INTELLIGENT GAZE-BASED SCREENING SYSTEM FOR AUTISM

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***Abstract*— Autism Spectrum Disorder (ASD) is a mental disorder characterized by difficulties with socializing, repetitive behaviors, speech and non-verbal communication. It is diagnosed within the first three years of life. The earlier the diagnoses, the sooner the intervention can start. Previous studies showed that early interventions for ASD children result in higher success rate. Thus, early diagnosis is an important research goal. Clinical instruments currently used for measuring ASD signs and symptoms are time consuming and highly influenced by subjective observations. These limitations delayed diagnosis and further intervention. Therefore, scientists found that atypical gaze movement is among the earliest biomarkers for ASD. Accordingly, in our research, we are aiming to speed up diagnoses by combining gaze-based screening with intelligent methods such as machine learning which would act as a transformative step for identifying ASD at early stages. In this research we used Support Vector Machine (SVM) algorithm to examine the performance in terms of four different measures which are accuracy, sensitivity, specificity and Area under the curve (AUC). Results revealed that SVM accomplished high classification performance when applied on our collected eye movement data set.**

Keywords*— *Autism Spectrum Disorder, Intelligent, Machine Learning, early diagnoses, speed up screening, early intervention

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is among the most upsetting disorders of childhood in terms of prevalence, morbidity, outcome, the effect on the family, and cost to society where recent report in the United States estimates that 1 in every 68 children is diagnosed with autism [1]. The increasing number of patients and the limited clinical resources led to difficulties in receiving early diagnoses and interventions. Since early interventions help significantly in changing ASD outcomes, diagnostic indicators that are effective before 2 years of age are a priority. For achieving this goal, researchers are focusing on discovering possible early signs that found from parents' reports and/or clinics observations [2]. Results prove that eye-gaze promise to be a key biomarker for diagnosing ASD [3] [4] .

Recently, aassistive technologies have shown a great potential for improving capabilities of individuals with disabilities. Some of these technologies aim specific symptoms of ASD to help investigate them early. Eye-tracker is one technology that offers great opportunities for Human-Computer Interaction (HCI) to both individuals with and without disabilities. Eye movement analysis acts as an essential component for screening programs in general, and autism in particular. It has been recently recognized as a quantitative and objective diagnostic tool with a great need, yet little progress has been made [5]. Moreover, the process of integrating machine learning into a screening system is still under research and has not been yet implemented [6]. This is what our system aims to resolve.

Gaze-based screening for ASD has been the topic of research for decades. In contrast, a limited number of researches have introduced the great benefit of applying machine learning methods on individuals' eye movements. Mainly it helps to reduce the screening time which further increases the number of patients who benefit from the early diagnosis and intervention. Moreover, the available clinical trials didn't have sufficient power to conclude the effectiveness of automatic gaze-based prediction models on the screening accuracy for ASD. The lack of enough evidence warrants more research on the combination of eye tracking and intelligent methods for ASD screening. Precisely, we notice a shortage number of Arabic researches on Autism in general and ASD intelligent screening in particular, where the confirmed number of ASD cases is still unknown clearly, and available reports suggest that the occurrence of ASD is 1.4, 29, and 59 per 10,000 children, respectively, in [7] Oman, [8] the United Arab Emirates, and [9] Saudi Arabia [10][11].

Thus, our contribution in this research is twofold: first, to develop an Arabic screening system that collects eye-gaze data using remote eye tracking and second integrating an automated data-driven prediction model by applying machine learning algorithms on the collected data for categorizing a child visual attention as typical (non-ASD) or atypical (ASD).

II. LITERATURE REVIEW

Screening for ASD has evolved recently from subjective clinical assessments to objective metrics acquired from sensing devices such as gaze-tracking, motion sensors, and speech analytics. Gaze-based screening, in particular, has been shown to identify key markers of ASD and differentiate between typically developing children and those with ASD. Murias et al. [12] validated the strong association between eye gaze tracking (EGT) of social communication outcomes with five well-validated caregiver reported outcomes that are commonly used in the clinical trials. Moreover, Riby et al. [13], used Tobii Studio package to track gaze patterns of 24 ASD children (6 to 17 years old) while they were involving into two tasks that require them

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to look at a range of pictures. All Participants were individually matched to a typically developing individual. The analyses focused on fixation length within Region of Interest (ROI) and time to the first fixation within the face ROI across participant group. Results show that there is no difference between the two groups overall viewing time at the stimuli as a whole. On the other hand, there is a significant difference between the two groups on the time taken to fixate upon the hidden face where participant with Autism takes longer time to locate the face with less time fixating on it. The study results confirmed that an ASD child avoids looking at the faces, and specifically, the eyes. Frazier et al. [3], used eye-gaze tracking for examining 40 children with ASD and 39 children with other developmental conditions (3 to 8 years old). The results stated that aggregating gaze dwells time to social and non-social Region of Interests strongly discriminated children with ASD from those without ASD.

These findings demonstrate the strong relationships between eye-gaze tracking and the gold-standard measure of autism symptom resulting in the viability of adapting clinic based remote eye gaze assessment as an objective diagnostic aide. More researches have been conducted using variety of commercially-available eye tracking systems with similar experimental setups and procedures. All experiments were usually involved two participant's groups who view visual stimuli (e.g., still images or dynamic videos) with predefined Region of Interests such as face, eyes and mouth. The target's gaze patterns were tracked through a device, then the collected data analyzed for finding atypical patterns in the gaze behavior using the subject x and y coordinates of gaze fixations with respect to time. Approaches used in these studies ranged from facial viewing patterns [12] [14] [15] to video viewing patterns [3] [13] [16].

Besides, the power of machine learning adoption is not yet fully discovered within autism research. Generally, machine learning consists of feature extraction, feature selection, model learning and classification/prediction. Several studies [17] [18] [19] [20] have largely focused on how to select the most effective features from a large feature set on the clinical diagnostic tools to shorten the diagnosis time. Clinical diagnostic methods have competitive performance in ASD screening. However, the process of clinical ASD diagnosis may be lengthy and vary among cases. Consequently, the adoption of intelligent methods based on machine learning helps in speeding up the screening time and improve the accuracy. Thebtah [6] believes that machine learning will be the next era in screening tools where manual classification methods will be replaced with automated predictive models that guide specialists with fast yet accurate diagnosis decisions. The author investigated the improvement results and challenges of machine learning in ASD recent studies. At present, researchers are using ready software packages such as WEKA - Waikato Environment for Knowledge Analysis- to execute classification tasks by loading the dataset and choosing a specific machine learning algorithm. On the other hand, some researchers are willing to enhance autism classification through implementing predictive models as in the following studies. Cho et al. [21] explored a new ASD screening approach, namely Gaze-Wasserstein, which is fast and widely accessible. The proposed method provides an objective gaze-based measurement by analyzing gaze tracking data. Gaze data gathered via any mobile technologies with a front camera. 32 participants were engaged in this study divided into 16 ASD children and 16 typically developing children. Tobii EyeX Controller used to track the gaze pattern in response to the visualization of 8 stimuli (4 social scenes, 4 non-social scenes) each displayed for 5 s. Authors uses KNN classifier (K=3) and leave-one-out cross-validation. Results show F-score for the system overall performance equals 93.96% while performance of the system with social scene alone and performance with only non-social stimuli equals 91.74%, and 89.52% respectively. Therefore, utilizing social scene for Gaze-Wasserstein approach is recommended over using non-social scene.

A different study by Liu et al. [22] intended to explore how can machine learning algorithms helps in classifying ASD based on their eye movements while viewing faces. The dataset used in this research include three groups of participants as follows 29 ASD children, 29 age-matched typical development children and 29 IQ matched typical children. Children eye movements recorded using Tobii T60 eye-tracker while they are viewing a set of face images and asked to recognize what they memorized from them. The whole machine learning process was performed on MATLAB platform. Authors used leave-one-out cross-validation strategy and SVM classifier. The study results are considered as promising evidence for using machine learning algorithm on the face scanning patterns to predict ASD where the proposed framework achieves a classification accuracy of 88.51%. Despite their promising accuracy, one limitation in using face stimuli and structured recognition task that it is highly dependening on the knowledge about ASD which in response limits the model generalizability to other clinical populations or young children who may fail to understand or fulfill with the task instruction. Therefore, Jiang et al. [23] proposed approach that is data-driven and free of assumption for objective diagnoses of ASD using eye tracking and deep neural networks. Eye tracking data were collected from 20 adults with ASD and 19 healthy subjects with matched characteristic. To differentiate between the two clinical populations by what they fixated, they have extracted the deep neural network features to build the learning-based model by optimizing the network to the difference of fixation (DoF) maps to differentiate the two populations. Next, SVM is trained using these features to find a linear decision boundary with a maximum margin separating the two groups. For testing, the learned SVM model made a classification for each eye's fixation with a corresponding confidence score that is compared with a threshold to determine the final class label. The proposed method performance was assessed using leave-one-out cross-validation in term of accuracy, sensitivity, specify and (AUC). Findings show that a small set of natural-scene images can reliably recognize individuals with a complex and heterogeneous neurodevelopmental disorder. This work can be extended to include a larger database of eye-tracking data with various subject groups to develop a comprehensive model.

To the best of our knowledge, a limited number of researches were aimed at applying machine learning to Autism. According to this fact, Attention deficit hyperactivity disorder (ADHD) is one of the most common comorbid disorder in individuals with ASD where their comorbidity rate reaches 59% [24], we found that more investigation on machine learning studies applied to ADHD will help us design our methodology. For example, Galgani et al. [25] developed three data-mining methodologies in C++ to improve the diagnosis process of ADHD disorders. They collected the eye movement data of two groups during a free image viewing task each for 5s. A group of typically devolving (TD) individuals and a group of ADHD affected individuals in which the first consist of 18 volunteers while the second has 25 participants. For recording eye movements, ISCAN Polhemus VisionTrak Binocular Desktop 300 System used for first group and Eyegaze System from LC. Technologies Inc used for the second group. Raw eye-movement data are converted to fixations that were clustered on each image to define the ROIs that help in automatic classification. Forming the training and testing sets, bootstrap technique was used, through sampling with the replacement they form ten training and test sets, and the result is averaged over the ten iterations. The first approach was based on Expectation Maximization (EM) that builds a model to differentiate between the two groups distribution of fixations over an image resulting in two clusters then to classify a new subject compare his/her distribution of fixations within the current image to the two sets of clusters using statistical likelihood of his fixations' locations. The second approach follows Levenshtein, string-edit and distance method to compare the similarity between two scanpaths by using the amount of differences between them. To do so, the sequence of fixations is translated into a sequence of symbols that defines fixations areas on ROIs. In such case of having two groups, to classify a new instance, we compare its sequence with all in the TD group and compute the average similarity as well apply the same with the ADHD group and find another average similarity then a subject is classified based on the higher similarity value. The third approach was based on the analysis of transitions between ROIs in which new subject classification compare matrices of transitions between different ROIs of that subject with those of the TD and ADHD groups then average them and assign him/her to the more similar group. For testing the effectiveness of these three methods, the authors used the number of errors (or misclassified subjects). Levenshtein distance method showed the best results with an average error of 11.8% while the other two have higher error rate.

In conclusion, all presented studies, adopted machine learning differently yet there is no automatic prediction model integrated within a screening tool to be used in clinics.

III. Proposed Solution

According to the literature overview, it appears that intelligent screening is still an open area for the researchers, especially for Autism. Most of the mentioned studies do not consider automatic prediction as well as lack of Arabic content. Therefore, we aim to develop an Arabic automated intelligent screening system through adapting eye-tracking and machine learning technologies. This automated processing depends on some measurements gathered by eye-tracking -described in Table I- to analyze the visual patterns of a subject in response to different stimuli and then produce a prediction model that assist therapists in identifying new subjects as Autistic or non-Autistic.

Table I Eye-Tracking Metrics

Metric	Description
Fixations duration for each ROI	The duration of all individual fixations within a ROI in the stimulus.
Total fixation duration for all ROIs in the stimuli	The duration of all individual fixations in the stimuli.
Mean fixation duration	The duration average for all individual fixations within a ROI.

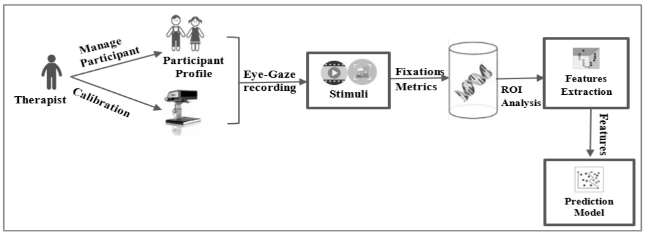

Fig1. Proposed System Components

The key components of our methodology, shown in Fig1, include eye-tracking data collection, feature extraction and prediction model building. The system detailed workflow consists of three main phases as follow:

1. ***Pre-analysis***: in this phase, the therapist should get the patient information and medical history then set up the eye-tracker device to ensure it reads the eye's position correctly[1].
2. ***Eye-tracking data collection***: when the session starts and stimuli[2] begins to appear, eye movement data will be captured using Tobii X120 Eye Tracker.
3. ***Build a prediction model***: for each stimulus viewed by a participant, the mean fixation duration; within each Region of Interest (ROI) will be incorporated as temporal and spatial feature. As a result, a single feature vector will be defined to represent the time distribution of each participant visual attention. Given the labeled features, the process of building a prediction model includes the following steps:
    a. The generation of the training and testing data sets using "leave-one-out" cross validation strategy to separate the original data into training and testing. "leave-one-out" strategy has been widely used in machine learning due to its capability in building an accurate model and its ability to return a fair estimate of the error possibility [26]. It works by selecting one out of all participants as the testing participant while the prediction model is learned according to the features from the rest of the participants.
    b. The Support Vector Machine (SVM) classifier will be trained with the extracted features, to find a linear decision boundary with a maximum margin separating the two populations' data. We have chosen SVM as in the literature and for its great capability as a binary-class classifier [26].

[1] Eye tracking data collection followed recommendations from [3].

[2] Arabic visual stimuli that are closely aligns with the existing English language visual stimuli in [3].

c. To classify a new participant, the learned SVM model, will produce a classification label for the target participant using his/her feature vector.
d. Lastly, after testing a number of subjects, we will evaluate our model in term of a number of measures such as accuracy –number of correctly classifies test cases-, Sensitivity-true positive rate- , Specificity –true negative rate- and Area under the Curve (AUC).

IV. Results & Discussion

Experiment results show a proof of concept about the strong potential for remote eye tracking as an objective tool for predicting autism. As shown, using ROIs as features for analysis prove clearly the levels of discrimination between ASD and non-ASD patients. We adopted a data-driven feature extraction method and SVM to do the classification. Encouraging results were achieved by our SVM model for classifying ASD and TD groups in which accuracy 88.6%; specificity 92.31%; sensitivity 86.63%; AUC 0.96. In a word, our findings evidently show the effectiveness of applying machine learning algorithm using videos as stimuli and eye patterns for classifying and predicting ASD.

We can notice proposed model achieves comparable results with other models, yet it has the best AUC results which mean it works well regardless of the class distribution (i.e. when data are new/unknown). Overall, our research provides promising findings in regard to early identification through a computer-aid diagnostic tool. Today, the accuracy of the diagnosis is heavily depending on the clinical expertise and their background experience, hence applying an intelligent model for diagnoses will improve early detection by providing a more objective, cost and effort effective approach. To the best of our knowledge, our study is one of the limited number of researches to address these challenges, especially for Arab populations.

To sum up, experimental results show promising performance with high sensitivity and specificity. The significant analytical values resulted from SVM classification can be valuable to support the clinical approaches of diagnosing ASD.

V. Conclusion

ASD is a harming developmental disorder that is manifested in children and may persist into the adulthood. In order to minimize its persistent, we need to enhance early screening that perhaps leads to early interventions. For that reason, ASD screening is actively being sought in recent investigations/research. Our proof-of-concept model has shown promising results as it is considered one of the first researches applying intelligent methods for identifying ASD at early stages.

In summary, the proposed system is intended to positively impact Autism field locally as well globally. In terms of local impact, there is a lack in the systems that are available to assist therapists in Saudi Arabia. Our system can serve them as a diagnostic tool for ASD. It will be designed to provide an Arabic interface and it is planned to be used in Autism centers or hospitals. Globally, this research provides a novel contribution to the HCI research by designing assistive technologies for Arabic populations within healthcare domains.

There are several future directions. For example, our model and findings should be replicated in the future with larger datasets in order to validate our machine learning algorithm performance. In addition, we may need to apply other classification techniques and compare their results with SVM.

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