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Evaluation of AI tools for healthcare networks at the cloud-edge interaction to diagnose autism in educational environments

Yue Pan[1] and Andia Foroughi[2*]

Abstract

Physical, social, and routine environments can be challenging for learners with autism spectrum disorder (ASD). ASD is a developmental disorder caused by neurological problems. In schools and educational environments, this disorder may not only hinder a child's learning, but also lead to more crises and mental convulsions. In order to teach students with ASD, it is essential to understand the impact of their learning environment on their interaction and behavior. Different methods have been used to diagnose ASD in the past, each with their own strengths and weaknesses. Research into ASD diagnostics has largely focused on machine learning algorithms and strategies rather than diagnostic methods. This article discusses many diagnostic techniques used in the ASD literature, such as neuroimaging, speech recordings, facial features, and EEG signals. This has led us to conclude that in schools and educational settings, autism can be diagnosed cheaply, quickly, and accurately through face analysis. To facilitate and speed up the processing of facial information among children in educational settings, we applied the AlexNet architecture designed for edge computing. A fast method for detecting autism spectrum disorders from the face can be applied to educational settings using this structure. While we have investigated a variety of methods, the face can provide us with appropriate information about the disorder. In addition, it can produce more interpretive features. In order to help students in schools who are suffering from this disease, key factors must be considered: potential clinical and therapeutic situations, efficiency, predictability, privacy protection, accuracy, cost-effectiveness, and lack of methodological intervention. The diseases are troublesome, so they should be identified and treated.

Keywords Autism spectrum disorder, Educational environments, Edge computing, Speech signals, EEG recordings, Facial features, Neuroimaging

*Correspondence:
Andia Foroughi
Foroughi.andia@gmail.com
[1]Chengdu Sport University, Chengdu 610041, China
[2]Department of Biomedical Engineering, Central Tehran Branch, Islamic Azad University, Tehran, Iran

Introduction

Educators must comprehend the impact of the learning environment on ASD children's engagement and conduct [1]. Classroom management strategies facilitate autonomous learning, promoting social interaction, facilitating adaptation to novel circumstances, and enhancing attendance and involvement among those on the autistic spectrum. Physical, sensory, and social factors influence the learning environment [2]. The subsequent sections include considerations, suggestions, and approaches for establishing an inclusive educational environment conducive to the needs of children diagnosed with autism spectrum disorder. Considering individual characteristics in decision-making processes is necessary for solutions applicable to children with autism spectrum disorder [3]. ASD is characterized by difficulties in interpersonal communication and interaction, as well as repetitive and restricted behavior patterns [4, 5]. Social situations, group activities, and communication are difficult for autism patients [6]. Pre-symptomatic onset is more common in boys than in females [7]. Several studies have shown that autism has no relation to a family's financial status, lifestyle, or education.

People with autism and other neurological and developmental disorders often struggle with verbal and nonverbal communication, emotional engagement, and interpersonal communication [8]. Spectrum autism refers to a variety of disorders, each with its own unique symptoms and challenges [9]. Due to rigid and routine behaviors, ASD patients face communication and socialization challenges. Psychiatric authorities identify three primary problems with social interaction in autism children [10, 11]. In these children's social interactions, nonverbal behaviors such as fewer eye contacts [12], fewer emotion expressions [13], and fewer visible body characteristics [14] are often observed. Slow social interaction and difficulty forming enduring relationships are signs of second-degree interpersonal communication impairment. Communication and social interaction problems are at the heart of autism [15].

Language skills of autistic children before school age are little understood [16]. The reason for this is that they are not usually identified until three or four years old. Typically developing children at around one year respond less to their own name or speaker's voice than children with autism. In studies with toddlers, autism is the only developmental disorder associated with a reversal in language skills after a typically developing start. Using conventional methods, diagnosing autism in young children takes a lot of time and effort.

The outward manifestations of people's emotions, including their behavior and physiological responses, are often used to examine their emotions. The conductance of the skin, the heart rate, the brain waves, and the movement of facial muscles are physiological indicators of an individual's emotional and mental state. Autism kids display erratic facial expressions [17]. According to Keltner and Gross [18], children have difficulty explaining their own emotions. According to the study's authors, families and therapists have difficulty identifying autistic children's emotions. An expression appears immediately when a child with autism spectrum disorder moves their face [19]. In children with autism spectrum disorders, facial alterations can be extremely difficult to detect, even by doctors. In order to speed up the diagnostic process, we need an automated system that can detect signs of the disorder even in young children.

A variety of instruments and approaches have been proposed for automated autism diagnosis, and each has its own advantages and disadvantages. In order to examine neuroimaging, magnetic resonance imaging (MRI) may be used [20]. Clinical data about children can be evaluated in many ways [21]. A number of studies [22, 23] have examined speech signals and electroencephalograms (EEGs). Nevertheless, each approach suffers from ambiguity and difficulty diagnosing. Children with autism should be diagnosed as soon as possible, but diagnostic approaches have considerable limitations.

This issue may prevent the patient from receiving the proper education to manage and treat his condition. This could adversely affect his quality of life. About half of the children referred for diagnosis are placed on a "watch and wait" list instead. Their ailments or anomalies are delayed. This is primarily motivated by the need to ensure that these individuals receive the same diagnosis every time. Detecting autism in children early is crucial for mitigating adverse outcomes because it paves the way for individualized treatment and care strategies. Autism children have a greater chance of reaching their full potential while their brains are still plastic and young. As a result of this method of intervention, both parents and children receive sufficient guidance.

The difficulty in recognizing autism and the availability of external signs make it difficult to diagnose and identify the disorder. In studies investigating the challenge of diagnosing autism, facial characteristics, brain recordings, speech signals, and neuroimaging have all been examined; however, most studies rely on clinical testing. However, these analytical methods can help provide a more accurate diagnosis. Therefore, the development and implementation of an AI-based autism screening system **is** urgently needed. It is not safe to physically contact children in this way, even if it is completely safe [24].

Various methods have been employed to diagnose ASD, including neuroimaging, speech recordings, facial features, and EEG signals. This paper discusses these diagnostic approaches. Based on our research, it can be inferred that the data presented in this study provide evidence to substantiate the efficacy of face analysis. This is a means of promptly, economically, and precisely diagnosing autism in school environments. This was accomplished through the application of a transfer learning system and an algorithm based on the AlexNet architecture for machine learning. Moreover, edge computing [25, 26] is used to enhance and speed up information processing of children's faces in educational environments. Edge computing platforms refer to software solutions that facilitate the automated deployment, updating, and administration of horizontally distributed applications. The present approach exhibits high efficacy and may be implemented within educational settings to facilitate prompt identification of ASDs using face analysis. After conducting thorough investigations into alternative approaches, it has become evident that the facial region is the most effective instrument for collecting precise data on the frequency of the disease and for designing characteristics that are more comprehensible. In order to be applicable in educational settings for children, it is imperative that certain requirements are satisfied in terms of clinical and therapeutic potential, efficiency, predictability, privacy protection, accuracy, cost-effectiveness, and absence of methodological intervention. Identification and management of debilitating ASD is crucial in educational environments.

Edge computing can help analyze large amounts of data in real-time, providing accurate and reliable results [27, 28]. It can also detect patterns and provide personalized treatment recommendations. Moreover, this technology has significant potential for improving the diagnosis and treatment of ASD detection based on different data. The novelty of this research is that it evaluates the potential of AI tools to diagnose autism in educational environments. It looks at how these tools can be used to improve the accuracy of diagnoses and provide better support for children with autism. The research also examines how AI tools can be used to help teachers better understand the needs of children with autism and create more effective learning environments. Various clinical and therapeutic settings are compared regarding diagnostic accuracy, privacy, lack of invasion, and the applicability of these methods.

Section 2 of this analysis discusses automated diagnosis methods and ways to identify autistic disorders through medical testing. In Sect. 3, our method is presented. The study's findings are presented in Sect. 4 of the publication.

Automated diagnosis of autism

The children themselves and their parents are highly knowledgeable about children with ASD's particular needs. These assessments serve a number of purposes, including a precise diagnosis. They also include educating parents and children about the disease and connecting them to valuable resources [29, 30]. To provide the best possible care for children with ASD, it is crucial to comprehend the diagnostic procedure and how families cope with it. As a result, current diagnosis methods must appraise parents' opinions and information. Parents' experiences leading up to identification of their child with ASD have received scant consideration in diagnosis and evaluation thus far [31, 32]. These are some of the ways autism spectrum disorder can be recognized.

Neuroimaging

Disorders of the brain and nervous system, such as ASD, can be diagnosed with diagnostic tools like neuroimaging techniques. Clinicians are becoming more interested in neuroimaging methods, such as structural imaging modalities and functional methods, due to their potential to diagnose a wide variety of neurological diseases [32, 33]. In functional neuroimaging, functional magnetic resonance imaging (fMRI) is a non-invasive data collection approach. Due to its high spatial resolution, functional magnetic resonance imaging (fMRI) is an effective tool for studying interactions across different brain networks [34]. Functional magnetic resonance imaging data is used for resting state fMRI (RS-fMRI) and task-based fMRI (T-fMRI). It's possible to segment the brain's 3D volume. As fMRI data has a tensor structure, it may be used to track certain areas' activity over time. But fMRI isn't perfect; it's expensive and can be affected by motion artifacts [35–39]. Diffusion tensor imaging (DTI) and structural magnetic resonance imaging (MRI) have been employed to examine the neural connections and architecture of the brain (SMRI). One of the many benefits of structural neuroimaging approaches is that they are both very cost-effective and broadly accessible [40]. Medical professionals have employed SMRI to analyze autism's dimensional features in autistic patients [41–43]. The brain architecture of 25 ordinarily developing children was compared to that of 51 children with ASD by Hazlett et al. [44].

Artifacts diminish the MRI's already low accuracy in diagnosing autism [45], despite the test's obvious benefits. Patients with ASD who get an MRI are scanned using a range of slice thicknesses and procedures. As a result, doctors need to be extra cautious as they carefully examine each MRI slice. An autism misdiagnosis is only one example of how busy physicians may make mistakes. MRI scans provide challenges in evaluation due to their limited accuracy, suboptimal quality, and insufficient segmentation resulting from the inability to discriminate features and distinguish different regions within the image.

Moreover, the utilization of neuroimaging techniques enables the diagnosis of ASD and the exclusion of other medical conditions. In addition, they offer valuable understanding of the fundamental cerebral irregularities present in individuals with ASD. The field of neuroimaging encounters several restrictions stemming from inter-individual variations in brain structure and development, which might potentially compromise its overall accuracy. Consequently, it requires the utilization of further diagnostic techniques.

EEG records

Fisher's linear discriminant was used by Alhaddad et al. [46] to accurately categorize a sample of 12 children, 8 of whom had ASD (5 boys and 3 girls) and 4 of whom did not (all males). The accuracy of their classification was up to 90%. In other studies, the correct **autism diagnosis has** been shown to be higher than Alhaddad's 80.27%. Alsaggaf et al. [47] employed the same analysis protocols when analyzing their information. ASD is classified based on electroencephalographic and thermographic information by Brihadiswaran and Haputhanthri [48]. Additionally, they calculated the mean, standard deviation, and entropy of EEG signals as well as the average temperature of selected areas of the face. By combining EEG and thermographic data, multilayer perceptron (MLP) and logistic regression (LR) models achieve 94% accuracy. In addition to feature extraction, preprocessing, and categorization methods, evaluation methods were also examined. Various methods of categorizing ASD are discussed, along with their difficulties, potential solutions, and limitations.

From raw data, Pham et al. [49] constructed a two-dimensional picture using the bispectrum. Locality-sensitive discriminant analysis is employed to clarify the resulting non-linear attributes. When only these five characteristics were taken into account, the probabilistic NN classifier was nearly accurate (98.70%).

By employing a short-time Fourier transform (STFT), Tawhid et al. proposed efficient preprocessing of raw EEG signals [50], dereferencing, filtering, and normalizing EEG data before converting it into 2D images. In order to classify the information, they used a support vector machine (SVM) classifier trained with principal component analysis (PCA). A 95.25% accuracy rate was achieved by the method. Using both linear and non-linear properties, Abdolzadegan et al. [51] proposed a method for characterizing EEG signals. By reducing artifacts while increasing resilience, density-based clustering reduces artifacts. As a result, they use SVM and k-NN classifiers. The accuracy of SVM is 90.57%, but the accuracy of k-NN is only 72.77%. Based on discrete wavelet transforms (DWTs), Sinha et al. [52] use a digital filter to extract frequency and temporal features from previously recorded EEG data. In sub-space k-NNs, time-domain features provided the highest accuracy (92.8%).

Ali et al. [53] used deep learning (DL) to classify EEG scans. This classification task was accomplished using a multilayer perceptron network. The results were more precise and time-saving.

Using visually evoked EEG activity,

A method for detecting ASD from EEG recordings using sparse coding-based feature mapping, the Douglas-Peucker (DP) process, and deep CNNs was proposed by Ari et al. [54].

EEG-based ASD detection models were created using machine learning methods applied to individual information. While deep learning has shown promise in a number of applications, it has not yet been implemented to automate the diagnosis of ASD. Deep learning can also be used to categorize ASDs. DL strategies employ spectrogram images to represent EEG data in 2D.

EEG data obtained from neural activity may facilitate comprehension of brain functioning. However, EEG interpretation is a complex task that needs trained professionals. Moreover, artifacts in EEG recordings are prevalent issues that might impede accurate diagnosis. Hence, to ensure accurate diagnoses, a thorough examination of EEG data is required. Signal processing techniques can effectively mitigate artifact interference, leading to more effective diagnostic outcomes.

Speech records

Based on audio and textual data, Cho et al. [55] developed an automatic categorization system. The method developed by Cho et al. may be useful for triaging and screening individuals with autism spectrum disorder. Lin et al. [56] suggested an interlocutor-modulated attentional long-short-term memory (IM-aLSTM) structure to study autism-related auditory traits. In the training of the network, interlocutor-modulated attention was used. As Gale et al. [57] mention, automatic speech recognition (ASR) systems have been developed for children with ASD or language difficulties. A SVM classifier was used by Asgari et al. [58] to classify patients with autism spectrum disorders. Voice-related low-level descriptors (LLD), harmonic network ratios (HNR), signal energy, and a few other factors were used by Marchi et al. [59] to identify children with ASD.

The speech sounds of children with ASD were analyzed and categorized using acoustic-based classifiers by Mohanta and Mittal [60]. With 98.17% precision, they were able to distinguish autistic and typically developing children's speech based on acoustic features.

No studies have examined how children with ASD use unique vowels in their immediate environment, according to the literature review. Additionally, children's speech was affected by a widespread lack of information about autism spectrum disorder. These findings may potentially serve as acoustic indicators for the early diagnosis of autism spectrum disorder in children through their speech.

Speech signals in an ASD diagnosis are often difficult to interpret. Signals can also be affected by external factors, such as noise or distractions. Additionally, ASD diagnosis can be affected by the age of the person being evaluated. Therefore, it is imperative to take all of these factors into account when diagnosing. Additionally, it is critical to consider the person's cultural background and language when interpreting speech signals.

Facial attributes

Researchers at the University of Missouri discovered that autistic children differ from typically developing children in one key facial feature [61]. There is also a shorter midface and a bigger upper face (those facial features consist of cheeks, noses, as well as wide-set eyes) than the lower face. For computer vision, identifying facial abnormalities associated with developmental diseases poses a significant challenge. Although human faces have many unique characteristics, they can be used to infer a person's identity, conduct, age, and emotions [62].

Goulart et al. [63] examined thermal imaging of children's faces to learn about the range of emotions that they experience. In total, 11 unique regions of the face were identified, allowing the extraction of 14 individual characteristics. In order to determine which characteristics would be highlighted, a principal component analysis was conducted. Linear discriminant analysis had a total accuracy of 85% in identifying people's moods.

Beary et al. [64] used the VGG19 TL technique in a validation test, and they were able to get an accuracy of 84%. Haque and Valles [65] applied a ResNet50 TL model to obtain 89.2% accuracy on a small dataset consisting of 19 typically developing and 20 ASD children. In recent years, thermal and visual imaging has been used to diagnose autism spectrum disorders. Despite its limitations, the method has revealed previously obscured aspects of the condition. Although people value the individuality and appropriateness of their faces, thermal photos of children's and adults' faces are often considered less invasive than visual images. Facial attributes can help diagnose ASD. These attributes include facial expressions, eye contact, and body language. They can provide clues to a child's social engagement and communication. Machine learning algorithms can detect subtle differences in facial attributes that may indicate ASD. This can help identify children early and implement appropriate interventions. Additionally, machine learning can be used to compare the facial attributes of children with ASD to those of typically developing children.

Comparison of ASD diagnostic methods

Every method for identifying ASD in children has advantages and disadvantages. Our decision-making is made more difficult by the complexity of neuroimaging, EEG data, and speech signals. While maintaining confidentiality throughout each diagnostic examination, confidentiality is upheld. Table 1 compares and contrasts methods for identifying ASD, along with criteria that describe each method's advantages and disadvantages.

The use of learning techniques, however, can make the identification of ASD far easier. Because deep learning algorithms require a lot of parameters, training them takes a long time. On the other hand, classic machine learning algorithms often need many hours of training time. We reverse the scenario during rehearsals. Deep learning algorithms require substantially less time to execute tests than conventional methods. Yet, a conventional learning strategy will lengthen examinations as data volumes increase. Yet, certain machine learning algorithms have short evaluation times as well. This is why many techniques for ASD screening stay away from deep learning, whose results are infamously ambiguous.

Our proposed model

Artificial intelligence (AI) techniques have the potential to be utilized for the detection and recognition of ASD indicators within educational settings. This has the potential to assist educators, including teachers, in the early identification of autism and the implementation of more efficacious therapies. AI techniques can also monitor the longitudinal development of autism patients. AI technologies can also detect behavioral patterns that may indicate the presence of autism. Edge computing can help to detect and diagnose autism in children by analyzing their facial expressions. It can also help to identify areas of improvement and provide personalized treatments. Edge computing can also be used to track the progress of patients over time. In autism surveillance, edge computing can automate the process of collecting and analyzing data. A diagram can be developed to illustrate the

Table 1 We evaluate and contrast several strategies for identifying ASD based on a number of criteria

Diagnostic model	Complexity	Cost	Uncertainty	Generalizability	Efficiency	Amount of usage	Privacy protection
Facial attributes	Medium	Medium	Medium	High	Low	High	Low (Visible images) High (Thermal imaging)
Speech recordings	High	Low	Medium	Medium	Medium	Medium to high	Medium
EEG recordings	High	Low	Low	Medium	Medium	Medium to high	High
Neuroimaging models	High	High	Low	Medium	High	Medium to high	High

process of collecting data and analyzing it, as shown in Fig. 1. There should be a diagram that shows the data sources, the processing steps, and the output.

Additionally, these techniques can be utilized to assess the efficacy of therapies implemented for autism patients. This will empower instructors to make well-informed judgments about the most effective approaches to providing support to autism patients. Facial recognition algorithms have the capability to identify nuanced alterations in facial expressions, hence potentially serving as a means to detect indications of autism among high school pupils. This would enable educators to get a more comprehensive understanding of the behavior and requirements of pupils diagnosed with autism, hence facilitating the provision of suitable assistance. Based on this, a model focused on feature extraction based on deep learning using a transfer learning strategy is proposed and applied to a huge set of image data of children in schools and educational environments. In this context, the role of deep learning architecture, which is a simple AlexNet architecture, is used to produce rich features. Classification is also a Softmax structure. Children's faces

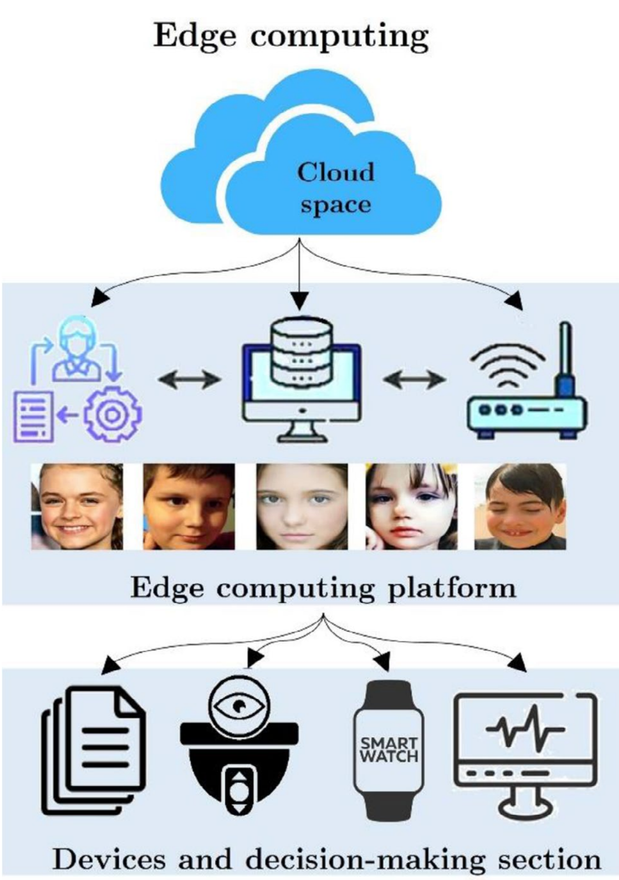

Fig. 1 As shown in the diagram below, edge computing platform can be used to collect data and analyze it to detect autism in facial images (disclaimer: the data was collected on the web by the providers of the benchmark datasets for research, available under license CC0: Public Domain)

in the ratio 60:20:20 are considered for training, validation and testing, respectively. All image sets are about 3000 images taken from the Kaggle database [64]. Figure 2 shows a collection of these pictures that some children have definite autism symptoms.

Motivation and method steps

Given the absence of a facial-based autism diagnostic system and its comparative advantages over other approaches discussed earlier, the objective is to develop an effective decision-making model capable of identifying ASD using facial analysis. This will be achieved by leveraging an edge computing platform. Edge computing involves the processing of data acquired by a deep learning algorithm. This platform can be installed and linked to smartphones, enabling its installation on a mobile device. It also facilitates the identification of illnesses through the reception of face images of children. The notable feature of the AlexNet model is that it is able to detect objects even when different cameras are employed within school premises. As shown in Fig. 3, AlexNet's input is children's images in an educational environment. Moreover, for classification of ASD based on facial images of children, a pseudo-code of the AlexNet method is displayed in **algorithm 1**.

Algorithm 1 In this algorithm, pseudo-code of AlexNet method is displayed.

Algorithm 1: Classification procedure using AlexNet structure

[NonTest,Test] = spilt (Facial Dataset of Children)

Initialize: S is variable and M is model

Input: Batch size, Learning rate, No. layers, S=[A,B,C,D]

```
for S = 1 to S=[Setting A,B,C,D] do
    for M = [AlexNet with epochs 50, 100,150,200] do
        for 1 = 1:10
            [train(i),valid(i)] = split (NonTest)
            Model(M,S,i) = TrainNetwork(M = Model,
            S = Setting,train(i),valid(i))
            PrefValid(M,S,i) = Predict(Model(M,S,i),valid(i))
        end for
        PrefValid(M,S,i) = mean(PrefValid(M,S,i),valid(i))
    end for
end for
```

Output: M* and S*

[M*,S*] = argmax((PrefValid(M,S))

Since AlexNet captures well, it uses fewer parameters than other models, making it faster and more accurate [67]. In classification sections, it is typically used since it produces more accurate results more quickly. In many studies, AlexNet is used because it is straightforward to comprehend and interpret. Furthermore, it is highly efficient, making it ideal for commercial applications. Due to its scalability, AlexNet is capable of handling large

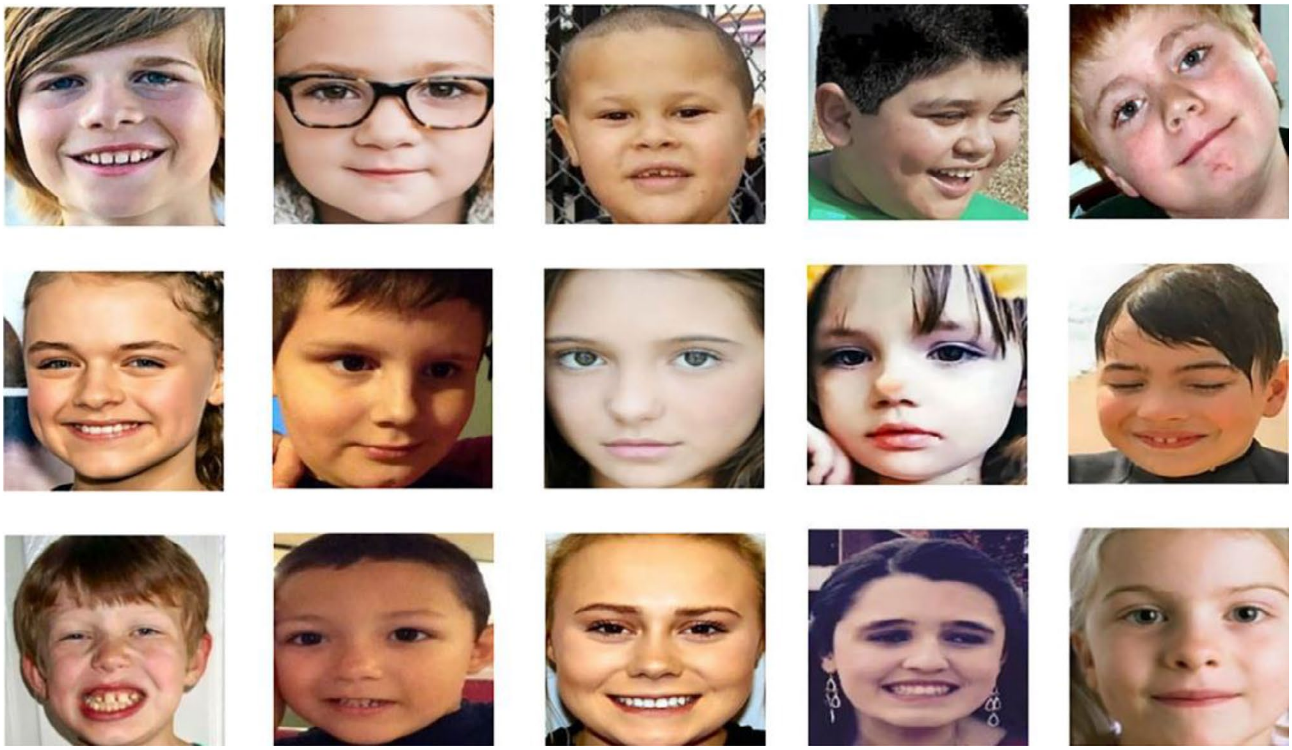

Fig. 2 Some Kaggle datasets contain pictures that indicate that some children have definite symptoms of autism [66] (disclaimer: the data was collected on the web by the providers of the benchmark datasets for research, available under license CC0: Public Domain)

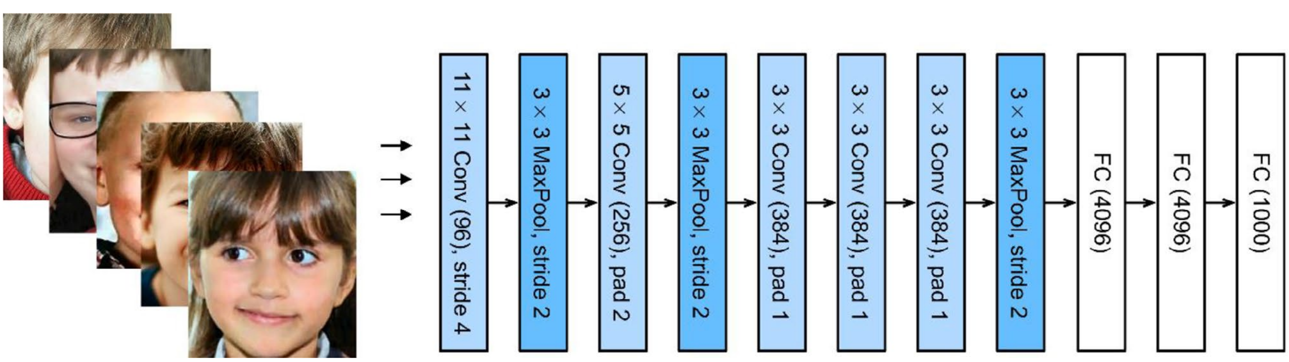

Fig. 3 Based on children's facial images, the structure represents the application of autism in the educational environment (disclaimer: the data was collected on the web by the providers of the benchmark datasets for research, available under license CC0: Public Domain)

datasets. For multiclassification applications, it is ideal because it can perform multiple tasks at once.

Results

These report present scale-dependent discoveries derived from the AlexNet deep learning model. For this investigation, the uppermost levels of the AlexNet model were excluded. Hence, the model lacks completely linked layers. As a result, the model exhibited enhanced proficiency in extracting features from images. The ultimate outcome of this approach was the creation of a "feature map" that encompassed the extracted features. The dimensions of the input shape of the model were adjusted to conform to AlexNet's standard size, which is 224×224 pixels with 3 color channels. Various images scales were examined to classify feature extraction outcomes from facial images. Table 2 displays the outcomes obtained from AlexNet implementation with the SoftMax model. AlexNet's accuracy is 92.18%. Notwithstanding the relatively low incidence of autism, timely detection is important in order to ensure appropriate therapeutic interventions for individuals in educational environments. This measure is implemented to mitigate any further harm experienced by these individuals. The effectiveness of the methodology employed in appropriately diagnosing the child has

Table 2 displays the outcomes obtained from AlexNet implementation with the SoftMax model

Scale	Architecture	Accuracy	Recall	Computational complexity
High (100%)	CNN	89.30%	88.78%	Low
	VGG-16	90.44%	90.12%	Moderate
	VGG-19	92.60%	91.76%	High
	AlexNet	93.24%	93.01%	Moderate
Moderate (50%)	CNN	88.83%	85.41%	Low
	VGG-16	88.53%	86.74%	Moderate
	VGG-19	89.90%	89.25%	High
	AlexNet	90.73%	89.79%	Low
Low (30%)	CNN	86.14%	84.90%	Low
	VGG-16	87.38%	85.47%	Moderate
	VGG-19	88.29%	87.02%	High
	AlexNet	89.39%	88.18%	Low

been shown to be a contributing factor to the low incidence of this ailment in young individuals.

Consequently, machine learning techniques might prove advantageous in identifying young students in educational settings and offering them further assistance. Our study indicates that we have achieved a precision rate of 90%, which is advantageous for elementary school students and non-autistic youngsters. This suggests that it has achieved a diagnostic accuracy rate of 92% for autism. The process of cleaning data collection will significantly enhance accuracy.

K-fold and repetition are evaluated based on the decreasing epochs by testing the accuracy of the machine learning model after each epoch. If the accuracy does not decrease significantly, the model is considered to be valid. As shown in Fig. 4, this process is repeated multiple times with different random folds and iterations based on the 50, 100, 150, and 200 epochs. The model with the highest accuracy is chosen as the final model. The model is then tested again with the same folds and iterations to verify the accuracy of the results. Finally, the results are reported and analyzed. The accuracy is then averaged and used to determine the model's performance based on the maximum and minimum accuracy for ASD recognition from facial images of children. The model with the lowest average accuracy is deemed to be the best one for ASD recognition. The model is then used to generate predictions on new unseen test data. This process helps to ensure that the model is accurately able to identify

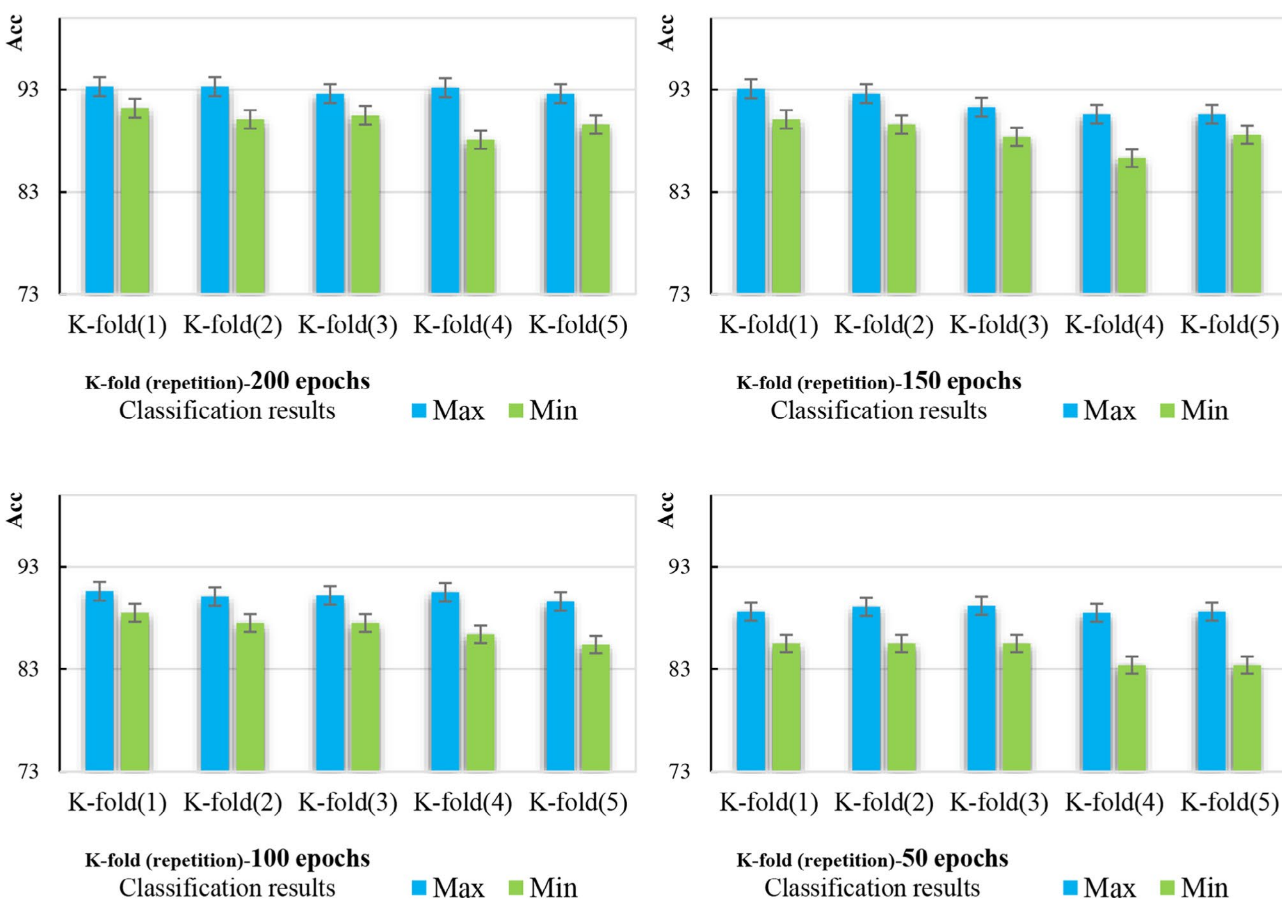

Fig. 4 Repeating this process multiple times with different random folds and iterations based on the 50, 100, 150, and 200 epochs is evaluated in facial autism detection based on the decreasing epochs.

ASD and that it is not overfitting to the test data. The model with the lowest average accuracy is usually the most accurate, as it is less likely to be overfitting to the test data. The model is then used to generate predictions on new unseen test data to verify that it is actually able to identify ASD.

Computational complexity

Due to the large number of students in most schools, accurate analysis of their data is doubly important to diagnose ASD cases quickly. An expert in this field may be called in to identify the sick person if the symptoms cannot be recognized from the face. However, this is a time-consuming process and may not go smoothly due to the large number of students in a school. Therefore, it is very important to have a fast model like the one discussed in the previous subsection. AlexNet has an advantage over other neural networks due to its low computational complexity. This makes it more suitable for use on resource-constrained devices, such as smartphones. Additionally, its high accuracy makes it an effective tool for ASD facial classification. As can be seen in Fig. 5, a comparison with other similar and high-speed processing methods is shown in terms of the average time spent on each image. The comparison shows that the processing time of the proposed method is significantly lower compared to the other methods, making it a more efficient way of processing images. As a result, the proposed method is better suited for certain applications where speed is essential. Additionally, it is less computationally intensive, which makes it more suitable for applications with limited resources. Although methods such as MobileNet have a higher speed than AlexNet in processing information, AlexNet also processes in less than one second. It can act like a real-time system. In contrast, it should be accurate in processing and identifying children with ASD in schools. AlexNet is reliable and has high accuracy rates, making it an ideal tool for diagnosing children with ASD in schools. It can also be used to monitor their progress over time.

We also used edge computing platform in our analysis to speed up processing speed. Therefore, edge computing reduces the computational complexity of processing data, as it eliminates the need to transport large amounts of data to a central processing unit. This reduces latency, as data can be processed locally and in real-time. Although models based on deep learning are largely time-consuming, the use of methods based on transfer learning and time optimization algorithms in processing [68, 69], which are dependent on new data processing algorithms in spaces such as the Edge and Cloud platforms, the ability of real-time analysis will provide [70].

The proposed approach allows for more accurate predictions and is more efficient in processing the data. It also eliminates manual input, which reduces human error and saves time. Additionally, the enhanced approach provides for better scalability, allowing larger data sets to be processed quickly and easily. This means that school monitoring for ASD children can get better results faster, enabling them to make more informed decisions and take action faster. The proposed approach also reduces the cost of AI-based ASD systems, making them more accessible to a wider range of school work. Additionally, the improved scalability of the updated approach allows for more accurate and reliable results. This approach eliminates manual data labeling, which can be time-consuming and costly. Additionally, the proposed approach allows for the use of larger data sets, which improve results accuracy.

One limitation of this approach is that it relies on high-quality images availability. Additionally, this approach may not be effective for individuals with mild ASD symptoms. This is because the approach requires a high level of visual processing, which may not be possible for those with very mild ASD symptoms. Additionally, this approach may not be suitable for individuals with autism who experience difficulty visual processing. Furthermore,

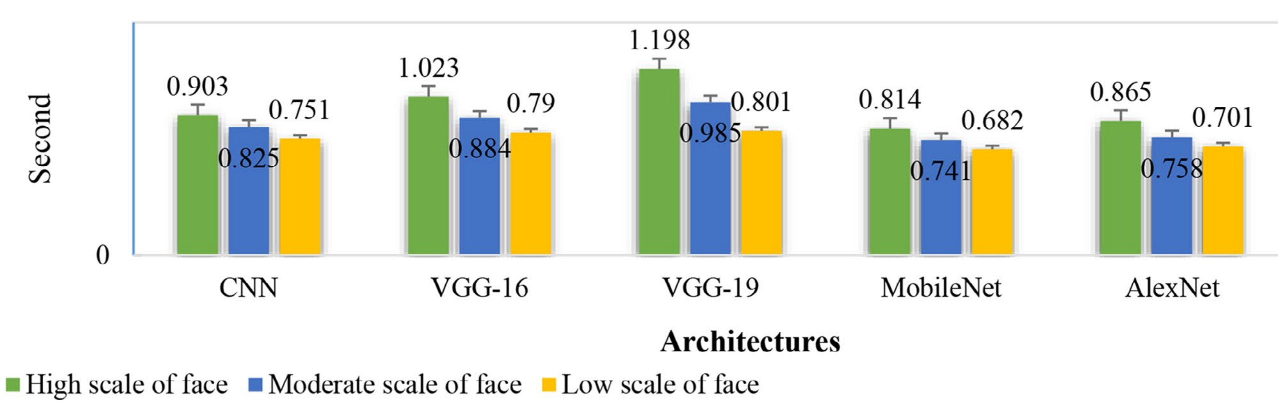

Fig. 5 Comparison of processing time and computational complexity by calculating the average time to process each image for different algorithms in ASD detection

this approach may not be suitable for individuals with autism who have difficulty understanding the instructions or have a non-verbal communication style.

Conclusion

A diagnosis of ASD condition must now be made based on observable behavioral characteristics alone. However, the time and speed of processing will help students accurately identify this activity in schools. It is imperative to note that any assessment of an activity has some degree of interpretive bias. There are several approaches, sources, and technologies for behavior analysis, each with advantages and disadvantages in terms of methodology, accuracy, cost, and time. Despite their potential, these technologies have not received much independent testing. It has been shown in this study that machine learning can be used to analyze facial images in a safe, fast, accurate, and precise way to identify early ASD in schools. Diagnostic techniques offer various advantages and disadvantages, which are generally common in Big Data and machine learning. They can be applied to diagnosis in schools and even to closed circuit cameras so that information about the person and his privacy is not leaked. Machine learning algorithms trained on massive data sets outperform simpler models. It is essential that the data set is representative of the target population to avoid creating chronically skewed models. While prediction accuracy is high, inferential inference cannot always be achieved using machine learning models. Because machine learning models are complex, more processing power must be available to use them. Large amounts of data are required for training and classification in deep learning. Future research will address multiple classification schemes for face-based ASDs and Down syndrome in educational settings, methods for combining data from different diagnostic tools. We hope to develop our model based on AI and IoT technology to facilitate and speed up autism detection in children and adults in the future. Speech, facial expressions, and body language can be analyzed by AI-driven algorithms to detect signs of autism spectrum disorder. We will also use IoT sensors to monitor children's behavior patterns and detect autism signs in the next study.

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Authors' contributions
The experiments were planned by Yue Pan and Andia Foroughi. Implementation of the proposed model was carried out by Andia Foroughi. Andia Foroughi and Yue Pan contributed to the interpretation of the results. In writing the manuscript, Yue Pan and Andia Foroughi took the lead. Andia Foroughi and Yue Pan reviewed the manuscript and provided critical feedback.

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Data availability
The data used in this article was obtained from the Kaggle database, and this data is available to the public and has been used in numerous articles. A releaser of Autistic Children's Facial photos, the Kaggle database, has been cited in reference [66].

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
Competing interests do not exist.

Disclosure
The photo data for the children illustrated in Figures 1, 2, and 3 have been obtained from Kaggle (Kaggle database).

Disclaimer
The authors will remain neutral as to consent to the use of the Autistic Children Facial Dataset from the Kaggle database.

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