AI

Editorial

Artificial Intelligence in Healthcare: ChatGPT and Beyond

Tim Hulsen

Data Science & AI Engineering, Philips, 5656 AE Eindhoven, The Netherlands; tim.hulsen@philips.com

Artificial intelligence (AI), the simulation of human intelligence processes by machines, is having a growing impact on healthcare [1]. As healthcare all around the globe is suffering from personnel shortages [2], AI can be of crucial importance. It can help in three ways: by helping health researchers, by helping medical staff, and by helping patients. Via AI, researchers can provide new approaches to merge, analyze, and process complex "big data" and gain more actionable insights, understanding, and knowledge at an individual and population level [3]. Medical staff can be helped by AI-assisted clinical decision support (CDS), by machine learning (ML) and deep learning (DL) models analyzing large medical datasets, by summarizing radiology and pathology reports using Natural Language Processing (NLP), by automating repetitive but time-consuming tasks, and much more [4]. Patients can talk to chatbots who have access to all medical knowledge in the world, including the patient's medical history, and provide personalized advice [5]. The increasing use of AI in healthcare provides many new and interesting possibilities but also causes issues around trust (the "black box" problem: what does the AI algorithm actually do? [6]) and privacy. This Special Issue intends to show some examples of how AI impacts healthcare, with some discussion on potential future developments as well as challenges. Since this Special Issue contains papers from 2023 and 2024, the era of Generative AI (GenAI) [7], naturally there are papers related to ChatGPT and chatbots. There are also papers on prediction modeling in primary care, polychronic conditions, and heart disease. Other papers focus on the classification of colon cancer and Alzheimer's disease. Finally, there are papers on orthodontic diagnosis and treatment planning, anxiety treatment, and explainable AI (XAI).

"Chat GPT in Diagnostic Human Pathology: Will It Be Useful to Pathologists? A Preliminary Review with 'Query Session' and Future Perspectives" by Cazzato et al. (contribution 1) conducts a systematic review on the use of ChatGPT in pathology. It follows the PRISMA guidelines and uses literature from the PubMed, Scopus, and Web of Science (WoS) databases. Five publications were included after screening for eligibility and inclusion criteria. They also performed a 'query session' with ChatGPT regarding pathologies such as pigmented skin lesions, malignant melanomas and variants, and Gleason's score of prostate adenocarcinomas. ChatGPT is shown to be able to advise the pathologist by providing large amounts of scientific data for use in routine microscopic diagnostic practice. However, there are certain limitations that need to be addressed and resolved, such as bias in the training data, the amount of data available, and 'hallucination' phenomena. The authors also stress that an AI-driven system should always provide support and never have a decision-making motive during the histopathological diagnostic process.

"Design of an Educational Chatbot Using Artificial Intelligence in Radiotherapy" by Chow et al. (contribution 2) shows how to design an AI-enabled chatbot for educational purposes in radiotherapy, using the dialogue tree and layered structure with AI features such as NLP. The chatbot can provide humanlike communication to users requesting information on radiotherapy, based on the question-and-answer approach. When the user may not be able to pinpoint the question exactly, it will be user-friendly and reassuring, offering a list of questions for the user to select. The NLP system helps the chatbot predict the intent of the user and provide the most accurate and precise response. Preferred

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educational features in a chatbot are functional features such as mathematical operations, which should be modified and updated regularly. The authors conclude that an AI-enabled educational chatbot can be created to provide information transfer to users with different levels of radiotherapy knowledge (e.g., patients, the general public, or radiation staff). The chatbot should be upgraded and fine-tuned regularly, while its performance should be tested and evaluated.

"Machine-Learning-Based Prediction Modelling in Primary Care: State-of-the-Art Review" by El-Sherbini et al. (contribution 3) summarizes the potential of ML and its subsets in influencing two domains of primary care: pre-operative care and screening. ML can be utilized in preoperative treatment to predict postoperative results and assist physicians in selecting surgical interventions. Clinicians can reduce risk and improve patient outcomes using ML algorithms. ML can also improve the precision and effectiveness of screening tests. Healthcare professionals can identify diseases at an early and curable stage by using ML models to scan medical images for diseases or anomalies. ML can be used to identify people at an increased risk of developing specific disorders or diseases, even before any symptoms are visible. It can assess patient data such as medical history, genetics, and lifestyle factors to identify patients at higher risk, enabling targeted interventions such as lifestyle adjustments or early screening. In conclusion, the use of ML in primary care can potentially improve patient outcomes, reduce healthcare costs, and boost the productivity of healthcare personnel.

"Predictive Analytics with a Transdisciplinary Framework in Promoting Patient-Centric Care of Polychronic Conditions: Trends, Challenges, and Solutions" by Wan and Wan (contribution 4) comments on an innovative approach to the development of predictive analytics, which is centered on the development of predictive models for varying stages of chronic disease through integrating all types of datasets, adding various new features to a theoretically driven data warehousing, creating purpose-specific prediction models, and integrating multi-criteria predictions of chronic disease progression based on a biomedical evolutionary learning platform. This commentary identifies trends, challenges, and solutions in conducting innovative AI-based healthcare research, improving understandings of disease-state transitions from diabetes to other chronic polychronic conditions. Therefore, better predictive models could be further formulated to expand from inductive to deductive inquiries in care management research.

"Evaluating the Performance of Automated Machine Learning (AutoML) Tools for Heart Disease Diagnosis and Prediction" by Paladino et al. (contribution 5) discusses the creation of ten machine learning models using the standard practices of exploratory data analysis (EDA), data cleansing, feature engineering, and others, utilizing the Python "sklearn" library. Their toolkit included an array of models: logistic regression, support vector machines, decision trees, random forest, and various ensemble models. Employing five-fold cross-validation, these traditionally developed models demonstrated accuracy rates spanning from 55% to 60%. Automated machine learning (AutoML) tools perform better and have superior capability in generating predictive models. Their findings suggest that AutoML tools can simplify the generation of robust ML models with higher performance than models created by traditional ML methodologies. However, the limitations of AutoML tools must be considered, and strategies need to be developed to overcome them. The successful deployment of ML models designed via AutoML could revolutionize the treatment and prevention of heart disease globally.

"Convolutional Neural Networks in the Diagnosis of Colon Adenocarcinoma" by Leo et al. (contribution 6) analyzes different architectures and ensembling strategies to develop the most efficient network combinations to improve binary and ternary classification of colorectal cancer. They propose a two-stage pipeline approach to diagnose colon adenocarcinoma grading from histological images in a similar manner to that of a pathologist, using a transformer architecture with subsequent classification using a convolutional neural network (CNN) ensemble, which improved the learning efficiency and shortened the learning time. Moreover, they prepared and published a dataset for clinical validation of the developed artificial neural network, which suggested the discovery of novel histological phenotypic alterations in adenocarcinoma sections that could have prognostic value. They conclude that AI can significantly improve the reproducibility, efficiency, and accuracy of colon cancer diagnosis, which are required for precision medicine to personalize cancer treatment.

"A new Convolution Neural Networks and Graph Convolution Networks-based architecture for AI applications in Alzheimer's Disease Stages Classification" by Hasan and Wagler (contribution 7) proposes a computer-assisted method based on an advanced DL algorithm to differentiate between people with varying degrees of dementia. They developed the following four separate models for classifying different dementia stages: (1) CNNs built from scratch; (2) pre-trained VGG16 with additional convolutional layers; (3) graph convolutional networks (GCNs); and (4) CNN-GCN fusion models. These models were trained and evaluated using 6,400 whole-brain magnetic resonance imaging (MRI) scans obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI). A five-fold cross-validation technique was applied to all the models. Particularly, the CNN-GCN model shows excellent performance in classifying different stages of dementia. Understanding the stages of dementia can assist researchers in uncovering molecular markers and pathways connected with each stage.

"AI and Face-Driven Orthodontics: A Scoping Review of Digital Advances in Diagnosis and Treatment Planning" by Tomášik et al. (contribution 8) highlights the current digital advances that, thanks to AI tools, allow us to implement facial features beyond symmetry and proportionality and incorporate facial analysis into diagnosis and treatment planning in orthodontics. The topics with the greatest research potential within digital orthodontics over the last five years were identified. The most researched and cited topic was AI and its applications in orthodontics. AI can be applied in automated 2D or 3D cephalometric analysis, facial analysis, decision-making algorithms, and the evaluation of treatment progress and retention.

"A Flower Pollination Algorithm-Optimized Wavelet Transform and Deep CNN for Analyzing Binaural Beats and Anxiety" by Rankhambe et al. (contribution 9) discusses binaural beats, a low-frequency form of acoustic stimulation that can help reduce anxiety as well as alter other psychological situations and states by affecting mood and cognitive function. They analyzed the level of anxiety when hearing binaural beats using a novel optimized wavelet transform in which optimized wavelet parameters are extracted from the electroencephalogram (EEG) signal using the flower pollination algorithm, whereby artifacts are effectively removed from the EEG signal. They applied deep CNN-based signal processing, in which deep features are extracted from optimized EEG signal parameters. The proposed model outperforms existing techniques. Therefore, the optimized wavelet transform with a deep CNN can perform an effective decomposition of EEG data and extract deep features related to anxiety to analyze the effect of binaural beats on anxiety levels.

Finally, "Explainable Artificial Intelligence (XAI): Concepts and Challenges in Healthcare" by Hulsen (contribution 10) discusses the term XAI, which has been gaining momentum recently. XAI tries to ensure that AI algorithms (as well as their decisions) can be understood by humans, transforming "black box" algorithms to more transparent "glass box" algorithms. The paper mentions some central concepts in XAI, such as transparent and post-hoc models, AI-assisted decision-making, and explanation methods. It also describes several challenges around XAI in healthcare, such as legal and regulatory compliance, privacy and security, the balance between explainability and accuracy/performance, and explainability metrics. It provides discussion on whether XAI can really help healthcare advance, for example, by increasing understanding and trust, and offers future research possibilities in the area of XAI.

The manuscripts in this Special Issue give us only a brief overview of the wide use of AI in healthcare. It shows how Generative AI can help pathologists and educate patients, how AI can help build predictive models based on medical data, how it can help classify diseases, how it can assist with treatments, and it explains the concept of XAI. As the importance of

AI, and specifically Generative AI with its Large Language Models (LLMs) consuming TBs of data and using many MWhs of electricity during training [8], is growing, data quality as well as sustainability are becoming more prominent as well. LLMs in the healthcare arena need high-quality, reliable medical data to work with. The large computing power needed to run LLMs causes sustainability issues in a world that is already heading towards an energy crisis. Luckily, researchers are working on ways to minimize computation power by inventing methods to reduce computations while preserving model accuracy [9]. While AI is gaining importance, there is also more focus on responsible AI (RAI) [10], which tries to prevent negative effects, especially in Generative AI, such as toxicity and hallucinations. AI in healthcare needs to be both explainable and responsible to make sure that clinical decisions are fully transparent and ethical. In the future, AI might also converge with other technological trends such as the Digital Twin [11] and the Metaverse [12], offering many opportunities to improve healthcare.

Conflicts of Interest: The author is an employee of Philips.

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