A Review on the Use of Artificial Intelligence for Human Microbiota Analysis in Clinical Tasks

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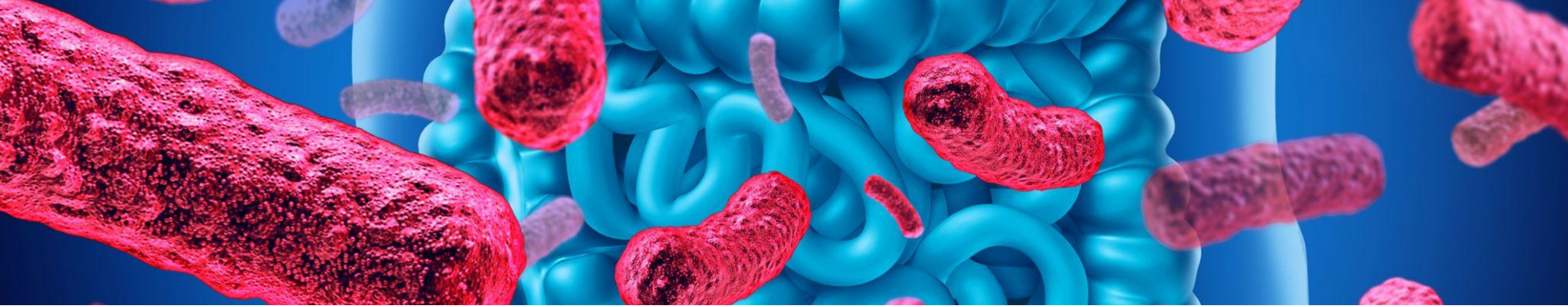
Agenda

- Background
- Why AI for Microbiota
- Methodology
- Overview of Selected Studies
- Machine Learning Approaches
- Deep Learning Approaches
- Clinical Applications
- Limitations
- Future Directions
- Conclusion

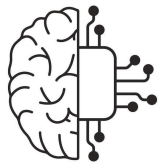


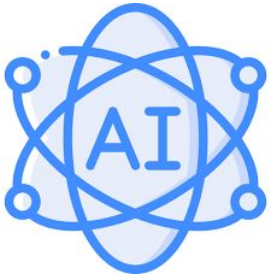
Background : Microbiota

1. Trillions of microorganisms across gut, oral, skin, urogenital sites
2. Key roles: Immunity, Metabolism, Pathogen resistance
3. Dysbiosis linked to major diseases:
   a. Colorectal cancer
   b. T2 Diabetes
   c. IBD
   d. Liver disease
4. High-dimensional, sparse, noisy data → analytical challenges

Why AI For Microbiota?

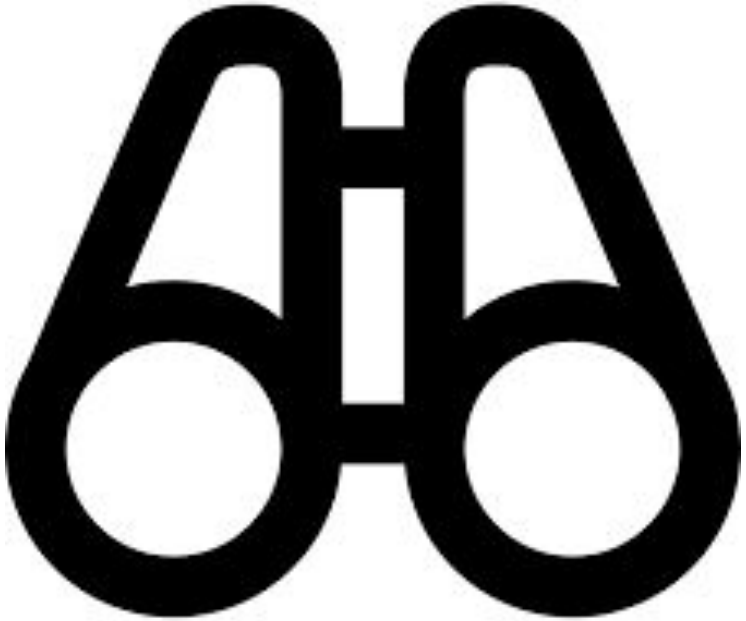
- Learns patterns in complex microbial ecosystems
- Handles high dimensionality and non-linearity
- Supports:
  - Disease prediction
  - Prognosis
  - Patient stratification
  - Biomarker discovery
- Potential pathway to precision medicine





Methodology(PRISMA INSPIRED)

- Databases: PubMed, IEEE Xplore, ScienceDirect, SpringerLink
- Keywords: microbiota · microbiome · ML · DL · clinical
- Inclusion:
- • Human data
- • Peer-reviewed
- • Empirical AI models
- Extracted: model type, data source, clinical goal, performance, limitations



Overview Of Selected Studies

- Majority use classical ML
- Smaller but growing set uses DL, especially CNNs
- Data types:
  - 16S rRNA
  - Whole-metagenome
  - Metabolomics
  - Imaging + microbiota
- Clinical focus: cancer, liver disease, IBD, oral disease, dermatology, drug interactions

Machine Learning Approaches

- Dominant: Random Forest (robust, interpretable)
- Others: SVM · Logistic Regression · XGBoost · Extra Trees
- Applications:
  - Cancer subtype prediction
  - Liver disease prognosis
  - CD vs UC classification
  - Preterm birth prediction
  - CVD screening
  - Drug–microbiota interaction modeling

Deep Learning Approaches

- Mostly CNN-based architectures
- Phylogeny-aware CNNs using taxonomic structure
- Used for:
  - Liver disease staging
  - Dermatology + microbiota multimodal tasks
  - High-resolution ASV identification
- Strength: feature representation
- Weakness: interpretability, data requirements

Clinical Applications of AI

- Diagnosis / Classification
- Colorectal cancer · Liver disease · IBD · Oral lichen planus · Dermatology
- Prognosis / Risk Prediction
- Survival · CVD · T2D (microbial rhythmicity)
- Therapeutic Support
- Immunotherapy response · Drug metabolism/bioaccumulation
- Multi-disease frameworks emerging

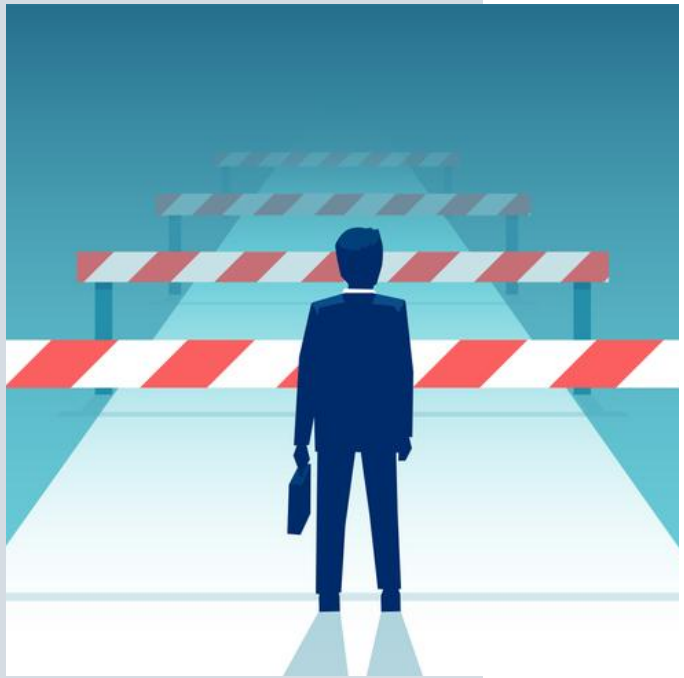
Data Types & Processing

- Mostly gut microbiota (stool samples)
- Growing use of oral & skin microbiota
- Profiling methods:
  - 16S rRNA (common, low resolution)
  - WGS (higher resolution, costly)
- Challenges:
  - Heterogeneous preprocessing
  - OTUs vs ASVs
  - Compositionality (CLR, ALR, TSS)

Key Limitations

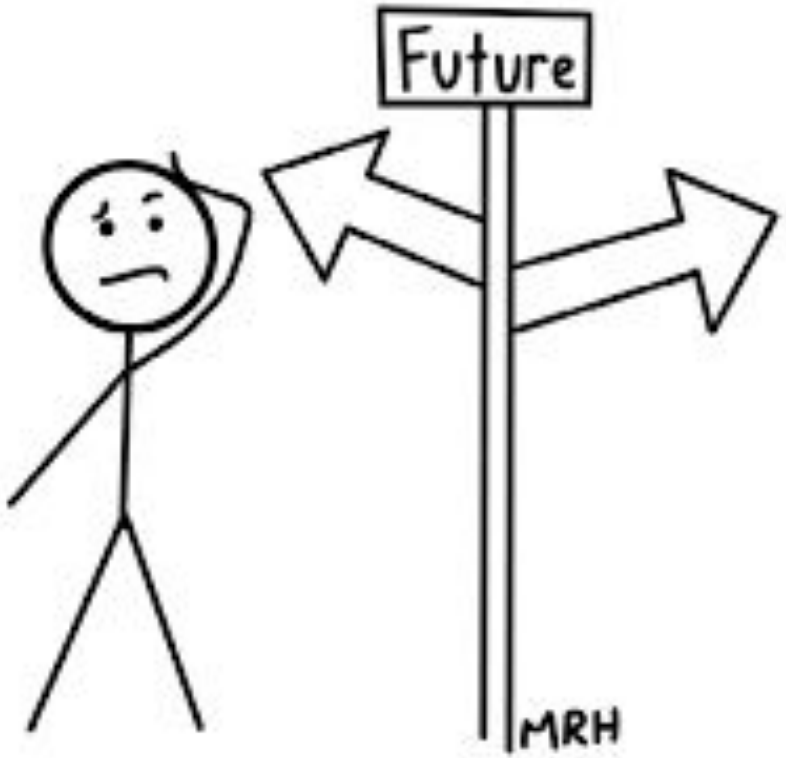
- Small, single-center datasets
- Weak external validation
- Batch effects & inter-study variability
- Inconsistent preprocessing pipelines
- Limited interpretability
- Minimal code / pipeline transparency

Challenges: What They Mean



- High AUC ≠ reliable model
- Models may learn site-specific artifacts instead of biology
- Poor generalization across regions, devices, populations
- Limited trust due to lack of explainability
- Biological noise + sequencing differences distort patterns

Future Directions



- Standardize microbiome preprocessing workflows
- Multi-center, diverse datasets for validation
- Integrate explainability (SHAP, LIME, attention)
- Expand to oral, skin, vaginal niches
- Multimodal learning (microbiota + metabolomics + imaging + metadata)
- Causal ML & temporal modeling
- Federated learning for privacy-preserving cross-site collaboration

Conclusions

- AI shows strong promise for microbiota-based clinical tasks
- ML dominates; DL excels in multimodal contexts
- Major gaps: generalization, standardization, interpretability
- Clinical translation requires rigorous validation and transparency
- Microbiota + AI → emerging pillar for personalized medicine
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Speaker: Rohith Janwadkar

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