# CNN Based ASD Early Screening for Chinese Children

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**Abstract.** Autism spectrum disorder (ASD) is a neurodevelopmental condition that can result in significant healthcare costs, with early diagnosis being crucial in reducing these costs. Behavioral data-based early screening for ASD is an easily implemented, time-efficient, and cost-effective method that can aid health professionals in informing individuals whether they should pursue formal clinical diagnosis. In this study, a Convolutional Neural Network (CNN) classifier and a support vector machine (SVM) classifier were compiled and trained on an open dataset of 1–18-year-old children and teenagers collected by the Computer Science Department of the University of Arkansas. The dataset included 10 behavioral features (Q-CHAT-10), age, gender, history of jaundice, and family history of ASD. Results showed that the CNN model outperformed the SVM model on indicators such as accuracy, precision, and recall. The validity of the trained model was further tested using data collected from Chinese children and teenagers through a questionnaire. The research exhibits the potential for the development of an accurate, low-cost, widely applicable, and easy-to-operate tool for early screening of ASD for Chinese children and teenagers especially for those in regions with limited medical resources, promoting early intervention..

**Keywords:** ASD screening; Behavioral data; Q-CHAT-10; CNN

## 1 Introduction

### 1.1 Background

Autism spectrum disorder (ASD) is a heterogeneous neurodevelopmental disorder characterized by restricted or repetitive behaviors or interests. People with ASD have different levels of deficit in social interactions and activities, all of which engender their lives to be challenging. According to the U.S. Centers for Disease Control and Prevention, the prevalence of autism spectrum disorders in 2021 was 1 in 44, an increase of nearly 240.9% compared to 1 in 150 in 2000 to 2002 [1]. The number of people diagnosed with ASD in China has also boomed in recent years. Although the estimated percentage of child population with ASD varies in different research, the trend of annual growth in ASD diagnosis has raised the awareness of the public and promoted the advancement in research about the early screening of ASD [2].


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Early detection of ASD is crucial as it enables early intervention, which has been shown to be effective in managing the condition. Scientists and policymakers advocated for early detection of ASD among the population since early intervention has been proven to be effective in limiting the development of condition. Nevertheless, certain obstacles exist in the detection process for the majority of the public. ASD is detected based on "impairment in communications and language development, as well as certain rigid and repetitive behaviors and preoccupations" and the diagnosis procedure relies heavily on external behavioral observation and subjective assessment by the evaluators based on their former experiences [3]. Former diagnoses rely on standardized tools and assessment of children, including psychological and educational measurement, medical examination, parent or guardian interview, daily observation, etc.. However, despite its accuracy, the traditional clinical diagnosis process is criticized as "time-consuming", since various diagnostic instruments, including The Modified Checklist for Autism in Toddlers, Revised (M-CHAT-R) and ASD Diagnosis Interview-Revised (ADI-R), with multiple questions and activities need to be evaluated. Furthermore, the requirement of highly professional and theoretical knowledge as well as clinical experiences make the standard of being clinicians capable of diagnose ASD relatively high, which result in a dearth of qualified clinicians. The situation is especially severe in China. A study in 2019 identified new cases of ASD in schools in Shenzhen, Jilin, and Jiamusi cities, indicating current under-diagnosis of autism in Chinese society [4].

### 1.2 Related Works

To promote early screening in pediatric care for alleviating further development disorder in children and relieving family burden, scientists have focused on developing time-saving screening tools by introducing machine learning and deep learning to the field of ASD detection. Moreover, with the protracted times taken to finish the comprehensive assessments and diagnosis procedure, the invention of ASD screening tools based on machine learning has become more and more essential and would greatly improve the efficiency of the clinical decision making [5].

In recent years, as research proves that early intervention improves prognosis of autism spectrum disorder, there has been a surge of interest in developing models for early detection of ASD. The diagnosis of autism can be completed as early as 18–24 months in the toddler age, in which typical symptoms of ASD can be identified and distinguished from other mentally developmental delay or specific conditions [2]. Due to the urgent need of a time-saving and easy-to-use screening tools and since machine learning and deep learning are capable of finding the trend and pattern among massive dataset and establish a model for prediction based on newly collected data, current studies in ASD detection using machine learning have attempted to implement different techniques based on diverse datasets, which can be grouped into several research subfields ranging from classical task behavior data, recognition based on brain imaging data to other categories [6] [7].

In the domain of brain imaging, a multitude of investigations have amassed data through the utilization of electroencephalography (EEG), structural magnetic resonance imaging (sMRI), and functional magnetic resonance imaging (fMRI). This data has been utilized to construct models using convolutional neural network (CNN). Regarding behavioral data, scientists have developed autism identification models primarily based on facial expression and emotion data, eye movement data, motor control, and motor patterns. For instance, Alex Net and colleagues obtained facial features from facial images, developed a binary classification task for autism screening utilizing support vector machines (SVM), and achieved an average precision of 93.33% in autism classification [7].

Many researchers have employed traditional machine learning models, including Support Vector Machine (SVM) and decision tree (DT). SVM, in particular, has been frequently utilized for deriving Autism Spectrum Disorder (ASD) classification models due to its high predictive power during the learning phase. However, traditional algorithms especially SVM often classify samples directly based on features without performing or only performing one feature transformation and selection, which can result in sensitivity to missing data, overfitting in the treatment of multi-classification problems. Such limitations may pose challenges when dealing with the complex etiology and expression of ASD.

Present studies highlight the nascent state of research about ASD early screening detection based on machine learning and deep learning in China, primarily focusing on the development of early screening models using brain imaging diagnostic systems. Specifically, research efforts have been directed towards constructing an ASD screening tool based on the NMI statistical matrix derived from fMRI images, as well as the implementation of a neural network utilizing a CNN network to classify functional magnetic resonance imaging data [8] [9]. Notably, however, there is a dearth of ASD screening investigations from a behavioral perspective. Furthermore, the application and efficacy of such screening approaches on Chinese pediatric populations have yet to be explored.

Given the increasing number of diagnosed cases of autism and the shortage of diagnostic resources in Chinese society, the aim of this study is to develop an early screening model for autism that is easy to operate, low cost, widely applicable, and accurate in its results. To achieve this goal, we constructed a CNN model and a SVM model, and trained them using a publicly available dataset. The model takes 10 behavioral data questions from Q-CHAT-10, as well as gender, jaundice history, age, and family history of ASD, for a total of 14 coefficients. Our CNN model was built upon the research conducted by Dr. Fadi Thabtah from Manukau Institute of Technology, Auckland–Autism AI: a New Autism Screening System Based on Artificial Intelligence with some modification. In our research, CNN outperformed SVM in their ability to detect ASD.

Since ASD is associated with the environment in which children grow up, models based on foreign children's datasets may not be applicable to children growing up in China. Therefore, we collected behavioral data of 51 children in China through offline survey among parents. We tested the accuracy of ASD detection of the model using Chinese children’s data to verify the CNN model’s applicability and efficacy on Chinese pediatric population.

### 1.3 Objectives and Methods

The objective of this study is to develop an early screening model for ASD that is easy to use, cost-effective, widely applicable, and accurate. To achieve this goal, we constructed a Convolutional Neural Network (CNN) model and a Support Vector Machine (SVM) model. We then trained them with publicly available datasets collected and released by Dr. Fadi Thabtah [10]. However, since the dataset for this study consisted of behavioral data collected through questionnaires, factors such as the influence of the environment, parents' understanding and cognition of the questionnaires, and the medical system's attitude towards early ASD diagnosis can all impact the data. Therefore, it is necessary to collect real data from Chinese families and validate the model's validity. To address this, we collected behavioral data from Chinese families through an offline survey and tested the accuracy of the CNN models using this dataset.

The findings of this study have the potential to provide a simple and cost-saving early screening tool for ASD to local clinics and parents. By optimizing the screening process, the model can save time in clinical decision-making, leading to timely interventions such as speech therapy and special education. By optimizing the screening process, our model can save doctors judgment time and avoid unnecessary delays in healthcare services such as speech therapy and special education. Ultimately, the application of this model can contribute to early detection and intervention for more children with ASD, alleviating the burden on families and reducing the economic impact of the disorder.

## 2 Research Methods

### 2.1 Dataset and Data Preprocessing

In this study, a Convolutional Neural Network (CNN) classifier and a support vector machine (SVM) classifier were compiled and trained on open datasets. We selected ten indicators from the Q-CHAT-10 questionnaire, along with age, sex, history of jaundice, and family history of ASD, making a total of 14 variables from in the dataset as features of ASD detection.

We initially utilized a dataset collected by Dr. Fadi Thabtah for training purposes [11]. This dataset comprised a total of 1054 samples, encompassing children aged between 12 and 36 months. Based on Dr. Fadi Thabtah's work, our fine-tuned CNN model achieved a 99% accuracy rate of ASD traits detection which outperformed the original model. However, in China, the minimum age of diagnosis of ASD is 36 months, thus making it challenging to gather behavioral data of children within the 12–36-month age range with a clear a classification of ASD. Consequently, we expanded the age range to 3-16 years old, and replaced the training dataset we used and opted for another publicly available dataset collected by the Computer Science Department of the University of Arkansas [12]. This dataset consisted of 1985 samples, ranging in age from 1 to 17 years, and included detailed indicators such as language disorders, learning disabilities, and developmental abnormalities. From this dataset, we selected Q-CHAT-10, age, gender, family history of ASD, and jaundice as 14 variables to train the CNN and SVM models separately.

After reconstructing the models based on the new dataset, we proceeded to compare the outcomes of ASD detection achieved by the CNN and SVM models. Our evaluation focused on key indicators such as accuracy, precision, and recall. However, considering that models built solely on open datasets might not yield accurate screening results for Chinese children, we deemed it necessary to conduct an external validity study. We gathered behavioral data through questionnaires offline, eventually receiving 17 samples from normal children and 34 samples from children with suspected ASD in China for model testing.

The Quantitative Checklist for Autism in Toddlers (Q-CHAT) was created with the purpose of categorizing autism in the toddler stage [13]. It has gained significant popularity in its utilization.

We made certain modifications to the original questionnaire by adjusting the expressions such as "always," "usually," "sometimes," "rarely," and "often" to better align with the understanding of Chinese parents and reduce the impact of questionnaire language on data quality. Additionally, due to the under-diagnosis of ASD in children in China, we made modifications to the questionnaire options and judgments for ASD_traits, dividing them into four categories: “confirmed diagnosis,” “visited but not diagnosed,” “not visited but suspected,” “asymptomatic (healthy),” in the external data collection process. Three options in the child's ASD diagnosis status as “confirmed diagnosis,” “visited but not diagnosed,” “not visited but suspected,” were encoded as 1, while the “asymptomatic (healthy)" was encoded as 0. We processed the Sex, Jaundice, Family_mem_with_ASD metrics in the same way as the training and testing dataset.

**Table 1. Features Collected Based on the Q-CHAT-10 Questionaire**

| Variable in Dataset | Corresponding Q-chat-10-Toddler Features |
|---|---|
| A1 | Does your child look at you when you call his/her name? |
| A2 | How easy is it for you to get eye contact with your child? |
| A3 | Does your child point to indicate that s/he wants something? (e.g. a toy that is out of reach) |
| A4 | Does your child point to share interest with you? (e.g. pointing at an interesting sight) |
| A5 | Does your child pretend? (e.g. care for dolls, talk on a toy phone) |
| A6 | Does your child follow where you’re looking? |
| A7 | If you or someone else in the family is visibly upset, does your child show signs of wanting to comfort them? (e.g. stroking hair, hugging them) |
| A8 | Would you describe your child’s first words as: |
| A9 | Does your child use simple gestures? (e.g. wave goodbye) |
| A10 | Does your child stare at nothing with no apparent purpose? |

Q-CHAT-10 questions

**Table 2. Types and Descriptions of Features**

| Feature | Type | Description |
|---|---|---|
| A1: Question 1 Answer | Binary (0, 1) | The answer code of the question based on the screening method used |
| A2: Question 2 Answer | Binary (0, 1) | The answer code of the question based on the screening method used |
| A3: Question 3 Answer | Binary (0, 1) | The answer code of the question based on the screening method used |
| A4: Question 4 Answer | Binary (0, 1) | The answer code of the question based on the screening method used |
| A5: Question 5 Answer | Binary (0, 1) | The answer code of the question based on the screening method used |
| A6: A6: Question 6 Answer | Binary (0, 1) | The answer code of the question based on the screening method used |
| A7: Question 7 Answer | Binary (0, 1) | The answer code of the question based on the screening method used |
| A8: Question 8 Answer | Binary (0, 1) | The answer code of the question based on the screening method used |
| A9: Question 9 Answer | Binary (0, 1) | The answer code of the question based on the screening method used |
| A:10 Question 10 Answer | Binary (0, 1) | The answer code of the question based on the screening method used |
| Age | Number | Child (years) |
| Score by Q-chat-10 | Number | 1-10 (Less that or equal 3 no ASD traits; > 3 ASD traits |
| Sex | Binary (0, 1) | Male as 1 ang Female as 0 |
| Born with jaundice | Boolean (yes or no) | Whether the case was born with jaundice |
| Family member with ASD history | Boolean (yes or no) | Whether any immediate family member has an ASD |

Features collected and their descriptions

## 2.2 Structure of CNN Model

The CNN model began with a 1D convolutional layer (Conv1D) that performed convolution on the input data using 32 filters. Each filter had a kernel size of 3, and the 'relu' activation function was applied to introduce non-linearity. To maintain the input size, the padding parameter was set to 'same'. Additionally, a 1D max pooling layer (MaxPooling1D) was added to down sample the output by taking the maximum value within each pool of size 2. Then, another convolutional layer and max pooling layer were added to the model. This further enhanced the model's ability to extract relevant features from the input data. Following the convolutional and max pooling layers, a flatten layer was introduced. This layer transformed the 2D feature maps into a 1D feature vector, preparing the data for the fully connected layers. Two fully connected layers (Dense) are then added to the model. Each dense layer consists of 64 neurons and applies the 'relu' activation function. To prevent overfitting, dropout regularization is applied after each dense layer with a rate of 0.5. The final dense layer contains a single neuron with a sigmoid activation function, producing a binary output. The structure of the CNN model is shown in Figure 1.

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv1d_3 (Conv1D) | (None, 14, 32) | 128 |
| max_pooling1d_3 (MaxPooling1D) | (None, 7, 32) | 0 |
| conv1d_4 (Conv1D) | (None, 7, 64) | 6208 |
| max_pooling1d_4 (MaxPooling1D) | (None, 3, 64) | 0 |
| conv1d_5 (Conv1D) | (None, 3, 64) | 12352 |
| max_pooling1d_5 (MaxPooling1D) | (None, 1, 64) | 0 |
| flatten_1 (Flatten) | (None, 64) | 0 |
| dense_3 (Dense) | (None, 64) | 4160 |
| dropout_2 (Dropout) | (None, 64) | 0 |
| dense_4 (Dense) | (None, 64) | 4160 |
| dropout_3 (Dropout) | (None, 64) | 0 |
| dense_5 (Dense) | (None, 1) | 65 |

Total params: 27,073
Trainable params: 27,073
Non-trainable params: 0

**Figure 1.** Structure of the constructed CNN model

## 3 Experimental Results and Analysis

We utilized three metrics, namely accuracy, precision, and recall, to compare the performance of the SVM model and the CNN model on the detection dataset, as well as their effectiveness in ASD detection.

Eq. (1) defines Accuracy, which is measured as the ratio of correct classifications to the number of total tests, including true positives and true negatives, and n represents the number of total tests.

$$\text{Accuracy}=\frac{\text{True Positives}+\text{True Negatives}}{n} \tag{1}$$

Eq. (2) defines precision, which quantifies the number of positive class predictions that actually belong to the positive class.

$$\text{Precision}=\frac{\text{True Positives}}{\text{True Positives}+\text{False Positives}} \tag{2}$$

Eq. (3) defines recall, which quantifies the number of positive class predictions made out of all positive examples in the dataset.

$$\text{Recall}=\frac{\text{True Positives}}{\text{True Positives}+\text{False Negatives}} \tag{3}$$

We trained our CNN model using a dataset collected by Dr. Fadi Thabtah [11]. We randomly divided the dataset into a training set (75% of the data) and a validation set (25% of the data). The trained model achieved an accuracy of 100% on the validation set in predicting ASD traits. We applied the same training with the SVM model which achieved 98.48% accuracy. Such high accuracy can be partly attributed to the quality of the dataset. However, the performance of the CNN model may decline due to a larger sample size and wider age range with lower data quality.

We then trained the CNN model using a dataset collected by the Computer Science Department of the University of Arkansas with the same method which included a wider age range [12]. The model achieved a 88.39% accuracy on the validation dataset in the training process, the training process is shown in Fig. 2.

When the applying the trained CNN model to predict the testing set, we collected in Chinese families, the model achieved an accuracy of 91.84%, precision of 92.86%, and recall of 92.86%. In comparison, the SVM model achieved an accuracy of 86.88%, precision of 87.60%, and recall of 86.50% on the same test sample set. In terms of accuracy, precision, and recall metrics in predicting ASD traits, the CNN model outperformed the SVM model.

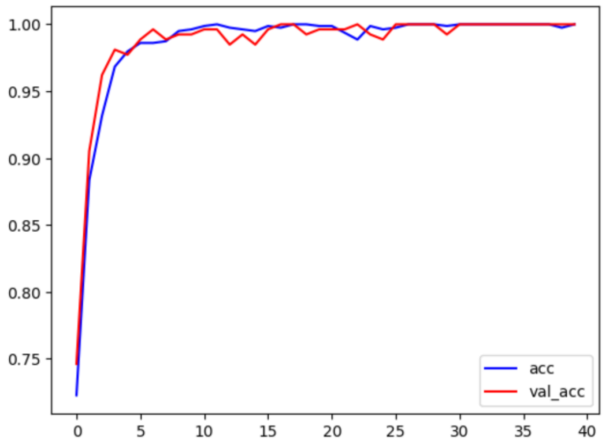

**Figure 2.** Training process of the CNN model on the Dr. Fadi Thabtah dataset with 75% training data and 25% validation data. The horizontal axis represents the training epochs, while the vertical axis represents the accuracy on the validation dataset.

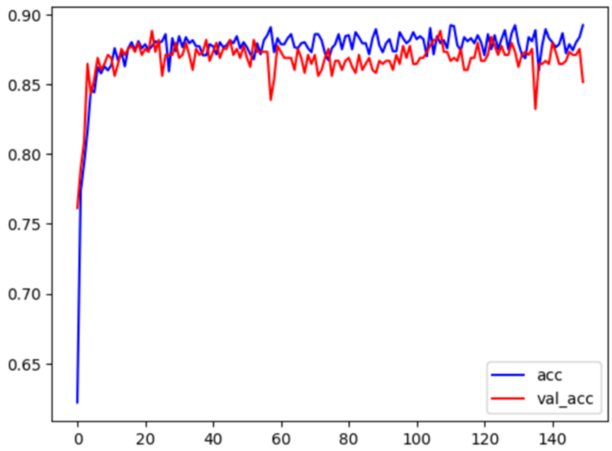


**Figure 3.** Training process of the CNN model on the University of Arkansas dataset with 75% training data and 25% validation data. The horizontal axis represents the training epochs, while the vertical axis represents the accuracy on the validation dataset.

**Table 3. Two Samples of Data Cases with Abnormal Behavioral Features**

| No. | A1 | A2 | A3 | A4 | A5 | A6 | A7 | A8 | A9 | A10 | Age | Sex | Jaundice | Family_mem_with_ASD | ASD_traits |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 4 | 4 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 2 | 15 | 2 | 2 | 2 | 4 |
| 2 | 1 | 1 | 1 | 1 | 3 | 1 | 1 | 1 | 1 | 5 | 7 | 2 | 1 | 2 | 1 |

Two data samples with abnormal behavioral data

Overall, the model performed well in the population with ASD tendencies, making comprehensive judgments and identifying children with ASD tendencies as much as possible. The promising metrics indicate that the CNN model trained on publicly available datasets can be used for early screening of ASD in Chinese children.

Furthermore, when examining the misclassified data, we discovered several instances of abnormal data. For example, in data sample number 1 from the TABLE III, based on our experience, the child's behavioral characteristics exhibited strong tendencies towards ASD. Therefore, the model classified it as positive. However, the questionnaire indicated a negative response.

Conversely, in data sample number 2, the child exhibited slight abnormal behavior only in question A5, "Does your child pretend? (e.g. care for dolls, talk on a toy phone)?" but performed well in other questions. Our model classified the case into negative, but this case was diagnosed as ASD.

## 4 Conclusion and Future Work

In this study, we developed a deep learning-based model for early screening of ASD in Chinese toddlers. The prevalence of ASD has been on the rise globally, including in China, necessitating the development of screening tools to support early intervention in addition to the traditional clinical diagnosis processes which is more time-consuming. To address these challenges, we leveraged machine learning and deep learning techniques to construct a CNN model and a SVM model and tested their abilities in ASD traits detection.

Our CNN model, trained on a publicly available dataset collected by Dr. Fadi Thabtah, achieved an accuracy of 100% in predicting ASD traits. However, considering the need for an applicable model for Chinese children, we expanded the age range of the dataset and utilized another dataset collected by the Computer Science Department of the University of Arkansas. Training the CNN model and SVM model on both datasets, it consistently outperformed the SVM model in all performance metrics, demonstrating its effectiveness as an early detection model.

To evaluate the external validity and effectiveness of the model in Chinese children and families, we made modifications to the Q-CHAT-10 questionnaire based on Chinese language conventions and used it to collect behavioral data from Chinese children and adolescents. The CNN model exhibited good performance in identifying ASD tendencies in diagnosed or suspected autistic children.

In conclusion, our deep learning-based model's performance shows promise in early screening for ASD in Chinese toddlers. It offers a simple, cost-effective, and widely applicable screening tool that can potentially reduce the burden on families and healthcare services. By optimizing the screening process, the model has the potential to promote early detection and intervention of ASD. Further research is needed to refine the model's performance in predicting ASD traits accurately in normal children and to explore its applicability in diverse populations.

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