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Background The objective of this study is to develop and evaluate machine learning (ML) techniques to predict bacterial resistance to specific antibiotics, based on bacterial identification, infection site, and patient demographic data. This approach aims to assist clinicians in selecting appropriate empirical antibiotic therapy, thereby improving treatment decisions and promoting the rational use of antibiotics to help reduce the impact of misuse on antimicrobial resistance.

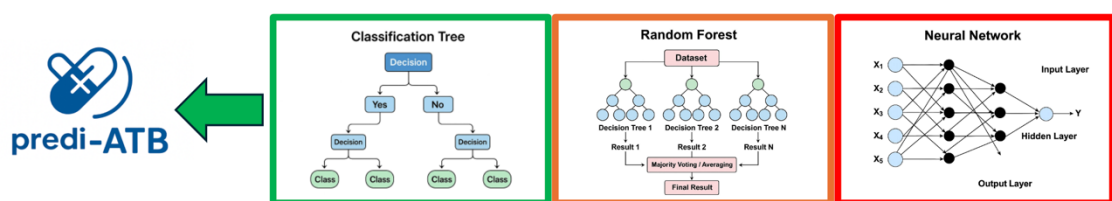
Methods

Based on 95,775 antibiograms, a total of 23,632 machine learning (ML) models including decision trees, random forests, and neural networks were developed to predict antibiotic susceptibility for 471 bacterial species and 66 antibiotics.

The models were trained using microbiology laboratory data, including patient demographics, culture results, and susceptibility profiles, without relying on clinical data. Model performance was evaluated using the Area Under the Curve (AUC) metric.

Figure 1 : Comparison of AI Models

Criteria	Classification Tree	Random Forest	Neural Network
Interpretability	++++	++	+
Performance	++	+++	+++
Robustness	++	+++	+++
Complexity	+	++	++++



The **choice of a classification tree model** is natural, as its performance is comparable to or equal to that of Random Forest or Neural Networks, while being less complex and **more interpretable**, making it well-suited for medical applications.

Predi-ATB V11.4.1

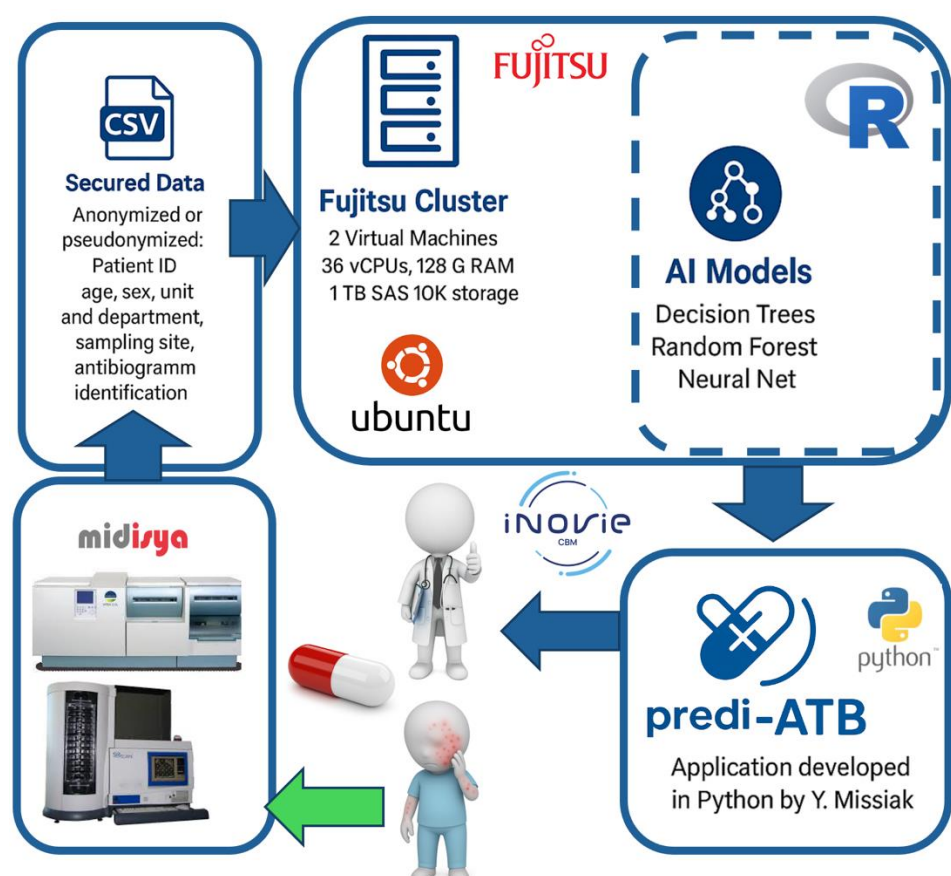


Figure 2 : Example of AUC for classification tree prediction

P.AERUGINOSA	AUC	n	E.COLI	AUC	n	S.AUREUS	AUC	n
MEROPENEME	0.98	2553	AZTREONAM	1.00	17211	FURANES	1.00	5956
AMIKACINE	0.98	2901	MEROPENEME	1.00	47009	MINOCYCLINE	1.00	5733
COLISTINE	0.97	2547	IMIPENEME	1.00	19096	TEICOPLANINE	1.00	5954
TOBRAMYCINE	0.96	2905	ERTAPENEME	1.00	48029	VANCOMYCINE	1.00	5920
AZTREONAM	0.93	2792	FURANES	1.00	48019	TIGECYCLINE	1.00	5732
IMIPENEME	0.92	2894	AMIKACINE	0.99	48037	LINEZOLIDE	1.00	5947
CEFEPIME	0.92	2900	FOSFOMYCINE	0.98	44473	PRISTINAMYCINE	1.00	5951
CEFTAZIDIME	0.90	2904	CEFOXITINE	0.98	47841	DAPTOMYCINE	1.00	4942
CIPROFLOXACINE	0.89	2902	CEFEPIME	0.98	46421	RIFAMPICINE	1.00	5954
PIPER.TAZO	0.87	2884	CEFOTAXIME	0.97	13572	OXA.CLOXA	0.89	5956
CEFTRIAZONE	0.00	2875	CEFTAZIDIME	0.97	47971	LEVOFLOXACINE	0.88	4950
ERTAPENEME	0.00	2905	CEFTRIAZONE	0.96	47585	CIPROFLOXACINE	0.82	5906
COTRIMOXAZOLE	0.00	385	LEVOFLOXACINE	0.91	46061			
			CIPROFLOXACINE	0.90	48046			
			PIPERA.TAZO	0.87	44271			

Results

The ML model accurately predicts antibiotic susceptibility across key pathogens.

For *E.coli*, predictions are influenced by sample type, clinical service, age, and sex.

S. aureus shows >99.9% accuracy for key antibiotics (vancomycin, daptomycin, linezolid) and >87% for methicillin resistance.

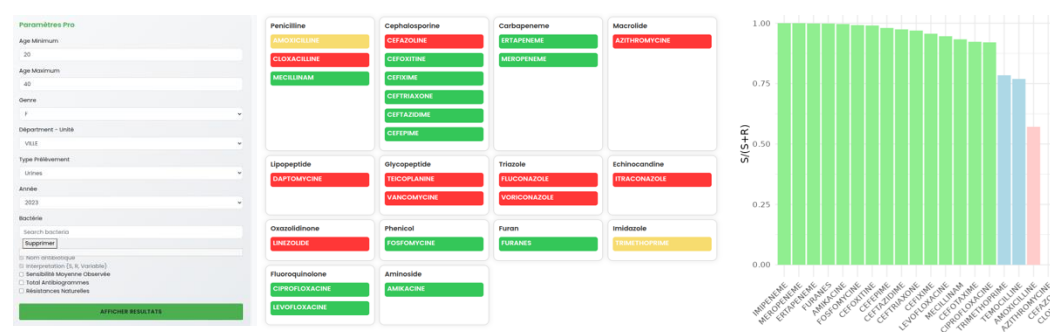
P.aeruginosa predictions exceed 85%, outperforming antibiogram timing.

S.agalactiae and *E.faecalis* show >99.9% accuracy, including cystitis treatment in women with amoxicilline or furadantine.

Conclusion

This study demonstrates the potential of ML to predict antibiotic susceptibility using only microbiological and demographic data. The approach is especially valuable in resource-limited settings. Decision tree models offer interpretable and accurate predictions, supporting better empirical antibiotic choices and enabling rapid treatment reassessment, even before or without antibiogram results.

Figure 3: Api Web Application predi-ATB (UI Client, Data Server)



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Data Privacy Method:
"CNIL Recherche Interne"

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Conflict of interests:
No conflict of interest