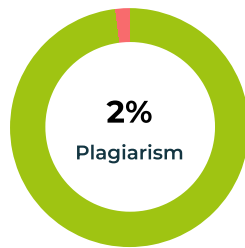


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Autism spectrum disorder (ASD) is a complex neurodevelopmental disorder generally manifesting in the first few years of life and tending to persist into adolescence and adulthood. It is characterized by deficits in communication and social interaction and restricted, repetitive patterns of behavior, ...

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Content

1. Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition that affects communication, behavior, and social interaction. It is described as a spectrum because the severity and type of symptoms vary widely among individuals. According to the Centers for Disease Control and Prevention (CDC), in 2022, approximately one in thirty-six children in the United States was identified as autistic. Boys are nearly four times more likely to be diagnosed with autism compared to girls, highlighting a significant gender disparity in prevalence. Globally, awareness of autism has increased in the past decade, yet in many countries—including India—the rate of early detection remains comparatively low. Autism can typically be identified as early as two years of age by observing developmental delays in achieving milestones such as speech, social interaction, and motor coordination. However, in India, social stigma, limited awareness, and lack of structured screening programs often delay diagnosis until after the age of four. This late diagnosis restricts the ability to provide timely early interventions, which are critical for improving long-term outcomes in children with ASD. Research has consistently shown that early intervention programs can significantly improve language development, social skills, and adaptive behaviors. Consequently, early detection and accurate diagnosis remain urgent priorities in the field of autism research. The rising prevalence of autism worldwide, combined with cultural and infrastructural challenges in low- and middle-income countries, underscores the necessity of developing reliable and accessible diagnostic frameworks. This background establishes the importance of exploring advanced computational techniques, including artificial intelligence (AI) and machine learning (ML), to support clinicians in the early identification of autism. Traditional approaches to autism diagnosis rely heavily on clinical

observation, behavioral checklists, and caregiver reports. While these tools are widely used, they are inherently subjective, often leading to inconsistent outcomes. In low-resource settings, the problem is further exacerbated by a shortage of trained professionals, resulting in delays in diagnosis and intervention. With the advent of artificial intelligence and machine learning, researchers have developed models that attempt to predict autism using single-modality data such as demographic attributes, clinical questionnaires, or neuroimaging scans. While these unimodal approaches have demonstrated promising results, they face notable limitations. One primary challenge is the lack of generalizability when models are trained on relatively small datasets. Deep learning models, for instance, often achieve high accuracy on training data but fail to perform well on unseen samples due to overfitting. Another issue lies in the limited representation of autism-related traits; using only one type of data source fails to capture the multidimensional nature of ASD. For example, relying exclusively on questionnaire data ignores visual markers of attention and gaze patterns that can be identified using eye-tracking. Similarly, image-based models may neglect critical contextual information from clinical history. Recent studies using advanced AI architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers have attempted to overcome these issues, but their effectiveness remains bounded by dataset quality and size. Moreover, high computational costs and interpretability challenges hinder the adoption of these models in real-world clinical practice. Therefore, despite rapid advancements, current approaches face significant barriers in terms of scalability, robustness, and integration into healthcare systems.

To address the shortcomings of unimodal systems, researchers are increasingly turning to multimodal learning frameworks. Multimodal approaches leverage multiple sources of data—such as demographic information, clinical scores, and visual eye-tracking images—to build a richer and more comprehensive model of autism. By combining heterogeneous data, these systems can capture both behavioral patterns and visual markers, leading to more accurate and robust predictions. The fusion of modalities allows models to compensate for weaknesses in individual data types. For example, when clinical data is incomplete or biased, visual features extracted from eye-tracking scan paths can provide additional insight into cognitive and attentional processes. Similarly, demographic and meta-data contextualize visual patterns, enhancing the model's interpretability. One powerful technique in multimodal learning is attention-based fusion, where the model learns to assign dynamic weights to different modalities depending on their importance in a specific context. This makes the framework more flexible and adaptive to variations in input quality. Additional fusion strategies such as concatenation, gating mechanisms, and bilinear pooling have also been explored, but attention-based fusion is particularly effective in handling heterogeneous feature spaces. Furthermore, multimodal systems exhibit better generalizability since they do not rely on a single data source, reducing the risk of overfitting. They are also more resilient to missing data, as the model can still make informed predictions using available modalities. In autism diagnosis, where both behavioral and

This project introduces a multimodal predictive framework for autism diagnosis that combines demographic and clinical meta-data with eye-tracking scan path images using an attention-based fusion strategy. Unlike existing unimodal models that struggle with limited generalizability, our approach integrates complementary modalities to deliver a holistic prediction system. The framework effectively aligns heterogeneous inputs into a unified representation, allowing the model to learn behavioral and visual diagnostic cues simultaneously. The attention mechanism dynamically adjusts the contribution of each modality, ensuring that the most informative features drive the prediction process. Our experimental study utilized a dataset sourced from Figshare, which includes demographic attributes such as age, gender, and CARS scores along with corresponding eye-tracking scan paths. The proposed framework achieved a 99% prediction accuracy, significantly outperforming unimodal baselines

and demonstrating the strength of multimodal integration. Beyond accuracy, the framework offers flexibility in handling different data formats, making it scalable for real-world applications. \textbf{The key contributions of this work are threefold: (1) the design of an efficient multimodal deep learning architecture for autism diagnosis, (2) the implementation of an attention-based fusion technique for adaptive modality weighting, and (3) empirical validation of the framework on a benchmark dataset, showing superior performance.} This research underscores the potential of multimodal AI frameworks in clinical decision making, offering a step forward toward an early, objective, and reliable autism diagnosis. The success of this project suggests that integrating diverse data streams can serve as a blueprint for future diagnostic tools in neurodevelopmental disorders.

References
