Through the Youth Eyes: Training Depression Detection Algorithms with Eye Tracking Data

Derick A. Lagunes-Ramírez, Gabriel González-Serna, Leonor Rivera-Rivera, Nimrod González-Franco, María Y. Hernández-Pérez, and José A. Reyes-Ortiz

***Abstract*— Depression is a prevalent mental health disorder, and early detection is crucial for effective intervention. Recent advancements in eye-tracking technology and machine learning offer new opportunities for non-invasive diagnosis. This study aims to assess the performance of different machine learning algorithms in. predicting depression in a young sample using eye-tracking metrics. Eye-tracking data from 139 participants were recorded with an emotional induction paradigm in which each participant observed a set of positive and negative emotional stimuli. The data were analyzed to find differences between groups, where the most significant features were selected to train prediction models. The dataset was then split into training and testing sets using stratified sampling. Four algorithms—support vector machines (SVM), random forest (RF), a multi-layer perceptron (MLP) neural network, and gradient boosting (GB)—were trained with hyperparameter optimization and 5-fold cross-validation. The RF algorithm achieved the highest accuracy at 84%, followed by SVM, GB, and the MLP neural network. Performance metrics such as accuracy, recall, F1-score, precision recall area under the curve (PR-AUC), and Matthews Correlation Coefficient (MCC) were also used to evaluate the models. The findings suggest that eye-tracking metrics combined with machine learning algorithms can effectively identify depressive symptoms in the young, indicating their potential as non-invasive diagnostic tools in clinical settings.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/9049

***Index Terms* — Machine Learning, Affective Computing, Emotion in human-computer interaction, Biometrics.**

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D. A. Lagunes-Ramírez, G. González-Serna, N. González-Franco, and M. Y. Hernández-Pérez are with the Tecnológico Nacional de México, Cuernavaca, Morelos, México (e-mails: d18ce078@cenidet.tecnm.mx, gabriel.gs@cenidet.tecnm.mx, nimrod.gf@cenidet.tecnm.mx, and yasmin.hp@cenidet.tecnm.mx).

L. Rivera-Rivera is with the Instituto Nacional de Salud Pública, Cuernavaca, Morelos, México (e-mail: lrivera@insp.mx).

J. A. Reyes-Ortiz is with the Universidad Autónoma Metropolitana, Azcapotzalco, Cdmx, México (e-mail: jaro@azc.uam.mx).

I. Introduction

RECENTLY, many fields have adopted Artificial Intelligence (AI) and Machine Learning (ML) to create more efficient solutions for their respective domain. Implementing AI and ML technologies has ushered in transformative changes, redefining how we approach problem-solving, decision-making, and automation.

AI and ML are applied to analyze extensive datasets in healthcare, assisting in disease diagnosis, personalized treatment plans, and drug discovery. However, each ML implementation demands precise training and data. The success of a prediction model depends on the quality of the training data, ensuring the algorithm learns to recognize patterns and makes accurate predictions tailored to the unique characteristics of the problem, such as depression detection in young people.

Mental health is crucial and recognized as a global objective for many countries around the world and one of the main mental health concerns is depression which has been increasing. Depression is a prevalent mental illness in which the affected person presents negative emotions and feelings alongside physical symptoms. When diagnosed by an expert it is also known as clinical depression or major depressive disorder (MDD). It affects not only those who suffer from it but also their families, friends, and the economy in general [1].

Since young people generally enjoy good physical health, depression stands out as a leading cause of illness and disability in this group. Emotional disorders can profoundly affect everyday activities like schoolwork, attendance, and social interaction which can increase isolation and loneliness which could lead to attempting suicide.

Traditionally, to evaluate a patient suspected of having depression, the person's circumstances, biographical history, symptoms, family history, and history of alcohol and drug use are considered. A mental status examination that looks for the presence of negative thoughts, hopelessness, pessimism, self-harm, suicide, and even electroencephalography (EEG) tests are also usually implemented. The use of depression rating scales is another common practice. However, they are not used to diagnose depression, rather they serve to assess the intensity of the symptoms. Examples of those scales include the hamilton rating scale for depression [2] or the beck depression inventory (BDI-II).

In this paper, we aim to demonstrate the results obtained from using ML algorithms to predict depression through eye-tracking data collected from a young demographic. Our goal is to contribute to the identification of eye behaviors associated with depression in youth and to establish a foundation for future studies on depression.

A. Background

The accessibility of eye-tracking technology has significantly increased, thanks to the commercialization and simplification of eye-tracking sensors, coupled with advancements in digital camera technology [3].

Eye tracking enables us to analyze the movement of the eyes as users observe visual stimuli, including images, videos, mobile or desktop applications, web pages, or any conventional object. Examining ocular characteristics, such as pupil dilation, fixations, saccades, and blinks, yields valuable insights into users' affective states, behavior, and attention [4].

Compared to other methods like EEG, eye tracking can be less invasive, cheaper, and easier to analyze and understand, however, EEG analysis is also useful and a common practice for depression detection.

Studies have shown that clinical depression may be characterized by increases in attention for negative stimuli and decreases for positive stimuli compared to healthy individuals [5], [6]. The attention biases that represent difficulties in diverting attention from negative information and changing it to positive information, play an important role in the appearance and maintenance of the disorder [7].

To analyze these biases, we can use eye tracking technologies to capture the movement of a person's eyeballs while a visual stimulus is being observed and thus find out behavior patterns like attention biases and visual engagement. Researchers relate certain eye behaviors to cognitive load [8]–[11]. Furthermore, studies relate eye movement patterns when facing emotional stimuli [12]–[14].

B. Related Work

Similar studies have used eye-tracking features, often combined with other data types, to predict depression across diverse populations and settings. They employed various algorithms, including SVM, different neural network (NN) implementations, ensemble methods, logistic regression (LR), and k-nearest neighbors (KNN).

S. Alghowinem et al. [1] utilized video data to classify subjects as depressed or non-depressed using SVM and a hybrid model, achieving a 75.00% accuracy. Their study highlighted that depressed individuals had smaller eyelid openings and longer blink durations. Stolicyn et al. [15] achieved 79.00% accuracy by employing an SVM with a Gaussian kernel, classifying depression based on behavioral and eye movement data.

In contrast, Zhu et al. [16], [17] utilized a context-based ensemble method (CBEM) combining EEG and eye-tracking data, reaching an accuracy of 82.50% with eye-tracking alone and 92.65% with EEG. They found that RF performed best with non-integrated data, while SVM with a radial basis function kernel excelled with integrated data. In another work by S. Alghowinem et al. [18] the authors achieved 86.00% accuracy by fusing eye, speech, and head movement features using SVM and decision fusion.

Shen et al. [19] achieved 77.00% accuracy in classifying depression using eye-tracking data from emotional stimuli tasks and SVM. Pan et al. [20] combined reaction times and eye movement data to train an SVM, reaching 86.00% accuracy in depression detection. H. Wang et al. [21] merged self-reported data with eye-tracking and other features, achieving up to 93.02% accuracy with LR.

Al-gawwam & Benaissa [22] focused on blink features from video data in AVEC datasets, achieving 92.95% accuracy for reading tasks and 88.00% for interviews using AdaBoost. Zhu, Wang, La, et al. [23] integrated EEG and eye movement data with neural networks, attaining 83.42% accuracy with a linear SVM. Ding et al. [24] combined EEG, eye-tracking, and galvanic skin response (GSR) data for depression detection, with LR yielding a 79.63% accuracy.

X. Li et al. [25] utilized eye movement data and KNN to achieve 81.00% accuracy in detecting depression. Shafiei et al. [26] employed a recurrent neural network with long-short term memory (RNN-LSTM) with visual metrics to classify mental health, achieving 95.00% accuracy in predicting well-being. Gavrilescu & Vizireanu [27] used eye features and a feed forward neural network (FFNN) system to predict depression, anxiety, and stress, reaching an accuracy of 87.20% for depression.

M. Li et al. [28] combined ocular behavior features with an affective bandwidth feature using a kernel extreme learning machine (KELM) algorithm, achieving 91.00% accuracy. Similarly, S. Lu et al. [29] achieved 88.55% accuracy using only eye image data.. Yuan & Wang [30] applied a NN to eye movement trajectories, obtaining an accuracy of 83.17%. Table I provides a comprehensive compilation of these related works.

Despite the promising findings in depression detection using eye-tracking, a notable gap exists in the literature regarding younger populations. Most studies focus on adults, leaving a scarcity of research on how these behaviors manifest in adolescents and young adults. To address this gap, we focused exclusively on a young demographic (aged 15-21) and used only eye-tracking sensor data for feature extraction, unlike multimodal approaches that integrate additional data like EEG. This study aims to explore the potential of single-sensor data for detecting depression in youth, providing insight into whether similar patterns observed in adults hold true for younger individuals. Additionally, by applying four machine learning algorithms optimized through hyperparameter tuning, we conduct a comparative analysis of algorithmic performance to identify the most effective techniques for this specific dataset.

TABLE I
RELATED WORKS IN DEPRESSION DETECTION

Study	Publication year	Algorithm	Reported accuracy	Data: Image	Data: Eye-Tracking	Data: Others	Features
[1]	2013	SVM	75.00%	✓			126
[16]	2020	KELM	91.00%	✓			28
[17]	2020	SVM	79.17%	✓			132
[18]	2020	RNN-LSTM	94.52%	✓			20
[19]	2019	CBEM	78.50%	✓		✓	87
[20]	2018	SVM & Fusion	86.00%	✓		✓	128
[21]	2018	Adaboost	92.00%	✓			3
[22]	2021	SVM	77.00%		✓		--
[23]	2020	KELM	88.55%	✓			--
[24]	2020	CBEM	82.50 %	✓		✓	87
[25]	2019	FFNN	79.80%	✓			30
[26]	2019	SVM	86.00%		✓		82
[27]	2019	LR	93.02%		✓		20
[28]	2019	NN	83.17%		✓		30
[29]	2019	Lineal SVM	83.42%		✓	✓	1846
[30]	2019	LR	79.63%	✓		✓	--
[31]	2016	KNN	81.00%		✓		6

C. Paper Structure

This paper is structured as follows: Section II, Methodology, details the approach and procedures used to carry out the study. Section III, Results, presents the findings from the experiments, highlighting the performance metrics of the different models and comparing their effectiveness. In Section IV, Discussion, the results are analyzed in depth, discussing their implications, the significance of the findings, and potential limitations of the study. Finally, Section VII, Conclusion, summarizes the key insights of the research and outlines directions for future work.

II. METHODOLOGY

In this study, we employed a randomized controlled experiment design to collect eye-tracking data from a sample of young students.

A. Apparatus

The primary tool employed was the Gazepoint 3GP HD eye tracker sensor. Through the device API we collected the eye-tracking data from the participants, enabling a detailed examination of their ocular behaviors about depression. We paired the sensor with an HP v185es monitor (1366 x 768). Additionally, the study incorporated two well-established depression evaluation scales: The patient health questionnaire-2 (PHQ-2) [31], for a quick depression assessment, and The depression, anxiety and stress scale-21 (DASS-21) [32].

B. Population

The study involved 172 young participants aged 15 to 21 years old ($\bar{x}$ = 16.53) randomly selected from 2 different high schools. All participants, their parents, and the school authorities provided informed consent, and ethical approval was obtained from Mexico's "instituto nacional de salud publica" (INSP) ethics committee. After excluding 33 participants based on the following inclusion criteria: being between 15 and 21 years old, not taking any medication, having no eye-related issues, and consenting to participate in the study, we classified the participants into the healthy control (n=82) and depressed (n=57) groups by their score results from the DASS-21 depression.

C. Emotional Stimuli

The images used in this study were selected from the international affective picture set (IAPS). Based on a Mexican population context study where young adults rated the valence dimension (how positive or negative the image was [33]) on a set of IAPS images. We selected 15 images from each category: 1) positive and 2) negative. Table II shows the used IAPS stimuli identifier alongside its category.

TABLE II
SELECTED EMOTIONAL STIMULI

Category	IAPS Id	Measured valence
Positives	2057	6.75
	2091	7.58
	2151	7.01
	2155	6.52
	2165	6.83
	2332	7.57
	2340	7.35
	2341	6.86
	2347	7.22
	2540	6.49
	2655	7.41
	4612	6.88
	8170	6.74
	8190	7.22
	8496	7.51
Negatives	2095	1.67
	2104	2.10
	2396	1.61
	2397	2.59
	2410	1.78
	2456	2.04
	2495	2.14
	2575	1.84
	2595	2.75
	2688	2.59
	2703	1.96
	2745.1	2.23
	2850	2.03
	6212	1.96
	9002	2.43

D. Ethical Considerations

In adherence to ethical standards and guidelines, the study received approval from the INSP's Ethical Committee. This included the consent form for the young participants, their parents, and school authorities.

The INSP approval and participants' consent underscores the commitment to ensuring the rights, well-being, and privacy of the study participants. The ethical oversight provided by the INSP added a crucial layer of credibility and integrity to the research process, reinforcing the ethical foundations that underpin the entire study.

E. Visual Task and Data Collection

In the visual task paradigm employed for this study, participants engaged in free viewing, a dynamic approach that allowed them the autonomy to explore and scrutinize stimuli presented on the screen without any imposed restrictions. By granting participants the freedom to navigate and focus on the stimuli according to their inherent preferences, the study aimed to obtain natural and meaningful data.

Furthermore, the presentation of visual stimuli was standardized to ensure consistency across participants. Each image was systematically displayed after a fixed 3-second interval, providing a brief anticipation period before the onset of the visual stimulus. This deliberate temporal arrangement aimed to control for potential variations in initial attentional states and ensure that participants were prepared for the subsequent visual input. Once presented, each image persisted for 30 seconds, allowing sufficient time for participants to engage with and explore the content comprehensively. This timed presentation strategy was employed to strike a balance between providing participants with ample opportunity for detailed examination and preventing prolonged exposure that might lead to habituation or reduced attention over time.

While participants freely looked at the stimuli, their behavioral data was concurrently recorded using the API in charge of the eye-tracking sensor. A comma-separated value file, in which each participant was labeled, was used to store the behavior data.

F. Feature Extraction

Some of the common ocular metrics linked to attentional cognitive processes and reported in the literature include fixations (e.g., duration, count, total number, spatial density, and the number of points per area of interest), saccades, blinking, pupil dilation, dwell time, attention-switching frequency, heat maps, and gaze plots. In this work, Python was used to process the sensor's raw data and generate features related to the participants' ocular behavior.

The strategy for feature extraction centered around 30 CSV files generated for each participant, where each file represented a visual stimulus observed, referred here as an 'event'. Each event contained raw eye-tracking sensor recordings captured during the free-viewing task. These recordings were processed to derive additional features, including the number of fixations, average fixation duration, saccade amplitude, saccade velocity, saccade latency, saccade duration, the number of blinks, average blink duration, and the blink rate per minute. Moreover, for each feature, descriptive statistics such as means, variances, standard deviations, kurtosis, minimums, and maximums were calculated.

Fixation and saccade metrics, have been widely reported in the state of the art as relevant to cognitive processes. Additionally, other features were extracted to evaluate their significance in later analyses, providing a broader exploration of the potential relationships between eye-tracking data and cognitive states.

G. Data Analysis

After obtaining the data files with the characteristics, R was used to perform data analysis aimed at handling outliers and preparing the data for feeding into machine learning algorithms. In this study, it was decided that outliers could provide relevant information about the behavior of individuals with depression, so they were retained in the data vectors and processed.

Our approach to detecting outliers in the data vectors involved measuring how far each numerical feature deviated from the median, expressed in terms of standard deviations. By calculating the distance of each feature from the median, we could identify values that were unusually far from the center of the distribution, helping us flag potential outliers. This method leverages the median, which is more robust to extreme values than the mean, and the standard deviation, which provides a consistent way to quantify how much a data point differs from typical values. We then applied an inverse exponential function (1) to assign weights to the data based on this distance. Specifically, for each data point x_i, we computed its distance from the median d_i (in terms of standard deviations) and assigned a weight w_i as follows:

$$w_i = e^{-\alpha d_i} \tag{1}$$

Where α is a tuning parameter that controls how rapidly the weight decreases as the distance increases. We then multiplied the original values x_i by their corresponding weights w_i to obtain the weighted values as in (2):

$$x_i^{weighted} = w_i \cdot x_i \tag{2}$$

This weighting process downscales the influence of outliers while preserving the contribution of data points closer to the median.

The next step involved normalizing the data (3) so that the numerical features were scaled to a range between 0 and 1. This process ensured that features with larger numeric ranges do not disproportionately influence the model. Let x_i *represent* the original value of the feature, x_{min} and x_{max} represent the minimum and maximum values of the feature, respectively, and x_i' be the normalized value as follows:

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (3)$$

Due to the class imbalance between subjects with depression and control subjects, discussed earlier, data augmentation techniques (SMOTE) were also employed using the DMwR package in R, resulting in a balanced sample of classes (114 with depression and 114 control).

Finally, a dataset was compiled containing 46 features for each image viewed by the participants (30 images x 139 participants). This dataset included 37 numerical features related to eye-tracking metrics, including (a) fixation count, (b) fixation duration, (c) saccade amplitude, (d) saccade velocity, (e) saccade latency, (f) saccade duration, (g) blink count, (h) blink duration, and (i) blink rate. Additionally, for each of the following eye-tracking features: (j) X_fixation_data, (k) Y_fixation_data, (l) left pupil size, and (m) right pupil size, we calculated statistical measures such as maximum, minimum, mean, variance, standard deviation, skewness, and kurtosis. The dataset also included nine categorical features derived from assessment tools: (n) sex, (o) depression score, (p) depression level, (q) anxiety score, (r) anxiety level, (s) stress score, (t) stress level, (u) medication use, and (v) energy drink consumption on the observation day.

H. Selected Features

Supervised machine learning algorithms rely on identifying differences between two or more classes. However, when the data from both classes do not show significant differences, the performance of these algorithms can be considerably affected. For this reason, we decided to perform a feature selection process based on those features that exhibit the greatest differences between the depression and control groups.

In this study, we used Mann-Whitney U tests on the original datasets for each visual stimulus (without synthetic samples) to examine the differences between the groups. Table III shows the results of the U-tests for specific features, indicating which stimulus specifically revealed differences between groups.

Based on the U-tests results, we selected the eye-tracking data that showed significant differences between the groups to create a dataset representing participants' behavior. This dataset was composed of 21 features. For pupil size, we included the maximum values, skewness, and kurtosis for both the left and right pupils. Eye fixation metrics comprised fixation count, variance and standard deviation of both X and Y coordinates, maximum and minimum values of the X coordinate (side-to-side view), and the mean, skewness, and kurtosis of the Y coordinate (up-and-down view). Additional eye-tracking metrics included blink count, blink rate per minute, saccade velocity, and saccade latency. The dataset also features the target variable 'Class,' which indicates the classification outcome. Ultimately, the dataset consisted of 228 data vectors (114 for the depression group and 114 for the control group), each with 21 numerical features. This dataset was used to train supervised ML algorithms with a binary classification strategy, where class 0 represents the control group, with a non-depressed score on the DASS-21, and class 1 represents the depressed group, with a depressed score.

TABLE III

FEATURE DIFFERENCES BETWEEN GROUPS

Feature	Event	U statistic	p-value
AVG_Blink_Per_Minute	12	1829.5	0.038
	14	1804	0.029
	20	1803.5	0.028
	26	1117	0.001
AVG_Blink_Duration	26	1062	0.0004
AVG_Saccade_Latency	21	2797	0.034
AVG_Saccade_Velocity	13	2847	0.019
	23	2660	0.033
Blink_Count	14	1797.5	0.026
	20	1748	0.014
	26	1140.5	0.001
Fixation_Count	14	2775.5	0.043
Left_Pupil_Size_Kurt	3	1621	0.002
Left_Pupil_Size_Max	16	2787	0.038
	20	2770	0.045
	27	1948	0.032
Left_Pupil_Size_Mean	25	2312	0.027
Left_Pupil_Size_Min	30	1478	0.041
Left_Pupil_Size_SK	3	2925	0.007
Right_Pupil_Size_Kurt	4	2948	0.005
	9	2765	0.048
	22	2802	0.032
Right_Pupil_Size_Max	20	2811	0.029
	26	2232	0.005
	27	2024	0.010
Right_Pupil_Size_Mean	26	2084	0.047
	29	1822	0.007
Right_Pupil_Size_Min	2	2777	0.042
	3	1841	0.043
Right_Pupil_Size_SK	4	1617	0.002
	9	1781	0.022
	11	1807	0.030
	22	1754	0.016
	29	1036	0.023
X_Fixation_Data_Max	14	2777	0.042
X_Fixation_Data_Min	21	2620	0.018
X_Fixation_Data_SD	12	1674	0.006
	15	1584	0.001
X_Fixation_Data_Var	12	1733	0.012
	14	2903	0.010
	15	1578	0.001
	22	1793	0.025
Y_Fixation_Data_Kurt	14	1718	0.010
	24	1575	0.046
Y_Fixation_Data_Mean	8	2817	0.027
	16	2845	0.020
Y_Fixation_Data_Min	26	1999.5	0.044
Y_Fixation_Data_SD	10	1830	0.038
Y_Fixation_Data_SK	13	2897	0.010
	20	1699	0.008

Note: The event refers to a specific emotional image stimulus observed by all participants.

I. Machine Learning Algorithms

In this study, we selected SVM, RF, an implementation of a MLP neural network, and GB as the primary algorithms due to their proven effectiveness in related works, particularly when dealing with numerical characteristics. SVM was chosen because it has demonstrated strong performance in high-dimensional spaces and has shown promising results in similar studies. RF was selected for its robustness and ability to reduce overfitting by averaging across multiple decision trees, making it well-suited for both classification and regression tasks. The MLP neural network was included for its capability to capture complex, non-linear patterns in the data, providing a neural approach to predictive modeling. Lastly, GB was chosen for its high accuracy and sequential nature, which helps correct errors iteratively, making it particularly effective on structured data. The combination of these algorithms allows for a thorough evaluation and comparison in terms of accuracy, generalization, and interpretability.

Each classification algorithm operates differently, requiring an exploration of the optimal hyperparameters. To address this, we used GridSearchCV from Python's Scikit-learn library, which exhaustively evaluates all possible combinations of hyperparameter values within a predefined space (a hyperparameter grid). In addition, the dataset was split into training and testing sets using the "train_test_split" function from Scikit-learn, where 80% of the data was allocated for training and 20% for testing. Stratified sampling was also employed to maintain the same proportion of each class (depression and control) in both sets.

To ensure a thorough search for the best hyperparameters, a portion of the training set was set aside specifically for this purpose. Given the relatively small size of the dataset in this study, a k-fold cross-validation was applied on the training set to evaluate different hyperparameter configurations. After identifying the optimal hyperparameters through cross-validation, the final model was trained using the full training set with the best parameter values. This final model was then evaluated on the separate test set to assess its performance.

III. III. RESULTS

Python was used to train various models by employing the GridSearchCV object to optimize a range of hyperparameters for each algorithm. Specifically, we fine-tuned SVM with hyperparameters including a regularization parameter C set to 0.1, a polynomial kernel with degree 4, a coefficient *coef0* of 1, and a gamma value of 0.1. For the RF model, hyperparameters were configured with an unlimited max_depth, a minimum of 1 sample per leaf, 2 samples required to split an internal node, and 200 estimators, with a random state of 11. The GB model was optimized with a learning rate of 0.1, a maximum depth of 3 for the trees, a minimum of 3 samples required to split an internal node, and 200 estimators. For the MLP, we set a batch size of 16, 30 epochs for training, a dropout rate of 0.25, and hidden layer sizes configured as (64, 32, 16, 8), using the rmsprop optimizer with a learning rate of 0.001.

This rigorous and iterative approach allowed us to determine the optimal hyperparameters for each model, thereby enhancing their performance. Each model was validated using 5-fold cross-validation to prevent overfitting. The final models were tested on a separate dataset that did not include the augmented data, ensuring an unbiased evaluation.

The effectiveness of these models was evaluated using several metrics, including accuracy, recall, F1-score, PR AUC, and MCC [34], which is especially useful for providing a balanced measure of predictive performance, particularly in the context of imbalanced datasets. The detailed performance results are presented in Table IV.

TABLE IV
MACHINE LEARNING ALGORITHMS' PERFORMANCE RESULTS

Model	Accuracy		Recall		F1-score		PR-AUC	MCC
	Class 0	Class 1	Class 0	Class 1	Class 0	Class 1		
SVM	86%	83%	74%	83%	77%	79%	83%	0.57
RF	86%	83%	83%	87%	84%	85%	88%	0.69
MLP	81%	76%	74%	83%	77%	79%	83%	0.57
GB	95%	81%	78%	96%	86%	88%	89%	0.75

In the evaluation of the classification models for depression detection based on eye-tracking features, the GB model achieved the highest MCC of 0.75, reflecting its superior ability to correctly classify both positive and negative classes. The RF model, with an MCC of 0.69, followed closely, demonstrating strong performance as well. Notably, while GB outperformed RF in terms of MCC, the RF model achieved a higher overall accuracy of 84% compared to 82% for GB. This suggests that, although GB had a slightly better ability to balance the classification of both classes, the RF model delivered better overall predictive performance. The comparative analysis highlights that ensemble methods, such as RF and GB, generally outperform single algorithms like SVM and MLP in this task. This underscores the advantage of leveraging multiple decision trees and boosting techniques to enhance prediction accuracy in detecting depression from eye-tracking data.

IV. IV. DISCUSSION

This study highlights the potential of eye-tracking metrics combined with machine learning algorithms to effectively identify depressive symptoms in a young population, paving the way for innovative diagnostic tools in mental health care.

The use of eye-tracking data to detect depression raises important ethical considerations. First, the collection of sensitive biometric data, such as eye movements, poses privacy concerns, as individuals may not fully understand the extent to which this data reveals information about their mental health. Informed consent becomes crucial to ensure that participants are aware of how their data will be used, stored, and shared. Additionally, there is a risk of stigmatization if such technology is used inappropriately, leading to potential discrimination in contexts such as employment or insurance. Furthermore, the accuracy of eye-tracking systems in diagnosing depression must be scrutinized to avoid misdiagnoses, which could cause unnecessary distress or lead to improper treatment. Researchers and developers must ensure that such technologies are developed and used responsibly, with a focus on protecting individuals' autonomy, privacy, and mental well-being.

In our analysis of eye-tracking characteristics, not all features showed significant differences between young individuals with depressive symptoms and healthy controls. For each feature and event, we conducted a U-Test to evaluate the statistical significance of the differences between the two groups. The results indicated that only certain features from specific images or stimuli displayed significant differences between healthy controls and participants classified with depression. This variability might suggest that not all eye-tracking metrics or stimuli are equally sensitive to depressive symptoms, highlighting the importance of careful feature selection and further analysis to identify the most relevant indicators.

While the background studies have correlated adult eye-tracking behaviors with depression, there is a paucity of research focusing on younger populations. Our observations indicate that eye-tracking behaviors associated with depression in young individuals are similar to those observed in adults.

Many state-of-the-art studies that examine eye-tracking behaviors in adults with depression have consistently found correlations between certain ocular metrics and depressive symptoms, such as altered fixation patterns, increased blink rates, and changes in saccadic movements [35]–[46]. Our findings align with these studies, indicating that similar eye-tracking behaviors are present in younger individuals with depressive symptoms. For instance, metrics such as fixation duration and saccade velocity, which have been linked to depression in adults, were also observed to differ significantly in our younger cohort. This suggests that despite developmental differences between age groups, the underlying cognitive and attentional mechanisms associated with depression may manifest similarly across different populations. These results reinforce the relevance of eye-tracking features as potential biomarkers for depression, not only in adults but also in younger individuals, an area that has been less explored in current research.

However, some studies have reported differences in behavior among children. For instance, research involving children at risk for or diagnosed with depression has yielded mixed results. Gibb et al. [47] found that children of depressed mothers tend to avoid negative stimuli, while Platt et al. [48] did not find a significant correlation between attention tests and depressive symptoms in at-risk children.

In contrast, results are more consistent among adults, who generally struggle to shift their attention away from negative stimuli. This suggests that at some point during the development or progression of depression, individuals may lose the ability to redirect their attention from sad stimuli. Nonetheless, some studies have reported a negative bias in children with depressive symptoms, indicating a need for further investigation. For example, Owens et al. [49] proposed that this bias might be related to genetic factors. Therefore, additional research is necessary to understand the correlation between attentional cognitive processing in young individuals with and without depression. Therefore, further research is needed to correlate attentional cognitive processing in young individuals with and without depression.

We explored the implementation of various machine learning algorithms to test for depression in young people based on eye-tracking metrics. Our results demonstrated that the RF algorithm achieved the highest mean accuracy (84% for both depression and healthy classes), followed by SVM, GB, and MLP neural network. However, it should be noted that different algorithms had better precision to identify the healthy class (Class 0) which can be useful in a practical scenario.

To ensure that the findings are applicable to a broader population, it is essential to incorporate more generalized and diverse datasets in testing. Using data from various demographic groups—such as different ages, genders, ethnicities, and socio-economic backgrounds—would enhance the model's robustness and reduce potential biases. This approach allows the system to better account for variability across populations, ensuring that it performs well across different groups and improving the generalizability of the results beyond a narrowly defined sample.

These findings align with previous background research using different algorithms for depression detection in various populations. In the reviewed state-of-the-art studies, the predominant use of SVM is evident. Despite each study having its unique characteristics in terms of experimental paradigms, data, and specific algorithm configurations, SVM consistently yield good results [1], [15], [18]–[20]. No studies were found using RF or GB algorithms; however, several studies employing various neural network approaches reported accuracies ranging from 79% to 94% [16], [18], [23], [25], [28].

The implementation of a web-based system for depression classification would allow for more efficient, objective, and rapid diagnosis by healthcare professionals. In this setup, desktop software would utilize conventional webcams to capture a patient's behavior, such as eye movements or facial expressions, during a consultation. The extracted data would then be securely transmitted over the internet to a web server where a pre-trained machine learning model processes the information in real time. The server analyzes the behavioral data using advanced algorithms to detect potential signs of depression. The results are then provided to healthcare experts, offering them an additional layer of objective insight to support their clinical assessments. This approach could streamline the diagnostic process, enabling doctors to make faster, data-driven decisions while maintaining high levels of patient privacy and data security.

The implications of this study are significant both theoretically and practically. Theoretically, our results suggest that eye-tracking metrics are reliable indicators of depression, potentially leading to the development of non-invasive diagnostic tools. Practically, clinics, and schools could integrate eye-tracking technology into their diagnostic procedures, aiding in the early identification of depressive symptoms in young people.

V. Conclusion

This study demonstrated that the RF algorithm achieved the highest accuracy (84%) in predicting depression based solely on eye-tracking metrics for a young sample. These findings advance current research in mental health and human-computer interaction, supporting the use of machine learning in mental health applications. Integrating eye-tracking technology into clinical settings could offer a non-invasive and efficient method for the early detection of depressive symptoms.

However, the study is limited by a relatively small sample size and a lack of diversity among participants. By generalizing the data, the model could be applied to a broader range of contexts and populations, enhancing its applicability and relevance. Future research should aim to confirm these findings with larger and more diverse populations. Additionally, implementing advanced feature selection techniques could further enhance the specificity of the data and improve classification models.

Eye-tracking technology is highly versatile and can be easily integrated into various settings, such as schools, businesses, and initial consultations with doctors. In educational environments, it could help monitor students' attention and emotional states, enabling early intervention for those at risk of depression. In the business world, eye-tracking could enhance understanding of employee well-being and productivity by identifying stress or fatigue levels. For first-contact doctor consultations, it offers a non-invasive tool to assess mental health and guide further evaluation and treatment. This broad applicability underscores the potential of eye-tracking technology to contribute significantly to mental health support across different contexts.

Overall, this work highlights the potential of combining eye-tracking data with machine learning algorithms for the early detection of depression in young people, paving the way for innovative approaches in mental health care. Further research should explore the applicability of eye-tracking metrics across different demographic groups and investigate depression prevention applications, particularly in young populations, given that depression significantly impacts cognitive development and is a leading cause of illness and disability among them. Moreover, as digital health solutions continue to evolve, eye-tracking technology may play a crucial role in personalized mental health interventions, allowing for tailored approaches that address individual needs. As such, fostering interdisciplinary collaborations among mental health professionals, data scientists, and technologists will be essential to maximize the effectiveness and implementation of these innovative solutions in real-world settings.

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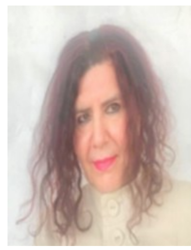
Derick A. Lagunes-Ramírez, received his Bachelor’s Degree in Information Technologies, from the Technological University Emiliano Zapata, Emiliano Zapata (UTEZ), Morelos, Mexico in 2018. The Master’s Degree in Computer Sciences, in 2020 from National Center for Technological Research and Development (TecNM/CENIDET), Cuernavaca, Morelos, Mexico. His studies are funded by the National Council of Humanities, Sciences, and Technologies (CONAHCYT). He is currently a Ph.D. student at TecNM/CENIDET and a teacher in UTEZ Emiliano Zapata, Morelos, Mexico. His research fields include Affective computing, Human-Computer Interaction, Eye tracking, User Experience, and Emotion recognition.

Gabriel González-Serna, is a computer Systems Engineer who graduated from the Technological Institute of Acapulco (TecNM/ITA), Acapulco de Juárez, Guerrero, México in 1992. He received his Master’s Degree in Computer Sciences from the National Center for Technological Research and Development (TecNM/CENIDET), Cuernavaca, Morelos, Mexico in 1995. He obtained his Ph.D. degree in Computer Sciences from the National Polytechnic Institute (CIC-IPN), Gustavo A. Madero, Ciudad de Mexico, Mexico in 2006. He joined TecNM/CENIDET as a researcher in the Intelligent Hybrid Systems area in 1992. From 1995 to date, he has worked as a Professor-Researcher for the Department of Computational Sciences at TecNM/CENIDET. Dr. González-Serna is a member of CONACyT’s National System of Researchers at level I (SNI I). He is a member of review committees for journals and conferences in engineering and computer science.



Leonor Rivera-Rivera, is a Medical Surgeon who graduated from the Faculty of Medicine of the Autonomous University of Nayarit. She received her Master's Degree in Health Sciences in Reproductive Health at the National Institute of Public Health, Cuernavaca, Morelos, Mexico, and her Ph.D. in Psychology and Health from the Faculty of Psychology of the National Autonomous University of Mexico, Coyoacán, Ciudad de México, Mexico.

She is a researcher in Medical Sciences at the National Institute of Public Health of Mexico. She has led several research projects, and her scientific publications cover topics such as violence against women, dating violence, depressive symptomatology, suicidal behavior, sexual abuse, reproductive health, mental health, and addiction issues.

Dr. Rivera is a member of the National System of Researchers (SNI II) of the National Council of Humanities, Sciences, and Technologies (CONAHCYT).

Nimrod González-Franco, received a Ph.D. degree in computer science in 2017 from National Center for Technological Research and Development (TecNM/CENIDET), Cuernavaca, Morelos, Mexico.

He joined the TecNM/CENIDET, Cuernavaca, Mexico as a research professor in the Intelligent Hybrid Systems area in 2019. His research areas include brain-computer interface systems and machine learning.

María Y. Hernández-Pérez, received a PhD degree in Computer Sciences from Tecnológico de Monterrey, Cuernavaca, Mexico; she received a ScM in Computer Sciences from the Cenidet, Cuernavaca, Mexico; and she received a Bs in Computer Systems from the Instituto Tecnológico de Ciudad Madero, Madero, Mexico. As part of her PhD, she did a research stay at the University of British Columbia, UBC, in Vancouver, Canada.

She is a professor at the National Center of Research and Technological Development, TecNM/CENIDET, in Cuernavaca, Mexico. Dr. Hernández is a member of the National System of Researchers (SNI) of Mexico, the Researchers System of Morelos State (SEI), the Mexican Society of Computer Science (SMCC), Mexican Society of Computing (Amexcomp), Mexican Association of Natural Language Processing (AMPLN), and the Artificial Intelligence Mexican Society (SMIA).

José Alejandro Reyes-Ortiz, received his Master's degree in Computer Science from the National Center for Research and Technological Development, Cuernavaca, Morelos, Mexico (2008), and his Ph.D. in Computer Science from the National Center for Research and Technological Development, Cuernavaca, Morelos, Mexico (2013). He is a full-time professor in the Systems Department at the Metropolitan Autonomous University, Azcapotzalco. He is currently the Head of the Systems Department at the Metropolitan Autonomous University, Azcapotzalco. His research interests include knowledge representation, natural language processing, machine learning, and deep learning.