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- Training cohort: 1,088 *A. baumannii* isolates.
- Independent test cohort: 508 *A. baumannii* isolates.
- Whole-genome data were quality-controlled using BUSCO, retaining genomes with >95% completeness.
- Coding sequences were annotated with Prokka, followed by KEGG orthology assignment using eggNOG-mapper.
- A KO abundance matrix was constructed and used to train six machine learning models
- Model performance was evaluated using five-fold cross-validation and an independent test cohort.
- SHAP values and XGBoost feature importance were used to identify resistance-associated KO

Data Collection and Processing

Original WGS data (NCBI) → Excluding genomes with <95% completeness scores (BUSCO) → Coding Sequence Identification (Prokka) → genome-wide functional annotation (EGGNOG-MAPPER, KEGG Orthology Annotation) → Training set (1088 samples) + Test set (508 samples)

Models Construction

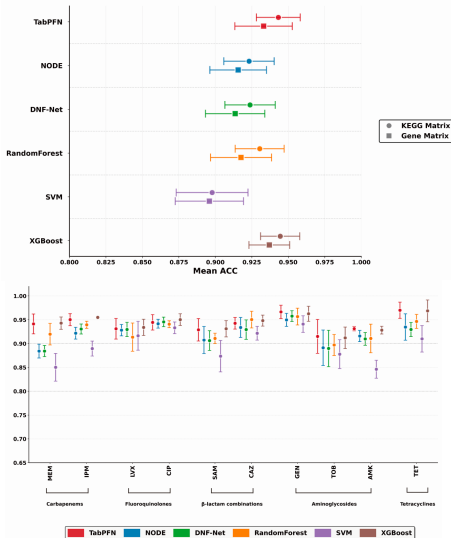
KO Features Matrix (Table below) → Different Models Comparison → Best Model

Sample	K00001	K00002	K00003	...
Strain 1	1	0	1	...
Strain 2	2	0	0	...
Strain 3	1	0	0	...
Strain 4	1	0	1	...
Strain 5	1	0	0	...
...	...	...	...	...

Prediction and Interpretability

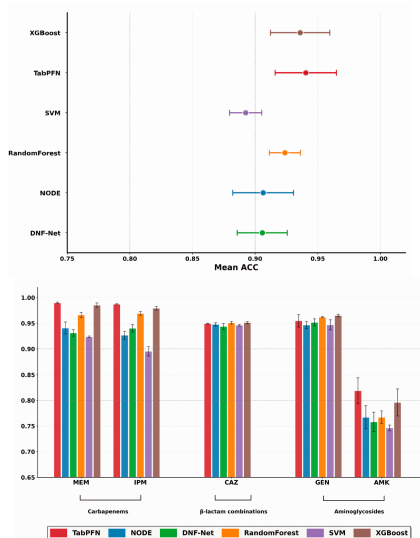
Training data set → Test data set → Training • Cross-validation • Testing → Resistant/Susceptible → Model Assessment (ROC curve) → SHAP Value → Pathway Analysis → Biomarker Identification

A. Model Performance Comparison



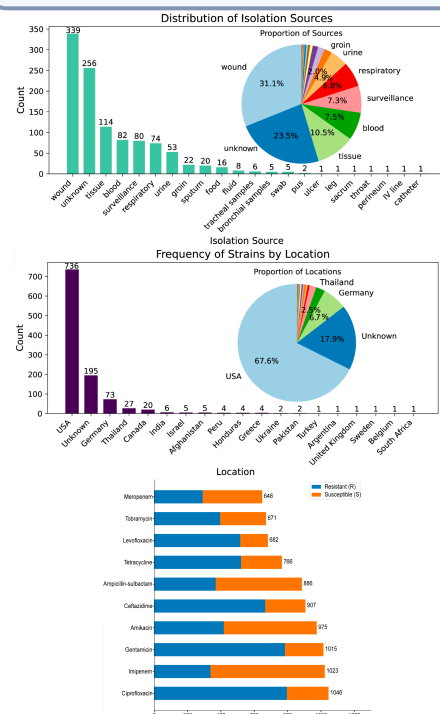
1. KEGG orthology-based functional representation consistently outperformed gene presence-absence encoding across all machine learning models.
2. In five-fold cross-validation, XGBoost achieved the highest weighted accuracy of 94.44%, followed closely by TabPFN at 94.32%.

B. Test Performance



1. XGBoost performed strongly for carbapenem resistance prediction, while TabPFN maintained robust performance across multiple antibiotics.
2. Amikacin showed a notable generalization gap in the independent cohort

C. Epidemiology&Resistance Overview

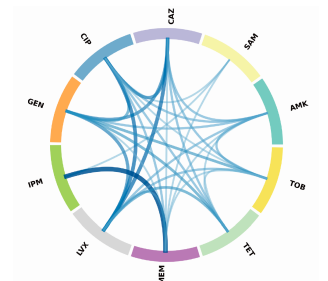


Pathway enrichment highlighted β -lactam resistance pathways.

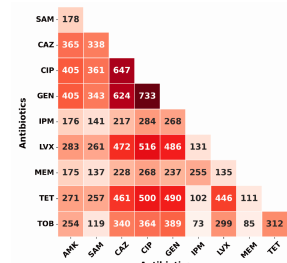
Top Predictive KO Terms (XGBoost Feature Importance)

KO Term	Gene / Function
K19213	<i>bla</i> _{OXA-12} (carbapenemase)
K18974	<i>sul1</i> (multidrug efflux)
K21801	<i>iaaH</i> (indole-3-acetamide hydrolase)
K19299	<i>aphA6</i> (aminoglycoside phosphotransferase)
K19300	<i>aph(3')-Ia</i> (aminoglycoside phosphotransferase)
K08151	<i>tetA</i> (tetracycline efflux)
K18476	<i>tetR</i> (tetracycline repressor)
K02022	<i>ampC</i> (β-lactamase)
K07410	<i>oprD</i> (porin D)
K03321	<i>gyrA</i> (DNA gyrase subunit A)

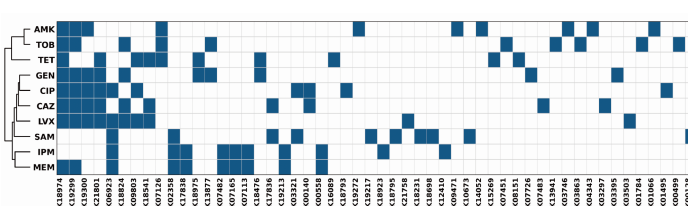
A. Shared Resistance Network



B. Co-resistance Matrix (Number of co-resistant Isolates)



C. Molecular Connectivity Heatmap (Top 10 Resistance-related KOs)



The framework combines strong predictive performance with biological interpretability.



Results reveal both canonical resistance genes and broader metabolic or signaling contributors to resistance.



This provides a foundation for rapid genome-based AMR prediction and future precision antimicrobial therapy.