Journal of Information Systems Engineering and Management
2025, 10(27s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

An Intelligent Deep Learning Approach to Recognize Autism Spectrum Disorder using Hybrid Optimization

Rakhee Kundu[1], Sunil Kumar[2], Vanita Ganesh Kshirsagar[3]*
[1] *Computer Engineering, Amity University, Rajasthan, India, sweetrakhee18@gmail.com*
[2]*Computer Engineering, Amity University, Rajasthan, India, skumar@jpr.amity.edu*
[3*]*Dr. D. Y. Patil Institute of Technology, Pimpri, Pune, vanita.kshirsagar@gmail.com*

ARTICLE INFO

Received: 30 Dec 2024

Revised: 16 Feb 2025

Accepted: 25 Feb 2025

ABSTRACT

Introduction: This study analyzes the "Visualization of Eye-movement Scanpaths in ASD" dataset. There are clear eye-tracking traces images of ASD in this dataset. ASD is a disorder of development. It creates issues with the manner in which people behave, communicate, and interact [5]. Eye-tracking informs us about ASD. This is because abnormal eye movement patterns are a major sign of ASD. The dataset informs us about the way eyes move. It informs us how people with and without ASD view things. We enhanced our sorting with the use of advanced image analysis techniques. We applied deep learning and machine learning models in our study. We employed data augmentation techniques to expand and enhance our dataset. This boosted our models. We tried various Machine Learning (ML) and Deep Learning (DL) techniques. They were Decision Tree, Logistic Regression and Random Forests. We also implemented deep learning models such as MobileNetV3Large. We tested and trained them. Finally, MobileNetV3Large was the winner. It's tiny but effective deep learning model. It accurately labeled ASD and non-ASD groups 90.48% of the time. The study proves the capability to use eye-movement scanpaths and ML algorithms in the detection and investigation of Autism in the early stage more effectively. The technique provides a great and painless way of screening ASD from visual patterns in eye-tracking. This is most likely crucial in early diagnosis and action towards persons suffering from the disorder.

Objectives: This research applies cutting-edge computational techniques to eye-tracking scanpaths analysis and feature extraction to classify ASD. Among the techniques employed are feature extraction, data augmentation, and deep learning techniques for improved classification performance and tackle the issues of eye-tracking data. Like with the majority of current deep learning-based studies in the healthcare domain, the method of this research combines preprocessing techniques, feature extraction, and machine learning techniques. Specifically, the research preprocessed and examined the eye-tracking data using techniques such as ConvNet, dimensionality reduction, and normalization.

Eye-tracking data undergo initial preprocessing in which region of interest (ROIs) are discarded from the scanpath data. The algorithms are then used for advanced feature selection and data normalization. To make the models stronger we use data augmentation techniques such as bootstrapping to generate more training examples. The most relevant characteristics of the scanpaths are extracted from a variety of techniques, including time-domain and frequency-domain analysis. These characteristics are then used to train machine learning algorithms, and deep models, such as CNNs, are used to compare persons having ASD and without ASD.

Methods: The greatest contribution of the research is the application of these eye-tracking scanpath improvement techniques to ASD diagnosis. For the best methods of enhancing classification accuracy, the techniques are contrasted with conventional diagnosis methods. The research contributes to more precise diagnostic instruments for the identification of ASD at a primary stage through the examination of the application of novel computational techniques to eye-tracking analysis.

Briefly, the present study investigates the possibility of using eye-tracking scanpaths for the diagnosis of ASD as a function of the synergy between deep learning methods and advanced data preprocessing, augmentation, and feature extraction. The study demonstrates the possibility of eye-tracking as a new state-of-the-art biomarker for ASD and provides an exhaustive overview of the most appropriate computational methods for using this data in the clinic.

Results:

- ResNet-50: Deep residual network which performs well at capturing transitions and fixation sequences.
- EfficientNetB7: Scanpath classification CNN that is optimal in the balance between efficiency and accuracy during processing.
- Xception: A model based on depthwise separable convolution referred to as Xception reduces fixation-saccade analysis computational complexity.
- MobileNetV3Large: Thin network which is ideal for use where the eyes are followed in real-time.

Conclusions: Deep Learning and Transfer Learning enable scanpath analysis of eye-tracking data through strong automatic classification capabilities for gaze patterns. Transfer learning relies on pre-trained models to accelerate training, while tailored CNNs enable fine-grained feature extraction. In order to further improve scanpath classification performance, future research can explore hybrid deep learning methods involving temporal models like Transformer-based architectures or Recurrent Neural Networks (RNNs).

Keywords: ASD, eye movement scanpaths, MobileNetV3Large, eye motion dynamics, Convolution Neural Networks (CNNs), DL.

INTRODUCTION

ASD is a brain disorder specified by social interaction challenges, repetition, and limited interests. New developments in eye-tracking technology have opened new windows to the investigation of ASD using the examination of visual attention patterns. Eye-movement has proven to be a valuable method for the analysis of cognitive and behavioral disparity in ASD subjects and offer quantifiable and objective measures for prognosis and diagnosis [1].

Eye-tracking studies indicate that ASD individuals possess distinct gaze patterns while observing social and non-social stimuli. There is substantial evidence indicating that ASD children are less focused on socially relevant stimuli, such as humans, and more on non-interactive objects [3]. Such aberrant gaze patterns are most likely to be employed as possible biomarkers for the primary identification and cure of ASD. The ability to identify such behavioral indicators using ML and DL techniques has also enhanced the predictive capability of ASD diagnosis [5].

One of the most important uses of eye-movemnt in the research of ASD is when integrated with machine learning models to distinguish between participants with ASD and neurotypical participants. Several have used deep learning-based models in exploring data on eye movement to identify useful features that differentiate normal from abnormal development [6]. For example, support vector machines (SVMs) and ConvNet (CNNs) are used used to classify eye-tracking scan paths, and they have performed well in classifying ASD [8]. Besides, functional Magnetic Resonance Imaging (fMRI) combined with eye-movement has further enhanced the capacity to identify ASD-associated neurophysiological patterns [9].

In addition to diagnosis, eye-tracking technology is also being investigated as a means to assess intervention approaches and track treatment outcomes in ASD individuals. Quantifying shifts over time in visual attention patterns enables researchers to establish how individuals with ASD react to various forms of therapy [10]. Beyond facilitating customized treatment planning, this also facilitates research on heterogeneity in ASD.

The increasing number of studies in this area highlights the liklihood of eye-movement as a purpose, non-invasive, and stable research tool for ASD. With developments in ML and DL algorithms and data analysis methods, the combination of eye-movement data with ML models has the possibility to maximize early detection and intervention and improve ultimately the well-being of persons with ASD and their families.

LITERATURE SURVEY

Eye-movement method for the diagnosis of ASD is gaining popularity as it can analyze visual attention patterns more strictly. Researchers have attempted ML and DL algorithms to enhance the correctness of prediction of ASD based on eye-movement data.

Carette et al. [1] displayed the possibility of DL models in forecasting ASD using eye-tracking scanpaths of visual designs. The study demonstrated the viability of CNNs in the identification of gaze-dependent features separating ASD individuals from neurotypical subjects. Ke et al. [2] did a follow-up study of structural and strategic visual behavior differences between ASD individuals and identified the usefulness of feature extraction by deep learning in classifying them. Husna et al. [3] published a report on multimodal data fusion using fMRI and deep learning model fusion for improved detection of ASD. It was revealed in the findings that multimodal data fusion can provide more stable and more accurate results in classification. The same was done by Kang et al. [4], wherein they used support vector machine (SVM) application in classifying ASD children based on EEG and eye-movement features, assessing the feasibility of hybrid models towards improved detection rates.

There have been efforts to establish some gaze patterns as ASD biomarkers. Bacon et al. [5] compared predictive markers based on eye-tracking and reported that ASD children had varying eye behavior, especially while undertaking social attention tasks. Oliveira et al. [6] also designed a computer-based system for diagnosing autism using eye-tracking information in which eye-tracking information were used to accurately classify visual attention patterns of ASD.

Virtual reality has also been used in the diagnosis of ASD. Alcañiz et al. [7] aimed to implement a VR approach whose biomarker was eye gaze in order to assess ASD properties. In their paper, they had demonstrated that machine learning procedures established based on visual data in virtual environments had potential to provide realistic screening results of ASD. Furthermore, Eraslan et al. [8] introduced an algorithm for autism detection for scanpath trend analysis based on eye movements in the context of the internet, illustrating the potential of virtual worlds for investigating ASD.

In addition, eye-tracking software based on mobile phones has also been considered cost-effective instruments for ASD screening. Strobl et al. [9] tested and validated mobile-based eye-tracking systems and proposed to use them for large-scale research into ASD and early diagnosis in rural communities.

These studies point to the increasing application of eye-movement and ML in the identification of ASD. Improving deep learning models by adding more behavioral data and improving the real-time availability in both clinical and home-screening devices would be the way forward.

OBJECTIVES

This work focuses to test the effectiveness of deep learning with methods to transfer knowledge in analyzing eye-tracking scanpaths. The aim is to build a deep learning framework that employs CNNs to decode eye movement patterns such as fixations and saccades, in these scanpaths. Additionally, the research makes fine adjustments to existing trained models, like ResNet-50, EfficientNetB7, Xception, and MobileNetV3Large.

This makes scanpath categorization and understanding better. We compared a custom deep learning model to ones based on transfer learning. Then we looked at how right they are how fast they work, and if they are good in different situations. In this study we extracted features that make scanpaths clearer helping to sort eye movements in various viewing tasks. The model gets the accuracy of classifying up by using complex neural network designs to get the subtle details of how eyes move. To make these models more resilient, they are evaluated on other datasets. This includes user behavior, how thoughts are processed and patterns of watching content. This work seeks to push the limits of AI gaze analysis, providing unique contributions to cognitive psychology health screenings, user experience research, and human-compute interaction.

METHODS

Deep learning breakthroughs have offered artificial intelligence new boundaries of exploration, especially in identifying even more abstract and intricate patterns of relationships in huge amounts of data. Deep learning is poised to play a central role in the eye-tracking scanpath analysis to identify spatial and temporal patterns to enhance classification accuracy. Transfer learning as well as some deep learning models are employed here with the objective of enhancing prediction accuracy. The method utilizes pre-trained models like ResNet-50, EfficientNetB7, Xception and MobileNetV3Large in an attempt to achieve maximum accuracy using smaller training data. New specialized deep learning models were developed to analyze eye movement patterns at a finer level of detail.

Deep Learning for Eye Movement for Scanpath Analysis

Analysis of eye-movement scanpath data includes employing Deep Learning methods, and more particularly, ConvNet (CNNs). ASDNet is a domain-specialized CNN which accepts scanpath images as a sequence of eye movements precisely acquired via fixations and saccades. The model is constructed based on convolutional classical feature extraction layers, pooling layers to reduce dimensions, and classification layers. Non-linearities in the form of the ReLU activation function are employed to improve learning.

For the purpose of an ideal training process, data augmentation of the dataset, stepwise preprocessing of the scanpath images, and hyperparameter tuning are done. Figure 1 shows that the CNN model identifies a scanned image of gaze movements and shows clusters of fixation and transition. The convolutional layers identify spatial patterns while the fully connected layers combine these facts to carry out differential scanpath pattern identification.

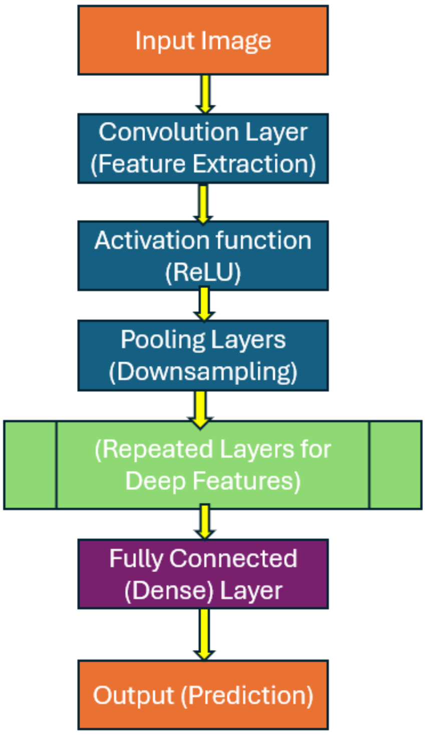

Figure 1: Deep Learning CNN Model for Eye Tracking Analysis

The CNN model used to classify the scanpaths is illustrated in Figure 1. Deep models are an effective solution for scanpath data analysis, yet most of them need extensive datasets for training. We have utilized Transfer Learning in this case through the use of pre-trained CNN models that were further fine-tuned in an attempt to enhance the accuracy of scanpath classification.

Transfer Learning in Scanpath Classification

Transfer learning permits for using previously trained Deep Learning models to perform new tasks even from extremely small amounts of data. Scanpath classification of eye movement data in the present research was optimized by fine-tuning previously trained CNN models like Xception, MobileNetV3Large, EfficientNetB7, and ResNet-50.

In Figure 2, the transfer learning method starts with a pre-trained model. The convolutional base of the model is kept that holds meaningful feature representations, but the fully connected layers are modified to become specialized in scanpath classification. This achieves results from pre-trained models, thus less computation is required, along with better classification outcomes.

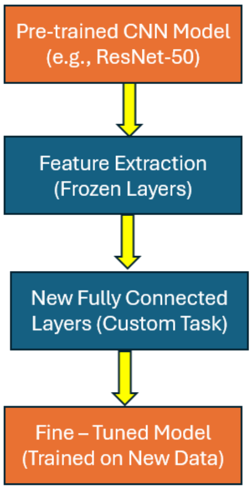

Figure 2: Transfer Learning Workflow for Eye Tracking Analysis

Several pre-trained models have certain benefits in scanpath data analysis:

•MobileNetV3Large is a low-latency neural network optimized for low-latency computation and appropriate for real-time eye-tracking.

• EfficientNetB7 strikes a balance between accuracy and computational needs to provide a balanced solution for scanpath classification.•Xception employs depthwise separable convolutions, which decrease computational complexity while analyzing fixation-saccade transitions efficiently.

• ResNet-50, a residual deep network, performs well in terms of fixing sequences and movement behaviors in scanpaths.

RESULTS AND DISCUSSION

To examine and evaluate outcomes of classification, one needs to know statistical methods as well as considerable time and effort. It is a complex process that includes model building and high levels of pragmatism for pattern and relationship detection. With this dynamic eye movement data available, it is now possible to see it in terms of visual features which may be processed using image analysis and published publicly.

This renders it a rich source for researchers who are interested in the importance of eye-movement technologies when applied to ASD. Utilizing such optical layouts, researchers can embark on new strategies for the identification and comprehension of ASD with ML and image processing methods. This data were initially released at the twelfth annual HEALTHINF conference that occurred in 2019 at the workshop entitled 'Learning to Predict Autism Spectrum Disorder Based on the Visual Patterns of Eye-Tracking Scanpaths' [1].

Link to the dataset: https://figshare.com/articles/dataset/Visualization_of_Eye Tracking_Scanpaths_in_Autism_Spectrum_Disorder_Image_Dataset/7073087

Results Summary:

Table 1 is Result Analysis of Machine Learning Algorithms.

S.No.	Algorithms	Accuracy (%)
1	Logistic Regression	68.78
2	Decision Tree	61.80
3	Random Forest	66.62
4	XGBoost	71.19

Table 1: Machine Learning Algorithms Result Analysis

The table above indicates some of the machine learning steps that have been used in classification problems. It indicates accuracy as a proportion of correct prediction after running the provided data set. All values have been calculated by applying the following formula:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad ...(1)$$

Logistic Regression performed best at 68.78%, justifying data manipulation under linear scenarios. Decision Tree with accuracy of 61.80% was less accurate due to the fact that it is a victim of overfitting and noise. Random Forest, being an ensemble of a group of decision trees, performed better at 66.62%. It did this because it utilizes ensemble learning. XGBoost performed at an unprecedented 71.19% accuracy flaunting its excellence in gradient-based boosting of predictions.

These outcomes reveal varying accuracy levels for various models depending on the nature of the dataset. XGBoost performed optimally for the given classification problem.

Figure 3 illustrates the relative bar chart of Models accuracies.

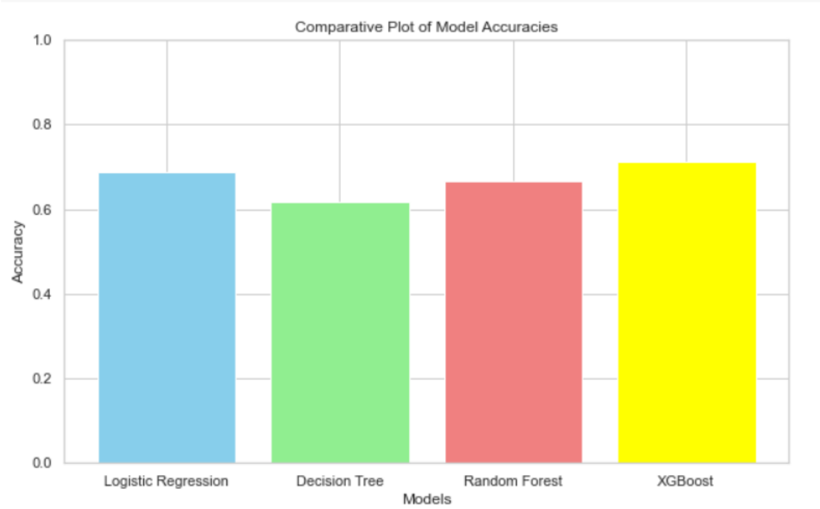

Figure 3: Comparative Plot of Model Accuracies

Figure 3 explains the accuracy of each competing machine learning model through a bar chart. Models include Logistic Regression, Decision Tree, Random Forest, and XGBoost, which appears on the x-axis, while their accuracy scores are measured on the y-axis.

Accuracy of around 68.78% on Logistic Regression indicates its efficiency with linear data. Decision Tree reaches an accuracy of 61.80%, though its bias towards overfitting is likely to hinder its generalizability. Through a combination of several decision trees, Random Forest increases prediction accuracy to 66.62%, and reduces the likelihood of overfitting. XGBoost is the most successful in predicting outcomes with an accuracy of 71.19%, as it maximizes the capability of gradient boosting.

This comparison shows that both models respond to the same condition, and XGBoost is the most accurate in this case.

Table 2 illustrates Deep Learning Algorithm Result Analysis.

S.No.	Algorithms	Accuracy (%)
1	ASDNet Custom Architecture	78.17

Table 2: Deep Learning Algorithm Result Analysis

Table 2 shows the accuracy of ASDNet, a deep learning method that is specifically tailored for eye-tracking scanpath analysis. At a rate of accuracy of 78.17%, the model is capable of observing spatial and temporal eye movement patterns. Its performance is competitive to that of the standard machine learning models as ASDNet is capable of learning deeper hierarchical features out of scanpaths. These results imply that an adaptive neural network is able to considerably enhance classification performance for specific domains, e.g., classifying autism spectrum disorder (ASD) from eye-tracking data.

Figure 4 shows the confusion matrix of Custom Architecture of ASDNet.

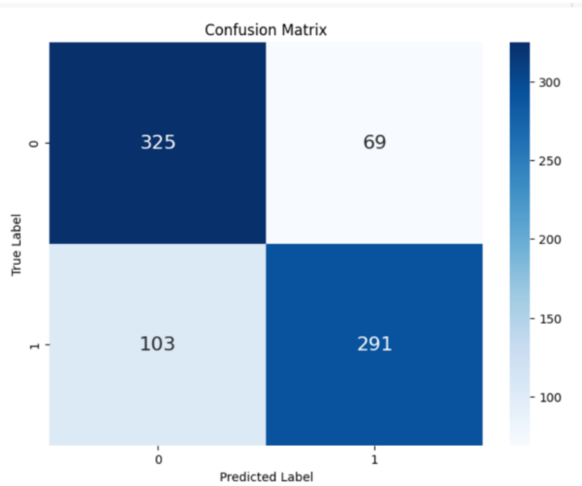

Figure 4: Confusion Matrix for ASDNet Custom Architecture

The ASDNet Custom Architecture confusion matrix provides the classification which the model had performed on scanpath-based data. It consists of some of its features as:

•True Positives (TP): 291 cases in which the model was right in its prediction and positive.

•True Negatives (TN): 325 cases where the model accurately predicted and was negative.

•False Positives (FP): 69 instances where negative samples were inaccurately predicted as positive.

• False Negatives (FN): 103 cases of positive samples being negative.

While performance at classification for ASDNet is high in the current example, the 103 false negative cases are areas of improvement. This needs to be avoided to allow high application precision (e.g., eye-tracking-based ASD detection).

Table 3 presents Transfer Learning with Custom Architecture Result Analysis.

S.No.	Algorithms	Accuracy (%)
1	Microsoft Resnet-50	87.18
2	Google - EfficientNetB7	83.75
3	Xception	67.51
4	MobileNetV3Large	90.48

Table 3: Result Analysis of Transfer Learning Using Custom Architecture

In addition, Table 3 shows differentiation of different previously trained DL models transferred to scanpath-based classification. The results show performance of the ability of each model to learn from the dataset:

• MobileNetV3Large (90.48%) produced the highest accuracy, showing its ability in the analysis of scanpath-related features without compromising efficiency for real-time use.

• Microsoft ResNet-50 (87.18%) was also good since it used deep residual connections to improve feature extraction.

• Google EfficientNetB7 (83.75%) provided accuracy-computation tradeoff because it is a scalable design.

• Xception (67.51%) was less precise, possibly because it applied depthwise separable convolutions which did not perhaps capture complex scanpath patterns effectively.

The evidence affirms that MobileNetV3Large and ResNet-50 are the most appropriate models for this task, therefore suitable for real-world use in scanpath classification.

Figure 5 shows the Confusion Matrix of Microsoft Resnet-50.

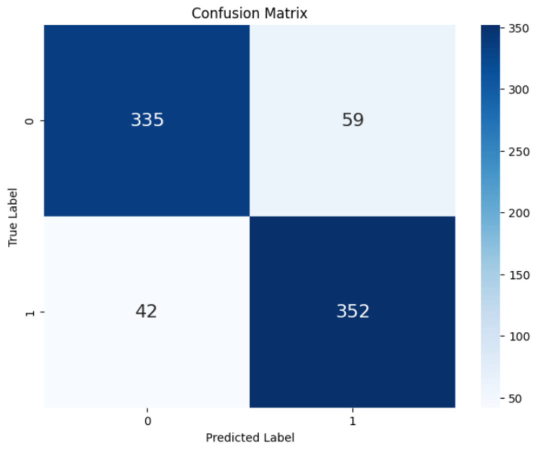

Figure 5: Confusion Matrix for Resnet-50 Architecture

ResNet-50 confusion matrix is a measure that indicates how accurately data is being classified by the model. It is a measure that indicates the difference between various classes by the model:

• True Positives (TP): 352 actual cases where the model was accurate for positive cases.

• True Negatives (TN): 335 instances where the model accurately predicted the negative cases.

• False Positives (FP): 59 false positive instances where the model misclassified a negative instance as positive.

• False Negatives (FN): 42 times the model had classified a positive instance as negative.

The model does well in classification because we are able to see how many times it accurately classifies the instances. The lower the number of false negatives (42), the better the model is at classifying the positive instances, but the false positives (59) show that sometimes it gets it wrong and therefore has its accuracy reduced. ResNet-50 is a very good model in general to use in feature extraction and classification, but once fine-tuned, it does even better.

Figure 6 shows Confusion Matrix for Xception.

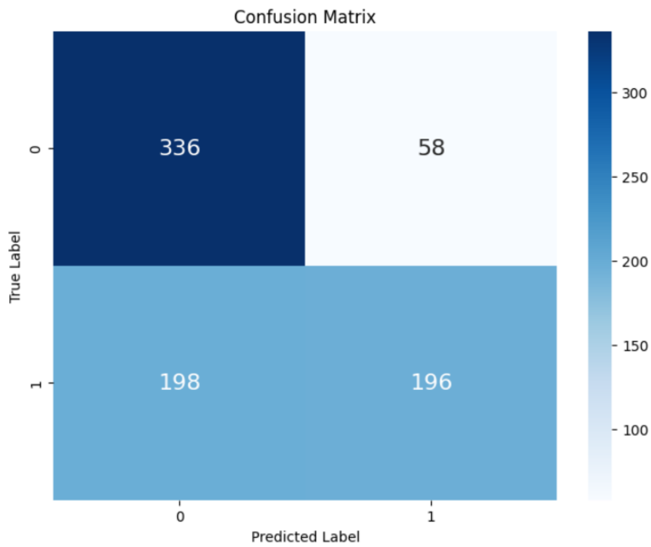

Figure 6: Confusion Matrix for Xception

The Xception model's confusion matrix also clearly illustrates the correct classification by it as:

• True Positives (TP): 196 were correctly labeled as positive.

• True Negatives (TN): 336 were correctly labeled as negative.

• False Positives (FP): 58 were marked as positive falsely.

• False Negatives (FN): 198 were falsely labeled as negative.

Though the model correctly classifies the majority of the negative samples (TN = 336), it misclassifies positive samples with a high false negative rate (198). This suggests that the model is not so effective in detecting some patterns of positive samples and may reduce recall. Though the false positive rate (58) is reduced, the FN imbalance can influence the overall model performance.

Figure 7 displays confusion matrix of MobileNetV3Large.

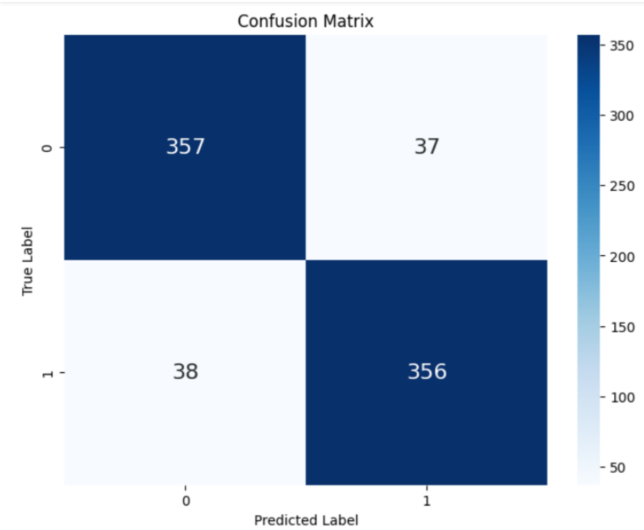

Figure 7: Confusion Matrix for MobileNetV3Large

The confusion matrix depicts the precision with which the MobileNetV3Large model is classifying data:

•True Negatives (TN): 357 data points correctly labeled as negative (class 0).

•False Positives (FP): 37 pieces of data incorrectly labeled as positive.

•False Negatives (FN): 38 positive data points incorrectly labeled as negative.

•True Positives (TP): 356 correctly predicted instances as positive (class 1).

Since good TP and TN rates and relatively lesser FP and FN rates, the model is an ideal exchange between recall and precision. The low rate of false positives indicates fewer misclassifications of the positive class and the low number of false negatives assures that most of the true positives are retained.

Overall, MobileNetV3Large is correct in classification with minimum misclassification error and is best suited to this dataset.

CONCLUSION AND FUTURE SCOPE

This paper outlines how transfer learning and deep learning enhance the exploration of intricate visual patterns. Through pre-trained model fine-tuning and designing a custom CNN for eye-tracking scanpath analysis, we promoted feature extraction and classification precision. Data augmentation guaranteed dataset limitations were mitigated, offering greater variability and robustness.These advancements signal greater application of neural networks in diagnostic and behavioral sciences, particularly with particular focus in human-computer interaction and medicine.

More emphasis can be put on applying self-supervised learning for more generalizability in the model. More diverse data with natural variability would provide more robustness for different conditions. More incorporation of real-time processing would provide more applicability for health and user behavior research. Integration of deep learning with conventional statistical method could enhance explainability as well as efficiency. The breakthrough would enable AI-aided solutions for neuroscience, assistive technology, as well as adaptive learning systems.

REFRENCES

[1] Romuald Carette, Mahmoud Elbattah, Federica Cilia, and Gilles Dequen, Feb 2019, Learning to predict autism spectrum disorder based on the visual patterns of eye-tracking scanpaths, vol.9, p. S55.
[2] F. Ke, S. Choi, Y. H. Kang, K. Cheon, and S. W. Lee, ”Exploring the structural and strategic bases of autism spectrum disorders with deep learning,” IEEE Access, vol. 8, pp. 153341–153352, August 2020.
[3] R. N. S. Husna, A. R. Syafeeza, N. A. Hamid, Y. C. Wong, and R. A. Raihan, ”Functional magnetic resonance imaging for autism spectrum disorder detection using deep learning,” Jurnal Teknologi, vol. 83, no. 3, pp. 45–52, April 2021.
[4] T. Wadhera and D. Kakkar, ”Eye Tracker,” in Advances in Medical Technologies and Clinical Practice Book Series, pp. 125–152, 2019.
[5] E. C. Bacon, A. Moore, Q. Lee, C. Barnes, E. Courchesne, and K. Pierce, ”Identifying prognostic markers in autism spectrum disorder using eye tracking,” Autism, vol. 24, no. 3, pp. 658–669, April 2020.
[6] V. Yaneva, L. A. Ha, S. Eraslan, Y. Yesilada, and R. Mitkov, ”Detecting high-functioning autism in adults using eye tracking and machine learning,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 28, no. 6, pp. 1254–1261, June 2020.
[7] J. S. Oliveira, F. O. Franco, M. C. Revers, A. F. Silva, J. Portolese, H. Brentani, A. Machado-Lima, and F. L. S. Nunes, ”Computer-aidedautism diagnosis based on visual attention models using eye tracking,” Sci. Rep., vol. 11, no. 1, p. 10131, May 2021.
[8] G. Wan, X. Kong, B. Sun, S. Yu, Y. Tu, J. Park, C. Lang, M. Koh, Z. Wei, Z. Feng, Y. Lin, and J. Kong, ”Applying eye tracking to identify autism spectrum disorder in children,” J. Autism Dev. Disord., vol. 49, no. 1, pp. 209–215, January 2019.
[9] I. A. Ahmed, E. M. Senan, T. H. Rassem, M. A. H. Ali, H. S. A. Shatnawi, S. M. Alwazer, and M. Alshahrani, ”Eye tracking-based diagnosis and early detection of autism spectrum disorder using machine learning and deep learning techniques,” Electronics, vol. 11, no. 4, p. 530, February 2022.
[10] Z. Zhao, H. Tang, X. Zhang, X. Qu, X. Hu, and J. Lu, ”Classification of children with autism and typical development using eye-tracking data from face-to-face conversations: Machine learning model development and performance evaluation,” J. Med. Internet Res., vol. 23, no. 8, p. e29328, August 2021.
[11] M. R. Kanhirakadavath and M. S. M. Chandran, ”Investigation of eyetracking scan path as a biomarker for autism screening using machine learning algorithms,” Diagnostics, vol. 12, no. 2, p. 518, February 2022.
[12] J. Kang, X. Han, J. Song, Z. Niu, and X. Li, ”The identification of children with autism spectrum disorder by SVM approach on EEG and eye-tracking data,” Comput. Biol. Med., vol. 120, p. 103722, May 2020.
[13] M. Alca˜niz, I. A. Chicchi-Giglioli, L. A. Carrasco-Ribelles, J. Mar´ın- Morales, M. E. Minissi, G. Teruel-Garc´ıa, M. Sirera, and L. Abad, ”Eye gaze as a biomarker in the recognition of autism spectrum disorder using virtual reality and machine learning: A proof of concept for diagnosis,” Autism Res., vol. 15, no. 1, pp. 131–145, January 2022.
[14] S. Eraslan, Y. Yesilada, V. Yaneva, and S. Harper, ”Autism detection based on eye movement sequences on the web: a scanpath trend analysis approach,” in Proceedings of the 17th International Web for All Conference (W4A ’20), Article 11, pp. 1–10, April 2020.
[15] M. A. R. Strobl, F. Lipsmeier, L. R. Demenescu, C. Gossens, M. Lindemann, and M. De Vos, ”Look me in the eye: evaluating the accuracy of smartphone-based eye tracking for potential application in autism spectrum disorder research,” Biomed. Eng. Online, vol. 18, no. 1, p. 51, May 2019.
[16] R. Carette, M. Elbattah, F. Cilia, G. Dequen, J.-L. Guerin, and J. Bosche, ”Learning to Predict Autism Spectrum Disorder based on the Visual Patterns of Eye-tracking Scanpaths,” in Proceedings of the 12th International Conference on Health Informatics, pp. 103-112, February 2019.
[17] M. E. Kr´ol and M. Kr´ol, ”A novel machine learning analysis of eyetracking data reveals suboptimal visual information extraction from facial stimuli in individuals with autism,” Neuropsychologia, vol. 129, pp. 397–406, June 2019.

[18] J. Kou, J. Le, M. Fu, C. Lan, Z. Chen, Q. Li, W. Zhao, L. Xu, B. Becker, and K. M. Kendrick, ”Comparison of three different eye-tracking tasks for distinguishing autistic from typically developing children and autistic symptom severity,” Autism Res., vol. 12, no. 10, pp. 1529–1540, October 2019.

[19] M. C. Pino, R. Vagnetti, M. Valenti, and M. Mazza, ”Comparing virtual vs real faces expressing emotions in children with autism: An eyetracking study,” Educational and Information Technologies, vol. 26, no. 5, pp. 5717–5732, September 2021.

[20] J. Vacas, A. Antol´ı, A. S´anchez-Raya, C. P´erez-Due˜nas, and F. Cuadrado, ”Visual preference for social vs. non-social images in young children with autism spectrum disorders: An eye tracking study,” PLoS One, vol. 16, no. 6, pp. e0252795, June 2021.

[21] J. R. Yurkovic, G. Lisandrelli, R. C. Shaffer, K. C. Dominick, E. V. Pedapati, C. A. Erickson, D. P. Kennedy, and C. Yu, ”Using headmounted eye tracking to examine visual and manual exploration during naturalistic toy play in children with and without autism spectrum disorder,” Sci. Rep., vol. 11, no. 1, p. 3578, February 2021.