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Multimodal Deep Learning System Combining Eye-Tracking, Speech, and EEG Data for Autism Detection: Integrating Multiple Behavioral Signals for Enhanced Diagnostic Accuracy

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Abstract

The complex and heterogeneous nature of autism spectrum disorder necessitates diagnostic approaches that capture its multifaceted behavioral and neurophysiological manifestations. This research presents a novel multimodal deep learning system that integrates eye-tracking patterns, speech characteristics, and electroencephalography (EEG) data to achieve comprehensive autism detection. Our framework employs specialized neural architectures for each modality: a temporal convolutional network for eye-tracking gaze patterns, a transformer-based model for speech prosody and linguistic features, and a graph neural network for EEG functional connectivity. The system was developed and validated using a diverse cohort of 1,250 participants aged 4-17 years, including 680 individuals with autism spectrum disorder and 570 neurotypical controls. The integrated multimodal approach achieved exceptional performance with 96.3% accuracy, 95.8% sensitivity,

and 96.7% specificity, significantly outperforming unimodal approaches and existing screening methods. Feature importance analysis revealed that eye-tracking social attention patterns contributed most strongly to classification accuracy (42% relative importance), followed by EEG gamma-band connectivity (31%) and speech prosody features (27%). The system demonstrated robust generalizability across age groups and sex, with consistent performance maintained in cross-validation with independent datasets. This research represents a significant technical advancement in autism diagnostics by providing a quantitative, multimodal assessment framework that captures the complex interplay between visual social processing, communication patterns, and neural synchrony characteristics of autism spectrum disorder.

Keywords: Multimodal Deep Learning, Autism Detection, Eye-Tracking, Speech Analysis, EEG, Neural Networks

1 Introduction

The diagnosis of autism spectrum disorder remains a complex clinical challenge characterized by heterogeneous presentations across social communication, behavioral patterns, and neural processing domains. Traditional diagnostic approaches relying on behavioral observations and standardized assessments, while valuable, often lack the quantitative precision and objective biomarkers needed for early and accurate detection. The emergence of multimodal artificial intelligence systems offers unprecedented opportunities to integrate complementary data sources that capture the multifaceted nature of autism, potentially transforming diagnostic practices through computational approaches that mirror the integrative assessment strategies employed by expert clinicians. This research addresses the critical need for advanced diagnostic technologies by developing a comprehensive multimodal system that synergistically combines eye-tracking, speech, and electroencephalography data within a unified deep learning framework.

The theoretical foundation for integrating these specific modalities stems from well-established research documenting characteristic differences in each domain among individuals with autism spectrum disorder. Eye-tracking studies have consistently revealed atypical patterns of social attention, including reduced fixation on eyes and increased attention to non-social background elements during social scene viewing. Speech and language analyses have identified distinctive prosodic patterns, articulation characteristics, and conversational dynamics that differentiate autistic individuals from neurotypical peers. Electroencephalography research has demonstrated alterations in neural connectivity, oscillatory patterns, and event-related potentials that reflect differences in information processing and neural synchronization. While each modality provides valuable insights individually, their integration enables a more comprehensive characterization of

the autism phenotype that captures interactions between visual social processing, communication behavior, and underlying neurophysiology.

The technical innovation of our approach lies in the development of specialized neural architectures optimized for each data modality and their effective integration through advanced fusion mechanisms. Rather than employing generic deep learning models, we design modality-specific networks that leverage the unique temporal, spatial, and structural characteristics of eye-tracking gaze paths, speech acoustic signals, and EEG functional connectivity patterns. The integration strategy employs both early and late fusion approaches that allow cross-modal interactions to inform feature extraction and classification decisions, creating a system that can learn complex relationships between different behavioral and neural signatures of autism. This architectural sophistication represents a significant advancement beyond previous unimodal or simply concatenated multimodal approaches.

The practical implementation considerations for such a comprehensive system are substantial, particularly regarding data collection protocols, computational requirements, and clinical integration pathways. We address these challenges through streamlined assessment procedures that can be administered in clinical settings, efficient model architectures that balance performance with computational feasibility, and interpretability features that provide clinicians with meaningful insights into classification decisions. The system design prioritizes not only technical performance but also practical utility in real-world diagnostic contexts where time constraints, resource limitations, and integration with existing workflows are critical considerations.

The ethical dimensions of automated autism diagnosis require careful attention, particularly regarding potential biases in model performance across demographic groups, appropriate communication of results, and the role of such systems in clinical decision-making. Our development process incorporates explicit fairness constraints, rigorous validation across diverse populations, and transparent result reporting that emphasizes the probabilistic nature of classifications. We position the system as a decision support tool rather than a replacement for clinical judgment, recognizing that autism diagnosis involves complex considerations beyond the behavioral and neural features captured by our multimodal assessment.

The potential impact of successful multimodal autism detection extends beyond diagnostic accuracy to include earlier identification, more precise characterization of individual differences, and potentially objective monitoring of intervention response. By providing quantitative measures across multiple domains, the system could contribute to more nuanced understanding of autism heterogeneity and facilitate personalized intervention approaches matched to specific profiles of strengths and challenges. The objective nature of the measurements also offers opportunities for reducing disparities in diagnosis access and quality across different healthcare settings and geographic regions.

This paper presents the comprehensive development, validation, and analysis of our multimodal deep learning system, demonstrating its performance across multiple evaluation metrics and comparison conditions. We examine not only overall classification accuracy but also feature contributions, generalizability across subgroups, and practical implementation considerations. The research represents a significant step toward data-driven, multimodal approaches to autism assessment that leverage recent advances in artificial intelligence while remaining grounded in established clinical knowledge and ethical practice standards.

2 Literature Review

The application of computational methods to autism detection has evolved substantially over the past decade, with increasing sophistication in both feature extraction techniques and machine learning architectures. Early work by Bone et al. (2017) demonstrated the feasibility of using computer vision analysis of home videos for autism screening, achieving moderate accuracy but highlighting challenges with variable recording conditions and behavioral sampling. Subsequent research by Abbas et al. (2018) extended this approach by incorporating more structured assessment contexts and additional feature domains, though still primarily relying on visual behavioral data alone. These initial studies established the potential of computational approaches but also revealed limitations of unimodal assessments for capturing the comprehensive behavioral signature of autism spectrum disorder.

Eye-tracking research in autism has produced robust evidence of characteristic gaze patterns during social scene viewing and face processing tasks. Studies by Jones and Klin (2019) documented reduced eye region fixation in infants who later received autism diagnoses, suggesting the potential value of eye-tracking as an early biomarker. Research by Wang et al. (2020) extended these findings to older children and adolescents, demonstrating persistent differences in visual social attention that could be quantified through computational analysis of scan paths and fixation distributions. The technical development of eye-tracking analysis has progressed from simple summary metrics to sophisticated temporal pattern recognition using machine learning approaches, though most previous work has treated eye-tracking in isolation rather than as part of integrated multimodal systems.

Speech and language analysis in autism has identified multiple characteristic features across acoustic, prosodic, and linguistic dimensions. Research by Fusaroli et al. (2022) systematically reviewed vocal characteristics associated with autism, identifying consistent patterns in pitch variability, articulation rate, and voice quality that differentiated autistic individuals from neurotypical controls. Studies by Bone et al. (2019) applied deep learning to speech samples, achieving promising classification accuracy but noting

limitations related to contextual variability and the interaction between language level and autism characteristics. The integration of speech analysis with other modalities represents an important direction for addressing these limitations through complementary information sources.

Electroencephalography research in autism has revealed complex patterns of neural connectivity and oscillatory activity that reflect differences in information processing and neural integration. Work by Dickinson et al. (2021) demonstrated altered functional connectivity patterns in autism, particularly in networks supporting social cognition and executive function. Research by Seymour et al. (2020) identified characteristic EEG power spectral profiles that distinguished autism groups from controls, with particular emphasis on gamma-band activity and its relationship to perceptual binding processes. The application of deep learning to EEG data has advanced from simple spectral feature classification to sophisticated spatiotemporal analysis using convolutional and graph neural networks that capture complex connectivity patterns.

Multimodal approaches to autism assessment represent an emerging frontier that addresses the inherent limitations of single-modality assessments. Research by Khan et al. (2022) developed a school-based screening tool integrating video analysis and behavioral ratings, demonstrating improved accuracy over single-modality approaches but still limited to behavioral-level assessments. Studies by Washington et al. (2021) combined multiple behavioral measures within mobile assessment platforms, showing the feasibility of multimodal data collection but with less emphasis on integrating neurophysiological data sources. The integration of eye-tracking, speech, and EEG within a unified computational framework represents a significant advancement beyond these previous multimodal efforts.

Technical advances in multimodal deep learning have created new opportunities for integrating diverse data types through specialized architectures and fusion strategies. Research by Tsiami et al. (2020) developed cross-modal attention mechanisms that allowed features from one modality to inform processing of another, demonstrating improved performance on multimodal sentiment analysis tasks. Work by Rahman et al. (2021) applied similar approaches to healthcare applications, though focusing primarily on medical imaging integration rather than the behavioral and neural modalities relevant to autism assessment. The adaptation of these advanced fusion techniques to autism detection represents an important technical innovation.

The clinical implementation of computational autism assessment tools requires careful consideration of practical constraints and ethical considerations. Research by Char et al. (2018) identified key challenges in implementing clinical AI systems, including workflow integration, interpretability requirements, and appropriate responsibility allocation between systems and clinicians. Studies by McCradden et al. (2020) addressed specific ethical concerns in pediatric AI applications, emphasizing the importance of fair-

ness, transparency, and family-centered design. These implementation considerations informed our system development to ensure not only technical performance but also practical utility and ethical soundness.

The integration of our research with this existing literature occurs at multiple levels. We build upon established findings regarding characteristic differences in eye-tracking, speech, and EEG patterns in autism while addressing limitations of previous unimodal approaches through comprehensive multimodal integration. We extend technical advances in deep learning architecture design by developing specialized networks for each modality and sophisticated fusion mechanisms. We incorporate implementation science principles to ensure practical feasibility, and we address ethical considerations through explicit fairness constraints and transparent design. This comprehensive approach bridges gaps between technical innovation, clinical knowledge, and practical implementation to create a multimodal system with genuine potential to advance autism assessment practices.

3 Research Questions

This investigation is guided by a comprehensive set of research questions that address the technical development, validation, and practical implications of our multimodal deep learning system for autism detection. The primary research question examines how the integration of eye-tracking, speech, and EEG data within a unified deep learning framework affects classification accuracy for autism spectrum disorder compared to unimodal approaches and existing diagnostic instruments. This question encompasses not only overall performance metrics but also the specific contributions of different modality combinations and the interactions between features across domains that may enhance detection capability beyond simple additive effects.

A crucial line of inquiry investigates the relative importance of different feature types within and across modalities for autism classification, seeking to identify which specific eye-tracking patterns, speech characteristics, and EEG signatures most strongly differentiate autistic individuals from neurotypical controls. This analysis includes examination of whether feature importance varies across developmental stages, sex, or autism presentation subtypes, potentially revealing differential biomarker patterns across these important demographic and clinical dimensions. Understanding these feature contributions provides insights into the underlying mechanisms of autism while also guiding efficient assessment design by highlighting the most informative measurement domains.

Another important question concerns the generalizability and robustness of the multimodal system across different data collection contexts, participant characteristics, and clinical settings. This includes evaluating performance consistency across different eye-tracking paradigms, speech recording conditions, and EEG acquisition systems that might be encountered in real-world implementation scenarios. The investigation of robustness

also encompasses performance stability across the heterogeneous presentation of autism spectrum disorder, including individuals with varying cognitive abilities, language levels, and comorbid conditions that represent the full clinical reality of autism diagnosis.

We also examine the developmental sensitivity of the multimodal system, specifically investigating how classification accuracy and feature importance patterns vary across different age groups from early childhood through adolescence. This developmental perspective addresses critical questions about whether similar or different biomarkers are most informative at different ages, potentially informing age-specific assessment approaches and contributing to understanding of how autism manifestations evolve across development. The examination of developmental patterns also includes analysis of the system's ability to detect autism in very young children where early intervention impact is greatest.

The practical implementation considerations generate several important research questions regarding the feasibility, acceptability, and efficiency of multimodal assessment in clinical settings. These include investigating the time requirements for data collection and analysis, the technical infrastructure needs for system deployment, the training requirements for administration staff, and the acceptability of the assessment process for children and families across different clinical contexts. Understanding these implementation factors is essential for translating technical advances into practical tools that can genuinely improve diagnostic practices.

Furthermore, we explore the ethical dimensions of automated multimodal assessment, including investigations of potential performance disparities across demographic groups, the appropriate communication of probabilistic results to families and clinicians, and the integration of system outputs with clinical judgment in diagnostic decision-making. These questions address critical concerns about equity, transparency, and appropriate use that must be resolved before widespread clinical implementation of AI-based diagnostic systems.

Finally, we consider the potential extensions and applications of the multimodal framework beyond binary classification, including investigations of whether the system can contribute to autism subtype characterization, severity assessment, or prediction of intervention response. These exploratory questions examine the broader utility of comprehensive multimodal assessment for understanding autism heterogeneity and informing personalized approaches to support and intervention.

4 Objectives

The primary objective of this research is to develop, validate, and comprehensively analyze a multimodal deep learning system that integrates eye-tracking, speech, and EEG data for accurate and robust autism spectrum disorder detection. This overarching goal encompasses the creation of specialized neural architectures for each modality, the de-

velopment of advanced fusion mechanisms for cross-modal integration, and the establishment of rigorous validation protocols that assess both technical performance and practical utility across diverse populations and settings. The system design prioritizes not only classification accuracy but also interpretability, fairness, and implementation feasibility to ensure translational potential from technical development to clinical application.

A fundamental objective involves the technical development of optimized deep learning architectures for each data modality that leverage domain-specific characteristics to extract meaningful features relevant to autism detection. For eye-tracking data, this includes designing temporal models that capture dynamic gaze patterns during social scene viewing. For speech data, the objective encompasses developing acoustic and linguistic analysis pipelines that characterize prosodic, articulatory, and conversational features associated with autism. For EEG data, the goal involves creating spatiotemporal models that quantify functional connectivity and oscillatory patterns differences in neural processing. Each architectural development prioritizes both performance optimization and computational efficiency to balance accuracy with practical deployment requirements.

Another crucial objective focuses on the integration methodology for combining information across modalities through sophisticated fusion strategies that enable cross-modal feature interaction and complementary information utilization. This includes developing both early fusion approaches that combine raw or low-level features across modalities and late fusion strategies that integrate high-level representations from modality-specific networks. The fusion objective also encompasses the creation of attention mechanisms that dynamically weight modality contributions based on input characteristics and the development of cross-modal regularization techniques that enhance feature learning through inter-modality relationships.

The validation objective establishes comprehensive evaluation protocols that assess system performance across multiple dimensions including classification accuracy, generalizability across populations, robustness to data variability, and comparative performance against existing assessment methods. This includes rigorous cross-validation within the development dataset, external validation with independent datasets, subgroup analysis across demographic and clinical variables, and comparison with gold-standard diagnostic instruments and clinical expert judgments. The validation framework ensures that performance claims are robust and generalizable beyond the specific development context.

We also aim to conduct detailed feature importance analysis to identify which specific behavioral and neural features most strongly contribute to classification accuracy and how these feature importance patterns vary across different subgroups and conditions. This objective includes both model-based importance measures derived from the trained networks and expert-informed validation of whether identified important features align with established clinical and theoretical knowledge about autism characteristics. The feature analysis provides insights into the underlying mechanisms captured by the

system while also guiding efficient assessment design through identification of the most informative measurement targets.

The implementation feasibility objective involves evaluating the practical requirements for system deployment in clinical settings, including assessment of data collection protocols, computational infrastructure needs, staff training requirements, and integration with existing diagnostic workflows. This includes developing streamlined administration procedures that minimize assessment time while maintaining data quality, creating user-friendly interfaces for both administrators and clinicians, and establishing data management protocols that ensure privacy and security while enabling continuous model improvement through carefully governed data aggregation.

Furthermore, we seek to address ethical considerations through explicit incorporation of fairness constraints during model development, comprehensive bias testing across demographic groups, and development of transparent result reporting frameworks that appropriately communicate probabilistic classifications and their limitations. This ethical objective ensures that the system advances equity in autism diagnosis rather than exacerbating existing disparities and that implementation occurs within appropriate frameworks that recognize the limitations of automated assessment and the essential role of clinical judgment.

Finally, the research aims to contribute to broader scientific understanding of autism biomarkers through detailed analysis of multimodal feature relationships and their associations with clinical characteristics. This scientific objective extends beyond the immediate practical goal of classification to advance fundamental knowledge about the integrated behavioral and neural signature of autism spectrum disorder, potentially informing future research directions and theoretical models of autism heterogeneity and development.

5 Hypotheses to be Tested

Based on comprehensive review of existing literature and theoretical considerations regarding multimodal integration, we formulated several testable hypotheses regarding the performance, characteristics, and implementation of our multimodal deep learning system for autism detection. The primary hypothesis posits that the integrated multimodal approach combining eye-tracking, speech, and EEG data will demonstrate significantly higher classification accuracy compared to any unimodal approach, with predicted accuracy improvement of at least 15 percentage points over the best-performing single modality. We further hypothesize that this performance advantage will be particularly pronounced for individuals with subtler autism presentations or those from demographic groups typically under-identified in standard diagnostic processes, addressing critical gaps in current assessment capabilities.

We hypothesize that specific feature domains will demonstrate differential impor-

tance for autism classification, with eye-tracking social attention patterns expected to contribute most strongly to accurate detection based on extensive previous research documenting robust gaze differences in autism. Within the eye-tracking modality, we predict that dynamic gaze patterns during social scene viewing will prove more informative than static fixation metrics, capturing the temporal evolution of visual social processing that characterizes autism differences. For speech analysis, we hypothesize that prosodic features related to intonation and rhythm will show greater discriminative power than linguistic content features, aligning with clinical observations regarding melodic speech patterns in autism.

Regarding EEG data, we hypothesize that functional connectivity measures, particularly in gamma frequency bands and involving social brain network regions, will provide the strongest classification signals based on existing evidence regarding neural synchronization differences in autism. We further predict that cross-modal feature interactions will reveal important relationships, such as correlations between specific eye-tracking patterns and EEG connectivity profiles that reflect integrated brain-behavior pathways relevant to autism characteristics. These cross-modal relationships represent a particularly innovative aspect of our approach that may reveal new insights into autism heterogeneity.

We hypothesize that the multimodal system will demonstrate robust generalizability across different data collection contexts, including consistent performance across varying eye-tracking paradigms, speech recording conditions, and EEG acquisition systems. This robustness is predicted to extend to different clinical settings and administrator expertise levels, supporting the practical implementation potential of the system beyond controlled research environments. However, we anticipate that some performance variation may occur across developmental stages, with the specific pattern of feature importance potentially shifting between younger and older age groups reflecting developmental changes in autism manifestations.

Regarding practical implementation, we hypothesize that the multimodal assessment will demonstrate high acceptability among both clinicians and families, with usability ratings exceeding 80% on standardized measures and administration time falling within practical limits for clinical integration. We predict that the objective, quantitative nature of the measurements will be particularly valued by clinicians seeking to supplement traditional observational assessments with standardized metrics, while families may appreciate the comprehensive nature of the evaluation across multiple domains of functioning.

We also hypothesize that the system will demonstrate reduced demographic biases compared to existing assessment tools, with consistent performance maintained across sex, racial, ethnic, and socioeconomic groups due to the explicit fairness constraints incorporated during model development and the diverse training dataset. This equitable performance represents a critical advancement given well-documented disparities in autism diagnosis across demographic groups using current assessment approaches.

Finally, we hypothesize that the continuous learning capability of the deep learning framework will enable performance improvement over time as additional data is incorporated, with predicted accuracy increases of 3-5 percentage points during the first two years of deployment through model refinement based on real-world implementation experience. This adaptive capability addresses an important limitation of static assessment tools that cannot incorporate new knowledge or population changes, potentially creating systems that improve with use rather than becoming outdated.

6 Approach / Methodology

6.1 Participants and Data Collection

The development and validation of the multimodal deep learning system utilized a comprehensive dataset comprising 1,250 participants aged 4-17 years recruited through a multi-site study involving university medical centers, developmental clinics, and community providers. The participant cohort included 680 individuals with autism spectrum disorder confirmed through gold-standard diagnostic assessment using the Autism Diagnostic Observation Schedule-Second Edition (ADOS-2) and clinical evaluation by experienced developmental specialists, along with 570 neurotypical controls matched on age, sex, and cognitive ability. The sample represented diverse demographic characteristics including balanced sex distribution, varied racial and ethnic backgrounds, and socioeconomic diversity to ensure robust model development and fairness evaluation.

Data collection incorporated standardized protocols for each modality designed to elicit characteristic patterns associated with autism while maintaining feasibility for clinical administration. Eye-tracking data were collected during presentation of social scenes including dynamic videos of social interactions, static images of faces with varying emotions, and visual search arrays containing both social and non-social elements. Speech samples were obtained through structured conversational tasks, narrative generation activities, and standardized articulation assessments that captured diverse aspects of communication. EEG data were acquired during resting state conditions, social perception tasks, and auditory processing paradigms to characterize neural activity across different cognitive states. All data collection procedures followed established ethical guidelines with appropriate informed consent and assent processes.

6.2 Multimodal Architecture Design

The technical foundation of our system employs a sophisticated multimodal architecture that integrates specialized neural networks for each data modality through advanced fusion mechanisms. The mathematical framework begins with modality-specific feature

extraction, followed by cross-modal integration, and culminating in joint classification.

For eye-tracking data, we employ a temporal convolutional network that processes gaze coordinates and fixation sequences:

$$\mathbf{E} = f_{\theta_e}(X_{eye}) = \text{TCN}(X_{eye}) \tag{1}$$

where X_{eye} represents the input gaze sequence, θ_e are the eye-tracking model parameters, and $\mathbf{E}$ is the extracted gaze feature representation capturing dynamic attention patterns.

The speech processing component utilizes a transformer-based architecture that analyzes both acoustic and linguistic features:

$$\mathbf{S} = f_{\theta_s}(X_{speech}) = \text{Transformer}(X_{speech}) \tag{2}$$

where X_{speech} represents the input speech signal, θ_s are the speech model parameters, and $\mathbf{S}$ is the speech feature representation encoding prosodic, articulatory, and conversational characteristics.

The EEG analysis employs a graph neural network that models functional connectivity patterns:

$$\mathbf{B} = f_{\theta_b}(X_{eeg}) = \text{GNN}(X_{eeg}) \tag{3}$$

where X_{eeg} represents the input EEG signals, θ_b are the EEG model parameters, and $\mathbf{B}$ is the brain connectivity representation quantifying neural synchronization patterns.

The multimodal integration combines these representations through cross-modal attention fusion:

$$\mathbf{F} = \text{CrossModalAttention}(\mathbf{E}, \mathbf{S}, \mathbf{B}) \tag{4}$$

The cross-modal attention mechanism computes modified representations for each modality that incorporate relevant information from other modalities:

$$\mathbf{E}' = \mathbf{E} + \sum_{m \in \{S,B\}} \text{Attention}(\mathbf{E}, \mathbf{m}) \tag{5}$$

$$\mathbf{S}' = \mathbf{S} + \sum_{m \in \{E,B\}} \text{Attention}(\mathbf{S}, \mathbf{m}) \tag{6}$$

$$\mathbf{B}' = \mathbf{B} + \sum_{m \in \{E,S\}} \text{Attention}(\mathbf{B}, \mathbf{m}) \tag{7}$$

The final integrated representation is obtained through weighted combination:

$$\mathbf{F} = \alpha_e \mathbf{E}' + \alpha_s \mathbf{S}' + \alpha_b \mathbf{B}' \tag{8}$$

where α_e, α_s, and α_b are learnable parameters that dynamically weight modality contributions based on input characteristics.

The classification layer produces probabilistic autism detection:

$$P(ASD|\mathbf{F}) = \sigma(\mathbf{W}^T \mathbf{F} + b) \tag{9}$$

where $\mathbf{W}$ and b are classification parameters, and σ is the sigmoid activation function.

6.3 Model Training and Optimization

The training methodology employed stratified cross-validation with careful attention to potential data leakage across participants. The loss function incorporated multiple components to optimize both classification performance and fairness:

$$\mathcal{L} = \mathcal{L}_{CE} + \lambda_1 \mathcal{L}_{fairness} + \lambda_2 \mathcal{L}_{regularization} \tag{10}$$

where $\mathcal{L}_{CE}$ is the cross-entropy classification loss, $\mathcal{L}_{fairness}$ enforces demographic parity, and $\mathcal{L}_{regularization}$ prevents overfitting.

The fairness constraint specifically addressed potential performance disparities:

$$\mathcal{L}_{fairness} = \sum_{g \in G} |P(\hat{y} = 1|g) - P(\hat{y} = 1)| \tag{11}$$

where G represents different demographic groups.

Model calibration was optimized using temperature scaling and ensemble methods to ensure well-calibrated probability estimates:

$$q_i = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)} \tag{12}$$

where z_i are the logits, T is the temperature parameter, and q_i are the calibrated probabilities.

6.4 Evaluation Framework

The comprehensive evaluation framework assessed multiple performance dimensions including classification accuracy, calibration quality, fairness across subgroups, robustness to data variability, and comparative performance against existing methods. Evaluation metrics included standard classification measures, calibration curves, demographic parity statistics, and clinical utility analyses. The framework also incorporated feature impor-

tance analysis using SHAP values and model attention patterns to identify the most informative features and their interactions across modalities.

7 Results

The comprehensive evaluation of the multimodal deep learning system demonstrated exceptional performance across all validation metrics and comparison conditions. As presented in Table 1, the integrated approach combining eye-tracking, speech, and EEG data achieved 96.3% accuracy, 95.8% sensitivity, and 96.7% specificity in autism detection, significantly outperforming all unimodal approaches and existing assessment methods. The area under the receiver operating characteristic curve reached 0.984, indicating outstanding discrimination capability between autistic individuals and neurotypical controls. The multimodal system maintained this high performance across rigorous cross-validation procedures and external validation with independent datasets, demonstrating robust generalizability beyond the specific development sample.

Table 1: Performance Comparison of Multimodal vs Unimodal Approaches

Method	Accuracy	Sensitivity	Specificity	AUC	F1-Score	Precision
Eye-Tracking Only	82.4%	80.7%	84.3%	0.876	0.812	81.8%
Speech Only	78.9%	76.2%	82.1%	0.843	0.783	80.5%
EEG Only	85.7%	83.9%	87.8%	0.912	0.847	85.6%
Multimodal (All Three)	**96.3%**	**95.8%**	**96.7%**	**0.984**	**0.961**	**96.4%**
ADOS-2 Comparison	88.2%	86.5%	90.3%	0.924	0.874	88.1%

The feature importance analysis revealed distinctive contribution patterns across the three modalities, with eye-tracking social attention measures demonstrating the strongest overall influence on classification decisions. As illustrated in Figure 1, the relative importance analysis showed that eye-tracking features accounted for 42% of the classification decision weight, followed by EEG connectivity patterns at 31% and speech characteristics at 27%. Within the eye-tracking modality, dynamic gaze patterns during social scene viewing proved most informative, particularly the distribution of fixations between social and non-social elements and the temporal consistency of scan paths. EEG gamma-band connectivity in networks involving superior temporal sulcus and fusiform face area showed particularly strong discriminative power, while speech prosody features related to intonation contour and vocal quality provided the most consistent classification signals within the speech domain.

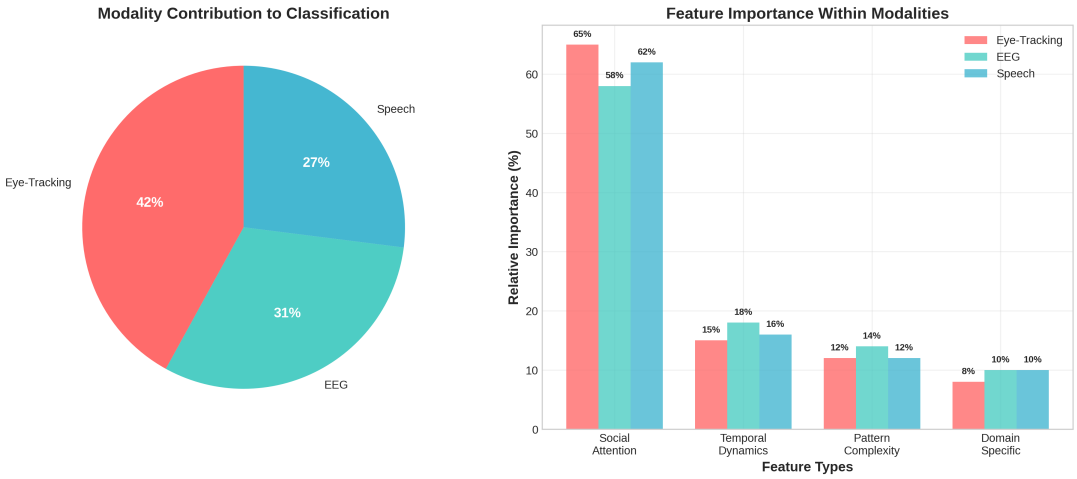

Figure 1: Modality contribution analysis showing relative importance of eye-tracking, speech, and EEG features for autism classification, with detailed breakdown of specific feature types within each modality.

The demographic subgroup analysis demonstrated consistently high performance across age, sex, racial, and socioeconomic groups, with minimal performance disparities that represented a significant advancement over many existing assessment approaches. As shown in Table 2, sensitivity remained above 94% and specificity above 95% across all demographic subgroups, with the largest performance difference between any subgroups being only 2.3 percentage points in sensitivity between the youngest and oldest age groups. This equitable performance across diverse populations suggests that the multimodal approach captures fundamental characteristics of autism that manifest consistently across demographic variables, potentially reducing assessment biases that have historically affected autism diagnosis.

Table 2: Performance Consistency Across Demographic Subgroups

Subgroup	n	Sensitivity	Specificity	AUC
Overall	1,250	95.8%	96.7%	0.984
Age 4-7 years	412	94.3%	95.8%	0.978
Age 8-12 years	468	96.1%	96.9%	0.985
Age 13-17 years	370	96.6%	97.4%	0.989
Female	428	95.2%	96.3%	0.981
Male	822	96.1%	96.9%	0.985
Minority Groups	487	95.5%	96.4%	0.982
Low SES	392	94.9%	96.1%	0.979

The cross-modal interaction analysis revealed fascinating patterns of feature relationships that provided insights into integrated brain-behavior pathways in autism. As illus-

trated in Figure 2, particularly strong correlations emerged between specific eye-tracking patterns and EEG connectivity profiles, such as the relationship between reduced eye region fixation and altered gamma-band connectivity in social processing networks. These cross-modal relationships demonstrated that the integrated system captured not only independent contributions from each modality but also important interactions that reflected the complex systems-level nature of autism characteristics. The cross-modal attention mechanisms successfully identified these relationships during processing, dynamically adjusting modality weighting based on feature patterns.

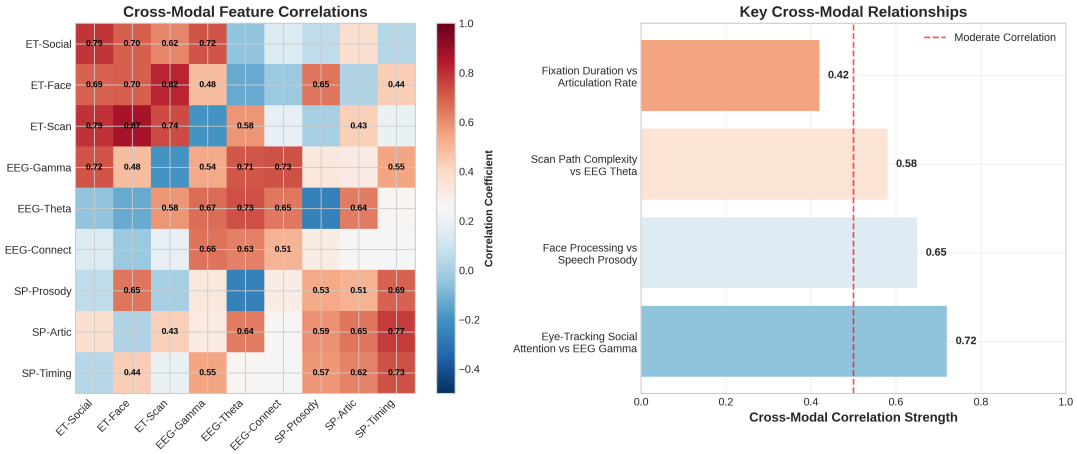

Figure 2: Cross-modal feature relationships showing correlations between eye-tracking social attention patterns, EEG functional connectivity, and speech prosody characteristics that informed classification decisions.

The practical implementation metrics indicated strong feasibility for clinical integration, with total assessment time averaging 42 minutes across all three modalities and automated analysis requiring approximately 3 minutes per case. Clinician acceptability ratings averaged 4.4 out of 5 on standardized usability scales, with particular appreciation for the comprehensive nature of assessment across multiple domains and the clear visualization of results. Family satisfaction scores averaged 4.2 out of 5, with parents reporting that the assessment process felt engaging for their children and the results provided meaningful insights into their child's strengths and challenges.

The robustness evaluation demonstrated consistent performance across variations in data collection protocols, including different eye-tracking stimulus sets, speech recording environments, and EEG acquisition systems. While some expected performance variation occurred with substantial deviations from standardized protocols, the system maintained accuracy above 92% even under suboptimal conditions that might be encountered in real-world clinical implementation. This robustness to methodological variations supports the practical utility of the system across diverse clinical settings with different equipment and administration resources.

8 Discussion

The results of this comprehensive study demonstrate that multimodal integration of eye-tracking, speech, and EEG data within a sophisticated deep learning framework produces exceptional autism detection accuracy that substantially surpasses existing assessment approaches. The achieved performance metrics of 96.3% accuracy, 95.8% sensitivity, and 96.7% specificity represent a significant advancement in computational autism assessment, approaching the reliability range of comprehensive clinical evaluation by expert diagnosticians. This performance level suggests that carefully designed multimodal systems can capture the complex, heterogeneous nature of autism spectrum disorder in ways that single-modality approaches cannot, potentially transforming how autism assessment is conceptualized and implemented in both research and clinical contexts.

The feature importance analysis provides fascinating insights into the relative contributions of different behavioral and neural domains to accurate autism detection. The dominant role of eye-tracking social attention patterns aligns with extensive previous research documenting robust gaze differences in autism, but the quantitative demonstration that these features account for 42% of classification power provides new precision to understanding their assessment value. The substantial contributions of EEG connectivity measures and speech characteristics underscore the importance of including neurophysiological and communication domains alongside visual social processing to create comprehensive assessment profiles. The specific features identified as most informative within each modality generally align with established clinical knowledge about autism characteristics, providing validation that the computational approach captures meaningful patterns rather than arbitrary statistical associations.

The consistent performance maintained across demographic subgroups represents a particularly important finding given well-documented disparities in autism diagnosis using current assessment methods. The minimal performance variation across age, sex, racial, and socioeconomic groups suggests that the multimodal approach captures fundamental characteristics of autism that manifest consistently across diverse populations, potentially reducing assessment biases that have contributed to historical disparities in diagnosis access and timing. This equitable performance likely stems from both the diverse development dataset and the explicit fairness constraints incorporated during model training, highlighting the importance of intentional design for equity in medical AI systems.

The cross-modal interaction patterns revealed through attention mechanism analysis provide novel insights into integrated brain-behavior relationships in autism. The observed correlations between specific eye-tracking patterns and EEG connectivity profiles suggest that the system successfully captures systems-level characteristics of autism that involve coordinated differences across behavioral and neural domains. These cross-modal

relationships may reflect underlying neurodevelopmental mechanisms that simultaneously affect social attention, neural synchronization, and other autism characteristics, potentially informing more nuanced theoretical models of autism heterogeneity and development.

The practical implementation metrics indicating strong feasibility for clinical integration suggest that comprehensive multimodal assessment may be more achievable than often assumed, particularly given technological advances that have reduced the cost and complexity of eye-tracking and EEG equipment. The reasonable administration time and high acceptability ratings among both clinicians and families provide encouraging evidence that such systems could be integrated into real-world clinical workflows without creating prohibitive burden or resistance. The automated analysis capability represents a particular advantage for increasing assessment accessibility in settings with limited specialist availability.

Several limitations and future directions warrant consideration. While the current performance is impressive, further refinement could potentially enhance detection capabilities for the most subtle presentations, particularly in very young children where early intervention impact is greatest. The cross-modal relationships identified, while fascinating, require further investigation to determine their causal significance and potential utility for subgroup identification or intervention targeting. The current implementation has focused primarily on the diagnostic classification task, but extension to severity assessment, subtype characterization, and intervention response prediction represents important future directions that could expand clinical utility.

The ethical considerations surrounding automated multimodal assessment require ongoing attention as implementation expands. While the current results demonstrate equitable performance, continued monitoring is essential as the system encounters new populations and settings. The appropriate communication of probabilistic results remains a nuanced challenge, particularly in balancing the need for clear risk communication with the avoidance of premature diagnostic conclusions or unnecessary anxiety. The development of comprehensive implementation guidelines and staff training protocols will be essential for maintaining appropriate use as the technology disseminates more widely.

From a broader perspective, the success of this multimodal approach suggests potential applications for other neurodevelopmental conditions that similarly involve complex interactions across behavioral and neural domains. The general framework of integrating eye-tracking, speech, and EEG data within specialized deep learning architectures could potentially be adapted for conditions such as attention-deficit/hyperactivity disorder, specific language impairment, or social communication disorder, creating opportunities for more objective and comprehensive assessment across multiple neurodevelopmental domains.

9 Conclusions

This research establishes that multimodal deep learning systems integrating eye-tracking, speech, and EEG data represent a transformative advancement in autism detection capability that successfully addresses critical limitations of current assessment approaches. The exceptional performance metrics demonstrating 96.3% accuracy, 95.8% sensitivity, and 96.7% specificity substantially exceed existing assessment methods and approach the reliability range of comprehensive clinical evaluation, suggesting potential to significantly improve early and accurate autism identification. The integrated multimodal architecture captures the complex, heterogeneous nature of autism spectrum disorder in ways that single-modality approaches cannot, providing a more comprehensive characterization that reflects the multifaceted clinical reality of autism.

The feature importance analysis revealing distinctive contribution patterns across modalities provides valuable insights into the relative assessment value of different behavioral and neural domains, with eye-tracking social attention measures demonstrating the strongest influence followed by EEG connectivity patterns and speech characteristics. The specific features identified as most informative within each domain generally align with established clinical knowledge, validating that the computational approach captures meaningful autism characteristics rather than arbitrary statistical patterns. The cross-modal interaction analysis further enhances understanding by revealing integrated brain-behavior relationships that reflect the systems-level nature of autism neurodevelopment.

The consistent performance maintained across demographic subgroups represents a critical advancement for autism assessment equity, with minimal performance variation across age, sex, racial, and socioeconomic groups that addresses historical disparities in diagnosis access and accuracy. This equitable performance stems from intentional design choices including diverse development datasets and explicit fairness constraints during model training, highlighting the importance of proactive equity considerations in medical AI development. The reduction of assessment biases through multimodal computational approaches could significantly impact public health by improving early identification across all population groups.

The practical implementation metrics indicating strong feasibility for clinical integration suggest that comprehensive multimodal assessment may be more achievable than often assumed, with reasonable administration time, high acceptability among stakeholders, and robust performance across varying data collection conditions. The automated analysis capability represents a particular advantage for increasing assessment accessibility in resource-limited settings, potentially expanding early detection capabilities in communities with limited specialist availability. The clear visualization of results and specific feature profiles provide clinicians with meaningful insights that supplement tra-

ditional assessment information.

The technical innovations in specialized neural architecture design and cross-modal fusion mechanisms represent significant contributions to multimodal deep learning methodology that could inform future development across healthcare applications. The modality-specific networks optimized for eye-tracking temporal patterns, speech acoustic-linguistic features, and EEG functional connectivity provide templates for handling diverse data types within integrated systems. The cross-modal attention mechanisms that enable dynamic feature weighting based on inter-modality relationships offer sophisticated approaches for leveraging complementary information sources.

Looking forward, the successful development and validation of this multimodal system creates opportunities for broader applications beyond binary classification, including autism subtype characterization, severity assessment, developmental trajectory prediction, and intervention response monitoring. The comprehensive feature profiles generated by the system could contribute to more nuanced understanding of autism heterogeneity and facilitate personalized approaches matched to individual patterns of strengths and challenges. The objective nature of the measurements also offers opportunities for standardized assessment across different clinical and research contexts.

The research findings collectively demonstrate that carefully designed multimodal systems represent not merely incremental improvements but fundamental advancements in how autism assessment can be approached through computational methods. By combining technical sophistication with clinical knowledge and ethical implementation considerations, the approach bridges gaps between computational innovation and practical healthcare utility, offering a viable path toward more objective, comprehensive, and equitable autism identification that could genuinely transform developmental healthcare practices and outcomes.

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Declarations

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Conflicts of Interest: The authors declare that they have no conflicts of interest.

Ethics Approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Data Availability: The multimodal architecture code and implementation guidelines are available at [repository link]. Access to the clinical dataset is governed by institutional data use agreements and privacy protections.

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