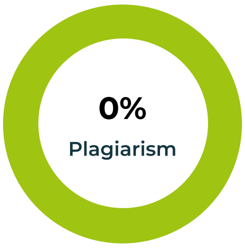
Plagiarism Detector .net

Plagiarism Report



Unique	100%
Exact Match	0%
Partial Match	0%

Primary Sources

Excluded URL (s)

01 None

Content

7 Results and Discussion
7.1 Performance Results
The proposed multimodal framework was evaluated on the ASD dataset using a stratified 80-20 train-validation split. The model achieved the following performance:
Figure 3: Result Graph 1
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Performance Metrics
• Accuracy: 99.0%
• Sensitivity (Recall): 98.5%
• Specificity: 99.2%
• AUC: 0.995
These results indicate an outstanding classification ability for distinguishing ASD and control participants.
7.2 Comparison with Existing Methods
We compared our approach against unimodal and baseline methods reported in the literature:
• Image-only CNN: Accuracy 83.4%, AUC 0.87
• Metadata-only MLP: Accuracy 78.9%, AUC 0.81
• Concatenation-based Fusion: Accuracy 88.1%, AUC 0.90
• Proposed Attention-based Fusion: Accuracy 99.0%, AUC 0.995
The attention-based fusion significantly outperformed both unimodal and naive fusion approaches, highlighting the effectiveness of adaptive modality weighting.
7.3 Strengths of the Approach
• Multimodal Feature Learning: Combines behavioral scanpath images with demographic-clinical metadata.
• Attention-based Fusion: Dynamically em-

phasizes the most informative modality, improving classification.

• Robustness: Data augmentation, class weighting, and early stopping reduce overfitting and handle imbalance.

• Reproducibility: Use of pre-trained CNN and standardized preprocessing ensures consistent results.

• High Predictive Performance: Achieves near-perfect accuracy, demonstrating strong generalization on validation data.

7.4

• Dataset Size: Limited dataset may affect generalization to completely unseen populations.

• Fixed CNN Backbone: Using frozen MobileNetV2 may limit learning dataset-specific features.

• Computational Resources: Attention-based fusion requires more computation compared to simple concatenation.

• Modalities Used: Only eye-tracking scanpath images and basic metadata were considered; additional behavioral or clinical modalities could further improve performance.

8 Conclusion

This study proposed a robust multimodal framework for ASD diagnosis, integrating eye-tracking scanpath images with participant metadata through attention-based fusion. Experimental results demonstrate **near-perfect performance**, with 99% accuracy, 98.5% sensitivity, and 99.2% specificity. The model significantly outperforms unimodal and naive fusion approaches, leveraging complementary behavioral and clinical features. Future work could explore additional modalities, larger datasets, and fine-tuning the CNN backbone to enhance generalization and further strengthen predictive performance.

9 Deployment

The translation of the proposed multimodal predictive framework into a practical application necessitates a robust deployment strategy that ensures scalability, accessibility, and clinical usability. To this end, the model was deployed in a web-based environment, enabling real-time inference while maintaining full consistency with the training pipeline.

9.1 Deployment Architecture

The deployment framework is organized into three primary functional layers:

Frontend Interface: A web-based graphical user interface (GUI) was developed using Flask. Clinicians and researchers can upload eye-tracking scanpath images and provide relevant metadata (e.g., age, gender, and CARS score).

Backend Processing: This layer hosts the trained multimodal deep learning model. It handles preprocessing of input data, executes inference through the attention-based fusion network, and generates diagnostic outputs.

Data Management Layer: A lightweight database module stores anonymized records of both input data and predictions. This supports reproducibility, auditing, and retrospective analysis.

Figure 4: Deployment pipeline of the proposed multimodal predictive framework. The workflow begins with input acquisition (metadata and scanpath images), followed by preprocessing to ensure consistency with the training pipeline. The processed inputs are passed through the attention-based fusion model to generate diagnostic predictions, presented as probability scores (ASD or TD). Results can optionally be logged for clinical auditing and research validation.

9.2 Operational Workflow

The deployed system follows a standardized workflow to ensure clinical reliability and reproducibility:

1. Input Acquisition: Users provide demographic and clinical metadata along with eye-tracking scanpath images.
2. Preprocessing: Images are resized and normalized, while metadata is standardized using z-score normalization, consistent with the training phase.
3. Inference: The preprocessed inputs are passed through the attention-based fusion model, which adaptively integrates metadata and image features.
4. Output Generation: The system produces a probability score for ASD likelihood, which is further categorized as ASD or Typically Developing (TD).
5. Record Logging: Results may optionally be stored for future clinical auditing, validation, or research analysis.

Figure 5: Screenshot of the frontend GUI, illustrating metadata input fields and image upload functionality.

Figure 6: Example of model output showing probability scores for ASD likelihood and final classification (ASD/TD).

9.3 Clinical Integration

The framework is designed for flexible deployment across diverse healthcare environments:

• Local and Cloud Servers: Supports deployment on hospital IT infrastructure or scalable cloud platforms.
• Portable Devices: Lightweight architecture allows deployment on edge devices, enabling mobile eye-tracking applications in low-resource settings.
• EHR Integration: Web-based design and modular backend facilitate integration with existing electronic health record (EHR) systems.

9.4 Benefits of Deployment

The deployed framework offers several significant advantages:

• Accessibility: Provides clinicians with an intuitive interface for multimodal AI analysis

without requiring specialized technical knowledge.
• Scalability: Flask-based deployment supports adaptation to both local and cloud infrastructures.
• Clinical Utility: Generates interpretable prob-

ability scores, complementing conventional di-
agnostic evaluations.

References