

Vision-Based Approach for Autism Diagnosis Using Eye Tracking based on Machine Learning and Deep Learning

Ali F. Rashid, Shaimaa H. Shaker*

Institute of Informatics for Graduate Studies, University of Technology, Baghdad, Iraq

Abstract: Although the early diagnosis of autism spectrum disorder (ASD) is highly sought, it is still a challenging task that requires a battery of cognitive tests and hours of clinical exams to be properly accomplished. ASD may manifest itself in various ways, which makes diagnosing it even more challenging. However, although diagnostic tests are generally devised by specialists, human mistakes are still possible. Computer-assisted technologies can be quite useful in this respect for aiding in the selection procedure. The use of eye tracking as a crucial component of ASD screening evaluation based on the distinctive characteristics of the eye gaze is continued in this article. This research adds to the growing body of evidence that eye tracking technologies may help in ASD screening. Eye tracking, visualization, using machine learning and deep learning are part of the suggested solution. Eye-tracking scan paths were first converted into a visual representation in the form of a series of pictures. After that, an image classification job was taught to a convolutional neural network. The findings of the experiments showed that using a visual representation simplified the diagnostic process while also achieving excellent accuracy. The convolutional neural network model, in particular, can attain promising classification accuracy. This shows that visuals are capable of encoding information about gaze movements and its underlying dynamics. Based on the greatest information coefficient, we examined potential relationships between autism severity and eye movement dynamics. The results demonstrate that using the great potential in combining eye tracking, visualization, machine learning, and deep learning to create an impartial tool to help in ASD screening. Generally, the approach we propose may be used to identify various diseases, including neurodevelopmental problems.

Keywords: autism spectrum disorders, eye tracking, deep learning, machine learning.

基于视觉的自闭症诊断方法使用基于机器学习和深度学习的眼动追踪

摘要: 尽管自闭症谱系障碍

(自闭症谱系障碍)

的早期诊断备受追捧,但它仍然是一项具有挑战性的任务,需要一系列认知测试和数小时的临床检查才能正确完成。自闭症谱系障碍可能以各种方式表现出来,这使得诊断它更具挑战性。然而,尽管诊断测试通常由专家设计,但人为错误仍然存在。计算机辅助技术在这方面对帮助选择程序非常有用。本文继续使用眼动追踪作为基于眼睛注视的独特特征的自闭症谱系障碍筛查评估的重要组成部分。这项研究增加了越来越多的证据表明眼动追踪技术可能有助于自闭症谱系障碍筛查。眼动追踪、可视化、使用机器学习和深度学习是建议解决方案的一部分。眼动追踪扫描路径首先被转换为一系列图片形式的视觉表示。之后,将图像分类工作传授给卷积神经网络。实验结果表明,使用视觉表示简化了诊断过程,同时还实现了出色的准确性。特别是卷积神经网络模型可以获得有希望的分类精度。这表明视觉能够编码有关注视运动及其潜在动态的信息。基于最大的信息系数,我们检查了自闭症严重程度与眼球运动动力学之间的潜在关系。结果表明,利用眼动追踪、可视化、机器学习和深度学习相结合的巨大潜力来创建一个公正的工具来帮助进行自闭症谱系障碍筛查。一般来说,我们提出的方法可用于识别各种疾病,包括神经发育问题。

Received: May 23, 2022 / Revised: June 14, 2022 / Accepted: July 10, 2022 / Published: August 30, 2022

About the authors: Ali F. Rashid, Shaimaa H. Shaker, Institute of Informatics for Graduate Studies, University of Technology, Baghdad, Iraq

Corresponding author Shaimaa H. Shaker, shaimaa.h.shaker@uotechnology.edu.iq

关键词：自闭症谱系障碍、眼动追踪、深度学习、机器学习。

1. Introduction

Autism spectrum disorders (ASD) are a complex neurodevelopmental illness characterized by difficulty in social communication and interaction, as well as repetitive behavior patterns in children and adults. In early infancy, these symptoms begin manifesting themselves, affecting social interaction and communication as well as academic performance and adaptive development [1]. Regarding social and interpersonal communication, children with autism spectrum disorder (ASD) have challenges, as well as hurdles in verbal and nonverbal communication. They also have a propensity to engage in repeated behavior. Children, on the other hand, exhibit various symptoms and severity of the condition. Two children with the same diagnosis may have vastly different talents and capabilities than one another. According to the Centers for Disease Control and Prevention (CDC), around one in every 68 children in the United States is presently diagnosed with autism spectrum disorder (ASD). The occurrence of this disease has grown tenfold in the last 40 years. This increase is mostly due to improvements in diagnostic quality, more public knowledge, and the extension of diagnostic criteria, although it is possible that the prevalence of the disease may rise because of these factors as well [2]. Studies have also shown that the prevalence of autism in males is four to five times higher than that in girls. According to current estimates, one in every 42 males has been diagnosed with autism, compared to one in every 189 girls. Autism spectrum disorder is thought to be caused by a combination of factors that are currently unknown. Autism spectrum disorder (ASD) is associated with variations in brain development function. Brain imaging using various technologies has shown abnormalities in brain shape and structure, as well as changes in brain activity and connection patterns, between children with autism spectrum disorder (ASD) and typically developing children [3]. Although there are established associations between particular genomes and ASD, it is difficult to pinpoint a single genetic etiology for the disorder. In certain circumstances, the likelihood of developing ASD is inherited. For example, if there is a kid with autism in a household, the likelihood of a child being born with autism in the future is as high as 20 percent, further demonstrating the hereditary foundation of this condition. The genetic model linked with autism spectrum disorder (ASD) is, on the other hand, very intricate. Numerous genes may be implicated, and many of them have a distinct association with autism spectrum disorder; however, many of them may also be associated with other disorders. According to family

studies, relatives of children with ASD may have symptoms that are similar to their child's, such as delayed language development or social difficulties. Nonetheless, they do not exhibit all the signs of ASD [4]. ASD is sometimes linked to a novel gene mutation that does not pass down through the family, and it may also be linked to the parents' age at the time of diagnosis. As a result, the genetic basis of autism spectrum disorder (ASD) is neither specific nor consistent. Recently, it has been noted that ASDs represent the extreme superior of a pattern of socio-emotional and communication behaviors that continually contribute to the broader public. Because certain autistic behaviors are moderately to highly heritable, children who have both parents' high score on autistic behaviors are more likely to be autistic themselves [5]. According to this study, ASDs are phenotypes of severe autistic behavior, and autistic behaviors may serve as genetic risk factors for the disorder development. In this regard, the importance of genetic effects in the development of autism spectrum disorder (ASD) has been demonstrated in twins and relatives, with concordance for the monozygotic in the range of 60–80 percent and estimations of heritability superior to higher than 90 percent being discovered. In the case of ASDs, the probability of recurrence is estimated to be 6–7 percent, which implies a significant increase in risk of siblings compared to the general population. Genetics, on the other hand, is not only applicable to autism, but also to more subtle characteristics connected with cognitive and socioemotional abnormalities comparable to autism. For those who have autism spectrum disorders, reading facial expressions and deciphering emotions may be tough tasks. However, the reason for this is not due to the brain's capacity to encode neural signals, as has long been assumed, but rather due to difficulties in interpreting information. The research is the product of an extensive analytical effort that included the use of machine learning methods [6]. It might aid in the examination of the technique used to assist persons with ASD in learning to understand the emotions of other people.

2. Literature Review

Numerous studies attempted to use eye tracking for the investigation and analysis of ASD [7]. based on eye tracking research, revealed fascinating physiological components. Individuals who fell on different points on the autism spectrum had varied eye movements during face-to-face encounters. Particularly, it was shown that people with high levels of autistic characteristics had shorter and fewer saccades overall. Their findings

demonstrated that, compared with other groups, significantly greater time was spent fixating on dynamic geometric images in those with ASD. The eye-tracking technology attracted particular attention in ASD-related applications since abnormalities of eye gazing have often been considered as the distinguishing hallmark of autism in general. Numerous studies that examined eye movements in response to verbal or visual cues as indicators may be found in the psychological literature [8]. Numerous studies have attempted to use eye-tracking technologies in the context of autism considering this. [9] worked on analyzing the face-focused eye movements during discussions. The six major facial regions, according to their analysis, were the nose, left eye, right eye, mouth, jaw, and outside the face. This was done on people with fragile X syndrome (FXS), a developmental disorder. Because of discrepancies found between the two patient groups, male and female patients with FXS were split into two groups. The categorization of female and male patients with FXS, according to the set of classification models that were tested, is different, their results could achieve excellent prediction accuracy of 86% and 91% [10]. Individuals with strong or low autism features had varied eye movements during face-to-face interactions. Particularly, people with high levels of autistic characteristics exhibited shorter and fewer saccades. Another research employed eye-tracking to determine kids with ASD based on the length of fixation and quantity of saccades [11]. According to their findings, compared to other diagnostic categories, participants with ASD spent noticeably more time fixating on dynamic geometric pictures [12]. Similar to this, long-term research examined newborns' patterns of eye fixation between the ages of 2 and 6 months. They showed that infants with an ASD diagnosis had a mean drop of eye fixation, which was not observed in infants without an ASD. Additionally, research revealed that eye-tracking has a significant potential to be an objective technique for measuring the risk of autism and determining the degree of symptoms [13]. They showed excellent diagnostic precision in this area. Eye-tracking methods are still being used in this work to investigate and assess ASD. The methods we used to visualize the eye tracking data are described in the sections that follow.

3. Dataset Description

There were 547 photos in the output dataset. Particularly, 219 photographs for the TS class and 328 images for the non-ASD class. By using common picture augmentation methods, the dataset may be increased to multiples of its present size. This might be helpful for creating machine learning apps, for instance. 640x480 pixels were chosen as the default picture size. The dataset is divided into two major files, which are labeled as follows: I Images and (ii)

Metadata. Two subfolders called TC Images (i.e. Non-ASD) and TS Images are located in the Images folder (i.e., ASD-Diagnosed). Some metadata files are also present. The main participant attributes are contained in a single metadata file called Metadata Participants.csv (e.g., gender, age, CARS). A unique ID was also given to each participant. A few samples of metadata are shown in Table 2. The mapping of picture files to participants is kept up to date using two additional metadata files. Some instances are given in Table 3 in this respect. The metadata are given in a single JSON-formatted file for increased use. The Figshare data repository makes the dataset available to the general audience. Direct downloads of the photos and their associated metadata are available at <https://figshare.com/s/5d4f93395cc49d01e2bd>.

4. Preprocessing and Augmentation

A selection of image processing methods were first used as follows. First, as much of the white backdrop as possible was cut off. The Open CV library was used to implement the cropping [14]. Second, every picture was uniformly shrunk to 256x256 size. Additionally, data augmentation was used to improve the dataset's size and the variety of photos. A common strategy to improve model generalization and lower the danger of overfitting is augmentation. Most of the research on machine learning and deep learning suggested that augmentation enhanced the performance of categorization models [15] with five artificial samples. A seemingly random sequence of picture changes, including rotation and shearing, was used to construct the synthetic samples. The Keras library, which has built-in functions for that purpose, greatly improved the installation of data augmentation, the synthetic set was only introduced to the train data during the model training. A selection of images and video situations that were specifically created to drive eye movement across the screen were used in the eye-tracking trials. Approximately 60 centimeters separated the participants' seats from the monitor. To prevent visual distractions, physical barriers were also put up around the screen. To enable analysis of the ocular activity from various angles and levels, the movies' content and length changed. We took advantage of additional stimuli that the SMI Experiment Center Software offered. The Stimuli includes a range of forms that are frequently used in eye-tracking studies. For instance, static face or object stimuli, cartoons, and other joint attention stimuli, as well as dynamic and static realistic settings with and without a receptive language. Some videos also had live presenters. Generally, the presenter's job was to draw participants' attention to objects around the display area that may be visible or unseen. Typically, eye-tracking studies lasted five minutes. Regarding the quality of their eye contact with the presenter and their level of attention to other components, the participants were observed. A five-

point calibration system was used. The calibration technique was followed by a series of verification processes. To create the final dataset, 25 eye-tracking studies were conducted. Many CSV files containing more than 2M records made up the dataset.

5. Our Approach

The output of an eye-tracking system is high-dimensional and raw, and it frequently includes several variables that describe eye movements and gaze location. Finding a feature representation appropriate for creating machine learning and deep learning models is, therefore, a key difficulty. In this way, the goal of our strategy was to provide a visual representation of eye-tracking data. The main concept was to graphically represent the gaze activity by condensing long-tailed eye-tracking data into a group of graphics. The prediction issue might be tackled as an image classification challenge in this way. Additionally, the visual representation served as a link to enable the employment of high-performing models that had been previously trained on big picture datasets. The models were trained on a large number of images within several algorithms of machine learning and deep learning, and, each time, they obtained highly accurate diagnosis results.

5.1. Visualization of Eye-Tracking Records

The methodology's main concept is to create a visual depiction of the dynamics of eye motion. In this section, we'll go over how these visual patterns were created from the eye-tracking data. In more detail, an image is created as follows:

A. A line is drawn for each change in position. $[x(t), y(t)]$ to $[x(t+1), y(t+1)]$, where t designates a certain moment in the experiment;

B. The dynamics of eye movements were depicted by the color shift that occurred across the line. Based on the velocity, acceleration, and jerk at each instant, the RGB values were adjusted (t). The maximum value for each value was set at one-fourth of the screen's diagonal. With this cap, photographs depicted fixation as cyan and saccade as yellow or white (white denoting extremely quick movements, surpassing the cap). The y origin was at the bottom of the screen, so the images created were vertically mirrored. The eye motion was modeled using three color gradients. For instance, the velocity values range from low (black) to high (red) (i.e., high). In this way, darker red values eventually converge at greater velocity levels. Using green and blue gradients, respectively, acceleration and jerk were represented using the same principle as shown in Fig. 1. Constraining photographs to include nearly the same amount of information was another problem of concern. As a result, we decided on a certain number of points to be drawn (i.e., a threshold limit). The goal was to set the threshold high enough to adequately capture the pattern of eye activity. However, too high

numbers might increase the likelihood of crowded representations. In this regard, many experiments were carried out to determine the ideal threshold limit value. Images were drawn with fewer lines when the limit was placed at 100–150, which appeared to make it difficult to distinguish between the two participant groups. We finally settled on 200 as the upper limit since it essentially established an appropriate balance to represent the essential aspects of eye movements. Examples of visualization are shown in Fig. 2 and 3, respectively, for people with and without ASD. In both situations, the figures might be used to show the participants' scattered vision. The person with an ASD diagnosis had a propensity to stare near the bottom of the screen, which is where the eye-tracking device was situated. Python was used to implement the data transformation procedure in its entirety. The Matplotlib library [16] created the visuals. It is remarkable that the SMI RED's internal software may generate photos that are quite similar. Such visual routes can be used by specialists to help with the diagnosis, such as psychologists.



Fig. 1 The eye motions are represented by colour gradients

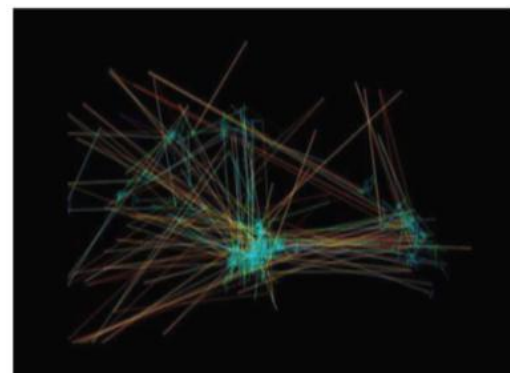


Fig. 2 A person with an ASD diagnosis [7]

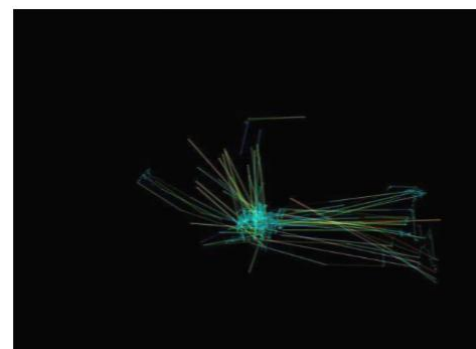


Fig. 3 A person without autism [7]

5.2. Machine Learning (ML) Model

By using machine learning the following models for training and test the dataset 'XGB','LGBM','LR','DT','NB','RF','KNN','SVM'.

5.2.1. XGB Algorithm

The gradient boosting framework is used by the open-source software library XGB to develop optimal distributed gradient boosting machine learning algorithms. By using this model, the result was of high accuracy.

5.2.2. LGBM Algorithm

A gradient boosting system called Light GBM uses tree-based learning techniques. It has the following benefits and is dispersed and effective in design.

5.2.3. LR Algorithm

A linear relationship between continuous variables is modeled by linear regression. Two factors are considered in basic linear regression: the predictor or independent variable (x) and the response or dependent variable (y).

5.2.4. DT Algorithm

A common technique in data mining is decision tree learning. The objective is to build a model that uses many input variables to forecast the value of a target variable.

5.2.5. NB Algorithm

Naive Bayes is a straightforward method for building classifiers. These models assign class labels to problem cases, which are represented as vectors of feature values, and the class labels are chosen from a finite set. For training such classifiers, there is not just one technique, but rather a family of algorithms built on the premise that, given the class variable, the value of one feature is independent of the value of every other feature.

5.2.6. RF Algorithm

Supervised machine learning algorithms like random forest are frequently employed in classification and regression issues. On various samples, it constructs decision trees and uses their average for classification and majority vote for regression.

5.2.7. SVM Algorithm

A supervised machine learning approach called "Support Vector Machine" (SVM) can be applied to classification or regression problems. However, classification issues are where it is most frequently used. When using the SVM algorithm, each data point is represented as a point in n-dimensional space (where n is the number of features you have), with each feature's value being the value of a certain coordinate.

Next, we perform classification by identifying the hyper-plane that effectively distinguishes the two classes (look at the below snapshot)

All these models were used for training dataset and testing. The results were very close and of high accuracy (Table 1 and Fig. 4.1-4.3), except the algorithm LR (linear regression). The results showing less than the other algorithms are in Table 2 and Fig. 5.1-5.3.

Table 1 Performance analysis of the models

accuracy = 100.0	precision	recall	f1-score	support
0	1.00	1.00	1.00	306
1	1.00	1.00	1.00	204
accuracy			1.00	510
macro avg	1.00	1.00	1.00	510
weighted avg	1.00	1.00	1.00	510

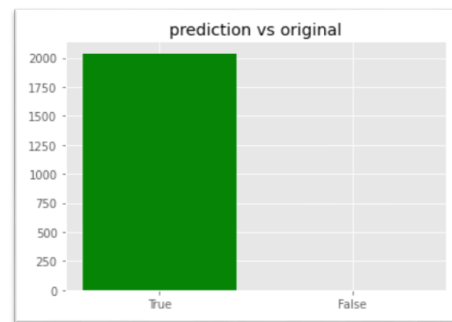


Fig. 4.1 Performance analysis of the models (ML model)

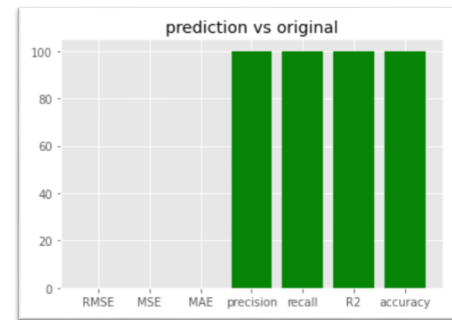


Fig. 4.2 Performance analysis of the models (ML model)

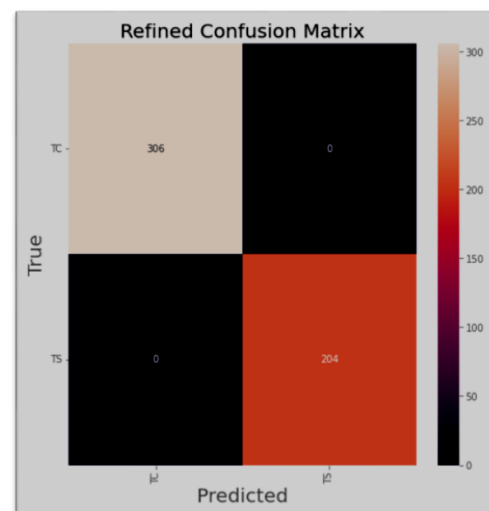


Fig. 4.3 Performance analysis of the models (ML model)

Table 2 Performance analysis of the LR models

accuracy = 92.94117647058823	precision	recall	f1-score	support
-2	0.00	0.00	0.00	0
-1	0.00	0.00	0.00	0
0	1.00	0.88	0.94	306
1.0	0.92	1.00	0.96	204
accuracy			0.93	510
macro avg	0.48	0.47	0.47	510
weighted avg	0.97	0.93	0.95	510

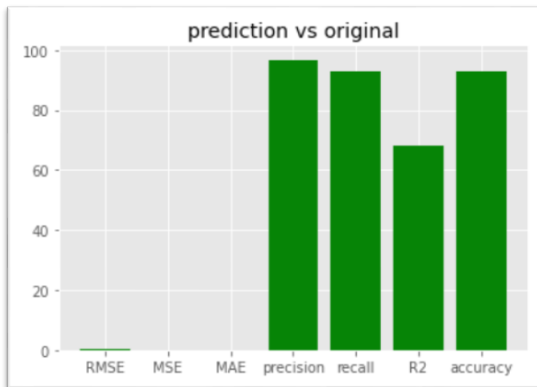


Fig. 5.1 Performance analysis of the LR model

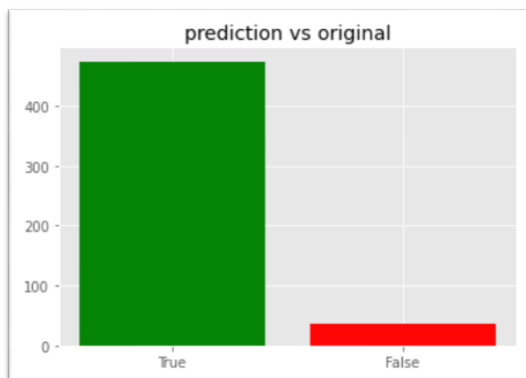


Fig. 5.2 Performance analysis of the models (LR model)

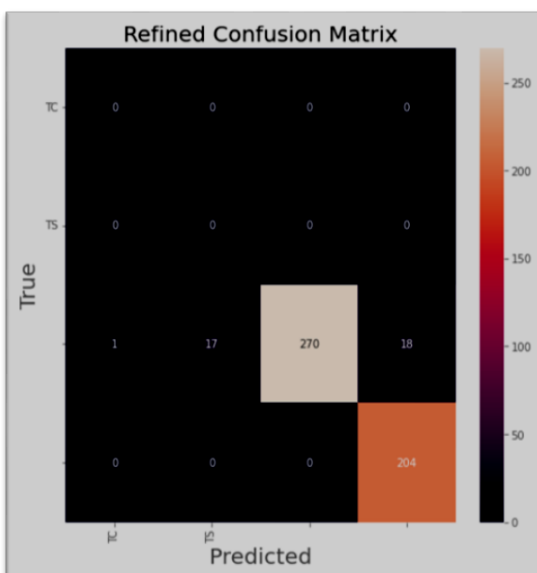


Fig. 5.3 Performance analysis of the LR model

5.3. Deep Learning Models - CNN Algorithms

Artificial neural networks have been widely used in machine learning for a while, but their popularity recently experienced a surge after it was discovered that deep networks, which have many layers, are capable of solving various real-world problems with accuracy levels that rival those of other machine learning techniques. Deep learning has become a significant area of R&D during the past decade. Convolutional neural networks (CNN) have achieved very good results in image analysis. The term designates a subset of neural networks with a particular network architecture, where each "hidden layer" typically consists of two separate layers: the first stage is the result of a local convolution of the preceding layer (the kernel has trainable weights), and the second stage is a "max-pooling stage," where the number of units is typical (Fig. 6) [17].

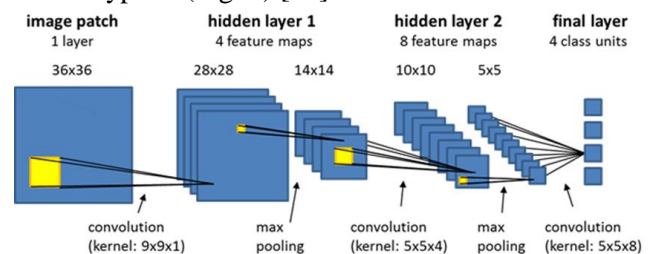


Fig. 6 CNN algorithm stages

The results using this algorithm showed high accuracy results, as shown in Table 3 and Fig. 7.1-7.3.

Table 3 Performance analysis of the CNN models

accuracy = 100.0	precision	recall	f1-score	support
0	1.00	1.00	1.00	505
1	1.00	1.00	1.00	345
accuracy			1.00	850
macro Avg	1.00	1.00	1.00	850
weighted Avg	1.00	1.00	1.00	850

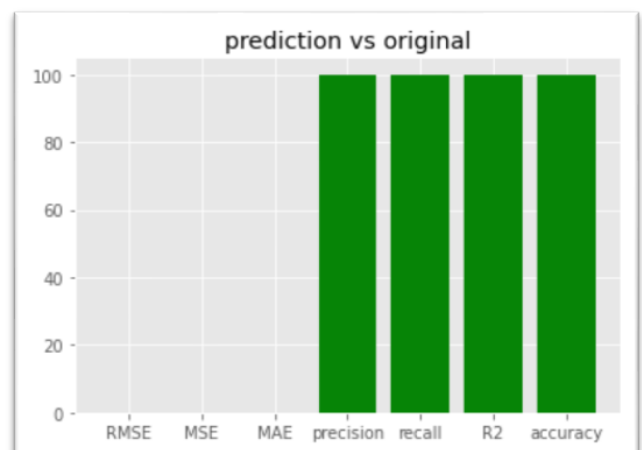


Fig. 7.1 Performance analysis of the CNN model

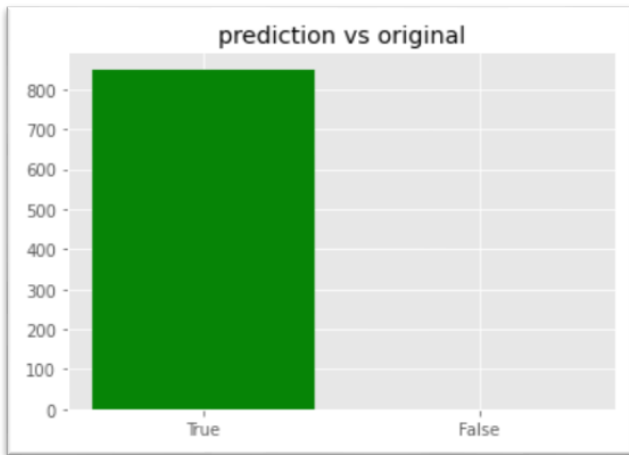


Fig. 7.2 Performance analysis of the CNN model

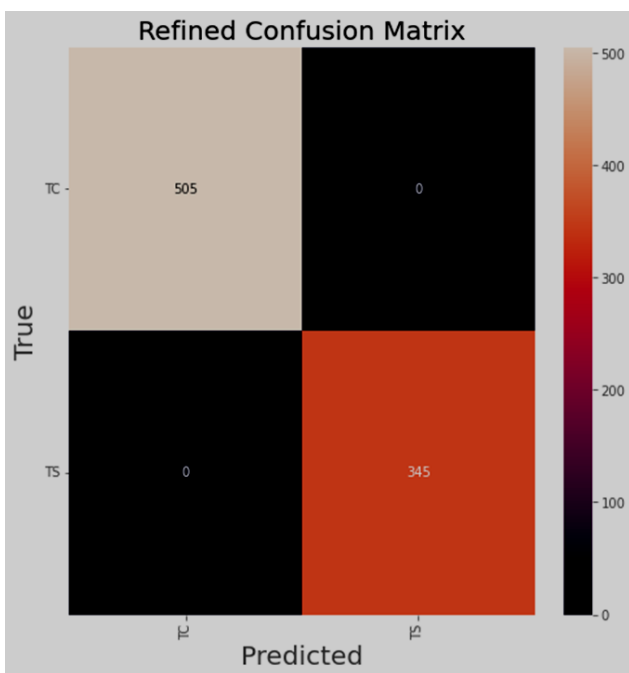


Fig. 7.3 Performance analysis of the CNN model

6. Dataset Validation

In this section, we will present some simple machine learning and Deep Learning examples to show how the visualization technique and dataset may both be used. We created a straightforward binary classification model for differentiating between the two participant classes using the image dataset. The objective was to develop a binary classifier that, using eye-tracking data, could determine whether a subject belonged to the ASD or Non-ASD group. In the beginning, the photos were shrunk to lessen the complexity of the dataset. All photographs were specifically scaled to 100x100 proportions. Since most photographs had a significant amount of free space at their original sizes, it was anticipated that little information would be lost during the resizing. For further simplification, photos were then changed into a gray scale format. Once more, it helped decrease the dimensionality from 100x100x3 to 100x100x1. A conventional logistic regression model was

subsequently trained. On the basis of 10-fold cross validation, we attained AUC 0.99 (Fig. 8). The promising classification accuracy, albeit using a simple model, strongly supports the validity of the visual-based representation. In other words, the pictures that were produced had a strong ability to convey information about eye-motion dynamics. Since the missing temporal information prevents the photographs from being restored to their original format, this may be used as a stand-in for the validation of our approach and the dataset.

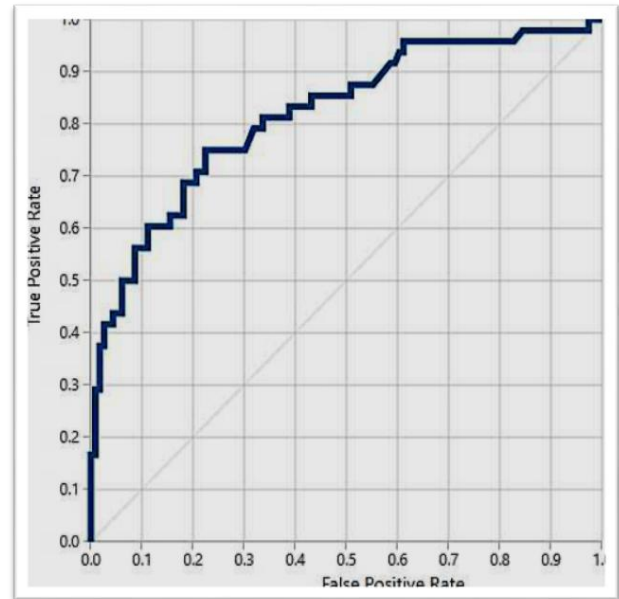


Fig. 8 The classification model's ROC curve

7. Limitations

1- Video examples Given that video situations are sometimes extremely brief, it should be viewed as a restriction. Longer scenarios may have enabled a more detailed visual representation of the ASD behavior;

2- Another restriction to note is the generated dataset's relatively small size. To generate more synthetic sample data, however, commonly used methods (such as augmentation and generative adversarial nets) [18] can be used successfully.

8. Conclusions

The fundamental patterns of ASD behavior were successfully captured by the eye-tracking records visualization approach. A straightforward logistic regression model's promising prediction accuracy clearly showed the relevance and validity of our technique. To aid in the diagnosis of ASD, more advanced prediction models can be developed. Additionally, it is thought that using the available dataset to study ASD will be possible. By using image analysis techniques with machine learning and deep learning in this regard, additional research might use the dataset. In a larger sense, the article provided yet another use for how eye-tracking might be put to use to help with developmental problem identification.

References

- [1] GRIFFITHS S., JARROLD C., PENTON-VOAK I. S., WOODS A. T., SKINNER A. L., and MUNAFÒ M. R. Impaired Recognition of Basic Emotions from Facial Expressions in Young People with Autism Spectrum Disorder: Assessing the Importance of Expression Intensity. *Journal of Autism and Developmental Disorders*, 2019, 49(7): 2768–2778. <https://doi.org/10.1007/s10803-017-3091-7>
- [2] MANFREDONIA J., BANGERTER A., MANYAKOV N. V., NESS S., LEWIN D., SKALKIN A., BOICE M., GOODWIN M. S., DAWSON G., HENDREN R., LEVENTHAL B., SHIC F., and PANDINA G. Automatic Recognition of Posed Facial Expression of Emotion in Individuals with Autism Spectrum Disorder. *Journal of Autism and Developmental Disorders*, 2019, 49(1): 279–293. <https://doi.org/10.1007/s10803-018-3757-9>
- [3] BANIRE B., AL-THANI D., MAKKI M., QARAQE M. K., ANAND K., CONNOR O. B., KHOWAJA K., and MANSOOR B. Attention Assessment: Evaluation of Facial Expressions of Children with Autism Spectrum Disorder. In: ANTONA M., & STEPHANIDIS C. (eds.) *Universal Access in Human-Computer Interaction. Multimodality and Assistive Environments. HCII 2019. Lecture Notes in Computer Science()*, Vol. 11573. Springer, Cham, 2019: 32–48. https://doi.org/10.1007/978-3-030-23563-5_4
- [4] LI B., MEHTA S., ANEJA D., FOSTER C., VENTOLA P., SHIC F., and SHAPIRO L. A Facial Affect Analysis System for Autism Spectrum Disorder. Proceedings of the IEEE International Conference on Image Processing, Taipei, 2019, pp. 4549–4553. <https://doi.org/10.1109/ICIP.2019.8803604>
- [5] SENJU A., & JOHNSON M. H. Is eye contact the key to the social brain? *Behavioral and Brain Sciences*, 2010, 33: 458–459. <http://dx.doi.org/10.1017/S0140525X10001275>
- [6] OMA K. S., MONDAL P., KHAN N. S., RIZVI M. R. K., and ISLAM M. N. A Machine Learning Approach to Predict Autism Spectrum Disorder. Proceedings of the International Conference on Electrical, Computer and Communication Engineering, Cox'sBazar, 2019, pp. 7–9. <https://doi.org/10.1109/ECACE.2019.8679454>
- [7] CARETTE R., ELBATTAH M., DEQUEN G., GUÉRIN J. L., and CILIA F. Visualization of eye-tracking patterns in autism spectrum disorder: method and dataset. Proceedings of the Thirteenth International Conference on Digital Information Management, Berlin, 2018, pp. 248–253. <https://doi.org/10.1109/ICDIM.2018.8846967>
- [8] COONROD E. E., & STONE W. L. Early concerns of parents of children with autistic and nonautistic disorders. *Infants and Young Children*, 2004, 17(3): 258–268. <https://doi.org/10.1097/00001163-200407000-00007>
- [9] PUSIOL G., ESTEVA A., HALL S. S., FRANK M., MILSTEIN A., and FEI-FEI L. Vision-based classification of developmental disorders using eye-movements. In: OURSELIN S., JOSKOWICZ L., SABUNCU M., UNAL G., and WELLS W. (eds.) *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016. MICCAI 2016. Lecture Notes in Computer Science()*, Vol. 9901. Springer, Cham, 2016: 317–325. https://doi.org/10.1007/978-3-319-46723-8_37
- [10] VABALAS A., & FREETH M. Brief Report: Patterns of Eye Movements in Face to Face Conversation are Associated with Autistic Traits: Evidence from a Student

- Sample. *Journal of Autism and Developmental Disorders*, 2016, 46: 305–314. <https://doi.org/10.1007/s10803-015-2546-y>
- [11] PIERCE K., CONANT D., HAZIN R., STONER R., and DESMOND J. Preference for geometric patterns early in life as a risk factor for autism. *Archives of General Psychiatry*, 2011, 68(1): 101–109. <https://doi.org/10.1001/archgenpsychiatry.2010.113>
- [12] JONES W., & KLIN A. Attention to eyes is present but in decline in 2-6-month-old infants later diagnosed with autism. *Nature*, 2013, 504(7480): 427–431. <https://doi.org/10.1038/nature12715>
- [13] FRAZIER T. W., KLINGEMIER E. W., BEUKEMANN M., SPEER L., MARKOWITZ L., PARIKH S., WEXBERG S., GIULIANO K., SCHULTE E., DELAHUNTY C., AHUJA V., ENG C., MANOS M. J., HARDAN A. Y., YOUNGSTROM E. A., and STRAUSS M. S. Development of an objective autism risk index using remote eye tracking. *Journal of the American Academy of Child & Adolescent Psychiatry*, 2016, 55(4): 301–309. <https://doi.org/10.1016/j.jaac.2016.01.011>
- [14] BRADSKI G., & KAEHLER A. Histograms and Matching. In: *Learning OpenCV*. O'Reilly Media, Sebastopol, California, 2008: 193–221. <https://www.bogotobogo.com/cplusplus/files/OReilly%20Learning%20OpenCV.pdf>
- [15] XU Y., JIA R., MOU L., LI G., CHEN Y., LU Y., and JIN Z. Improved relation classification by deep recurrent neural networks with data augmentation. Proceedings of the 26th International Conference on Computational Linguistics: Technical Papers, Osaka, 2016, pp. 1461–1470. <https://aclanthology.org/C16-1138.pdf>
- [16] WASKOM M. L. Seaborn: statistical data visualization. *Journal of Open Source Software*, 2021, 6(60): 3021. <https://doi.org/10.21105/joss.03021>
- [17] RAMMO F. M., & AL-HAMDANI M. N. Detecting The Speaker Language Using CNN Deep Learning Algorithm. *Iraqi Journal for Computer Science and Mathematics*, 2022, 3(1): 43–52. <https://doi.org/10.52866/ijcsm.2022.01.01.005>
- [18] MAHDIZADEHAGHDAM S., PANAH A., and KRIM H. Sparse generative adversarial network. Proceedings of the International Conference on Computer Vision Workshop, Seoul, 2019, pp. 3063–3071. <https://doi.org/10.1109/ICCVW.2019.00369>

参考文献:

- [1] GRIFFITHS S., JARROLD C., PENTON-VOAK I.S., WOODS A.T., SKINNER A.L. 和 MUNAFÒ M.R. 对患有自闭症谱系障碍的年轻人面部表情的基本情绪识别受损：评估表情强度的重要性。自闭症与发育障碍杂志，2019，49(7)：2768–2778。 <https://doi.org/10.1007/s10803-017-3091-7>
- [2] MANFREDONIA J., BANGERTER A., MANYAKOV N.V., NESS S., LEWIN D., SKALKIN A., BOICE M., GOODWIN M.S., DAWSON G., HENDREN R., LEVENTHAL B., SHIC F. 和 PANDINA G. 自闭症谱系障碍患者面部表情表情的自动识别。自闭症与发育障碍杂志，2019，49(1)：279–293。 <https://doi.org/10.1007/s10803-018-3757-9>

- [3] BANIRE B., AL-THANI D., MAKKI M., QARAQE M. K., ANAND K., CONNOR O. B., KHOWAJA K. 和 MANSOOR B. 注意力评估：自闭症谱系障碍儿童面部表情的评估。在：ANTONA M., & STEPHANIDIS C. (编辑。) 人机交互中的通用访问。多模式和辅助环境。HCII 2019. 计算机科学讲义(), 卷。11573. 施普林格, 湛, 2019: 32-48. https://doi.org/10.1007/978-3-030-23563-5_4
- [4] LI B., MEHTA S., ANEJA D., FOSTER C., VENTOLA P., SHIC F. 和 SHAPIRO L. 自闭症谱系障碍的面部影响分析系统。IEEE国际图像处理会议论文集, 台北, 2019, 第4549-4553页。 <https://doi.org/10.1109/ICIP.2019.8803604>
- [5] SENJU A., & JOHNSON M. H. 眼神接触是社交大脑的关键吗? 行为与脑科学, 2010, 33: 458-459. <http://dx.doi.org/10.1017/S0140525X10001275>
- [6] OMA K. S., MONDAL P., KHAN N. S., RIZVI M. R. K. 和 ISLAM M. N. 预测自闭症谱系障碍的机器学习方法。电气、计算机和通信工程国际会议论文集, 考克斯巴扎尔, 2019年, 第7-9页。 <https://doi.org/10.1109/ECACE.2019.8679454>
- [7] CARETTE R., ELBATTAH M., DEQUEN G., GUÉRIN J. L. 和 CILIA F. 自闭症谱系障碍眼动追踪模式的可视化：方法和数据集。第十三届数字信息管理国际会议论文集, 柏林, 2018年, 第248-253页。 <https://doi.org/10.1109/ICDIM.2018.8846967>
- [8] COONROD E. E. 和 STONE W. L. 自闭症和非自闭症儿童父母的早期担忧。婴幼儿, 2004, 17(3): 258-268. <https://doi.org/10.1097/00001163-200407000-00007>
- [9] PUSIOL G., ESTEVA A., HALL S. S., FRANK M., MILSTEIN A. 和 FEI-FEI L. 使用眼球运动对发育障碍进行基于视觉的分类。在：OURSELIN S., JOSKOWICZ L., SABUNCU M., UNAL G. 和 WELLS W. (编辑) 医学图像计算和计算机辅助干预 - MICCAI 2016. MICCAI 2016. 计算机科学讲义(), 卷。9901. 施普林格, 湛, 2016: 317-325. https://doi.org/10.1007/978-3-319-46723-8_37
- [10] VABALAS A. 和 FREETH M. 简要报告：面对面对话中的眼动模式与自闭症特征相关：来自学生样本的证据。自闭症与发育障碍杂志, 2016, 46: 305-314. <https://doi.org/10.1007/s10803-015-2546-y>
- [11] PIERCE K., CONANT D., HAZIN R., STONER R. 和 DESMOND J. 生命早期对几何图案的偏好是自闭症的危险因素。普通精神病学档案, 2011, 68 (1) : 101-109. <https://doi.org/10.1001/archgenpsychiatry.2010.113>
- [12] JONES W., & KLIN A. 对眼睛的注意力存在, 但在后来被诊断患有自闭症的2-6个月大的婴儿中有所下降。自然, 2013, 504 (7480) : 427-431. <https://doi.org/10.1038/nature12715>
- [13] FRAZIER T. W., KLINGEMIER E. W., BEUKEMANN M., SPEER L., MARKOWITZ L., PARIKH S., WEXBERG S., GIULIANO K., SCHULTE E., DELAHUNTY C., AHUJA V., ENG C., MANOS M. J., HARDAN A. Y., YOUNGSTROM E. A. 和 STRAUSS M. S. 使用远程眼动追踪开发客观自闭症风险指数。美国儿童与青少年精神病学学会杂志, 2016, 55(4): 301-309. <https://doi.org/10.1016/j.jaac.2016.01.011>
- [14] BRADSKI G., & KAEHLER A. 直方图和匹配。在：学习开放式简历。奥莱利媒体, 加利福尼亚州塞瓦斯托波尔, 2008: 193-221. <https://www.bogotobogo.com/cplusplus/files/OReilly%20Learning%20OpenCV.pdf>
- [15] XU Y., JIA R., MOU L., LI G., CHEN Y., LU Y., 和 JIN Z. 通过具有数据增强的深度递归神经网络改进关系分类。第26届计算语言学国际会议论文集：技术论文, 大阪, 2016年, 第1461-1470页。 <https://aclanthology.org/C16-1138.pdf>
- [16] WASKOM M. L. 海博恩：统计数据可视化。开源软件学报, 2021, 6(60): 3021. <https://doi.org/10.21105/joss.03021>
- [17] RAMMO F. M. 和 AL-HAMDANI M. N. 使用美国有线电视新闻网深度学习算法检测说话者语言。伊拉克计算机科学与数学杂志, 2022年, 3(1): 43-52. <https://doi.org/10.52866/ijcsm.2022.01.01.005>
- [18] MAHDIZADEHAGHDAM S., PANAH A. 和 KRIM H. 稀疏生成对抗网络。计算机视觉研讨会国际会议论文集, 首尔, 2019年, 第3063-3071页。 <https://doi.org/10.1109/ICCVW.2019.00369>