

Convergent gut microbiome signatures of Autism Spectrum Disorder across independent pediatric cohort

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Abstract. Autism Spectrum Disorder (ASD) is increasingly prevalent, and evidence implicates gut-brain interactions, motivating evaluation of gut microbiome signals in ASD phenotypes. Prior studies link ASD with gastrointestinal comorbidity and dysbiosis, but taxonomic findings are heterogeneous across cohorts and methods, leaving uncertainty about which microbial features are most reproducible and informative. We analyzed two public pediatric cohorts (shotgun metagenomic and 16S rRNA) to assess cross-dataset separability of ASD versus neurotypical controls and to identify convergent microbial signals. After standard quality control and feature scaling, we trained logistic regression, random forest, and gradient boosting models, evaluated performance with confusion-matrix metrics and ROC-AUC, and compared taxa- and pathway-level importance to prioritize robust candidates. Models reliably distinguished ASD from controls, highlighting *Prevotella* and *Bacteroides* as consistent signals, with pathway analysis implicating short-chain fatty acid and tryptophan metabolism. Results support a biological role for microbiome dysbiosis in ASD, nominate reproducible genera and pathways as candidate biomarkers, and motivate longitudinal, strain-resolved, and interventional studies, including targeted probiotics or microbiota transfer, to test causality and therapeutic potential.

Keywords: Autism Spectrum Disorder, gut microbiome, machine learning modeling, inflammation, metabolism, *Prevotella*

1. Introduction

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition now recognized to affect a substantial portion of the population [1, 2]. Recent estimates indicate that roughly 1% of children worldwide are diagnosed with ASD [3]. In the United States, the identified prevalence of ASD has continued to rise—for example, about 1 in 36 eight-year-old children had ASD in 2020, increasing to approximately 1 in 31 (3.2%) in 2022 according to the latest Centers for Disease Control and Prevention (CDC) surveillance data [4, 5]. This upward trend in diagnoses underscores the growing public health impact of ASD and has spurred interest in potential contributing factors beyond genetics, including the role of the gut microbiome (the community of microorganisms residing in the Gastrointestinal (GI) tract) in ASD pathology [6]. Accumulating evidence suggests that ASD is often accompanied by GI issues and alterations in gut microbial composition, pointing to a possible connection between the brain and gut in this disorder. The following sections review known associations between ASD and the gut microbiota, and explore the microbiota-gut-brain axis as a framework for understanding how intestinal dysbiosis might influence neurodevelopment and behavior in ASD [6, 7].

Multiple studies have observed that children with ASD tend to harbor an imbalanced gut microbiome compared to neurotypical peers [8, 9]. Although no single microbial species change has been universally found across all studies—likely due to differences in diet, age, and other factors, certain recurring patterns have been reported. Notably, many ASD cohorts show a reduction in beneficial anaerobic bacteria such as *Bifidobacterium* spp. in their fecal microbiota [8, 10]. For instance, several independent studies have found significantly lower abundances of *Bifidobacteria* in ASD children relative to controls, a genus known to support gut health [8, 9]. On the other hand, some potentially pathogenic or pro-inflammatory taxa appear at higher levels in ASD. Children on the spectrum frequently exhibit an overrepresentation of certain Firmicutes, including clostridial bacteria [9, 10]. Increased abundances of *Clostridia* have been noted in ASD fecal profiles [9], along with other genera like *Sarcina* and *Parabacteroides* that have also been reported to be elevated in ASD patients [9, 10]. These microbial shifts are often accompanied by GI disturbances—indeed, GI symptoms such as constipation, diarrhea, and abdominal pain are common in ASD, affecting approximately 46.8% of individuals according to systematic reviews, with constipation affecting 22.2% and diarrhea affecting 13.0% [11, 12]. The co-occurrence of gut dysbiosis and GI issues in ASD has led researchers to hypothesize a

mechanistic link between altered microbiota and the central nervous system. In summary, ASD is associated with notable changes in gut microbiota composition, characterized broadly by a loss of certain beneficial microbes and a proliferation of others, which suggests that gut microbial dysbiosis could be entwined with ASD symptoms and thus warrants examination through the lens of the gut-brain axis.

The microbiota-gut-brain axis refers to the bidirectional communication network linking the gut microbiome and the brain via neural, endocrine, immune, and metabolic pathways [13, 14]. In the context of ASD, this concept is particularly compelling because gut microbiota alterations might influence brain function and behavior through the production of neuromodulatory metabolites, immune regulation, or vagal nerve signaling [14, 15]. Recent datasets profiling the gut microbiome in children with ASD provide evidence of pronounced dysbiosis that could perturb this gut-brain crosstalk. For example, 16S rRNA gene sequencing data from multiple cohorts have revealed clear shifts in the fecal bacterial community of ASD patients compared to neurotypical controls [16, 17]. At the phylum level, studies have shown mixed findings regarding Firmicutes and Bacteroidetes ratios, with some ASD groups showing significantly elevated levels of Firmicutes and decreased relative abundance of Bacteroidetes compared to controls, while others have reported the opposite pattern [9, 10, 18]. These conflicting findings likely reflect methodological differences and population heterogeneity, but consistently point to disrupted microbial balance in ASD. Whole-genome shotgun metagenomic sequencing studies have further demonstrated that ASD individuals often show altered microbial diversity patterns, with some studies reporting reduced species-level richness despite changes at higher taxonomic levels [10, 19]. Such imbalances can have functional consequences, as the ASD-enriched taxa include bacteria capable of producing metabolites that may affect the nervous system. For instance, children with ASD have been found to harbor altered levels of *Clostridium* species and other potentially pro-inflammatory bacteria, which can produce compounds that may influence gut-brain signaling [19, 20]. Likewise, sulfate-reducing bacteria such as *Desulfovibrio* have been reported to be altered in some ASD microbiomes, generating metabolites that could affect gut barrier integrity and immune responses [20, 21]. The net effect of these microbial changes is often a pro-inflammatory gut milieu and altered production of neurotransmitter precursors (e.g., short-chain fatty acids, amino-acid metabolites) that travel through the bloodstream or interact with the vagus nerve, thereby affecting brain development and behavior [14, 22]. In summary, the perturbations in gut microbiota observed in ASD—characterized by altered microbial diversity and shifts in potentially beneficial versus pro-inflammatory taxa—are believed to disrupt normal gut–brain biochemical signaling. This provides a biological basis for the gut–brain axis hypothesis in ASD, whereby microbiome dysbiosis could contribute to neurological and behavioral manifestations of the disorder.

In the present study, two publicly available gut-microbiome cohorts were analyzed to identify microbial signatures that distinguish children with autism spectrum disorder from neurotypical peers. One cohort provided shotgun metagenomes from matched fecal samples. DNA was sheared to short fragments, end-repaired, adapter-ligated, and PCR-amplified before Illumina sequencing. Compared with controls, autistic subjects showed broader diversity at the phylum and genus levels but reduced species richness; gene catalogs from the two groups were of comparable scale. The second cohort contained sixteen-S rRNA amplicon profiles summarized as operational taxonomic units by participants. Bacteroidetes and Firmicutes dominated in both groups, with autism associated shifts toward Firmicutes, Proteobacteria, and Actinobacteria and a corresponding decrease in Bacteroidetes. After standard quality control and feature scaling, taxonomic and gene features served as inputs to supervised learning. A logistic-regression baseline supplied interpretable coefficients linking individual taxa and pathways to diagnosis. Two tree-based ensembles—random forest and gradient boosting—modeled non-linear structure and interactions among microbial features. Discrimination was assessed with confusion-matrix-derived metrics alongside threshold-independent ROC analysis, and model importances were compared across datasets to prioritize convergent signals. Together, this pipeline integrates complementary data types and algorithms to test separability of cases and controls, quantify predictive utility, and nominate biologically plausible hypotheses for future wet-lab validation.

2. Materials and methods

2.1. Datasets

Two publicly available gut microbiome datasets were analyzed in studies examining fecal samples from children diagnosed with ASD compared to neurotypical controls [9]. The first dataset, ASD meta abundance, contains 5,619 rows and 61 columns, where each row represents a bacterial taxon and each column represents an individual fecal sample. The second dataset, GSE113690 16S rRNA OTU dataset, contains 1,322 rows and 256 columns, where each row represents an Operational Taxonomic Unit (OTU) and each column represents an individual sample from either ASD or control groups.

2.2. ASD classification models

To investigate which gut microbiota profiles distinguish ASD from neurotypical controls, a few supervised classification algorithms, including logistic regression, random forest, and gradient boosting classifier, were implemented using the two

datasets above as feature inputs.

2.3. Logistic Regression

Logistic Regression (LR) was used as a baseline linear model for classification. Specifically, a logistic function models the probability of ASD diagnosis as a weighted sum of the microbial features. The model's coefficients provide an interpretable indication of which bacteria are positively or negatively associated with ASD.

2.4. Random Forest

Random Forest (RF) ensemble was also used to leverage non-linear relationships among microbial features. RF constructs an ensemble of decision trees using bootstrapped subsets of the data and aggregates their votes for the final prediction. This method is well-suited for microbiome classification and is robust to noise and overfitting, especially with an abundance of correlated features.

2.5. Gradient boosting classifier

Furthermore, a gradient boosting classifier (GradientBoosting) was applied to the classification task. Gradient Boosting is an ensemble learning technique that builds additive decision trees sequentially, where each new tree attempts to correct the residual errors made by the previous ensemble.

2.6. Confusion matrix

A confusion matrix is a 2×2 table summarizing a classifier's predictions versus actual outcomes. It enumerates True Positives (TP) and True Negatives (TN) (correctly predicted ASD and non-ASD cases, respectively) as well as False Positives (FP) and False Negatives (FN) (incorrect predictions). This matrix provides a complete snapshot of performance, forming the basis for derived metrics. Accuracy is defined as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

2.7. Precision and recall

From the confusion matrix, precision and recall are key performance measures. Precision, or positive predictive value, is the proportion of positive predictions that were actually correct:

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

It reflects how reliable the model's ASD predictions are. Recall, or sensitivity, is the proportion of actual positives correctly identified:

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

Recall measures the model's ability to catch ASD cases. High recall means few ASD cases go undetected, whereas high precision means few non-ASD are incorrectly flagged as ASD.

2.8. F_1 score

The F_1 score is the harmonic mean of precision and recall, offering a single metric balancing both. It is defined as follows:

$$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (4)$$

F_1 quantifies how well the model is simultaneously identifying ASD cases and avoiding false alarms.

2.9. ROC curve and AUC

The Receiver Operating Characteristic (ROC) curve plots the true positive rate (recall) against the false positive rate:

$$\text{False Positive Rate (FPR)} = \frac{FP}{FP+TN} \quad (5)$$

Across different classification thresholds, the Area Under the ROC Curve (AUC) quantifies the overall ability of the model to discriminate between classes, independent of any particular threshold. AUC can be interpreted as the probability that a randomly chosen ASD case is ranked higher by the classifier than a randomly chosen control case. An AUC of 0.5 indicates no better-than-chance performance, while 1.0 indicates perfect separation.

3. Results

The first dataset contains metagenomic sequencing data of gut microbiota from children with Autism Spectrum Disorder (ASD) and healthy controls (30 ASD vs. 30 controls). Microbial DNA was extracted from fecal samples, fragmented, and sequenced using Illumina technology. The dataset reports microbial abundance profiles across taxonomic levels (phylum, genus, species), with 1,312,364 analytes detected in ASD samples and 1,335,835 analytes in controls.

Table 1 shows relative abundances of five of the bacterial taxa in control (B-prefixed) stool samples. Each row represents bacteria taxonomy, with genus and species, and each column represents healthy control subjects (sample IDs prefixed with "B"). Each cell represents the raw read abundance per sample, with columns corresponding to individual participants.

Table 1. Relative abundances of five key bacterial taxa in neurotypical control stool samples

Taxonomy	B1	B2	B3	B5	B6	B7	B8	B13	B14	B28	...	B120	B127	B132	B141	B142	B143	B152
g__Faecalibacterium; s__Faecalibacterium prausnitzii	4,269	4,397	4,499	6,126	7,020	5,404	4,404	5,811	3,360	4,141	...	4,471	5,868	6,561	4,910	4,492	2,812	5,303
g__Hungatella; s__Hungatella hathewayi	1,217	6,238	2,325	5,004	2,829	2,192	2,921	4,303	2,793	3,671	...	2,126	4,429	2,598	4,222	4,925	5,753	1,261
g__Clostridium; s__uncultured Clostridium sp.	3,853	4,624	3,842	4,399	3,916	3,355	5,165	4,453	1,999	3,974	...	4,085	6,041	6,188	3,960	4,403	2,841	2,746
g__Butyricimonas; s__Butyricimonas virosa	1,624	1	703	43	46	1,505	32	1,474	2	52	...	2,065	21	27	55	35	8	884
g__Alistipes; s__Alistipes indistinctus	2,452	3	819	2,761	691	2,768	25	1,095	13	4	...	90	22	30	1,027	2,641	4	1,587

Table 2 shows relative abundances of five of the bacterial taxa in ASD (A-prefixed) stool samples. Each row represents bacteria taxonomy, with genus and species, and each column represents Autism Spectrum Disorder (sample IDs prefixed with "A"). Each cell represents the raw read abundance per sample, with columns corresponding to individual participants.

Table 2. Relative abundances of five key bacterial taxa in autism spectrum disorder stool samples

Taxonomy	A3	A5	A6	A9	A31	A51	A52	A53	A54	A59	...	A101	A109	A113	A114	A115	A142	A144
g__Faecalibacterium; s__Faecalibacterium prausnitzii	4,998	5,060	2,905	5,745	4,822	3,889	4,646	6,337	5,064	6,359	...	3,833	3,771	5,489	6,762	3,045	6,205	6,048
g__Hungatella; s__Hungatella hathewayi	5,803	5,612	4,109	1,432	2,652	4,175	3,891	894	4,903	2,970	...	6,849	4,390	2,091	1,638	4,613	2,601	1,892
g__Clostridium; s__uncultured Clostridium sp.	3,793	2,795	1,355	5,558	5,383	3,505	5,541	4,429	4,121	3,258	...	4,586	1,014	4,100	4,336	2,301	6,372	4,020
g__Butyricimonas; s__Butyricimonas virosa	64	1,385	725	1,553	40	53	33	175	58	1,636	...	3,285	30	54	1,168	50	38	49
g__Alistipes; s__Alistipes indistinctus	15	20	723	620	3,261	43	83	37	43	1,114	...	3,159	61	2,606	2,821	21	2,276	3

Logistic Regression (LR) model shows precision = 0.43, recall = 0.75, F1 = 0.55, AUC-ROC = 0.78125. ROC curve and Precision-Recall curve are as follows (Figure 1 and Figure 2).

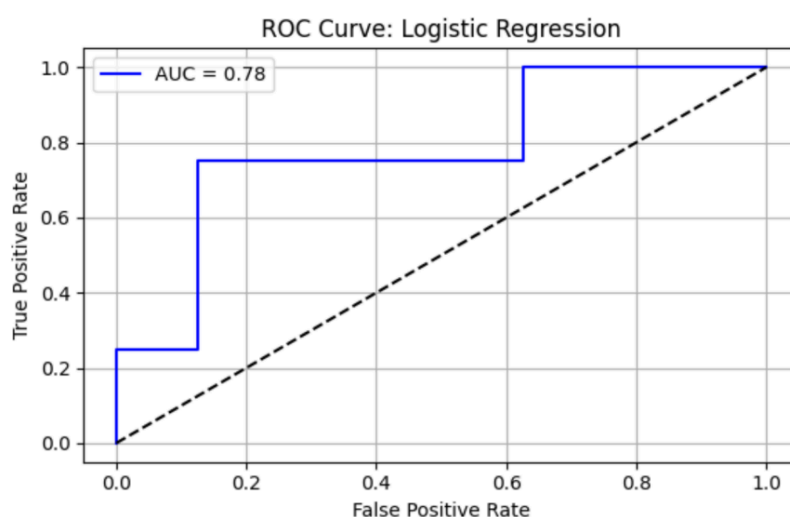


Figure 1. ROC curve of LR model

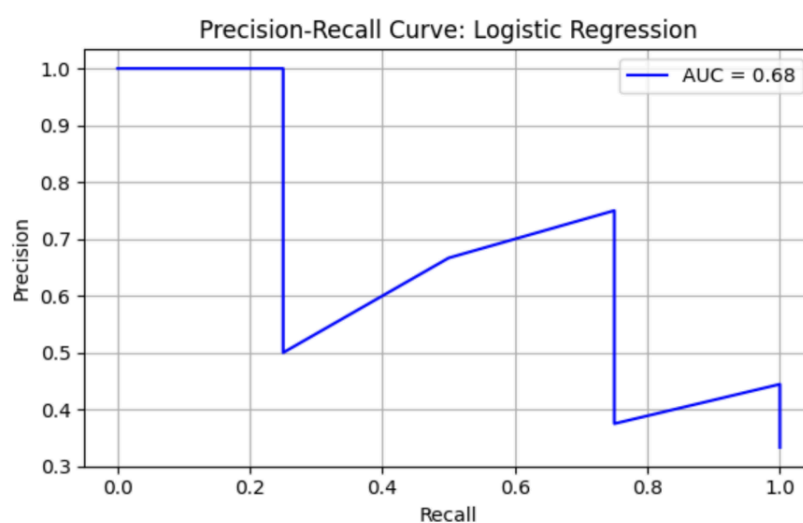


Figure 2. Precision-Recall curve of LR model

The top three most important genus are Porphyromonas, species Porphyromonas macacae (importance value = 0.028017), followed by Prevotella, species Prevotella sp. oral taxon 299 (importance value = 0.025634), and Prevotella, species Prevotella amnii (importance value = 0.025554) (Table 3).

Table 3. Top 10 feature importance of bacterial taxa in the Logistic Regression (LR) model

Full Name	Importance	Norm Importance
g__Porphyromonas; s__Porphyromonas macacae	0.028017	1.000000
g__Prevotella; s__Prevotella sp. oral taxon 299	0.025634	0.914935
g__Prevotella; s__Prevotella amnii	0.025554	0.912085
g__Unclassified; s__Bacteroidales bacterium KHT7	0.025151	0.897702
g__Prevotella; s__Prevotella sp. P5-125	0.024578	0.877273
g__Prevotella; s__Prevotella pallens	0.024077	0.859382
g__Prevotella; s__Prevotella sp. CAG:1185	0.023658	0.844413
g__Parabacteroides; s__Parabacteroides sp. CAG:409	0.023558	0.840836
g__Virgibacillus; s__Virgibacillus salinus	0.023544	0.840357
g__Bacteroides; s__Bacteroides caccae CAG:21	0.023478	0.837992

The table shows the top 10 bacterial genera and species contributing to the LR model used to distinguish ASD from healthy controls. "Importance" indicates the raw contribution of each feature to model performance, while "Norm Importance" represents the normalized importance relative to the most influential taxon. Higher values indicate greater relative importance in model prediction.

Random Forrest (RF) model shows precision = 0.43, recall = 0.75, F1 = 0.55, AUC-ROC = 0.78125. ROC curve and Precision-Recall curve are as follows (Figure 3 and Figure 4).

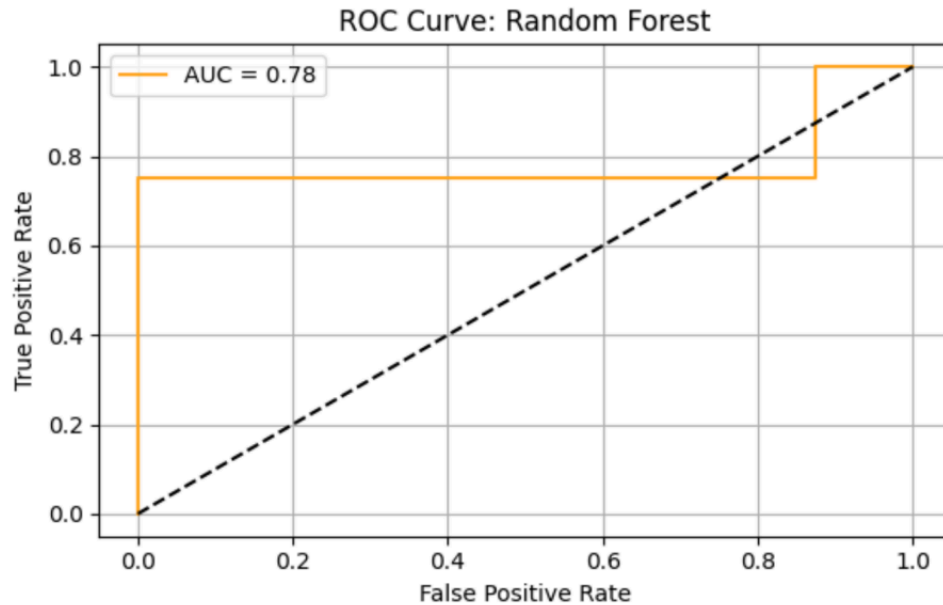


Figure 3. ROC curve of RF model

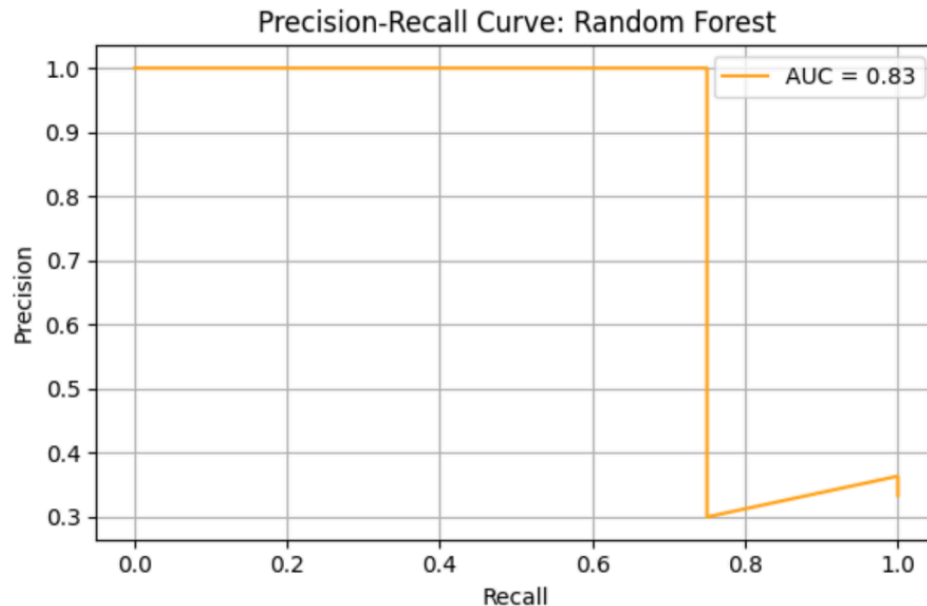


Figure 4. Precision-recall curve of RF model

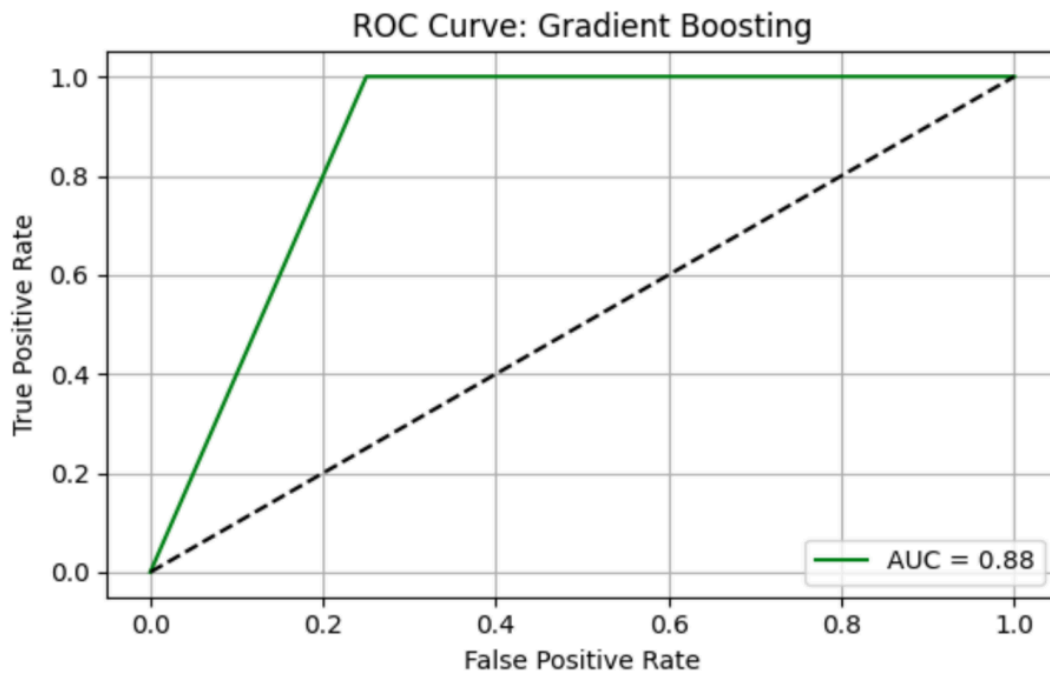
The top three most important genus are Prevotella, species Prevotella ruminicola (importance value = 0.028678), followed by Bacteroides, species Bacteroides finegoldii (importance value = 0.022608), and Prevotella, Prevotella sp. 109 (importance value = 0.020872) (Table 4).

Table 4. Feature importance of bacterial taxa in the Random Forest (RF) model

Full Name	Importance	Norm Importance
g__Prevotella;s__Prevotella ruminicola	0.028678	1.000000
g__Bacteroides;s__Bacteroides finegoldii	0.022608	0.788361
g__Prevotella;s__Prevotella sp. 109	0.020872	0.727813
g__Bacteroides;s__Bacteroides sp. CAG:770	0.015970	0.556863
g__Prevotella;s__Prevotella sp. CAG:279	0.015749	0.549163
g__Unclassified;s__Bacteroidaceae bacterium MS4	0.013588	0.473834
g__Prevotella;s__Prevotella sp. CAG:255	0.013431	0.468360
g__Prevotella;s__Prevotella sp. CAG:1058	0.013371	0.466242
g__Bacteroides;s__Bacteroides acidifaciens	0.013113	0.457257
g__Barnesiella;s__Barnesiella viscericola	0.012606	0.439563

The table lists the top microbial genera and species contributing to the RF model used to classify ASD and healthy control samples. "Importance" indicates the raw contribution of each feature to model performance, while "Norm Importance" represents the normalized importance relative to the most influential taxon. Higher values indicate greater relative importance in model prediction.

Gradient Boosting (GB) model shows precision = 0.67, recall = 1.00, F1 = 0.80, AUC-ROC = 0.87500. ROC curve and Precision-Recall curve are as follows (Figure 5 and Figure 6).

**Figure 5.** ROC curve of GB model

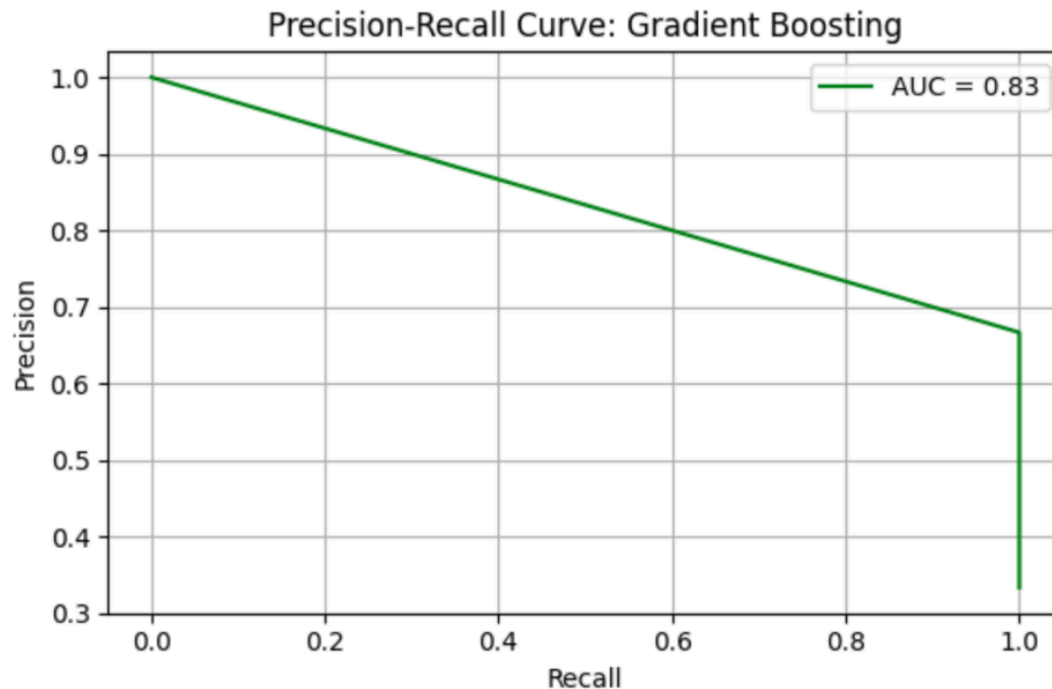


Figure 6. Precision-recall curve of GB model

The top three most important genus are *Prevotella*, species *Prevotella* sp. 109 (importance value = 0.778462), followed by *Prevotella*, species *Prevotella ruminicola* (importance value = 0.078688), and *Bacteroides*, *Bacteroides thetaiotaomicron* (importance value = 0.055255) (Table 5).

Table 5. Feature importance of bacterial taxa in the Gradient Boosting (GB) model

Full Name	Importance	Norm Importance
g__Prevotella;s__Prevotella sp. 109	0.778462	1.000000
g__Prevotella;s__Prevotella ruminicola	0.078688	0.101081
g__Bacteroides;s__Bacteroides thetaiotaomicron...	0.055255	0.070980
g__Lactobacillus;s__Lactobacillus plantarum	0.024748	0.031791
g__Jeotgalibacillus;s__Jeotgalibacillus malays...	0.011714	0.015048
g__Parabacteroides;s__Parabacteroides sp. CAG:2	0.009493	0.012194
g__Ruminococcus;s__Ruminococcus sp. CAG:624	0.007708	0.009901
g__Tolypothrix;s__Tolypothrix campylonemoides	0.006267	0.008051
g__Halotheca;s__Halotheca sp. PCC 7418	0.005102	0.006553
g__Diplosphaera;s__Diplosphaera colitermitum	0.004156	0.005339

The table lists the top microbial genera and species contributing to the GB model used to classify ASD and healthy control samples. "Importance" indicates the raw contribution of each feature to model performance, while "Norm Importance" represents the normalized importance relative to the most influential taxon. Higher values indicate greater relative importance in model prediction.

Overall, the GB model has the best performance, with an AUC-ROC = 0.87500, and LR and RF models performed the same (AUC-ROC = 0.78125). The top three most important genus from the LR, RF and GB models are *Prevotella* (appearance frequency in top 10 importance from the three models = 12 out of 30), followed by *Bacteroides* (appearance frequency = 6 out of 30), and *Parabacteroides* (appearance frequency = 2 out of 30) (Figure 7).

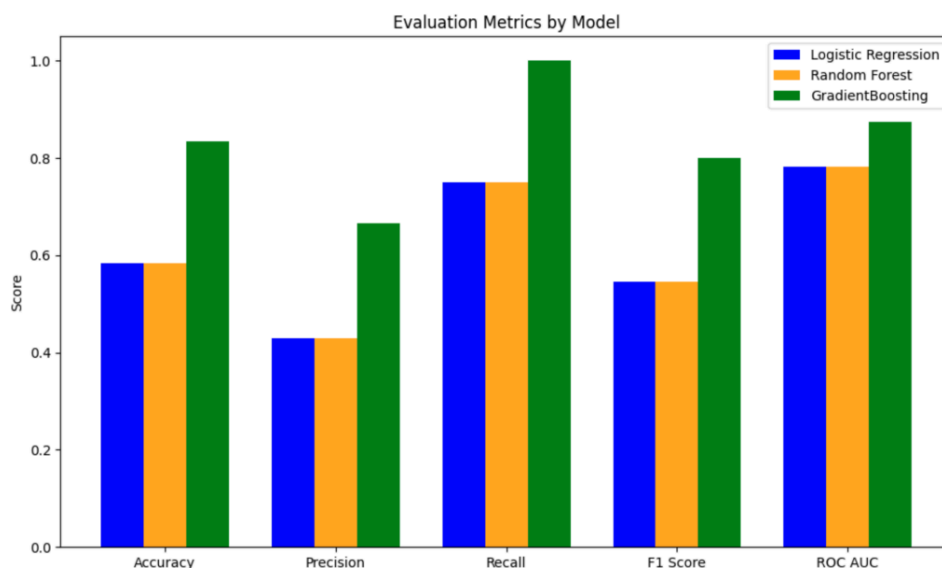


Figure 7. Summary of the accuracy, precision, recall, F1, ROC-AUC scores and highlight GB as the most reliable model for discriminating ASD-associated microbial signals identified across datasets

The second dataset contains 16S rRNA sequencing data of gut microbiota from children with Autism Spectrum Disorder (ASD) compared with healthy controls. A total of 1,322 Operational Taxonomic Units (OTUs) were identified from the sequence data. The dominant phyla in both groups were Bacteroidetes and Firmicutes, but their relative abundances differed significantly between ASD and controls.

Table 6 shows the abundance profiles of selected bacterial taxa in ASD (A group) samples. Each row represents a bacterial taxon, and each column represents individual ASD samples (A1-A95). Cell values indicate raw abundance counts.

Table 6. Heatmap of bacterial taxa abundance profiles in Autism Spectrum Disorder (ASD) samples

Short_Taxonomy	A1	A10	A100	A101	A102	A105	A106	A108	A109	...	A88	A89	A9	A90	A91	A92	A93	A95
Lachnospiraceae_bacterium_feline_oral_taxon_001	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
Sphingopyxis_granuli	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
Faecalicoccus	0	0	0	0	0	0	2	0	0	...	0	0	0	0	0	0	0	0
Streptococcus_anginosus_subsp._anginosus	0	0	0	0	0	0	0	0	1	...	0	0	0	0	1	0	0	1
Mollicutes_RF9	0	0	1	0	0	1	3	2	0	...	0	0	0	0	0	0	1	1

Table 7 shows Abundance profiles of selected bacterial taxa in control (B group) samples. Each row represents a bacterial taxon, and each column represents individual control samples (B1-B59). Cell values indicate raw abundance counts.

Table 7. Heatmap of bacterial taxa abundance profiles in control samples

Short_Taxonomy	B1	B10	B100	B101	B103	B104	B105	B106	B107	B108	...	B52	B54	B55	B56	B57	B58	B59
Lachnospiraceae_bacterium_feline_oral_taxon_001	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0
Sphingopyxis_granuli	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0
Faecalicoccus	0	0	0	0	0	0	0	0	1	0	...	0	0	0	0	0	0	0
Streptococcus_anginosus_subsp._anginosus	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0
Mollicutes_RF9	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0

LR model shows precision = 0.81, recall = 0.88, F1 = 0.85, AUC-ROC = 0.92462. ROC curve and Precision-Recall curve are as follows (Figure 8 and Figure 9).

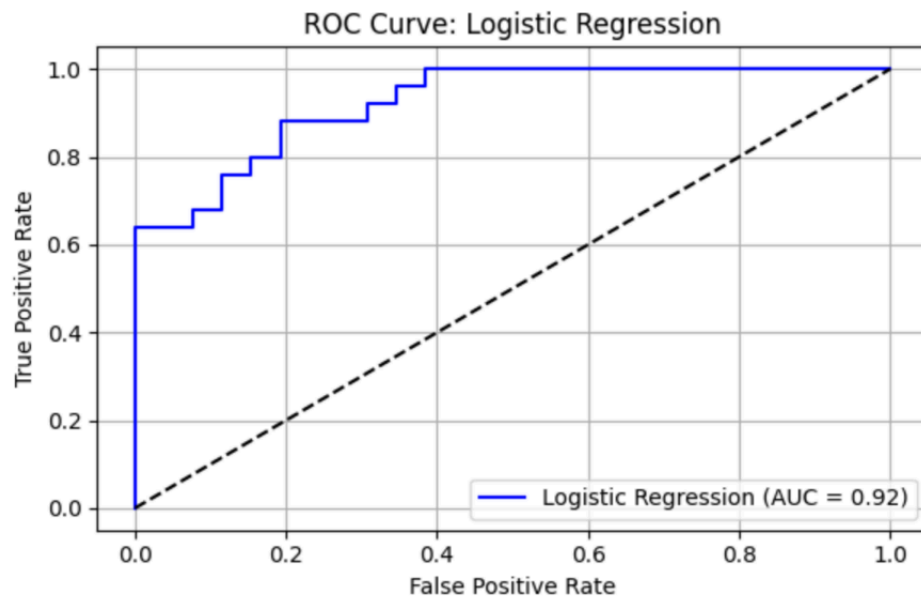


Figure 8. ROC curve of LR model

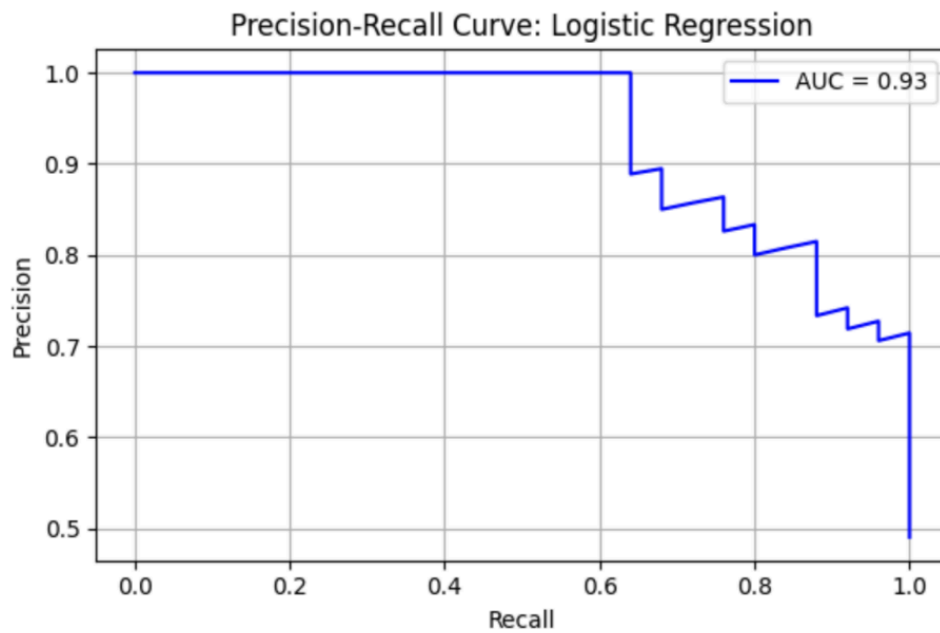


Figure 9. Precision-recall curve of LR model

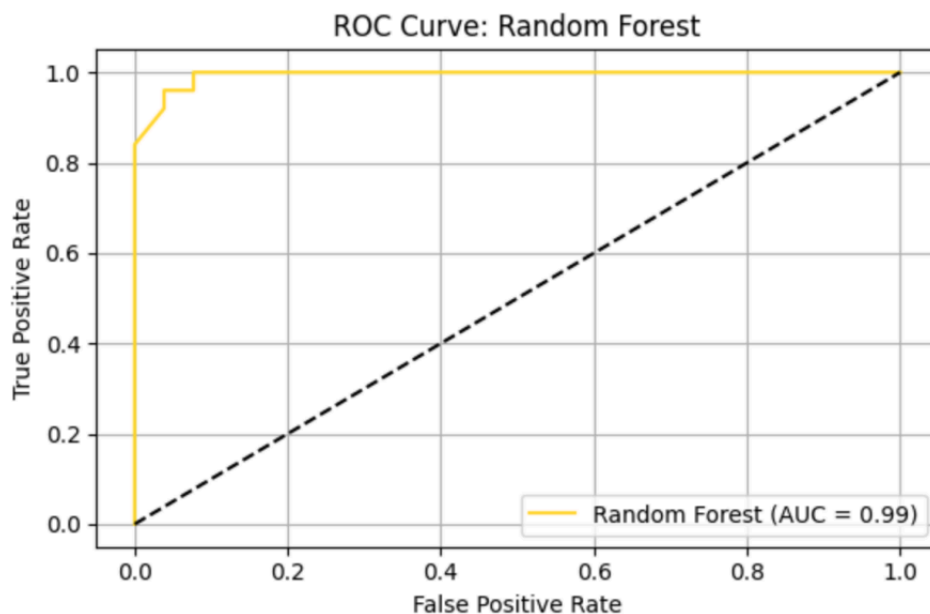
The top three most important genus are *Alistipes* (importance value = 0.036909), followed by *Acidaminococcus* (importance value = 0.034989), and *Uminiclostridium* (importance value = 0.034476) (Table 8).

Table 8. Top bacterial taxa contributing to the Logistic Regression (LR) model

Full Name	Importance	Norm Importance
d_Bacteria; k_norank; p_Bacteroidetes; c_Bacteroidia; o_Bacteroidales; f_Rikenellaceae; g_Alistipes; s_uncultured_organism_g_Alistipes	0.036909	1.000000
d_Bacteria; k_norank; p_Firmicutes; c_Negativicutes; o_Selenomonadales; f_Acidaminococcaceae; g_Acidaminococcus; s_unclassified_g_Acidaminococcus	0.034989	0.947988
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Ruminococcaceae; g_Ruminiclostridium_6; s_[Eubacterium]_siraeum_DSM_15702	0.034476	0.934080
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Ruminococcaceae; g_Ruminococcus_1; s_Ruminococcus_bicirculans	0.030622	0.829654
d_Bacteria; k_norank; p_Bacteroidetes; c_Bacteroidia; o_Bacteroidales; f_Prevotellaceae; g_Prevotella_2; s_uncultured_organism_g_Prevotella_2	0.029501	0.799294
d_Bacteria; k_norank; p_Bacteroidetes; c_Bacteroidia; o_Bacteroidales; f_Porphyromonadaceae; g_Parabacteroides; s_Parabacteroides_merdae	0.028867	0.782114
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Lachnospiraceae; g_Lachnospira; s_uncultured_organism_g_Lachnospira	0.028247	0.765324
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Lachnospiraceae; g_Lachnoclostridium; s_human_gut_metagenome_g_Lachnoclostridium	0.027654	0.749243
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Ruminococcaceae; g_norank_f_Ruminococcaceae; s_unclassified_g_norank_f_Ruminococcaceae	0.026571	0.719921
d_Bacteria; k_norank; p_Proteobacteria; c_Deltaproteobacteria; o_Desulfovibrionales; f_Desulfovibrionaceae; g_Bilophila; s_Bilophila_wadsworthia	0.024331	0.659230

The table lists the most important Operational Taxonomic Units (OTUs) identified from ASD and healthy control gut microbiome samples. "Importance" reflects the absolute contribution of each taxon to the LR classifier, while "Norm Importance" represents the relative importance normalized to the highest-ranked feature. Key taxa include members of the phyla Bacteroidetes (e.g., Alistipes, Prevotella, Parabacteroides) and Firmicutes (e.g., Ruminococcus, Lachnospira, Eubacterium), suggesting that both phyla contribute substantially to distinguishing ASD from controls.

RF model shows precision = 0.93, recall = 1.00, F1 = 0.96, AUC-ROC = 0.99638. ROC curve and Precision-Recall curve are as follows (Figure 10 and Figure 11).

**Figure 10.** ROC curve of RF model

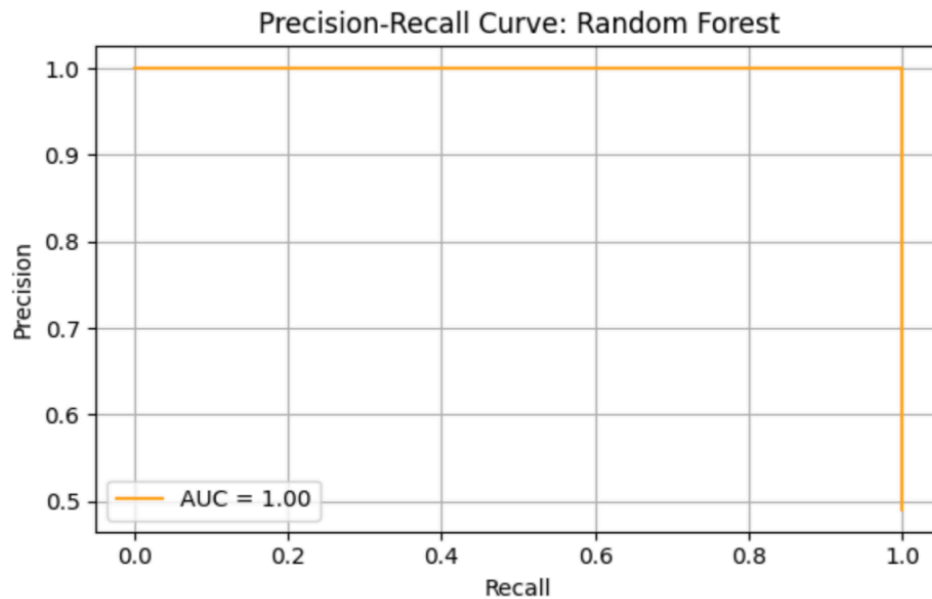


Figure 11. Precision-recall curve of RF model

The top three most important genus are *Lachnoclostridium* (importance value = 0.021960), followed by *Ruminococcaceae_UCG-014* (importance value = 0.020574), and *Barnesiella* (importance value = 0.018044) (Table 9).

Table 9. Top bacterial taxa contributing to the Random Forest (RF) model

Full Name	Importance	Norm Importance
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Lachnospiraceae; g_Lachnoclostridium; s_uncultured_Clostridiales_bacterium_g_Lachnoclostridium	0.021960	1.000000
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Ruminococcaceae; g_Ruminococcaceae_UCG-014; s_unclassified_g_Ruminococcaceae_UCG-014	0.020574	0.936892
d_Bacteria; k_norank; p_Bacteroidetes; c_Bacteroidia; o_Bacteroidales; f_Porphyromonadaceae; g_Barnesiella; s_uncultured_organism_g_Barnesiella	0.018044	0.821664
d_Bacteria; k_norank; p_Bacteroidetes; c_Bacteroidia; o_Bacteroidales; f_Prevotellaceae; g_Prevotella_9; s_uncultured_organism_g_Prevotella_9	0.016655	0.758433
d_Bacteria; k_norank; p_Proteobacteria; c_Betaproteobacteria; o_Burkholderiales; f_Comamonadaceae; g_Comamonas; s_unclassified_g_Comamonas	0.014245	0.648698
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Ruminococcaceae; g_[Eubacterium]_coprostanoligenes_group; s_uncultured_bacterium_g_[Eubacterium]_coprostanoligenes_group	0.013887	0.632373
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Ruminococcaceae; g_[Eubacterium]_coprostanoligenes_group; s_uncultured_bacterium_g_[Eubacterium]_coprostanoligenes_group	0.013879	0.631997
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Ruminococcaceae; g_Ruminiclostridium_6; s_[Eubacterium]_siraeum_DSM_15702	0.012114	0.551630
d_Bacteria; k_norank; p_Bacteroidetes; c_Bacteroidia; o_Bacteroidales; f_Prevotellaceae; g_Prevotella_2; s_uncultured_bacterium_g_Prevotella_2	0.011761	0.535584
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Ruminococcaceae; g_Ruminiclostridium_6; s_unclassified_g_Ruminiclostridium_6	0.011373	0.517922

The table displays the most influential Operational Taxonomic Units (OTUs) identified in ASD versus healthy control samples. "Importance" indicates the contribution of each feature to the RF classifier, while "Norm Importance" normalizes this score relative to the highest-ranked feature. The top-ranked taxa belong primarily to Firmicutes (e.g., *Lachnoclostridium*,

Ruminococcaceae UCG-014) and Bacteroidetes (e.g., Barnesiella, Prevotella), with additional contributions from Proteobacteria (Comamonadaceae). These results highlight the multi-phylum microbial signals that the RF model leverages to distinguish ASD from control gut microbiomes.

GB model shows precision = 0.93, recall = 1.00, F1 = 0.96, AUC-ROC = 0.98308. ROC curve and Precision-Recall curve are as follows (Figure 12 and Figure 13).

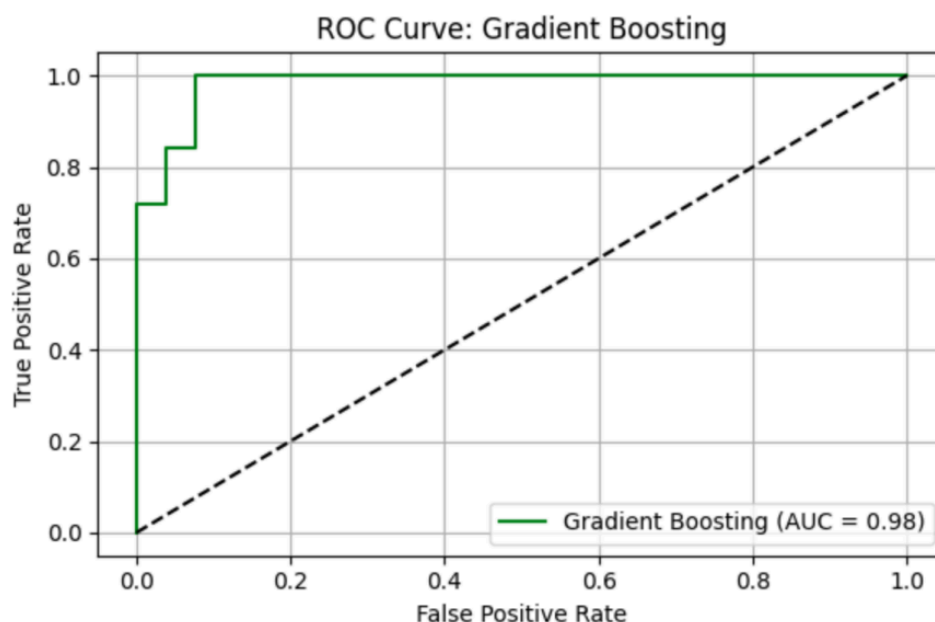


Figure 12. ROC curve of GB model

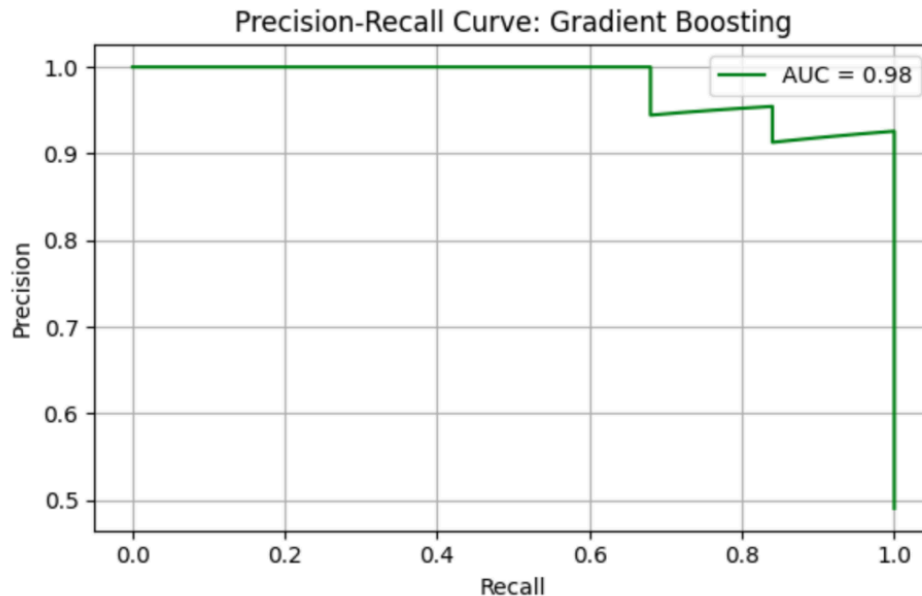


Figure 13. Precision-Recall curve of GB model

The top three most important genus are Prevotella_2 (importance value = 0.356231), followed by Anaerotruncus (importance value = 0.091146), and Megasphaera (importance value = 0.058656) (Table 10).

Table 10. Top bacterial taxa contributing to the Gradient Boosting (GB) model

Full Name	Importance	Norm Importance
d_Bacteria; k_norank; p_Bacteroidetes; c_Bacteroidia; o_Bacteroidales; f_Prevotellaceae; g_Prevotella_2; s_uncultured_organism_g_Prevotella_2	0.356231	1.000000
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Ruminococcaceae; g_Anaerotruncus; s_uncultured_organism_g_Anaerotruncus	0.091146	0.255862
d_Bacteria; k_norank; p_Firmicutes; c_Negativicutes; o_Selenomonadales; f_Veillonellaceae; g_Megasphaera; s_uncultured_bacterium_g_Megasphaera	0.058656	0.164656
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Lachnospiraceae; g_Lachnoclostridium; s_uncultured_Clostridiales_bacterium_g_Lachnoclostridium	0.049170	0.138029
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Lachnospiraceae; g_Lachnoclostridium; s_[Clostridium]_scindens	0.046248	0.129826
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Lachnospiraceae; g_norank_f_Lachnospiraceae; s_unclassified_g_norank_f_Lachnospiraceae	0.033643	0.094441
d_Bacteria; k_norank; p_Fusobacteria; c_Fusobacteriia; o_Fusobacteriales; f_Fusobacteriaceae; g_Fusobacterium; s_Fusobacterium_mortiferum	0.032311	0.090702
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Ruminococcaceae; g_Ruminococcaceae_UCG-005; s_unclassified_g_Ruminococcaceae_UCG-005	0.026538	0.074498
d_Bacteria; k_norank; p_Bacteroidetes; c_Bacteroidia; o_Bacteroidales; f_Bacteroidaceae; g_Bacteroides; s_Bacteroides_plebeius	0.023210	0.065153
d_Bacteria; k_norank; p_Firmicutes; c_Clostridia; o_Clostridiales; f_Lachnospiraceae; g_Lachnospiraceae_UCG-004; s_uncultured_organism_g_Lachnospiraceae_UCG-004	0.021597	0.060627

The table highlights the most influential Operational Taxonomic Units (OTUs) identified for differentiating ASD and healthy control samples in the GB model. "Importance" indicates the raw contribution of each taxon to the classifier, while "Norm Importance" is normalized relative to the highest-ranked feature. The strongest feature was *Prevotella* (phylum Bacteroidetes), followed by multiple taxa within Firmicutes (e.g., *Anaerotruncus*, *Megasphaera*, *Lachnoclostridium*, *Clostridium scindens*), and additional contributions from Fusobacteria. This pattern suggests that GB placed the greatest weight on specific taxa-level shifts, especially within *Prevotella* and *Lachnospiraceae*, to achieve its high classification accuracy.

Overall, the RF model has the best performance, with an AUC-ROC = 0.995, followed by the GB model (AUC-ROC = 0.983) and the LR model (AUC-ROC = 0.925). The top three most important genus from the LR, RF and GB models are *Lachnoclostridium* (appearance frequency in top 10 importance from the three models = 4 out of 30), followed by *Prevotella* (appearance frequency = 4 out of 30), and *Eubacterium* (appearance frequency = 2 out of 30) (Figure 14).

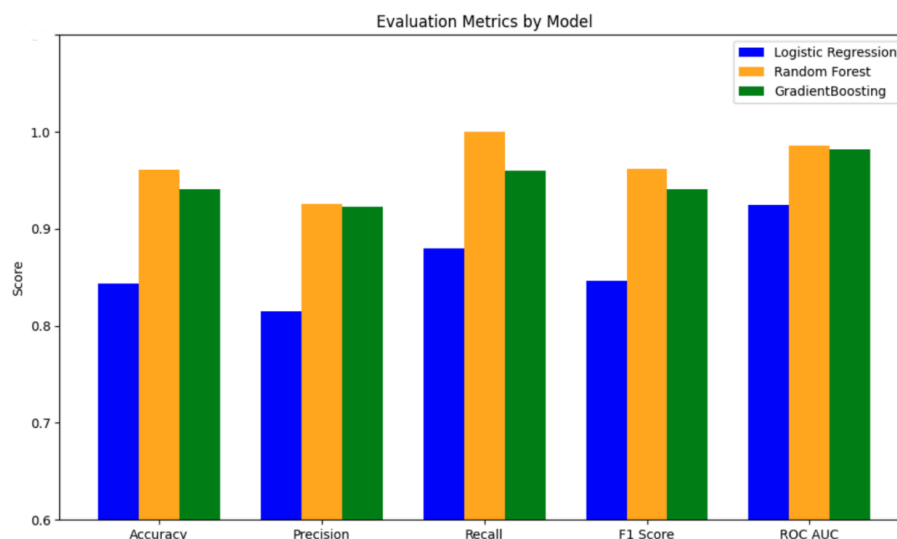


Figure 14. Summary of the accuracy, precision, recall, F1, ROC-AUC scores for dataset 2 and highlight RF as the most robust classifier for this dataset

In summary, considering both datasets, *Prevotella* is the most important genus, followed by *Bacteroides*, *Parabacteroides*, and *Lachnospirillum*.

4. Discussion

In the present study, we identified *Prevotella* as the most consistent microbial marker distinguishing ASD from controls, appearing 16 times across models and datasets (12 occurrences in gut abundance dataset: LR = 5, RF = 5, GB = 2; 4 occurrences in 16S dataset: LR = 1, RF = 2, GB = 1). *Bacteroides* ranked second with 6 total occurrences (LR = 2, RF = 3, GB = 1), while *Parabacteroides* appeared 2 times (LR = 1, GB = 1). In contrast, *Lachnospirillum* showed dataset-dependent relevance, detected 4 times exclusively in the 16S dataset (LR = 1, RF = 1, GB = 2). Gradient Boosting achieved the highest predictive performance (AUC-ROC = 0.88; F1 = 0.80), indicating strong classification ability. These findings suggest *Prevotella*-driven gut dysbiosis as a robust feature of ASD microbiome profiles.

Prevotella

In our analyses, *Prevotella* consistently emerged as a key genus differentiating ASD from controls. It appeared 12 times in models using the ASD gut abundance dataset (LR = 5, RF = 5, GB = 2) and 4 times in models using the 16S rRNA dataset (LR = 1, RF = 2, GB = 1), making it one of the most frequently selected taxa across all three machine learning approaches [23, 24].

Several studies report *Prevotella* significantly enriched in the gut microbiota of ASD children compared to neurotypical controls [25], which is consistent with our findings. A 16S rRNA study in Chinese cohorts also observed elevated *Prevotella*, suggesting that higher levels may contribute to ASD-related gut dysbiosis. Mechanistically, *Prevotella* can function as an intestinal pathobiont, triggering mucosal inflammation and upregulating cytokines such as Interleukin-6 (IL-6) and IL-8 through TLR4-mediated pathways, leading to chronic inflammation that affects the gut-brain axis and may worsen ASD symptoms [26]. In addition, *Prevotella* species produce short-chain fatty acids including propionate, a neuroactive metabolite that, when in excess, has been linked to autism-like behaviors in rodent models [27].

Conversely, other studies identify *Prevotella* depletion in ASD, suggesting it can play a protective role [28]. Kang et al. reported significantly lower *Prevotella* abundance in autistic children versus neurotypical peers. Restoration of *Prevotella* through microbiota interventions shifted the ASD gut microbiome toward a more neurotypical composition and reduced symptom severity [19]. This protective effect is likely mediated by the production of beneficial SCFAs like acetate and butyrate, which strengthen both the gut and blood-brain barriers and reduce systemic inflammation [29]. Furthermore, a clinical trial using Fecal Microbiota Transfer Therapy (FMT) demonstrated that increasing *Prevotella* abundance led to sustained improvements in GI function and behavior in ASD children [19].

The conflicting results across studies likely stem from differences in diet, geography, and microbial strain diversity [30-33]. Western ASD populations often consume low-fiber diets, leading to markedly lower *Prevotella*, while cohorts from regions with high fiber intake, such as parts of Asia, frequently report higher levels in ASD. Moreover, strain-level variation within *Prevotella* may result in some species exhibiting pro-inflammatory effects while others are beneficial, explaining why the genus can appear either enriched or depleted depending on population and environmental factors [25, 28].

Bacteroides

In our ASD gut microbiome dataset, *Bacteroides* appeared as a top-ranking feature in 6 model runs: Logistic Regression = 2, Random Forest = 3, and Gradient Boosting = 1, indicating moderate importance in distinguishing ASD from control samples.

Consistent with our results, the genus *Bacteroides* is frequently reported at higher relative abundance in children with ASD compared to neurotypical controls [7]. Multiple studies have found *Bacteroides* to be over-represented in ASD fecal samples, consistent with meta-analyses showing elevated *Bacteroides* in ASD populations [7]. One mechanism linking *Bacteroides* to increased ASD risk is propionate production [27]. *Bacteroides* spp. are major producers of propionic acid, and excess propionate can cross the blood-brain barrier and induce neurobehavioral changes characteristic of ASD in rodent models [27]. Another mechanism involves endotoxin-mediated inflammation [31]. Being Gram-negative bacteria, *Bacteroides* shed Lipopolysaccharides (LPS), which are potent endotoxins that can strongly activate immune pathways, potentially causing systemic inflammation that disrupts neurodevelopment [31].

Some studies report higher *Bacteroides* levels in neurotypical controls, suggesting a protective role [16]. An analysis found significantly lower mucosa-associated *Bacteroides* in ASD patients compared to controls, indicating that increased *Bacteroides* abundance may sometimes reflect a healthy gut ecosystem [16]. A key protective mechanism involves gut barrier and metabolite modulation [34]. Colonization by *Bacteroides fragilis* in ASD mouse models strengthens the intestinal barrier and corrects abnormal metabolite profiles, leading to improvements in communication and anxiety-like behaviors [34]. *Bacteroides fragilis* also metabolizes harmful neuroactive compounds, reducing their systemic levels and ameliorating ASD-like symptoms [34]. Another mechanism is immunoregulation through production of polysaccharide A, which promotes regulatory T-cell development and anti-inflammatory IL-10 secretion, countering the heightened pro-inflammatory state frequently observed in ASD [35]. Clinical studies using *Bacteroides fragilis* have demonstrated reductions in gastrointestinal dysfunction and ASD symptom severity [36].

Differences in *Bacteroides* patterns across studies likely result from population and diet variations [30]. Western high-fat, high-protein diets favor *Bacteroides*, whereas high-fiber diets suppress its abundance, leading to variability in associations with ASD [30]. Methodological differences also play a role, as some studies detect *Bacteroides* elevation in stool samples while intestinal biopsy samples show decreases, highlighting the importance of sampling sites [20]. In addition, variation in sequencing platforms and bioinformatics pipelines can lead to discrepancies in taxa detection and interpretation [7].

4.1. Parabacteroides

In our ASD gut microbiome dataset, *Parabacteroides* was identified as a top feature in 2 model runs: Logistic Regression = 1, Random Forest = 0, and Gradient Boosting = 1, suggesting a low-to-moderate role in distinguishing ASD from controls.

Several studies report that *Parabacteroides* levels are significantly altered in children with ASD compared to neurotypical peers [16]. Machine-learning analyses across multiple cohorts have highlighted *Parabacteroides* as one of the genera associated with ASD-related microbiome changes. One mechanism involves pro-inflammatory metabolite production [37]. Certain *Parabacteroides* species produce succinate, which functions as a pro-inflammatory signal that drives immune cells toward a pro-inflammatory phenotype and stimulates cytokine release, including IL-1 β and IL-6, thereby promoting gut and systemic inflammation [37]. Another mechanism involves endotoxin diversity, as some *Parabacteroides* strains carry genes that alter LPS structure, potentially amplifying gut immune dysregulation linked to ASD.

In contrast, other evidence shows *Parabacteroides* may have protective functions in maintaining gut health [7]. A key protective mechanism is anti-inflammatory immune modulation [38]. *Parabacteroides distasonis* (*P. distasonis*) produces secondary bile acids that inhibit inflammatory T-cell differentiation and enhance regulatory T-cell activity through specific receptor pathways, shifting the immune response toward an anti-inflammatory state [38]. Another mechanism is immune homeostasis maintenance, as certain *Parabacteroides* species produce LPS variants that act as immune modulators, helping prevent excessive immune activation associated with neuroinflammation.

Differences in *Parabacteroides* findings across studies stem from cohort and methodological variability [7]. Regional dietary patterns, including fiber content and fermented food intake, strongly influence *Parabacteroides* abundance [30]. Additionally, health status, medication use, and antibiotic exposure vary across studies, adding confounding factors [7]. As a moderately low-abundance genus, detection of *Parabacteroides* is sensitive to sequencing depth, primer selection, and bioinformatics thresholds. These methodological limitations contribute to inconsistent reports of *Parabacteroides* being either enriched or depleted in ASD [7].

4.2. Lachnospiraceae

In our analyses, *Lachnospiraceae* was not a top feature in the general ASD abundance dataset (0 occurrences), but it appeared 4 times in the 16S rRNA-based dataset (LR = 1, RF = 1, GB = 2). This suggests that *Lachnospiraceae*'s importance may depend on the dataset used and the feature selection approach, indicating its potential relevance under certain microbiome analysis conditions.

Some studies have found *Lachnospiraceae*, a genus in the *Lachnospiraceae* family, to be altered in children with ASD, especially those with gastrointestinal symptoms [16]. Elevated *Lachnospiraceae* abundance has been reported in certain ASD cohorts, indicating a possible association with the disorder [9]. One mechanism involves altered tryptophan metabolism, as increased *Lachnospiraceae* correlates with changes in tryptophan metabolites, suggesting disruption of serotonin pathways critical for neurodevelopment [39]. Another mechanism relates to metabolic dysfunction, as *Lachnospiraceae* abundance has been linked with altered fatty acid profiles in ASD children, potentially contributing to neurodevelopmental dysfunction through metabolic stress [9].

Conversely, other studies report decreased *Lachnospiraceae* in ASD, implying a protective role when present at normal levels [16]. In these cases, higher *Lachnospiraceae* abundance in neurotypical children may reflect a healthier gut ecosystem supporting neurodevelopment. One protective mechanism is beneficial SCFA production, as *Lachnospiraceae* species ferment dietary fibers into butyrate, an anti-inflammatory short-chain fatty acid that strengthens intestinal epithelial integrity and positively influences brain function [26]. A second mechanism involves antioxidant functions, as these bacteria contribute to metabolic processes that produce compounds reducing oxidative stress and protecting neuronal tissues [16].

Conflicting findings on *Lachnospiraceae* likely arise from population and dietary differences [9]. Different dietary patterns are associated with varying *Lachnospiraceae* levels across populations [16]. Technical factors also influence results, as gut microbiota composition evolves with age, and methodological differences in sequencing platforms, primer selection, and sample type can alter detection accuracy [39]. Additionally, confounding factors such as gastrointestinal symptoms or medication use, both common in ASD, may independently affect *Lachnospiraceae* abundance [9]. These factors contribute to reports of both increases and decreases in this genus across studies.

5. Limitations

Major gaps remain in understanding the role of the microbiota in ASD. Causality is unclear: it is not known whether gut dysbiosis contributes to ASD pathogenesis or is instead a consequence of ASD-related factors (such as restricted diets, selective eating, or genetic influences). Findings on specific microbial taxa have been inconsistent across studies and populations. In fact, gut microbiome studies in ASD rarely agree on the same set of differentially abundant bacteria. Differences in sequencing methods, dietary habits, and cohort demographics (including the use of neurotypical versus sibling controls) likely contribute to these inconsistencies. Another open question is the role of low-abundance or previously under-recognized microbes (including anaerobes, fungi, and bacteriophages) in ASD. Most studies to date focus on common bacterial taxa, yet recent machine-learning analyses have pointed to less prominent genera (such as *Turicibacter* or *Catenibacterium*) as potential ASD biomarkers. To capture the complex biology, researchers are increasingly employing multi-omics and integrative approaches. Emerging studies combine 16S rRNA gene sequencing with metagenomics, metabolomics, and host transcriptomics to identify functional pathways linking the microbiome to host neurobiology [6]. For example, a 2023 multi-cohort analysis found that ASD-associated microbiota changes (in genera like *Bifidobacterium*, *Prevotella*, and *Desulfovibrio*) correlated with altered microbial metabolism of amino acids and fatty acids as well as with differences in host brain gene expression and inflammation profiles [6]. Advanced computational models have also shown promise in classifying ASD versus neurotypical status based on gut microbial profiles, though with moderate accuracy (area-under-curve ~75-80%). These approaches underscore that the gut microbiome is strongly associated with ASD, but also highlight its complexity. Going forward, longitudinal studies and controlled trials (e.g. dietary or microbiota-targeted interventions) are needed to determine if microbiome changes can causally influence neurodevelopmental outcomes in ASD.

6. Conclusion

In conclusion, this study demonstrates that children with ASD harbor a distinct gut microbiome profile compared to neurotypical peers, and that these differences can be leveraged for predictive modeling. Across two complementary datasets, ASD gut samples showed altered diversity and composition—for instance, higher relative abundances of certain genera (e.g., *Prevotella*, *Bacteroides*) alongside a reduction in beneficial microbes like *Bifidobacterium*, indicative of dysbiosis [6, 25]. Using these microbial features, supervised classifiers were able to distinguish ASD cases from controls with high accuracy (exceeding 80% and an AUROC ~0.9 in cross-validation), underscoring the robust signal inherent in the gut microbiome. Notably, *Prevotella* emerged as a key discriminative genus, consistently selected by multiple models, appearing 16 times out of 60 different genera being abundant across the three models in both datasets, in line with reports of its elevated levels in ASD cohorts [25]. Likewise, an overrepresentation of pro-inflammatory or opportunistic taxa (e.g., certain *Clostridia* and *Parabacteroides*) and a loss of neuroprotective, short-chain fatty acid producers in ASD further support a pro-inflammatory gut milieu in the disorder [7]. Together, these findings underscore the involvement of the microbiota–gut–brain axis in ASD pathophysiology, suggesting that gut microbial shifts may influence neurodevelopmental outcomes and behavioral symptoms in affected children.

Looking ahead, future studies should validate these candidate microbial biomarkers in larger, diverse cohorts and investigate the causal mechanisms linking gut microbes to ASD. Controlled intervention trials modulating the microbiome are especially warranted. For example, transplanting beneficial bacteria or whole microbiota has shown promise—an open-label fecal microbiota transfer therapy yielded sustained improvements in gastrointestinal and autism symptoms [19]—and a recent probiotic trial using *Bacteroides fragilis* reported significant and safe improvements in abnormal behavior and gastrointestinal symptoms in children with ASD [36]. Such efforts, alongside longitudinal and multi-omics approaches, will be crucial to confirm whether correcting dysbiosis can mitigate core ASD symptoms and to identify novel microbiome-targeted therapeutics.

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