ADVANCED COMPUTING SOLUTIONS FOR HEALTHCARE

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Advanced Computing Solutions for Healthcare

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FOREWORD I

In the ever-evolving landscape of healthcare, where the amalgamation of technology and innovation is steering the course of progress, "Advanced Computing Solutions for Healthcare" emerges as a beacon illuminating the transformative potential that lies at the intersection of advanced computing and the well-being of humanity.

Over the past decade, we have witnessed an unprecedented shift in healthcare systems, propelled by the relentless march of technology—morphing our conventional understanding into a realm dominated by computers, the internet and mobile devices. This paradigm shift has not only ushered in remarkable advancements but has also presented us with a host of challenges that demand scholarly deliberation.

I am delighted to introduce this comprehensive volume, meticulously curated by astute editors, which not only acknowledges the complexities of this technological metamorphosis but also provides an insightful platform for scholarly discourse. "Advanced Computing Solutions for Healthcare" is a compendium that navigates the intricate landscape where cutting-edge computing meets the imperatives of healthcare, thereby revolutionizing patient care, research methodologies and administrative processes.

This book ventures into the forefront of technological innovation, presenting a panorama of solutions that hold the promise of revolutionizing healthcare outcomes. From the realm of AI-driven diagnostics, predictive analytics and secure data management to the far-reaching implications of telemedicine, each chapter offers a deep dive into the potential of technology to shape a healthier future.

I extend my heartfelt congratulations to the editors for providing a robust platform for researchers to showcase their findings and achievements in this dynamic field. This book serves not only as a repository of knowledge but also as a catalyst for further research and exploration in this critical domain.

As you embark on this enlightening journey through the pages of "Advanced Computing Solutions for Healthcare," I am confident that you will gain profound insights that will inspire, inform and shape the future of healthcare. May this volume contribute significantly to the ongoing dialogue, fostering innovation and paving the way for a healthier and more technologically advanced world.

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FOREWORD II

In the dynamic confluence of technology and healthcare, the pages of "Advanced Computing Solutions for Healthcare" unfold a compelling narrative that transcends the boundaries of conventional medical practices. This meticulously curated anthology stands as a testament to the transformative power of advanced computing, unravelling a spectrum of innovations that are reshaping the very essence of patient care, diagnosis and medical research.

As we delve into the chapters of this volume, a diverse tableau of cutting-edge topics unfolds, each contributing a vital piece to the puzzle of the healthcare revolution. From the intricacies of patch antenna design for on-off body communication to the profound implications of the 5G revolution in healthcare, this collection epitomizes the multidimensional impact of technology on the well-being of individuals and communities.

The chapters navigate the landscape of machine learning applications, from investigating transfer learning techniques for classifying Alzheimer's disease datasets to the revolutionary impact of machine learning in women's health, spanning skin, breast, ovarian cancers and polycystic ovary syndrome (PCOS). Venturing further, the realms of augmented reality (AR) and virtual reality (VR) unveil themselves as integral tools for healthcare exploration, paving the way for emerging applications that transcend the boundaries of traditional medical practices.

As we journey through the chapters on cyber ethics for artificial intelligence-assisted healthcare systems, data-driven decision support systems, and the empowering fusion of haptic-enabled language to pulse devices for communicative impairments, it becomes evident that this volume encapsulates the diversity, complexity, and limitless potential of advanced computing in healthcare.

In the pursuit of knowledge, this compendium serves as a compass, guiding researchers, practitioners, and enthusiasts through the intricate web of technological advancements. "Advanced Computing Solutions for Healthcare" is not just a book; it is a collaborative expedition into the future of healthcare, where data science, artificial intelligence, and innovative technologies converge to chart a course toward a healthier, more connected world.

May this anthology spark inspiration, ignite curiosity and foster a collective commitment to leveraging technology for the betterment of healthcare, paving the way for a future where advanced computing solutions are synonymous with improved patient outcomes and enhanced well-being.

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PREFACE

Welcome to "Advanced Computing Solutions for Healthcare," a pioneering compilation that navigates the ever-evolving landscape at the intersection of cutting-edge technology and the healthcare sector. In this era of rapid innovation, the dynamic synergy between advanced computing and healthcare has ushered in a new era of possibilities, redefining patient care, research methodologies, and administrative frameworks.

This comprehensive volume, comprising 22 insightful chapters, is a testament to the transformative potential of technology in enhancing healthcare outcomes. From AI-driven diagnostics and predictive analytics to secure data management and telemedicine, our contributors explored a myriad of solutions that stand at the forefront of technological innovation.

As we embark on this journey through the realms of smart systems, personalized healthcare, artificial intelligence, machine learning, and data science, readers will gain a deeper understanding of the challenges and strategies shaping the future of healthcare. This exploration extends to the Internet of Things (IoT), image and signal processing techniques, wireless networks, and sustainable technologies, providing a holistic view of the intricate landscape in which advanced computing converges with healthcare.

Each chapter is a beacon of knowledge that sheds light on topics such as federated learning, neuromorphic systems, and secure, robust, and efficient computing solutions. The culmination of these insights paves the way for a healthier future, emphasizing the critical role of technology in revolutionizing the healthcare industry.

As editors, we are proud to present this indispensable guide, hoping it will inspire researchers, practitioners, and enthusiasts to explore the limitless possibilities that lie at the nexus between advanced computing and healthcare. This volume stimulates further innovation and contributes to the ongoing transformation of healthcare globally.

Chapter 1 delves into neurons, which are electrically sensitive cells vital for cellular communication. It explores neuronal classification, function, anatomy, and histology. This chapter also examines neuron models, including biological and compartmental neuron models. Experts' contributions to neuro-inspired designs and methodologies are highlighted, with a focus on applications in massively parallel systems. The chapter concludes by briefly outlining the imminent applications of neuromorphic computing.

Chapter 2 explores the pivotal role of data mining in the 21st century, propelled by technological strides and a surge in medical data. Essential for clinical decisions and innovation, medical data are harnessed using descriptive and predictive data-mining techniques, unraveling profound insights. By demonstrating significant implementation, data mining enhances diagnosis accuracy, reduces diagnosis time, and minimizes errors. This chapter underscores the transformative potential of data mining, promising advancements in healthcare systems and overall public health.

Chapter 3 explores Data-Driven Decision Support Systems (DD-DSS), vital for managing escalating data volumes. This computerized program, integrating machine learning and statistical analysis, aids informed decision-making in healthcare. By merging expert knowledge and diverse data, this chapter investigates the benefits, features, and real-world applications of DD-DSS through a blend of literature review and case studies.

Chapter 4 explores the rapid growth of deep convolutional neural networks (CNN) in recent years, particularly their application in healthcare through hardware accelerators such as Field Programmable Gate Arrays (FPGAs). Focusing on edge computing and the potential for implementing CNNs in safety-sensitive biomedical applications, this study provides a comprehensive analysis of the challenges in FPGA-based hardware acceleration. This survey offers valuable insights for researchers engaged in artificial intelligence, FPGA-based hardware accelerators, and system design for biomedical applications.

Chapter 5 discusses the revolutionary integration of smart sensors in smartwatches for health monitoring. Recent advancements include biometric sensors, environmental sensors, and activity trackers. This review evaluates the accuracy, reliability, and potential use of machine learning and addresses challenges such as privacy concerns and battery life. This is a valuable resource for researchers and healthcare professionals.

Chapter 6 explores the crucial role of design thinking in integrating data science into health care. It delves into the impact of data quality, integration, and visualization on patient outcomes, predictive modeling, unsupervised learning, and ethical considerations. This chapter envisions a future shaped by AI, precision medicine, and ethical data practices.

Chapter 7 explores the transformative impact of Internet of Things (IoT) integration in healthcare. This underscores how IoT enables real-time patient monitoring, personalized treatment plans, and preventative care through continuous data gathering. While enhancing diagnostic precision and resource utilization, challenges such as data security and interoperability require resolution for IoT in healthcare to reach its full potential. This chapter emphasizes the significant effects of the IoT on healthcare delivery and the importance of a comprehensive strategy for navigating this rapidly evolving landscape.

Chapter 8 delves into the transformative impact of 5G technology on the medical industry by revolutionizing disease diagnosis, treatment, and management. Examining the evolution of wireless networks, this article explores 5G's fundamental features—high speed, low latency, and reliability. It analyzes the synergy of 5G with disruptive technologies, such as AI and IoT in healthcare, emphasizing data security and privacy. The chapter envisions a future in which 5G transforms healthcare delivery, fosters innovation, and enhances user-friendliness, cost-effectiveness, and efficiency.

Chapter 9 explores the transformative potential of Tiny Machine Learning (Tiny ML) in healthcare, marked by low power consumption and compact size. This emphasizes real-time monitoring, early disease identification, personalized treatment plans, and improved medical imaging. While Tiny ML enhances patient outcomes and reduces healthcare costs, challenges such as data privacy, ethics, and regulatory compliance require careful consideration. The future holds promise for widespread adoption, enhanced telemedicine, improved diagnostics, and a patient-centric, efficient healthcare ecosystem, provided that ethical considerations are prioritized for Tiny ML's responsible utilization.

Chapter 10 illuminates the integration of techniques and resources, collectively known as artificial intelligence (AI), in healthcare to elevate patient care and streamline administrative tasks. Its increasing relevance stems from its potential to enhance the efficacy, accuracy, and accessibility of healthcare services. AI's capacity to analyze vast medical data aids decision-making, personalizes treatment, and forecasts disease outbreaks, ultimately improving patient outcomes and healthcare affordability. As its influence has grown, AI has become a transformative force in healthcare.

Chapter 11 explores the crucial role of cutting-edge image processing in medical research. This book comprehensively covers concepts and methodologies, emphasizing the importance of image processing in healthcare for diagnosis, treatment planning, and patient care across various medical fields.

Chapter 12 delves into recent strides in science and technology, uncovering the evolving landscape and prospects of Augmented Reality (AR) and Virtual Reality (VR) in healthcare. Highlighting their potential to transform medical education, patient treatment, and surgical procedures, this chapter provides an overview of the AR and VR principles. It emphasizes their distinct features, operations, strengths, and limitations in healthcare, focusing on medical education, patient treatment, and surgical planning. This work showcases successful applications in medical education, patient interventions, and surgical procedures through case studies, illustrations, and academic examples.

Chapter 13 discusses the widespread use of chembioinformatic tools in modern medical science. These tools play pivotal roles in genomic and proteomic data analysis, gene prediction, genome annotation, and building biological networks. This chapter underscores the clinical applications of chem-bioinformatics, revealing its significance in cancer biomarker identification, personalized therapeutics, and drug design. It explores how bioinformatics tools facilitate the study of host-pathogen interactions, diagnosis of infectious diseases, treatment of metabolic disorders, and point-of-care diagnostics. By manipulating biological datasets, these tools contribute to the control, monitoring, and modification of various clinical processes and offer a comprehensive overview of their applications in the medical sector.

Chapter 14 presents the challenging task of diagnosing white blood cell diseases, such as Leukemia and Myeloma, with an emphasis on restoring the balance of the immune system. This study introduces a Computer-Aided Diagnosis (CAD) model using a Deep Convolutional Neural Network (DCNN) to classify leukocyte types. Employing a Gaussian distribution and k-means clustering for image segmentation, the gray-level covariance matrix method extracts texture features for DCNN training. The proposed model achieved a notable classification accuracy of 97.8%, surpassing existing deep learning classifiers in terms of precision, recall, and F1 score. This chapter elucidates the efficacy of the CAD model for early-stage leukocyte cancer detection.

Chapter 15 introduces the “Haptic-Enabled Language to Pulse” device, a transformative solution for empowering those with speech impairments. Utilizing Python, TensorFlow Lite's DeepSpeech model, and Raspberry Pi, the system converts spoken language to Morse code conveyed through haptic feedback. Beyond aiding in communication, it serves as an educational tool that contributes to inclusive solutions for diverse abilities.

Chapter 16 addresses Alzheimer's disease (AD), which is a serious mental health concern that causes cognitive decline. This study employed transfer-learning techniques, including VGG16, InceptionResNet-V2, Resnet50, Resnet101, and Resnet152, to classify AD datasets. The results were compared and analyzed using metrics such as accuracy, loss, validation accuracy, and validation loss. Obtained from the Kaggle repository, this study aims to enhance the accuracy of AD prediction models through deep learning.

Chapter 17 explores the pivotal role of ML in medical diagnostics and predictions. Highlighting AI's learning capacity, it focuses on improving clinical decisions, automating healthcare tasks, and enhancing women's health by addressing specific issues, such as skin cancer, breast cancer, ovarian cancer, and PCOS.

Chapter 18 explores the extensive use of mathematics for the design of physiological models. With a rich history, mathematical modeling in physiology involves the creation of representations of real-life conditions. This chapter delves into the creation of mathematical representations for physiological systems, aiding in understanding complex biological relationships and predicting system behavior in diseased states. Recent advancements in high-throughput data production techniques have further strengthened the reliance on computational approaches and mathematical modeling in the study of biological systems.

Chapter 19 focuses on developing a healthcare web application for predicting various diseases using machine learning models, such as decision trees, SVM, KNN, and Random Forest. The proposed system aims to offer a user-friendly and accurate solution by consolidating multiple disease predictions in one accessible platform.

Chapter 20 explores on-body communication using antennas, which are crucial for applications such as healthcare monitoring and IoT connectivity. Focused on 2.4 GHz on-off body communication, this study investigates custom patch antenna designs for efficient data exchange. Using FR-4 and copper, the antenna exhibited exceptional performance in free space and on-body, demonstrating resilience against environmental factors for practical applications.

Chapter 21 presents a comparative study of an 8051-controlled syringe that uses servo and stepper motors for precise fluid injection. This study evaluates the design, performance, and functionality by comparing the continuous fluid delivery of a servo motor-driven pump to the precise steps of a stepper motor-driven pump. Experiments assess the accuracy, response time, and disturbance impact, providing insights for system selection based on application requirements, such as accuracy and speed. This study contributes to the optimization of fluid delivery systems across various industries.

Chapter 22 introduces a simple, cost-effective ECG analyzer prototype for real-time signal acquisition and display through IoT devices, such as mobiles. The prototype, equipped with a pre-trained Deep Learning model, classifies ECG signals to diagnose conditions such as Arrhythmia, Congestive Heart Failure, and Normal Sinus Rhythm. This innovative tool offers quick insights into potential medical care needs.

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CHAPTER 1

A Review of Biological Neurons *Versus* Artificial Neuron Models for Neuromorphic Computing Applications

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Abstract: A neuron, or nerve cell, is an electrically sensitive cell that communicates with different cells through specific associations known as neurotransmitters. Aside from wipes and placozoa, this is the principal segment of sensory tissues within the entire organism. Vegetation's well-being as an organism does not depend on nerve cells. This paper analyzes the neuron's classification, functions, anatomy, and histology. The authors also aim to analyze neuron models, such as the biological and compartmental neuron models. Several experts are involved in neuro-inspired designs, methodologies, learning approaches, and software platforms to investigate the massively parallel system and various relevant applications. A new era of medicine may emerge in neuromorphic engineering, which replicates brain-like behaviours using neural systems models in hardware and software. It suggests minimal power consumption, low latency, a smaller footprint, and large bandwidth solutions. Additionally, the applications of neuromorphic computing will be discussed shortly in this survey.

Keywords: Biological neurons, Compartmental neuron model, Dendritic, Neuromorphic computing, Spiking neurons.

INTRODUCTION

Biological neurons are of three kinds based on their dimensions. Tangible neurons respond to stimuli like touch, sound, or light, which impacts the cells of the tactile organ. They also convey messages to the vertebral string, otherwise the brain. Motor neurons receive signals from the brain and the spinal cord to control all functions, as the muscles contract to move. Interneurons connect neurons to various other neurons within a specific region of the brain or spinal cord. A group

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of interconnected neurons is known as a neural circuit. A typical neuron consists of a cell body (soma), dendrites, and a single axon, as illustrated in Fig. (**1**). This represents the anatomical and functional components of the nervous system [1].

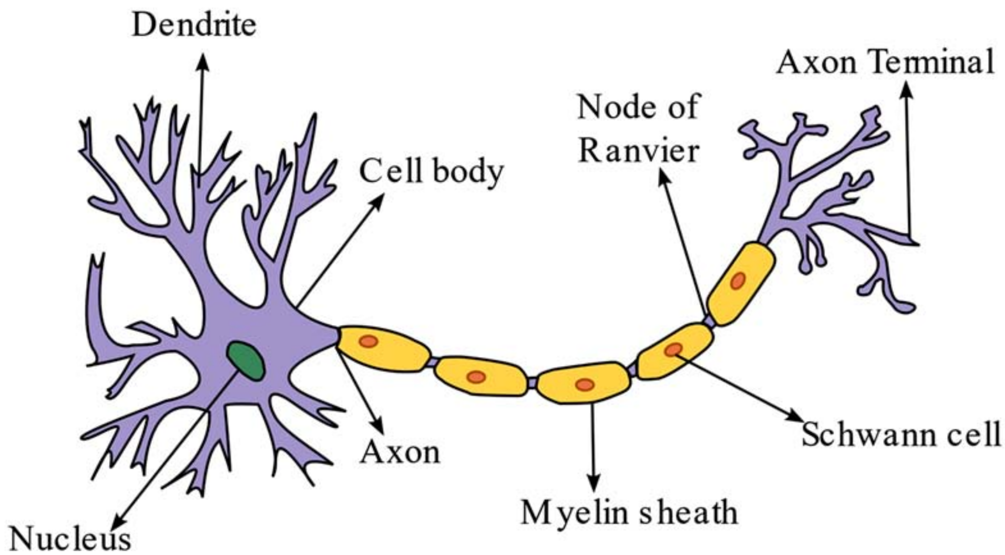

Fig. (1). Anatomy of a multipolar neuron.

Generally, the soma has minimized. The axons, as well as dendrites, have fibers that expel from them. Dendrites commonly diverge abundantly and widen two or three hundred micro meters as of the soma. The axon leaves the soma on an expanding hillock that can travel as far as one meter as humans but not as far as different species. This divergence typically maintains a consistent width. At the furthest point of the axon's branches are their terminals, through which neurons can communicate signals through neurotransmitters to additional cells. Neurons may require dendrites; otherwise, they do not have axons. The name neurite is used to describe a dendrite or an axon, especially once the cells are distinguishable [2].

Utmost neurons get signals through the dendrites and the soma, conveying signals downward through the axon. For most neurotransmitters, the signal crosses the axon of a single neuron towards the dendrite of another. However, neurotransmitters can connect an axon with another axon or a dendrite with another dendrite. The signalling process is partly electrical and primarily chemical. Neurons are electrically active due to the presence of voltage gradients across their membranes. When the voltage changes sufficiently over a short period, the neuron generates an impulse that would otherwise disrupt electrochemical signals, known as an action potential. These potentials travel rapidly along the axon and activate synaptic connections as they propagate [3]. Synaptic signs may be excitatory or inhibitory, rising or diminishing the net voltage that persists at the soma. The neuron can be produced from neurally undifferentiated organisms in youth mental health. Neurogenesis largely halts in several brain regions during adulthood.

BIOLOGICAL NEURON ANATOMY AND HISTOLOGY

Neurons have been exceptionally particular about preparing and broadcasting cellular signs. Characterized by its variety of functions acting on different pieces of the sensory system, it has an extensive assortment of shapes, sizes, and electrochemical assets. For example, the soma of a neuron could differ by 4 to 100 micrometers in measurement [4]. The biological neuron system has anatomical and functional modules.

- The soma is the physical structure of the neurons. Since it contains a nucleus, the maximum protein synthesis occurs at this point. The nucleus can range from 3 to 18 micrometers in diameter.
- Neuron dendrites contain cellular augmentations through numerous branches. These general shapes and designs are allegorically referenced, like a dendritic tree. This is where most of the contribution to the neuron happens through the dendritic vertebrae.
- The axon has been a better link as projections, which can expand ten, hundred, or even a massive number of times the length of the soma. The axon fundamentally transmits nerve signals on or after the soma and carries limited information.
- Several neurons contain only one axon; however, these axons might, as well as ordinarily, undergo extensive branching, allowing communication with several target cells.
- The portion of the axon that appears through soma is acknowledged. However, as an anatomical structure, the axon hillock attains the optimal thickness of voltage-gated sodium channels.
- It performs most effortlessly empowering parts of the neurons and spiking the commencement region of the axon. In electrophysiological terminology, this includes the most adverse edge potential. The axons and the axon hillock are two different types most commonly associated with data transmission, and these areas could similarly acquire and receive inputs from various neurons.

The acknowledged perspective on the neuron attributes specific functions to its various anatomical segments; in any case, dendrites and axons regularly act in manners despite their purported fundamental capacity [5].

CHAPTER 2

A Review on Data Mining Techniques and Their Applications in Medicine

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Abstract: Data mining is a crucial aspect of the 21st century. Technological advancements and the exponential expansion of medical data have driven it. Medical data is mandatory for clinical judgment, scientific projects, and innovation. Data-mining methods include descriptive and predictive techniques. They have been used to extract insights from massive, diverse, and erratic medical datasets. These methods have massive implementation; they enhance diagnosis accuracy and decrease diagnosis time. They also provide quantified temporal information on crucial medical behaviors, minimizing errors. They offer opportunities for healthcare transformation, improving the overall healthcare system and general health.

Keywords: Artificial intelligence, Chinese medicine, Clinical data, Comparative analysis, Data mining, Data science, Databases, Data privacy, Drug discovery, Early diagnosis, Ehr, Experimental data, Fraud detection, Machine learning, Patient record, Precision medicine, Predictive analysis, Regression analysis, Supervised learning, Survival analysis.

INTRODUCTION

The 21st century is the birth of "Big Data." Technological advancements and the subsequent exponential expansion of data have driven this concept. Big data were represented through the five Vs: volume, variety, velocity, veracity, value, and variability. Medical data are the cornerstone of the healthcare system. They direct clinical judgments, scientific projects, and innovation. These data come from several sources, including public records, patient portals, Electronic Health Records (EHRs), payer records, search engine data, generic databases, smart devices, research studies, wearable technology, and public databases [1].

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Data-mining methods have emerged as a result of the constraints of traditional data management and analysis tools for handling big data. Data science is an interdisciplinary field that combines techniques, including math, statistics, artificial intelligence, and machine learning. Data mining is a crucial element in this field. The core of data mining is the extraction of implicit, significant, and novel insights from massive, noisy, diverse, and erratic datasets. The primary types of data-mining techniques are descriptive and predictive. Predictive methods are used to predict unknown or future values of variables; descriptive methods identify patterns, associations, and trends in data [2, 3].

Data mining has been widely used in the medical field. A recent study used the bibliometric visualization tools VOSviewer and CiteSpace. They looked at the geographical distribution, international collaborations, and citation patterns of studies that used data mining in medicine. Notably, they discovered that these publications and citations have rapidly increased since 2013. This increase demonstrates the efficiency and effectiveness of this approach in the medical domain. It has improved diagnosis accuracy, reduced diagnosis time, provided quantifiable temporal data on critical medical behaviors, and reduced medical errors. It effectively guides doctors in their daily clinical practice [1, 4].

Finally, data mining provides numerous opportunities for healthcare transformation. Through ongoing evolution, it has the potential to improve the healthcare system and overall health. This chapter offers insight into medical data and data-mining methods, including their applications in medical fields and their challenges.

MEDICAL DATA

In the twenty-first century, the concept of "Big Data" emerged due to technological advancements and the exponential growth of data. Big data refers to large and complex data collections that conventional technologies cannot manage. Douglas Laney described it using the three Vs: volume, variety, and velocity. Later, additional Vs were added to the list. It contains veracity, value, and variability. The volume emphasizes how much information there is. The variety reflects the types of data that exist. Velocity indicates how quickly the data are generated. Veracity indicates how accurate and reliable the collected data is. Values show the value of the collected data. Variability illustrates how big data can be used and organized [1].

Medical data serve as the foundation of the healthcare system. They contain massive, frequently updated, imperfect, and time-sensitive data. These data highlight the diverse nature of disease, treatment, and outcome. They also reveal the complexities of data collection, processing, and interpretation. Examples of medical data collection methods include government organizations, patient portals, electronic health records (EHRs), payer records, search engine data, generic databases, smartphones, research studies, wearable technology, image data, and public records. Medical data comprise several categories, with clinical data taking up most of the space [1].

Clinical Data

Clinical data include information about the management of a patient. They include past prescriptions, medical and family histories, symptoms, physical examination, vital signs, and treatment plans and outcomes. Medical charts, electronic patient records (EPRs), electronic health records (EHRs), and electronic medical records (EMRs) are tools for collecting medical data. Healthcare specialists use electronic medical records (EMRs). Healthcare settings such as hospitals use EPRs. They are more comprehensive but limited in scope. According to the Institute of Medicine, a National Academies of Sciences and Engineering division, EHRs are the most extensive and integrated electronic health information system. They offer a comprehensive and long-term record of a patient's health and medical history. Healthcare organizations share their EHRs.

Medical data collection tools have expanded with the emergence of wearable technology and the Internet of Things (IoT). These tools include blood glucose monitors, cell phones, and fitness tracker platforms. Multinational corporations, such as Apple and Google, invented these platforms. These platforms allow the gathering of real-time data such as heart rate, blood glucose level, calories burned, sleep cycle patterns, and cortisol levels at low cost [1, 5].

Other Types of Medical Data [1, 2]

- **Laboratory Data:** This consists of test results from several specimens, such as bone marrow, hair and nails, urine, semen, sputum, stool, tissue, saliva, cerebrospinal fluid (CSF), and nasal or throat swabs. These findings shed light on a patient's current state of health and may help with tailored medicine, specifically by using genetic testing.
- **Imaging Data:** Medical imaging is obtained using various methods, such as computed tomography (CT), ultrasound, positron emission tomography (PET), magnetic resonance imaging (MRI), and X-rays. These images aid in the diagnosis and observation of numerous medical conditions.
- **Administrative Data:** The administrative departments of the healthcare facility gather non-clinical data, including patient demographics, insurance information, billing, and scheduling.

CHAPTER 3

A Comprehensive Study on Data-driven Decision Support System and its Application in Healthcare

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Abstract: Due to the growing amount of data collected and generated, organizations are pressured to make sense of this data and use it to inform their decisions. DD-DSS (data-driven decision support system) is a computerized program that helps organizations make decisions, judgments, and plans by analyzing large amounts of data. Machine learning and statistical analysis are typically used to build these decision support systems, so combining expert knowledge with data gathered from various sources reduces the risk of making poor decisions and provides insight into the impact of different strategies before they are implemented. This article aims to enumerate the benefits of DD-DSS implementation, and the features associated with it, as well as explore the scope, frameworks used, and applications of DD-DSS in healthcare. The research was conducted through a combination of a literature review and case studies of various frameworks and applications implemented based on DD-DSS.

Keywords: Big data, Data mining, Data analytics, Data-driven model, Data science, Decision support system, Data-driven decision support, Healthcare, Healthcare informatics, Machine learning, Medical treatment, Statistical analysis.

INTRODUCTION

Data plays an important role in healthcare as well as in any other field since it can be used to create comprehensive patient views, which can be used to personalize treatments, aid in advancing treatment methods by providing insights into the effectiveness of different treatments, provide practical insights into the health system, and aid in making strategic decisions [1, 2].

With the help of advanced technologies, many laboratories and healthcare units are generating data at an unprecedented rate, and these datasets are used to make various decisions [3]. In the process of deciding, a variety of alternatives are identified and evaluated, and the most appropriate option is selected. Recent years

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have seen an increase in the utilization of various types of decision support systems (DSS), which aid in making better and more informed decisions.

The DSS acts as a computerized information system, functioning autonomously or within intricate computing setups. It is designed to make reasoned choices using diverse methodologies derived from the fusion of cognitive science, artificial intelligence, and pattern recognition techniques. We are now able to combine methods from statistics and operational research [4, 5].

Providing users with reliable information is the purpose of DSS, which is done by combining knowledge and data from a variety of sources and areas. Hence, it is an information-based application that supports decisions, judgments, and analyses of large amounts of data, accumulating comprehensive information based on various data sources that can be used to solve problems [6]. With DSS, organizations can make better and more informed decisions, increase efficiency, and reduce costs, utilizing powerful augmented analytics or modelling to make analysis recommendations and identify patterns and trends in data, allowing them to predict future outcomes more accurately.

Data-Driven Decision Support System (DD-DSS) is one of the many types of DSS that use machine learning and statistical analysis to produce comprehensive information reports for pattern recognition and detection. This can be beneficial in the healthcare sector, where decisions tend to be based on the experience of physicians [7]. With DD-DSS, large amounts of data can be analysed using a computer-based approach that can aid in enhanced approaches to detecting security problems with equipment and robust techniques to analyze alternatives to symptoms, prevention, and treatment [8, 9].

The advancement of information technology in healthcare has paved the way for the convergence of healthcare and technology, which is causing a transformation in the research outlook that merges patient care, public health, and preventive health. According to a 2018 article, around 30% of the global data volume originates from the healthcare sector. By 2025, the compound annual growth rate of data for healthcare will reach 36%. That's 6% faster than manufacturing, 10% faster than financial services, and 11% faster than media and entertainment [10].

Some of the major data sources in healthcare are digital health tools (like wearable medical devices), electronic health records of patients, online patient applications of the patients (called patient portals), data collected by government and private agencies, and various research studies. As a result, big data is gathered from these sources in healthcare, which can then be analysed to make better decisions, reduce healthcare costs, and improve patient outcomes [11, 12].

Our discussion starts with what DSS is, its classification and its components and characteristics. This section explains DD-DSS, its features, benefits, subcategories, software used, and applications in the healthcare sector. The final section of this article summarizes and discusses the research's contributions and limitations. A thorough understanding of the essential elements leading to the successful implementation of DD-DSS is provided, as is its potential impact on the organization.

Decision Support System

Before diving into DD-DSSs, it is important to have a basic understanding of DSS. There is no universally agreed-upon definition for DSS, and it can vary from author to author. Following are some of the definitions provided by various authors on DSS:

1. In his description of such a model, Little stated, “It provides a model-based set of procedures for processing data and making decisions to assist managers” [13].

2. In Sprague and Carlson's statement, “DSS is an interactive computer-based system that assists decision makers in solving unstructured problems using data and models” [14].

3. As Keen and Morton explained, “Decision Support Systems combine the intellect of individuals with the capabilities of computers to enhance decision quality. This system aids management decision-makers in solving semi-structured problems” [15].

4. In Finlay's view, “a computer-based decision-support system aids decision-making” [16].

5. Described by Moore and Chang as “extensible systems capable of supporting ad-hoc analysis of data and decision modelling that is oriented toward future planning but used irregularly and unpredictably” [17].

6. Turban describes “a computer-based system that is flexible, interactive, and adaptable to address non-structured management challenges” [18].

7. According to Shim, “Computer technology solutions can be used for complex problem-solving and decision-making” [19].

8. Power describes these systems as “interactive computer-based systems that enable people to communicate, analyze documents, and make decisions as a result of computer-based information” [20].

CHAPTER 4

Review on FPGA-based Hardware Accelerators of CNN for Healthcare Applications

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Abstract: In recent years, Deep Convolutional Neural Network (CNN) has been the fastest-growing area of Artificial Neural Network (ANN). In addition to image classification and segmentation, CNN can detect objects in video and recognize speech. This is because CNNs take a lot of computation. The CNN function also lends itself to programmable hardware such as Field Programmable Gate Arrays (FPGAs). Recently, hardware accelerators have become incredibly popular for a broad spectrum of healthcare applications. The emergence of edge computing has made it possible to combine a large number of sensors and process information using lightweight computing. Deep learning algorithms have advanced significantly over time, providing intriguing prospects for their use even in safety-sensitive biomedical and healthcare applications. This study presents a thorough analysis and discussion of several difficulties in the implementation of FPGA-based hardware acceleration for healthcare applications. There are some clear advantages that a variety of generalized new architectures and devices have over traditional processing units. This survey is expected to be useful for researchers in the area of artificial intelligence, FPGA-based hardware accelerators of CNN for Biomedical applications, and system design.

Keywords: Convolutional neural networks, FPGA, Hardware accelerator, Power efficiency, Reliability, Security.

INTRODUCTION

Digital circuit design has evolved rapidly over the last 25 years. Earlier digital circuits were designed with vacuum tubes and transistors. ICs were then involved where logic gates were placed on a single chip. IC designers have been relying on different types of semiconductor scaling to achieve high performance. In the complexity of circuit design, the number of cores and the complex system on chips, such as mobile phone processors, will combine application processors, GPUs, and DSPs, therefore, performance improvements are needed. Engineering

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applications such as AI are demanding heavy computational performance that cannot be met by conventional architectures, therefore, for a fixed task or limited task, energy scaling works better for a wide range of tasks, it leads to domain-specific hardware accelerators. A hardware computing engine is specialized for a particular domain of applications, that is termed domain-specific accelerator or domain-specific architecture. Future opportunities in computer architectures are evolving towards the concept of domain-specific architectures because of the inefficiency of GPU architectures.

A hardware accelerator shown in Fig. (**1**) is a special kind of hardware unit that performs a set of tasks with higher efficiency than a general purpose CPU. AI accelerator is a powerful machine learning hardware chip that is specifically designed to run artificial intelligence and machine learning applications smoothly. Examples include GPU, VPU, FPGA, ASIC, and TPU.

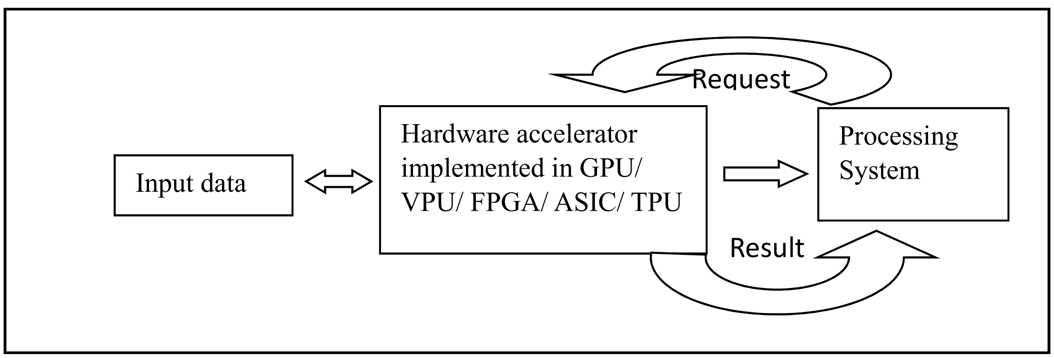

Fig. (1). Block diagram of hardware accelerator. .

Modern-age healthcare systems heavily rely upon electronics and internet technology to enable accurate, rapid diagnosis and advanced treatments, whereas electronic hardware is critical in healthcare systems for processing medical data, *e.g.*, compression, decompression, and filtering. The size of medical data (images) generated from MRI or CT scans is very large and therefore requires a large storage capacity to store and process them locally [1]. This demands a compression of medical images for low-capacity storage and low bandwidth transmission. The systolic array may be used as a coprocessor in combination with a host computer where the data samples received from the host computer pass through the processing elements (PE) and finally, reset is returned to the host computer [2]. So, you can imagine there is a lot of traffic from the accelerator to the memory. Hence, suitable CNN hardware accelerators with compression techniques are used to reduce traffic and improve performance.

Applications in the biomedical and healthcare fields are a key area where various AI techniques can be very helpful [3 - 5]. These uses include monitoring [5], early-stage prediction [6], prognosis [7], diagnosis [8], and even long-term treatment [9] regimen planning.

Fig. (**2**) illustrates how a smart deep learning (DL) system might handle patient data, including bio-samples, medical imaging, movement, temperature, and so on, to monitor the patient for abnormalities and/or to anticipate diseases. Prognosis and treatment choices can be recommended by DL systems, which further influences prediction and monitoring in a closed-loop setting. From the deep learning system, it is clear that based on the needs of the end user, the predictive models are customized and treatment plans are facilitated. The cloud, edge nodes, and edge devices are the three IoT tiers on which the various components of the CNN-based healthcare system can operate.

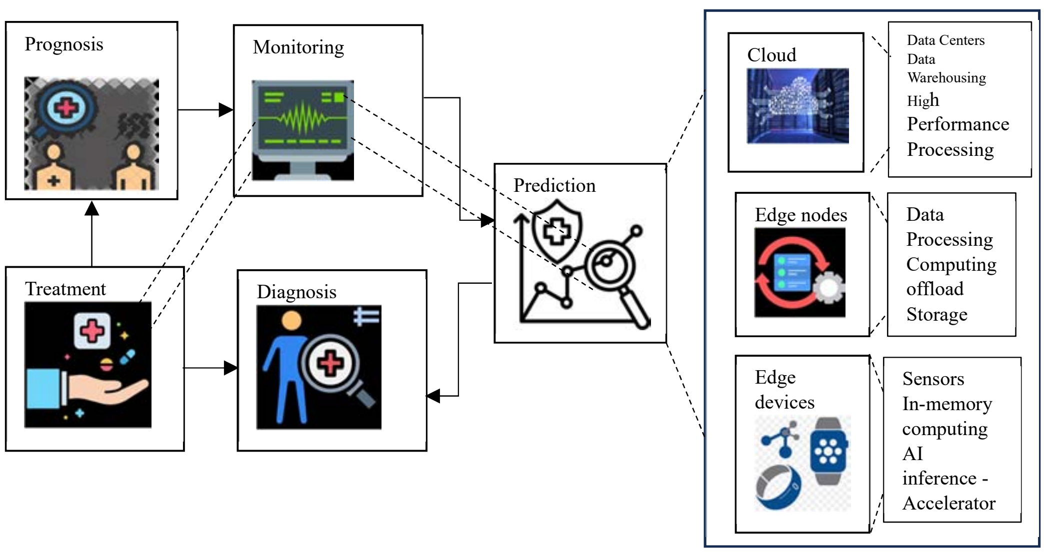

Fig. (2). The closed-loop scenario of healthcare and biomedical system.

The new AI techniques have given rise to computer systems that are sophisticated in their perception and understanding of the visual environment, and even smarter than humans in several activities. The ability to be intelligent is mostly based on both the methods and the data produced by a computer vision system and their hardware implementations, which allows us to offer a class from vision, that a computer can comprehend the physical environment. Thanks to AI and deep learning, the field of medical science has made impressive strides in the last few years that have resulted in a precise classification of brain tumors. CNN is imple-

CHAPTER 5

Advancements in Smart Sensor Technology for Enhanced Health Monitoring in Smart Watches

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Abstract: The integration of smart sensors in wearable devices, particularly smart watches, has revolutionized the landscape of personal health monitoring. This review paper provides a comprehensive analysis of recent advancements in smart sensor technology and their application in smartwatches for health monitoring. The paper begins with an overview of the evolution of smartwatches and their transition from timekeeping devices to sophisticated health monitoring tools. It then delves into the key components of smart sensor technology, encompassing biometric sensors, environmental sensors, and activity trackers. The review extensively covers the diverse range of health parameters that can be monitored by smartwatches, including physical activity levels, oxygen saturation, blood pressure, and heart rate. Furthermore, the paper evaluates the accuracy and reliability of these sensors, considering factors such as sensor placement, calibration, and data processing techniques. The paper also explores the potential integration of machine learning and artificial intelligence in data analysis and interpretation, highlighting their potential to enhance the effectiveness and efficiency of smartwatch health monitoring. In addition, the review addresses challenges and limitations associated with smartwatch health monitoring, including privacy concerns, data security, and battery life. This paper provides an up-to-date overview of smart sensor technology as applied to health monitoring in smartwatches. It serves as a valuable resource for researchers, healthcare professionals, and technology enthusiasts interested in understanding the potential and limitations of this rapidly evolving field.

Keywords: Healthcare, Machine learning, Smart watch, Smart sensor, Wearable.

INTRODUCTION

The fast proliferation of healthcare monitoring systems in hospitals and other health centers over the past ten years has led to a great deal of interest in wireless healthcare monitoring devices employing various technologies in many nations

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across the world. For example, taking a blood sample for laboratory analysis might be an inconvenience for patients, but wearable smart health applications aim to continuously monitor vital physiological indicators so that patients can go about their day as normal. For instance, the essential indicator of ventilation efficacy, reflecting respiratory acid-base status, is referred to as the partial pressure of arterial carbon dioxide, which is measured invasively from the arteries. Therefore, we can briefly track it in a clinical context when we draw a blood sample from the arterial system.

Transcutaneous carbon dioxide monitoring is a non-invasive surrogate approach for determining the partial pressure of arterial carbon dioxide, however, it is currently only used in specialized settings such as intensive care units and requires a bulky bedside device [1]. Polluted air poses a serious threat to human health, and lowering pollution levels could reduce the prevalence of diseases including asthma, cancer, and stroke. The MQ family of gas sensors is a useful tool for detecting pollution in the air and enforcing other safety measures. This article aims to construct an affordable air quality monitoring system, suitable for both indoor and outdoor use, using MQ sensors and an Arduino Mega. It also uses techniques such as discriminant analysis (DA) and the probabilistic neural network (PNN) to track the data back to its source. The system consists of four MQ fuel sensors and one Arduino Mega. We assess the MQ-2, MQ-3, MQ-7, and MQ-135 sensors based on their reactions in both indoor and outdoor environments [2]. On-device DL finds its application in various fields such as computer vision, image processing, NLP, and audio categorization. There has been a rise in interest in mobile and wearable sensing applications. Given that these devices incorporate a wide range of sensors and generate copious quantities of data, on-device DL can be of great assistance to them [3].

A pulse oximeter, a portable health monitor, can track an individual's heart rate and the percentage of oxygen in their blood. However, heart rate variability provides a great deal more information than just the heart rate itself. We need to put more effort into developing high-tech pulse oximeters that can not only condense HRV data but also analyze the effects of exercise, to better monitor one's health. This study addressed urgent issues at hand by combining a sophisticated (Internet of Things and artificial intelligence-friendly) programming language, Python, with a low-cost photoplethysmogram (PPG) sensor [4]. The installation-specific nature of accelerometers magnifies the number of sensors required to detect whole-body motion, as they can only measure acceleration signals at their installation sites. Since they are inherently noisy, processing them takes more time and is more difficult. For the first time, this research offers a strain sensor system integrated into a body-worn suspender, which would record the periodicity of body movement and allow for less noisy readings and non-localized observations [5].

The Internet of Things, or IoT, is now a rapidly developing field. Diverse technological fields have played a role in its advancement. A great deal of research has gone into expanding this field. A smartwatch's many sensors now allow it to track the wearer's health status. As a result, developing a health monitoring system is feasible. The development of a health monitoring system is thus feasible. Using this sphere, you can realize benefits like reduced costs and wireless data transmission. Oxygen and intensive care unit beds were also scarce in the country [6]. For many people with nicotine dependence, quitting smoking is an extremely difficult task. Using self-reporting or sensor monitoring approaches, cell phones have become the primary data-gathering tool for studies investigating the effects of quitting smoking on health. Over the past five years, the proliferation of smartwatches has prompted studies to investigate whether the accelerometer of the device can infer a user's habitual motions. The primary goal of earlier smoke detection techniques was to classify users' actual smoking habits [7].

The various IoT capabilities and devices that must continuously monitor a patient's health indicators necessitate constant advancements in healthcare monitoring. Due to the importance of healthcare, a variety of concepts and methods have led to the creation of numerous devices. Several nations have introduced air ambulances as examples of these devices to meet the growing demand for healthcare during emergencies and expedite patients' recoveries [8]. Incredible technological progress in wearable electronics has enabled a wide variety of health monitoring multi-functions, but this has increased power requirements, making larger batteries and more frequent charging a necessity. However, the downtime caused by battery replacement or charging is unacceptable for health monitoring. Despite the potential for thermoelectric power generation from body heat, wearable devices have not been able to generate enough consistent power for the continuous operation of commercial health monitoring sensors [9]. Doctors can safely store patient clinical data in the cloud, simplifying their retrieval when needed. Problems such as communication lag, insecure connections, and power loss in IoT sensors can impact the service quality. A remote patient monitoring system employs cost-effective and energy-efficient IoT sensors to address patient safety concerns [10].

RELATED WORK

Nowadays, patient health status monitoring for a specific risk is a demanding task. Obstacles arise when doctors have to constantly monitor their patients and treat

CHAPTER 6

Data Science and Data Analytics for Healthcare: Transforming Patient Care Through a Design Thinking Approach to Data Science

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Abstract: Design thinking is essential for the successful integration of data science in healthcare. The healthcare industry is undergoing a profound transformation driven by the power of data. In this book chapter, we delve into the pivotal role of data science in healthcare, exploring its importance, ethical considerations, and various stages of data collection, pre-processing, analysis, and visualization. With the potential to revolutionize patient care, reduce costs, and drive medical innovations, data in healthcare holds immense promise. The chapter highlights the critical role of data quality, integration, and data visualization in healthcare analytics, emphasizing their impact on patient outcomes and healthcare decision-making. It explores predictive modeling, including supervised learning and model evaluation, showcasing their applications in risk prediction and disease subtyping. Unsupervised learning and anomaly detection are discussed in the context of uncovering hidden patterns and irregularities in healthcare data. Text analytics and natural language processing emerge as essential tools for mining clinical notes and understanding patient sentiment. As healthcare evolves into a data-driven field, data visualization and dashboard design are discussed as tools for conveying complex data in a comprehensible manner. The chapter highlights the importance of design thinking in creating visualizations that are intuitive and easy to interpret for healthcare professionals. The future of healthcare analytics is explored, including AI advancements, precision medicine, and the critical role of telemedicine. Additionally, the chapter addresses ethical and regulatory considerations surrounding data privacy, informed consent, and regulatory compliance. Design thinking principles can guide the development of user-friendly privacy policies and consent forms. This chapter offers a comprehensive perspective on the challenges and opportunities in the field of data science in healthcare, highlighting its potential to revolutionize patient care, improve outcomes, and safeguard the rights and privacy of individuals in a data-driven healthcare landscape.

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Keywords: Anomaly detection, Big data, Data science, Data integration, Data visualization, Healthcare, Predictive modeling, Precision medicine, Text analytics, Unsupervised learning.

INTRODUCTION

In the modern era, healthcare is on the brink of a data revolution. The advent of data science and data analytics has reshaped the landscape of the healthcare industry, offering unprecedented opportunities to enhance patient care, optimize operational efficiency, and propel medical research to new heights. In this book chapter, we embark on a journey into the realm of data science and data analytics in healthcare, exploring the profound impact these technologies have on the delivery of healthcare services, clinical decision-making, and the overall well-being of patients.

Data has become the lifeblood of the healthcare sector, flowing from diverse sources such as electronic health records (EHRs), medical devices, genomic data, and patient-generated data. The sheer volume and complexity of this healthcare data necessitate advanced analytical techniques to unlock its potential. Proper management and analysis of this data have the power to uncover valuable insights, predict disease outbreaks, personalize treatment plans, and improve the overall quality of healthcare services.

However, harnessing the potential of data in healthcare is not without its challenges. The ethical considerations surrounding data privacy and security are paramount, as healthcare data is sensitive and personal. Regulatory compliance, informed consent, and data protection are critical aspects that require careful attention. Additionally, the integration and interoperability of disparate data sources pose technical challenges, demanding innovative solutions for seamless data flow within healthcare systems.

This chapter takes a comprehensive journey through the key facets of data science and data analytics in healthcare. We explore the importance of data quality, data integration, and data visualization in the context of healthcare analytics. We delve into predictive modeling techniques that empower healthcare professionals with the ability to foresee critical health events. The chapter also addresses the power of unsupervised learning and anomaly detection in identifying hidden patterns and irregularities within healthcare data.

Text analytics and natural language processing emerge as invaluable tools for mining clinical notes and understanding patient sentiments, enabling the development of personalized healthcare plans and improved patient outcomes. The role of data visualization and dashboard design in conveying complex healthcare data in an understandable manner is discussed, highlighting their significance in aiding healthcare decision-makers.

The future of healthcare analytics is examined through the lens of AI advancements, precision medicine, and the growing influence of telemedicine. We also delve into the ethical and regulatory considerations that underpin data science in healthcare, safeguarding patient privacy, ensuring informed consent, and adhering to regulatory compliance. As we progress through this chapter, we will gain a deeper understanding of the transformative potential of data science and data analytics in healthcare.

DATA SCIENCE IN HEALTHCARE

Importance of Data in Healthcare

Data plays a crucial role in healthcare as it has the potential to improve patient care, lower costs, and revolutionize medical therapies. The healthcare industry generates massive amounts of data from various sources such as hospital records, medical examinations, and biomedical research [1, 2]. Proper management and analysis of this big data are essential to derive meaningful information and improve public health [3, 4]. Data analytics is becoming an escalating tool in healthcare systems, allowing for descriptive, diagnostic, predictive, and prescriptive analysis [5]. By using data efficiently, healthcare organizations can monitor performance, prevent hospitalizations, combat opioid abuse, improve antimicrobial stewardship, and reduce pharmaceutical spending. However, there are challenges in data acquisition, integration, and usability that need to be addressed for effective implementation [6 - 9]. Implementing better data management and integration can bridge gaps in care, improve data analysis, and contribute to a healthier population. In Fig. (**1**) , which can be seen in the following section, a flowchart vividly illustrates the intricate data flow within healthcare systems, underlining the interdependence of diverse data sources and the processes of analysis.

Ethical Considerations

Ethical considerations of data in healthcare are crucial due to the sensitive nature of health information and the potential risks to individuals' rights and opportunities. Reasonable security standards are needed to protect electronic health records (EHRs) [10]. Healthcare informatics professionals should be informed of their rights, duties, and responsibilities, and have guidelines and ethical tutoring to prevent conflict or misconduct in handling patient information [11]. The availability of diverse sources of health data and the advancements in data science raise ethical and regulatory challenges in the use of biomedical big

CHAPTER 7

The Internet of Things for Healthcare: uses, Particular Cases, and Difficulties

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Abstract: Internet of Things (IoT) integration in healthcare has completely changed patient care and administration. The revolutionary effects of IoT technology on the healthcare industry are examined in this abstract. The Internet of Things (IoT) enables real-time monitoring of patient's vital signs through the seamless connectivity of medical equipment and sensors, guaranteeing prompt intervention and customized treatment programs. Healthcare providers may obtain vital information through remote patient monitoring, which improves diagnostic precision and maximizes resource use. Furthermore, IoT-powered innovative healthcare systems provide preventative care by continually gathering and evaluating patient data, which makes it possible to identify health problems early. Notwithstanding these developments, issues like data security and interoperability still need to be resolved if IoT in healthcare is to reach its full potential. The significant effects of IoT on healthcare delivery are highlighted in this abstract, highlighting the necessity of a comprehensive strategy to handle both possibilities and problems in this quickly changing environment.

Keywords: IoT technology, (IoT) Internet of Things, Medical equipment, Smart healthcare system, Sensors.

INTRODUCTION

The "Internet of Things" (IoT) refers to various applications, technologies, protocols, and initiatives. It is fundamentally a network of objects that are linked to the Internet. These include IoT-enabled physical items and IoT-enabled equipment. Things and data are the foundation and core of what IoT is and what it

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enables. IoT assets and devices have electronic parts and software for data collection, organization, and sharing. The phrase “Internet of Things” was coined by Kevin Ashton. He researched radio frequency identification (RFID) in the late 1990s.

This technique enables information to be stored on tiny radio frequency tags attached to various objects and read from a distance [1]. It allows, for example, following the flow of products, enhancing the supply management system, and even preventing theft. It is a little sticker or customized label in a plastic casing. These RFID tags are now often used in the trade sector. Additionally, Kevin Ashton used the phrase “Internet of Things” while describing the fundamental concept of his creation. He previously predicted that everything on the Internet of Things (IoT) will have a digital equivalent that will serve as its virtual image. The scope of applications for RFID technology is expanding right now. This technique is commonly used to automate industrial operations, particularly when sophisticated manufacturing of automobiles and appliances (refrigerators and washing machines) is involved.

Certain libraries, like the Vatican Library, which has more than two million copies of books in its collection, have adopted RFID to expedite inventory and book searches, automate book deliveries, and prevent theft. This technique is being used or implemented by more than 700 of the biggest libraries in the world [2, 3]. In several nations worldwide, new passports also come with RFID tags. These forms of identification are known as biometrics or electronic passports, and they have a chip with the same data as the printed version. This technology is “taking root” in medicine more and more.

RFID bracelets, for instance, are used in maternity facilities to link the baby's identity to the mother. They are accustomed to monitoring the movements of patients who require continual care in traditional hospitals. It was recently proposed that a wireless sensor network be used to track and manage things by coupling a tracker to a heart rate monitor [4]. Today's gadgets connect with smartphones, social networks, cloud computing, big data analytics, and GPS devices to enable the contemporary IoT.

Since the 2000s, as the number of devices linked to the Internet rose quickly, the direction of IoT has been actively developing. The vast quantity of big data utilized by the Internet of Things raises privacy concerns for its consumers. Preserving users' rights is the main goal of developing and implementing the General Data Protection Regulation (GDPR). Alexia Kounoudes and associates examined the challenges of implementing GDPR in the Internet of Things. To properly investigate the issue of user privacy, the writers carried out a thorough literary analysis [5].

The Organization for Economic Cooperation and Development's group of twenty (G20) Artificial Intelligence (AI) Guidelines and the General Principles for Human G20, as well as the European Commission's Coordination Plan and Ethical Recommendations on AI Reliability, should all be considered when working with the Internet of Things. Specifically, human-centered values and justice, sustainable growth and prosperity, transparency and clarity, dependability, protection, security, and accountability are five interconnected principles that should be followed [6 - 8].

For IoT to function continuously and with high quality, it needs a specialized environment that has platforms for controlling the network, devices, and apps. This environment must also include various “smart” devices that are directly connected and have sensors, network access, and information transfer capabilities. This system cannot function without at least one of these parts. Governments, corporations, mobile and Internet service providers, and even regular citizens will need to work closely together to fully realise the Internet of Things promise.

This chapter looks at the IoT foundations inside the healthcare system, emphasizing the use of IoT technology for rapidly developing customized health. It discusses the newest and most advanced IoT-derived methods and well-known health cases. This study also focuses on the financial, ethical, and technical barriers to creating a more advanced healthcare system that can identify and diagnose illnesses early on. These cutting-edge health systems might be useful to healthcare practitioners, giving them access to the relevant patient information at the right moment. As a result, quickly and effectively taking care of medical issues.

This chapter covers IoT technology's function and uses in the healthcare industry. It then presents a few chosen medical scenarios that illustrate an IoT-driven healthcare system and addresses the possible obstacles to its widespread adoption.

IoT and Healthcare

IoT applications in healthcare are among the most noble. Physicians may use the Internet to aid patients through IoT. Using portable Internet of things-based health monitoring devices may greatly decrease patient-physician distance. You may assess each patient individually using IoT, determine the best course of action based on their health situation, and choose how best to treat them. Physicians may remotely monitor and provide real-time care for their patients by using portable sensors.

CHAPTER 8

The 5G Revolution in Healthcare: Shaping the Future of Medicine

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Abstract: The next generation of cellular network technology, 5G, is poised to transform the medical industry completely. 5G has the potential to bring novel and forward-thinking approaches to the diagnosis, treatment, and management of diseases thanks to its fast speed, low latency, and large capacity. The proposed article digs into the incredible impact that 5G technology has had on the healthcare field, ushering in a new era that will be distinguished by unprecedented connectedness and innovation. Initially, the evolution of wireless networks is examined, laying the historical groundwork for the paradigm-shifting arrival of 5G is explored. Then, the fundamental features of 5G, focusing on its high speed, low latency, and reliable characteristics, which, when combined, push the limits of what is currently thought to be possible in the healthcare sector, are explored. We then analyse the synergy of 5G in different disruptive technologies like AI and IoT in the proliferation of healthcare care technology. The necessity of data security and the privacy of 5g in healthcare technology are analysed further. Our goal is to provide an illuminating look into the world of medicine in the not-too-distant future when 5G has the potential to transform the way healthcare is delivered, eliminate barriers based on location, and project medical innovation to new heights. This article lets readers understand how 5G will revolutionise the healthcare industry by making it more user-friendly, cost-effective, and efficient.

Keywords: 5g, AI, Disruptive technologies, Health care, IoT, Telemedicine.

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INTRODUCTION

The most recent advancement in cellular network technology is 5G, which stands for the fifth generation. It is aimed to deliver more dependable connections, have lower latency, and quicker speeds than those provided by earlier generations. 5G may completely change many businesses, including the medical, transportation, and manufacturing sectors. 5G can achieve higher performance by utilising various emerging technologies. The Millimetre-wave spectrum, often the mmWave spectrum, is among the most significant. The frequency band known as the mmWave spectrum is far higher than those utilised by earlier cellular network generations [1]. Because of this, 5G can carry more data at once and achieve higher download rates.

The Core Concepts Behind 5G

It is intended that 5G technology will overcome the constraints of its forerunners, such as 4G (LTE) and 3G, by delivering unrivalled speeds, reducing the amount of latency experienced, and increasing the capacity for connectivity. These characteristics, taken together, have a transformative effect on the digital world, opening up doors to opportunities in various fields, including medicine, transportation, manufacturing, and the entertainment industry [1].

Millimetre Wave (mmWave) Spectrum: The Key to Increasing Transmission Speed

Utilisation of millimetre wave (mmWave) spectrum is an essential pillar supporting the development of 5G technology. This spectrum runs at higher frequencies than the bands used by earlier cellular networks. Because of this, 5G can carry enormous amounts of data at speeds that have never been seen before. 5G can reach download and upload speeds of up to 20 gigabits per second (Gbps) by utilising mmWave technology. This incredible speed is nearly 100 times quicker than 4G, which will profoundly change how we interact with digital content. However, it is essential to keep in mind that the mmWave technology does come with some drawbacks. The combination of its shorter wavelength and higher frequency results in less coverage when compared to bands that operate at lower frequencies. Consequently, mmWave technology is optimal for use in urban areas, dense city centres, and sites with a high demand for data.

The capacity multiplier is known as Massive MIMO

Massive Multiple Input, Multiple Output, or MIMO for short, is yet another ground-breaking technology that is essential to 5G. Massive MIMO is a method for sending and receiving data concurrently that requires the installation of massive arrays of antennas at base stations and on user devices. Because of this enormous breakthrough in antenna technology, 5G's capacity to accommodate a large number of users and devices at the same time has been significantly improved. The capability of Massive MIMO to generate numerous data streams contributes significantly to an increase in the effectiveness of the network. The dependability of connections and the amount of data that can be sent within a given frequency range are improved due to this improvement in spectral efficiency. This technology has far-reaching ramifications for applications like the Internet of Things, which require constant communication for many devices. Fig. (**1**) shows the mmWave band in 5G and Fig. (**2**) shows the implementation of Massive MIMO in 5G.

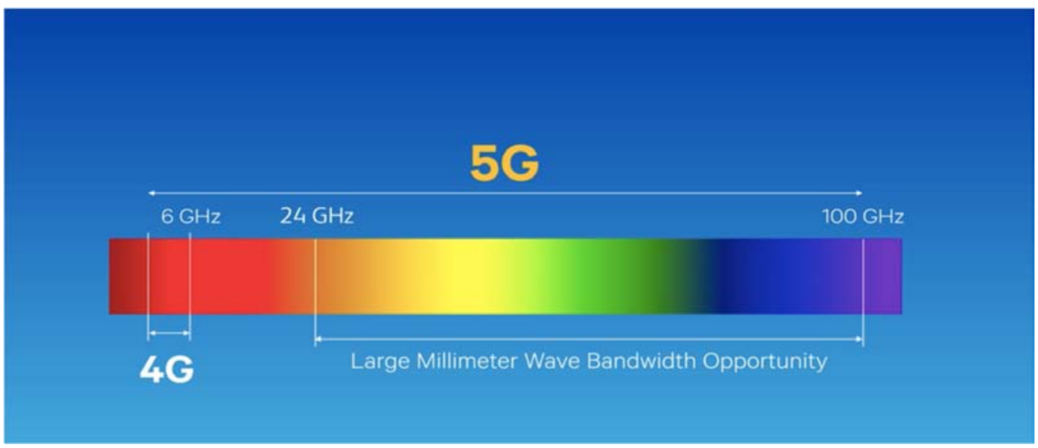

Fig. (1). mmWave band in 5G.

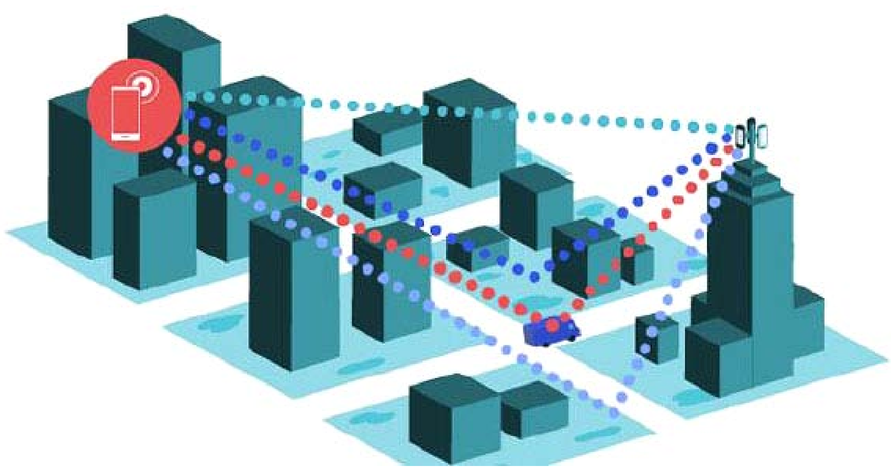

Fig. (2). Massive MIMO implementation in 5G.

CHAPTER 9

Generative Adversarial Networks in Medical Imaging: Recent Advances and Future Prospects

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Abstract: Generative Adversarial Networks (GANs) represent a significant breakthrough in the realms of machine learning and deep learning, providing novel solutions to the constraints of conventional generative models. This article explores the transformative uses of GANs in the domain of medical imaging, specifically focusing on super-resolution applications in Magnetic Resonance Imaging (MRI), generation of synthetic images for skin lesion categorization, and overall improvement in diagnostic accuracy. The fundamental structure of GANs, comprising a Generator and a Discriminator engaged in adversarial training, facilitates the creation of high-fidelity synthetic medical images. These developments play a crucial role in fortifying machine learning models through the amalgamation of synthetic data with authentic medical datasets, thereby enhancing the precision of diagnostic algorithms and the standard of healthcare provision. Notable innovations encompass the Fused Attentive GAN (FA-GAN) for enhanced MRI clarity and the employment of Pix2Pix GANs for precise brain imaging. Moreover, GAN-centric techniques for the classification of skin lesions, leveraging the ISIC dataset, have showcased substantial enhancements in diagnostic efficacy. Despite their considerable potential, the incorporation of GANs in the healthcare domain necessitates careful navigation of key ethical considerations like patient confidentiality and bias alleviation. It is vital to underscore the need for robust assessment metrics beyond visual accuracy to ensure the clinical applicability of GAN-generated data. This manuscript underscores the continual progressions and the imperative requirement for ethical governance in the utilization of GANs, which hold the potential to transform personalized healthcare, expedite pharmaceutical discoveries, and enrich telemedicine, representing a significant stride forward in medical research and patient welfare.

Keywords: GANs (Generative Adversarial Networks), Medical Imaging, MRI (Magnetic Resonance Imaging), Super-resolution, Skin lesion classification image synthesis.

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INTRODUCTION

Generative Adversarial Networks (GANs) are an assortment of artificial neural networks that are utilized in the domains of machine learning and deep learning. They were first introduced in 2014 by Ian Goodfellow and his colleagues as a solution to the limitations encountered by previous generative models, which faced difficulties in generating data that accurately depicted the intricacy and statistical properties of real-world data [1]. Traditional methodologies, such as manual feature engineering and probabilistic models like Gaussian Mixture Models, proved inadequate in producing diverse and realistic data. The realm of medical imaging stands as a fundamental pillar of contemporary healthcare, furnishing crucial insights into the internal structures and functions of the human body. Modalities like Magnetic Resonance Imaging (MRI), Computed Tomography (CT) scans, and diverse forms of microscopy serve as indispensable instruments for healthcare practitioners. Nevertheless, these technologies come with inherent constraints such as image resolution, clarity, and the availability of meticulously labeled datasets. Herein lies the transformative potential of GANs, which offer innovative solutions to enrich the quality and applicability of medical images.

To confront these challenges, the invention of GANs occurred, presenting a more adjustable and potent approach to generative modeling [2]. The core structure of GANs, as depicted in Fig. (**1**), consists of a dual-network architecture with a generator and a discriminator that participate in adversarial training. The generator, which functions as a transfer function, employs input noise to generate data that closely aligns with the desired data distribution [2 - 6], while the discriminator is tasked with differentiating between authentic data and synthetic data. The triumph of a GAN model is determined by achieving an overall loss of 0.5, as indicated in Equation (1).

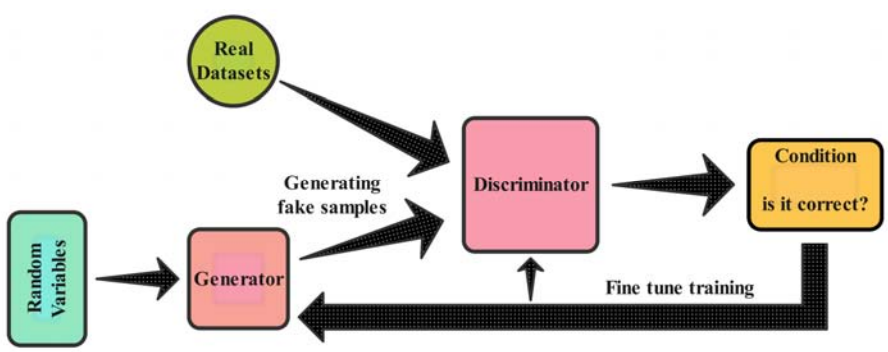

Fig. (1). The fundamental structure of Generative Adversarial Networks (GANs).

GANs have a significant impact on the healthcare sector due to their profound applications. Particularly, they demonstrate immense potential in the generation of synthetic medical images, which are essential in the training and assessment of algorithms used for medical image processing [6 - 10, 12 - 19]. The integration of synthetic data into real medical datasets through GANs enhances the resilience of machine learning algorithms, thereby enhancing the accuracy of diagnoses and the overall quality of healthcare. Furthermore, GANs play a pivotal role in the development of predictive models that can identify subtle patterns in patient data, enabling early detection and prognosis of diseases [12].

A compelling application of GANs in medical imaging materializes in the refinement of MRI images through super-resolution methodologies. Traditional MRI technology, while informative, often grapples with limitations in image resolution. High-resolution images play a pivotal role in precise diagnostic and therapeutic determinations, especially in intricate anatomical sites like the brain. Tailored for super-resolution tasks, GANs have exhibited the capacity to substantially amplify the clarity and intricacy of MRI images. Techniques such as the Fused Attentive GAN (FA-GAN) harness the adversarial training process to generate images with heightened resolution and diminished noise, thereby facilitating more precise and confident diagnoses. Another notable application of GANs emerges in the creation of synthetic images for skin lesion classification. Skin cancer, encompassing melanoma, stands as a critical domain where early and precise diagnosis can profoundly influence patient outcomes. Machine learning models trained on extensive datasets of skin lesion images are increasingly leveraged to aid in diagnosis. Nonetheless, acquiring adequate labeled data poses a significant hurdle. GANs tackle this challenge by producing realistic synthetic images to supplement existing datasets. By augmenting the diversity and volume of training data, GANs contribute to enhancing the accuracy and resilience of diagnostic algorithms. For instance, through the utilization of the International Skin Imaging Collaboration (ISIC) dataset, GAN-generated images have played a pivotal role in refining the performance of machine-learning models dedicated to classifying skin lesions.

$$\min_{G}\max_{D} V(D,G) V(D,G) = \mathbb{E}_{x\sim pdata(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z))] \quad \textbf{(1)}$$

G = Generator

D = Discriminator

$P_{data}(x)$ = distribution of real data

P(z) = distribution of generator

CHAPTER 10

AI Revolutionizing Healthcare: Current State and Future Prospects

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Abstract: Artificial intelligence (AI) in healthcare is the collection of techniques and resources to improve several facets of the healthcare industry, such as patient care and administrative tasks. Its growing relevance is due to its potential to enhance further healthcare services' efficacy, accuracy, and accessibility. AI can analyze enormous volumes of medical data, assisting healthcare practitioners in making decisions and treatment programs and even forecasting disease outbreaks, which will improve patient outcomes and make healthcare delivery more affordable. As a result of its growing influence, AI is becoming a more significant and transformational force in healthcare.

Keywords: Disease outbreaks, Healthcare practitioners, Healthcare delivery, Personalized treatment programs, Patient outcomes, Transformational force.

INTRODUCTION

Artificial intelligence (AI) refers to a collection of intelligent processes and behaviors produced through computer models, algorithms, or rules that enable machines to replicate human cognitive skills like learning and problem-solving [1, 2]. The term AI refers to computational technologies that replicate the support mechanisms of human intelligence, such as cognition, deep learning, adaptation, engagement, and sensory comprehension [3, 4]. Generally, human interpretation is required for this role, but some devices can perform decision-making [5, 6]. Many fields, including medicine and health, can use these multidisciplinary methods. Since doctors initially attempted to use computer-aided programs to enhance their diagnosis in the 1950s [7, 8], AI has been present in medicine. These developments raise questions about how these talents could assist or per-

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haps improve human decision-making in health and medical care. The accessibility of pertinent data strongly correlates with AI's potential [9]. The health domain has an abundance of data [10]. Gathering and sharing health data is difficult compared to other forms of data because, on the one hand, it is subject to privacy concerns. For instance, collecting health data in longitudinal research and clinical trials can be costly, necessitating strict security measures once collected.

Additionally, the inability of electronic health record systems to communicate with each other [11], the incompetency to gather relevant social data, and the lack of interoperability among these systems impede the use of even the most basic computational techniques [12]. Meanwhile, as evidenced by the abundance of companies focused on AI in health and health care, the private sector is extremely interested in healthcare data and applications. Customers of CB insights can gather, sort, and map firms based on funding, industry, and a wide range of other factors by using the company's current Expert Collections or creating their custom collections [13]. AI can improve healthcare and empower patients by giving them more control over their health. Recent applications of AI to enhance healthcare delivery include personalized health information, virtual consultations, and remote monitoring [14]. Personalized health information is one of AI's main advantages in healthcare [15].

The anamnesis and lifestyle characteristics are just two examples of the patient data that AI analyzes. AI systems can provide patients with individualized advice on how to stay healthy. With this information, patients can make more informed decisions about their care and gain a better understanding of their health. Remote monitoring is one of the most important AI applications in healthcare. AI-powered remote monitoring devices track and record patients' vital signs, alerting medical personnel to potential problems. As a result, there may be a need for fewer in-person visits to healthcare institutions, earlier intervention, and better patient results. Virtual consultations are another way AI is enhancing healthcare delivery. Patients can obtain medical care without visiting a hospital or facility by offering remote medical care [16]. This can be especially helpful for people with mobility problems or those who live in distant places.

Another area where AI can be useful in empowering individuals is medication administration. AI algorithms can assist healthcare providers in better-managing medicine and reducing the likelihood of adverse drug reactions by analyzing patient data, such as prescription histories and vital signs. This approach can enhance patient safety and improve health outcomes. AI can also promote openness in the healthcare industry by providing consumers with more information about their health and the treatments they are receiving. This can allow patients to take control of their healthcare decisions and foster trust between them and the care provider. The application of AI in medical imaging has the potential to enhance patient outcomes and diagnostic precision. AI can improve medical radiology in many ways because it is critical for diagnosing and treating different medical disorders.

OPPORTUNITIES

AI in healthcare is a rapidly developing topic with various potential prospects. Here are some significant fields where AI is having an impact and opening:

Diagnostic and Medical Imaging

Radiology: AI can help radiologists find anomalies in X-rays, CT scans, and MRIs, possibly increasing accuracy and speeding up diagnosis [17].

Pathology: AI algorithms can detect malignant cells or other quirk in tissue samples and pathology slides.

Ultrasound: AI aids in the understanding of ultrasound pictures for numerous applications, such as obstetrics and cardiology.

Medicines Discovery and Development: By analyzing massive datasets to identify prospective medication candidates and forecast their efficacy and safety, AI speeds up the drug discovery process [18]. Additionally, it can enhance clinical trial designs to make them more effective and economical.

Healthcare Administration and Operations

AI-driven technologies can automate administrative activities such as billing, scheduling, and patient information management, thereby reducing the administrative workload for healthcare practitioners [19]. Predictive analytics may help hospitals and clinics make the best use of staff scheduling and resource allocation.

Specialized Medicine

AI can enhance treatment effectiveness by adjusting treatment regimens and medication dosages based on a patient's genetic and clinical data. It can anticipate how patients react to treatments, minimizing medical trial and error. By predicting patient reactions to therapies, it helps healthcare practitioners avoid costly mistakes.

CHAPTER 11

Application of Image Processing Methods in the Healthcare Sector

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Abstract: The thorough reference book "Image Processing Techniques for Healthcare: Advances and Applications" addresses the fascinating nexus between medical research and cutting-edge image processing techniques. It comprehensively elucidates the concepts, methodologies, and healthcare-related image processing applications. As an essential part of contemporary healthcare, medical imaging supports diagnosing, managing, and overseeing various medical problems. New image processing techniques are required to extract useful information, boost diagnostic precision, and improve patient care from the growing amount and complexity of medical pictures. These critical areas of application and their influence are highlighted in this abstract, which summarises the crucial role that image-processing technologies play in healthcare. It explores how image-processing techniques are essential for enhancing the quality of medical images, supporting clinical decision-making, and advancing medical research in an era where medical imaging is critical for diagnosis, treatment, and patient care. The book covers many subjects, from the core concepts of digital image processing to the most recent developments in medical image analysis. This book covers picture preprocessing, image segmentation, image registration, and three-dimensional reconstruction. A combination of machine learning and artificial intelligence algorithms for automated diagnosis and prognosis is also covered in depth. The main focus is how image processing methods are used in real-world settings in areas of medicine like radiology, cardiology, pathology, and neurology. Disease identification, planning of therapy, and surveillance of patients in healthcare settings. Investigations and actual-life scenarios are used to demonstrate how these strategies are applied.

Keywords: Classification, Feature extraction, Image acquisition, Medical imaging, Registration, Segmentation, Visualization.

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INTRODUCTION

Medical imaging is now essential for diagnosing, planning, and managing many illnesses in contemporary healthcare. The everyday production of enormous numbers of medical images, encompassing X-rays, magnetic resonance imaging, computed tomography scans, and ultrasound images, has increased the need for improved image processing methods [1]. These approaches are essential for raising wellness standards, promoting patient outcomes, and streamlining healthcare provision. This chapter offers an overview of some essential image-processing methods used in healthcare, concentrating on their uses and advantages.

Medical imaging in the realm of healthcare has four main uses. Printing images of the inside parts and body processes is one of these. Beginning with the classification of complex or otherwise undetectable medical illnesses, imaging methods are utilized by healthcare professionals to identify them. Using these photos as a guide facilitates meticulous treatment scheduling and therapy preparation. For example, computed tomography scans assist healthcare professionals in planning chemotherapy for cancer patients by determining the location and size of the tumour [2]. The progression of diseases over time must be monitored *via* medical imaging, which brings us to our third point. Additionally, scientists utilize these pictures to investigate the nuances of human anatomy and physiology and the effects of diseases and treatments on human beings.

Medical imaging (MI) has grown significantly in various biomedical studies and therapeutic applications. Biologists use MI techniques in biology to examine cells and produce detailed 3D confocal imaging information [3]. Researchers in neuroscience use MI techniques such as positron emission tomography, functional Magnetic Resonance Imaging, and nuclear magnetic resonance spectrum imaging to identify specific metabolically engaged areas of the brain. Conversely, Virologists rely on MI to turn micrographs into detailed 3D representations of viruses. Radiologists also use MI to precisely measure and pinpoint tumours in MRI and CT images.

Medical imaging (MI) uses a range of approaches, including X-rays, ultrasounds, and nuclear medicine imaging (NMI). X-ray assessments, which use X-ray radiation, produce images that focus on bone structures [4]. Ultrasound equipment, on the other hand, uses sound waves to visualize the body's inside organs. In nuclear medicine imaging (NMI), a small amount of radioactive material is delivered into the body to provide images of internal organs, blood circulation, and metabolic activities.

On the other hand, medical image analysis continues to be difficult for scientists. Fig. (**1**) depicts seven essential functions commonly included in healthcare imaging processing. The first phase is picture collection, which entails collecting medical pictures from several MI techniques, including X-rays, CT scans, MRI scans, and ultrasound scans. Following that, preprocessing begins, which includes duties like noise reduction, distortion correction, and contrast enhancement, all to improve and perfect medical images. On the contrary, segmentation entails separating areas of interest from the surrounding backdrop and identifying unique structures within the image [5]. Ultimately, the registration procedure comprises synchronizing various medical pictures to form an integrated picture that provides a broader awareness of anatomy and pathology.

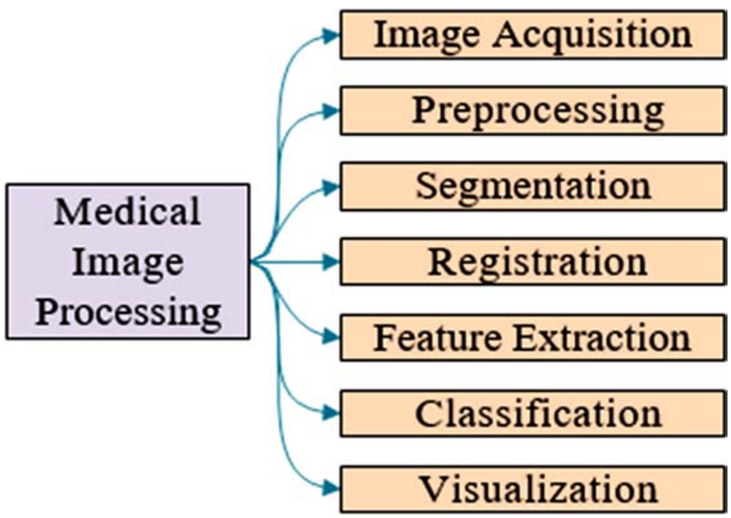

Fig. (1). Depicts the seven most prevalent operations in medical image processing.

Indeed, feature extraction in medical image processing aims to extract critical features from these pictures, such as the dimension, form, texture, and brightness of various features. On the other hand, identification is in charge of categorizing different structures within medical pictures based on their distinct traits and characteristics. Finally, visualization is critical in producing two-dimensional or multidimensional graphic representations of medical images. These visualizations are essential in assisting research efforts, assisting in the diagnostic process, and simplifying medical therapy preparation [6].

- First and foremost, medical image processing (MIP) is critical in assessing crucial parameters such as tumour or organ dimensions, volume, blood vessels, and blood or other fluid flow properties. Furthermore, using more traditional

CHAPTER 12

Augmented Reality (AR) and Virtual Reality (VR): A Study on Exploring the Emerging Applications and Future Directions in Healthcare

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Abstract: Recent advances in science and technology investigate the emerging operations and untapped potential of Augmented Reality (AR) and Virtual Reality (VR) in the healthcare industry. AR and VR technologies have the potential to revolutionize healthcare by improving medical education and training, refining patient treatment and recovery, and optimizing surgical techniques. Based on an overview of the description and introduction concepts of AR and VR, it emphasizes their features and operations in the healthcare industry while also comparing those technologies, highlighting their respective strengths and limits. The study focuses on two key areas: medical education training, patient care and recovery. In medical education training, AR and VR technologies provide immersive technology for simulating medical procedures, improving anatomical understanding, and creating interactive literate environments. Case studies and exemplifications indicate successful medical education implementation. AR and VR technologies provide evidence-based therapies, pain relief improved treatment technology in patient care and recovery. It also demonstrates the implicit benefits through academic exemplifications and case studies as well as investigates the emerging applications of AR and VR in surgical planning and visualization. It examines how these technologies can aid with preoperative planning, surgical process simulation and training, and real-time surgical guiding. The influence of AR and VR on surgical concerns is demonstrated through case studies and examples.

Keywords: Augmented Reality(AR), Healthcare, Patient care, Surgical planning, Virtual Reality(VR).

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INTRODUCTION

Augmented Reality (AR) and Virtual Reality (VR) technologies have gained significant attention in recent times due to their eventuality to revise healthcare assistance. It offers immersive and interactive technology that can transfigure medical education, enhance patient care, and facilitate surgical procedures. The integration of these technologies in healthcare has the implicit ability to improve individual delicacy, ameliorate treatment issues, and give innovative results for patient engagement and recovery. The capability of augmented reality (AR) and virtual reality (VR) to ground the gap between the real world and the virtual world, giving healthcare professionals cutting-edge tools and chops to improve patient care, is the main significance of AR and VR in healthcare [1]. These technologies give fresh approaches to imaging medical information, exercising medical ways, and delivering supported curatives. AR and VR have the eventuality to ameliorate medical training, boost individual delicacy, and transfigure patient gestures by furnishing the healthcare labor force with better visualization, real-time guidance, and interactive knowledge exploits. The main objective of this work is to explore the rising operations and unborn directions of AR and VR in healthcare, dissect their impact on medical opinion, patient treatment, and surgical procedures, and show the implicit benefits and challenges associated with their perpetration. It also aims to give perceptivity into the transformative eventuality of AR and VR technologies and their applicability in the healthcare industry. It also gives a comprehensive overview and covers the principles of AR and VR, their comparison, and the applicability and implicit impact of these technologies in the healthcare sector. By this, the study aims to contribute to the understanding of the transformative eventuality of AR and VR in healthcare and give precious perceptivity to healthcare professionals, experimenters, and policymakers.

Section 2 presents a detailed review done over the recent works on classifying and examining the use of AR and VR in healthcare assistance. Section 3 explains about emerging applications of AR and VR in various healthcare applications. Section 4 demonstrates the future directions and ethical considerations to be followed. Section 5 concludes with the use of AR and VR in various healthcare operations and provides the way for healthcare assistance.

RELATED WORKS

The use of Augmented Reality (AR) and Virtual Reality (VR) in healthcare has garnered significant interest in recent times, leading to extensive exploration of their potential applications and benefits [1]. A substantial body of work has emerged, examining the effectiveness of AR and VR in various healthcare disciplines, including medical education, patient treatment and rehabilitation, and surgical procedures [2, 3]. In medical education and training, researchers have focused on using AR and VR technologies to enhance the learning experience for medical students and professionals [3, 4]. Numerous studies have explored the impact of immersive simulations and virtual environments on improving anatomical understanding, procedural skills, and diagnostic abilities [1, 4]. These studies have shown that AR and VR can create realistic and engaging educational environments, enabling interactive exploration of anatomical structures, virtual patient interactions, and realistic surgical simulations [1, 4]. The use of AR and VR in medical education has been found to enhance knowledge retention, spatial understanding, and decision-making skills, ultimately contributing to the development of competent healthcare professionals [4].

In the field of patient treatment and recovery, researchers have explored the potential benefits of AR and VR technologies [5]. Studies have investigated their effectiveness in managing pain, reducing anxiety, and facilitating the recovery process [5]. VR has been used to create immersive experiences that distract patients from painful procedures, such as wound care or dental treatments, resulting in reduced pain perception and increased patient comfort [5]. AR has been employed to provide personalized interventions and remote monitoring, enabling healthcare professionals to deliver targeted treatments and support patients in their recovery journeys [5]. The integration of AR and VR into therapy sessions has shown promise in improving patient engagement and motivation, as well as facilitating motor recovery and cognitive training [5]. Research in this area has demonstrated the potential of AR and VR to enhance patient outcomes, increase treatment adherence, and improve overall patient satisfaction [5].

In the field of surgical procedures, researchers have focused on employing the capabilities of AR and VR for surgical planning, simulation, and real-time guidance [6]. Studies have explored the use of AR to overlay patient-specific information, such as preoperative imaging data or vital signs, onto the surgical field, providing surgeons with valuable visual guidance during procedures [6]. VR simulations have been used to practice and refine surgical techniques, allowing surgeons to gain experience in a risk-free environment and enhancing their skills and confidence [6]. The integration of AR and VR in surgical workflows has the potential to improve surgical precision, reduce operative time, and minimize complications [6]. Research in this area has highlighted the benefits of AR and VR technologies in enhancing surgical outcomes, optimizing resource utilization, and supporting surgical training and skill acquisition [6].

While the body of research has shed light on the potential applications and benefits of AR and VR in healthcare, several challenges and limitations need to be

CHAPTER 13

Chem-bioinformatics: Computational Alternatives to Clinical Diagnosis, Treatment and Preventative Measures

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Abstract: Nowadays, chem-bioinformatics tools are widely used for genomic and proteomic data analysis, gene prediction, genome annotation, expression profiling, biological network building, and many more purposes. Clinical applications of such computational approaches are also needed to ensure real-life implementation of findings from the fields of cheminformatics and bioinformatics. Despite being a new field of science, studies found huge significance and interconnectivity of cheminformatics and bioinformatics approaches in modern medical science. Identification of cancer biomarkers, for instance, has been possible *via* bioinformatics tools mediated in-depth genome analysis, resulting in cancer susceptibility being easily calculated nowadays using a bioinformatics approach. In addition, bioinformatics tools are helping docking studies in the prediction of anticancer drug structures as well. Also, genome analysis of patients using bioinformatics techniques is the initial requirement for personalized therapeutics designing in cancer treatment. Additionally, in recent times, computer-aided drug designing has benefited since bioinformatics tools offer easier determination of effective active sites and potential side-effects of the predicted drug on system biology and genetics constitution. Besides, diagnosis and treatment of infectious diseases often require a suitable bioinformatics approach to study host-pathogen interaction. Moreover, treatment of metabolic disorders, complex genetic disorders, point of care diagnostics, observation of drug efficacy, *etc*. are controlled, monitored, and modified using multiple bioinformatics tools by manipulating the biological data sets. Such various applications can benefit the medical sector in multiple clinical processes. Realizing these, this book chapter aims to explore some of such major applications of chem-bioinformatics studies in the medical sector; mostly in terms of diagnosis, treatment, and prevention of diseases.

Keywords: Bioinformatics, Cheminformatics, Diagnosis and treatment, Genomic data, Proteomic data, Medical science.

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BACKGROUND

Today's world highly relies on data science and not a single sector is refrained from using mass-scale data to advance its traditional workflows. The biomedical and overall health sector is, thus, no different from being highly data-driven. The study of biological and biochemical data has drastically gained much popularity over the past few decades [1]. Being an interdisciplinary field of science, cheminformatics, and bioinformatics explore and analyze biochemical data using software and analyzing tools. Cheminformatics, an area of information technology closely associated with chemical information, is also essential to collect, retain, examine, and organize chemical aspects of biological data [2]. Cheminformatics has digitized and reshaped traditional clinical processes drastically with the help of bioinformatics applications. Bioinformatics tools are widely used for genomic and proteomic data analysis, gene prediction, genome annotation, expression profiling, biological network building, and many more. Researchers are constantly exploring further opportunities to be created by chem-bioinformatics tools and bridging the gaps, particularly to save resources and time needed for lengthy and uncertain on-hand experiments [3]. The current scope of chem-bioinformatic research is also abundant as evidenced by the wide number of tools available for various biological and biochemical analyses.

Apart from its huge research prospects, clinical applications of bioinformatics are one of the most crucial sectors that require real-life implementation of findings from the field of bioinformatics. Due to the rapid accumulation of large quantities of biological data sets, computer-based approaches associated with machine learning and other tools offer huge opportunities for manipulation to extract and analyze useful information and newer data dimensions [4]. Though this arena of study experience lacks expert manpower and study materials, it is yet an emerging field with huge prospects not only to lessen the workload of existing biological research-based implications but also to open wide opportunities for biological research at a minimal cost and timespan [5]. This is why, despite the challenges and ethical concerns associated with bioinformatic-based approaches, their popularity is still expanding.

Considering the wide scope of bioinformatic applications, the huge utility of bioinformatics-related discoveries has been noticed in multiple stages of medical science as well. Disease diagnosis, treatment, and prevention-all these stages have experienced multiple applications of bioinformatics. The implications of such activities are too vast to wrap up in a few hundred pages. Also, the variety of opportunities offered by medical science-related approaches to bioinformatics is a matter of attraction for many researchers. For instance, cancer biomarkers have been identified through in-depth analysis of the genome using bioinformatics tools. As a result, the susceptibility of cancer can be easily calculated nowadays using a bioinformatics approach [6]. At the same time, personalized therapeutics designing, a potential means of cancer treatment, requires genome analysis of patients using bioinformatics techniques [7]. Such dependency on bioinformatics is also noticed in the case of computer-aided drug designing for other diseases, as bioinformatics tools help to design more effective active sites and determine potential side-effects of the designed drug on system biology and genetics constitution [8]. Besides, diagnosis and treatment of microbial diseases may require a suitable bioinformatics approach so that host-pathogen interaction is studied properly before deciding on corresponding treatment and preventative strategies [9]. Gene therapy, controlled manipulation over genes' constitution and expression to design treatment of several diseases is another emerging field of bioinformatics, as it requires in-depth genetic analysis using bioinformatics tools [10]. Moreover, the treatment of metabolic disorders, complex genetic disorders, point-of-care diagnostics, observation of drug efficacy, *etc*. is controlled, monitored, and modified using multiple bioinformatics tools by manipulating the data sets as per the professionals' interests.

Considering all such different applications and connective associations between bioinformatics and medical science, this book chapter aims to explore some of the major applications of bioinformatics studies in medical science; especially in terms of diagnosis, treatment, and prevention of diseases.

DISEASE DIAGNOSIS

Disease diagnosis has multiple stages that are traditionally conducted using biochemical or microbiological approaches. Adopting a chem-bioinformatic approach to the diagnosis of diseases is becoming popular because of the reduced cost and time associated with this process [11]. The process of disease diagnosis solely depends on the type of disease to be diagnosed; however, bioinformatics-based approaches have often made diagnosis-related tasks easier, cheaper, and handier. Major contributions of bioinformatics for disease diagnosis have been briefly discussed in the following subsections.

Pathogen Identification

Next-Generation Sequencing (NGS) is the rapid and sophisticated mechanism for sequencing which is getting popular for research and clinical activities that puts huge public health and clinical importance on the process. Metagenomic NGS helps to detect pathogens present in the infected body fluids. This uses cell-free DNA of the body fluids to perform 16s rRNA PCR [12]. In this regard, NGS works under certain stages *i.e*. PCR amplification, sequence assembly, and finally

CHAPTER 14

Computer-aided Diagnosis Model for White Blood Cell Leukemia and Myeloma Classification using Deep Convolutional Neural Network

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Abstract: Diagnosing white blood cell (leukocyte) diseases (Leukemia and Myeloma) is a thought-provoking task in the body. The abnormal growth of the leukocytes leads to an unbalanced immune system. Therefore, the automatic detection and classification of leukocytes will be the best aiding tool for the physician. This research work proposes a Computer-aided Diagnosis (CAD) model using the Deep Convolutional Neural Network (DCNN) to classify the white blood cell Acute Myeloid Leukemia (AML), Acute lymphoblastic leukemia (ALL), Myeloma, and its sub-types. The Gaussian distribution and k-means clustering segment the input image for future extraction. We utilized the Gray Level Covariance Matrix method to attain the texture features required to train the proposed DCNN model. The DCNN classifier is trained and tested with the mined features, and it detects the early stage of leukocyte cancer and achieves a classification accuracy of 97.8%. The precision, recall, and F1 score are achieved as 0.977, 80.955, and 0.966, respectively. We compared the performance of the proposed CAD model with the existing deep-learning classifier models. The analysis reveals that the proposed CAD model outperforms the existing methods.

Keywords: Computer-aided diagnosis, Convolutional neural networks, Gray level covariance matrix, Leukemia, Myeloma, White blood cells.

INTRODUCTION

The blood is vital for many organs to function correctly. We assessed the healthiness of the blood by using blood cells. Out of three blood cells, white cells (leukocytes) play a significant role in the organs' proper function [1]. The leukocytes are generated in the bone marrow, responsible for the body's immune system. The statistical report released by the World Health Organization (WHO) stated that the most deaths occur due to cancer, and led to 10 million deaths in the

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year 2020. If cancer is diagnosed and treated at an early stage, then it can be cured easily, but if not diagnosed early, it can be life-threatening.

The symptoms of white blood cell cancer diseases are not easy to detect. These diseases have many subcategories, each having almost similar symptoms. So, even if the disease is detected at an early stage, chances for misdiagnosis by the doctor are very high. A detailed survey of feature extractions using traditional image processing techniques to classify white blood cells was presented for better understanding [2]. As we know, the first step to solving the problem is to identify the problem accurately. Nowadays, we rely on automated systems to diagnose such diseases so they can be cured.

A digital image is the processing of a 2-D picture by a digital computing system. It is represented using the finite value of bits, which may be natural or complex numbers. We can process this digitized Image for further directions. Image processing is a technique used to extract the required features. White blood cell cancer is also one of the major diseases that can affect many people in the world. Leukemia and Myeloma are the major diseases in blood cells [3].

The bone marrow causes Leukemia, which generates abnormal leukocytes. Therefore, it does not function normally, leading to chronic or acute disease. Acute Myeloid Leukemia (AML) is further divided into various stages as M0, M1, M2, M3, M4, M5, M6, and M7 levels, whereas Acute lymphoblastic Leukemia (ALL) is divided into various stages as L1, L2, and L3 levels. Myeloma disease is a cancer formed in the plasma cells in the bone marrow.

The identification and classification of leukocytes have been exciting in the recent past. Due to technological advancements, many automated leukocyte disease prediction methods have been proposed by many researchers [4 - 10]. The autonomous detection of leukocytes is generally achieved using advanced image preprocessing techniques such as image enhancement, segmentation, feature extraction, and classification. Typically, the automatic leukocyte classification method's performance depends on suitable segmentation techniques. The researchers suggested many segmentation techniques, such as segmentation by clustering using the standard features [4], segmentation by various thresholding mechanisms [5, 6], morphological-based segmentation [7], feature extraction using edge detection, and region-growing-based segmentation [8]. The various reported techniques have their own merits and demerits.

Many researchers have concentrated on fuzzy-based and machine learning (ML) based white blood cell cancer detection for efficient implementation. An image processing-based detection method was proposed for early-stage detection [9 - 11]. The authors suggested using the k-means nearest neighbor (k-NN) clustering technique for segmentation and a support vector machine to classify the various stages of blood leukemia. Mohapatra *et al*. [10] demonstrated a Fuzzy logic-based segmentation to detect and classify blood Leukemia. The classification of AML M1 and M2 using ML was proposed and the various morphological, radiomics, and clinical features were extracted to train and validate the classifier [11]. The random forest classifier was proposed to classify the ALL and its subcategory from microscopic images [12].

Due to the era of artificial intelligence, researchers have deployed many autonomous systems to solve classification problems. Researchers developed and deployed many machines and deep learning-based models to analyze and predict medical-related issues [13 - 15]. Due to their intelligent nature, the Deep Neural Networks can predict the region of interest and mine the essential features for the provided dataset [16, 17]. The neural network-based classification [18] and Generative Adversarial Network [19] based classification have been deployed. Yao *et al*. [20] proposed a white blood cell classification technique using the two-module weighted CNN model. The convolutional neural networks have been demonstrated to effectively classify multiclass and binary blood cell samples fully automated [21, 22].

Various optimization techniques, such as particle swarm optimization, genetic algorithm, grey wolf optimization algorithms, and blood cell morphology, were used to optimize the CNN model to better classify white blood cells and predict ALL and AML subcategories [23, 24]. Khandekar *et al*. trained and implemented YOLO V4 using the Object Detection algorithm to detect and classify ALL blood cells from microscopic images [25]. The Chronological Sine Cosine method-based DCNN model from single blood cell smear images was proposed to detect and classify the ALL and its subtypes [26]. They have used mutual information-based hybrid methods to segment the images. The authors used the robust global and local extracted features to train and test the Al-Net model, which was suggested for detecting ALL cells [27]. The advantages and disadvantages of the existing state-of-the-art (SOTA) methods and algorithms are summarized in Table **1**.

Research Contributions

Despite notable technological advancements, the existing methods still have a few limitations/drawbacks. Most reported techniques detected and classified white blood cancer cells as AML or ALL. However, those methods failed to identify the subcategories of each type. Therefore, effectively detecting and classifying Myeloma and Leukemia is challenging for physicians. The significant contributions of the proposed research are as follows.

CHAPTER 15

Empowering Inclusive Communication with the Haptic-Enabled Language to Pulse Device: A Novel Assistive Technology Solution for Communicative Impairments

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Abstract: In the rapidly evolving technological landscape, inclusivity and accessibility in communication are paramount. This research paper introduces the "Haptic-Enabled Language to Pulse" device, a ground-breaking solution designed to empower individuals with speech impairments. The device represents a fusion of advanced technology and assistive healthcare technology, including Python programming, TensorFlow Lite's DeepSpeech model, and Raspberry Pi hardware, all integrated through shell scripting. This comprehensive system enables effective communication by capturing user input in spoken language, processing it into text, and translating it into Morse code for visualization. The vibration patterns from a haptic feedback device then convey the encoded Morse code to the specially-abled user. Beyond its primary function as a communication aid, this device also serves as an educational tool for Morse code learning. Its versatility accommodates diverse contexts, making it valuable for individuals with speech impairments and their communities. This research paper showcases the innovative use of Raspberry Pi alongside software components, contributing to inclusive and accessible communication solutions for speech-impaired and visually impaired individuals.

Keywords: Assistive healthcare, Deepspeech model, Haptic feedback, Morse code, Python programming, Raspberry pi, Shell scripting, Speech impairments, Speech to Text, Tensorflow lite, Visual impairments.

INTRODUCTION

In this ever-evolving world, technology has brought ease of living and the comfort of innovation to our doorstep. We have automated all parts of our lives and

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upgraded ourselves to a better quality of life. From driverless cars to keyless locks, all are revelations of accessible and inclusive technology. The same quest for inclusivity and accessibility in communication has become more pressing than ever before.

Individuals with speech and visual impairments experience significant challenges with traditional verbal communication. So, this research endeavors to introduce an innovative solution that bridges these communication gaps.

This paper introduces the “Haptic-Enabled Language to Pulse” (HELP) device, an amalgamation of the latest software and hardware technology. At its core, the HELP device empowers users by capturing spoken language, converting it into textual form, and translating it into Morse code. Realizing this code through vibration patterns enables effective communication, not only for speech-impaired individuals but also for visually impaired people.

HELP is not just about technology. It is about inclusion. It is about breaking down the barriers to communication. It signifies a step towards the progressive pursuit of creating accessible solutions for individuals with speech and visual impairments.

OBJECTIVES

The main aims of this research are to:

- Develop a robust system that accurately converts recorded spoken language into textual form using TensorFlow Lite’s DeepSpeech model, ensuring precise representation of user input.
- Create a Python script that efficiently translates the textual output into Morse code and converts it into vibration stimulus, facilitating an effective visual communication form.
- Employ Raspberry Pi hardware to enhance processing power, enabling real-time speech-to-text conversion, and Morse code encoding without compromising the device's portability and usability.

The ultimate objective is to empower individuals with hearing impairments by providing them with a reliable, easy-to-use communication tool that fosters inclusivity and independence, allowing them to participate actively in various communication contexts.

LITERATURE REVIEW

To attain our objectives, exhaustive research of the proposed and existing methodologies in a similar theme was conducted. The aim is to actuate the device in a cost-effective, faster, and accurate direction. The reference papers are listed below for the conceptualization of the research.

In 2006, Huggins-Daines *et al*. introduced “Pocketsphinx,” a real-time continuous speech recognition system for hand-held devices. This system addresses the need for efficient, portable speech recognition technology, particularly for mobile and embedded applications [1]. In 2010, Cheng, Abdulla, and Salcic presented significant contributions to the field of work of embedded speech recognition. This research, published in the Proceedings of the IEEE International Symposium on Signal Processing and Information Technology, developmentally focused on the speech recognition system tailored for real-time embedded applications. The authors' work addresses the critical need to optimize speech recognition accuracy and efficiency within resource-constrained environments, further advancing the applicability of speech-based interfaces in real-time embedded systems [2]. In 2011, Pan *et al*. discussed the implementation of speech recognition systems on FPGA-based embedded systems with System-on-Chip (SOC) architecture. Their research focuses on integrated speech recognition in FPGA-based embedded systems, including its potential benefits and challenges [3]. In the same year, Qu and Li developed an embedded speech recognition module based on STM32 microcontrollers, contributing to the integrated speech interfaces in embedded systems [4]. In 2012, Reddy investigated “Text to Speech Conversion Using Raspberry Pi for Embedded System.” This research delved into the practicality of implementing text-to-speech conversion on the Raspberry Pi platform and its relevance in embedded systems [5]. In 2014, Varshney and Singh contributed to the field of embedded speech recognition with their paper titled “Embedded Speech Recognition System.” published in the International Journal of Advanced Research in Electrical, Electronics, and Instrumentation Energy, the research explored the development and integration of speech recognition technology into embedded systems. The research showcased practical applications and progressed in this area, providing valuable insights into the field [6]. Also in 2014, Hannun *et al*. presented “Deep Speech,” a groundbreaking work in scaling up end-to-end speech recognition. This research, documented in an arXiv preprint, focused on large-scale, deep learning-based models for speech recognition. It significantly advanced the capabilities of deep neural networks in the sector of automatic speech recognition, marking a crucial milestone in the progress of speech recognition technology [7]. In 2015, Vanitha *et al*. entailed the implementation of text-to-speech for real-time embedded systems using the Raspberry Pi processor. The research explored the utilization of Raspberry Pi to create text-to-speech

CHAPTER 16

Investigation of Various Transfer Learning Techniques for Classifying Alzheimer's Disease Dataset

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Abstract: Alzheimer's disease, also called dementia, is a severe psychological disorder that affects the cerebrum, causes cognitive decline, and impairs a person's ability to reason. During the initial stage, AD patients encounter the standard adverse effects. Usually, they lose track of their everyday tasks and obligations. They find it challenging to communicate verbally with people. They also have a diminished ability to think critically, among other things. Currently, research is ongoing to determine the underlying cause of AD. We are now quite concerned about AD because the majority of its patients are older than sixty. Nervous system specialists typically perform multiple tests to differentiate AD. Human errors occur from time to time. We require high-performing deep-learning models to diagnose and forecast the illness better. This study looks at how well VGG16, InceptionResNet-V2, Resnet50, Resnet101, and Resnet152 classified the AD dataset and compares and contrasts their results. Accuracy, loss, validation accuracy, and validation loss were the performance indicators we utilized to assess the models. You may find the dataset on the Kaggle repository.

Keywords: Alzheimer's disease, Classification, Deep neural network, Healthcare, Machine learning, Transfer learning.

INTRODUCTION

Alzheimer's Disease International (ADI) states that 3/4 of AD patients do not receive the same level of care, according to the World Alzheimer's Report 2022 [1]. In underdeveloped nations, this rate is around nine out of ten. An estimated 55 million people have dementia each year. The most recent data from the World Health Organization (WHO) predicts a rise to 139 million dementia cases in 2050.

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Dementia is a condition with side effects of impeded memory, thinking, conduct, and profound control issues, leading to a deficiency of independence. Alzheimer's disease is the most widely recognized and notable type of disease. Unusual proteins disrupt synapses and nerves, disrupting the transmitters that transmit messages in the mind, particularly those responsible for storing memories.

A biomarker is any physiological, biochemical, or anatomic limit objectively assessing regular biological cycles, neurotic cycles, or responses to a corrective intervention. Clinical preliminary analyses and ongoing symptomatic interventions generally accept five promotional biomarkers as suitable. Three are cerebrum imaging measurements, and two are proteins found in the cerebrospinal fluid (CSF) [2].

Although we cannot predict AD in its early stages, we can analyze it. From the large volume of biological data sets, AI algorithms can diagnose a variety of neuropsychiatric and neurodegenerative disorders, including AD. Specialists dealing with the underlying analysis of AD can benefit from using magnetic resonance imaging (MRI) filters. To produce excellent and high-quality 2D and 3D images of the brain's architecture, magnetic resonance imaging (MRI) uses radio waves and attractive fields. However, by measuring the human essential visual cortex and identifying the topography of the cerebrum, functional magnetic resonance imaging (fMRI) provides insightful information on mental activity. Similarly, Positron Emission Tomography (PET) studies mental activity using radiotracers like fluorodeoxyglucose and amyloid [3].

Researchers in various domains have expressed interest in developing deep neural network approaches for MRI image-based AD detection [4]. Transfer learning approaches perform better than non-transfer learning-based approaches, according to Tufail *et al*. [5]. Ahmad [6] employed DNN and CAD-based techniques to achieve a 97% accuracy rate [7], while Ebrahimi used ResNet-18 and achieved 96.88% accuracy. Chao Li *et al*. [8] added two improved ResNet algorithms to the traditional ResNet residual blocks. Dong Nguyen [10] and Mingjin Liu [9] used residual network approaches to diagnose illnesses using 3D MRI images. To arrive at a final diagnosis and prognosis, we used patient demographics, cognitive exam findings, and the predictions of ResNet and XGBoost. Farheen Ramzan *et al*. [11] carefully assessed the RS-18 architecture over fMRI images. However, Wei Li *et al*. [12] worked on 4D fMRI images using deep learning methods.

M. Abdelaziz *et al*. [13] achieved an accuracy of 98.22% for NC *vs*. AD by utilizing a unique method that combined clinical score regression activity with CNN classification. Nevertheless, S. Buyrukoglu [14] found that the Random Forest method performed better when working on a predictive model. Rule induction, k-nearest neighbors (k-NN), Naive Bayes, decision trees (DT), generalized linear models (GLM), and deep learning algorithms were all used by M. Shahbaz *et al*. [15] on the ADNI dataset. Nonetheless, GLM accurately categorized the AD phases at a rate of approximately 88.24%. M. Odusami *et al*. achieved 98.86% accuracy in AD classification using ResNet18 and DenseNet201 [16]. H. S. Zaina *et al*.'s research [17] focused on four modules: pre-processing, feature extraction, categorization of AD using deep learning, and multi-layer perceptron. Their accuracy rate with both white matter and gray matter was 96.15%. Assmi *et al*. [18] looked at how well six pre-trained networks did at classifying. For VGG-19, VGG-16, ResNet-50, InceptionV3, Xception, and DenseNet169, the overall accuracy was 92.86%, 92.83%, 91.04%, 90.57%, 85.99%, and 88.64%. Nonetheless, Shukla *et al*. [19] used a variety of convolutional network models, including Alz-XceptionConvNet, Alz-DenseConvNet, Alz-ResConvNet, and Alz-VGGConvNet, in addition to Alz-MobileConvNet. Alz-MobileConvNet, Alz-MobileConvNet, and Alz-VGGConvNet achieved the best multiclass and binary classification results, with respective accuracy rates of 94% and 99%.

This chapter covered five distinct innovative deep learning-based techniques for identifying Alzheimer's disease in its initial stages. We used four stages of MRI brain images to test CNN-based transfer learning models: very mild, mild, moderate, and not dementia. The models are VGG16, InceptionResNet-V2, ResNet50, ResNet101, and ResNet152.

The Various Transfer Learning Techniques

The initial pre-processing step involves loading the model's image to perform augmentation. In this case, we divide the information into four groups: very mild, mild, moderate, and non-dementia. Fig. (**1**) displays representative brain pictures for all four categories.

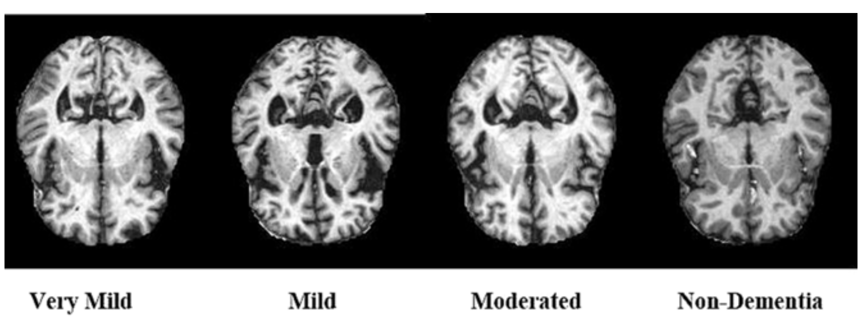

Fig. (1). Categories of brain images present in the Kaggle dataset.

CHAPTER 17

Machine Learning in Women's Health: An Insight into the Role of Machine Learning in Skin, Breast, and Ovarian Cancers and PCOS

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Abstract: Concerning the diagnostic or predictive analysis of medical data, machine learning is currently receiving a significant amount of attention. Artificial intelligence and machine learning already learn and make corrections, and feedback may help them further increase their accuracy. This approach examines structured data to group patient attributes and subsequently forecasts the likelihood that a disease would manifest. Large medical data sets are mined for insights that can be utilized to improve clinical decision-making and patient outcomes, automate daily tasks for healthcare personnel, speed up medical research, and increase operational effectiveness. Even today, many women still struggle with access to basic healthcare facilities. They are biologically more vulnerable to a variety of illnesses. As a result, AI and machine learning suggest a significant improvement in women's health. Several of these machine learning tools target the particular health problems faced by them. Following these methods, this chapter presents an insight into how these algorithms aid in detecting skin cancer, breast cancer, ovarian cancer, and PCOS.

Keywords: Breast cancer, Cancer, Cervical cancer, Machine learning, Ovarian cancer, PCOS, Skin cancer, Women's health.

INTRODUCTION

Cancer affects millions of women globally. Millions of women die each year as a result of family history, hormones, and reproductive variables. Unfortunately, a lot of people die from the seriousness of different types of cancer since doctors cannot detect them until it is too late [1]. However, through the early diagnosis of

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diseases, AI, data analytics, and machine learning (ML) are laying a solid foundation for women's health. They essentially enable a computing system to learn by making predictions about the data that is fed, which has evolved powerfully into deep learning algorithms [2]. When it comes to diseases like skin cancer, breast cancer, PCOS, and ovarian cancer, it can improve survival rate, treatment, and diagnosis rates. Given the high expense of medication and the significance of the disease, early detection is the most efficient way to reduce the disease's effects on both health and the economy. Self-testing is uncommon since cancer is frequently found when it has already spread. Recently, machine learning has been extensively utilized in healthcare to forecast various diseases. It is a modeling method that depicts extracting knowledge from data and uncovering hidden associations. Some studies employed simply demographic risk indicators (lifestyle and laboratory data) to predict cancer, while others used data from patient biopsies or other characteristics [3]. Others have shown how genetic information can be used to predict cancer. For better prognostication and stratification of patients toward personalized therapy, ML specifically enables the integration or combination of several layers of data, including those from medical pictures, laboratory results, clinical outcomes, biomarkers, and biological features [4]. Applied computational methodologies and usability issues prevent these prediction models from being widely deployed despite the substantial academic interest in this area of study. As a result, the current work intends to explore and evaluate multiple machine learning techniques for identifying and diagnosing skin, breast, ovarian, and cervical cancer while taking into account diverse modeling parameters and algorithms.

METHODOLOGY

The following algorithms are commonly used in machine learning to detect and predict the discussed types of cancers:

Random Forest

A supervised machine-learning technique is employed for both classification and regression. To obtain a more precise and reliable forecast, it constructs and blends numerous decision trees.

Decision Tree

A decision tree is a supervised learning method used to visually display all potential solutions to a given problem. The classification and regression tree algorithm, or CART algorithm, was utilized.

Support Vector Classifier

Support vector classifiers can split or categorize the data by returning the best fit for the input data. The numbers are nearer to the hyperplane and alter the hyperplane's position and orientation.

Logistic Regression

Logistic regression is a form of supervised learning method used to address classification issues. It uses a set of independent factors to predict the categorical dependent variable using machine learning, and the cost function can only be between 0 and 1.

K Nearest Neighbor

The supervised learning algorithm K Nearest Neighbor, sometimes referred to as the lazy learner algorithm, is used for both classification and regression. Instead of learning the dataset right away, it initially stores it before taking action on it when it comes time to classify.

XGBRF

PCOS is categorized using an ensemble method called XGBoost with Random Forest (XGBRF). A gradient boosting approach is called XGBoost, and a bagging algorithm is called Random Forest. A modified version of the XGBoost classifier is called XGBRF. The usage of XGBRF to avoid the over-fitting issue is a benefit.

CatBoost Classifier

CatBoost is used for regression and classification. It works with a variety of data types, including audio, text, and image data, as well as historical data. This algorithm's method involves converting categorical values into numbers utilizing various statistics on categorical feature combinations and categorical feature combinations with numerical characteristics.

Skin Cancer

Skin cancer refers to abnormal growth in skin cells. It usually occurs due to excess exposure to the sun's ultraviolet rays. There are many types of skin cancer, including basal cell carcinoma (BCC), squamous cell carcinoma (SCC), melanoma, cutaneous t-cell lymphoma, dermatofibrosarcoma protuberans (DFSP), Merkel cell carcinoma (MCC), and sebaceous carcinoma (SC).

CHAPTER 18

An Insight into the Mathematical Modeling of Physiological Systems

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Abstract: Mathematics is extensively used in designing physiological modeling. There exists a long and rich history of mathematical modeling in physiology. Mathematical modeling refers to creating a mathematical representation of a real-life condition. Physiological modeling is creating a physiological system's representation in mathematical form. Mathematical models for many aspects of human pathology and physiology have been produced in recent decades. Understanding the connections between the parts of a complicated system may be accomplished with the use of mathematical models. In the biological context, mathematical models aid in our understanding of the intricate web of relationships among the various components (signaling molecules, DNA, enzymes, proteins, *etc*.) in a biological system. This improved interpretation allows us to predict and understand the behavior of the system in a diseased state. Understanding of several intricate biological systems, including metabolic networks, gene regulatory networks, enzyme kinetics, signal transduction pathways, and electrophysiology, has improved because of mathematical modeling. The study of biological systems has grown even more reliant on computational approaches and mathematical modeling as a result of recent developments in high throughput data production techniques.

Keywords: Enzymes, Mathematics, Physiological modeling, Proteins, Signaling molecules.

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INTRODUCTION

In physiology, mathematical modeling has a long and illustrious history [1]. It is helpful to quickly explain the general modeling technique before describing how models have advanced our understanding. Mathematical modeling starts with a well-formulated hypothesis based on prior findings, like experimental research. There are broadly four different types of mathematical modeling (Fig. **1**). The mathematical model is a quantitative depiction of the main idea. For instance, Otto Frank developed a mathematical model of the arterial pulse in the late nineteenth century [2]. Over the years, the same types of mathematical techniques to comprehend the mechanical features and characteristics of the circulatory system have persisted, as Bunberg and colleagues recently reviewed [3]. Hodgkin and Huxley's foundational study on the propagation and development of neural action potentials was documented around the middle of the last century [4], from which cardiac electrophysiology models quickly developed and spread [5]. Mathematical modeling in physiology quickly transitioned from analytical techniques to computational applications of governing equations and simulation to utilize the newly emerging capability of the first analog and digital computers. The problems of larger size may be addressed and examined due to this progress. For instance, Arthur Guyton and his collaborators created an elaborate representation of the balance of fluid and electrolyte in the late 1960s that is still significant and relevant today due to the range of physiology it covers [5].

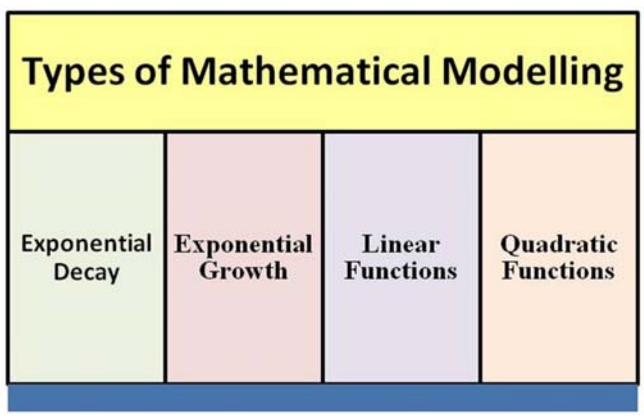

Fig. (1). Types of mathematical models.

Since the period of original research by Guyton, physiological modeling has moved from specialized and frequently single-purpose computers to the regular computer of the researcher. It is possible to assemble small-scale computer clusters at an affordable cost. This is due to the extensive availability of high-performance computing power, which is relatively cost-effective and has a high storage capacity. Numerous quantities of biomedical, biological, and even clinical data may be gathered and saved as a part of specialized research initiatives or during clinical patient treatment, thanks to technical developments in computer power and digital storage media. The need to simultaneously link observed data stream characteristics technically to the system and its properties under study, and potentially in real-time, as often needed by some clinical applications [6], is even more urgent. With the help of this, the vast amount of biomedical data is converted to give a better interpretation of the biological systems themselves is possible. It links the mathematical, mechanistic, and computational modeling of biological systems at all lengths, breadths, and time scales of physiological systems of the human body, as revealed by the Physiome project [1, 7, 8].

Mechanistic Mathematical Physiological System Models

Mechanistic mathematical models represent the knowledge we now have about the functional relationships that control the entire behavior of the system that is under study. By putting our understanding of physiology into the context of dynamical systems (stochastic or deterministic), we make it possible to make exact quantitative predictions and compare them to the outcomes of carefully selected trials. Mechanistic mathematical models frequently enable us to investigate a system in much greater depth than is feasible in experimental research and can thus help to determine the reason behind any specific discovery [6]. Mathematical models and experiments work very well when integrated into a scientific program, as the presence of one increases the value of the other. In addition to illuminating experimental findings, allowing for discrimination between competing scientific hypotheses, and aiding in experimental design, models depend on experiments for defining and improving parameter values [6]. The application of mathematical models sheds light on the molecular and ionic processes underlying inherited and acquired diseases. Dr. Yoram Rudy's lab's work has been essential to this attempt. Notably, the Luo-Rudy dynamic model and its variations continue to rank among the most often mentioned models of cardiac action potentials and are frequently used to explore the fundamentals of cardiac electrophysiology [9 - 13]. Additionally, investigations utilizing these models have shown the effectiveness of computational methods in producing fresh mechanistic insights into cardiac arrhythmia [14 - 17].

Mathematical Modeling of the Reproductive System

Men and women differ significantly in many organ systems, including the architecture of the brain, the functioning of the immunological and stress systems, and the metabolic and cardiovascular systems. They also differ in the reproductive system and reproductive behaviors [18]. The creation of successful sex-based

CHAPTER 19

Diverse Disease Prognostication through Machine Learning Models

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Abstract: Today's generation faces various diseases due to the current atmosphere, pollution, poor quality of food, and their living habits. It is difficult for doctors to predict and analyze all the diseases manually; in most cases, the prediction of diseases goes wrong due to the large number of samples. The work aims to build a healthcare web application for identifying and predicting multiple diseases like heart disease, diabetes prediction, liver disease, breast cancer, kidney disease, *etc*., and machine learning models such as Decision trees, SVM, KNN, Random Forest, *etc*., used to accomplish this. To improve the accuracy level, datasets were gathered for every condition and trained them. we created an end-to-end web application using Flask framework where the user enters data to view the outcomes of various diseases' predictions. The drawbacks of the existing system are the users have to go to different sites to get different disease predictions, it becomes difficult for the user to move from one site to another, and in many cases, there is no proper user-friendly web application for disease prediction with no proper accuracy level mentioned. The proposed system focuses on developing a web application that offers users a variety of disease predictions based on their preferences. Multiple models were taken into consideration for training and testing the data. The evaluation results of each model were collected and then compared using a box plot.

Keywords: Decision tree, KNN, Random forest, SVM.

INTRODUCTION

The WHO has published an updated list of diseases that cause death in this generation, which includes diabetes, heart disease, kidney disease, *etc*. According to a WHO statistic, there are more than 20 million fatalities worldwide each year as a result of various diseases. As per the statistics, some of the leading causes of illness and mortality among the global population are heart disease, kidney disease, diabetes, liver disease, and breast cancer.

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In recent years, the current generation has seen a gradual rise in the worldwide disease burden. Several studies have been conducted in an attempt to identify the primary risk factors for this kind of disease and precisely estimate the total risk. It causes death without evident signs; this type of sickness is even called a silent killer. Making decisions on lifestyle modifications for high-risk patients depends on early detection of these diseases, which lowers complications and death rates.

Here, machine learning repeatedly demonstrated its ability to help with decision-making and forecasting using the vast amounts of data generated by various healthcare-related companies. The purpose of this study is to make predictions for several kinds of diseases, such as diabetes, heart disease, renal disease, liver illness, and others. Through analysis, the patient data uses machine learning models to categorize whether or not the patient has this type of condition. Machine learning models have been used in this situation. Even though diseases can present in various ways, there is a common set of basic risk factors that can establish whether an individual is ultimately at risk by obtaining data from various sources and classifying it appropriately.

While numerous websites and platforms exist to forecast diseases, none exist for the simultaneous prediction of multiple diseases. When the user wants to predict one disease, he must go to a different location to diagnose another. In some situations, there are multiple disease prediction techniques available, although the forecast accuracy varies greatly. The major goal of this study is to anticipate diseases in advance and save time by using existing cases, which can predict various diseases with higher accuracy. One can recover easily from diseases in advance. The problem will be addressed with the help of machine learning approaches. With the help of machine learning, one can build a model and import that model into the web application with the help of the Python Flask framework. Here, the user can diagnose the type of disease and view the current health status.

Motivation

Building an intuitive web application that can be used to anticipate many diseases without visiting different websites is the primary objective of this study, keeping in mind the existing circumstances. In this study, we have built a multiple-disease web application for diabetes, heart disease, liver disease, kidney disease, *etc*. Predicting diseases in advance can effectively lower mortality rates and optimize time by conducting simultaneous checks for multiple conditions. In some cases, disease accuracy levels are lower, leading to potential future issues. In these instances, machine learning techniques can help predict diseases with higher accuracy. The first step here is analyzing the data. This work has some advanced features of machine learning techniques like one hot encoding and feature scaling.

With the help of these two techniques, anyone can easily pre-process the 100% clean data, and better accuracy results can be achieved.

Literature Survey

The authors eloquently highlighted the machine-learning techniques utilized for diabetes-related disease classification, early detection, and prediction. As an additional feature, it also provides an IoT-based method for monitoring diabetes, enabling both healthy and affected individuals to monitor their blood glucose levels [1]. They predicted diabetes using various machine learning classification techniques such as LR, KNN, Naive Bayes, SVM, RF, and DT. Comparing the models, SVM showed the highest accuracy of 81.21% [2].

Eight different algorithms were considered, and each model's results were compared with the other to see which would yield the highest accuracy prediction [3]. The author suggested a remote monitoring system using advanced-level machine learning for diabetes risk prediction and management. This end-to-end application utilizes personal health devices like smartwatches and smartphones. By developing a support vector machine (SVM) model using the Pima Indian Diabetes dataset, the author achieved an accuracy of 93.23%, a sensitivity of 97.21%, and an F-score of 88% [4]. An application for accurately diagnosing several diseases was created using machine learning classification models. Users gain from the work since it makes it accessible to them to remotely check their status, which increases life expectancy and saves time [5].

To predict cardiac disease, a machine learning classification model and a user-friendly online application were developed. The prediction process takes into consideration 13 factors in total, such as BMI, sex, and age. The author achieves 80% accuracy using random forest and implements the model in a web page using the Python Streamlit framework for single-site web applications. Users can enter the necessary fields and click the prediction button to check their disease status [6]. The author aims to achieve 100% accuracy by comparing and training multiple algorithms. They conduct a comparative study on these algorithms, predicting and ranking their accuracy levels. The results are visualized using bar charts and ROC curve graphs [7].

The author investigates preprocessing and training techniques to improve the accuracy of diabetes prediction. They employ supervised learning algorithms, including DT, KNN, LR, SVM, and random forest. Random forest achieves the highest accuracy of 97%. Utilizing the Python Flask framework, the author created a web application to enable result checking and uses one-hot encoding to further improve accuracy [8].

CHAPTER 20

Patch Antenna Design for 2.4 GHz for On-Off Body Communication

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Abstract: On-body communication is a crucial technology, finding applications ranging from healthcare monitoring to IoT connectivity. Using antennas, on-body communication technology exploits specific frequency bands and tailored antenna designs to facilitate efficient data exchange between devices on or near the human body. This study delves into patch antenna designs customized for on-off body communication at 2.4GHz frequencies. As the demand surges for seamless connectivity with diminutive, inconspicuous form factors, an in-depth exploration of antenna design becomes indispensable. The antenna, crafted with FR-4 (a lossy material) possessing a dielectric constant of 4.4, employs copper for the patch and ground layers. Simulation is carried out utilizing the CST Studio Suite, confirming and documenting key antenna parameters: Gain of 5.65dB, bandwidth of 96.8MHz, return loss of -41.83dB, and VSWR of 1.05. Through simulation, a thorough analysis of the antenna's performance in both free space and on the body is conducted, unveiling its exceptional performance in these scenarios. Furthermore, the proposed design optimizations exhibit resilience against environmental factors, making them well-suited for practical on-body communication applications.

Keywords: Antenna, Antenna parameters, Bandwidth, Biomedical application, Gain, ISM band, Microstrip antennas, Patch antennas, Resonant frequency, Radiation pattern, Return loss, Specific absorption rate, VSWR.

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INTRODUCTION

In an era marked by escalating interconnectivity, the demand for effective and dependable on-body communication systems has experienced a notable upsurge, propelled by a spectrum of applications spanning from wearable health monitoring to the Internet of Things (IoT). Body-centric communication (BCC) delineates into three primary classifications predicated on interaction modes: in-body, off-body, and on-body communications [1]. Central to the architecture of body-centric wireless systems are antennas and signal propagation, which are pivotal components in developing compact, high-efficiency RF sensor nodes, optimizing both spectrum utilization and power efficiency. Additionally, they play a pivotal role in ensuring the robustness of communications within, on, and off the body [2].

Microstrip patch antennas are assuming an increasingly pivotal role in the advancement of contemporary wireless communication systems. This significance stems from the burgeoning demand for diverse wireless applications among end-users. Researchers and scientists are actively immersed in this domain, driven by the myriad opportunities afforded by wireless technology [8]. A microstrip patch antenna comprises a radiating patch positioned on one facet of a dielectric substrate, with a ground plane situated on the opposing side. Typically fashioned from conductive materials like copper or gold, the patch can adopt various geometries. Both radiating patches and feed lines are conventionally fabricated *via* photolithography on the dielectric substrate [9]. To facilitate analysis and performance projection, patches are often configured in standardized shapes such as square, rectangular, circular, triangular, elliptical, or other commonly employed forms [10].

Furthermore, a considerable number of antennas presently in operation are undergoing significant size reduction [7]. This research paper delves into the domain of on-off body communication using patch antennas, intending to investigate their design, performance, and optimization for robust and efficient communication within the intricate on-body environment. In typical healthcare monitoring scenarios, ensuring effective radio communication is paramount. This involves the antenna emitting signals uniformly in all directions across the body's surface (omnidirectional) while also directing its signal towards devices situated off the body. The goal is to optimize radio channel performance both on and off the body, primarily focusing on minimizing signal attenuation to enhance power efficiency [3].

Patch antennas present numerous advantages over traditional antenna platforms, encompassing a low profile, compact size, facile manufacturing process, cost-effectiveness, and seamless integration with "monolithic microwave integrated circuits (MMICs)" [4]. Moreover, they demonstrate inherent resonance capabilities and commendable narrow bandwidth performance [5]. Consequently, the design and optimization of patch antennas have emerged as a focal area of research, given their direct impact on the caliber and resolution of microwave images. This paper undertakes a comprehensive investigation, delving into the meticulous design of patch antennas customized for 2.4GHz on-off body communications.

In the dynamic realm of wireless communication and remote sensing, the "Industrial, Scientific, and Medical (ISM)" band operating at 2.4GHz has emerged as a pivotal cornerstone for on-off body communications. The ISM band presents a favorable equilibrium between resolution and penetration depth, aligning well with numerous applications necessitating non-ionizing radiation. This research unfolds as a pioneering endeavor in the pursuit of harnessing the potential of patch antenna designs meticulously crafted for the 2.4GHz ISM band within the domain of on-off body communications.

Related Works

A study [11] amplifies the directivity of a compact ultra-wideband (UWB) antenna by incorporating a reflector inspired by the Yagi-Uda design. The resulting reflector-loaded antenna (RLA) exhibited significant enhancements, such as a 4 dB rise in realized gain and a notable 14.26 dB increase in transmitted field strength within a human breast model. Moreover, it sustained high signal fidelity, boasting a 94.86% correlation factor. Comparable enhancements in directivity were observed when a validated head imaging antenna was similarly outfitted with a reflector.

A study [12] presents a novel design for an aperture-fed annular ring (AFAR) microstrip antenna, emphasizing simplification in fabrication by leveraging 3D-printed and solderless 2D materials. Comprising three layers-an aperture-fed patch, a ground plane slot for power transmission, and a microstrip line for feeding-the antenna underwent optimization *via* the finite element method (FEM) in four iterative steps, targeting distinct parameters. The optimized 3D AFAR antenna achieved an S11 of approximately 17 dB, a front-to-back ratio exceeding 30 dB, and a gain of around 3.3 dBi, making it conducive for streamlined manufacturing and deployment across antenna technologies.

A study [13] elucidates the development and experimental validation of a deeply implanted conformal printed antenna. In this innovative design, the hip implant serves as the ground plane for a trapezoidal radiator, which is fed by a coaxial cable and specifically tailored to transmit biological signals captured within the

CHAPTER 21

Performance Evaluation of Syringe Control Systems: Servo Motors *versus* Stepper Motors

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Abstract: This academic paper presents a comparative analysis of 8051-controlled syringes utilizing servo and stepper motors for precise fluid injection. The study thoroughly investigates the design, performance, functionality, and other relevant aspects of both systems. It evaluates the servo motor-driven syringe pump for its continuous and smooth fluid delivery capabilities, while the stepper motor-driven syringe pump is recognized for its discrete and precise steps. Various experiments are conducted to assess each system's capabilities and limitations, including fluid dispensing accuracy, response time, and resilience to external disturbances. The findings of this comparative research offer valuable insights for selecting the most appropriate system based on specific application requirements, such as accuracy and speed. Ultimately, this study contributes to the optimization of fluid delivery systems across various industries.

Keywords: Healthcare, Precise injection, Ring and pinion, Rack and pinion, Syringe, Stepper motor, Servo motor, 8051 controller.

INTRODUCTION

The accurate and controlled administration of medication is crucial in healthcare. The effectiveness and safety of medical treatments depend on precise dosing and delivery. Advanced technological solutions have led to innovative approaches to medication administration, particularly in cases where precision and customization are essential. Our research introduces a groundbreaking development: an 8051 microcontroller-based syringe control system that uses a servo motor for the meticulous and controlled dispensing of medications in medical applications.

Medication management in healthcare is complex, with different patients, conditions, and treatments requiring diverse dosages and delivery profiles. Manual administration of medication, while common, is prone to errors and lacks

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the precision needed in modern medical settings. In response to these challenges, our research explores the integration of cutting-edge technology to provide a more accurate and adaptable solution for a variety of medical scenarios. At the heart of this innovation is the 8051 microcontroller, a versatile and programmable platform that serves as the core control unit for our syringe control system. Combined with a precision servo motor, this system offers an unprecedented level of control over the syringe's plunger movement, maintaining the exact dosage and delivery rate throughout treatment. The integration of an intuitive user interface empowers healthcare professionals to customize medication delivery to the unique needs of each patient, thereby enhancing the safety and effectiveness of treatment plans.

The implications of this research are significant. The 8051 microcontroller-based syringe control system, enhanced by a servo motor, offers a novel approach to improving patient care, addressing the need for precision and customization in medication administration across various medical settings. By ensuring accurate and reliable medication delivery, this research contributes to the progress of medical technology, furthering the safety and effectiveness of patient treatment.

The remainder of this paper is organized as follows:

Section 2 provides a literature review of various techniques proposed for driver drowsiness detection. Sections 3 and 4 describe the execution principle and experimental setup in detail. Section 5 provides a detailed workflow of the system built. Section 6 presents the experimental results and the evaluation of the proposed method.

Literature Review

The research paper authored by Ashmi M., S. Jayaraj, and K. S. Sivanandan addresses the development of a control system for motorized assistive devices, particularly prosthetic legs. The primary aim is to achieve more natural and coordinated limb movements, recognizing the increasing demand for advanced artificial limbs due to the rising number of individuals with lower limb weakness or amputations. The paper highlights the importance of replicating human gait patterns, focusing on the coordination of muscles, bones, and joints in prosthetic legs. The authors detail a control system that employs an 8051 microcontroller to govern 12V DC series motors responsible for controlling knee and hip joint movements. The direction of motor rotation is managed using an H-bridge converter, specifically the L293D. The study demonstrates the system's functionality *via* simulations using Keil µVision and Proteus software, illustrating its capacity to control DC motors for actions like locking/unlocking legs and moving knee and hip joints. The research suggests that for further improvement, incorporating feedback mechanisms like optical encoders to transition to a closed-loop system would enhance the precision and functionality of prosthetic leg movements. This work contributes to the advancement of prosthetic limb technology, potentially improving mobility and overall quality of life for individuals with limb impairments [1].

In the article “Development of a Microcontroller-Based Motor Speed Control System Using Intel 8051”, researchers delve into the development of a motor speed control system employing the Intel 8051 microcontroller. This system is designed to regulate the speed of Direct Current (DC) motors, which are integral to numerous applications. The article introduces various speed control methods, including Phase-Locked-Loop (PLL) control and Pulse-Width Modulation (PWM) [2]. It emphasizes the microcontroller's role in processing feedback from optical encoders and adjusting the motor's voltage supply based on user-defined speed settings. Detailed descriptions of the hardware components, such as the motor drive and optical encoder, are presented, and the software interface is created using Visual Studio and C#. The conducted experiments highlight the system's precision in maintaining desired motor speeds under varying loads. The article concludes by suggesting potential areas for future research, such as mathematical modeling and the implementation of advanced control methods, including PID controllers and Fuzzy Logic Controllers [2].

The conference paper discusses the development of a control system for a syringe infusion pump. Infusion pumps are crucial in medical settings for accurately delivering fluids, like medications and nutrients, into a patient's bloodstream. This paper focuses on syringe infusion pumps, known for their precision in delivering low-flow rates, making them suitable for pediatric and intensive therapy applications [3]. The control system is divided into four key components: the electrical/mechanical unit of the infusion pump, a module with a stepping motor and its controller, an Arduino microcontroller module, and an LCD for visual feedback. A web interface facilitates the input of infusion parameters and provides a means to manage patient records. The Arduino microcontroller calculates and manages infusion parameters, triggers alarms, and communicates with the pump. Alarms can indicate the absence of a syringe, the end of an infusion, and battery voltage levels. All relevant data, including equipment parameters, user details, and patient records, are stored in a database. The paper suggests possible improvements, including better mechanical control and additional features like numerical keypads for enhanced functionality [3].

A team comprised of A. Andrew Silva, N. Chiranjeevi, V. Kaushikan, and R. Venkatesh, under the guidance of Prof. Muhammadu Sathik Raja, conducted research and developed a syringe pump system that is controlled by a Raspberry

CHAPTER 22

Real-time ECG Analysis and Classification Using Neural Networks in IoT Devices

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Abstract: This paper presents the development of a simple, cost-efficient, and accessible ECG analyzer. The proposed prototype can acquire ECG signals from subjects and display them in real time through IoT devices such as mobile phones. It can diagnose conditions by classifying subjects as having arrhythmia, congestive heart failure, or normal sinus rhythm. The prototype includes a pre-trained deep learning model that helps with ECG signal categorization, delivering rapid insights about the subject's probable medical care needs.

Keywords: Convolutional neural network, ECG, IoT, Neural networks.

INTRODUCTION

Heart-related problems are among the most common health issues faced by humans today. A recent survey reported that nearly one in three people have heart disease. Heart disease encompasses various conditions, including heart valve disease, heart infection, disease of the heart muscle, congenital heart defects, heart rhythm issues, coronary artery disease, and more. Some heart problems are genetic and unavoidable, while others are preventable. Risk factors include age, sex, family history, poor diet, smoking, high blood pressure, obesity, stress, physical inactivity, and more. The most common and low-cost tool used in healthcare for analyzing the heart's electrical signals is the Electrocardiogram (ECG). ECG can detect different types of arrhythmias. Despite the availability of deep learning-based automated arrhythmia classification techniques with high accuracy, healthcare professionals have not widely adopted them. The primary problems involve the utilization of imbalanced data for categorization, as well as the classification methods [1]. Continuous wavelet transform (CWT) is used to decompose ECG signals to obtain different time-frequency components, and the

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surrounding four RR interval features are extracted and combined with CNN features to input into a fully connected layer for ECG classification [2]. Ribeiro *et al*. proposed a lightweight solution using quantized one-dimensional deep convolutional neural networks, which are ideal for the real-time continuous monitoring of cardiac rhythm. Raw input data is used as input for the classifier, eliminating the need for complex data processing on low-powered wearable devices; data analysis can be carried out locally on edge devices, providing privacy and portability [3]. Granados *et al*. detailed the implementation of an IoT platform for real-time analysis and management of a network of bio-sensors and gateways, as well as a cloud-based deep neural network architecture for the classification of ECG data for multiple cardiovascular conditions [4]. In 2022, Kumar *et al*. proposed an approach where ECG signals collected using IoT nodes are processed to generate the QRS complex and the RR interval for establishing the feature vector for arrhythmia classification. The proposed Coy-Grey Wolf optimization-based deep convolution neural network (Coy-GWO-based Deep CNN) classifier detects anomalies in the ECG signal [5]. A paper presents a 1-dimensional convolutional neural network (CNN) for heartbeat classification from ECG signals obtained from an ambulatory device, classifying heartbeats into five classes as specified in the AAMI standard and tested using the Physionet MIT-BIH Arrhythmia database [6]. Another study proposed a compressed learning (CL) algorithm combined with a one-dimensional (1-D) convolutional neural network (CNN) that directly learns on ECG signals in the compression domain without expanded normalization, bypassing the reconstruction step and minimizing the raw input data dimension, significantly reducing processing power [7]. Li *et al*. conducted a study using convolutional neural networks to classify ECG image types using IoT to develop ECG signal measurement prototypes and simultaneously classify signal types through deep neural networks. The obtained signal is divided into QRS widening, sinus rhythm, ST depression, and ST elevation, with three models—ResNet, AlexNet, and SqueezeNet—developed with 50% of the training set and test set [8]. Another study used data from the MIT-BIH database for experiments, pre-processed the signals using different filters such as low pass filter and median filter, and utilized the discrete wavelet transform (DWT) technique to extract features, leading to the use of a deep neural network (DNN) for the classification model [9]. ECG machines are not typically set up at home, are not portable, and are expensive.

Related Works

The main concerns include imbalanced data for classification and the algorithm used for classification [12 - 15]. Continuous wavelet transform or CWT is used to decompose ECG signals to obtain different time-frequency components, and the surrounding four RR interval features are extracted and combined with CNN features to input into a fully connected layer for ECG classification [9]. Ribeiro *et al*. proposed a quantized one-dimensional deep convolutional neural network to monitor the cardiac rhythm. They have used the raw data to evaluate the classifier and eliminate the burden of data pre-processing on lighter devices with less power consumption. Data analysis is carried out on edge devices, ensuring mobility and privacy [10]. Granados *et al*. discussed the IoT platform implementation for real-time data management of bio-sensor networks. Also, they performed classification on multiple cardiovascular conditions using ECG data through deep neural networks [11].

In 2022, Kumar *et al*. [5] suggested a strategy in which IoT nodes gather ECG data and create the QRS complex and RR interval. Later, it was used to construct feature vectors to accomplish arrhythmia classification using the proposed Coy-Grey Wolf optimization-based deep convolution neural network (Coy-GW--based Deep CNN) classifier, which finds abnormalities in the ECG data. A paper discusses using a one-dimensional convolutional neural network (CNN) to classify heartbeats from an ambulatory device into various classes as specified by the AAMI standard, tested using the Physionet MIT-BIH Arrhythmia database [6]. Also, in another study, a compressed learning or CL algorithm combined with a CNN that directly learns on ECG signals in the compression domain is proposed, where such an approach bypasses the reconstruction step and minimizes the raw input data dimension, which significantly reduces the processing power [7]. Li *et al*. carried out a study that uses convolutional neural networks to classify ECG image types using the Internet of Things (IoT) to develop ECG signal measurement prototypes and simultaneously classify signal types through deep neural networks, divided into QRS widening, sinus rhythm, ST depression, and ST elevation, where three models, ResNet, AlexNet, and SqueezeNet, are developed with 50% of the training set and test set [8].

In an additional study, the MIT-BIH database was used, and the signals were pre-processed with a variety of filters, including low-pass and median filters. To improve efficiency, the discrete wavelet transform (DWT) approach was used for feature extraction and a deep neural network (DNN) for classification [9]. ECG machines cannot be set up at home, are awkward, and are not inexpensive.

Proposed Methodology

Input

Conductive pads, known as electrodes, are attached to the skin to record electrical currents. These electrodes connect to a signal conditioning block, AD8232, which gathers the electrical activity, collects the signal, and performs elementary pre-processing on the acquired signal.

Appendix

The neuromorphic computing application of spiking neural network-related datasets and Python codes are available in the following links.

A. DATASETS

i. https://archi ve.ics.uci.edu/ml/datas ets/Exase ns

ii. https://physionet.org/content/chbmit/1.0.0/.

iii. https://physionet.org/content/mitdb/1.0. 0/.

iv. http://ninaweb.hevs.ch/node/3.

v. https://figshare.com/s/d03a91081824536f12a8

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vi. http://www2.imse-cnm.csic.es/caviar/MNISTDVS.html

vii. http://www.garrickorchard.com/datasets

B. PYTHON CODES FOR SNN IN NEUROMORPHIC COMPUTING

i. https://github.com/Pouya-SZ/Bioneuromorphics/blob/master/Analog2Binary_ Conversion. ipynb

ii. https://github.com/djlouie/snntorch

iii. https://github.com/nengo/nengo

iv. https://github.com/norse/norse

v. https://github.com/SynSense/rockpool

APPENDIX

The following table presents the Python source codes for the several transfer learning strategies used in this chapter.

Table 2. Python codes for various transfer learning techniques

Python Source Code
VGG Net 16

// Importing all necessary libraries
from keras.layers import Input,Lambda,Dense,Flatten
from keras.models import Model
from keras.applications.vgg16 import VGG16
from keras.applications.vgg16 import preprocess_input
from keras.preprocessing import image
from keras.models import Sequential
from keras.preprocessing.image import ImageDataGenerator
import numpy as np
from glob import glob
import matplotlib.pyplot as plt
// Taken image default size as a 224*224
image_size=[224,224]
// Load the dataset from the drive

(Table 2) cont.....

Python Source Code

train_path='/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/train'
test_path='/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/test'
// Create object for VGG 16 pretrained model
vgg=VGG16(input_shape=image_size+ [3],weights='imagenet',include_top=False)
for layer in vgg.layers:
layer.trainable=False
folders = glob('/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/train/*')
x = Flatten()(vgg.output)
prediction = Dense(len(folders), activation='softmax')(x)
model = Model(inputs=vgg.input, outputs=prediction)
model.summary()
// Compile the model
model.compile(
loss='categorical_crossentropy',
optimizer='adam',
metrics=['accuracy']
)
// Generating more number of images using data augmentation
from keras.preprocessing.image import ImageDataGenerator
train_datagen = ImageDataGenerator(rescale = 1/255,
shear_range = 0.2,
zoom_range = 0.2,
horizontal_flip = True)
test_datagen = ImageDataGenerator(rescale = 1./255)
training_set = train_datagen.flow_from_directory('/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/train',
target_size = (224, 224),
batch_size = 32,
class_mode = 'categorical')
test_set = test_datagen.flow_from_directory('/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/test',
target_size = (224, 224),
batch_size = 32,
class_mode = 'categorical')
r = model.fit_generator(
training_set,
validation_data=test_set,
epochs=30,
)
// Plotting the graph for the following performance metrics training accuracy and validation accuracy.
plt.plot(r.history['accuracy'],label='train_accuracy')
plt.plot(r.history['val_accuracy'],label='validation_accuracy')
plt.xlabel('Number of epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
// Plotting the graph for the following performance metrics training loss and validation loss.
plt.plot(r.history['loss'],label='train_loss')
plt.plot(r.history['val_loss'],label='validation_loss')
plt.xlabel('Number of epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

Resnet 50
// Importing all necessary libraries from keras.layers import Input,Lambda,Dense,Flatten from keras.models import Model from keras.applications.inception_resnet_v2 import InceptionResNetV2 from keras.applications.resnet_v2 import ResNet50V2 from google.colab import drive drive.mount('/content/drive') from keras.applications.vgg16 import preprocess_input from keras.preprocessing import image from keras.models import Sequential from keras.preprocessing.image import ImageDataGenerator

(Table 2) cont.....

Python Source Code

import numpy as np
from glob import glob
import matplotlib.pyplot as plt
// Set image default size as 224 * 224
image_size=[224,224]
// Load the dataset from the drive
train_path='/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/train'
test_path='/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/test'
// Create object for ResNet50V2 pretrained model
res50=ResNet50V2(input_shape=image_size+ [3],weights='imagenet',include_top=False)
for layer in res50.layers:
layer.trainable=False
folders = glob('/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/train/*')
x = Flatten()(res50.output)
prediction = Dense(len(folders), activation='sigmoid')(x)
model = Model(inputs=res50.input, outputs=prediction)
model.summary()
// Compile the model
model.compile(
loss='binary_crossentropy',
optimizer='adam',
metrics=['accuracy']
)
// generate more images using Data Augmentation
from keras.preprocessing.image import ImageDataGenerator
train_datagen = ImageDataGenerator(rescale = 1./255,
shear_range = 0.2,
zoom_range = 0.2,
horizontal_flip = True)
test_datagen = ImageDataGenerator(rescale = 1./255)
training_set = train_datagen.flow_from_directory('/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/train',
target_size = (224, 224),
batch_size = 32,
class_mode = 'categorical')
test_set = test_datagen.flow_from_directory('/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/test',
target_size = (224, 224),
batch_size = 32,
class_mode = 'categorical')
// Fit and prediction of model
r = model.fit_generator(training_set,
validation_data=test_set,
epochs=30,
steps_per_epoch=len(training_set),
validation_steps=len(test_set)
)
// Plotting the following metrics such training accuracy and validation accuracy
plt.plot(r.history['accuracy'],label='train_accuracy')
plt.plot(r.history['val_accuracy'],label='validation_accuracy')
plt.xlabel('Number of epochs')
plt.ylabel('accuracy')
plt.legend()
plt.show()
// Plotting the following metrics such training loss and validation loss
plt.plot(r.history['loss'],label='train_loss')
plt.plot(r.history['val_loss'],label='validation_loss')
plt.xlabel('Number of epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

ResNet 101
// Import all necessary libraries from keras.layers import Input,Lambda,Dense,Flatten from keras.models import Model from keras.applications.resnet_v2 import ResNet50V2

(Table 2) cont.....

Python Source Code

```
from keras.applications.resnet_v2 import ResNet101V2
from keras.applications.vgg16 import preprocess_input
from keras.preprocessing import image
from keras.models import Sequential
from keras.preprocessing.image import ImageDataGenerator
import numpy as np
from glob import glob
import matplotlib.pyplot as plt
// Set image sizes as 224*224
image_size=[224,224]
// Load the dataset from the file
train_path='/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/train'
test_path='/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/test'
// Create a ResNet V2101 pretrained Model
res101=ResNet101V2(input_shape=image_size+ [3],weights='imagenet',include_top=False)
for layer in res101.layers:
layer.trainable=False
folders = glob('/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/train/*')
x = Flatten()(res101.output)
prediction = Dense(len(folders), activation='softmax')(x)
model = Model(inputs=res101.input, outputs=prediction)
model.summary()
// Compile the model
model.compile(
loss='categorical_crossentropy',
optimizer='adam',
metrics=['accuracy']
)
// Generating more images using Data Augmentation
from keras.preprocessing.image import ImageDataGenerator
train_datagen = ImageDataGenerator(rescale = 1./255,
shear_range = 0.2,
zoom_range = 0.2,
horizontal_flip = True)
test_datagen = ImageDataGenerator(rescale = 1./255)
training_set = train_datagen.flow_from_directory('/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/train',
target_size = (224, 224),
batch_size = 32,
class_mode = 'categorical')
test_set = test_datagen.flow_from_directory('/content/drive/MyDrive/Colab Notebooks/Alzheimer_s Dataset/test',
target_size = (224, 224),
batch_size = 32,
class_mode = 'categorical')
r = model.fit_generator(
training_set,
validation_data=test_set,
epochs=30,
steps_per_epoch=len(training_set),
validation_steps=len(test_set)
)
// Plotting the graph for training accuracy and validation accurcy
plt.plot(r.history['accuracy'],label='train_accuracy')
plt.plot(r.history['val_accuracy'],label='val_accuracy')
plt.xlabel('Number of Epochs')
plt.ylabel('Accuracy vs Validation Accuracy')
plt.legend()
plt.show()
// Plotting the graph for training loss and validation loss
plt.plot(r.history['loss'],label='train_loss')
plt.plot(r.history['val_loss'],label='val_loss')
plt. xlabel('Number of Epochs')
plt.ylabel('Loss vs validation Loss')
plt.legend()
plt.show()
```

Resnet 152

(Table 2) cont.....

Python Source Code

```
// Import all necessary libraries
from keras.layers import Input,Lambda,Dense,Flatten
from keras.models import Model
from keras.applications.resnet_v2 import ResNet152V2
from keras.applications.resnet_v2 import ResNet50V2
from keras.applications.resnet_v2 import ResNet152V2
from keras.applications.vgg16 import preprocess_input
from keras.preprocessing import image
from keras.models import Sequential
from keras.preprocessing.image import ImageDataGenerator
import numpy as np
from glob import glob
import matplotlib.pyplot as plt
image_size=[224,224]
train_path='/content/drive/MyDrive/Colab Notebooks/Skin_Cancer_dataset/Train'
test_path='/content/drive/MyDrive/Colab Notebooks/Skin_Cancer_dataset/Test'
// Create an object for ResNet152V2 pretrained model
res152=ResNet152V2(input_shape=image_size+ [3],weights='imagenet',include_top=False)
for layer in res152.layers:
layer.trainable=False
folders = glob('/content/drive/MyDrive/Colab Notebooks/Skin_Cancer_dataset/Train/*')
x = Flatten()(res152.output)
prediction = Dense(len(folders), activation='softmax')(x)
model = Model(inputs=res152.input, outputs=prediction)
model.summary()
model.compile(
loss='categorical_crossentropy',
optimizer='adam',
metrics=['accuracy']
)
// Create more number of images using Data Augmentation
from keras.preprocessing.image import ImageDataGenerator
train_datagen = ImageDataGenerator(rescale = 1./255,
shear_range = 0.2,
zoom_range = 0.2,
horizontal_flip = True)
test_datagen = ImageDataGenerator(rescale = 1./255)
training_set = train_datagen.flow_from_directory('/content/drive/MyDrive/Colab Notebooks/Skin_Cancer_dataset/Train',
target_size = (224, 224),
batch_size = 32,
class_mode = 'categorical')
test_set = test_datagen.flow_from_directory('/content/drive/MyDrive/Colab Notebooks/Skin_Cancer_dataset/Test',
target_size = (224, 224),
batch_size = 32,
class_mode = 'categorical')
// Fit and predict the model
r = model.fit_generator(
training_set,
validation_data=test_set,
epochs=50,
steps_per_epoch=len(training_set),
validation_steps=len(test_set)
)
// Plot the graph for training accuracy and validation accuracy
plt.plot(r.history['accuracy'],label='train_accuracy')
plt.plot(r.history['val_accuracy'],label='val_accuracy')
plt.ylabel('Accuracy vs Validation Accuracy')
plt.xlabel('Number of Epochs')
plt.legend()
plt.show()
Plot the graph for training loss and validation loss
plt.plot(r.history['loss'],label='train_loss')
plt.plot(r.history['val_loss'],label='val_loss')
plt.xlabel('Number of Epochs')
plt.ylabel('Loss vs Validation Loss')
plt.legend()
plt.show()
```

SUBJECT INDEX

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L

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Dr. B. Prabadevi is an Associate Professor in the School of Computer Science Engineering and Information Systems, Vellore Institute of Technology, Vellore, Tamilnadu, India. She received her Ph.D. in Computer Science and Engineering with Networking as a specialization from Vellore Institute Technology, Vellore, India, in 2018. She completed her undergraduate and post-graduation under Anna University, Chennai, in 2010 and 2012, respectively. She has twelve years of teaching experience and published 35 research articles in journals of international repute, 20 international conference papers, 7 book chapters, and two edited books. She is an invited research fellow at INTI International University Malaysia. Her areas of interest are Decision support systems, Predictive analytics, Deep learning, Machine Learning, Blockchain, and Edge computing.