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Detection of Autism Spectrum Disorder Using A 1-Dimensional Convolutional Neural Network

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Abstract

Autism Spectrum Disorder, also known as ASD, is a neurodevelopmental disease that impairs speech, social interaction, and behavior. Machine learning is a field of artificial intelligence that focuses on creating algorithms that can learn patterns and make ASD classification based on input data. The results of using machine learning algorithms to categorize ASD have been inconsistent. More research is needed to improve the accuracy of the classification of ASD. To address this, deep learning such as 1D CNN has been proposed as an alternative for the classification of ASD detection. The proposed techniques are evaluated on publicly available three different ASD datasets (children, Adults, and adolescents). Results strongly suggest that 1D CNNs have shown improved accuracy in the classification of ASD compared to traditional machine learning algorithms, on all these datasets with higher accuracy of 99.45%, 98.66%, and 90% for Autistic Spectrum Disorder Screening in Data for Adults, Children, and Adolescents respectively as they are better suited for the analysis of time series data commonly used in the diagnosis of this disorder.

Keywords: Autism Spectrum Disorder, Classification, Deep Learning, Machine Learning, One-Dimensional-Convolutional Neural Network.

Introduction

ASD is a neurodevelopmental disease that affects speech, social interaction, and behavior[1]. The existing measure of diagnosing ASD is exactly based on long-winded behavioural observations from caregiver interviews or expert experts. Despite efforts to formalise evaluation mechanisms, the validity and reliability of the results are uncertain with respect to the subjectivity of the ratings due to discrepancies in exercise and knowledge expertise. As a result, there is a growing need for an additional accurate approach that could provide rapid and accurate detection of ASD [2,3].

Most ASDs have grown worldwide in recent years. In April 2018, the Centres for Disease Control and Prevention published a report that followed the majority of ASD among children aged eight years with records from 11 locations in a monitoring network. The prevalent spread of ASD in 2010 was 1.47%, whereas the percentage of nearly 1.68% in 2014. The prevalence of ASD is 3.72% of injured children aged 8 years in various precincts in 2017 [4].

A considerably influential field that would help to decrease the duration of processing is health care. The efficiency and speed of diagnostics in human health matters are essential. In autism, the essential challenge faced in multiple healthcare needs is the diagnosis period[5]. It takes more than six months to fully diagnose an injured with autism due

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to the lengthy process, and an injured child must be shown to many different specialists to analyse the disease, beginning with developmental paediatricians, psychologists, and neurologists. In existing traditional methods, the time taken to complete the Autism diagnosis is relatively lengthy. Therefore, machine learning approaches can construct the appropriate modifications to accelerate process [6].

ML is a branch of AI that programmes computer systems to successfully examine large data sets, recognize patterns, and make judgments[7]. Classification in supervised ML might be accomplished by using a mathematical strategy to predict a given class of distributed data characteristics based on training data. ML techniques are capable of modelling exceedingly complicated and high-dimensional input data with a minimal number of mentions. Linear discriminant analysis (LDA), Random Forest (RF), K-Nearest Neighbour (KNN), Nave Bayes (NB), Decision Trees (DT), Support Vector Machine (SVM), and random forest are all widely used methods. Due to the various data structures, features, and sample sizes, no approach is the most suitable for every data set. Investigators usually execute more than one ML approach for prediction or classification and choose the best [8].

Recently, the neural network algorithm has seen rapid growth, attracting attention in many fields due to its impressive ability to learn autonomously. Several types of neural network algorithms have been developed and used, including Deep Neural Networks (DNN), Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNNs)[9]. However, because of the limit of the number of layers, the ANN is not sufficiently powerful to underestimate the accurate operation. With the expanded number of hidden layers, the DNN can overpower the issues induced by the ANN. Additionally, the difficult parameters of DNN constantly conduct to restrict the network in image recognition tasks. This issue of disproportionate network parameters can well be exceeded by the two-dimensional CNN [10].

The main motivation for the ASD approach is to preserve the lives of people, especially children, through early diagnosis of autism symptoms, which helps speed treatment, thus reducing health expenses. In recent years, there has been a surge in research focussing on using machine learning algorithms to determine whether people have ASD or not. However, there are several challenges to the accuracy of machine learning models in the classification of ASD. This research proposed deep learning (DL) model 1D-CNN for classification ASD detection to improve accuracy.

The data obtained were investigated using the 1DCNN approach, using ASD in three datasets (child, adolescents, and adults). The paper is structured by the following sections: section 2 is a literature review, section 3 provides methods used for the classifier, section 4 is the result and discussion of the classifier according to the classification accuracy, and section 5 is the conclusion.

Related Work

Baranwal et al. [11] used the ASD screening dataset to investigate and predict potential problems in adolescents, adults, and children. The data sets for an individual of the age groupings are investigated and assumptions are pulled from them. Prediction is accomplished using ML approaches such as Logistic Regression (LR), Artificial Neural Networks (ANN), Decision Tree (DT), Support Vector Machines (SVM), and Random Forest (RF).

Sun et al. [12] analysed statistical discrepancies in large-scale resting-state networks (RSN) in 103 patients with ASD and 192 healthy controls (HC) using a separate component investigation. Second, an image-based meta-analysis was used to learn the texture of spatial practices from various sites. Then, using these practices as features, this study used the SVM technique to determine whether a subject was suffering from ASD or not. Accuracy was determined to evaluate the performance of the proposed system.

Raj and S. Masood [13] investigate the potential to employ NB, SVM, LR, KNN, CNN, and ANN for the classification and investigation of ASD issues in adolescents, adults, and children. The presented techniques are estimated on three publicly available ASD datasets. After utilizing various Machine Learning techniques and handling missing values, the proposed CNN-based classification models showed high results and performed well on the data sets with increased accuracy for Autism Spectrum Disorder (ASD).

Hossain et al. [14] aimed to identify key features and automate the diagnosis process using various classification methods to improve diagnosis accuracy. The study examined data sets for autism spectrum disorders (ASD) of toddlers, adults, children, and adolescents. The latest classification and feature selection techniques were applied to determine the most effective classification methods and feature selection for these four ASD datasets. The results of the experiments showed that the multilayer perceptron classification method outperformed all other methods for the data sets of toddlers, adults, children, and adolescents.

Guwahati et al. [15] explored the feasibility of using various machine learning techniques to automate the diagnosis of autism, using a dataset of 701 samples that includes 10 fields from the AQ-10-Adult questionnaire and 10 individual characteristics. The study evaluated two scenarios. The first scenario is the optimal case, where there are no missing values, and SVM, RF, and ANN techniques are applied to the preprocessed data set. In the second scenario, where missing values are present, Recursive Feature Elimination (RFE) is utilized to reduce computational complexity, and then LR, RF, DT, and SVM techniques are used to handle this scenario.

Mashudi et al. [16] proposed a study, this study utilized a variety of ML approaches. These approaches are SVM, KNN, J48, stacking, bagging, AdaBoost, and NB. The simulations were carried out within a simulated environment using the WEKA platform. The performance of the proposed methods was then evaluated in terms of specificity, accuracy, and sensitivity. The comparison of the results between the different machine learning techniques showed that SVM, J48, and stacking achieved the best performance with the lowest error rate.

Alwidian et al. [17] investigated the Association Classification (AC) method as a data mining approach to indicate whether an individual has autism or not. Consequently, seven algorithms are employed to perform an investigation and evaluation of the performance of the AC method in terms of determining correlations between the features to determine early autism. The evaluation metrics for the performance in the classification tasks are Recall, Precision, Accuracy, and F-measure. The results indicate more acceptable performance with high accuracy.

However, the accuracy of detection can still be improved. This study proposed a deep learning technique using 1D CNN to improve the detection of ASD. Applying 1D CNN to deep learning could improve the performance of ASD detection accuracy.

Research Methodology

As shown in Fig 1 ,the design of this study consists of five phases. The first phase is the preparation of datasets where the autism dataset used is from three datasets (Child, Adolescent, and Adult). The second phase will contain preprocessing tasks such as categorical encoding and standardization. The third phase aims to split the dataset into 30% testing and 70% as training. The fourth phase contains the proposed 1D CNN structure. The fifth phase will address the evaluation (accuracy, precision, recall, and f1 score).

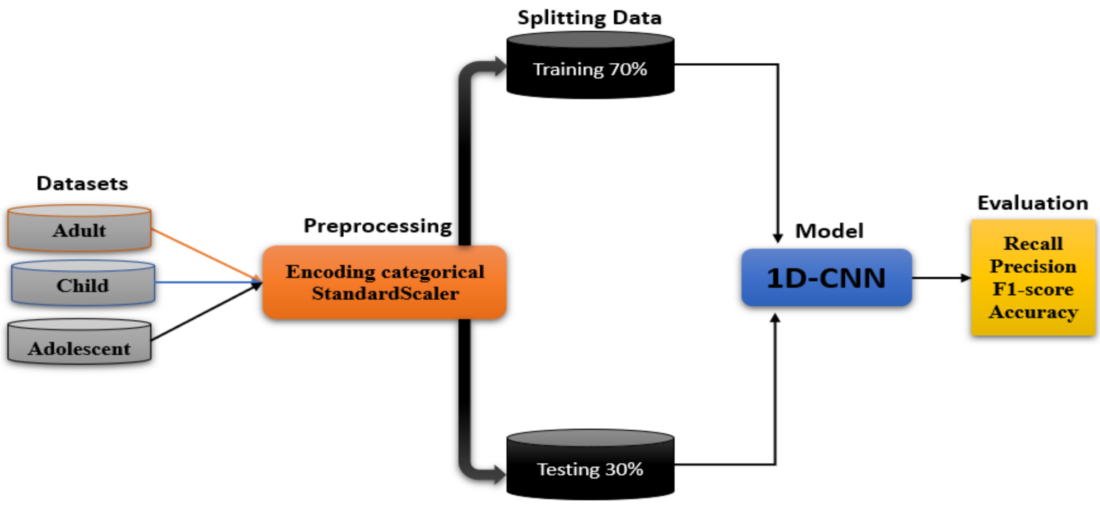

Figure 1. Research methodology.

Dataset

In this paper, databases are utilized that correlate with specific age groups, which are children, adults, and adolescents [18]. Each data set contains ten behavioural questions for each age group, and several features that affect the final

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evaluation of the state are used in the analytical data set. The affecting features include gender, age, jaundice, ethnicity, autism, country, used app, result numeric, age_desc, and relation. Table 1 displays these features with the type and the description for each feature.

Table 1. Dataset Details

Attribute	Type	Description
A1 – A10	Binary	YES/NO, the answer code of the question based on the screening method used
Age	Number	Age in years
Gender	String	Male or Female
Ethnicity	String	List of common ethnicities in text format
Jaundice	Boolean (yes or no)	Whether the case was born with jaundice
Autism	Boolean (yes or no)	Whether any immediate family member has a PDD
Relation	String	Parent, self, caregiver, medical staff, clinician, etc.
Result numeric	Number	Results abstain from app
Country	String	List of countries in text format
Used_app	Boolean (yes or no)	Whether the user has used a screening app
Age_desc	String	Age and injury description

Preprocessing

This stage used two-step for preprocessing data as follows:

1. **Encoding categorical data** refers to the process of representing categorical variables, which are variables that have a limited number of possible values. Examples of categorical data include gender (male/female), etc. This study used to encode to represent categorical data. Encoding is the process of converting categorical variables into numerical representations, which can then be used as inputs to a 1D CNN. In this step, the columns "Gender, Ethnicity, Country, Used, Desc, and relation" of the data frame are transformed from categorical data to numerical data using the LabelEncoder method. The method creates a mapping between each unique category and a unique integer, and then applies the mapping to the "Gender, Ethnicity, Country, Used, Desc, and relation" columns, transforming the categorical data into numerical data. Encoding categorical data can improve the performance by providing a more meaningful representation of the variables and reducing the dimensionality of the data so encoding categorical data is a crucial step in preparing data for deep learning models. This is because deep learning models are typically designed to work with numerical data and are not able to handle categorical data directly.

2. **StandardScaler** is a preprocessing technique used to normalise numerical data in deep learning. The purpose of normalisation is to scale the data to have zero mean and unit variance.

The StandardScaler calculates the mean and standard deviation of the data and transforms it such that the mean is 0 and the standard deviation is 1. This is achieved by subtracting the mean from each data point and dividing it by the standard deviation. This helps minimize the impact of outliers, thus improving the performance of algorithms.

1D Convolutional Neural Network (CNN)

A 1D CNN is a type of deep learning model used for classification tasks on numerical data represented as 1D sequences. The model takes a sequence of numbers as input and applies a series of layers to produce a compact representation of the data that is used to make a final classification decision.

This study proposed 1D CNN architecture for binary classification might consist of the following layers:

- **Input layer**: This layer takes in the raw input signal, which could be a sequence of numerical data (20 features).

- **Convolutional layer**: The core component of a 1D CNN is the convolutional layer, which applies a set of filters to the input data to extract meaningful features. These filters slide along the time dimension of the input sequence and produce a feature map that represents the output of the layer. The activation layer is then used to introduce non-linearity into the network, transforming the linear

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output of the convolutional layer into a non-linear representation. The strides=1 and padding='same'.

• **Activation Function**: The activation layer introduces non-linearity into the network by applying an activation function, such as ReLU or softmax, to the output of the convolution layer. The activation function converts the linear output of the convolution layer into a non-linear output.

• **Pooling layer**: This layer reduces the spatial dimension of the feature map produced by the convolutional layer, condensing the data into a compact representation. This helps reduce the computational complexity of the network and makes it more robust to small variations in the input data. Finally, the compact representation produced by the previous layers is fed into a fully connected layer, which uses a set of weights to make the final classification decision. pool_size=2, strides=1

• **Fully connected layer**: This layer produces the final layer in a 1D CNN, which is the fully connected layer, which takes the compact representation produced by the previous layers and applies a set of fully connected weights to produce the final classification decision. The fully connected layer is trained to predict the class label of the input data based on the learnt features. The output of this layer is a single binary prediction that indicates whether the input signal belongs to a class (yes) or a class (no).

The filters in the convolutional layer and the weights in the fully connected layer are learnt during the training process, where the model is fed a labelled data set and updated its parameters to minimise a loss function. The resulting model can then be used for the prediction of new, unseen data.

The general structure of the proposed 1D CNN is shown in Fig 2. To make a final classification decision based on the learnt features of the data. The filters and weights of the model are learnt during the training process to minimise a loss function.

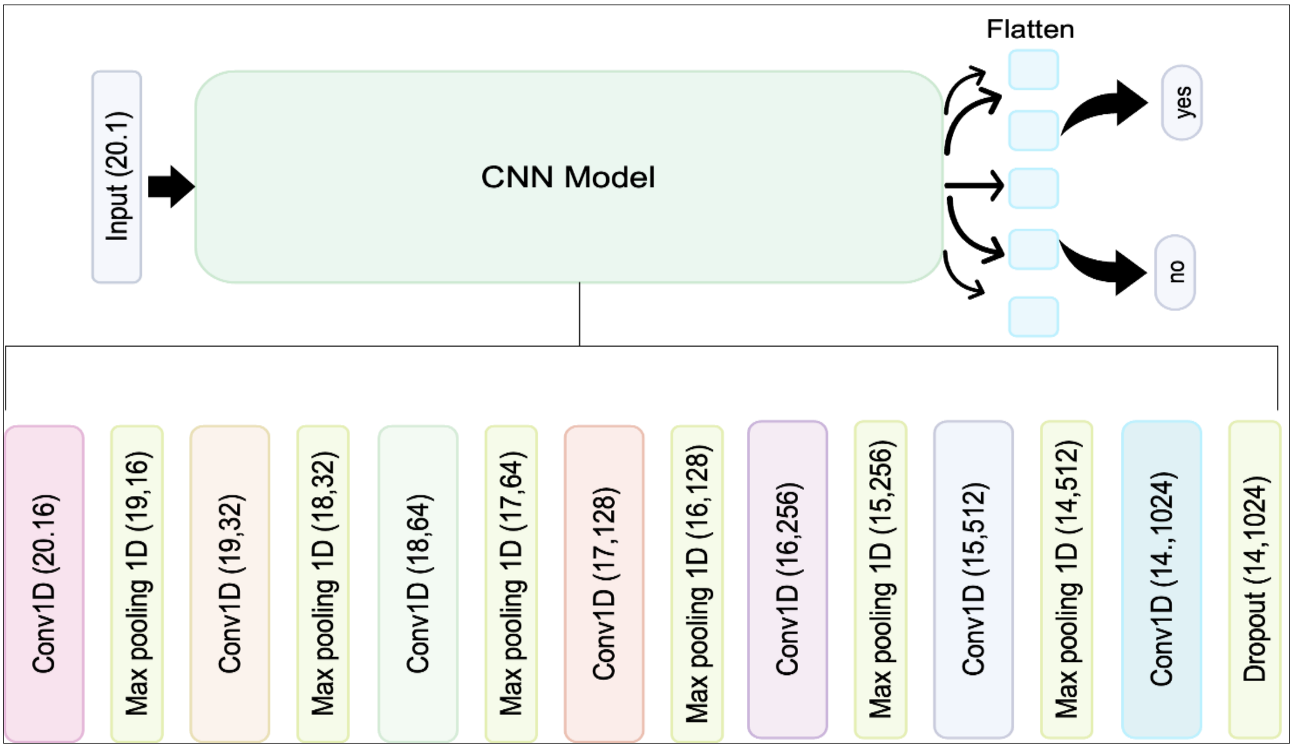

Figure 2. Proposed model 1D CNN

Table 2. The parameters used in the proposed 1D CNN model

Layer	Kernel Size	Output Shape	No. of Parameter
Conv1D	2	(20,16)	48
Max pooling 1D	2	(19,16)	0
Conv1D	2	(19,32)	1056
Max pooling 1D	2	(18,32)	0
Conv1D	2	(18,64)	4160
Max pooling 1D	2	(17,64)	0
Conv1D	2	(17,128)	16512
Max pooling	2	(16,128)	0
Conv1D	2	(16,256)	65792
Max pooling	2	(15,256)	0
Conv1D	2	(15,512)	262656
Max pooling	2	(14,512)	0
Conv1D	2	(14,1024)	1049600
dropout	0.5	(14,1024)	0
Flatten	-	14336	0
Dense	-	2	28674

In training the 1D CNN model for ASD diagnosis, the number of epochs was set to 100, the batch size set to 32, and the early stopping set to monitor the validation loss with a patience of 5 epochs. This means that the model would be trained for 100 epochs, with 32 samples in each batch, and training would be stopped early if the validation loss did not improve for 5 consecutive epochs.

Evaluation

This study used four metrics for evaluating the performance of a proposed 1D CNN model to classify autism disorders as Recall, Precision, F-score, and precision.

Recall: Recall is the fraction of true positive predictions among all positive instances, and can be calculated as follows[19,20]:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{TN}} \qquad 1$$

Here False Negatives (FN) are the number of instances that are incorrectly classified as negative. A recall is a measure of how many positive instances are correctly identified by the model.

Precision: Precision is the fraction of true positive predictions among the positive predictions made by the model and can be calculated as follows[21,22].

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad 2$$

False Positives (FP) refer to instances that have been misclassified as positive. Precision assesses the accuracy of the positive predictions.

F-Score is a widely used evaluation metric for a classification model. It combines precision and recall by taking the harmonic mean and provides a single score that balances both metrics. The calculation of the F-Score can be determined as follows[23,24]:

$$\text{F} - \text{Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad 3$$

The F score, which ranges from 0 to 1, measures the balance between precision and recall, with 1 indicating perfect precision and recall, and 0 indicating that either precision or recall is absent. Precision and recall are the metrics mentioned in my previous post.

Accuracy: Accuracy is the fraction of correct predictions made by the model, and this can be calculated by the following Eq[25,26].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{Total}} \qquad 4$$

True Positives (TP) refer to the instances that are accurately classified as positive, True Negatives (TN) refer to the instances that are accurately classified as negative, and the Total represents the overall number of instances.

Results and Discussion

Table 3 shows the results of the f score and accuracy and precision and recall using the proposed 1D CNN. Evaluating the classification based on the proposed model via the Child dataset showed 1.0 precision, 97.67 recall, 98.81 f-score, and 98.66 accuracy for the autism classification. Furthermore, the precision

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was 72.72, the recall was 1.0, the f score was 84.2, and the precision 98.66 was based on the proposed model through the Adolescent Data set. While the proposed model via the Adult dataset the evaluation showed 99.25 for precision, 1.0 for recall, 99.62 for f-score, and 99.45 accuracy. The results show that the proposed method using 1D CNN achieved competitive performance in terms of f-score and accuracy compared to the study results in state of the art.

Table 3. Comparison of the results of the proposed 1D CNN between different data sets (child, adolescents, and adults).

	Accuracy	Precision	Recall	F1-score
Child	98.66	100	97.67	98.81
Adolescent	90	72.72	100	84.2
Adult	99.45	99.25	100	99.62

Fig 3 Displays the evaluation of compare results proposed 1D CNN via different datasets (Child, Adolescent, and Adult)

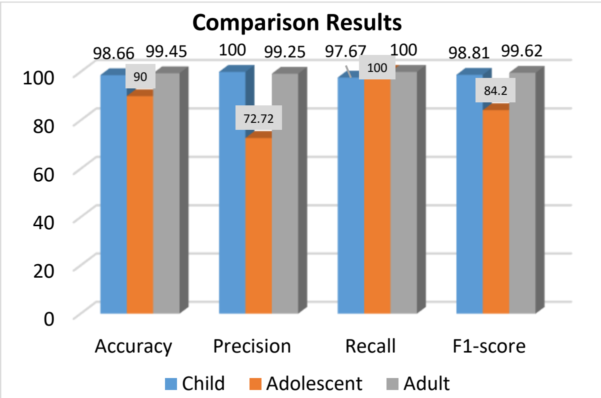

Figure 3. Comparison of results on the proposed 1D CNN

It is important to discuss cutting-edge strategies that used state-of-the-art techniques. Devika Varshini G [6] used ML techniques such as KNN, RF, and LR, and achieve performance with an F1 of 69.20%. Li Y, Mache MA [8] This study employed six supervised machine learning classifiers to classify postural control in individuals with Autism Spectrum Disorder (ASD) based on variables related to the centre of Pressure (COP). The proposed classification accuracy achieved a performance rate of 90%. Jia-Wei Sun [12] extracted ASD using the SVM method, achieving an accuracy of 98.80%. Alsaade FW [27] this study evaluated the precision of three deep learning algorithms to identify individuals with Autism Spectrum Disorder (ASD) based on facial features, namely NASNETMobile, Xception, and VGG19. The models were trained using a publicly accessible dataset found online, with the Xception model yielding the highest classification accuracy of 91%. In this study, a convolutional neural network (CNN) model was proposed and found to have an accuracy of 88% in distinguishing between individuals with autism and those without [28].

As shown in Table 4, the table compares different state-of-the-art models for Autism Spectrum Disorder (ASD) diagnosis that utilize various deep learning models.

Table 4. A Comparison proposed model with different state-of-the-art models

Model Name	Architecture	Dataset(s) Used	Accuracy	Recall	Precision	F1-score
Heinsfeld et al. 2018 [18]	CNN	ABIDE	%83.7	0.77	0.90	0.84
Devika et al. 2020 [6]	KNN, RF, and LR	Adults and Toddlers.	69.2%	0.32	0.71	0.47
Yang et al. 2020 [29]	DNN	ABIDE	0.75	0.74	0.78	0.75
Li et al. 2020 [8]	six supervised machine learning classifiers	(CPAS-C)	0.90	0.82	100	0.89
Almuqhim et al. 2021 [31]	ASD-SAENet	ABIDE	70.8	62.2	79.1	0.687
Murari et al. 2022 [30]	Multichannel DANN	ABIDE	0.73	0.74	0.73	0.73
Alsaade et al. 2022 [27]	Xception	from Kaggle	0.94	0.88	0.91	0.91
Proposed model	1D-CNN	ABIDE	99.45	99.25	100	99.62

According to experiences, the accuracy increases with the Epoch exponentially and attains the maximum accuracy at 18 Epochs, then it attains saturation after that. The proposed 1D CNN achieved higher accuracy results with the Adult dataset 99.45. This case appears when the three datasets that are tested. The training and evaluation accuracy is predicted at the same number of epochs. Fig.4 clearly illustrates the child training and validation accuracy for the proposed 1D CNN, and also illustrates the training and validation loss. The key limitation of the proposed model was trained on a relatively small dataset. Increasing the size of the dataset may improve the accuracy and generalizability of the model.

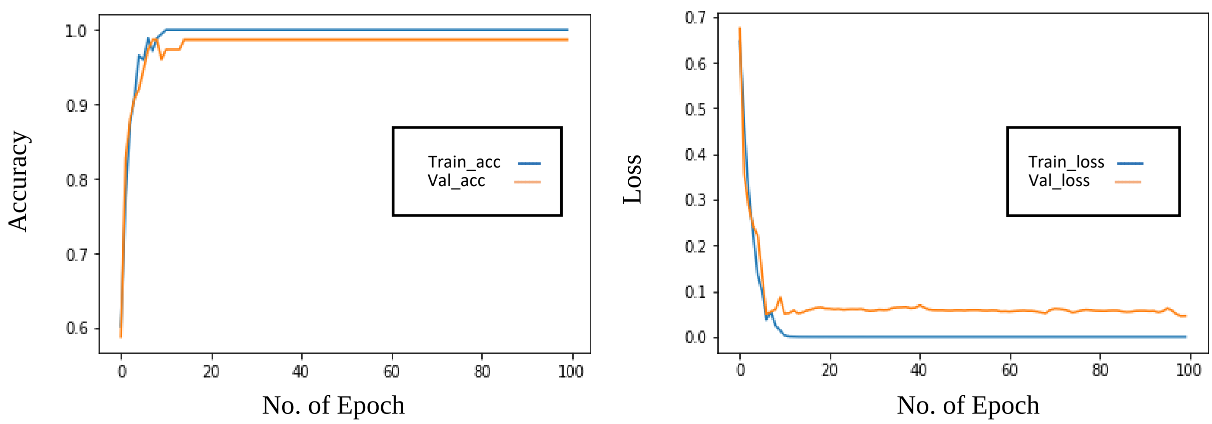

Figure 4. Child Training and Validation Accuracy & the training and validation loss

Fig 5 clearly illustrates the accuracy of the adolescent's training and validation for the proposed 1DCNN, also illustrating the training and validation loss.

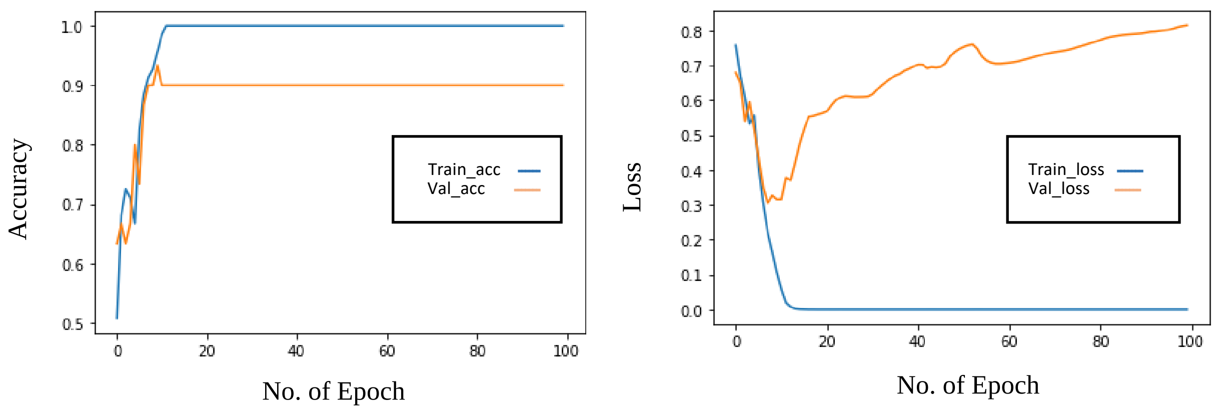

Figure 5. Accuracy of Adolescent Training and Validation Accuracy & the training and Loss of Training and Validation

Fig 6 clearly illustrates the Adult training and validation accuracy for the proposed 1D CNN, and also illustrated the training and validation loss.

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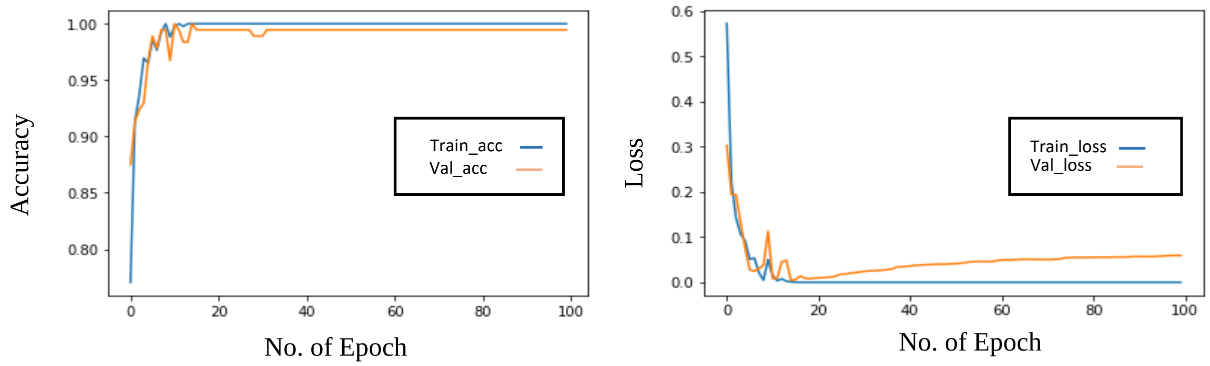

Figure 6. Adult Training and Validation Accuracy & the training and validation loss

According to the results in Fig. 4, and Fig. 6 the training and evaluation accuracy is predicted at the same number of epochs. And their values remain close until we get to epoch 100. But the results in Fig 5 show that there are various values between the training and validation. This is due to the lack of data used in this experiment.

The theoretical implications of this research are centered around the use of deep learning models (specifically, 1D CNN) for detecting Autism Spectrum Disorder (ASD). The study demonstrates the potential of using such models in improving the accuracy of ASD diagnosis, which could ultimately lead to earlier interventions and improved outcomes for individuals on the autism spectrum. Additionally, the study contributes to the field of deep learning by exploring the use of a novel method for detecting ASD and providing insights into the performance of 1D CNN models. On the practical side, the findings of this study have significant implications for healthcare providers, researchers, and individuals with ASD and their families. The proposed 1D CNN model has the potential to provide a non-invasive and cost-effective method for detecting ASD, which can lead to earlier interventions and improved outcomes. This model can be used by healthcare providers to screen individuals for ASD and potentially reduce the wait times for diagnosis. Furthermore, the study provides a valuable resource for researchers in the field of ASD, as it highlights the potential of deep learning models for this application and provides a benchmark for future studies.

Conclusion

This study utilized 1D CNN deep learning models for the detection of Autism Spectrum Disorder (ASD) and evaluated their performance. The study found that the 1D CNN model achieved the highest classification accuracy of 99.45% in identifying individuals with autism from those without autism. These results indicate that deep learning models can aid in early and accurate detection of autism, potentially leading to earlier interventions and better outcomes for individuals on the autism spectrum. The main contribution of this research is the development of a new method for detecting ASD using deep learning (1D-CNN), improving the accuracy of ASD diagnosis with a non-invasive and cost-effective approach. However, there are limitations to the proposed 1D CNN model, such as the potential impact of cultural and socioeconomic factors on the reliability and generalizability of the model. Future research should address this limitation by including more diverse and representative samples in the dataset and exploring the impact of cultural and socioeconomic factors on the model's performance. Furthermore, future work could include examination of the generalization of the proposed 1D CNN model on larger and more diverse datasets, including data from different geographical locations, ethnicities, and age groups. Additionally, a multi-task learning framework could be developed for jointly detecting ASD and comorbidities. Overall, this study provides valuable insights into the use of deep learning for autism detection and opens up avenues for further exploration in this field.

Author's Declaration

- Conflicts of Interest: None.
- I/We hereby confirm that all the Figures and Tables in the manuscript are mine/ours. Besides, the Figures and images, which are not mine/ours, have been given the permission for re-publication attached with the manuscript.
- Authors sign on ethical consideration's approval
- Ethical Clearance: The project was approved by the local ethical committee in Universiti Kebangsaan Malaysia (UKM).
- The material in this article is original and has not been published in any journal previously. The lead author confirms that all co-authors have reviewed and approved the work and that there are no ethical issues.

Author's Contribution Statement

AKK, MMA, AAN contributed to the design and implementation of the research, to the analysis of the results, and to the writing of the manuscript.

References

1. Voinsky I, Fridland OY, Aran A, Frye RE, Gurwitz D. Machine Learning-Based Blood RNA Signature for Diagnosis of Autism Spectrum Disorder. Int J Mol Sci. 2023; 24(3): 2082. https://dx.doi.org/10.3390/ijms24032082
2. Song DY, Topriceanu CC, Ilie-Ablachim DC, Kinali M, Bisdas S. Machine learning with neuroimaging data to identify autism spectrum disorder: a systematic review and meta-analysis. Neuroradiology. 2021; 63: 2057–72. https://dx.doi.org/10.1007/s00234-021-02774-z
3. Minissi ME, Chicchi Giglioli IA, Mantovani F, Alcaniz Raya M. Assessment of the autism spectrum disorder based on machine learning and social visual attention: A systematic review. J Autism Dev Disord. 2022; 52(5): 2187–202. https://dx.doi.org/10.1007/s10803-021-05106-5
4. Lai M, Lee J, Chiu S, Charm J, So WY, Yuen FP, et al. A machine learning approach for retinal images analysis as an objective screening method for children with autism spectrum disorder. E Clinical Medicine. 2020; 28: 100588. https://dx.doi.org/10.1016/j.eclinm.2020.100588
5. Mellema CJ, Nguyen KP, Treacher A, Montillo A. Reproducible neuroimaging features for diagnosis of autism spectrum disorder with machine learning. Sci Rep. 2022; 12(1): 3057. https://dx.doi.org/10.1038/s41598-022-06459-2
6. Devika Varshini G, Chinnaiyan R. Optimized machine learning classification approaches for prediction of autism spectrum disorder. Ann Autism Dev Disord 2020; 1(1): 1001. https://www.remedypublications.com/annals-of-autism-developmental-disorders-abstract.php?aid=5957
7. Nafea AA, Omar N, AL-Ani MM. Adverse Drug Reaction Detection Using Latent Semantic Analysis. J Comput Sci. 2021; 17(10): 960–70. https://dx.doi.org/10.3844/jcssp.2021.960.970
8. Li Y, Mache MA, Todd TA. Automated identification of postural control for children with autism spectrum disorder using a machine learning approach. J Biomech. 2020; 113: 110073. https://dx.doi.org/10.1016/j.jbiomech.2020.110073
9. Li X, Lu R, Wang Q, Wang J, Duan X, Sun Y, et al. One-dimensional convolutional neural network (1D-CNN) image reconstruction for electrical impedance tomography. Rev Sci Instrum. 2020; 91(12): 124704. https://dx.doi.org/10.1063/5.0025881
10. Ma D, Shang L, Tang J, Bao Y, Fu J, Yin J. Classifying breast cancer tissue by Raman spectroscopy with one-dimensional convolutional neural network. Spectrochim Acta Part A Mol Biomol Spectrosc. 2021; 256: 119732. https://dx.doi.org/10.1016/j.saa.2021.119732
11. Gaonkar S, Dessai NF, Costa J, Borkar A, Aswale S, Shetgaonkar P. A survey on botnet detection techniques. In: 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE). IEEE; 2020. p. 1–6. https://dx.doi.org/10.1109/ic-ETITE47903.2020.Id-70
12. Sun JW, Fan R, Wang Q, Wang QQ, Jia XZ, Ma HB. Identify abnormal functional connectivity of resting state networks in Autism spectrum disorder and apply to machine learning-based classification. Brain Res. 2021; 1757: 147299. https://dx.doi.org/10.1016/j.brainres.2021.147299
13. Raj S, Masood S. Analysis and detection of autism spectrum disorder using machine learning techniques.

Procedia Comput Sci. 2020; 167: 994–1004. https://dx.doi.org/10.1016/j.procs.2020.03.399
14. Hossain MD, Kabir MA, Anwar A, Islam MZ. Detecting autism spectrum disorder using machine learning techniques: An experimental analysis on toddler, child, adolescent and adult datasets. Heal Inf Sci Syst. 2021; 9: 1–13. https://dx.doi.org/10.1007/s13755-021-00145-9
15. Kumar CJ, Das PR. The diagnosis of ASD using multiple machine learning techniques. Int J Dev Disabil. 2022; 68(6): 973–83. https://dx.doi.org/10.1080/20473869.2021.1933730
16. Mashudi NA, Ahmad N, Noor NM. Classification of adult autistic spectrum disorder using machine learning approach. IAES Int J Artif Intell. 2021; 10(3): 743. https://dx.doi.org/10.11591/ijai.v10.i3.pp743-751
17. Alwidian J, Elhassan A, Ghnemat R. Predicting autism spectrum disorder using machine learning technique. Int J Recent Technol Eng. 2020; 8(5): 4139–43. https://dx.doi.org/10.35940/ijrte.E6016.018520
18. Heinsfeld AS, Franco AR, Craddock RC, Buchweitz A, Meneguzzi F. Identification of autism spectrum disorder using deep learning and the ABIDE dataset. NeuroImage Clin. 2018; 17: 16–23. https://dx.doi.org/10.1016/j.nicl.2017.08.017
19. AL-Ani MM, Omar N, Nafea AA. A Hybrid Method of Long Short-Term Memory and Auto-Encoder Architectures for Sarcasm Detection. J Comput Sci. 2021; 17(11): 1093–8. https://dx.doi.org/10.3844/jcssp.2021.1093.1098
20. Mohammed BA, Al-Shareeda MA, Manickam S, Al-Mekhlafi ZG, Alreshidi A, Alazmi M, et al. FC-PA: Fog Computing-based Pseudonym Authentication Scheme in 5G-enabled Vehicular Networks. IEEE Access. 2023, 11: 18571-18581. https://dx.doi.org/10.1109/ACCESS.2023.3247222.
21. Mahmood RAR, Abdi A, Hussin M. Performance evaluation of intrusion detection system using selected features and machine learning classifiers. Baghdad Sci J. 2021; 18(2): 884–98. https://dx.doi.org/10.21123/bsj.2021.18.2(Suppl.).0884
22. Rabani ST, Khan QR, Khanday A. Detection of suicidal ideation on Twitter using machine learning & ensemble approaches. Baghdad Sci J. 2020; 17(4): 1328. https://dx.doi.org/10.21123/bsj.2020.17.4.1328
23. Bassel A, Abdulkareem AB, Alyasseri ZAA, Sani NS, Mohammed HJ. Automatic malignant and benign skin cancer classification using a hybrid deep learning approach. Diagnostics. 2022; 12(10): 2472. https://dx.doi.org/10.3390/diagnostics12102472
24. Hassan FH, Omar MA. Recurrent Stroke Prediction using Machine Learning Algorithms with Clinical Public Datasets: An Empirical Performance Evaluation. Baghdad Sci J. 2021; 18(4): 1406. https://dx.doi.org/10.21123/bsj.2021.18.4(Suppl.).1406
25. Abdulmajeed AA, Tawfeeq TM, Al-jawaherry MA. Constructing a Software Tool for Detecting Face Mask-wearing by Machine Learning. Baghdad Sci J. 2022; 19(3): 642. https://dx.doi.org/10.21123/bsj.2022.19.3.0642
26. Al-Mekhlafi ZG, Al-Shareeda MA, Manickam S, Mohammed BA, Qtaish A. Lattice-Based Lightweight Quantum Resistant Scheme in 5G-Enabled Vehicular Networks. Mathematics. 2023; 11(2): 399. https://dx.doi.org/10.3390/math11020399
27. Alsaade FW, Alzahrani MS. Classification and detection of autism spectrum disorder based on deep learning algorithms. Comput Intell Neurosci. 2022; 2022: 1-10. https://dx.doi.org/10.1155/2022/8709145
28. Wang H, Avillach P. Diagnostic classificati;on and prognostic prediction using common genetic variants in autism spectrum disorder: Genotype-based deep learning. JMIR Med inform. 2021; 9(4): e24754. https://dx.doi.org/10.2196/24754
29. Yang X, Schrader PT, Zhang N. A deep neural network study of the ABIDE repository on autism spectrum classification. Int J Adv Comput Sci Appl. 2020; 11(4): 1-6. https://dx.doi.org/10.14569/IJACSA.2020.0110401
30. Murari A, Lungaroni M, Rossi R, Spolladore L, Gelfusa M. Complexity: Frontiers in Data-Driven Methods for Understanding, Prediction, and Control of Complex Systems 2022 on the Development of Information Theoretic Model Selection Criteria for the Analysis of Experimental Data. Complexity. 2022; 2022. https://dx.doi.org/10.1155/2022/9518303
31. Almuqhim F, Saeed F. ASD-SAENet: a sparse autoencoder, and deep-neural network model for detecting autism spectrum disorder (ASD) using fMRI data. Front Comput Neurosci. 2021; 15: 654315. https://dx.doi.org/10.3389/fncom.2021.654315

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الكشف عن اضطراب طيف التوحد باستخدام شبكة عصبية تلافيفية أحادية البعد

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الخلاصة

اضطراب طيف التوحد، المعروف أيضًا باسم ASD، هو مرض نمائي عصبي يضعف الكلام والتفاعل الاجتماعي والسلوك. التعلم الآلي هو مجال من مجالات الذكاء الاصطناعي يركز على إنشاء خوارزميات يمكنها تعلم الأنماط وتصنيف ASD بناءً على بيانات الإدخال. كانت نتائج استخدام خوارزميات التعلم الآلي لتصنيف ASD غير متسقة. هناك حاجة إلى مزيد من البحث لتحسين دقة تصنيف ASD. لمعالجة هذا الأمر، تم اقتراح التعلم العميق مثل 1D-CNN كبديل لتصنيف اكتشاف ASD. يتم تقييم التقنيات المقترحة على ثلاث مجموعات مختلفة من بيانات ASD المتاحة للجمهور (الأطفال والبالغون والمراهقون). تشير النتائج بقوة إلى أن 1D-CNN أظهرت دقة محسّنة في تصنيف ASD مقارنة بخوارزميات التعلم الآلي التقليدية، في كل مجموعات البيانات هذه بدقة أعلى تبلغ 99.45٪ و98.66٪ و 90٪ لفحص اضطراب طيف التوحد في البيانات للبالغين والأطفال والمراهقون على التوالي لأن النموذج المقترح أكثر ملاءمة لتحليل بيانات السلاسل الزمنية التي يشيع استخدامها في تشخيص هذا الاضطراب.

الكلمات المفتاحية: اضطراب طيف التوحد، التصنيف، التعلم العميق، التعلم الآلي، الشبكة العصبية التلافيفية أحادية الأبعاد.