensitivity (95.0%), while the decision tree model showed slightly higher sensitivity (95.5%). Although the decision tree model no longer demonstrated perfect training performance after reduced-feature retraining, its higher training performance compared with testing performance still suggests possible overfitting [39].

In the reduced-feature testing set, the support vector machine model demonstrated the strongest overall testing performance, with 94.5% accuracy, 98.0% sensitivity, 90.0% specificity, and 92.6% precision. Logistic regression also performed strongly, with 93.4% accuracy, 98.0% sensitivity, 87.5% specificity, and 90.9% precision. In contrast, the decision tree model had lower testing accuracy (78.0%) and sensitivity (70.6%), though it maintained relatively high specificity (87.5%) and precision (87.8%). The findings indicate that, after recalculating OSDI using the standard formula and retraining the models with model-specific selected features, the support vector machine model evidenced the strongest testing performance, followed closely by logistic regression, whereas the decision tree model showed lower generalizability in the testing dataset. Our findings are consistent with previous ophthalmic machine learning studies reporting strong classification performance of support vector machine and logistic regression models [18]. In contrast, the decision tree model may be more susceptible to overfitting, a recognized limitation of decision tree algorithms [39], which can reduce generalizability and lead to lower predictive accuracy in independent datasets [23].

The binary feature-importance analysis showed that different models emphasized different OSDI questionnaire items. The decision tree model identified item 1 ("eyes that are sensitive to light"), item 2 ("eyes that feel gritty"), item 8 ("working with a computer or bank machine [ATM]"), item 10 ("windy conditions"), item 11 ("places or areas with low humidity [very dry conditions]"), and item 12 ("areas that are air-conditioned") as informative predictors. These findings suggest that the decision tree model relied heavily on ocular discomfort symptoms and environmental triggers, particularly dryness-related conditions, windy environments, and air-conditioned places [40].

In contrast, the support vector machine and logistic regression models identified the same set of informative predictors: item 2 (“eyes that feel gritty”), item 3 (“painful or sore eyes”), item 4 (“blurred vision”), item 6 (“reading”), item 9 (“watching TV”), and item 12 (“areas that are air-conditioned”). The overlap between the support vector machine and logistic regression models supports the stability of these predictors across two different classification approaches. These items reflect a combination of ocular discomfort, visual disturbance, and visually demanding activities, suggesting that moderate-to-severe dry eye is strongly associated not only with irritation symptoms but also with functional visual limitations and reduced visual quality during daily activities [9, 13, 41].

Several selected questionnaire items are clinically consistent with the known pathophysiology of DED. Item 2, “eyes that feel gritty,” was selected by all three models, reinforcing the importance of foreign-body sensation as a core symptom of dry eye. DED is characterized by loss of tear-film homeostasis, tear-film instability, hyperosmolarity, ocular surface inflammation and damage, and neurosensory abnormalities, all of which may contribute to ocular irritation and gritty sensation [42]. Similarly, item 3, “painful or sore eyes,” was identified by both support vector machine and logistic regression models, supporting the role of ocular discomfort and sensory symptoms in more severe dry eye presentations [43].

Visual disturbance also appeared to be important. Item 4, “blurred vision,” was selected by both support vector machine and logistic regression models. This finding is consistent with previous evidence that tear-film instability can reduce optical quality and cause fluctuating or blurred vision in patients with DED [42, 44]. The inclusion of item 6 (“reading”) and item 9 (“watching TV”) as important predictors further highlights the role of sustained visual tasks. Such activities require prolonged visual attention and may reduce blink rate, thereby worsening tear-film instability and evaporative symptoms [45, 46].

Environmental triggers were also prominent in the updated analysis. The decision tree model identified item 10 (“windy conditions”), item 11 (“places or areas with low humidity [very dry conditions]”), and item 12 (“areas that are air-conditioned”) as important predictors, while logistic regression and support vector machine models both selected item 12 (“areas that are air-conditioned”). These findings support the role of environmental exposure in dry eye symptom worsening. Low humidity, airflow, and air conditioning can increase tear evaporation and destabilize the tear film, which may intensify ocular discomfort in susceptible individuals [1, 42]. The selection of item 12 by all three models is particularly notable, suggesting that air-conditioned environments may be a consistent and clinically relevant trigger in this population.

Compared with shortened dry eye questionnaires such as the OSDI-6 [13] and a short questionnaire for dry eye syndrome [47], the present approach offers a data-driven alternative for identifying the most informative items from the full 12-item OSDI. The OSDI-6 was developed to reduce questionnaire burden while maintaining acceptable measurement performance [13, 14, 47]. However, shortened fixed questionnaires may not fully capture the range of dry eye symptoms and environmental triggers across different populations [15]. In contrast, the present machine learning approach used the complete 12-item OSDI questionnaire for initial feature selection and then retrained each model using only its own selected predictors. This approach identified a mixture of discomfort symptoms, visual-function limitations, and environmental exposures, suggesting that model-based item selection may provide a flexible method for developing targeted screening tools.

Our findings indicate that recalculating OSDI using the standard formula and applying model-specific reduced-feature selection produced strong predictive performance, particularly for the support vector machine and logistic regression models. The support vector machine model achieved the highest reduced-feature testing accuracy, specificity, and precision; logistic regression displayed comparable sensitivity and strong overall performance. Logistic regression may be especially useful in clinical and research settings because of its interpretability, whereas the support vector machine model may provide slightly better classification performance in this dataset [19]. The decision tree model remained useful for identifying clinically interpretable symptom and environmental pathways; however, its weaker testing performance suggests lower generalizability compared with the support vector machine and logistic regression models. These findings are consistent with the growing evidence supporting the application of artificial intelligence and machine learning techniques in ophthalmology for disease classification, prediction, and clinical decision support [48].

This study has several strengths, including the use of recalculated standard 12-item OSDI scoring to improve methodological consistency, comparison of multiple supervised machine learning models, and application of model-specific reduced-feature selection to identify the most informative predictors of moderate-to-severe DED. In addition, the inclusion of separate training and testing datasets strengthened the evaluation of model performance and generalizability. Nevertheless, several limitations should be considered. First, the retrospective and cross-sectional design prevents causal interpretation of the identified predictors. Second, the analysis was based solely on questionnaire responses and did not include objective measures such as TBUT, Schirmer test, ocular surface staining, meibomian gland assessment, or inflammatory biomarkers. Third, although the recalculated 12-item OSDI score improves methodological consistency, external validation is needed to determine whether these models perform similarly in other populations. Finally, feature selection and model evaluation were performed within the same dataset, which may increase the risk of optimistic performance estimates. Future studies should incorporate larger datasets, cross-validation approaches, external validation cohorts, and combined symptom-clinical models to further confirm the robustness and clinical utility of these findings.

CONCLUSIONS

This study demonstrates that supervised machine learning approaches can effectively classify moderate-to-severe DED using recalculated standard 12-item OSDI scores and model-specific reduced feature sets. Among the evaluated models, the support vector machine model demonstrated the strongest reduced-feature testing performance, followed closely by logistic regression, whereas the decision tree model provided clinically interpretable feature patterns but showed lower generalizability. The identified predictors underscore the importance of ocular discomfort, visual disturbance, sustained visual activities, and environmental triggers, particularly air-conditioned environments, in dry eye symptom severity. These findings support the potential utility of machine learning-assisted tools for symptom-based dry eye screening and severity assessment. Further studies are warranted to validate these models in independent clinical populations and to evaluate their integration with objective diagnostic measures and standard clinical assessment methods.

ETHICAL DECLARATIONS

Ethical approval: Ethical approval was obtained from the International Islamic University Malaysia (IIUM) Research Ethics Committee (IREC 2024-KAHS/DOVS10).

Conflict of interests: None.

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