Guest Editorial
Insights of Machine Learning into Medical Decision Making Systems: From Research to Practice

MACHINE learning approaches, formerly utilized for making informed decisions, are now essential for incorporating into intelligent healthcare systems. Reliability is crucial for developing and evaluating machine learning models with quickly growing datasets. Machine learning may assist healthcare facilities in meeting increasing pharmaceutical needs, improving negotiations, and reducing expenses. Implementing machine learning advancements at the patient's bedside may assist healthcare professionals in efficiently identifying and treating diseases with more precision and tailored care. Studying the integration of machine learning in healthcare demonstrates how automation may enhance treatment practices and enhance patient outcomes. Researchers in the area of machine learning and machine intelligence may use algorithms to understand subgroups of patients, assist in scientific management, and enhance collaborative and patient-centered outcomes. This passage discusses the advantages of these instruments seen in different clinical settings and explains how the implementation of medical learning, when properly established, allows for enhancement throughout the COVID-19 pandemic. Due to these changes, a predictive model that initially shows high performance acknowledges the potential for a decrease due to a shift in patient status from being incapacitated for three weeks to less than a week. An individual's medical history may have originated from a previous hospitalization and might be accessed at subsequent time periods throughout treatment. Discharges rose at the height of the epidemic and fell as the number of new cases declined. Machine learning in healthcare may enhance patients' diagnosis and treatment choices, thereby improving the overall quality of healthcare services. Machine learning methods are used in healthcare decision-making in a popular manner. These scenarios need critical data analysis to be conducted before medical expertise may uncover hidden correlations or anomalies that may not be immediately evident. It is important to note that computational decision-making in healthcare is not always focused on detecting or forecasting conditions, biomedicine, or biomedical concept analysis.

This special issue explores the use of machine learning in areas such as disease analysis, medical imaging, medication repurposing, biomedical event prediction, and other aspects of healthcare. The journey that began with the integration of machine learning into computational medicine has finally reached its apex with the introduction of precise antibiotics. When examining the roles of machine learning in modern healthcare, it is evident that machine intelligence has been a significant benefit for drawing conclusions in the healthcare field due to several obvious aspects.

The special issue received a substantial amount of entries from academics and industry. Following rigorous peer review and intense competition, seven papers were approved for publication in this special issue. They address a range of themes within medical data analytics, AI-driven decision-making, and health symptom monitoring.

Alkhodari et al. [1] investigate the use of a deep learning method using the most recent self-attention transformer network to automatically forecast the presence of congenital murmurs in phonocardiography (PCG) recordings. The suggested method minimizes memory requirements for calculations by using a basic network structure and decreasing the dimensionality of input signals using wavelet feature processing. The PCG recording was converted into a series of wavelet-based features of a shorter duration, hence decreasing the complexity and dimensions of the input data. Furthermore, using deep learning to predict the presence or absence of heart murmurs enables the interpretation of choices across network levels, providing greater insights into how auscultation channels affect predictions.

Zogan et al. [2] use social media data to investigate the effects of COVID-19 on individuals' depression. They provide a comprehensive COVID-19 dataset suitable for analyzing depression. They have analyzed the tweets of individuals with depression and without depression both before and after the onset of the COVID-19 outbreak. They develop a new method using a Hierarchical Convolutional Neural Network (HCN) to extract detailed and pertinent information from users' past postings. HCN incorporates a hierarchical structure of user tweets and has an attention system that identifies important terms and tweets inside a user post, taking into account the surrounding context.

Turrisi et al. [3] work is the first effort to give a comprehensive guide on addressing data integration via collaboration between neuroscientists and computer scientists. Data integration is essential for analyzing complex multifactorial disorders like neurodegenerative diseases. The authors provide a plan for data scientists entering the field of data integration in the

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biomedical sector. They emphasize the obstacles that arise when working with diverse, extensive, and noisy data, and suggest potential solutions. The authors examine how data collecting and statistical analysis, often seen as separate and unrelated procedures, might be integrated as cross-disciplinary activities. The authors demonstrate a model application of data integration to tackle Alzheimer's disease, the prevalent multifactorial type of dementia globally. The authors analyze the most extensive and often used datasets in Alzheimer's disease and show how the rise of machine learning and deep learning techniques has greatly influenced our understanding of the condition, especially with early detection.

Domain-specific knowledge and explainability are essential for ensuring the accuracy and transparency of biomedical text summarizing techniques. Xie et al. [4] propose a new domain knowledge-enhanced graph topic transformer for explainable biomedical text summarization to tackle these challenges. The model combines the graph neural topic model and domain-specific information from the unified medical language system with transformer-based pre-trained language models to enhance explainability and accuracy.

Deep neural networks have not been widely used in clinical practice, partly because they lack explainability despite their impressive performance. Bender et al. [5] use explainable attribution techniques on a pre-trained deep neural network for abnormality detection in 12-lead electrocardiography. Their aim is to elucidate the "black box" and comprehend the connection between model prediction and acquired characteristics. The authors categorize data from two public datasets and the attribution algorithms award a "relevance score" to each sample of the categorized signals. The analysis of relevance scores for atrial fibrillation and left bundle branch block compared to healthy controls indicates that their mean values increase with higher classification probability and represent false classifications when around zero. These values also align with clinical recommendations on which lead to consider. In addition, the presence of visible P-waves and concordant T-waves leads to distinctly negative relevance scores in the categorization of atrial fibrillation and left bundle branch block, respectively.

Kolozali et al. [6] investigate the use of Internet of Things (IoT) devices and explainable AI algorithms to predict biomarker values related to gestational diabetes mellitus when measured 13–16 weeks before diagnosis. The biomarker values are estimated using sensory data gathered around week 12 of pregnancy, which includes continuous glucose readings, brief physical movement recordings, and medical history. The authors used machine learning models such as Decision Tree and Random Forest Regressors, in addition to Coupled-Matrix Tensor Factorization and Elastic Net approaches, exploring various combinations of these methods across many data modalities.

Sun et al. [7] provide a meta self-attention prototype incrementer (MAPIC) architecture for medical time series classification. MAPIC consists of three primary modules: an embedding encoder for extracting features, a prototype improvement module for enhancing interclass variance, and a distance-based classifier for decreasing intra-class variation. MAPIC uses a parameter protection approach to prevent catastrophic forgetting by freezing the settings of the embedding encoder module at different stages after training in the foundation stage. The authors create a composite loss function that includes the sample classification loss, the prototype non-overlapping loss, and the knowledge distillation loss. These components collaborate to minimize variations within the same class and prevent catastrophic forgetting.

We anticipate that the readers will get pleasure from this compilation of articles and that the special issue will ignite and encourage more study and growth in this field.

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