2024 MIT Art, Design and Technology School of Computing International Conference (MITADTSoCiCon)
MIT ADT University, Pune, India. Apr 25-27, 2024

2024 MIT Art, Design and Technology School of Computing International Conference (MITADTSoCiCon) | 979-8-3503-6287-9/24/$31.00 ©2024 IEEE | DOI: 10.1109/MITADTSoCiCon60330.2024.10575142

Predictive approach for Autism Detection using Computer Vision and Deep Learning

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***Abstract*—Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition that profoundly impacts social interactions, behavior, and communication in individuals. Accurate and timely detection of ASD is crucial for effective intervention and management of the disorder. In recent years, the field of artificial intelligence (AI) has significantly contributed to the diagnosis and screening of ASD, aiding clinicians and researchers alike. This article offers a comprehensive review of the current state of using AI for ASD detection. Various AI methodologies, including machine learning algorithms, natural language processing techniques, and deep learning models, are discussed in the context of ASD diagnosis. The paper highlights how AI can automate ASD assessment, enhance diagnostic accuracy, and identify early signs of the disorder. Additionally, the paper explores the challenges and limitations associated with AI-based approaches for ASD detection. Overall, this article serves as a valuable resource for clinicians, developers, and researchers interested in leveraging AI technologies to advance ASD detection and improve outcomes for individuals on the autism spectrum.**

***Index Terms*—cnn, deep learning, autism, autism in kids.**

I. Introduction

Autism Spectrum Disorder (ASD) stands as a diverse neurodevelopmental condition, portraying challenges in communication, repetitive behaviors, and social interaction struggles [1]. Prompt and precise ASD identification holds essential importance for timely intervention and effective management. Artificial Intelligence (AI) has garnered notable attention lately in aiding clinicians and researchers towards ASD detection. This article endeavors to comprehensively review the ongoing advancements in utilizing AI methods to identify ASD. The primary focus of this article is to assess the viability of Computer Vision models for swift Autism detection through images. This novel proposed approach promises a more convenient way to detect Autism, enabling earlier expert assistance during childhood. In this pursuit, the paper provides a thorough review of AI methodologies, including ML algorithms, NLP techniques, and deep learning models, within the context of ASD diagnosis. Additionally, it explores the challenges and limitations associated with AI-based approaches for ASD detection.The objectives of this article are:

- To evaluate the effectiveness of Computer Vision models in detecting Autism Spectrum Disorder (ASD) through image analysis.
- To provide insights into the potential benefits and challenges of utilizing AI methods for ASD detection.
- Discussing state-of-the-art AI methodologies employed in ASD diagnosis.
- To highlight the significance of early ASD detection and intervention facilitated by AI technologies.

II. EPIDEMIOLOGY OF ASD

In 2020, Autism Spectrum Disorder (ASD) remained a global public health issue [2]. Researchers noted rising ASD recognition, especially by the CDC, which reported 1 in 54 US children affected. Gender differences persisted, with higher ASD diagnoses in boys [3]. Efforts aimed to enhance early ASD detection and intervention, crucial for improved outcomes [4]. Ongoing research and awareness campaigns drive understanding and effective assistance strategies [4].

In India, autism affects approximately 1 in 54 children, with a male-to-female ratio of around 3:1 . Moreover, a community-based study reported a prevalence of 15 cases per 10,000 children aged 1–10 years in rural areas of India [5]. An estimated 18 million Indians are affected by autism, making it the third most common developmental disorder in the country.

III. CHALLENGES ASSOCIATED WITH ASD DIAGNOSIS

Diagnosing Autism Spectrum Disorder (ASD) is intricate, involving behavioral, developmental, and clinical factors. Challenges like symptom diversity, subjective assessments, delays, comorbidities, limited access, and biases hinder accurate identification. ASD's heterogeneity thwarts standardized diagnosis [6]. Subjective assessments vary, causing diagnostic

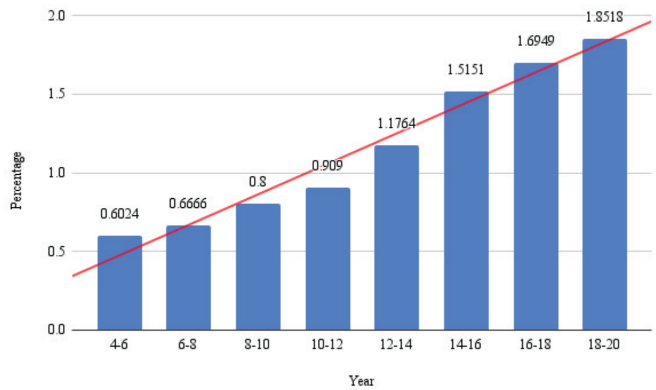

Fig. 1: Estimated autism prevalence in the United States for the year 2020.

discrepancies. Delays stem from subtle early signs. Comorbidities with other disorders blur distinctions. Scarce specialized services complicate matters, especially in underserved areas. Biases, linguistic or traditional, add inaccuracies, lacking cultural sensitivity. Addressing these issues mandates continuous research, innovation, and awareness. AI, like machine learning, aids by automating and enhancing diagnostics for more objectivity.

IV. THE POTENTIAL PERKS OF AI BASED APPROACHES IN AUTISM SPECTRUM DISORDER

The potential benefits of AI-driven approaches in detecting autism spectrum disorder (ASD) are substantial and hold the potential to enhance the accuracy, accessibility, and efficiency of ASD diagnosis. Below are some key potential advantages: AI methods like machine learning algorithms, deep learning models, and natural language processing techniques show considerable promise in ASD detection [7]. These techniques offer multiple advantages in identifying ASD, including:

- Objective and Quantitative Assessments: AI algorithms can analyze extensive datasets containing clinical assessments, behavioral observations, and genetic markers. This yields objective and quantitative ASD evaluations, minimizing the subjectivity and variability often linked with traditional diagnostics[8].
- Early Detection and Intervention: AI based methods can spot early ASD indicators by analyzing various cues like facial expressions, eye-tracking data, behavior traits, and speech patterns. This aids in early detection and intervention, resulting in enhanced outcomes for individuals with ASD.
- Enhanced Diagnostic Precision: Artificial Intelligence algorithms can process vast data and uncover intricate relationships between clinical and behavioral aspects linked to ASD. This enhances diagnostic accuracy and empowers clinicians to make more informed decisions.
- Automation and Efficiency: AI technologies automate various diagnostic aspects, lightening the workload for clinicians and boosting performance. AI driven systems can handle tasks like data collection, feature extraction, and risk assessment. This enables clinicians to focus on personalized care and analysis.AI Techniques for ASD Detection: Machine Learning, Deep Learning, and Natural Language Processing

A. MACHINE LEARNING ALGORITHMS EMPLOYED IN DETECTING ASD

Machine learning algorithms are broadly employed in detecting ASD, contributing to the development of accurate and efficient diagnostic frameworks. The most used machine learning algorithm in ASD detection are given below:

- Support Vector Machines (SVM): SVM classifies individuals as ASD-positive or ASD-negative by creating a high-dimensional separation boundary.
- Random Forests: This ensemble technique combines decision trees for predictions, with each tree trained on different data subsets.
- K-Nearest Neighbors (KNN): KNN assigns a class to a sample based on its similarity to its k nearest neighbours. 4. Decision Trees: Decision trees use a flowchart like structure to make decisions by analysing data features.
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- Gradient Boosting Algorithms: Techniques like AdaBoost and XGBoost create strong predictors by iterative training models and assigning weights based on performance.

These methodologies showcase their effectiveness in detecting autism spectrum disorder, each offering unique advantages and approaches to enhance diagnostic capabilities [9]. Here's table summarizing the machine learning algorithms employed in ASD detection, along with their reported accuracy rates and the sources used in their respective studies [10]:

TABLE I: Detecting ASD in children using ML techniques.

Algorithm	**Accuracy Rate**	**Sources**
Support Vector Machine	80%-90%	Behavioral assessments, neuroimaging data
Random Forests	75%-85%	Behavioral traits, demographic information
K-Nearest Neighbors	70%-80%	Cognitive profiles, physiological measurements
Decision Trees	70%-80%	Social communication skills, sensory responses
Gradient Boosting Algorithm	80%-90%	Multiple features from various domains

B. DEEP LEARNING MODELS FOR ASD DETECTION

Deep learning models have shown promise in ASD detection, leveraging their ability in learning complex relationships and patterns from large-scale data[11]. Here are some commonly employed deep learning models in ASD detection:

- Convolutional Neural Networks (CNNs): CNNs excel at processing visual data and have been applied in ASD detection to analyze facial expressions, eye-tracking data, and brain imaging scans. By extracting spatial features hierarchically, CNNs can identify patterns indicative of ASD related characteristics, such as facial cues or brain connectivity abnormalities[12].
- Recurrent Neural Networks (RNNs): RNNs are considered appropriate for analyzing sequential data, making them valuable in ASD detection. RNNs can capture temporal dependencies in behavioral sequences, speech patterns, or physiological data, enabling the identification of specific ASD related patterns that evolve over time[13].
- Long Short-Term Memory (LSTM): LSTM, a type of RNN addresses the problem of vanishing gradient,enabling the model to retain information over longer sequences. LSTMs have been used to analyze time-series data in ASD detection, such as continuous tracking of social behavior, physiological responses, or repetitive behaviors[14].
- Graph Convolutional Networks (GCNs): GCNs extend CNNs to graph-structured data, allowing for the analysis of complex relationships and interactions. GCNs have been employed in ASD detection to model brain connectivity networks derived from fMRI images[15].
- Transformer Models: Transformer models, such as the wellknown BERT (Bidirectional Encoder Representations from Transformers), have been utilized in natural language processing tasks related to ASD detection. These models can process textual data, such as clinical notes, medical reports, or questionnaires, to extract relevant information, semantic features, or linguistic patterns associated with ASD[16].

TABLE II: Various Deep Learning Techniques

Deep Learning Model	Accuracy	Sources
Convolutional Neural Network	85%-90%	Facial expressions, eye-tracking, brain imaging scans
Recurrent Neural Networks	80%-90%	Speech Patterns, Physiological responses
Long Short-Term Memory	75%-80%	Time-Series social behaviors, repetitive behaviors
Graph Convolutional Networks	75%-85%	Brain connectivity networks derived from fMRI or DTI data
Transformer Models	80%-90%	Clinical notes, medical reports

V. COMPUTER VISION IN AUTISM PREDICTION

Computer vision holds a vital role in detecting autism by examining visual information like facial expressions, eye motions, and gestures. It facilitates spotting nuanced behavioral cues and indicators, supporting early identification and precise ASD diagnosis. In this study, we crafted and assessed a binary image classifier using deep learning methods grounded in computer vision.

A. Dataset

The dataset used for this investigation was compiled from a diverse array of sources, including Kaggle[19], Google Images, and PubMed. It consisted of 1900 images portraying children with typical development and 1950 images depicting children diagnosed with autism. This study places particular emphasis on the early detection of autism in young children, thus the image collection encompassed a variety of youngsters from different races and genders, ”aged” between 2 and 8 years. Images of children under 2 years old were excluded due to the ongoing development of their facial features, which could potentially impact the model’s classification accuracy. Moreover, the dataset does not include images of children beyond 8 years, which could result in less accurate outcomes if the trained model is applied to images beyond this age range. Given the limited number of images available, Data Augmentation techniques were applied to generate synthetic images and effectively increase the dataset’s size. As a result, the dataset ultimately comprised an impressive 11500 images per class. In total, our dataset consist-ed of 23000 images.

B. Feature Extractor Architecture

The inception of a Convolutional Neural Network commences with the feature extraction process. Augmented feature extraction is intricately linked to an enhanced derivation of features, thereby furnishing the Dense layers with a more profound grasp of the data. To assume the role of our feature extractor, we opted for Xception[20], a robust convolutional neural network distinguished by its impressive 71 layer depth. The feasibility of employing a pretrained iteration of this network is evident, shaped through its exposure to a vast compilation of over one million images from the ImageNet database. This astutely pretrained network showcases its prowess by adroitly categorizing images across a wide ranging spectrum of 1000 object classes. This vast proficiency encompasses commonplace items like keyboards, mice, and pencils, extending to an assorted menagerie of animals. The network’s extensive exposure imparts intricate and sophisticated feature representations, aptly spanning a comprehensive array of images [21]. Notably, we adjusted certain parameters of the model. The weights were designated as “None,” the image size tuple was modified to 256 by 256, and the preceding layers were deactivated, set as non-trainable. This decision was driven by the intention to solely harness the feature extraction aspect of the model [22].In the diagram shown, we changed the activation function of the last layer from “Softmax” to “Sigmoid” because we were dealing with a Binary Classification Problem[23].

C. Dense Layer Architecture

We designed a 5 layer dense network for the purpose of the dense layer. Within this network, three hidden layers were established with sizes of 1000, 500, and 100 respectively.

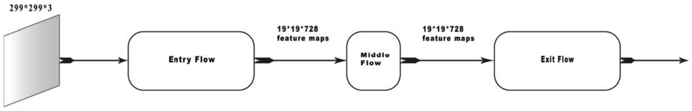


Fig. 2: Xception CNN architecture

The primary function of this layer involves the recognition of concealed patterns within the derived features[24]. These patterns are subsequently categorized into either the Autistic or Non-Autistic class. Notably, this specific layer encompassed a grand total of 5 million fully connected and trainable connections, contributing to its intricate nature.

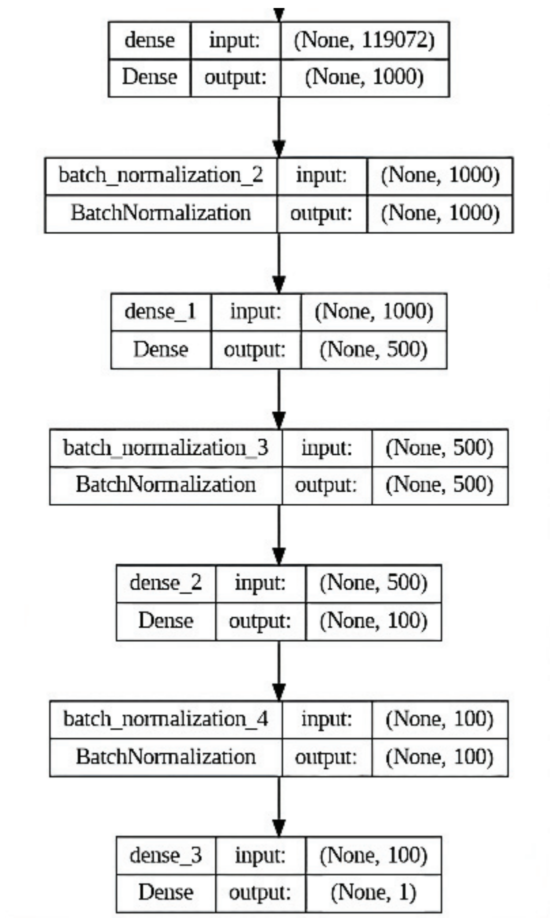


Fig. 3: Dense Layer Architecture

D. Model Training

For the Convolutional Neural Network (CNN), a comprehensive training approach was pursued. The model architecture included a 5 layer dense network, with three hidden layers featuring sizes of 1000, 500, and 100 respectively. The fundamental objective of this intricate layer was to discern concealed patterns within the extracted features, effectively classifying them into the categories of "Autistic" or "Non-Autistic." Notably, this layer comprised an impressive total of 5 million fully connected and trainable connections[25]. We trained the model for 100 rounds, also known as epochs. We used Google Collab and an Nvidia graphics card with 15 GB of VRAM to help with the computations. The graphics card's memory use peaked at 12 GB during the most intense parts of training. Each of the 100 training rounds took roughly 4.8 to 5.8 minutes. We tried different batch sizes—32, 64, 128, and 256—while training. Interestingly, we found that a batch size of 128 worked the best. We also tested different learning rates (0.1, 0.01, 0.001) to see which one suited our model best. Eventually, we settled on a learning rate of 0.01. To make the training process efficient, we used the "Adam" optimizer. This optimizer is known for its ability to handle complex situations and help the model improve its performance over time.

E. Models Loss and Accuracy Graphs

The model underwent training for a total of 100 epochs. Throughout this training period, there were no indications of overfitting, underfitting, or vanishing gradient problems. It's worth noting that if the training were extended further, it's highly likely that the accuracy would have continued to improve.

F. Confusion Matrix

We created a Confusion Matrix to assess the precision, accuracy, and recall of the model. These are some of the evaluation metrics used to analyze the performance of Machine Learning Models.

1) Precision: Measures the performance of a classification model. It is a measure of how many of the positively predicted instances are true positives. In the context of binary classification, precision is calculated using the following formula:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{1}$$

where:

$TP =$ True Positives (TP) are the instances that are correctly predicted as positive by the model

$FP =$ False Positives (FP) are the instances that are predicted as positive but are actually negative.

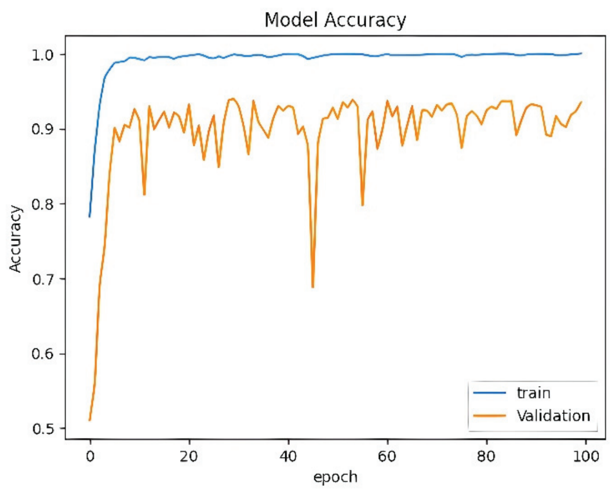
2) Recall: Considered as Sensitivity or True Positive Rate, measures that the model's ability to identify all relevant instances of a class, or in other words, its ability to avoid missing positive instances.

In the context of binary classification, recall is formulated using the following:

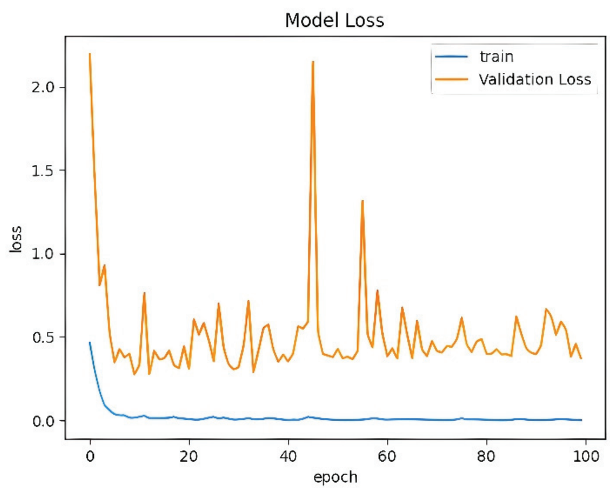
$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

where:

$FN =$ False Negatives (FN) are the instances that are actually positive but predicted as negative.



(a) Models Accuracy vs Epochs



(b) Models Loss vs Epochs

Fig. 4: Dense Layer Architecture

3) Accuracy: Presents the correctness of predictions made by a model across all classes.

In the context of binary classification, accuracy is calculated using the following formula:

$$\text{Accuracy} = \frac{TP + TN}{N} \tag{3}$$

where:

$TN =$ True Negatives (TN) are the instances that are correctly predicted as negative by the model

$N =$ Total Instances

From the Confusion Matrix given above we can calculate the precision, recall, and accuracy. The precision of the model is calculated to be 87.76%, recall of the model is calculated to be 89.59%, and accuracy is 88.87%.

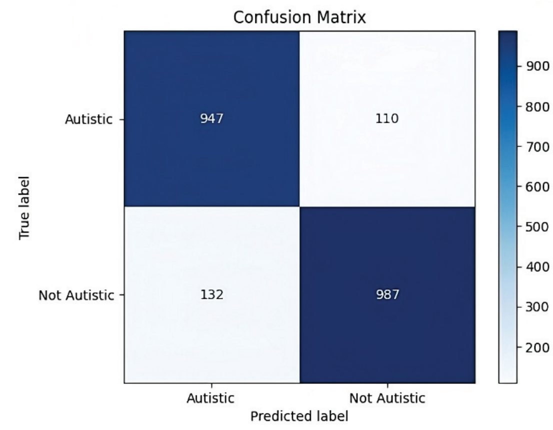


Fig. 5: Confusion Matrix

VI. Conclusion

Based on the extensive exploration of AI-driven approaches, particularly utilizing computer vision techniques for the early detection of Autism Spectrum Disorder (ASD), it is evident that such methodologies hold significant promise in revolutionizing the diagnostic landscape. Our research underscores the effectiveness of employing computer vision solely based on facial data, demonstrating its efficacy in detecting ASD at early stages. This finding is particularly noteworthy as it suggests a simpler yet powerful approach that can facilitate timely interventions, ultimately improving outcomes for individuals on the autism spectrum.

Moreover, our study highlights the potential of further refinement and development of this technique, through leveraging advancements in computer vision, machine learning, and deep learning, we can enhance the accuracy and efficiency of ASD detection methods. Furthermore, there is a compelling opportunity to translate these findings into practical solutions, such as the development of quick diagnostic applications. Such apps could empower parents and caregivers who may have concerns about their toddlers' development, providing them with accessible and actionable insights that can lead to early interventions and support.

This article,contributes to the growing body of literature on AI-driven ASD detection, emphasizing the significance of early identification and intervention. By harnessing the power of computer vision and AI technologies, we can pave the way for more accessible, efficient, and accurate diagnostic tools, ultimately improving the lives of individuals with ASD and their families. Moving forward, continued research and collaboration are essential to realize the full potential of these innovative approaches in addressing the complex challenges associated with ASD diagnosis and management.

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