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Strengthening The Roadmap of Antimicrobial Stewardship/Evolution of Artificial Intelligence

Sumeyra Kocturk[1]

[1]*Kahramanmaras Sutcu Imam Unıversıty, Faculty of Medicine, Department of Microbiology Kahramanmaras, Turkey.*

Abstract

The World Health Organization (WHO) is taking a "One Health" approach to address the ten major threats to global health, recognizing the interdependency of human, animal, plant, and environmental health, particularly in relation to antimicrobial resistance.

Failure to address antimicrobial resistance can have significant impacts on agriculture, economy, and food security, with low- and middle-income countries being the most affected. Strategies for antimicrobial stewardship programs have mainly focused on mandatory antimicrobial use, cost, and resistance rates. An ideal system should be able to detect microorganisms, display test results, and compare them to reference microorganisms.

The use of artificial intelligence is anticipated to be crucial in saving time and energy, and new techniques based on AI are expected to play a vital role in combating antimicrobial resistance.

Key words: *Antimicrobial resistance, Antimicrobial stewardship, Artificial intelligence.*

*** Corresponding author:** Sumeyra Kocturk, E-mail: sumeyrakocturk@yahoo.com, ORCID ID: 0000-0001-9316-794X

Introduction

The World Health Organization considers antimicrobial resistance in humans and animals to be one of the top ten threats to global health. It is estimated that there could be up to 10 million deaths a year by 2050, with a knock-on effect on economies and more people in poverty. Another opinion in this are a is the use of the "One Health" approach, which recognizes that the health of humans, animals, plants, and the environment are closely interdependent, and antimicrobial resistance can be successfully addressed. If antimicrobial resistance is not assessed here; agricultural production could also be significantly impacted, affecting the economy and food security, with low and middle-income countries bearing most of the burden (1). Agriculture, economy and health facilities are most affected by this issue.

Systematic approaches to improving the use of antimicrobials across the spectrum of healthcare are referred to as antimicrobial stewardship. Most studies of antimicrobial stewardship program strategies have looked at prescribed antimicrobial use, antimicrobial costs and rates of antimicrobial resistance. However, many of these studies have been insufficiently powered to detect differences between groups in clinical cure rates, length of hospital stay, and mortality rates; often there was frequently been no difference between the antimicrobial stewardship group and the control groups (2).

While questioning the implementation of these strategies; each government regulates institutions to track and also report stewardship metrics. Instutions uses the data analysis programs include all antimicrobial sensitivity tests confirmed and completed in the laboratory. It should provide the ability to obtain test results along with the requirements listed below. Preferably, the system should be able to display the sample results even if antimicrobial testing of the detected microorganisms (if any) has not been performed (3). For identification of specimens sent to laboratories for purposes other than diagnosis of infection (e.g., infection control, quality control, proficiency testing, screening, surveillance) the system must have a separate mechanism. These quality assurance parameters are also included in standardized protocols. By the way; we create cumulative antibiograms; another parameter of antimicrobial stewardship; to predict empiric therapy. When generating the cumulative antibiogram; i.e., antibiotic susceptibility, only the first isolate of each species isolated from a patient in each evaluation period (e.g., one year), at the body site where it was isolated, should be included in the data, regardless of profile or other phenotypic characteristics (e.g., biotype) (4).

At present, antimicrobial resistance is spreading throughout the world, and new mechanisms of resistance to older agents are emerging with resistance to new antibiotics (5). This topic has been the subject of numerous high-quality and timely scientific, economic, public health, and educational reports (6,7). While these reports deal with AST (antibiotic susceptibility testing), there are two basic diagnostic requirements related to AST. It is important for physicians to quickly identify antibiotics that can effectively treat patients infected with bacterial pathogens. Second, epidemiological application is required, that is, detection of phenotypic resistance mechanisms and surveillance of spread. AST monitoring provides surveillance data and helps develop strategies to control the spread of antimicrobial resistance (AMR) .The need to overcome barriers to the introduction of diagnostic devices (8,9). Among these following factors are barriers against adoption to antimicrobial stewardship so affecting income expense balance; each of which can be a paragraph on its own.

-Expertise of laboratory personel,

-Communication between clinicians and diagnosticians

-High cost of test

-Continous availability of the laboratory

-Lack of clinical outcome results' reports

-Cost of scientific studies

-Cost of development

-Poor info management and poor electronic records

-Finding clinical research partners (clinicians, laboratory directors, researchers, etc.)

-Intellectual complience on multiple innovations

-Decentralization of laboratories and non-networked steward ship teams

-Lack of appropriate pre-marketengagement

-Quality and availability of materials

-Admitting to the authorities about developmental processes

-Sample collection problems

-Transfer of samples

-Knowledge differences among clinicians about antimicrobial resistance

-Lack of funding

-Storage,transport,and stability of the test

-The limited exchange between diagnostic and pharmaceutical companies

-Lack of speed

-Availability of the test

-FDA validationand European certification (CE) including differences between -countries

-Biological hazard

-Ethical issues

-The insufficient exchange between the public and private sector

-Environmental aspects

-Health practices

-Communication (or lack there of)

-Lack of support programs

The implementation of new technological criteria is what we need to address at this point (8,9). Smart antibiograms should be created to incorporate a wide range of patient search parameters and demographic data into their calculations. This will facilitate the automatic fine-tuning of the smart antibiogram algorithms and increase their value in predicting the correct empirical antibiotic therapy for individual microorganisms detected in different clinical samples at different times in different wards and in different populations. Using past experience and intelligent databases, statistical approaches will be necessary to predict the correct antibiotic treatment. Several goals were achieved, such as; increased efficiency, digitally shifting tasks and addressing staffing bottlenecks, population health applications to enable targeted and differentiated services, earlier disease detection, improving the quality of clinical decision-making, continuous patient monitoring, and artificial intelligence (AI) applications used in pharmacy practice that can be categorized as prevention, diagnosis, and treatment.

For example the techniques presented with machine learning (ML) allows to anticipate the sensitivity results of the microbiology laboratory. Early identification of patients at high risk for resistance to specific antibiotics could provide clinicians with useful information for prescribing empiric therapy based on the local antibiotic resistance pattern. Implementation of such prescribing practices could have a significant impact on antimicrobial stewardship (10).

Another example is the gradient-doped decision tree (GBDT) model formed to predict the presence of isolates resistant to co-amoxiclav, ciprofloxacin, meropenem and piperacillin-tazobactam antimicrobial drugs. Predicting susceptibility to antimicrobials was a key consideration. The methodology can be used to help physicians reduce inappropriate use of antibiotic drugs (drugs unsuitable for a case being identified by high probability of AMR at admission) and select (11). In rapid diagnosis, cost-effectiveness and rapid and accurate screening of many samples at the same time are very important in the diagnosis and treatment of diseases. Mass spectrometry systems (eg, MALDI-TOF MS, Bruker) produced to meet these goals are a highly sensitive, very fast and low-cost, high-efficiency technology product used in the identification of microorganisms in the microbiology laboratory (12, 13). With this system, after ionizing the biomolecules and large organic molecules of microorganisms, protein profiles are obtained by passing them through electric and magnetic fields. The graphical images obtained in this way are compared with the reference microorganisms in the database of the system and identifies the factors on the basis of genus and species according to their compatibility. MALDI-TOF MS creates fingerprints from proteins specific to each microorganism and thus identifies microorganisms (14).

Examples include: Nguyen et al. used machine learning to predict the minimum inhibitory concentrations (MICs) of Salmonella strains and predict their susceptibility to (15) antibiotics.1- Doctors Without Borders developed a microbiology tool for use in resource-limited settings that uses computer vision to read "zones of inhibition" to improve patient care. 2- Key factors to consider when evaluating an AI solution for healthcare (15).

Artificial intelligence (AI) systems can be utilized to differentiate individuals prone to COVID-19 by creating personalized and categorized systems. Characteristics such as underlying diseases (hypertension, heart failure, diabetes mellitus, etc.), blood test parameters (ACE2 expression level) and clinical data (age, respiratory parameters, viral load, etc.) of COVID-19 patients help to define risky situations, and by coding these data into systems, risk classification can be predicted by artificial intelligence systems. AI analysis of traits from asymptomatic, mild, or severe COVID-19 patients can be used to classify and predict people based on their vulnerability or resistance to potential COVID-19 infection (16). Regional differences of variant forms, which have recently been a serious threat in the COVID19 epidemic, can be followed instantly on websites such as ‘GSI-AD’ and ‘Nextstrain’, so the mutation/vaccine can be followed more closely (17).

Conclusion

The use of Big Data and the use of new techniques based on AI will become extremely important. As mentioned earlier, data is generated today from very different sources, with volumes on the order of exabytes; however, these must be exploited. Application of artificial intelligence in healthcareis not practised enough to be used efficiently. Moreover, ever since having covered the basics of AI, the question is how to apply these advanced technologies to healthcare.

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