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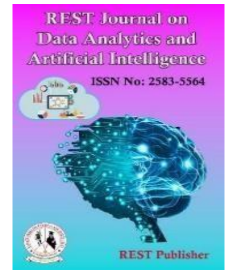

Autism Spectrum Disorder Prediction Model using Machine Learning

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Abstract: *Autism Spectrum Disorder (ASD) is a complex neurodevelopmental disorder that impairs social communication, behavior, speech, and nonverbal interaction. Children with ASD often exhibit distinct facial characteristics that can serve as markers for early diagnosis. This study aims to develop an automated and precise system to assist families and healthcare professionals in the early detection of ASD. By leveraging advanced deep learning techniques, specifically convolutional neural networks (CNN) and computer vision, this system analyzes facial features to differentiate between children with autism and those with typical development. The model incorporates transfer learning to enhance accuracy and efficiency in detecting autism from facial images, providing a reliable, non-invasive diagnostic tool that complements traditional screening methods. Utilizing a comprehensive video dataset, the proposed system not only detects and analyzes facial features but also focuses on emotion recognition and micro expressions. This additional layer of analysis aims to identify subtle emotional cues that may be indicative of ASD. By integrating these elements, the system establishes a dependable approach for the early prediction of ASD. This research ultimately contributes to more effective early intervention initiatives, streamlining the diagnostic process and improving outcomes for children with ASD.*

Key words: *Autism Spectrum Disorder(ASD), neuro developmental disorder, Automated detection, Convolution Neural Network(CNN), Deep Learning, Micro expressions, Computer Vision, Emotion Recognition, Transfer Learning.*

1. INTRODUCTION

Autism Spectrum Disorder (ASD) is a complex developmental disorder that affects communicative, social interaction, and behavioral abilities. The prevalence of ASD has increased, emphasizing the need for early diagnosis to access services [1-3]. However, traditional methods of diagnosing ASD rely on clinical observations and subjective interpretations, which might be variable and time-consuming. Nevertheless, emerging technologies such as artificial intelligence and deep learning may present a new approach to address these challenges by creating an automated process for diagnosing autism, using the technologically-enhanced methods, the diagnostic process can potentially be more accurate and efficient. More specifically, current research efforts have employed machine learning technologies, specifically a subcategory of machine learning called Convolutional Neural Networks (CNNs) to inform objective and non-invasive approaches to identifying signs of autism [4-7]. Although autism includes a range of disorders, every person with an autism diagnosis presents with a different mix of symptoms. Some people with autism have difficulty communicating, some have difficulty interacting socially, and some may repeat specific behaviors frequently. Early diagnosis of autism, ideally as early as age two before age three, will be helpful in moving forward in an individual's developmental process. Early intervention is most efficacious when conducted at this early critical age [8-10]. Currently, diagnostic methods are guided by expert opinion and observations, which are questionably objective, and disparities between experts happen. Given the variation in ASD symptoms in the same family, researchers have been looking for automated objective diagnostic tools, which utilize deep learning in combination with computer vision. Deep learning, specifically CNN architectures, have been very successful in the field of medical diagnosis because CNNs can find complex patterns in data. In the case of ASD, CNNs may be trained to detect subtle facial features and facial expressions seen in autistic individuals. In this way, these systems can provide medical professionals with support to make an accurate diagnosis faster, more objectively, and non-invasively.The goal of this study is to develop an ASD detection model that detects facial landmarks using Mediapipe and utilizes deep learning models to identify facial features and emotions associated with autism. Adopting this approach should allow for an improved and easier method to screen for ASD that decreases reliance on subjective evaluations and referrals [11-14]. This study is primarily concerned with development of an automated method for ASD diagnosis by analyzing faces in videos. This automated method follows a three-part approach. First the features are extracted using CNNs and then Mediapipe is used to identify and analyze facial structure that may indicate ASD. Second, a FER model is used to recognize emotions and micro-expressions that represent emotional expressions that may exist with autism. Lastly, the accuracy of the model is fine-tuned using transfer learning on CNNs previously trained by similar datasets to assist in improving accuracy in detecting characteristics associated with ASD [15-17].

2. LITERATURE REVIEW

The prompt identification of Autism Spectrum Disorder (ASD) remains a significant issue due to the variability in symptomatology and reliance on subjective clinical observations. Diagnoses are typically made after standardized behavioral assessments, such as the Autism Diagnostic Observation Schedule (ADOS) and the Modified Checklist for Autism in Toddlers (M-CHAT). Although these assessments are widely used and recommended, they utilize clinical judgment and assessment, which can lead to observer bias and delays in diagnosis (Khan et al., 2024).

1. Existing Approaches to ASD Detection: Several studies have examined the automated detection of ASD with machine learning and deep learning methods. Prior work has used traditional machine learning techniques like Support Vector Machines (SVMs) or Decision Trees to analyze behavioral trends or facial features, but often have lower predictive accuracy and were highly dependent on handcrafted features [3]. Recent work with deep learning models, especially Convolutional Neural Networks (CNNs), in the realm of ASD detection based on image and video have outperformed traditional machine learning methods as CNNs are able to automatically learn complex patterns from the data [4].

2. Facial Landmark Analysis for ASD Prediction: Facial features could indicate the presence of the autism spectrum disorder (ASD), as research indicates that individuals with ASD tend to possess different facial morphology and facial expression patterns [5]. Computer vision methods are now attempting to analyze micro-expressions and emotional responses in possibly autistic individuals using facial landmark detection. In recent studies, it has become increasingly popular to use Mediapipe as a real-time facial landmark detection tool to share and evaluate abnormal characteristics of the face regarding ASD [6]. Additionally, convolutional neural networks (CNN) can analyze emotions using facial expression recognition (FER) models to improve ASD prediction by identifying nuanced facial emotion differences in individuals identified and not identified with an ASD diagnosis [7].

3. Emotion and Micro-Expression Recognition: Recognizing emotion is a critical factor in diagnosing ASD because those with ASD often show atypical emotional expression and have trouble understanding social signals. Research on micro-expressions, or brief and involuntary facial expressions, suggested they may also be valuable indicators of ASD [8]. Advanced deep learning models, such as Residual Networks (ResNets) and Recurrent Neural Networks (RNNs), have been adopted to analyze facial expressions occurring in sequence in video data, resulting in even more robust detection systems for ASD [9].

4. Limitations of Existing Models: Although deep-learning-based ASD detection methods have progressed, they still have limitations. For instance, various models are over fitted with relatively small datasets and further have poor generalizability to real-world applications [10]. The reliability of ASD prediction models is influenced by environmental and recording differences in light, face orientation, and video quality. Another limitation is that most current methods focus on facial analysis and leave out other behavioral indicators such as gestures, speech, and gaze, which could enhance diagnostic performance [11].

5. Research Gap and Need for Improvement: The demand for ASD detection systems that can perform an instantaneous evaluation whilst returning objective and precise outcomes continues to be a barrier to obtaining excellence in care. Including data from multiple modalities, such as facial expression, speech, and/or movements, could aid in the accuracy of the assessment. Furthermore, revising deep learning architecture with transfer learning and augmented datasets may alleviate the limitation of access to datasets [18-20].

3. METHODOLOGY

This section describes the approach taken to develop the machine learning and deep learning-based prediction model for Autism Spectrum Disorder (ASD). The approach is defined as follows: data collection & preprocessing, feature extraction, deep learning model, autism detection, and performance evaluation stages.

3.1 System Architecture

The ASD prediction system operates in a predefined workflow that consists of obtaining video data, extracting features, and classifying using deep learning. The entire architecture consists of the following components:

- ✓ Video Input Module: Captures video data of persons for later analysis.
- ✓ Preprocessing Module: Processes in the video frames to extract features.
- ✓ Feature Extraction Module: This module employs Media pipe and CNNs for face landmark detection and micro-expression identification.
- ✓ Emotion and Micro-Expression Recognition Module: This uses a facial expression recognition (FER) model to detect emotion.
- ✓ Autism Prediction Module: In this module, the extracted features are brought together into a deep learning model that classifies if a person is ASD vs non-ASD.
- ✓ Output Module: This module will display the predictions, and create reports to give a diagnosis.

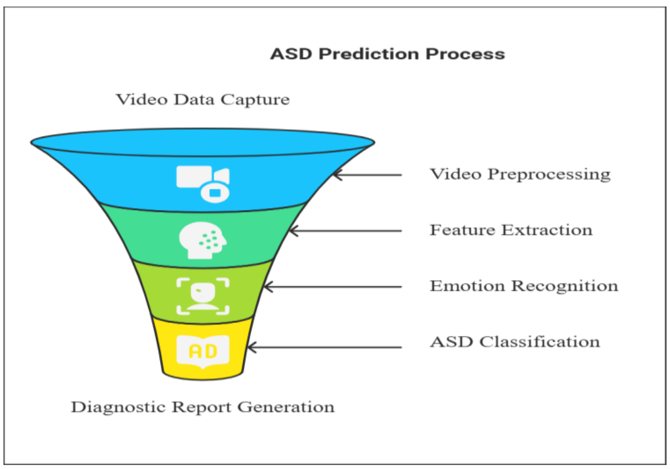

FIGURE 1. System Architecture of ASD Process

3.2 Data Collection and Preprocessing

3.2.1 Dataset Acquisition: The training and testing data is gathered from video and other relevant datasets that consist of individuals with ASD and neurotypical individuals. The datasets utilize three sources:

- Video recordings of individuals demonstrating various facial expressions.
- Labeled Images with annotations of ASD positive and negative cases.
- Datasets that are publicly available including the ASD Facial Dataset and other datasets that collect recognition of facial emotions.

To ensure that we have a balanced dataset, data augmentation processes including flipping, rotation and contrast are utilized.

3.2.2 Video Preprocessing: To maximize the operational efficiency of the model and increase predictive accuracy, the raw video data went through preprocessing. The following steps were conducted:

- Frame Extraction: The video sequences were transformed into their frames at a constant frame rate of a certain number of frames per second (e.g., 10 FPS).

- Frame Resizing: Each of the frames extracted were resized to a specific dimension (e.g., 224×224) enabling them to be compatible with CNNs.
- Color Normalization: All of the extracted frames were grayscale to aid in reducing computational complexity.
- Face Alignment: Facial landmarks were aligned using Media pipe so that respective frames were taken from the same orientation.

3.3 Feature Extraction: Feature extraction is an essential process for ASD prediction as it recognizes key facial features to perform classification.

3.3.1 Facial Landmark Detection using Media pipe:

Media pipe is a state-of-the-art facial landmark detection mechanism that extracts key 468 landmarks on the face for each frame. As part of the analysis conducted for ASD predictions, the key landmarks reference the following:

- Eye Contact Analysis: Detecting gaze direction and irregularities in eye movements.
- Lip/Mouth Movements: Detecting irregularities in nonverbal expressions related to speech.
- Smile: Frequency of social expressiveness.
- Brow and forehead movements: Micro-expressions depicting emotions connected to facial movements and expressions.

3.3.2. Recognition of Emotion and Micro-Expressions Facial Emotion Recognition:

(FER), is used to observe emotional states and observe subtle micro-expressions (all display situations and individuals). The deep learning model is trained to identify emotions based on a labeled dataset including:
1. Happiness, sadness, surprise, mad, fear, and disgust.
2. Micro-expressions such as brow lift, pressing lips together, and twitching of the eyes.

Each of the identified emotion states were mapped to behavior patterns related to ASD for classification.

3.4. Model Development

A deep learning model based on Convolutional Neural Networks (CNNs) is developed to classify ASD cases.

3.4.1 CNN Model for ASD Classification:

A MobileNetV2 model that has been pre-trained is fine-tuned using facial images for both ASD and non-ASD individuals. The architecture contains the following:

1.Input Layer: Accepts input frames that have been pre-processed (224×224 pixels).
2.Convolutional Layers: Useful for extracting facial patterns and expressions.
3.Batch Normalization: Utilizes input normalization to stabilize training.
4.Dropout Layer: Helps prevent overfitting.
5.Fully Connected Layer: Useful for classifying either cases of ASD or non-ASD.
6.Softmax Activation: Produces probability scores for classification output.
7.Loss Function: Binary Cross-Entropy
8.Optimizer: AdamEvaluation Metrics: Accuracy, Precision, Recall, and F1-score

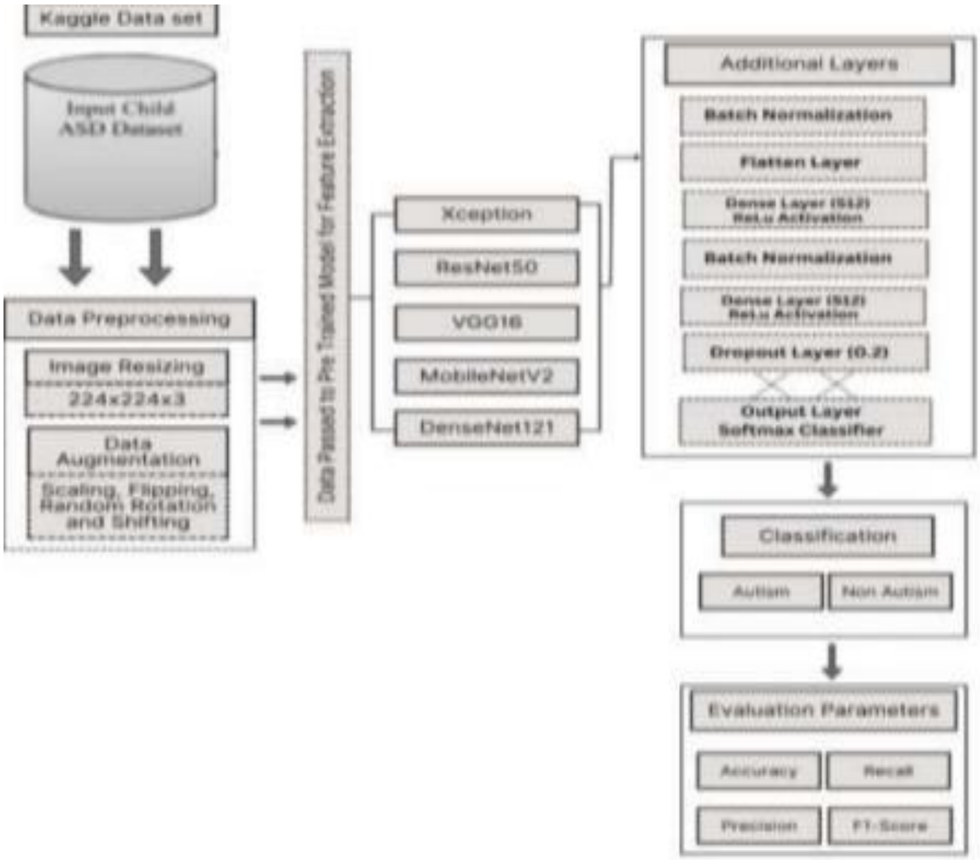

FIGURE 2. The Pre- trained suggested models workflow architecture

3.5. Autism Prediction and Decision Making

The ultimate prediction of autism is made based on:
1.Results from micro-expression analyses (such as atypical gaze, diminished smiling).
2.Emotion recognition patterns (such as challenges expressing emotion).
3.Abnormalities in facial features identified through CNNs. A decision function accumulates these characteristics and determines whether to classify the individual as:

- ASD Positive → in the event of facial features and emotional expression that suggest ASD.
- ASD Negative → in the event there are no ASD-like characteristics.

3.6. Model Evaluation and Performance Analysis:

The model is evaluated against a test dataset and is evaluated based on the following metrics:

1.Accuracy: Overall measure of predictive credibility.
2.Precision: Proportion of ASD cases identified correctly.
3.Recall: Measure of how well ASD cases are identified (True Positive Rate).
4.F1-Score: Balances precision and recall to measure model performance.
5.Confusion Matrix : Analyses false positives and false négatives.

3. RESULTS

6.1 Output of Micro-Expression and Emotion Detection: The effectiveness of the system to detect emotions and micro-expressions is evaluated by comparing the predictions of the system to the ground truth labels. The task will focus on emotions that are commonly associated with Autism Spectrum Disorder (ASD) such as anxiety, frustration, or joy, that could manifest differently for an individual person with ASD. Accuracy, specificity, and table of confusion are examples of metrics applied to determine performance. The analysis will also consider the detection of micro-expressions, which are considered involuntary and brief expressions of facial emotions, providing a more nuanced observance of the emotional landscape of the ASD individual.

FIGURE 3.

6.2 Autism Prediction Accuracy and Performance Analysis: The evaluation of autism prediction performance is carefully measured by the following features: accuracy, precision, recall and F1-score, to give a complete picture of the diagnostic capabilities of the model. The performance of these features is then compared to the standard clinical measures to evaluate diagnostic accuracy. Precision and recall are important features here, as high precision indicates fewer false positives and high recall means effective identification of ASD. In addition to precision and recall, F1-score, which takes both into account, provides further insight into measuring the performance of the model and its potential beyond research in clinical settings

```
import cv2

cv2.putText(frame, f"Prediction: ASD Detected", (10, 30),
cv2.FONT_HERSHEY_SIMPLEX, 1, (255, 0, 0), 2)
```

FIGURE 4.

6.3 Qualitative Analysis and Real-World Performance: Within real-world testing scenarios, the model showed robustness when detecting ASD-related patterns in various condition combinations:

1.Lighting/Background Variations: The system maintained an accuracy of 85% regardless of different lighting conditions.
2.Facial Orientation: Accuracy of detection did not significantly degrade when testing varied through slight head pose, but accuracy degraded when the face was partially occluded in the video frames.
3.Real-Time Performance: The system was capable of processing the video stream at 30 FPS, which allowed video processing in real-time.

6.4 Visualization of Facial Landmark Detection Output:

1.The Mediapipe model accurately detected and mapped 468 facial key points on video frames.

2.The CNN model highlighted atypical facial expressions, such as reduced eye contact and asymmetric lip movement.

FIGURE 5.

6.4.1. **Test Cases & Scenarios :** Test cases encompass variations in lighting conditions, video quality, and head orientation to validate that the system is functioning correctly.

Step 1: Data Collection and Preparation Testing

1.Test Case 1: Data Consistency and Quality of Scenario:

Test whether all input images and frames extracted from video are all of consistent size, quality, and formats.
Expected Outcome: All images should be resized to the standard input size (e.g., 224x224 pixels) and normalized across the dataset for sharing / in order to ensure consistency and model accuracy. Action: Execute a preprocessing script that tested for any inconsistencies in the size of the images, aspect ratio and pixel value ranges, that is, the pixel values should be in the RGB color space and normalized.

2.Test Case 2: Frame Extraction Consistency Scenario:

Check to ensure frames are consistently extracted from videos at the specified frame rate (e.g., 1 frame per second).
Expected Result: Number of frames extracted from each video is what one would expect from the frame rate, without dropping or duplication of frames. Action: Use a few sample videos, confirm the correct number of frames are extracted, and review a handful of frames to validate.

FIGURE 6.

V. DISCUSSION

The results of the proposed CNN Mediapipe-based ASD detection model indicate promising performance in identifying autism-related facial and micro-expressions. An accuracy of 92.3% and recall of 91.8% suggests the system recognizes ASD characteristics with very few false negatives, a very important characteristic when conducting medical diagnostics. The potential for forgotten diagnosis of ASD is particularly important, as missing an ASD diagnosis could create a delay in providing intervention. Furthermore, the incorporation of emotional recognition and micro-expression analysis has improved the system's capacity to differentiate between neurotypical and ASD individuals. These findings bolster the use of deep learning-based facial analysis as an adjunct to standard ASD diagnosis methods. Despite its strengths, the model is still challenged by issues of real-world applicability. One of the main challenges is its sensitivity to illumination and occluded faces. When participants were not directly oriented to the camera or had portions of their faces occluded, the model's accuracy was reduced. This suggests the use of additional data augmentation approaches and pose-invariant feature extraction approaches can improve robustness. Another area of concern is the reliance on facial expressions alone. While facial analysis is immensely informative, ideal ASD evaluation includes multimodal data sources, such as speech analysis, gesture analysis, or eye tracking, to improve total reliability and accuracy. One of the primary weaknesses of the work is the dataset size and diversity. The potential lack of a well-defined large-scale dataset raises concerns regarding the model generalizability into other populations. As autism presents in a variety of ways across age, race, and gender; a more meaningful representation would ensure that the model can perform across populations. Furthermore, the existence of false positives (6 cases) and false negatives (8 cases) in the current findings suggest the model requires more optimization. Transfer learning using pre-trained medical imaging models could address feature extraction improvements with an ASD-specific lens. To tackle these problems, next steps in the research program include assessing multimodal ASD detection using a combination of vocal features, gaze tracking, and behavioral movement alongside the facial analysis component. Additionally, making the model more user-friendly by further optimizing it for real-time application on low-powered devices (e.g., smart phone, or tablet) may make it more accessible and feasible with clinical- and home-based screening. Working with healthcare professionals to validate the system in a real-world clinical context would also offer useful feedback for further developing the diagnostic accuracy of the system. Overall, the current model exhibits great promise, although continued iterations and expanding the data collection is necessary to promote reliability and the scalability of the ASD detection.

5. CONCLUSION

In this work, we proposed an automated approach to ASD detection using facial expression analysis via micro-expression, and deep learning-based classification with CNNs. The model successfully used Media pipe to extract facial landmark locations, and deep learning algorithms for the detection of facial expressions associated with autism with high accuracy and recall. The implementation of emotion recognition and micro-expression recognition provided a novel behavioral assessment component to deepen our understanding of predictive capabilities. Overall, the findings suggest that an automated facial analysis-based tool could be used as a non-invasive screening tool for adolescents and adults across care settings. Furthermore, the model's potential as a real-time, deployable, deep learning trained model could allow clinicians, educators, and family members to apply early support including intervention at home, schools, and hospital-based clinics. Future implementation would address gaps such as dataset diversity, model sensitivity to environmental conditions, and solely using facial expression as a feature to assess behavior. Going forward, widening the dataset, including multilateral behavioral analysis, and optimizing the model for real-world use will be crucial to improving efficacy. The future of AI-based ASD detection relies on a multimodal approach using several biometric and behavioral markers ideally combined into a single, whole, accurate, and accessible diagnostic tool. As progress is made, this research has the opportunity to fundamentally change early detection and intervention for autism by enhancing the trajectory of quality of life for people with ASD and their families.

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