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Digital Molecular Magnetic Resonance Imaging

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Preface

In recent years, it has been discovered that heterogeneous diseases such as cardiovascular diseases, diabetes, hepatitis and cancer may be attacked effectively by developing specific treatment plans that are generally referred to as personalized treatments. This new approach in medicine involves using novel methodology as a bridge between diagnostic and therapeutic applications to form a single agent, allowing for diagnosis, drug delivery and treatment response monitoring at the molecular level. This method is time and cost effective because it is a one in all procedure which combines diagnosis and therapy. This novel methodology involving atomic nuclei could be studied with NMR/MRI since their unique resonant frequencies lead to the production of distinct spectra for diagnostic imaging. This book has been able to develop molecular imaging methods and computer programs for a computational analysis of non-communicable disease conditions based on digitally generated magnetic resonance signal using the fundamental Bloch NMR model equation, physics-informed neural networks (PNN) and artificial intelligence to design and deploy magnetic resonance systems with the capacity to work in a digital manner with features of low cost, high performance and accuracy. The computational techniques presented in this book point to the possibility of showing contrast between different stages of tissue diseases at the molecular level. The book is outlined as follows:

Chapter 1 introduces the possibility of advanced digital signal process technique and modular designed structure to generate arbitrary pulse sequence in order to meet the requirement of digital magnetic resonance imaging methods for medical use.

Chapter 2 briefly describes the principle of artificial intelligence (AI) in medicine, neural network in scientific computing, physics-informed neural networks and the use of partial differential equations (PDEs), neural network architecture in physics-informed neural network (PINNs) and evolution of physics-informed neural networks.

The partial differential equations employed in Chap. 3 are based on the Bloch NMR flow equations and NMR diffusion equation. Each physical problem solved in this chapter is described by a Bloch-related equation based on a close observation of how the system usually behaves in the presence of NMR magnetic fields. Diffusion

in physiological flows is dependent on the magnitude of the fluid velocity that is consistent with the tissue under investigation. One of the goals of this chapter is to develop a computational model from the wave equation and optical Bloch equation and Maxwell's equation for cellular imaging. The formulation to achieve this objective is presented in detail. The formulation is for a single spin and is very useful for cellular imaging. The optical NMR signals have been obtained in terms of transverse polarization function. Using Maxwell's equations, the polarization functions have been related to the optical properties of the cellular component under investigation. This is very important in developing new techniques for imaging the causes of human diseases. The chapter also provides a means of measuring microscopic polarization function in laboratory settings.

Chapter 4 develops a novel approach for enhancing the precision of molecular imaging in the diagnosis and treatment of adult brain tumors. This leveraged the power of artificial intelligence, specifically physics-informed neural networks (PINNs), to address spatial and temporal resolution problems in magnetic resonance molecular imaging.

Chapter 5 develops machine learning models to improve the accuracy of predictions and decision-making in different models by sorting across big datasets to identify hidden trends, patterns and insights and explore the data in the developed models for diagnosis of human medical conditions.

The purpose of Chap. 6 is to construct a high-accuracy deep learning algorithm with the best performing model for the diagnosis and classification of medical pictures related to Alzheimer's disease. The CNN model was used to train MRI brain images. In order to construct and deploy the model, we used specialized application software and libraries including Jupyter Notebook, Python 3, Keras and TensorFlow. The trained model was distributed as an application known as APK, which will make it accessible as an Android application for personal diagnosis. It will be a web service for diagnosing Alzheimer's disease and determining the stage of the disease remotely.

Chapter 7 addresses a critical need for improved precision in the application of hyperthermia for clinical purposes. The developed approach advances our understanding of the physical mechanisms behind medical interventions and opens the door to more effective and personalized clinical hyperthermia, which could lead to improved patient outcomes and advancements in medical management.

Chapter 8 demonstrates the prospective synergy between physics-based knowledge and machine learning approaches, which contributes to improved understanding of temperature distribution in biological tissues and its implications for a variety of healthcare applications.

The objectives of Chap. 9 are to: (i) evaluate the performance of machine learning classification of brain tumors with WEKA and Python programming using MRI scan images and (ii) deploy the best model for the brain tumor classification in WEKA and PYTHON programming. By developing and implementing machine learning models capable of interpreting MRI scans, the method improves the speed and accuracy of diagnosis for brain tumors and provides better patient outcomes.

Chapter 10 applies neural radiance fields (NeRFs) to improve the rendering of magnetic resonance images to establish a strong framework for the three-dimensional

rendering of MRI data, which will enhance the precision and depth of medical image interpretation. This will advance medical imaging technology and make a significant contribution to the visualization of anatomical structures with never-before-seen precision and details.

The aim of Chap. 11 is to develop computational magnetic resonance fingerprinting (MRF) methods based on Bloch NMR flow equations and artificial intelligence for differentiating intra-axial brain tumors. We calculate simultaneous measurement of multiple tissue properties in terms of T1 and T2 relaxation times for differentiating intra-axial brain tumors. Machine learning models for contralateral white matter, peritumoral white matter and solid tumors dataset are developed with graphic user interface (GUI) and shiny package for model implementation.

Chapter 12 explores the fundamental quantum physics based on the uncertainty principle, to initially describe the particle (electron or a biological cell) under study by a wave packet. Then, when the particle encounters a force (diseases such as cardiovascular diseases, diabetes, hepatitis and cancer, so its potential energy is no longer zero), the force modifies the wave packet. The chapter proposed first-order perturbation theory to find such propagation techniques and applied them appropriately to provide useful techniques for the design of low-field MRI that can be useful to find solutions to biological and medical problems which otherwise could not be easily solved.

The goal of Chap. 13 is to develop and implement a transfer learning approach for the artificial intelligence-based classification of brain tumors using MRI images by: (i) pre-processing magnetic resonance scans of brain tumors according to their class (glioma, meningioma or pituitary tumors), (ii) develop a transfer learning model capable of accurately classifying the various types of brain tumors and (iii) develop an easy-to-use web application/GUI based on the trained model.

Chapter 14 is a general conclusion of the book which amplifies the power of neural radiance fields (NeRFs) to completely transform the 3D rendering industry and provide more precise and thorough visualizations for applications such as medical imaging. NeRFs have the potential of greatly improving our understanding of complex 3D environments and open up new possibilities for a wide range of applications as they continue to develop and get better. NeRF techniques have great potential to advance the visualization and quantification of complex pathologies affecting important organs such as the brain and chest by allowing MRI's exceptional soft tissue perspectives to be unlocked.

Chapter 15 focuses attention on democratizing access of magnetic resonance imaging powered by quantum computing. Independent of artificial intelligence, quantum computing is going to be a big deal. However, coupled with AI, it will be a game changer. Quantum computing, an entirely new way of processing information, when combined with AI, has the potential, without exaggeration, to bring about a new computing revolution. The field of AI, particularly machine learning, is poised to experience a significant leap forward due to quantum computing. This advancement is largely attributed to quantum-specific algorithms tailored to enhance computational processes. A wide range of sectors in healthcare are expected to benefit

from integrating AI with quantum computing. This synergy promises more efficient problem-solving and innovation within medical fields. The fusion of AI with quantum computing is not just about incremental changes but about paving the way for transformative advancements. This combination will revolutionize our approach to magnetic resonance imaging and its applications in various fields of medicine.

The book is written for students, scientists, engineers, medical personnel and researchers who are interested in developing novel concepts for innovative MRI for the management of tissue diseases at low cost yet with maximum efficiency and accuracy utilizing fundamental mathematical concepts, physics-based knowledge and artificial intelligence for digital magnetic resonance imaging.

This book opens the door to ultra-powerful digital molecular MRI powered by quantum computing that can perform calculations that would take supercomputers millions of years.

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