applied sciences

MDPI

Editorial

Application of Artificial Intelligence in the Practice of Medicine

Hyo-Joong Suh [1], Junggab Son [2] and Kyungtae Kang [3,*]

[1] School of Computer Science and Information Engineering, The Catholic University of Korea, Bucheon 14462, Korea; hjsuh@catholic.ac.kr
[2] Department of Computer Science, Kennesaw State University, Marietta, GA 30060, USA; json@kennesaw.edu
[3] Department of Artificial Intelligence, Hanyang University, Ansan 15588, Korea
* Correspondence: ktkang@hanyang.ac.kr

check for updates

Citation: Suh, H.-J.; Son, J.; Kang, K. Application of Artificial Intelligence in the Practice of Medicine. *Appl. Sci.* **2022**, *12*, 4649. https://doi.org/10.3390/app12094649

Received: 24 April 2022
Accepted: 4 May 2022
Published: 6 May 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

1. Introduction

Advancements in artificial intelligence (AI) based on machine and deep learning are transforming certain medical disciplines. When combined with the rapid progress in high-performance computing, AI-based systems have enhanced the accuracy of diagnostics and the efficiency of therapeutics in many specializations. Advanced AI algorithms can extract features from a significant amount of healthcare data and then apply them to clinical practice. Furthermore, depending on feedback, the algorithm's accuracy is improved by its self-correcting abilities. Consequently, an AI-based healthcare support system can help physicians deliver optimal patient care by reducing diagnostic and therapeutic errors that unavoidably occur in human-based clinical practice [1]. In addition, such AI-based systems can extract meaningful information from a large patient population's data to draw real-time conclusions related to health risk alarms and health outcome projections.

According to experts, diverse healthcare sectors including chronic illness management and clinical decision-making can expect to be substantially impacted by AI. While AI algorithms are still in the early stages of deployment, they show promise in fields including radiology, pathology, ophthalmology, and cardiology [2]. Such progress poses interesting questions about whether AI will eventually displace clinicians, enhance their professional prospects, or some combination of both.

This Special Issue's objective is to advance research into a wide range of multidisciplinary perspectives on AI theory and its applications in medicine, medically oriented human biology, and general healthcare. The topics covered include (but are not limited to) AI in biomedicine and clinical medicine, machine learning-based decision support, robotic surgery, data analytics and mining, laboratory information systems, and AI in medical education. We stress the practical aspects of each study, emphasizing the importance of including a clinical evaluation of the utility and potential impact of the work.

2. Review of Issue Contents

This Special Issue presents ten original papers that cover the latest technologies and advances in the design of intelligent medical systems and applications. Moreover, each paper contributes to research that affords insights into the processing of medical data collected from patients.

Visual acuity (VA) measures the ability to distinguish the shapes and details of objects at a given distance. However, in some cases, such as unconsciousness or disease e.g., dementia, it may be impossible to measure VA using traditional chart-based methods. In [3], Kim et al. propose a machine-learning-based VA measurement method that determines VA from fundus images only. Three models, SVM, VGG-19, and EfficientNet-B7, were ensembled to predict categories. This is a precedent for applying artificial intelligence in medical practice to measure VA using fundus images.

Neuroimaging must often process a large amount of data with significantly fewer cases than the number of variables, which results in overmatching. To prevent this problem, Belenguer-Llorens et al. [4] propose a new dual Bayesian linear regression model with feature selection (DBL-FS) that effectively reduces the number of samples with high-dimensional features. This relies on including an automatic relevance determination prior (ARD) over the weight matrices, which automatically infers the features' relevance in the input feature space by assigning higher/lower relevance values when they contain more/fewer relevant features.

In addition, the DBL-FS Bayesian approach facilitated prior expert knowledge to guide the FS process and compensated for the limited number of samples available to train the model. The advantage of using DBL-FS allowed the detection and characterization of morphometric brain changes in a schizophrenic rodent model.

Image segmentation is used to analyze medical images quantitatively for diagnosis and treatment planning. This is because manual segmentation requires considerable expert effort and time. Ju et al. [5] propose a deep learning tool that easily creates training data to mitigate this inconvenience. This study was performed using two types of information: visual features and organ segment locations. The proposed model consists of two submodules: a feature encoder and a kernel function. The kernel function incorporates feature similarity density and Gaussian kernel density. The tool demonstrates competitive results when compared to state-of-the-art segmentation algorithms, such as UNet and DeepNetV3. The tool can be trained with minimal labeled data, uses anchor pixels from user interactions to segment organs easily, and refines the segmentation results by modifying the thresholds. Hofmann et al. [6] used machine learning to predict whether patients with schizophrenia exhibit aggressive behaviors. Up-sampling was used to process a small number of categories to balance the data, reduce variables using the random forest algorithm, and build machine learning models by including the logistic regression, trees, random forest, gradient boosting, k-nearest neighbor (KNN), support vector machines (SVM), and naive Bayes approaches. The performance of the SVM model was superior to the other machine learning algorithms. Negative behavior towards other patients was identified as the most indicative factor for distinguishing aggressive from non-aggressive patients. Its application may enable clinicians to identify high-risk patients at an early stage, modify their treatment accordingly, and prevent aggressive events during hospitalization.

Identifying the locations and extent of brain infarctions is essential for diagnosis and treatment. In general, deep learning requires large amounts of training data. To overcome this problem, Yoshida et al. [7] generated pseudo-patient images using CycleGAN, which performed image transformation without paired images. First, CycleGAN was used for data augmentation and to generate pseudo-cerebral infarction images from images of healthy specimens. Finally, U-Net was used to segment the cerebral infarction region using the CycleGAN-generated images. Regarding extraction accuracy, the U-Net-with-CycleGAN images showed an improvement over those of U-Net without CycleGAN, were efficient, and assisted in extracting the infarction area accurately while maintaining the detection rate.

STHarDNet [8] is a novel segmentation model for magnetic resonance imaging (MRI). In MRI segmentation, conventional approaches utilize U-Net models with encoder–decoder structures, segmentation models using vision transformers, or models that combine a vision transformer with an encoder–decoder model structure. However, conventional models are large with low computation speeds, and, in vision transformer models, the amount of computation sharply increases with the image size. To overcome these problems, the STHarDNet model is proposed, which combines Swin transformer blocks and a lightweight U-Net-type model that has a HarDNet block-based encoder–decoder structure. To maintain the features of the hierarchical transformer and shifted windows approach of the Swin transformer model, the Swin transformer is used in the first skip connection layer of the encoder, instead of in the encoder–decoder bottleneck.

STHarDNet improved the accuracy and speed of MRI image-based stroke diagnosis. In general, combined, the Swin transformer blocks and lightweight U-Net type model maintained the advantage of hierarchical feature extraction and demonstrated excellent segmentation performance. The Swin transformer restricts the computation of attention to each window, and this also maintains high calculation speeds.

The whole-slide image (WSI) is a digitized medical image. Processing WSIs to train neural networks is often intricate and labor-intensive. Neuner et al. [9] developed an open-source library dealing with recurrent tasks in the processing of WSIs and helped with the training and evaluation of neuronal networks for classification tasks. First, a large WSI is divided into multiple small tiles. Thereafter, the region of interest (ROI) is extracted using a filtering algorithm that stores each WSI's dimensions, ROI, and tile information. In addition, evaluations are available at each level while preserving the hierarchical structure. Neural network training continues using the fastai library, which applies filtered information for learning, reduces storage space, and increases the processing speed. This approach supplements the clinicopathological diagnoses of brain tumors.

Upper gastrointestinal endoscopy is widely performed to detect early gastric cancers (GCs). The automated detection of early GCs from endoscopic images involves an object detection model. However, the reduction of false positives involves challenges in the detected results. Teramoto et al. [10] propose an object detection model, U-Net R-CNN, based on a semantic segmentation technique that extracts target objects by performing local analysis on the images. The candidate regions were extracted using U-Net; however, many regions were over-detected in the detected candidate regions. Therefore, the candidate region was cut and input to the CNN to classify the candidate region as a GC or a false positive. Finally, the regions identified by the CNN were considered candidate regions. DenseNet169 was used as the convolutional neural network for box classification, which improved the detection performance compared with the previous method.

In [11] the authors verified that adversarial attacks were not negligible during open-source development. Open-source deep neural networks (DNNs) for medical imaging are significant in emergent situations, such as during the COVID-19 pandemic because they accelerate the development of high-performance DNN-based systems. The COVID-Net model, an open-source DNN model for detecting COVID-19 from chest X-ray images, is susceptible to backdoor attacks that modify DNN models and cause misclassification when a specific input trigger is added. The backdoor attacks are effective against models fine-tuned from the backdoored COVID-Net models, although non-targeted attacks are less successful. This indicates that the high-risk backdoored models can be spread by fine-tuning, thereby becoming a significant security threat. The findings show that protection must be emphasized during open-source development and in the practical application of DNNs for COVID-19 detection.

Finally, in [12], Calnares et al. present an automatic system for modeling clinical knowledge to follow a physician's reasoning during medical consultation. Instance-based learning was applied to provide suggestions for electronic medical records. A learning method was applied to determine the case types that best match the clinical scenarios of patients being evaluated according to an ad hoc similarity metric. A list of similar case types was suggested during evaluation whenever the physician modified the patient's information. The list of similar case types was updated when introducing or removing any clinical phase during medical consultation. This learning method can produce suggestions within a reasonable timeframe, even when processing large volumes of data. It is a novel tool that helps meet healthcare goals and reminds physicians to record essential data to fulfill care goals.

3. Conclusions

AI is a frontier where powerfully disruptive computer science advances have the potential to transform fundamentally the practice of medicine and healthcare delivery. It is profoundly changing the traditional model of medicine and significantly improving the level of medical services to assure various aspects of human health. Ever broader prospects are anticipated for the development of medical AI. Based on this trend, this special volume presents new and innovative research addressing some of the many scientific challenges associated with applying AI in medicine. We emphasize the need for a better understanding of AI's ongoing incorporation into routine medical practice. As such, the studies in this volume provide valuable perspectives on AI's future in healthcare, describe a roadmap for building effective, reliable, and safe approaches to AI in medicine, and discuss potential directions for developing AI-augmented healthcare systems.

Author Contributions: Conceptualization, H.-J.S., J.S. and K.K.; methodology, H.-J.S. and K.K.; validation, J.S.; investigation, K.K.; writing—original draft preparation, K.K.; writing—review and editing, H.-J.S.; supervision, J.S. and K.K.; funding acquisition, H.-J.S. and K.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Catholic University of Korea, Research Fund, 2021. This research was also supported by the Institute of Information & Communications Technology Planning & Evaluation (IITP) grant funded by the Korean government (Ministry of Science and ICT) (No. 2020-0-01343, Artificial Intelligence Convergence Research Center (Hanyang University ERICA) and 2021-0-01547, High-Potential Individuals Global Training Program).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Acknowledgments: This Issue would not have been possible without the help of a variety of talented authors, professional reviewers. First, we express our gratitude to the authors for their excellent contributions to this special issue on application of artificial intelligence in the practice of medicine. We are also grateful to all the reviewers for their time and effort in examining these papers, and for their valuable comments and constructive suggestions. We hope that this special issue will serve as a valuable reference for academicians, scientists, engineers, and practitioners working toward the application of artificial intelligence in the practice of medicine.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Buch, V.; Ahmed, I.; Maruthappu, M. Artificial Intelligence in Medicine: Current trends and future possibilities. *Br. J. Gen. Pract.* **2018**, *68*, 143–144. [CrossRef] [PubMed]
2. Briganti, G.; Moine, O. Artificial Intelligence in Medicine: Today and Tomorrow. *Front. Med.* **2020**, *7*, 27. [CrossRef] [PubMed]
3. Kim, H.J.; Jo, E.; Ryu, S.; Nam, S.; Song, S.; Han, Y.S.; Kang, T.S.; Lee, W.; Lee, S.; Kim, K.H.; et al. A Deep Learning Ensemble Method to Visual Acuity Measurement Using Fundus Images. *Appl. Sci.* **2022**, *12*, 3190. [CrossRef]
4. Belenguer-Llorens, A.; Sevilla-Salcedo, C.; Desco, M.; Soto-Montenegro, M.L.; Gómez-Verdejo, V. A Novel Bayesian Linear Regression Model for the Analysis of Neuroimaging Data. *Appl. Sci.* **2022**, *12*, 2571. [CrossRef]
5. Ju, M.; Lee, M.; Lee, J.; Yang, J.; Yoon, S.; Kim, Y. All You Need Is a Few Dots to Label CT Images for Organ Segmentation. *Appl. Sci.* **2022**, *12*, 1328. [CrossRef]
6. Hofmann, L.A.; Lau, S.; Kirchebner, J. Advantages of Machine Learning in Forensic Psychiatric Research—Uncovering the Complexities of Aggressive Behavior in Schizophrenia. *Appl. Sci.* **2022**, *12*, 819. [CrossRef]
7. Yoshida, M.; Teramoto, A.; Kudo, K.; Matsumoto, S.; Saito, K.; Fujita, H. Automated Extraction of Cerebral Infarction Region in Head MR Image Using Pseudo Cerebral Infarction Image by CycleGAN. *Appl. Sci.* **2022**, *12*, 489. [CrossRef]
8. Gu, Y.; Piao, Z.; Yoo, S.J. STHarDNet: Swin Transformer with HarDNet for MRI Segmentation. *Appl. Sci.* **2022**, *12*, 468. [CrossRef]
9. Neuner, C.; Coras, R.; Blümcke, I.; Popp, A.; Schlaffer, S.M.; Wirries, A.; Buchfelder, M.; Jabari, S. A Whole-Slide Image Managing Library Based on Fastai for Deep Learning in the Context of Histopathology: Two Use-Cases Explained. *Appl. Sci.* **2022**, *12*, 13. [CrossRef]
10. Teramoto, A.; Shibata, T.; Yamada, H.; Hirooka, Y.; Saito, K.; Fujita, H. Automated Detection of Gastric Cancer by Retrospective Endoscopic Image Dataset Using U-Net R-CNN. *Appl. Sci.* **2021**, *11*, 11275. [CrossRef]
11. Matsuo, Y.; Takemoto, K. Backdoor Attacks to Deep Neural Network-Based System for COVID-19 Detection from Chest X-ray Images. *Appl. Sci.* **2021**, *11*, 9556. [CrossRef]
12. Galnares, M.; Nesmachnow, S.; Simini, F. Instance-Based Learning Following Physician Reasoning for Assistance during Medical Consultation. *Appl. Sci.* **2021**, *11*, 5886. [CrossRef]