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Tevfik Yoldemir

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EDITORIAL

Artificial intelligence and women's health

Tevfik Yoldemir

ASSOCIATE EDITOR

Department of Obstetrics and Gynecology, Marmara University Hospital, Istanbul, Turkey

The use of artificial intelligence (AI) in medicine is currently an issue of great interest, especially with regard to the diagnostic or predictive analysis of medical data. As information technology in health care continues to develop, greater amounts of clinical medical data have been generated and will continue to expand every year. Diagnostic data, clinical trial data and data on medical staff behavioral health together form the largest data group. AI technology is now capable of deriving algorithms which can be used for diagnosis and treatment of disease and medical research[1].

AI already has learning and self-correcting abilities and may further improve its accuracy based on feedback. An AI system can assist physicians by providing up-to-date medical information from journals, textbooks and clinical practices to inform proper patient care. Additionally, AI may help to reduce diagnostic and therapeutic errors which are inevitable in human clinical practice. AI systems extract information from large patient populations, allowing them to provide real-time advice on health risks and also predict health outcomes[1].

AI devices are categorized into two major groups. The first group includes machine learning techniques that analyze structured data in an attempt to cluster patients' traits, and consequently predict the probability of disease outcomes. The second group includes natural language processing methods that extract information from unstructured data, such as clinical notes and medical journals, to supplement and enrich structured medical data. The natural language processing procedures turn texts into machine-readable structured data, which can then be analyzed by machine learning techniques[1].

AI is being employed in the medical field in at least four distinct ways: (1) in the assessment of risk of disease onset and in estimating treatment success prior to initiation; (2) in an attempt to manage or alleviate complications; (3) to assist with patient care during the active treatment or procedure phase; and (4) in research aimed at elucidating the pathology or mechanism of and/or the ideal treatment for a disease[2].

The forecasting of health outcomes in different body systems (i.e. risk assesment for any disease) has been extensively investigated. Cardiovascular, breast, bone, cervix and endometrium have been the areas of interest in AI research in women's health.

Artificial neural networks (ANNs) and classification and regression trees for the prediction of endometrial cancer in postmenopausal women have been investigated. Similarly, AI has estimated the impact of human papillomavirus types in influencing the risk of cervical dysplasia recurrence.

Extensive use of AI has been used in breast imaging where images from mammographic, sonographic and magnetic resonance imaging (MRI) were collected for study. The feasibility of automatically identifying normal digital mammography examinations with AI to reduce the reading workload of breast cancer screening was examined and it was found that incorporating an AI-based decision support system into ultasound image analysis improved diagnostic performance.

Predictive models for osteoporosis have been constructed based on popular machine learning algorithms such as support vector machines, random forests, ANNs, and logistic regression based on simple surveys. These machine learning models were later compared to four conventional clinical decision tools: the Osteoporosis Self-assessment Tool, the Osteoporosis Risk Assessment Instrument, the Simple Calculated Osteoporosis Risk Estimation, and the Osteoporosis Index of Risk. Likewise, the application of an ANN in optimizing the Osteoporosis Self-Assessment Tool for Asians score has been reported. Moreover, it was identified that there are several methods in the use of AI to help the screening of groups at risk for osteoporosis or fractures. However, such systems were limited to a specific ethnic group, gender or age.

Furthermore, a performance comparison of machine learning algorithms in predicting fragility fractures from MRI data was conducted where, among many classifiers, the random undersampling-boosted trees, logistic regression, and the linear discriminant are best for predicting osteoporotic fracture. Moreover, morphological, topological and mechanical bone features using AI methods were investigated. In a clinical trial, the performances of the Adaptive Neuro Fuzzy Inference System, support vector machines and genetic algorithms in classifying two populations of arthritic and osteoporotic bone samples were compared. Finally, AI was

CONTACT Tevfik Yoldemir tevfik.yoldemir@gmail.com Department of Obstetrics and Gynecology, Marmara University Hospital, Fevzi Cakmak District, Muhsin Yazicioglu Street No 10 Ust Kaynarca, Pendik, Istanbul, Turkey

employed for bone age assessment in evaluation of patients with endocrine and metabolic disorders.

Recently, AI techniques have been applied to decipher the data from stroke imaging and have demonstrated some promising results. Machine learning has been recently introduced to develop prognostic classification models that could be used to predict outcomes in individual cancer patients. So-called machine learning-based decision support systems extract prognostic information from routinely collected demographic, clinical and biochemical data of breast cancer patients. The model was used to stratify the testing set into two groups of patients with low or high risk of progression with a hazard ratio of 10.9.

ANNs have also been used in cardiology to stratify non-ST elevation myocardial infarction from non-cardiogenic chest pain, to predict patient risk after an acute coronary syndrome and to determine whether machine learning could further improve the predictive performance. Support vector machines and logistic regression have also been used as risk predictor models for stroke, heart failure and renal failure.

ANNs have been used to predict the risk of congenital heart disease in pregnant women. It was found that the model identified those patients at high risk of developing congenital heart disease early on in pregnancy.

Machine learning has been used in preventative medicine to predict which patients were at increased risk of cardiovascular disease, colorectal cancer and complications of type II diabetes such as retinopathy, neuropathy and nephropathy.

It has been suggested that AI might also play an important role in personalizing treatments for infertility with prediction for live birth, embryo implantation potentials, impact of endometriosis on outcomes of assisted reproductive technology and so on[3].

The scarcity of accurately annotated medical data has been a critical challenge for the application of machine learning methods to clinical questions. Researchers struggle to construct their cohorts or control groups in well-designed retrospective or prospective clinical trials and thus avoid biases and confounding factors. Machine learning research commonly uses real-world data from personal devices acquired for non-research purposes, including electronic health records and insurance claims[4]. Of course, underserviced populations will have fewer data, and hence data-derived models may not be generalized correctly to these populations. Additionally, both recognized and unrecognized biases distort the delivery of medical care in more complex ways. These biases are best reflected by data derived from the clinical work flow[4].

Since medical treatments and guidelines are commonly extrapolated from research data derived from largely white populations, data obtained from these sources do not represent the general population. As a result, the first steps to mitigating bias in data engineering should include the recognition of and vigilance for potential biases in the data sources[4]. Although prohibiting reuse of arbitrary data, minimizing collection to high-quality relevant data, and purpose limitation to collecting data for specific research aims might seem ideal, these may not be practical at the time of database construction[4].

In conclusion, formal regulations and guidelines must be established in accordance with the handling of patient data and the probable situations where AI should or can be used or not. In order to quantify and define the technology's abilities and limitations, thorough testing of AI systems in development should also be completed against human clinicians[2]. Last but not least, the social, legal, and ethical implications of using AI in medicine must be well established.

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ORCID

Tevfik Yoldemir http://orcid.org/0000-0001-6925-4154

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