An Ensemble Machine Learning Framework for Improving Autism Spectrum Disorder Classification using Multimodal Medical Data: A Comprehensive Survey

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Abstract
Autism Spectrum Disorder (ASD) is a complex neurodevelopmental condition characterized by persistent impairments in social interaction, communication, and behavioural patterns. Early and accurate diagnosis of ASD is crucial for effective intervention and improved developmental outcomes. In recent years, machine learning (ML) techniques have been increasingly employed to support ASD diagnosis using heterogeneous medical data sources such as clinicalassessments,behaviouralquestionnaires, neuroimaging, genetic information, and speech video data. However, the performance of individual ML models is often limited by data scarcity, class imbalance, noise, and weak inter-modal correlations. Ensemble machine learning approaches, which integrate multiple predictive models, have emerged as a promising solution to improve robustness, accuracy, and generalization. This survey presents a comprehensive and systematic review of ensemble-based ML techniques for ASD classification using multimodal medical data. The paper analyses data modalities, feature extraction methods, ensemble architectures, fusion strategies, evaluation metrics, and validation techniques. Key challenges, research gaps, ethical concerns, and future research directions are discussed, with an emphasis on explainable and clinically deployable ensemble frameworks.

Keywords:
Autism Spectrum Disorder, Ensemble Learning, Multimodal Medical Data, Machine Learning, Classification, Survey

Introduction

Autism Spectrum Disorder (ASD) is a lifelong neurodevelopmental condition marked by difficulties in social communication, impaired interaction skills, and the presence of restricted or repetitive behavioural patterns. Owing to its heterogeneous nature and wide variability in symptom severity, ASD presents substantial challenges for accurate and timely diagnosis. Recent epidemiological studies indicate a steady rise in ASD prevalence worldwide, underscoring the importance of early identification and intervention. Early diagnosis enables targeted therapeutic strategies that can significantly enhance cognitive development, behavioural adaptation, and long-term quality of life.

Conventional diagnostic practices for ASD primarily depend on expert-led clinical evaluations and standardized assessment instruments such as the Autism Diagnostic Observation Schedule and the Autism Diagnostic Interview–Revised. Although these methods are clinically validated, they are often resource-intensive, time-consuming, and susceptible to subjectivity and inter-observer variability. Moreover, limited access to trained clinicians in many regions further delays

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diagnosis, particularly during early childhood when behavioural indicators may be subtle or inconsistently expressed.

The growing availability of digital medical and behavioural data has accelerated the adoption of machine learning (ML) techniques in ASD research. Diverse data sources including clinical records, behavioral questionnaires, neuroimaging modalities, genetic markers, speech signals, and video-based observations have been explored to model ASD characteristics computationally. While numerous studies report encouraging classification performance, a significant proportion rely on single learning models and unimodal datasets. Such approaches often struggle with limited sample sizes, class imbalance, high-dimensional feature spaces, and noise inherent in medical data, leading to reduced generalization and robustness.

Ensemble machine learning methods have gained increasing attention as an effective strategy to address these limitations. By integrating multiple base learners, ensemble techniques exploit model diversity to reduce variance, improve stability, and enhance predictive accuracy. Methods such as bagging, boosting, stacking, and hybrid ensembles have demonstrated superior performance in complex medical classification tasks. When applied to ASD diagnosis, ensemble frameworks are particularly advantageous in handling heterogeneous and multimodal data, as they can capture complementary patterns across different data sources and mitigate the weaknesses of individual models.

Despite the growing body of work on machine learning–based ASD classification, research on ensemble approaches remains scattered and lacks systematic consolidation. Existing studies vary widely in terms of data modalities, feature engineering techniques, fusion strategies, and validation protocols, making it difficult to draw generalized conclusions. Furthermore, critical aspects such as interpretability, clinical trustworthiness, ethical implications, and real-world deployment feasibility are often insufficiently addressed. These gaps limit the translational impact of current research and highlight the need for a structured and comprehensive review.

In response to these challenges, this paper presents a comprehensive survey of ensemble machine learning approaches for improving Autism Spectrum Disorder classification using multimodal medical data. The primary objectives of this survey are to (i) examine the range of data modalities and feature extraction methods employed in ASD classification, (ii) systematically categorize ensemble learning techniques and fusion strategies, (iii) analyse performance trends and limitations across representative studies, and (iv) identify open research challenges and future directions with an emphasis on explainable and clinically deployable solutions.

Review Of Literature

The growing prevalence of Autism Spectrum Disorder (ASD) and the limitations of conventional diagnostic procedures have motivatedextensiveresearch into computational and data-driven diagnostic approaches. Over the past decade, machine learning (ML) techniques have emerged as a promising tool for supporting ASD identification by analyzing diverse medical and behavioral data. This section critically reviews existing literature related to ASD diagnosis, machine learning-based classification methods, multimodal data utilization, and ensemble learning strategies, with a focus on identifying limitations and research gaps that justify the needforensemble-basedmultimodal frameworks.

Traditional Diagnostic Frameworks for ASD

ASD diagnosis is clinically guided by behavioral and developmental criteria defined in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) [1]. Standardized assessment instruments such as the Autism Diagnostic Observation Schedule (ADOS) and Autism Diagnostic Interview Revised (ADI-R) are widely adopted to assist clinicians in evaluating ASD-related behaviors [2]. Although these tools offer high diagnostic validity, they rely heavily on expert judgment, prolonged observation, and structured interviews. Consequently, diagnostic outcomes may be affected by subjectivity, inter-observer variability, and limited availability of trained professionals, particularly in resource-constrained regions. These challenges often delay early diagnosis, which is critical for effective intervention.

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Machine Learning-Based ASD Classification

To address these limitations, researchers have increasingly explored machine learning techniques for automated ASD screening and diagnosis. Early studies employed traditional classifiers such as Support Vector Machines, Decision Trees, Random Forests, k-Nearest Neighbors, and Naïve Bayes using behavioral questionnaires and clinical datasets [3], [4]. Bone et al. provided one of the earliest comprehensive analyses of ML-based ASD diagnostics, highlighting both the potential and limitations of automated approaches [3].

With the emergence of large-scale neuroimaging datasets such as ABIDE, ML methods have been applied to functional and structural MRI data to identify neurobiological biomarkers associated with ASD [5]. Abraham et al. demonstrated that ML models trained on multi-site resting-state fMRI data could extract reproducible ASD-related features, though performance varied across sites [5]. Heinsfeld et al. further applied deep learning techniques to the ABIDE dataset and reported improved classification accuracy compared to conventional ML methods [6]. Despite these advances, many deep learning models suffer from overfitting, limited interpretability, and high computational requirements, particularly when trained on small or heterogeneous datasets [23].

Multimodal Medical Data in ASD Diagnosis

ASD manifests across multiple domains, including behavioral, neurological, genetic, and physiological dimensions. As a result, unimodal data representations often fail to capture the full complexity of the disorder. Recent research has therefore focused on multimodal learning approaches that integrate data from multiple sources, such as behavioral assessments, neuroimaging, speech signals, video recordings, and genetic information [7], [8].

Calhoun and Sui emphasized the importance of multimodal fusion in uncovering latent interactions across different brain imaging modalities and improving diagnostic accuracy for complex neurodevelopmental disorders [16]. Li et al. and Riaz et al. demonstrated that multimodal frameworks generally outperform unimodal systems in ASD classification tasks [17], [18]. However, multimodal learning introduces additional challenges, including feature heterogeneity, missing data, weak inter-modal correlations, and increased model complexity, which can negatively affect classification performance if not properly addressed.

Ensemble Learning in Medical and ASD Classification

Ensemble learning techniques aim to improve predictive performance by combining multiple base learners, thereby exploiting model diversity and reducing variance and bias. Foundational ensemble methods such as Bagging, Boosting, and Random Forests have been widely applied in medical diagnosis tasks [10]–[12]. Breiman's Random Forest algorithm has demonstrated robustness to noise and high-dimensional data, making it particularly suitable for healthcare applications [11].

In the context of ASD diagnosis, ensemble learning has shown promising results. Pulini et al. reported that ensemble-based decision-support systems outperform single classifiers in handling uncertainty and class imbalance in healthcare datasets [20]. Li et al. proposed a multi-site ensemble learning framework to address inter-site variability in neuroimaging-based ASD classification [21]. Despite these successes, many ensemble-based ASD studies focus on a single data modality and lack systematic multimodal integration.

Explainability and Clinical Deployment Challenges

While ensemble and deep learning models often achieve high classification accuracy, their lack of transparency remains a significant barrier to clinical adoption. Explainable Artificial Intelligence (XAI) techniques, such as SHAP and feature attribution methods, have been proposed to improve model interpretability and clinician trust [14], [22]. Choi et al. emphasized that explainability is essential for safe and ethical deployment of AI systems in healthcare [24]. However, the integration of explainability mechanisms into ensemble-based multimodal ASD classification frameworks remains limited in existing literature.

Research Gaps

Based on the reviewed studies, several critical research gaps are evident:

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- Limited availability of large-scale, standardized multimodal ASD datasets
- Predominant reliance on unimodal data or single classifiers
- Insufficient modeling of inter-modal feature relationships
- Limited incorporation of explainable AI in ensemble frameworks
- Lack of robust validation across diverse populations and real-world clinical settings

These gaps highlight the necessity for a comprehensive ensemble machine learning framework capable of effectively integrating multimodal medical data while ensuring robustness, interpretability, and clinical applicability.

Statement of the Problem

Despite the growing adoption of machine learning techniques for Autism Spectrum Disorder (ASD) classification, existing approaches remain constrained by limited multimodal data integration, inadequate utilization of ensemble learning strategies, poor generalization across datasets, and insufficient model interpretability. Many current models rely on unimodal inputs or single classifiers, restricting their ability to capture the heterogeneous and multidimensional nature of ASD and limiting their clinical reliability.

This research addresses the problem of improving ASD classification performance by systematically analyzing and synthesizing ensemble-based machine learning approaches applied to heterogeneous multimodal medical data. The study aims to identify effective ensemble architectures, data fusion strategies, evaluation practices, and explainability mechanisms,whilehighlighting methodological limitations and future research directions necessary for developing robust, accurate, and clinically deployable decision-support systems.

Objectives of the Study

The objectives of this study are:

- Review and categorize multimodal medical data sources used for Autism Spectrum Disorder (ASD) classification and analyze their relevance in computational diagnosis.
- Examine ensemble machine learning techniques applied to ASD classification, including their architectures, fusion strategies, and performance benefits over single-model approaches.
- Evaluate evaluation metrics, validation strategies, and interpretability methods used in ensemble-based ASD diagnostic systems.
- Identify research gaps and future directions for developing robust, explainable, and clinically deployable ensemble machine learning frameworks for ASD diagnosis.

Scope of the Study

This study presents a comprehensive survey of ensemble machine learning approaches for Autism Spectrum Disorder (ASD) classification using multimodal medical data. The review focuses on peer-reviewed journal articles and conference papers, with primary emphasis on Scopus-indexed and high-impact publications.

The scope includes multimodal data sources such as clinical and behavioral assessments, neuroimaging data (fMRI and sMRI), genetic and physiological information, and speech video-based behavioral signals. Studies employing machine learning and deep learning models within ensemble and multimodal fusion frameworks are considered.

This survey emphasizes ensemble learning strategies, multimodal data fusion techniques, evaluation metrics, validation practices, and explainability mechanisms relevant to clinical decision support. The study does not propose a new model but aims to synthesize existing research, identify limitations and research gaps, and highlight future directions for developing robust and clinically deployable ASD diagnostic frameworks.

Methodology of the Survey

This survey follows a structured and systematic review methodology to identify, analyze, and synthesize existing research on ensemble machine learning approaches for AutismSpectrumDisorder (ASD) classification using multimodal medical data. The review processwasdesignedtoensuretransparency,reproducibility,andcomprehensive coverage of relevant literature.

Literature Search Strategy

A systematic literature search was conducted across major scientific databases, including Scopus, IEEE Xplore, ScienceDirect, SpringerLink, PubMed, and ACM Digital Library. Keywords and search strings were

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formulated by combining terms related to ASD, machine learning, ensemble learning, and multimodal data. Typical search expressions included combinations such as "Autism Spectrum Disorder," "ensemble learning," "machine learning," "multimodal data," "neuroimaging," and "classification." The search was restricted to articles published in English.

Inclusion and Exclusion Criteria

Studies were selected based on predefined inclusion criteria:

- Peer-reviewed journal articles or conference proceedings,
- Research focused on ASD classification or diagnosis using machine learning or deep learning techniques,
- Studies involving ensemble learning methods or multimodal data integration,
- Publications indexed in recognized scientific databases, with priority given to Scopus-indexed sources.

Studies were excluded if they were non-peer-reviewed,purelyclinical without computational analysis, opinion-based articles, or unrelated to ASD classification.

Study Selection and Screening

The initial search results were screened based on titles and abstracts to remove duplicates and irrelevant studies. Full-text screening was then conducted to ensure relevance to ensemble learning and multimodal ASD diagnosis. Selected studies were independently reviewed to extract methodological details and key findings.

Data Extraction and Analysis

For each selected study, relevant information was systematically extracted, including data modalities used, feature extraction techniques, machine learning models, ensemble strategies, data fusion approaches, evaluation metrics, validation techniques, and reported performance outcomes. Studies were then categorized based on ensemble learning paradigms, multimodal integration strategies, and application domains.

Synthesis and Comparative Analysis

A qualitative and comparative analysis was performed to identify performance trends, methodological strengths, and recurring limitations across studies. Particular attention was given to model robustness, generalization capability, interpretability, and clinical applicability. Research gaps and future directions were identified based on observed inconsistencies and limitations in existing approaches.

This structured survey methodology ensures a comprehensive, unbiased, and reproducible review of ensemble machine learning frameworks for ASD classification using multimodal medical data.

Taxonomy of Multimodal Data and Feature Extraction

Autism Spectrum Disorder (ASD) is characterized by heterogeneous manifestations across behavioral, neurological, genetic, and physiological domains. To capture this complexity, recent studies increasingly rely on multimodal medical data, where complementary information from multiple sources is jointly analyzed. An effective taxonomy of data modalities and feature extraction techniques is essential for designing robust ensemble learning frameworks.

Multimodal Data Categories

Multimodal ASD datasets typically include clinical, neuroimaging, biological, and behavioral signals. Each modality captures distinct aspects of ASD and requires specialized preprocessing and feature extraction methods.

Table 1: Taxonomy of Multimodal Data and Feature Extraction Methods in ASD Classification

Data Modality	Description	Common Feature Extraction Techniques
Clinical & Behavioral	ADOS, ADI-R, questionnaires, medical records	Statistical scores, domain-specific indicators, severity indices
Neuroimaging	fMRI, sMRI, EEG	Functional connectivity matrices, cortical thickness, graph-based features
Genetic & Physiological	SNPs, gene expression, eye-tracking, heart rate	Genetic markers, time-series statistics, signal entropy
Speech & Audio	Vocal patterns, prosody, articulation	MFCCs, pitch, formants, spectral features
Video & Facial Data	Eye gaze, facial expressions, gestures	CNN embeddings, facial landmarks, spatiotemporal features

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Feature Extraction Challenges
Feature extraction in multimodal ASD analysis faces challenges such as high dimensionality, noise, missing modalities, and weak inter-modal correlations. Neuroimaging and video data often require dimensionality reduction, while behavioral and clinical features may suffer from subjectivity and inconsistency.

Relevance to Ensemble Learning
The diversity of extracted features across modalities motivates the use of ensemble learning, where different base learners can specialize in distinct feature spaces. Proper featurerepresentationand

modality-aware extraction are therefore critical for maximizing the effectiveness of ensemble-based multimodal ASD classification systems.

leveraging model diversity, ensemble frameworks mitigate overfitting, reduce bias and variance, and enhance classification reliability.

Ensemble Learning Techniques for ASD Classification
Ensemble learning techniques combine multiple base classifiers to improve predictive performance, robustness, and generalization compared to single-model approaches. In AutismSpectrumDisorder(ASD) classification, ensemble methods are particularly effective due to the heterogeneity, high dimensionality, and limited size of medical datasets. By

Major Ensemble Learning Paradigms
Ensemble learning techniques applied to ASD classification can be broadly categorized into bagging-based, boosting-based, stacking-based, and hybrid ensemble approaches.

Table 2: Ensemble Learning Techniques Used in ASD Classification

Ensemble Technique	Description	Common Base Learners	Key Advantages
Bagging (Bootstrap Aggregation)	Trains multiple models on bootstrapped samples	Decision Trees, SVM, k-NN	Reduces variance, robust to noise
Random Forest	Tree-based bagging with feature randomness	Decision Trees	Handles high-dimensional data, resistant to overfitting
Boosting (AdaBoost, Gradient Boosting, XGBoost)	Sequentially focuses on misclassified samples	Weak learners, Trees	Improves accuracy, handles class imbalance
Stacking	Combines outputs of multiple models using a meta-learner	SVM, RF, NN, Logistic Regression	Exploits complementary model strengths
Hybrid Ensembles	Integrates multiple ensemble strategies	Mixed ML/DL models	Enhanced robustness in multimodal settings

Application in ASD Classification
In ASD research, ensemble methods have been applied to behavioral data, neuroimaging datasets (e.g., ABIDE), and multimodal frameworks. Random Forests are widely used due to their interpretability and resilience to noise, while boosting-based methods improve sensitivity in imbalanced datasets. Stacking ensembles are increasingly adopted to integrate predictions from modality-specific classifiers, making them well-suited for multimodal ASD diagnosis.

Limitations
Despite performance gains, ensemble models increase computational complexity and may reduce interpretability. Additionally, improper ensemble design can lead to redundancy among base learners, limiting performance improvements. These challenges highlight the need for carefully designed ensemble architectures with explainability mechanisms for clinical adoption.

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Multimodal Fusion Strategies

Multimodal fusion strategies play a critical role in improving Autism Spectrum Disorder (ASD)classificationbyintegratingcomplementary information from heterogeneous medical data sources. Since ASD manifests across behavioral, neurological, genetic, and physiological domains, effective fusion mechanisms are essential to exploit cross-modal relationships and enhance ensemble learning performance.

Types of Multimodal Fusion Approaches

Multimodal fusion strategies used in ASD classification are generally categorized into feature-level fusion, decision-level fusion, and hybrid fusion approaches.

Table 3: Multimodal Fusion Strategies in ASD Classification

Fusion Strategy	Description	Advantages	Limitations
Feature-Level Fusion (Early Fusion)	Concatenation of features from multiple modalities before classification	Captures inter-modal correlations; simple implementation	High dimensionality; sensitive to missing data
Decision-Level Fusion (Late Fusion)	Combines outputs of modality-specific classifiers	Robust to missing modalities; flexible	Limited modeling of inter-modal dependencies
Hybrid Fusion	Integrates feature-level and decision-level fusion	Balances performance and robustness	Increased computational complexity

Application in Ensemble ASD

Models In ensemble-based ASD classification systems, decision-level fusion is widely adopted due to its flexibility and robustness in handling incomplete multimodal datasets. Each modality is typically processed by a dedicated base learner, and ensemble aggregation techniques such as majority voting, weighted averaging, or meta-learning are used to generate final predictions. Feature-level fusion, while effective in capturing joint patterns, often requires dimensionality reduction techniques to manage complexity.

Limitations

Despite their benefits, multimodal fusion strategies face several challenges. Feature-level fusion can suffer from the curse of dimensionality and noise amplification, particularlywithhigh-dimensional neuroimaging data. Decision-level fusion may overlook complex inter-modal interactions, limiting its discriminative power. Hybrid fusion approaches offer improved performance but at the cost of increased model complexity and reduced interpretability, which can hinder clinical deployment.

Overall, the choice of fusion strategy significantly influences ensemble performance and must be guided by data availability, modality characteristics, and clinical interpretability requirements.

Evaluation Metrics and Validation Approaches

Reliable evaluation and validation are essential for assessing the effectiveness, robustness, and clinical applicability of ensemble machine learning models for Autism Spectrum Disorder (ASD) classification. Given the challenges of class imbalance, limited sample sizes, and heterogeneous multimodal data, careful selection of evaluation metrics and validation strategies is critical.

Performance Evaluation Metrics

ASD classification studies commonly employ a combination of threshold-based and probabilistic metrics to capture different aspects of model performance.

Table 4: Common Evaluation Metrics Used in ASD Classification

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Metric	Description	Relevance in ASD Diagnosis
Accuracy	Overall proportion of correct predictions	May be misleading with class imbalance
Precision	Correctly predicted ASD cases among predicted positives	Important to reduce false positives
Recall (Sensitivity)	Correctly identified ASD cases	Critical for early ASD detection
Specificity	Correctly identified non-ASD cases	Prevents misdiagnosis
F1-Score	Harmonic mean of precision and recall	Balances false positives and false negatives
AUC–ROC	Discriminative ability across thresholds	Robust to class imbalance

Sensitivity and F1-score are particularly emphasized in ASD diagnosis, as false negatives can delay early intervention.

Validation Strategies

To ensure generalization and reduce overfitting, various validation techniques are employed in ensemble-based ASD studies.

Table 5: Validation Approaches in ASD Classification Studies

Validation Method	Description	Advantages
k-Fold Cross-Validation	Dataset split into k subsets for iterative training/testing	Reduces bias in small datasets
Stratified Cross-Validation	Preserves class distribution across folds	Suitable for imbalanced ASD data
Leave-One-Site-Out Validation	Trains on multi-site data and tests on unseen sites	Evaluates robustness across populations
External Validation	Testing on independent datasets	Supports clinical generalizability

Challenges in Evaluation

Many existing studies rely solely on cross-validation within a single dataset, limiting real-world applicability. Lack of standardized benchmarks and inconsistent reporting of metrics further complicate comparative analysis. These issues highlight the need for standardized evaluation protocols and multi-site validation to support clinically reliable ASD classification systems.

Challenges and Open Issues

Despite significant progress in applying ensemble machine learning techniques for AutismSpectrumDisorder(ASD) classification, several challenges and open research issues remain that limit their clinical translation and large-scale adoption.

Data Scarcity and Heterogeneity

The availability of large-scale, standardized multimodal ASD datasets is limited. Existing datasets often suffer from small sample sizes, missing modalities, noise, and inter-site variability. Heterogeneous data formats across clinical, neuroimaging, genetic, and behavioral sources further complicate effective feature alignment and integration in ensemble models.

Class Imbalance and Bias

ASD datasets frequently exhibit class imbalance, with fewer positive ASD cases compared to controls. Although ensemble methods can mitigate this issue to some extent, many studies do not systematically address imbalance, leading to biased performance estimates and reduced sensitivity in real-world screening scenarios.

Weak Inter-Modal Correlations

Multimodal ASD data often show weak or nonlinear relationships across modalities. Designingensembleframeworksthat effectively capture complementary and latent inter-modal interactions remains an open challenge, particularly when some modalities contribute limited or redundant information.

Model Complexity and Interpretability

Ensemble and deep learning models introduce increased architectural complexity, which can hinder interpretability and transparency. The lack of integrated explainability mechanisms

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reduces clinician trust and limits the adoption of ensemble-based ASD decision-support systems in clinical practice.

Generalization and Validation Limitations
Many existing studies rely on single-site datasets and internal cross-validation, resulting in limited generalization across populations, age groups, and clinical settings. Robust external and multi-site validation remains underexplored.

Ethical, Privacy, and Deployment Concerns
The use of sensitive multimodal medical data raises ethical issues related to privacy, consent, data security, and algorithmic bias. Additionally, the absence of standardized clinical deployment frameworks and regulatory guidelines poses challenges for real-world implementation.

Open Issues
Addressing these challenges requires the development of standardized multimodal datasets, explainable and privacy-preserving ensemble architectures, robust validation protocols, and clinically aligned evaluation frameworks. Resolving these open issues is essential for translating ensemble machine learning research into reliable and ethical ASD diagnostic support systems.

Future Research Directions
Future research should focus on developing large-scale, standardized multimodal ASD datasets to improve model generalization and benchmarking. Advanced ensemble architectures that effectively model inter-modal relationships, along with integrated explainable AI techniques, are needed to enhance transparency and clinical trust. Greater emphasis on robust multi-site validation, privacy-preserving learning, and real-world clinical evaluation will be essential for translating ensemble-based ASD classification systems into reliable and deployable clinical decision-support tools.

Conclusion
This survey has presented a comprehensive review of ensemble machine learning approaches for Autism Spectrum Disorder classification using multimodal medical data. The analysis highlights that integrating heterogeneous data sources such as behavioral assessments,neuroimaging,geneticinformation, and speech–video signals can significantly enhance diagnostic performance compared to unimodal and single-model approaches. Ensemble learning techniques, including bagging, boosting, stacking, and hybrid fusion models, demonstrate improved robustness, accuracy, and generalization by effectively leveraging model and data diversity.
Despitethese advancements, several challenges remain, including limited availability of large-scale multimodal datasets, weak inter-modal feature correlations, lack of standardized evaluation protocols, and insufficient model interpretability. The review also emphasizes that explainability, ethical compliance, and clinical validation are critical factors influencing real-world deployment of AI-based ASD diagnostic systems.
Overall, this survey underscores the potential of ensemble-based multimodal frameworks as a promising direction for improving ASD classification. By synthesizing existing research, identifying methodological trends, and outlining open research challenges, this work provides a structured reference for researchers and practitioners aiming to develop robust, explainable, and clinically deployable machine learning solutions for early and accurate ASD diagnosis.

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