International Journal of Pharmaceutical Research and Applications
Volume 10, Issue 5 Sept - Oct 2025, pp: 1133-1141 www.ijprajournal.com ISSN: 2456-4494

Role of AI in combating Antimicrobial Resistance (AMR)

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Date of Submission: 10-10-2025 Date of Acceptance: 20-10-2025

ABSTRACT
Antimicrobial resistance (AMR) has emerged as a critical global health threat, undermining the efficacy of existing therapies and posing significant challenges to modern medicine. Artificial intelligence (AI) and machine learning (ML) have recently become powerful tools in addressing AMR by enabling rapid, data-driven solutions. This review explores the applications of AI and ML in AMR management, including pathogen identification, understanding resistance mechanisms, predicting treatment outcomes, and discovering novel antimicrobial agents. By analyzing large-scale genomic and clinical datasets, ML algorithms can identify resistance-associated genetic markers, guide targeted therapy development, and improve the prediction of AMR trends with minimal human intervention. AI-based systems also support healthcare providers in selecting optimal antimicrobial therapies and enhancing antibiotic stewardship through improved prescribing practices. Furthermore, AI-driven surveillance facilitates early detection of resistance outbreaks and optimization of drug distribution strategies. While integration into clinical workflows faces challenges such as data security, ethical considerations, and algorithmic bias, continued advancements in AI and ML hold great promise for transforming AMR surveillance, diagnosis, and treatment.

Keywords: Artificial intelligence; Machine Learning; Antimicrobial Resistance; Pathogen Identification; Personalized treatment. Drug discovery; AMR Surveillance.

I. INTRODUCTION

Antibiotic resistance (AMR) is recognised as a global public health crisis driven by both epidemiological and economic factors. This growing threat has prompted the World Health Organisation (WHO) to develop an action plan to combat the issue.Artificial intelligence (AI) and machine learning (ML) have emerged as promising tools to address AMR by leveraging clinical and laboratory data for evidence-based decision-making, prediction, and surveillance. Machine learning provides advanced methods for analysing complex datasets, while AI enhances decision-making through rapid information processing and adaptive algorithms.[1]Unlike humans, AI systems are not constrained by fatigue, biases, or outdated cultural practices, enabling them to provide more consistent and accurate outputs.AI and ML have shown significant potential in improving the efficiency of research into complex health challenges such as AMR. Their applications include:Data analysis and predictive modelling to identify resistance trends.Drug discovery and design for developing novel antibiotics and alternative therapies.Surveillance systems that continuously monitor antibiotic use, outbreaks, and resistance patterns.Clinical decision support systems (CDSS) assist healthcare professionals in prescribing antibiotics more responsibly.[2]Traditional drug development methods are expensive and time-consuming, whereas AI systems can screen large chemical libraries, predict antibacterial activity, and identify promising candidates within a much shorter timeframe. Given the slow pace of current antibiotic research, accelerating innovation through AI is critical.[3]AMR has evolved into one of the most pressing public health challenges of the 21st century. It occurs when microorganisms—such as bacteria, viruses, fungi, and parasites—develop resistance to antimicrobial agents, including commonly used antibiotics. Key drivers include the inappropriate and excessive use of antibiotics across sectors such as healthcare, agriculture, food production, veterinary medicine, and even military operations.Often referred to as a "silent pandemic," AMR demands urgent and decisive global action. Without immediate precautions, AMR is projected to become the leading cause of death worldwide by 2050, with an estimated 10 million deaths annually. Alarmingly, in 2019 alone, AMR was directly responsible for over 1.2 million deaths worldwide.[4]

II. AI/ML IN DRUG DISCOVERY AND DESIGN

Advances in the discovery and design of drug products have been greatly enhanced through the application of artificial intelligence (AI) and machine learning (ML). These technologies facilitate the identification of new therapeutic targets and mechanisms of action, thereby improving drug effectiveness while increasing the accuracy of safety and efficacy predictions.A landmark achievement in this domain is AlphaFold, developed by DeepMind (a subsidiary of Google AI).[5] AlphaFold is an AI/ML framework capable of accurately predicting the three-dimensional (3D) structure of proteins, significantly accelerating and improving the precision of drug discovery processes. Similarly, pharmaceutical companies are leveraging IBM's Watson Health Platform to accelerate drug design and development. Watson Health can analyse large-scale biomedical databases to identify novel therapies, recognise potential drug targets, and predict safety profiles and clinical outcomes.[6]

In addition, biotechnology firms are also driving innovation. For example, BenevolentAI (often misspelt as "Benevolent Ki") integrates over two billion biomedical articles with diverse data sources to identify novel drug targets, particularly for rare diseases where treatment options remain limited. Furthermore, specialised AI models are being developed to design new molecules against multidrug-resistant pathogens. One such example includes research into creating drug candidates targeting Acinetobacter baumannii, a highly resistant "priority pathogen" identified by the World Health Organisation.[7]

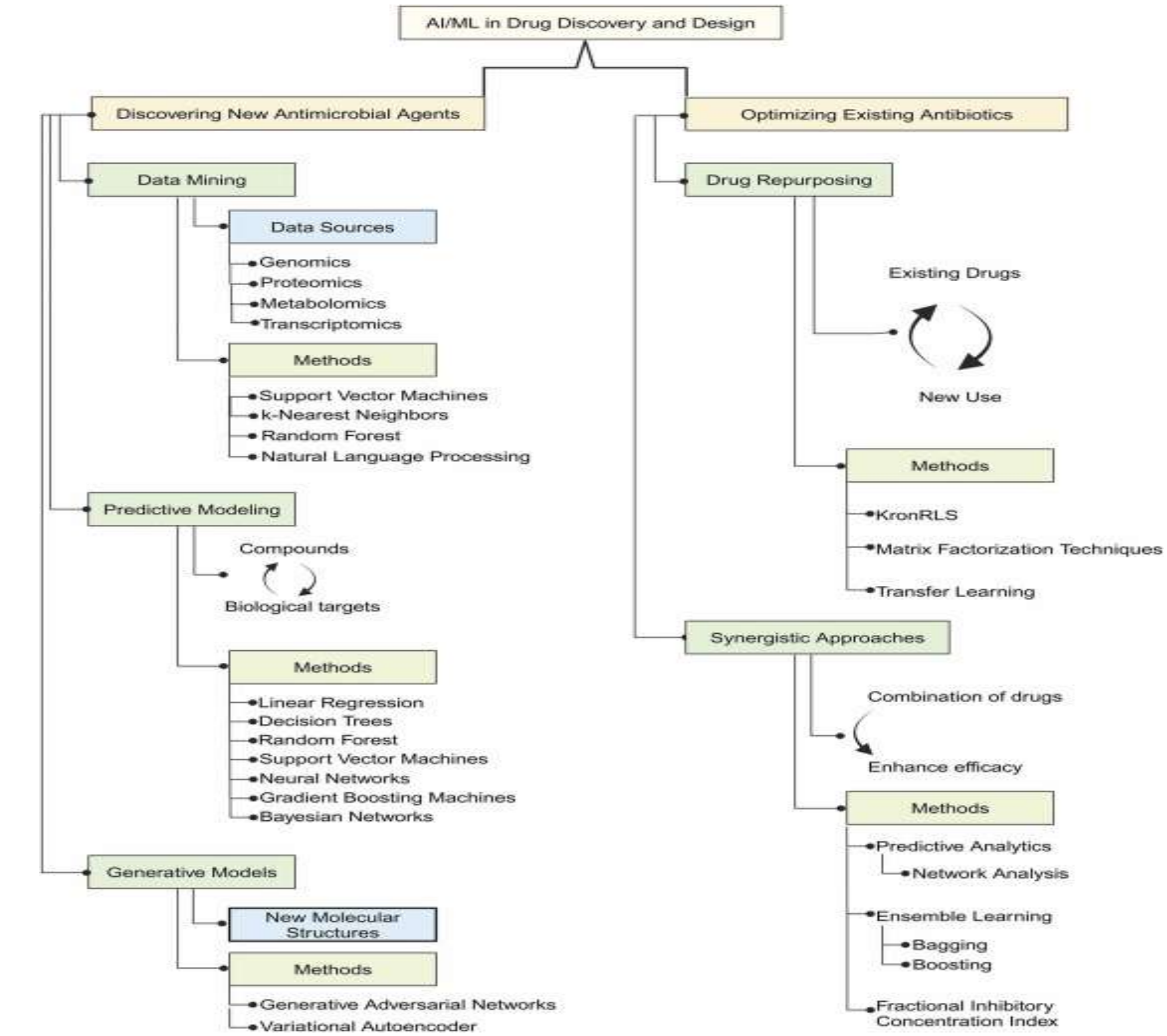

Figure 1: AI/ML in Drug Design and discovery

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Diagnosis in AMR via AI

Typically, essential strategies are employed to detect antimicrobial resistance (AMR). These include antibiotic susceptibility tests (AST) and whole-genome sequencing (WGS). While conventional methods are effective in evaluating antibiotic resistance, they often lack insight into the underlying resistance mechanisms. In contrast, WGS-AST provides reliable and accurate AMR detection, although it requires access to large multidimensional databases for proper information retrieval.[8]

Artificial intelligence (AI) plays a vital role in enhancing these established technologies, advancing research, and supporting the development of intelligent healthcare systems. AI-enabled applications include speech recognition, image recognition, natural language processing, and decision-making based on comprehensive data analysis. The progress of AI systems is closely tied to the availability of healthcare data and the continuous improvement in computational power.This advancement has facilitated the use of mathematical techniques such as neural networks (NNs) and machine learning/deep learning.[9]The expansion of deep neural network topologies—marked by increasing complexity in recent years—highlights the essential contribution of AI in strengthening conventional AMR detection strategies.Timely diagnosis of infectious diseases, distinguishing between infectious and non-infectious conditions, and ensuring appropriate treatment are critical in combating AMR. AI is an indispensable tool to address this global challenge and significantly supports effective healthcare responses.[10]Antibiograms remain crucial for monitoring susceptibility patterns and identifying high-risk infectious agents. In this context, the development of tailor-made machine learning models shows promise in predicting and mitigating AMR. By integrating predictive analytics, AI enhances early detection and ensures precise treatment of infections.Moreover, AI contributes to:Improving surveillance systems to track AMR trends.Identifying emerging resistant strains.Optimising healthcare system management.Accelerating drug discovery by predicting potential antibacterial candidates.Altogether, AI-driven approaches enable the development of effective and targeted antibacterial therapies (as illustrated in the Figure), and they summarise the broad potential applications of AI in the AMR domain.[11]

III. DL/ML MODELS FOR AMR PROGNOSIS

The essential principle behind deep learning (DL) and machine learning (ML) models is to use large datasets to capture the inherent non-linear correlations between input features and outputs, which are otherwise difficult to model. Training datasets serve as the starting point for developing both DL and ML models. Once trained, these models are evaluated using previously unseen data to assess generalizability.Before training, data must undergo preprocessing and feature extraction to ensure that only relevant and informative characteristics are included. The dataset is typically divided into training**,** validation, and testing subsets.[12]During training, the model optimizes its parameters to achieve the most favorable settings, while techniques such as cross-validation are applied to improve robustness and prevent overfitting.A DL model includes many hyperparameters, making it essential to carefully select the most suitable model depending on the application and the nature of the input data. Complex models tend to have high variance, whereas simpler models often exhibit higher bias but may perform better in situations requiring interpretability.[13]

For example, the integration of convolutional neural networks (CNNs) with conventional machine learning has enabled the rapid and accurate prediction of tuberculosis (TB) drug resistance based on genomic sequences. CNNs can identify specific mutations inMycobacterium tuberculosis associated with antimicrobial resistance. Similarly, DL has been applied to the detection of antimicrobial peptides(AMPs) derived from the human gut microbiome.Interpretable models are crucial in biomedical applications.[14]They should provide the ability to:Assess the contribution of individual input features,Allowbidirectional tracingof predictions, andEnable exploration of relationships between influencing factors and clinical outcomes.In addition, decision tree–based models act as hierarchical classifiers that evaluate features at internal nodes based on variance, applying clear criteria to classify data into distinct groups. Each node in these models is traceable, ensuring interpretability.[15]

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IV. IMPACT OF AMR ON THE ENVIRONMENT, ANIMALS AND HUMANS

The challenges of antimicrobial resistance (AMR) are escalating rapidly, affecting both human and animal health. In humans, drug-resistant infections lead to prolonged hospital stays, placing significant burdens on patients and healthcare systems while straining already limited resources. Extended recovery periods further reduce productivity, increase job absenteeism, and negatively impact economic performance. Managing AMR also requires stricter infection control measures, enhanced clinical testing, and more frequent outpatient visits. Each year, diseases linked to AMR are estimated to claim more than one million lives worldwide.[16]The scarcity of effective antibiotics heightens risks during routine medical procedures such as surgery, organ transplantation, chemotherapy, and neonatal care. In cases where conventional drugs lose efficacy, even minor infections resulting from small injuries can become life-threatening.

AMR is also closely linked to animal health and food safety. Excessive antibiotic use in livestock, both for disease management and for promoting growth, contributes significantly to resistance. This facilitates the spread of multidrug-resistant (MDR) bacteria such as Salmonella and Campylobacter through the food chain, directly exposing animal handlers and consumers.[17]Resistant bacterial strains can spread quickly across different settings. Animals may also indirectly acquire AMR from the environment, further accelerating disease transmission. For example, animal waste used as fertiliser can contaminate soil, water sources, and ultimately human food supplies, thereby amplifying ecological and public health risks.[18]Resistant bacteria also share AMR genes with the surrounding microbiota, affecting both human and environmental health systems.The absence of effective treatments for resistant animal diseases worsens epidemic outbreaks in livestock such as cattle, sheep, and poultry. In many cases, farmers are forced to cull diseased animals due to the lack of viable treatment options, resulting in significant financial losses and reduced food security.[19]

V. AI FOR AMR SIGNIFICANCE TO ICU

Patients in intensive care units (ICUs) require rapid and accurate assessment of diverse, multidimensional data, including medical images, numerical values, textual reports, and other clinically relevant information. Recognizing the complex and nonlinear relationships within these data types is essential. Traditional statistical methods typically represent data patterns through mathematical equations, but they often fail to capture such complexity.Deep learning (DL), with its ability to simultaneously process and analyze large and heterogeneous datasets, enables the development of predictive models based on anticipated outcomes. Within healthcare, three main DL techniques have been widely applied in critical care:Recurrent neural networks (RNNs)Convolutional neural networks (CNNs)Deep belief networks (DBNs).[20]

A significant example is a temporal computational model developed to predict blood culture outcomes. This model used nine clinical parameters combined with a bidirectional long short-term memory (BiLSTM) approach. Drawing from a robust dataset of 2,177 ICU patients, the deep learning methodology showed remarkable predictive performance, particularly in situations where uncertainty existed about the time gap between an expected event and its diagnosis.[21]The model achieved impressive mean area under the curve (AUC) values of 0.99 and 0.82 for receiver operating characteristic (ROC) curves. Importantly, the model demonstrated the capability to predict events hours in advance with minimal compromise in accuracy.Beyond ICUs, AI also offers significant benefits in clinical microbiology, where it is increasingly applied to analyze:Whole-genome sequences (WGS) of bacteriaMacroscopic and microscopic imagesMALDI-TOF mass spectraThese applications enhance the diagnostic capabilities of laboratory personnel and support faster, more reliable decision-making. As AI technologies continue to advance, more sophisticated and reliable tools are expected, promoting the seamless integration of AI into clinical microbiology laboratory workflows.[22]

VI. PREDICTIVE MODELS FOR AMR

Using AI and ML algorithms, predictive modelling can identify resistant pathogens and support the early detection and management of antimicrobial resistance (AMR). AI-driven predictive approaches are crucial for tracking AMR patterns, as these algorithms reveal hidden connections in complex datasets that would take humans much longer to analyse.Key applications of AI in AMR include time-series analysis, phylogenetic studies, and network assessments.

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Predictive models can detect unusual behaviours and clusters related to drug resistance or gene overexpression. Such early detection enables timely interventions, reducing the risk of transmission and limiting the escalation of resistance.[23]

AI systems also allow analysis of archived AMR datasets, making it possible to identify long-term trends, seasonal variations, and sudden outbreaks of resistance, thereby strengthening healthcare system preparedness. Moreover, AI and ML enhance the construction of phylogenetic trees, enabling the monitoring of pathogen lineages and providing valuable insights for hospitals and public health authorities. These approaches help trace AMR transmission networks within patients, facilities, and healthcare systems. They also support identification of outbreak-related sources, whether point-source or healthcare-associated, thus guiding targeted interventions and infection-control strategies.[24]Designing a robust AI/ML-based predictive model for AMR requires multiple critical steps:Data collection (clinical, genomic, microbial, and epidemiological information aligned with model goals).Feature engineering and selection (e.g., SNPs, k-mers, outbreak data, patient movement records, and treatment history).Model training and validation (ensuring reproducibility and minimising bias).Implementation and continuous monitoring (with periodic audits to ensure accuracy and integrity).A successful predictive model depends on high-quality, consistent, complete, and well-curated data. Regular data audits and integrity checks are essential to maintain reliability. When effectively developed, these models provide actionable insights for controlling AMR spread, optimising treatment strategies, and supporting both hospital-level and community-wide interventions.[25]

VII. CHALLENGES AND FUTURE DIRECTIONS

AI/ML has great potential to transform healthcare, particularly in AMR surveillance, epidemiology, and outbreak detection and response. However, several limitations remain.Ethical considerations regarding the use of genetic and clinical data highlight the importance of appropriate data recording and strict compliance with established protocols. Data protection and security concerns are critical, as patient information must be safeguarded to comply with regulations such as the U.S. Health Insurance Portability and Accountability Act (HIPAA), which protects sensitive health data. In addition, issues related to model transparency and accountability present major challenges for both governments and individual institutions.[26]Another barrier is EHR data distortion and heterogeneity across multiple sources, which reduces the effectiveness of AI/ML tools in mitigating AMR.Looking forward, the future direction of AMR management should focus on enhancing current models to achieve greater accuracy and scalability. Of particular importance is the accurate prediction of AMR emergence through real-time integration of clinical, environmental, and genomic data. To build trust in AI-driven insights, it is essential to develop explainable AI (XAI) models.[27]

Furthermore, AI-based AST (antimicrobial susceptibility testing) technologies must be advanced to enable rapid identification of resistant strains. Progress in this area will also require the development of individualised therapeutic strategies tailored to patient profiles and pathogen-specific resistance patterns. Achieving this will demand close collaboration among bioinformaticians, microbiologists, and clinicians.[28]

VIII. CONCLUSIONS

This overview highlights the potential impact of AI/ML on AMR management, focusing on areas such as improved monitoring, predictive modelling, and outbreak detection. These technologies enable healthcare professionals and policymakers to track resistance trends and uncover complex patterns of AMR dynamics by analysing large-scale datasets from diverse sources. AI/ML-driven early warning systems and predictive analytics strengthen the ability to respond swiftly to emerging resistance outbreaks. At the same time, key challenges—including ethics, privacy, and algorithmic bias—must be addressed. Collaborative initiatives involving technology developers, healthcare providers, and regulators are essential to ensure responsible and effective use of AI/ML in combating AMR. Furthermore, AI-powered diagnostic tools help minimise unnecessary antibiotic use by improving the accuracy of antimicrobial susceptibility testing and supporting more precise treatment decisions.

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