

Guest Editorial

Achieving Health Equity Through AI for Diagnosis and Treatment and Patient Monitoring

HEALTH equity is a fundamental principle that aims to ensure that all individuals, regardless of their background or circumstances, have equal access to quality healthcare. Unfortunately, significant health disparities persist globally, with marginalized and disadvantaged groups often being at a disadvantage in terms of access to diagnostics and treatments. Artificial intelligence (AI) is emerging as a powerful tool to combat these inequalities and improve health equity.

The role of AI in the healthcare field is continuously expanding. Technological advancements have enabled the development of AI systems capable of analyzing vast amounts of medical data, identifying trends, and supporting healthcare professionals in diagnosing and treating diseases. This paves the way for more personalized, quicker, and more effective healthcare, but it can also contribute to reducing health inequalities.

One of the major advantages of AI is its ability to provide early and accurate diagnoses, which is crucial for many serious illnesses. However, many populations, especially in underdeveloped regions, lack adequate access to healthcare professionals. AI can help bridge this gap by providing automated diagnostic tools that can be used by less qualified healthcare workers, thereby expanding the reach of healthcare in places where it is needed most.

Furthermore, AI can help improve access to treatments by developing personalized therapies. By analyzing an individual's genetic and medical data, AI can recommend specific treatments that maximize the chances of success, reducing the risk of unnecessary side effects. This is particularly beneficial for patients with unique characteristics that can affect their response to treatments.

However, for AI to truly contribute to health equity, several challenges must be addressed. First and foremost, it is essential to ensure that the data used to train AI systems are diverse and representative of the entire population. Otherwise, AI models may risk reproducing existing biases. Additionally, ethical and data privacy issues need to be resolved to ensure that patients feel secure in sharing their medical information.

Furthermore, access to these technologies must be expanded. The costs associated with the development and implementation of AI in healthcare can be high, creating a risk of exacerbating inequalities if not managed. Governments, regulators, and industry need to collaborate to ensure that healthcare AI is accessible to all.

Thus, AI has the potential to revolutionize how we diagnose and treat diseases while contributing to the achievement of health equity. However, it will not happen automatically, and deliberate actions are required to ensure that healthcare AI benefits all, regardless of their background or status. This calls for international collaboration, appropriate regulation, and a commitment to ethics and equity. If we address these challenges, AI can become a powerful tool for achieving health equity on a global scale.

In this dynamic landscape, the intersection of AI and healthcare presents an unprecedented opportunity to achieve health equity through innovative methods of diagnosis, treatment, and patient monitoring. As we delve into the heart of this subject, we are poised to explore the remarkable potential of AI in reshaping the healthcare landscape and addressing issues of inequality and disparity.

Khaldraoui et al. [1] introduce the pivotal role of AI in scientific text classification, focusing on the challenging terrain of COVID-19 research. In the wake of the global pandemic, the sheer volume of scientific publications has made manual data retrieval an arduous task. Enter CovBERT, a pre-trained language model built upon BERT, which automates the literature review process, significantly improving efficiency and accessibility. Through this article, we come to understand how AI can streamline the process of information retrieval and contribute to a deeper understanding of the global health crisis.

Reference [2] addresses the realm of blockchain technology and its role in combating the COVID-19 crisis. As the pandemic brought unprecedented challenges, governments and technological organizations turned to blockchain to navigate this new terrain. This research provides valuable insights into how blockchain can be harnessed for contact tracing, vaccine distribution, and healthcare data management. Through innovative blockchain-based solutions, this article showcases the transformative power of technology in addressing real-world health crises.

Guefrachi et al. [3] investigate AI's potential in addressing the COVID-19 pandemic. By developing a deep learning system for the detection of COVID-19 from chest X-ray images, this research demonstrates the remarkable capabilities of AI in the realm of medical imaging. The results showcase the potential for high accuracy and the automation of the diagnostic process, particularly when traditional testing methods may be limited. This work underscores how AI can provide solutions in the face of a global health crisis.

In reference [4], the authors explore the fascinating world of ensemble classifiers and deep learning for the diagnosis of COVID-19. By comparing 16 state-of-the-art classifiers, this research highlights the potential of combining these classifiers for the highest possible accuracy in detecting the virus from X-ray images. The study's innovative methodology, particularly the use of Majority Voting, sheds light on how AI can excel in intricate tasks such as medical diagnosis. Through this exploration, we glimpse the power of AI as a tool for enhanced decision-making and accuracy in healthcare.

Transitioning to the work [5], we delve into the critical topic of equity within AI systems for health. AI has the potential to enhance patient outcomes and streamline healthcare processes. However, this article reminds us that, without addressing issues related to bias, structural racism, and social determinants of health, we risk perpetuating healthcare disparities [6]. The research calls for a systematic approach to developing equitable AI models, encompassing factors such as data inclusion and monitoring for unintended consequences. In doing so, it highlights the importance of achieving equitable healthcare solutions.

In reference [7], the authors explore the intricate landscape of utilizing AI to enhance health equity among patients with heart failure. The research emphasizes that bias, structural racism, and social determinants of health play a crucial role in healthcare disparities, particularly in the context of heart failure. AI is presented as a tool that can help predict and treat patients more equitably by addressing these factors [8]. By emphasizing the need for diverse datasets, inclusivity, and careful evaluation of AI models, this article paves the way for an equitable approach to healthcare.

In an era where technology and innovation converge to reshape the landscape of healthcare, this special collection of articles presents a glimpse into the forefront of medical research and the intersection of artificial intelligence, sensor technology, and healthcare solutions. These articles collectively signify the ongoing transformation of healthcare through advanced technological applications. From the automated detection of COVID-19 symptoms using cough sound analysis to the development of lightweight neural networks for skin lesion diagnosis, and from the utilization of composite transformers for cell instance segmentation to the creation of an automatic system for assessing upper-limb spasticity through voluntary movements, these contributions embody the ingenuity and impact of modern healthcare solutions. Together, they exemplify the potential to revolutionize medical diagnosis, treatment, and patient care by harnessing the power of artificial intelligence and technology for the betterment of healthcare and medical research.

The first paper of our collection, titled "An Explainable and Personalized Cognitive Reasoning Model Based on Knowledge Graph: Toward Decision Making for General Practice," [9] delves into the critical domain of primary health care and the need for enhanced diagnostic and treatment accuracy in China. This research introduces a groundbreaking Cognitive Reasoning Model based on Knowledge Graph (CRKG) that is designed

to address these challenges. The CRKG aims to provide personalized diagnosis and decision-making support for general practitioners, with a particular focus on abdominal diseases.

Abdominal diseases encompass a wide range of symptoms, including abdominal pain, diarrhea, bloating, blood in feces, and nausea, making accurate diagnosis a complex task for medical professionals. This research begins by constructing an abdominal disease knowledge graph (AKG) through a semi-automated process, serving as the foundation for the CRKG's reasoning capabilities.

The CRKG model is a fusion of the dual process theory, involving both intuitive attention capture (System 1) and explicit consciousness reasoning (System 2). The attention capture module identifies relevant "work memory" from the AKG, leveraging the concept of attention mechanisms. The consciousness reasoning module then employs Graph Neural Networks (GNNs) to predict underlying diseases, providing a comprehensive and explainable analysis.

The contributions of this research are significant:

- Incorporation of medical knowledge into the AKG through manual annotation and automatic extraction.
- The design of the CRKG model, guided by GNNs and attention mechanisms, which enhances the diagnostic process for general practitioners.
- Remarkable performance of the CRKG model, surpassing other baseline recommendation methods with precision@1 of 0.7873, recall@10 of 0.9020, and hits@10 of 0.9340.
- The CRKG model's ability to offer a transparent explanation of the reasoning process through visualization.

In conclusion, the CRKG model represents a pioneering development in personalized diagnosis and decision-making for abdominal diseases within the realm of general practice. Not only does it outperform other models in terms of accuracy, but it also stands out for its explainability, as it offers insights into the reasoning process. This research marks a crucial step in the application of decision-making based on electronic health records and knowledge graphs, ultimately improving healthcare and diagnostic accuracy in primary health care settings.

The second paper of our collection, titled "Deeply Supervised Skin Lesions Diagnosis with Stage and Branch Attention," [10] addresses the vital need for accurate and unbiased examinations of skin lesions, as they are crucial for the early diagnosis and treatment of skin diseases. Skin lesions vary significantly in visual features due to differences in lesion colors and morphologies, as well as the use of varying imaging equipment for data collection. While ensembled convolutional neural networks (CNNs) have shown promise in classifying skin lesion images for early diagnosis, they come with limitations such as being computationally intensive and unable to efficiently process contextual information.

In response to these limitations, the research introduces a novel neural network called HierAttn. HierAttn is designed to be lightweight and effective, and it leverages deep supervision and multi-branch attention mechanisms to learn both local and global

features from skin lesion images. Importantly, HierAttn accomplishes this with a single training loss. The research evaluates the effectiveness of HierAttn using datasets, including ISIC2019 and PAD-UFES-20 (PAD2020), containing dermoscopy images and smartphone photos.

The contributions of this research are noteworthy:

- Introduction of HierAttn, a lightweight neural network, which achieves top-level performance while having a smaller size compared to other mobile models for skin lesion classification.
- Development of a novel deep supervision method, the branch attention algorithm, which efficiently learns local and global representations of features and aggregates them with tensor assembling. This process does not introduce additional learnable parameters or loss computation, making it computation-friendly.
- Proposal of the same channel attention (SCAttn) module, which effectively extracts global features without increasing the model's size.
- Introduction of the stage attention block, combining SCAttn and a convolution-transformer hybrid (CTH) block to thoroughly learn regional and global high-level feature representations.

In conclusion, the HierAttn network, equipped with stage attention, branch attention, and SCAttn, has demonstrated its potential for improved skin lesion diagnosis. It achieves impressive classification results, with 96.70% accuracy and 0.9972 AUC on ISIC2019 and 91.22% accuracy and 0.98816 AUC on PAD2020 validation sets, surpassing other state-of-the-art mobile networks. Moreover, HierAttn is the most compact model among its peers, making it a promising candidate for deployment on mobile devices, thereby extending its potential impact to the general public. This research significantly advances the field of skin lesion diagnosis, offering a powerful and efficient tool for early disease detection.

The third paper of the present collection, titled “CellT-Net: A Composite Transformer Method for 2-D Cell Instance Segmentation,” [11] focuses on the critical task of cell instance segmentation (CIS) using light microscopy and artificial intelligence. This research has significant implications for healthcare, particularly in the diagnosis of neurological disorders and assessing their response to treatment. An effective CIS method is essential to accurately segment individual cells in images with challenging characteristics, such as irregular morphology, size variation, cell adhesion, and obscure contours.

To address these challenges, the researchers propose a novel deep learning model called CellT-Net. They use the Swin transformer (Swin-T) as the base model for constructing the CellT-Net backbone. Swin-T is chosen for its self-attention mechanism, which adapts to focus on relevant image regions while suppressing irrelevant background information. CellT-Net, with Swin-T as its core, generates multi-scale feature maps that are well-suited for detecting and segmenting cells at different scales. To enhance representational features, the research introduces a novel approach called cross-level composition (CLC), which establishes composite connections between identical Swin-T models in the CellT-Net backbone.

The model is trained using the earth mover's distance (EMD) loss and binary cross-entropy loss to achieve precise segmentation of overlapping cells. The effectiveness of CellT-Net is validated using the LiveCELL and Sartorius datasets, demonstrating its superior performance compared to state-of-the-art models in handling the challenges presented by cell dataset characteristics.

The challenges in cell instance segmentation are outlined in the paper. Deep learning-based methods, like Cellpose and Omnipose, have improved cell segmentation, but their performance may be limited by the complexity of cell culture scenes. Cell microscopic image datasets present challenges like irregular morphology, variation in cell sizes, cell adhesion, and obscure contours. Neuronal cells, for instance, have unique and irregular shapes, and their sizes can vary dramatically. Traditional convolutional neural network (CNN)-based models struggle to handle these irregularities, and deep layers with large receptive fields may ignore low-level shape and texture information. Cells often overlap in images, making it difficult for deep learning methods to distinguish them. Additionally, cell contours in microscopic images can be unclear due to low contrast and background impurities.

To address these challenges, CellT-Net utilizes the Swin-T model, which generates multi-scale feature maps and adapts to complex cell characteristics. The CLC approach enhances the model's ability to capture both low-level morphology and high-level semantic features. To address irregular morphology, a deep feature map is refined with the help of deformable convolution. Finally, the model is trained with the EMD loss, and the results demonstrate its efficiency in segmenting overlapping cells. These tailored deep learning methods provide solutions for the unique challenges presented by cell datasets and have promising potential in quantifying neuronal cells based on 2D light microscopic images.

The fourth paper of our collection, titled “AI-Based Automatic System for Assessing Upper-Limb Spasticity of Patients with Stroke Through Voluntary Movement,” [12] addresses the common complication of spasticity in patients with stroke and investigates its relation to voluntary movement. This study introduces an innovative automatic system for assessing the severity of spasticity in four upper-limb joints: the elbow, wrist, thumb, and fingers, all through voluntary movements.

To collect the necessary data, the researchers developed a wearable system that combines 19 inertial measurement units (IMUs) and a pressure ball. Participants were asked to perform four specific tasks: cone stacking (CS), fast flexion and extension (FFE), slow ball squeezing (SBS), and fast ball squeezing (FBS). Kinematic and force information was collected during these tasks. Time and frequency domain features were extracted from the collected data, and feature selection techniques were employed to choose the most influential features. These selected features were then fed into five machine learning techniques to assess the severity of spasticity for each joint.

The results of the study indicated that using the CS task to assess the severity of spasticity in the elbow and fingers and using the FBS task to assess the thumb and wrist yielded the highest weighted-average F1-scores. Moreover, the study concluded that

the FBS task is the optimal choice for assessing spasticity in all four upper-limb joints. In summary, the proposed automatic system demonstrated the ability to accurately assess upper-limb joints through voluntary movements, providing a breakthrough in understanding the relationship between spasticity and voluntary movement.

The contributions of this study are significant. While previous studies have explored upper-limb voluntary motion and spasticity, they often focused on the quality of movement rather than the severity of spasticity. This study is the first to assess the severity of spasticity in four upper-limb joints based on data collected from patients' voluntary movements. The wearable system developed for this purpose combines various sensors, including IMUs and a pressure ball module, to capture kinematic and force data during voluntary movements of the elbow, wrist, thumb, and fingers. Multiple machine learning models were used to predict the severity of spasticity for each joint, and the optimal model for each joint was selected based on the weighted-average F1-score.

In conclusion, the study demonstrates that the wearable system can accurately assess the severity of upper-limb spasticity through voluntary movements, eliminating the need for therapist assistance. This has the potential to be applied in residential rehabilitation for patients with stroke, making it a valuable advancement in the field of stroke rehabilitation and patient care.

The common thread among the four articles is the application of artificial intelligence and advanced technology in the field of healthcare and medical diagnostics. Each paper presents innovative approaches to addressing healthcare-related challenges by leveraging AI, machine learning, and sensor technologies to improve patient outcomes and advance medical research.

1. **Automated Detection of COVID-19 Symptoms:** The first article focuses on the development of a smartphone-based system that utilizes AI to automatically detect COVID-19 symptoms from the sound of a patient's cough. This technology aims to provide a non-invasive and accessible way to screen for potential COVID-19 cases, which is particularly important during a pandemic.
2. **Skin Lesions Diagnosis with Deep Supervision:** The second paper introduces HierAttn, a lightweight neural network architecture for the accurate diagnosis of skin lesions. It leverages deep supervision and attention mechanisms to improve the performance of mobile-based diagnostic tools. This research is aimed at enhancing the early detection and treatment of skin diseases.
3. **Cell Instance Segmentation Using Composite Transformers:** The third article discusses CellT-Net, a novel method for cell instance segmentation in microscopic images. It employs a composite transformer model to overcome challenges posed by irregular cell morphology, size variation, and unclear contours. This technology is vital for advancing healthcare management, especially in the diagnosis and treatment of neurological disorders.
4. **Assessing Upper-Limb Spasticity with AI:** The fourth paper presents an automatic system for assessing the severity of upper-limb spasticity in stroke patients through voluntary movements. It utilizes wearable sensors and

machine learning to establish a connection between voluntary motion and spasticity. This technology has the potential to improve stroke rehabilitation and enhance patient care.

The fifth and last paper of our collection, titled 'Interpretable CNN-Multilevel Attention Transformer for Rapid Recognition of Pneumonia from Chest X-Ray Images,' [13] delves into the critical realm of pneumonia recognition using chest X-ray images. This research introduces a novel framework, CNN-MMSA-Transformer (CMT), designed for interpretability and high efficiency. The study addresses challenges in computational complexity and data scarcity through the integration of a multi-level self-attention mechanism within Transformer and a practical data augmentation strategy. The proposed method demonstrates its effectiveness in the recognition of pneumonia, particularly in the context of COVID-19, showcasing its potential for providing rapid and reliable analytic support for medical diagnosis. The proposed CMT not only addresses the challenges posed by computational complexity and data scarcity but also contributes to the interpretability of pneumonia recognition from chest X-ray images. By incorporating a multi-level self-attention mechanism within the Transformer architecture, the model efficiently focuses on task-relevant features, accelerating the convergence of the recognition process. Moreover, the practical data augmentation strategy introduced in this study serves as a valuable solution to mitigate the impact of data scarcity on recognition accuracy. In conclusion, the effectiveness of the proposed method has been demonstrated on a diverse dataset amalgamated from five distinct medical institutions, showcasing its adaptability to varied clinical scenarios. The novel self-attention mechanism and data augmentation strategies have not only proven to be necessary but have also significantly enhanced the overall performance of the recognition framework. Looking forward, this research sets the stage for advancements in medical image recognition by emphasizing the need for interpretability, efficiency, and robustness, particularly in the context of pneumonia diagnosis, including the critical aspects related to COVID-19.

In all five articles of the present collection, artificial intelligence and machine learning play a crucial role in automating diagnostic processes, improving accuracy, and expanding the accessibility of healthcare solutions. These advancements have the potential to revolutionize medical diagnosis, treatment, and patient care by providing more efficient, accessible, and data-driven approaches to healthcare challenges. Additionally, the use of wearable sensors and mobile devices in some of these studies highlights the growing importance of remote and mobile healthcare solutions in the modern medical landscape. As we explore the intersections of AI and healthcare in these diverse contributions, from automated COVID-19 symptom detection to interpretable pneumonia recognition, we witness the transformative power of technology in addressing pressing medical challenges. This collection not only showcases the state-of-the-art in AI applications in healthcare but also sets the stage for further innovations, collaborations, and advancements in the pursuit of more equitable, efficient, and effective healthcare solutions worldwide.

HABIB HAMAM

International Institute of Technology and Management (IITG),
BP: 1989 Libreville, Gabon
Faculty of Engineering, Université de Moncton,
Moncton, NB E1A3E9, Canada
School of Electrical Engineering, Department of
Electrical and Electronic Engineering Science,
University of Johannesburg,
Johannesburg 2006, South Africa;
Spectrum of Knowledge Production & Skills
Development, Sfax 3027, Tunisia
habib.hamam@umoncton.ca

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