Deep Learning to Detect Autism in Children from Facial Images

Harsh Ekambe

Department of Arts and Sciences, Lawrence Technological University

Abstract

This research presents an innovative approach to identifying Autism Spectrum Disorder (ASD) in children, utilizing facial images as a screening tool. By leveraging advanced deep learning techniques, specifically VGG16 transfer learning, we aimed to develop a robust model capable of accurately distinguishing between children with ASD and typically developing (TD) children. Our study stands out due to the utilization of a carefully curated dataset comprising clinically diagnosed ASD cases, ensuring the reliability and quality of the data. Through rigorous experimentation, our model achieved an impressive classification accuracy of 95%, demonstrating its effectiveness in accurately identifying individuals with ASD. Additionally, the F1-score, a metric that balances precision and recall, reached a high value of 0.95, further affirming the model's capability in ASD screening. In contrast to prior research efforts that relied on datasets of lower quality, such as the Kaggle ASD Facial Image Dataset sourced from internet searches, our study emphasizes the importance of utilizing robust data sources. This distinction is crucial as it ensures the validity and reliability of the findings, aligning more closely with clinical observations regarding facial phenotypic differences between ASD and TD children. Furthermore, our findings underscore the feasibility of employing deep learning methodologies for ASD screening, particularly through the analysis of facial images. This highlights the potential of such technology to complement existing diagnostic practices, potentially leading to earlier interventions and improved outcomes for individuals with ASD. Importantly, we also address the significance of considering racial and ethnic factors in the development and application of deep learning models for ASD screening. By acknowledging and accounting for these factors, we aim to ensure the accuracy and inclusivity of the screening process across diverse populations. In conclusion, this research not only presents a promising method for ASD screening using facial images but also emphasizes the importance of data quality, model performance, and inclusivity in the development of AI-based healthcare solutions.

Keywords: autism; facial images; machine learning; deep learning; race and ethnicity; diagnosis; screening; neural network; bias; ASD

1. **Introduction**

According to the Centers for Disease Control and Prevention (CDC), Autism Spectrum Disorder (ASD) is a developmental condition associated with notable challenges in social interaction, communication, and behavior. In the United States, ASD affects approximately 1 in 59 children aged 8 years and younger, with prevalence rates on the rise. However, disparities persist among different racial and ethnic groups regarding both the prevalence of ASD and access to intervention and treatment services. Research indicates that compared to White children, those from racial and ethnic minority backgrounds are less likely to receive an ASD diagnosis and are more prone to misdiagnosis or delayed identification. In 2018, while the overall estimated prevalence of ASD was 16.8 per 1000 children, non-Latino White children had a higher prevalence rate (17.2 per 1000) compared to non-Latino African American children (16.0 per 1000), Latino children (14.0 per 1000), and Asian/Pacific Islander children (13.5 per 1000). The delayed or inaccurate diagnoses experienced by minority racial groups lead to missed opportunities for early intervention in children with ASD. Clinical evidence indicates that early, thorough, and intensive intervention can result in substantial and lasting improvements. These improvements extend beyond intellectual, linguistic, and social skills to include a reduction in the severity of ASD symptoms. For instance, in two instances, children who underwent therapy based on the Early Start Denver Model (ESDM) ceased to meet the criteria for an ASD diagnosis.

A recent cost analysis conducted in the Netherlands revealed that initiating early intensive behavioral intervention before the age of 30 months could result in lifetime cost savings exceeding EUR 1 million per individual. These findings underscore the significant long-term benefits of early identification and intensive ASD-specific intervention for children with ASD. They also highlight the importance of extending such interventions to underserved community settings to improve outcomes for all children affected by ASD.

Several factors contribute to the disparities in ASD prevalence and delayed diagnoses in the United States:

1. Diagnosis subjectivity: ASD diagnosis relies on behavioral observation, making it challenging to diagnose reliably in children around 2 years old. On average, diagnosis typically occurs between ages 4 and 5, requiring experienced clinicians.
2. Limited access to experts: Many families, particularly those in underserved communities, lack access to specialists who can diagnose ASD.
3. Awareness and screening gaps: There is a lack of awareness and screening efforts, particularly in rural areas, contributing to delays in diagnosis.
4. Disparities in diagnosis rates among racial and ethnic minorities: Children from minority backgrounds who meet ASD criteria are less likely to receive a diagnosis compared to White children, increasing the likelihood of misdiagnosis.

Hence, there is a critical need for an objective, cost-effective, and easily understandable screening or diagnostic solution to facilitate early intervention for all families affected by ASD. To address this need, our research aimed to show the feasibility and accuracy of an early ASD screening approach utilizing only facial images and deep learning.

Clinical studies have indicated that there are discernible differences in facial features between children with ASD and typically developing (TD) children. For instance, research has highlighted specific facial phenotypic variations between boys with ASD and TD boys.

2. Materials and Methods

2.1. Datasets

2.1.1. East Asia ASD Children Facial Image Dataset (East Asian Dataset)

The East Asian dataset comprises 1122 images, evenly divided between children diagnosed with ASD and typically developing (TD) children of the same racial background. Approximately 600 facial images were sourced from the Elim Autism Rehabilitation Center in Shandong, China, a facility specializing in ASD treatment. Since its establishment in 2000, over 8000 children have undergone intervention programs at this center. Consent and privacy agreements were secured from the families of these children to utilize their images for research purposes. Additionally, 561 images of TD children were collected from various kindergartens and elementary schools in China. All images were of children aged between 2 and 12 years and belonged to the same racial group. This dataset served as the primary resource for developing our proposed solution and drawing accuracy conclusions.

2.1.2. Kaggle Autism Facial Dataset (Kaggle Dataset): The Only Publicly Available ASD Facial Image Dataset

The Kaggle dataset comprises 2936 facial images, evenly split between children diagnosed with ASD and TD children. Originally, the dataset contained 3014 images, but some were deemed problematic and removed. The images in the Kaggle dataset were obtained solely through internet searches, as stated by the contributor, who was unable to verify their sources. Notably, about 89% of the children in this dataset are White, with the remaining 11% representing children of color. We utilized this dataset solely to illustrate the influence of racial factors in the development of facial-image-based deep learning models.

The East Asian Dataset was meticulously curated, encompassing images from children diagnosed with ASD and TD children from the same racial background. These images were obtained from a reputable rehabilitation center specializing in ASD treatment, ensuring data quality and reliability. In contrast, the Kaggle Dataset, while publicly available, lacked the same level of oversight, as its images were sourced from internet searches without verification. This distinction highlights the importance of utilizing high-quality datasets, particularly in sensitive areas such as healthcare research. Additionally, the racial

composition of the Kaggle Dataset underscores the need to consider diversity and inclusivity in dataset selection and model development to ensure equitable outcomes across different racial and ethnic groups.

2.2 Methods