

CONNECTED HEALTHCARE DELIVERY

LEVERAGING IOT AND MACHINE LEARNING FOR ADVANCED MEDICAL SOLUTIONS



Editors:

Salil Bharany
Upinder Kaur
Ateeq Ur Rehman
Kapil Joshi
Keshav Kaushik

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Connected Healthcare Delivery: Leveraging IoT and Machine Learning for Advanced Medical Solutions

Edited by

Salil Bharany

*Chitkara University Institute of Engineering and Technology
Chitkara University, Rajpura, India*

Upinder Kaur

*Department of Computer Science and Engineering
Lovely Professional University, Phagwara, Punjab, India*

Ateeq Ur Rehman

*School of Computing, Gachon University
Seongnam, Republic of Korea*

Kapil Joshi

*Department of CSE, Uttaranchal Institute of Technology
Uttaranchal University, Dehradun, India*

&

Keshav Kaushik

*School of Computer Science, University of Petroleum and
Energy Studies, Dehradun, Uttarakhand, India*

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Editors: Salil Bharany, Upinder Kaur, Ateeq Ur Rehman, Kapil Joshi & Keshav Kaushik

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PREFACE

The intersection of healthcare and technology is reshaping the future of medicine at an unprecedented pace. In particular, the convergence of the Internet of Things (IoT) and Machine Learning (ML) is revolutionizing the way patient care is delivered, monitored, and managed. This book, *Connected Health: Leveraging IoT and Machine Learning for Advanced Medical Solutions*, aims to serve as a comprehensive guide to understanding and navigating the evolving landscape of smart healthcare technologies.

In this work, we delve into critical innovations that are driving sustainable healthcare monitoring systems, including wearable health technologies, deep learning models for predictive analytics, and IoT-enabled patient monitoring solutions. We explore the transformative impact of machine-learning-powered genomic data analysis, offering a glimpse into the era of personalized medicine and stress detection *via* cognitive and neurophysiological signals such as EEG.

Security, privacy, and regulatory compliance are paramount as healthcare data becomes increasingly digitized. Accordingly, we examine the role of blockchain for secure health data management and the legal implications of edge computing in real-time healthcare applications. Further, we investigate the powerful synergy among emerging technologies, such as quantum computing, robotics, and artificial intelligence, in advancing diagnostics, surgical procedures, and drug discovery.

Our chapters are designed not only to highlight technological advancements but also to present interpretable, explainable approaches—ensuring that machine learning models in healthcare remain transparent and trustworthy. Topics such as SHAP and LIME for interpretability, regulatory frameworks for AI-driven IoT in telemedicine, and the integration of blockchain and ML for advanced disease diagnosis are thoughtfully discussed.

This book is intended for researchers, healthcare professionals, technologists, and students who are passionate about the transformative possibilities at the nexus of IoT, machine learning, and healthcare. Whether you are seeking foundational knowledge or advanced insights, this volume aspires to bridge theory with practical applications, fostering a deeper understanding of how connected health solutions can enhance patient outcomes, improve healthcare delivery, and shape the medical innovations of tomorrow.

As we embark on this journey through connected health, we invite readers to imagine a future where technology empowers clinicians, personalizes treatment, and makes healthcare more accessible, efficient, and secure for all.

Salil Bharany

Chitkara University Institute of Engineering and Technology
Chitkara University, Rajpura, India

Upinder Kaur

Department of Computer Science and Engineering
Lovely Professional University, Phagwara, Punjab, India

Ateeq Ur Rehman

School of Computing, Gachon University

Seongnam, Republic of Korea

Kapil Joshi

Department of CSE, Uttarakhand Institute of Technology
Uttarakhand University, Dehradun, India

&

Keshav Kaushik

School of Computer Science, University of Petroleum and
Energy Studies, Dehradun, Uttarakhand, India

List of Contributors

Abhilasha Khandelwal	Department of Computer Science and Engineering, Poornima University, Jaipur, Rajasthan, India
Ahona Ghosh	Department of Computer Science and Engineering, Maulana Abul Kalam Azad University of Technology, Kolkata, West Bengal, India
A. Gowri	Department of Information Technology, Hindusthan College of Arts & Science, Coimbatore, India
Akash Saxena	Department of CSE, Compucom Institute of Technology and Management, Jaipur, India
Deepali Chaudhary	Department of Computer Science and Engineering, Poornima University, Jaipur, India
Deepika Ghai	School of Electronics and Electrical Engineering, Lovely Professional University, Phagwara, Punjab, India
Harpreet Kaur Channi	Department of Electrical Engineering, Guru Nanak Dev Engineering College, Ludhiana, Punjab, India
Komil Kumar	School of Education & Humanities, Jigyasa University, Dehradun, Uttarakhand, India
Kawerinder Singh Sidhu	Department of Management, Uttaranchal Institute of Management, Uttaranchal University, Dehradun, Uttarakhand, India
Konda Hari Krishna	Department of CSE, School of Computing, Mohan Babu University, Tirupati, Andhra Pradesh, India
Kriti Sankhla	Department of Computer Science and Engineering, Poornima University, Jaipur, India
Manoj Kumar Singh	Computer Science & Engineering, IMS Engineering College, Ghaziabad, Uttar Pradesh, India
Mayur Bhoyar	PCET'S & NMVPM'S Nutan College of Engineering and Research, Talegaon Dabhade, Maharashtra, India Department of CSE, Jagdambha College of Engineering and Technology, Yavatmal, India
Mirza Samiulla Beg	Department of Computer Science and Engineering, Poornima University, Jaipur, India
Navonita Mallick	Kalinga Institute of Industrial Technology (KIIT), Deemed to be University, Bhubaneswar-751024, India
Neha Sah	School of Fashion Design, Lovely Professional University, Phagwara, India
Nimisha Singh	Department of Skill Development, Baba Farid College of Engineering and Technology, Bathinda, Punjab, India
Nikita Sharma	Department of Computer Science and Engineering, Poornima University, Jaipur, India
Nisha Banerjee	NSHM College of Management and Technology, The Shmunis School of Biomedicine and Cancer Research, Tel Aviv, Israel

Parampreet Kaur	School of Computer Science and Engineering, Lovely Professional University, Jalandhar, India School of Engineering, Architecture and Interior Design, Amity University, Dubai, UAE
Pranay Prasada	School of Computer Science and Engineering, Lovely Professional University, Phagwara, Punjab, India
Priya Arora	Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab, India
Priyanka Gupta	School of Computer Science & Engineering, Lovely Professional University, Phagwara, Punjab, India
Rana Rohit	School of Education & Humanities, Jigyasa University, Dehradun, Uttarakhand, India
Raj Kumar	Department of CSE, School of Computing, Mohan Babu University, Tirupati, Andhra Pradesh, India
Rajeev Sobti	School of Computer Science and Engineering, Lovely Professional University, Jalandhar, India
Ramesh Chandra Sethi	Kalinga Institute of Industrial Technology (KIIT), Deemed to be University, Bhubaneswar-751024, India
Ramandeep Sandhu	School of Computer Science & Engineering, Lovely Professional University, Phagwara, Punjab, India
Rupika Nanda	School of Fashion Design, Lovely Professional University, Phagwara, India
Sanjeev Kumar Angadi	Computer Science & Engineering, IMS Engineering College, Ghaziabad, Uttar Pradesh, India Department of CSE, PCET'S & NMVPM'S Nutan College of Engineering and Research, Talegaon Dabhade, Maharashtra, India
Shairai Ali	Department of Computer Science and Engineering, Poornima University, Jaipur, India
Shashwata Sahu	Kalinga Institute of Industrial Technology (KIIT), Deemed to be University, Bhubaneswar-751024, India
Shikha Khullar	Department of Computer Science and Engineering, Poornima University, Jaipur, India
Sreejita Dutta	NSHM College of Management and Technology, The Shmunis School of Biomedicine and Cancer Research, Tel Aviv, Israel
Sriparna Saha	Department of Computer Science and Engineering, Maulana Abul Kalam Azad University of Technology, Kolkata, West Bengal, India
Upinder Kaur	School of Computer Science and Engineering, Lovely Professional University, Phagwara, Punjab, India
Ved Prakash Mishra	School of Engineering, Architecture and Interior Design, Amity University, Dubai, UAE
Vinny John	Department of Agriculture, Mangalayatan University Dehradun, Jabalpur, Madhya Pradesh, India

Vivek John

Department of Mechanical Engineering, Uttarakhand Institute of Technology,
Uttarakhand University, Dehradun, Uttarakhand, India

CHAPTER 1

Technological Innovations in IoT for Healthcare Applications

Priya Arora^{1,*}

¹ *Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab, India*

Abstract: Responsible Artificial Intelligence (AI) combines technology, ethics, safety, ecology, and innovation. This concern is influenced by the transparency of clinical decision-support technology, patient confidentiality in AI-enhanced EHR systems, and algorithmic impartiality in diagnosis. **In healthcare contexts, these principles translate to: (1) explainable diagnostic tools that clinicians can understand and verify, (2) secure patient data management in AI-driven systems, and (3) bias-free algorithms that work equally well across diverse populations.** Security, openness, equity, responsibility, user and data rights, stakeholder autonomy, and the general influence of artificial intelligence are topics that are strongly argued. Responsible AI follows ethical and legal principles to maximize social benefits and minimize harm. Trust in AI systems, explainability and openness, bias and impartiality, privacy, accountability and governance, and data security are evaluated. This chapter emphasizes human-centered design and collaboration by examining how artificial intelligence affects precision medicine, pharmaceutical development, and epidemic response. It concludes by discussing the pros and cons of responsible AI and how morality and law could facilitate its acceptance.

Keywords: AI for social good, Data protection, Human-centered design, Responsible AI, Telemedicine.

INTRODUCTION TO RESPONSIBLE AI

Responsible AI must consider a number of factors, including technology, ethics, psychology, economics, and the environment, to attain a relationship between advancement and safety. In healthcare applications, this means developing AI systems that:

* **Corresponding author Priya Arora:** Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab, India; E-mail: priya.sadana@chitkara.edu.in

- **Provide transparent decision-making** (e.g., showing how an AI arrived at a cancer diagnosis using techniques like SHAP values).
- **Protect sensitive patient data** while enabling analysis.
- **Perform equally accurately** across different demographic groups.

The beliefs of security, equity, diversity, accountability, and transparency form the foundation of ethical AI. The implications of AI, user and data rights, cooperation, and stakeholder autonomy are other noteworthy issues. Since these standards don't provide clear directions, systems must be thoroughly tested before being implemented. Their main right is that systems need to be closely watched to ensure that positive effects outweigh negative ones. Also, key stakeholders should regularly review and approve them [1]. AI has the potential to significantly assist those in need when properly observed, configured, and directed.

Responsible AI takes a proactive approach to address the legal, ethical, and societal issues surrounding AI and its applications. Improving current legal and ethical guidelines is one way to lessen harm and prevent unfavorable outcomes. Responsible AI incorporates the safeguarding hypothesis from system safety engineering, which emphasizes mistake management. By focusing on methodical techniques for detecting and reducing bias, lowering risks, and enhancing transparency, the strategy seeks to foster accountability and trust [2, 3]. We can develop and responsibly apply AI technology if we stay focused on the current task and create a strategic plan. The fundamental principles of Responsible AI are responsibility, transparency, safety, justice, and the rights of users and data, which are outlined in Fig. (1). The graphic representation improves comprehension of how these ideas relate to one another and how crucial they are to the overall development of an AI strategy. Stakeholders can better understand and implement the necessary guidelines for the ethical and responsible use of AI by consistently interacting with this framework.

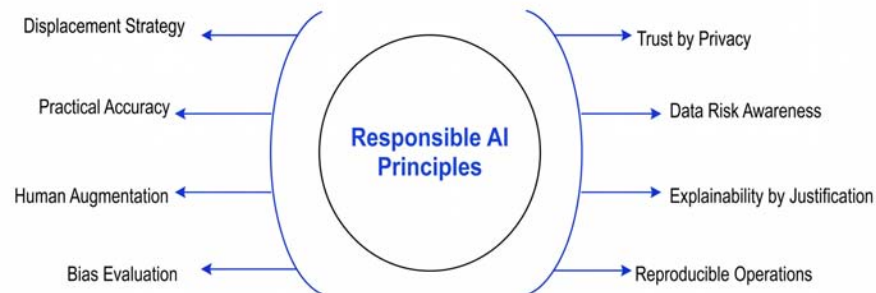


Fig. (1). Principles of responsible AI.

ETHICAL CONSIDERATIONS IN AI DEVELOPMENT

AI research, development, and application are growing increasingly burdened with ethical considerations as technology invades every aspect of human life. The ethical challenges created by the rapid development of artificial intelligence have exposed the anticipated common benefits of studying and utilizing new technology. These ethical problems have a substantial impact on both the growth and operation of AI systems.

The growth and execution of systems that protect human dignity and respect are at the forefront of ethical considerations in AI research. One of the most vital components of the industry is the development of artificial intelligence systems that do not help to address current injustices and imbalances. To ensure that all are treated equally, ethical artificial intelligence must hold the fundamental principles of impartiality, accountability, privacy, and openness.

Fairness and Bias

The development of AI systems depends on knowing what defines a "just" approach. Excessive dependence on artificial intelligence competencies may strengthen human biases instead of individual benefits. For example, a 2019 study found that an algorithm used in US hospitals to allocate care management programs systematically discriminated against Black patients by using healthcare costs as a proxy for health needs. For artificial intelligence to be truly unrestricted, it is vital that models or algorithms lack discrimination against any demographic, irrespective of gender, age, culture, or background. Developers must adhere to laws that identify and eliminate biases throughout the whole AI lifecycle, encompassing data collecting, pre-processing, model training, and deployment. Continuous evaluation and improvement of AI systems will be crucial to guarantee justice as values and society's expectations evolve. Apart from that, "authentic" artificial intelligence accomplishes assigned tasks precisely and does not exaggerate possible real-world problems throughout development. The development team ignores the several expectations of various groups impacted by cultural, sociological, philosophical, and other elements. This results in this issue. Using a decision tree classifier to predict the eligibility of loans for rural Bangladeshi farmers may lead to unexpected issues [4]. If moneylenders learn that the government and banks are working together to collect data and forecast which clients would access information services, women who would otherwise ask for loans may decide not to.

While preventing prejudice in AI may appear straightforward, it is actually a complex task. There are numerous ways in which it could occur. An initial and essential mistake is the misconception that AI is flawless and functions

CHAPTER 2

Stress Detection from Cognitive Aspects using Electroencephalogram: An Interpretable Approach using SHAP and LIME

Ahona Ghosh¹ and Sriparna Saha^{1,*}

¹ *Department of Computer Science and Engineering, Maulana Abul Kalam Azad University of Technology, Kolkata, West Bengal, India*

Abstract: Stress is defined as the human body's response to pressure in any situation or event. Today's competitive lifestyle all over the world leads to increased stress and anxiety, which in turn hinders the quality of life in individuals. Earlier detection of mental stress can reduce physical impairments associated with stress. Electroencephalogram (EEG), as a sensor for recording the brain's electrical activity, has proved its effectiveness in various cognitive pattern detection tasks. In this chapter, three cognitive tasks have been considered to be performed by eleven concerned subjects to detect their stress. An image-based object-finding task, a difference-finding task, a number-based instruction-induced coloring task, and a relaxation state have been repeated four times for each subject wearing EEG electrodes. After successful noise removal using a fourth-order Butterworth filter, twenty-five different features from the time domain and the frequency domain have been extracted from it. Random Forest (RF) has been applied to classify whether stress is observed during the experiment or not. After tuning the hyperparameters, the proposed RF has outperformed its competitors with 98.24% accuracy. Also, the experimental results have been interpreted using Shapley Additive Values and Local Interpretable Model-agnostic Explanation for a better understanding of its real-life applications. The proposed system provides a notable performance overcoming the shortcomings of existing systems, making it suitable for real-world stress detection scenarios.

Keywords: Brain-computer interface, Electroencephalogram, Explainable artificial intelligence, Frequency domain feature, Internet of Things, Random Forest, Signal processing, Stress detection, Time domain feature extraction.

INTRODUCTION

Several factors contribute to the rise in mental stress levels in modern society. These factors often stem from changes in lifestyle, work environment, technology,

* **Corresponding author Sriparna Saha:** Department of Computer Science and Engineering, Maulana Abul Kalam Azad University of Technology, Kolkata, West Bengal, India; E-mail: sahasriparna@gmail.com

and social dynamics [1]. Individuals readily acclimatize to stress as it gradually becomes manageable and alleviable over time. They neglect to recognize the detrimental consequences of sustained exposure to even minimal amounts of stress on their health. Therefore, it is essential to recognize the prevalent warning signs and symptoms of stress overload. Upon early detection of stress, solutions often require both individual-level interventions (*e.g.*, mindfulness, exercise) and systemic changes (*e.g.*, better work-life balance policies and mental health support systems) [2]. Sometimes, face expressions are analyzed to detect stress [3], for which image processing is performed. Some approaches use the temperature of the finger [4], human gestures [5], and eye blink [6] as a modality to detect stress.

Stress detection with an Electroencephalography (EEG) process using an Electroencephalogram device entails the examination of brain wave patterns to discern indicators of stress or psychological strain [3, 7]. EEG collects the brain's electrical activity using electrodes positioned on the scalp, with distinct frequency bands of brainwaves correlating to different mental states [4, 8]. Stress is mostly reflected in EEG data from the frontal lobe, as this area is associated with emotional regulation and decision-making [9 - 11].

EEG has been widely used in state-of-the-art literature for cognitive load analysis-based stress detection [12] by different means like game emotion recognition [13, 14], regular activity monitoring [15], handwriting pattern analysis [16], music emotion identification [17], *etc.* Two categories of brain connections exist: functional connectivity and effective connectivity [18]. The first one denotes the interactions among various brain regions, as indicated by the network's temporal coherence [19]. Diverse methodologies for assessing functional connectivity may yield disparate outcomes contingent upon variables such as the intensity of interactions across brain units, the nature of the stressor, and the quantity and positioning of electrodes [20]. This may also apply to data from the same modality and data acquired through the same activity [21]. The utilization of various interpretations of functional connections may result in contradictory outcomes [22]. Effective connection refers to the most basic circuit that delineates the experimentally established interaction between two neurons. It elucidates the influence of the brain system on other systems [23]. Effective connection, unlike non-directional and correlative functional connectivity, evaluates the directional influences among specific brain regions [24]. Consequently, functional and effective connection metrics are crucial for comprehending brain behavior in both stress and non-stress states [25].

The background survey has been described in Section 2. The implementation aspects of the proposed architecture have been elaborated in Section 3, and the experimental results, along with the performance evaluation, are described in

Section 4. Finally, the concluding statements and future scope in this area have been presented in Section 5.

LITERATURE SURVEY

The different phases of EEG signal processing as reported in existing literature include artifact removal, feature extraction, classification, and regression. Feature extraction can be mainly in three domains: time-domain features [5], frequency-domain features [6], and time-frequency domain features [7]. Machine Learning (ML) models like Support Vector Machines (SVM) [8], Random Forest (RF) [9], Decision Tree (DT) [10], Gradient Boosting [11], eXtreme Gradient Boosting (XGB) [12], and Back Propagation Neural Networks (BPNN) [13] can classify stress occurrence or stress levels based on extracted features [26].

SHapley Additive exPlanation (SHAP) [18] and Local Interpretable Model-agnostic Explanation (LIME) [19] as eXplainable Artificial Intelligence (XAI) models have recently become popular for interpreting the black-box ML models in terms of identifying the underlying reasons behind the predictions made, the importance of the considered features towards the outcome, and explaining a given instance [27]. SHAP and LIME can identify situations where the model is not making sense, such as giving too much weight to irrelevant features or ignoring important features [20]. This helps debug and improve the models [28].

The proposed framework of this chapter first collects 21-channel data from the EEG of eleven subjects, each performing three different cognitive tasks. A Butterworth filter has been applied to remove the noise associated with the data; twenty-five features from the time domain and frequency domain have been extracted after that. RF has classified the extracted feature matrix to identify whether stress has occurred during the task or not. SHAP and LIME have interpreted the predictions to make them transparent for common users of such healthcare systems [29, 30].

PROPOSED FRAMEWORK

The proposed framework involves data acquisition from EEG, noise removal using filtering, feature extraction, and classification. The stages are described in this section.

Introduction to EEG

An EEG measures the voltage potential of EEG signals elicited by brain activities, which are around 0.5-100 μ V with a frequency of 0.5 - 100 Hz [31]. It can detect stress by analyzing changes in the frequency of brain waves. Stress can cause

CHAPTER 3

Technological Innovation in IoT for Healthcare Applications, Medical Imaging, and A-Driven Predictive Analytics

Nikita Sharma^{1,*}, Shikha Khullar¹, Mirza Samiulla Beg¹ and Shairai Ali¹

¹ Department of Computer Science and Engineering, Poornima University, Jaipur, India

Abstract: The combination of the Internet of Things (IoT) and Artificial Intelligence (AI) in healthcare has changed how patients are treated and how operations are handled by enabling data originated decision making. This paper investigates the growing importance of the Internet of Things in healthcare, focusing on chronic disease management *via* wearable devices, smart medical devices, and telehealth. The paper analyzes how IoT can be used in this case by addressing the problem of real-time data collection, remote monitoring, and diagnostics augmented with AI capabilities, and applications of IoT in healthcare, including wearable devices and smart devices. Healthcare is being transformed by new technologies such as medical imaging assisted with artificial intelligence, personalized medicine based on Detailed imaging, and methods of predictive analytics. At the same time, these technologies and applications bring issues such as privacy, integration, and ethical concerns. The paper describes how IoT and AI technologies can be applied in the areas of chronic diseases, oncology, and emergency medicines including patient transport within each case study. Finally, it provides the future of health technology, elaborating that health care solutions must come from coordination, regulations, further development of artificial intelligence, and the Internet of Things formation.

Keywords: Artificial Intelligence (AI), Healthcare technology, Internet of Things (IoT), Remote monitoring, Smart medical devices, Telemedicine, Wearable devices.

INTRODUCTION

Definition and Scope of IoT in Healthcare

The Internet of Things (IoT) represents the connection among devices that can communicate with each other over a network [1]. IoT enables the exchange of data between these gadgets, permitting users to access valuable information in a

* Corresponding author Nikita Sharma: Department of Computer Science and Engineering, Poornima University, Jaipur, India; E-mail: nikita.sharma@poornima.edu.in

secure and efficient way. IoT includes the key ideas: "internet" and "thing". The "internet" refers to "the worldwide network of interconnected pc networks," while "thing" refers to "an object, not exactly identifiable," which means that each object in an IoT machine can be uniquely addressable through an Internet Protocol (IP) and might function in smart spaces consisting of healthcare, automation, and more [2].

IoT has the capacity to revolutionize healthcare delivery, presenting real-time fitness insights and advanced services. As an example, it permits patients and healthcare experts to monitor essential fitness signs remotely, lowering the need for in-person visits. The future of IoT in healthcare is anticipated to be driven by low-energy microprocessors and efficient wireless communication protocols.

Role of AI in Enhancing IoT Technologies

When IoT is blended with AI, it will become more powerful and effective in regions like smart gadgets, data storage, and lowering human effort. A good example is the data collection, processing, and even decision-making processes done by AI-based IoT systems, which do not require human intervention. AI enhances IoT through enhancing the functionality of smart assistants like Alexa and Siri, making them more able to expertise and execute user instructions [3]. In addition, AI is very important in enabling robots and other smart devices to be intelligent and work better to suit certain needs.

The combination of AI and IoT can add immense value in nearly all industries, but the potential application in the medical field is especially revolutionary.

Overview of IoT's Impact on Healthcare Delivery

The incorporation of the Internet of Things (IoT) in the medical field improves the delivery of healthcare services, greatly reduces costs, and enhances health outcomes. IoT has changed this dynamic with the aid of allowing remote health tracking [4].

Integration of IoT technology in healthcare enables service providers to incorporate more flexible and personalized offerings. For instance, IoT-enabled devices can check the glucose level of diabetic patients, monitor the heart rates of cardiac patients, or even remind older patients to take their medications. The data collected from these devices can be transmitted to healthcare providers in real-time, helping them to make prompt and informed decisions.

The scope of IoT in healthcare continues to develop, with the capability for future advancements being pushed by low-energy microprocessors and efficient wireless

communication protocols. Moreover, Artificial Intelligence (AI) performs a key role in improving IoT technology, automating tasks, and making clever gadgets more intelligent and powerful [3]. This mixture of AI and IoT has immense potential to transform healthcare, making it more accessible, efficient, and personalized.

Overall, IoT's impact on healthcare delivery is substantial, providing flexibility, convenience, and better service delivery. As the IoT generation continues to evolve, its applications in healthcare will be expanded, leading to enhanced outcomes, decreased expenses, and a higher quality of life for sufferers around the world [4].

IOT IN HEALTHCARE APPLICATIONS

Wearable Devices and Remote Monitoring: Managing Chronic Diseases and Real-Time Data Collection

Wearable devices play an essential role in the Internet of Things (IoT) healthcare applications, supplying real-time data collection and remote monitoring for continual disorder control. These devices, when connected with physician-led systems, require highly secure data transmission to ensure patient data is secured [1]. Wearable devices, like smart rings, smart clothing, health trackers, and different health-tracking gadgets, can be worn by sufferers to track their physiological parameters, providing vital health data. These devices can also monitor various aspects of a patient's well-being, such as physical activity and sleep patterns. Data collected through such wearable devices enables targeted treatment planning and timely corrective measures to be taken before the health situation worsens, thus negating the need for frequent healthcare visits.

Another innovative idea in IoT healthcare is Body Sensor Networks (BSNs), which consist of a network of wearable sensors that communicate with each other and external devices to provide a comprehensive view of the patient's health. These networks allow for seamless information exchange, ensuring that healthcare providers have more accurate and up-to-date information on the patient's health status [5].

Remote monitoring is another application of IoT in healthcare. Sensors and various IoT devices allow healthcare providers to monitor patients' health remotely in real-time, which can be seen in Fig. (1). The information gathered by the sensors can be used to provide timely guidance (tips), making sure that patients get immediate feedback on their health report.

CHAPTER 4

IoT-Enabled Patient Monitoring System Using Wearable Health Technology

Harpreet Kaur Channi^{1,*}, Ramandeep Sandhu², Nimisha Singh³ and Deepika Ghai⁴

¹ *Department of Electrical Engineering, Guru Nanak Dev Engineering College, Ludhiana, Punjab, India*

² *School of Computer Science & Engineering, Lovely Professional University, Phagwara, Punjab, India*

³ *Department of Skill Development, Baba Farid College of Engineering and Technology, Bathinda, Punjab, India*

⁴ *School of Electronics and Electrical Engineering, Lovely Professional University, Phagwara, Punjab, India*

Abstract: IoT-enabled Patient Monitoring Systems (IEPMS) can assist with several public health challenges, including chronic diseases, aging populations, and pandemics. Ongoing monitoring and early diagnosis can help to improve the management and control of these issues. The Internet of Things and wearable health technology have combined to enable continuous, non-intrusive patient monitoring. Vital health data, including heart rate, blood pressure, blood glucose levels, oxygen saturation, and ECGs, are continuously collected by wearable technology. Wearables intended for medical use, fitness trackers, and smartwatches are a few examples of these gadgets. By reducing the frequency of check-ups, optimizing the use of resources, and preventing readmissions to hospitals, the deployment of IoT-enabled monitoring systems can reduce healthcare costs. This cost-effectiveness benefits healthcare providers as well as patients. The goal of this approach is to inspire everyone to lead a more courageous and healthy life. These devices are equipped with sensors, and they are connected to Internet of Things networks *via* efficient wireless technologies such as Bluetooth, Wi-Fi, and cellular networks. The collected data is moved to cloud-based systems like Amazon Web Services (AWS) storage for real-time data processing, storage, and interpretation. Sophisticated machine learning algorithms examine the data to generate actionable insights and predictive analytics. The user-friendly interface, which offers 24/7 complete health reports, alarms, and real-time updates, is simple to use for both patients and medical professionals. The system's performance will be evaluated, along with its scalability, accuracy, and dependability, through extensive testing and validation. This study includes a case study in Dangiwada, Nepal, demonstrating the system's effectiveness in a real-world rural healthcare setting. This

* **Corresponding author Harpreet Kaur Channi:** Department of Electrical Engineering, Guru Nanak Dev Engineering College, Ludhiana, Punjab, India; E-mail: harpreetchanni@yahoo.in

study highlights the potential of integrating wearable technology with the Internet of Things to create proactive, scalable, and effective patient monitoring solutions, which would enhance patient care and allow for timely medical responses.

Keywords: Amazon web services storage, Internet of things, Patient monitoring system, User-friendly interface, Wearable technology.

INTRODUCTION

The rapid advancements in the healthcare technology aspect have revolutionized patient-monitoring systems: solutions to long-standing challenges emanating from diseases, aging, and global crises such as pandemics. They often rely upon periodic visits within medical facilities by patients, while real-time patient monitoring of vital parameters is not practically possible. With the advent of IoT and wearables in healthcare technology, which will enable continuing non-invasive monitoring in real time, the health gap has actually been bridged. IEPMS, one such system employing the use of sensors in intelligent wearables, collects such critical healthcare information as heartbeat, blood pressure, oxygen level saturation, levels of glucose, and electrocardiogram. These wearables, ranging from smartwatches and fitness trackers to medical-grade wearables, send data wirelessly using protocols like Bluetooth, Wi-Fi, and cellular networks to cloud-based servers [1]. Artificial intelligence processes this collected data deeply, allowing the device to be used for applications of predictive analytics and meaningful recommendations for application in time for medical intervention. Cloud platforms, such as Amazon Web Services (AWS), store, process, and analyze vast amounts of data, providing healthcare professionals with real-time updates and comprehensive health reports. By reducing hospital readmissions, maximizing resource utilization, and giving patients opportunities to take early actions regarding their own health, these systems provide a lot of value to both patients and providers alike. However, challenges faced in IoT-enabled systems include data privacy, scalability in rural and remote areas, and interoperability of devices. Addressing such issues requires a multidisciplinary approach that combines advancements in IoT, wearable technology, and AI. This paper discusses an IoT-enabled patient monitoring system integrated with wearable health technology, highlighting the architecture, functionality, and applications. Similar IoT-driven health monitoring solutions have shown promising results in remote communities across Southeast Asia, improving early detection of cardiac anomalies by 25% [2]. Kvedar *et al.* (2014) showed that connected health systems have reduced hospital readmissions and improved outcomes [3]. The study further evaluates the system's scalability, accuracy, and reliability through rigorous performance evaluations. This research thus underscores the transformative

potential of IoT and AI in enhancing patient care, ensuring timely interventions, and reducing healthcare costs.

Background and Motivation

Pressure on healthcare systems globally is mainly attributed to the rising prevalence of chronic diseases, aging populations, and the need to care for patients continuously. Traditional monitoring of patients has been less emphasized because it mainly depends on periodic check-ups and sometimes hospital visits, both time consuming and less appropriate for any real-time detection of critical health conditions. The advent of wearable health technology and the Internet of Things (IoT) has introduced a paradigm shift in healthcare delivery by enabling continuous, non-invasive monitoring of vital parameters. Wearable devices, such as fitness trackers, medical-grade wearables, and smartwatches, equipped with advanced sensors, can track health metrics like heart rate, blood pressure, oxygen levels, and glucose levels, providing real-time data to patients and healthcare providers. This innovation finds great synergy with the rising demands of personalized and proactive healthcare solutions [3]. Integration of IoT networks with wearable health technology can therefore form an elaborate patient monitoring system that gathers information and relies on cloud computing as well as artificial intelligence to support real-time analytics and prediction capabilities.

Such systems reduce the burden on healthcare facilities by minimizing hospital readmissions, optimizing resource utilization, and empowering patients to manage their health more effectively. Moreover, the scalability and versatility of IoT-enabled systems make them ideal for addressing healthcare challenges in remote and underserved areas, particularly in developing countries [4]. This research has been motivated by the imperative to create solutions that are efficient, cost-effective, and scalable for the improvement of healthcare outcomes. By solving challenges in data privacy, interoperability, and accessibility, this study hopes to contribute to the continued transformation of healthcare systems. The proposed IoT-enabled patient monitoring system utilizes wearable health technology to provide timely medical insights, enhance patient care, and support healthcare providers in delivering data-driven and personalized care solutions [5].

Opportunities for AI in Patient Monitoring

Artificial intelligence is the transformative force in healthcare, and it offers unparalleled opportunities to enhance patient monitoring systems. Healthcare providers can unlock the full potential of real-time data collection and analysis by integrating AI with IoT-enabled devices and wearable health technology. AI-powered algorithms process enormous amounts of data generated by wearable

IoT and Deep Learning for Smart Health and Driver Safety

Pranay Prasada¹ and Upinder Kaur^{1,*}

¹ School of Computer Science and Engineering, Lovely Professional University, Phagwara, Punjab, India

Abstract: The detection of driver drowsiness represents an essential area of inquiry with the goal of enhancing public safety by lessening fatigue-related fatalities. Important advances in both the precision and efficacy of tiredness indicators stemmed from novel advances in the discipline of deep computing. Highlighting academic publications published in the last two years, this review dives extensively into the most recent discoveries in the field. In addition to existing designs such as transformers, this research analyzes new approaches, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and mixed frameworks. Basic factors, such as projected ideas, feedback, preparatory tactics, and sample application, are fully investigated. Barriers related to details shortage, swift integration, and computer proficiency are brought up alongside possible fixes pointed out by the most recent findings. With the incorporation of outcomes from numerous analyses, this one check intriguing trends, exposes gaps in methods currently in use, and sets forth tools for increased study to develop reliable and configurable fatigue detection systems.

Keywords: Convolutional Neural Networks (CNNs), Driver Drowsiness Detection (DDD), Deep Learning (DL), Fatigue detection, Recurrent Neural Networks (RNNs), Transformers.

INTRODUCTION

The need to increase road safety and decrease drowsiness-related accidents has made identifying driver weariness a crucial area of research. Statistics illustrate that distracted drivers contribute substantially to road collisions, resulting in fatal injuries and deaths. This stresses the urgency for the development of credible devices to aid in sleepiness detection, in turn helping to mitigate such occurrences [1].

* Corresponding author Upinder Kaur: School of Computer Science and Engineering, Lovely Professional University, Phagwara, Punjab, India; E-mail: upinderkaur45@gmail.com

In recent times, deep machine learning has been recognized as an essential resource throughout numerous fields, particularly in computer vision and the interpretation of time-series data [2]. Its capacity to identify intricate links and trends in data is especially crucial for tackling the issues linked to detecting driver drowsiness. In frameworks renowned for their preciseness and potency, tactics using Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and recently introduced innovations such as transformers have generated exceptional results [3].

Focusing on documents released over the last two years, the present research explores the most current work concerning driver drowsiness detection utilizing deep learning. It investigates crucial methods like ingenious model layouts, pre-processing means, and the use of numerous datasets. Meanwhile, this article solves perennial problems such as inadequate accessibility of data with labels, high computing demands, and the practical deployment of real-time systems [4].

Through a close look at these modernized breakthroughs, this writing brings a detailed overview of the region's existing reality. It draws attention to deficiencies in current practices, defines fresh designs, and suggests various possibilities for future research to build more reliable and capable of scaling technologies. By sharing these insights, this study hopes to support the development of technology that improves road safety and reduces the risks related to sleepy driving [5].

BACKGROUND & RELATED WORKS

In an effort to further enhance the safety of drivers, the newest developments in driver fatigue recognition have proven notable advances, working with several types of strategies that encompass vision-based, physiological, and multimodal systems.

Vision-Based Approaches

This field is ruled by vision-based measures that study face traits such as head posture, yawning, and eye closure. Karakan [1] introduced a real-time deep learning framework using YOLO architectures, with YOLOv8 achieving 98.15% accuracy by analyzing ocular and oral movements. Jarndal *et al.* [3] proposed a non-invasive system using Vision Transformers (ViT), achieving 98.89% and 99.4% accuracy on the NTHU-DDD and UTA-RLDD datasets, respectively; Essel and colleagues [4] presented a methodology using the Dlib framework for the assessment of Eye Closure (ECR) and oral movements (MAR), achieving an accuracy rate of 98.2%. In a parallel endeavor, Alahrash *et al.* [5] designed a dual-camera configuration that combines Haar Cascade classifiers with YOLOv5 for the simultaneous detection of objects and drowsiness in real time [6].

CNNs and LSTMs, representing deep learning techniques, have seen widespread use. Makhmudov *et al.* [7] utilized CNN-based facial expression analysis, achieving 96.54% accuracy, while Soman *et al.* [8] proposed a CNN-LSTM architecture with 95% precision and 99% AUC using metrics like EAR, PUC, MAR, and MOE. Venkateswarlu and colleagues [9, 10] introduced DrowsyDetectNet, a basic convolutional neural network utilizing 68 facial landmark points and achieving an impressive accuracy of 99.23%. Conversely, Ramzan *et al.* [11] developed a hybrid architecture that integrates CNN, Histogram of Oriented Gradients (HOG), and Principal Component Analysis (PCA), achieving an impressive 99.6% accuracy on the YawDD dataset.

It has also been investigated how mobile applications and transfer learning might work together [12]. With an accuracy of 90–99.86%, Salem *et al.* [13] combined CNN and transfer learning into a smartphone application. Using the NTHU-DDD dataset, Yusuf *et al.* [14] achieved 97.3% accuracy in multidimensional facial cue analysis by combining CNN and LSTM [15]. While Jebraily *et al.* [16] optimized a CNN framework using a genetic algorithm, obtaining 99.8% accuracy, Madni *et al.* [15] used VGG-16 and LightGBM for visual motion evaluation, attaining 99% accuracy.

Recent studies have also focused on real-time monitoring and wearable technology. Using ECR, MOR, and deep transfer learning, Turki *et al.* [17 - 20] suggested systems that used VGG19 and ResNet50 to achieve 96–98% accuracy [21 - 23]. A wearable glass prototype [24 - 26] with a simplified CNN was shown by Li *et al.* [27], who showed excellent blink detection performance [28]. Additionally, Vijaypriya *et al.* [24] proposed an MCNN-FSA framework [29], achieving 98.38% accuracy on the YAWDD dataset, and Jahan *et al.* [30] constructed a 4D CNN model, achieving 97.53% accuracy on the MRL Eye dataset [31].

Physiological Approaches

To identify weariness, physiological approaches rely on measuring physiological indicators such as heart rate variability, electroencephalograms, and galvanic skin reactions [32]. While highly accurate, these approaches are often intrusive, requiring sensors to be attached to the driver's body. Recent advancements aim to minimize invasiveness, such as using wearable devices or contactless sensors, but these methods remain less common due to practicality and comfort concerns compared to vision-based systems [33].

Abdubrani *et al.* [2] introduced a hybrid deep learning architecture integrating a deep belief network with a recurrent neural network, achieving 99.98% accuracy and 100% sensitivity in detecting driver fatigue from EEG signals [34]. Amidei *et*

Blockchain for Secure Health Data Management, Decentralized Patient Records, Tamper-Proof Data Storage

Abhilasha Khandelwal^{1,*}

¹ Department of Computer Science and Engineering, Poornima University, Jaipur, Rajasthan, India

Abstract: In today's healthcare environment, data breaches and their management are important issues due to the proliferation of electronic medical records and the need for a good relationship between doctors. This section explores how blockchain technology can solve all these challenges through blockchain principle as decentralized structure, transparency, and immutability. Any manipulation of information will be done by a private network-based distributed consensus mechanism, which leads to the best solution of a centralized Authority. Blockchain is considered a solution to current challenges in patient information management, such as information silos, interoperability issues, and information security issues, and presents blockchain issues such as data sharing, patient management, and expanding data sharing through smart contracts. Furthermore, this study demonstrates the potential for real-time implementation of blockchain in the health care industry through electronic health records, better management of medication and supplies, which is essential for practical use in daily activities. The results indicate a substantial improvement in healthcare through enhance scalability, privacy, and transparency, and explore the future of Artificial Intelligence (AI) and the Internet of Things (IoT).

Keywords: Blockchain, Consensus mechanism, Electronic health record, Silos.

INTRODUCTION

The healthcare sector is undergoing a digital uprising, driven by the increasing complexity of medical systems and the growing need for secure [1], interoperable, and patient-centric solutions. Traditional approaches to health information management, however, are struggling to address the multifaceted trials of data discretion, integrity, and accessibility. Blockchain technology proposes a promising solution [1], providing a distributed, cryptographically [2] secure, and

* Corresponding author Abhilasha Khandelwal: Department of Computer Science and Engineering, Poornima University, Jaipur, Rajasthan, India; E-mail: abhilasha.khandelwal@poornima.edu.in

immutable ledger that can revolutionize how healthcare organizations manage and share patient information.

By leveraging blockchain's inherent strengths of distributed consensus, cryptographic security, and transparent yet privacy-preserving [3] mechanisms, healthcare systems can transition from siloed, fragmented information repositories to dynamic, patient-empowered platforms that prioritize data sovereignty, clinical precision, and seamless information exchange. In this chapter, the authors will deliberate on the competitive opposition of blockchain in the field [4] of healthcare by passing through its architecture principles, implementation policies, and real-life applications. In the coming chapters, digitalized patient records will address critical issues regarding data partitioning, challenges with interoperability, the privacy of the patient, and complicated frameworks regarding sharing medical data and managing consent [5].

The integration of blockchain in healthcare offers additional advantages involving decentralized patient records, immutable data storage, and improved safeguarding. It is instrumental in putting an end to data silos and the assurance of the integrity and veracity of medical [6] records, by providing patients the capacity to manipulate their health information and instilling confidence within the mediators. Through blockchain technology, its functionalities, its real use cases in health records, Dosage management, and supply chain are explained. Finally, the chapter re-emphasizes the challenges and considerations involved in its implementations in healthcare settings, going further by touching on the future directions of blockchain, especially its melding with IoT [7] and machine learning to create one large, holistic model of connected healthcare delivery systems.

THE BASICS OF BLOCKCHAIN TECHNOLOGY

Put simply, the groundbreaking technology of blockchains creates a digital ledger in which every transaction is recorded and verified through a decentralized, secure, and immutable means. It functions as a distributed database maintained by a web of lumps, someplace respectively transaction is cryptographically secured and grouped into blocks. These blocks [8] are chained together in chronological order, giving rise to the term "blockchain."

The blockchain technology is basically a distributed ledger technology in which blocks are continuously expanded, linked together, and secured using cryptographic principles.

Some of the general features of blockchain technology that provide it an edge over traditional systems are:

Decentralization

Instead of having one authority control the data like in classic centralized systems, blockchain shares the control among many participants (nodes). The architectural decentralization helps to:

Elimination of centralized authorities [9] reduces single points of failure. Ensures distribution of data among multiple nodes, adding reliability and access.

- No single point of failure.
- Data breaches reduction.
- Resilient Action for illegal changes.
- Distributed trust mechanisms.

Transparency and Immutability

Blockchain answers the challenge of finding an equilibrium between transparency and secrecy. All transactions scheduled on a blockchain are observable to all official contributors, thus keeping transparency.

Moreover, once a transaction enters the blockchain as a record, it cannot be changed or deleted, guaranteeing the truth of the information [10] and protection from fraud or tampering. Every transaction or data entry is:

- Recorded in a chronological, permanent ledger.
- Cryptographically sealed and linked to previous entries.
- Visible to authorized network participants.
- Impossible to alter retroactively without consensus.

Security through Consensus

Whereas all required transactions are visible to network participants, advanced cryptographic techniques like zero-knowledge proofs allow the sensitive information contained therein to fade into the background. Transactions are sealed and open to all lemon-likes on a PoW basis or on a PoS basis. This assurance ensures that only legitimate transactions are always added to the chain, thereby making the blockchain system extremely resilient to [11] cyberattacks and unsanctioned fluctuations. Advanced consensus mechanisms are utilized to secure blockchain:

- Cryptographic validation of each transaction.
- Distributed agreement protocols.
- Multi-step verification processes.
- Elimination of single-point manipulation risks.

CHAPTER 7

Predictive Analytics for Personalized Medicine

Kriti Sankhla^{1,*} and Deepali Chaudhary¹

¹ *Department of Computer Science and Engineering, Poornima University, Jaipur, India*

Abstract: Predictive analytics is changing the face of personalized medicine: using data to differentiate medical treatment from one patient to the next. This chapter provides a wide-ranging overview of the basic and advanced approaches that make predictive analytics such a strong player in personal medicine. We look at the cross-intersection of many sources of data, including genetic, electronic health record, and mobile sensor data, to generate an overarching patient profile. This also refers to the use of artificial intelligence with learning algorithms for identifying trends, predicting illnesses, and improving the treatment.

The application of predictive analytics in clinical practice has shown that it improves patient outcomes and the better use of healthcare. Several case studies are added to reflect on the ethical issues, including bias, data privacy, and comprehensibility of models. These are the primary ways in which the appropriate application of predictive analytics in the health industry will be ensured.

It ends with a discussion about prospects and challenges-the game-changing possibility of predictive analytics in making personalized medicine a reality.

The chapter pries into the current state and future directions, thereby offering a complete understanding of how predictive analytics can revolutionize the healthcare sector and equip it with the tailored treatment solutions that not only ameliorate patient care but also aid operational efficiency.

Keywords: Algorithmic bias, Data privacy, Electronic Health Records (EHRs), Genomic data, Mobile sensor data, Predictive analytics.

INTRODUCTION

Overview of Predictive Analytics

Predictive analytics has become highly prominent in the medical world and can change medical decision-making and personalized therapy.

* **Corresponding author Kriti Sankhla:** Department of Computer Science and Engineering, Poornima University, Jaipur, India; E-mail: kriti.sankhla@gmail.com

Predictive analytics is an application of statistical techniques, machine learning algorithms, and data mining in identifying patterns within current and past data events for the purpose of making predictions about future occurrences. Predictive analytics is a healthcare approach that predicts the development of disease, a patient's response to therapy, and patient outcomes through large datasets. Examples of these databases include EHRs, wearable technology, and genetic data. Using the provided projections would enable the medical staff to make appropriate use of the resources by providing the patients with more effective performance through tailored and proactive care.

Preprocessing is the initial phase of the predictive analytics procedure, which involves cleaning, transforming, and standardizing the healthcare data. Once prepared, many machine-learning algorithms are applied to the data set, including neural networks, decision trees, and support vector machines, to identify patterns. These models are then tested and validated to ensure correctness and are implemented within clinical systems for real-time decision support. Healthcare currently generates vast amounts of data, and due to this fact, predictive analytics is finally recognized as the vital tool needed in this new world of medicine, thereby underpinning more accurate, data-driven decision-making.

Importance of Personalized Medicine

Personalized medicine, also known as precision medicine, is the sub-branch of medicine that deals with planning and making specific treatments tailored to individual patients. The approach is slightly different from what general “one-size-fits-all” approaches to therapy since it considers the genetic makeup and lifestyle of the patient together with his or her medical history and environmental setting. Personalized medicine is considered vital in clinical practice because it reduces trial-and-error prescribing, improves patient outcomes, and delivers more effective medications with fewer side effects.

Tailored medicine using predictive analytics allows a deep understanding of the patient groups. For example, predictive models can identify which patients would not respond well to a particular treatment and those at high risk, therefore, better treated with aggressive measures. Genomic data is very important in the actualization of personalized treatment plans. Depending on his genetic makeup, it enables his doctor to prescribe him a medication that is more appropriate for him, through pharmacogenomics, which is the study of how one's genes affect a response to drugs. Personalized medicine does not just stop at pharmacology. It also reaches as far as preventing diseases. This is because predictive models can calculate how likely a person is to develop certain conditions, and thus help in early intervention and possible changes in lifestyle to reduce the risk.

Role of Predictive Analytics

Predictive analytics would be pivotal in deriving the benefits of personalized medicine because, for instance, it integrates data sources to form a comprehensive profile of the patient. This will include increasing genomic and Electronic Health Record (EHR) data and mobile sensor data. As the technologies of machine learning and AI continue to improve, increasingly more accurate disease progression, treatment effects, and overall health trajectories can be precisely predicted and stratified. Important information for aid in their treatment decisions would be derived from algorithms for predictive analytics that process and analyze streams of many real-time data sources.

For instance, AI-based models have been employed in the forecasting of the onset of diseases such as diabetes, cardiovascular diseases, and cancers, often before clinical symptoms appear. Predictive models by detecting patterns and anomalies in patient data signal high-risk individuals who could require early interventions that could make a huge difference. Predictive analytics also improve treatment planning by providing personalization through the prediction of which treatments are more likely to succeed with every patient. Predictive models, according to the studies of Goldstein *et al.* (2020), would have been able to accurately predict chemotherapy response in patients with cancer and, thus, inform and guide changes in the treatment plans to minimize side effects and maximize effectiveness.

Objectives and Scope of the Chapter

The objective of this chapter is to give a comprehensive overview of the change that predictive analytics is bringing within the scope of personalized medicine, further enhancing patient outcomes, therapeutic efficacy, and diagnostic efficiency. It covers some fundamental topics such as preprocessing and data gathering, which are elementary steps in establishing valid prediction models. We will also deal with advanced AI and machine learning techniques that make it possible to incorporate diverse data, such as from wearable sensors and genomic data, into prediction models.

This chapter provides several case studies of the applications of predictive analytics across a variety of clinical mental health settings, cardiovascular disease management, oncology, and many others. Such examples reveal how predictive models have been used to optimize patient outcomes and improve delivery. The ethical and legal issues of predictive analytics will be discussed, including openness, algorithmic bias, and data protection. Ethics associated with predictive analytics in applications can determine patient confidence and offer equity for healthcare services.

CHAPTER 8

Edge Computing in Healthcare: Legal Implications of Real-time Data Processing and Security

Shashwata Sahu^{1,*}, Navonita Mallick¹ and Ramesh Chandra Sethi¹

¹ Kalinga Institute of Industrial Technology (KIIT), Deemed to be University, Bhubaneswar-751024, India

Abstract: Edge computing enhances healthcare delivery by facilitating low-latency data processing and real-time exchange at the network periphery. However, it raises important legal and technical issues related to data protection and privacy. The objectives of this study are the following: (1) to analyze current legal regulations regarding healthcare edge computing, (2) to examine issues related to data security and privacy, and (3) to offer insights for improving the existing legal framework. Using a doctrinal research approach, this study examines legal texts, case laws, and regulatory frameworks to investigate the legal challenges presented by edge computing in healthcare. The study finds that legal frameworks often lag behind technological advancements. Therefore, updated regulations are necessary to address the new legal complexities introduced by edge computing today.

Keywords: Data privacy, Data security, Edge computing, Healthcare, Legal frameworks.

INTRODUCTION

“Technology is a useful servant but a dangerous master.”

-Christian Lous Lange

Over the years, with growing technology trends, the healthcare sector has also embraced technological advancements to improve and provide quality care efficiently. One example of these innovations is edge computing, where data is processed in a more distributed manner at its source or ‘edge’ instead of with centralized cloud systems [1]. The ever-increasing popularity of this technology in healthcare can be attributed to its speed in processing data, which allows users to get instant results. The influence has been proven decisive for predictive models

* **Corresponding author Shashwata Sahu:** Kalinga Institute of Industrial Technology (KIIT), Deemed to be University, Bhubaneswar-751024, India; Email: contactshashwata@gmail.com

necessary for medical decision-making and patient-facing health [2]. Edge computing has reduced latency and improved speed for wearable health devices and smart medical equipment, which can be a lifesaver in an emergency to react to data sooner. But along with this technology is the myriad of legal and regulatory challenges that come with increased adoption, especially concerns about data security and patient privacy.

This analysis is important as it breaks down legal liabilities in edge computing of healthcare, which holds particular importance today when data security and privacy become a concern more than ever. Edge computing has immense advantages. However, it is more vulnerable to data privacy breaches and cyberattacks because of its decentralized setup, a major challenge in healthcare where patient confidentiality is mandatory [3]. By laying out the failures in existing legal frameworks and suggesting actionable alternatives, this paper seeks to help inform future discussions on how to regulate new technologies that preserve the security of patient data. In a rapidly changing healthcare environment where the delivery of healthcare is increasingly dependent on technology, it is essential to recognize the legal ramifications surrounding such innovations.

RESEARCH OBJECTIVES

This paper focuses on the legal considerations surrounding edge computing in healthcare, with particular emphasis on real-time processing and security of data. The first step is to explore the current legislation governing the use of edge for healthcare, relevant at a national and international level. The second aim is to investigate the most significant issues related to security and privacy as vital issues when dealing with private patient data in decentralized systems. Finally, we envision the study to offer practical recommendations informing policy that seeks to fill these gaps so that the existing legal frameworks remain sound and flexible, given the rapid innovations of edge computing tech. Through these objectives, the research aims to provide a safer and legally compliant integration of edge computing in healthcare systems for better protection of patients and healthcare providers.

RESEARCH METHODOLOGY

This paper follows a doctrinal research methodology based on the examination of legal documents such as laws and regulations, case law, and other regulatory material in relation to edge computing in healthcare. This review process combined exhaustive reviews of scientific journals, regulatory texts in national and international healthcare frameworks, and important law cases in the fields to fill gaps in the existing legal context. The key regulations include HIPAA in the U.S. and GDPR in the EU; this study addresses a national and global audience.

With the help of this method, we can explore and analyse the legal barriers confronted by healthcare systems using Edge Computing technology.

EDGE COMPUTING IN HEALTHCARE

Edge computing is a distributed platform that moves computing, which forms the edge of the network, closer to the source of data. Networks are moving beyond Data centre networking, and hence, not many are familiar with it. Edge computing avoids the standard cloud mode of sending data to centralised data centres for processing by way of computations occurring in proximity to the place where it is needed [3]. Thus, this configuration is very cost-effective as it decreases the necessity of sending enormous amounts of data to remote servers and improves real-time data processing performance, which ultimately reduces latency (Fig. 1).

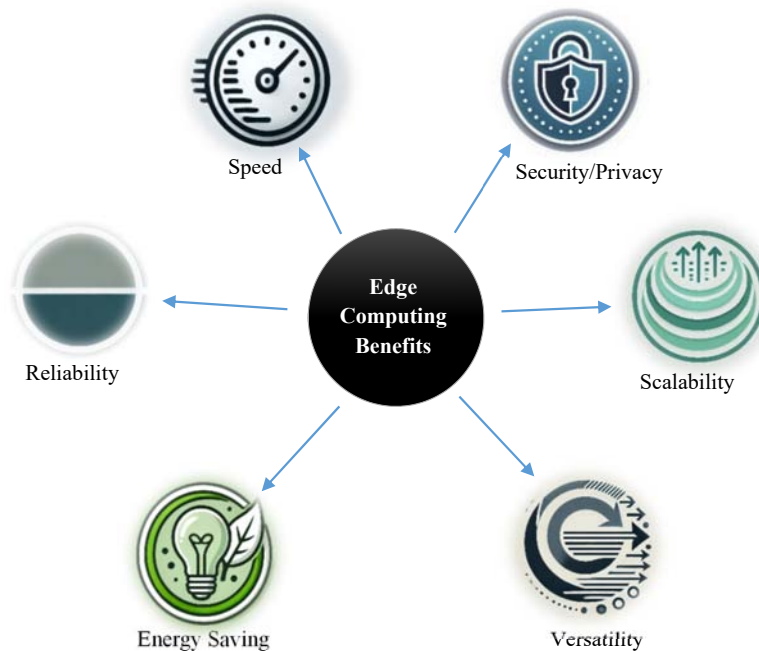


Fig. (1). Key benefits of edge computing in healthcare.

The above image shows the most important attributes of edge computing in healthcare, such as fast, scalable, secure, and privacy compliance, reliability in any network environment all around the globe, flexibility, and energy efficiency. That leads to benefits referred to as responsiveness of health systems, where data can be processed and analysed in real-time at the place it is generated. The adoption of wearable devices, IoT systems, and real-time health monitoring in

CHAPTER 9

Artificial Neural Network Application and Input Impact Using TiAlN Cutting Tool on Ti6Al4V Microwire-EDM Employing PVD Process for Medical Devices

Vivek John^{1,*} and Vinny John²

¹ *Department of Mechanical Engineering, Uttarakhand Institute of Technology, Uttarakhand University, Dehradun, Uttarakhand, India*

² *Department of Agriculture, Mangalayatan University Dehradun, Jabalpur, Madhya Pradesh, India*

Abstract: The growing demand for advanced materials with enhanced properties is driving material scientists to explore different variations of these materials. Biomaterials, which fall under the category of life-saving advanced materials, present a unique challenge in terms of shaping them according to specific requirements because of their distinctive mechanical properties. The Ti6Al4V is widely recognized due to its excellent mechanical suitability for human anatomy. Unconventional methods of milling are becoming popular, especially for their precision and accuracy, regardless of the type, shape, or hardness of the material being machined. One such method is Electrical Discharge Machining (EDM), which includes wire EDM (WEDM) and μ -WEDM, and has become the most commonly used efficient method for material removal. μ -WEDM, in particular, offers the advantage of removing excess material to achieve complex and intricate shapes, as well as a substantial reduction in roughness and finishing. In this work, we used μ -WEDM to examine the effects of multiple factors on the machined section (SR) reliability: voltage (SV), Wire Feed Rate (WFR), Wire Tension (WT), time (to), pulse-on (Ton), pulse-off (Toff), and Peak Current (PC). We coated the metal surface with an aluminium nitride (TiAlN) layer using Physical Vapour Deposition (PVD). The outcomes show a notable decrease in texture on the mechanically treated surfaces, supporting μ -WEDM's biological compatibility with human bodily tissues.

Keywords: Artificial neural network, Biomedical, Medical Devices, PVD process, μ -WEDM.

* **Corresponding author Vivek John:** Department of Mechanical Engineering, Uttarakhand Institute of Technology, Uttarakhand University, Dehradun, Uttarakhand, India; Email: vincentvivek09@gmail.com

INTRODUCTION

Titanium (Ti) is one of the most globally used metals known for its exceptional strength at high temperatures and its low weight. These characteristics make titanium a highly desirable alloy and essential in modern industries [1]. The titanium alloy is extensively employed in the aerospace industry due to its lightweight and its physico-mechanical properties. Alloys of Titanium are also acknowledged for their exceptional fatigue strength and corrosion resistance [2]. Titanium can function effectively in embedded applications for approximately 20 years in the forms of bars, plates, and rods. Among these alloys, Ti-6Al-4V is a prominent material used as implants for various medical applications. The remarkable corrosion and chemical resistance of titanium is primarily attributed to its stable oxide layer, which extends to depths of 10 nm. Additionally, titanium alloys offer the advantage of being non-ferromagnetic, allowing for the safe use of MRIs and NMRI in patients with various types of titanium implants [3].

Titanium alloys possess various characteristics that create hurdles in machinability and thereby make it challenging to work with. These characteristics consist of extraordinary tensile strength, reduced ductility, an elastic modulus that is 50% lower, and thermal conductivity that is approximately 80% less than that of steel. Known for its compatibility with tissues and bones, resistance to corrosion, strength, versatility, and suitability for bone integration, titanium is nowadays extensively recognized in various biomedical domain applications. It is aimed at various therapeutic applications, including external prostheses, knee and hip replacement surgeries, dental implants, as well as delicate machinery [4]. Additionally, titanium alloys exhibit excellent biomechanical compatibility with tissues and bones. However, the high cost, specific properties, and machinability challenges associated with titanium limit its broader application. The titanium orthopaedic implant is illustrated in Fig. (1).



Fig. (1). Orthopaedic hip joint Ti6Al4V-based implant.

It is extremely thought-provoking for researchers to machine titanium alloy materials, as this process generates significant heat and leads to increased wear in the cutting region. To address this issue, non-traditional techniques of machining, frequently referred to as advanced machining approaches, have been introduced. Because of its lower elastic modulus, the workpiece may deflect more and "spring back" more. Therefore, stiffer setups and larger tool clearances are needed. Such procedures are thought to be better suited for Electric Discharge Machining (EDM), which gives users the ability to adjust the distance between the workpiece and tool [5].

Since titanium and its alloys are well-known for their poor thermal properties, they are categorized as hard-to-machine materials. Any electrically conductive substance, regardless of its hardness, can be eroded by the thermal erosion process known as EDM. Consequently, the EDM process is a viable and economical way to manufacture titanium alloys. In contrast to traditional mechanical machining methods, which use shear forces to remove material from the workpiece, thus generating excessive heat gradients associated with the process, EDM produces a metastable martensitic microstructure. This results in components having enhanced tensile strength with limited flexibility [6].

Adequate cooling gap followed by flushing is critical for enhancing the electrical discharge machining of Ti6Al4V [7]. Inner flushing is one instance of a conventional flushing technique utilized in EDM. Most EDM processes, like micro and macro EDM, benefit from side flushing. Wire-EDM is more efficient for machining such materials and is broadly used to manufacture complex geometries [8]. Titanium, known for its poor thermal conductivity, presents challenges in machining due to its limited machinability, resulting in significant tool wear and increased machining costs. Substantial improvements in wear resistance have been observed through the use of TiAlN coatings applied *via* the Physical Vapor Deposition (PVD) process, as indicated by X-ray diffraction and optical microscopic investigations [9]. Enhancing the surface features of implants is imperative, and various techniques have been developed for coating these materials, including PVD [10]. The important qualities of materials for biomedical applications include biocompatibility, mechanical behaviour, corrosion resistance, processability, and availability [11]. Ti-6Al-4V not only exhibits superior biological and mechanical properties but also boasts excellent resistance to corrosion. Alloys of titanium outperform other metallic materials, like steels, alloys of Chromium-Cobalt, Commercially Pure (CP) Nb, and CP Ta, making titanium the most suitable metal for medical applications [12]. However, titanium's tribological behaviour limits its use in applications requiring high wear resistance or hard tissue replacement. To address these limitations, titanium alloys

Regulatory Compliance for AI-Powered IoT in Telemedicine and Remote Monitoring

Rohit Rana¹, Raj Kumar², Konda Hari Krishna³, Kawerinder Singh Sidhu^{3,*}, Mayur Bhoyar⁴ and Sanjeev Kumar Angadi⁵

¹ School of Education & Humanities, Jigyasa University, Dehradun, Uttarakhand, India

² Dept. of CSE, School of Computing, Mohan Babu University, Tirupati, Andhra Pradesh, India

³ Uttaranchal Institute of Management, Uttaranchal University, Dehradun, Uttarakhand, India

⁴ PCET'S & NMVPM'S Nutan College of Engineering and Research, Talegaon Dabhade, Maharashtra, India

⁵ Computer Science & Engineering, IMS Engineering College, Ghaziabad, Uttar Pradesh, India

Abstract: Utilizing telehealth and augmented intelligence is an exciting way to bridge the Healthcare Gap in Rural communities, where the main hurdles are medical infrastructure and distance. This study investigated the degree to which telemedicine and smart technology could collaborate to reduce rural healthcare inequities. AI-powered chatbots have made telemedicine a practical solution to the challenges of traditional healthcare delivery, enabling effective, easily-accessible, and personalized treatment, wherever patients are based. Predictive analysis with the usage of automation in telemedicine completes the healthcare improvement for the future. By offering sophisticated diagnostic tools, forecasting, and tailored treatment recommendations, Smart technology expands the potential of telemedicine. Chatbot agent enhances patient interaction, raises health literacy, and eventually improves healthcare results.

Forecasting systems can provide the most up-to-date medical information and best practices to doctors and nurses in remote places by providing clinical standards and tailored educational materials. Due to technological advancements and the demand for better accessibility to healthcare, the healthcare sector has seen a paradigm change in recent years towards digitization and remote treatment. Due to technological advancements and the demand for better accessibility to healthcare, the healthcare sector has seen a paradigm change in recent years toward digitalization and virtual treatment. Predictive systems can provide the most up-to-date medical information and best practices to medical providers in remote places by offering clinical standards and tailored educational materials.

* Corresponding author **Kawerinder Singh Sidhu:** Uttaranchal Institute of Management, Uttaranchal University, Dehradun, Uttarakhand, India; E-mail: kssidhu0410@gmail.com

Bots known as chat assess patient symptoms, provide a preliminary diagnosis, and recommend the most appropriate courses of action using sophisticated algorithms. This reduces unnecessary medical visits, maximizes resource allocation, and enables immediate intervention. Remote monitoring capabilities significantly enhance telemedicine services.

Keywords: AI-powered chatbots, Patient empowerment Initiatives, Remote surveillance, Telemedicine.

INTRODUCTION

A paradigm change in services related to health and wellness has been brought about by the confluence of data-driven systems and medical management, most notably with the advent of e-health services [1]. The overwhelming majority of healthcare options in India are either located in urban areas with a large number of clinical centers or are almost out of reach for people from the countryside due to the lack of medical specialists in the nation, which has a population of over 1.4 billion. Telehealth and intelligent systems have a lot of potential to remove these barriers and improve healthcare delivery in underserved areas [2]. Access to healthcare in rural areas has long been impeded by factors such as geographic remoteness, a lack of medical specialists, and poor infrastructure. This strategy is especially beneficial in disadvantaged rural areas where patients typically face significant obstacles to receiving timely care, and there are [3] limited alternatives to healthcare. Cognitive computing has proven crucial to the advancement of telemedicine as it has the ability to decipher human speech, analyze enormous amounts of data, and draw conclusions from encounters. We can elevate the standard for healthcare services generally, solve the problems of limited access to care, and enhance analytic capabilities. These virtual assistants use deep [4] network-based predictive algorithms and computational linguistics technologies to deliver information about diseases, treatment options, and preventative actions in a natural-sounding way.

Automated Pattern Recognition Systems can improve patient outcomes and diagnostic accuracy by identifying trends [5] and deviations, projecting the onset of diseases, and recommending the best course of treatment. For instance, conditions such as carcinoma, heart problems, and glucose intolerance in ongoing diseases are helped with prompt detection, enabling better treatment and earlier detection.

Beyond emergency relief, this approach provides comprehensive medical solutions, as well as long-term innovations in remote [6] regions. The future of healthcare delivery and ensuring that even the most remote people receive the care they need depend on how videoconferencing and computers with AI interact as

technology develops. The conversational assistant can set up for a telecommunication- getting together with a real therapist if necessary. After speaking with individuals, this virtual assistant evaluates their mental health and suggests resources [7] or coping mechanisms.

Additionally, telemedicine has grown as a result of the COVID-19 epidemic, suggesting that advancements are needed to support online therapy, can be seen in Fig. (1).

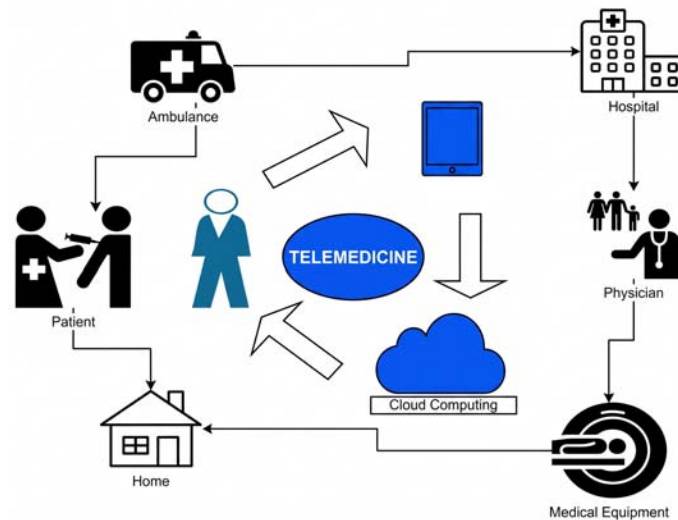


Fig. (1). Telemedicine Bridges the healthcare gap in rural areas.

With a boost in digital incidence, app-based [8] telemedicine is getting more popular; greater numbers of individuals globally may now access digital health records, remotely monitor their progress, and have virtual consultations. The growth of internet healthcare and the development [9] of specialized equipment using machine learning are causing a significant change in the way healthcare is delivered. By enabling doctors to diagnose, treat, and monitor patients remotely, telemedicine—made conceivable by breakthroughs in telecommunications technology—is improving access to care [10].

This has also created opportunities for innovative solutions, such as artificial intelligence-powered healthcare chatbots, to include machine learning into the network for telemedicine in order for better cardiac care. Using historical patient records, the clinic created an algorithm based on machine learning that identified patterns that would point to potential future concerns, such as cardiac difficulties. In addition to increasing [11] diagnostic accuracy, AI's predicting capabilities are

CHAPTER 11

Transforming Healthcare: A Synergistic Framework of Quantum Computing, Machine Learning, and the Internet of Things

Parampreet Kaur^{1,2,*}, Rajeev Sobti¹ and Ved Prakash Mishra²

¹ School of Computer Science and Engineering, Lovely Professional University, Jalandhar, India

² School of Engineering, Architecture and Interior Design, Amity University, Dubai, UAE

Abstract: Quantum computing, due to its capacity to do calculations that surpass the capabilities of classical computers, presents revolutionary solutions for drug development and genome research. By analyzing extensive datasets, Machine Learning improves predictive accuracy, enabling personalized treatment and enhancing clinical decision-making. A critical function of the Internet of Things is to facilitate ongoing patient monitoring using interconnected devices, therefore assuring prompt interventions and effective healthcare delivery. The chapter offers a framework for Quantum Machine learning and IoT for drug discovery in oncology. A detailed comparative analysis of the existing Quantum ML algorithms and practical uses of various technologies in the healthcare field, emphasizing their potential for interplay, has been discussed. Furthermore, it explores the obstacles that these technologies encounter, including data protection, ethical constraints, and technical scalability. In this study, we present comprehensive case studies in the fields of oncology and chronic disease management to illustrate the practical implications of these advancements. This chapter advocates making use of the combined abilities of these technologies to develop a healthcare ecosystem that is more efficient, accurate, and focused on the needs of people. This chapter examines how these cutting-edge technologies can seamlessly work together to solve important healthcare issues like correct disease diagnosis, personalized treatment, and constant patient tracking.

Keywords: AI and quantum synergy, Advanced diagnostics, Internet of Things (IoT) in healthcare, Machine learning in healthcare, Quantum algorithms, Smart healthcare.

INTRODUCTION

Quantum Computing has the amazing capability to disrupt the pharmaceutical industry and the diagnosis of diseases [1]. Machine Learning makes predictions

* Corresponding author Parampreet Kaur: School of Computer Science and Engineering, Lovely Professional University, Jalandhar, India. E-mail: paramnagpal16@gmail.com

from big data, which will assist with the development of better treatments for doctors and patients, as well as aid in diagnosis. The Internet of Things is important in making patient monitoring devices connected so that patient care can be immediately provided when needed [1 - 3]. The chapter describes the uses as well as the benefits of the applied technologies in the health sector. This article outlines how they will help in disease diagnosis accuracy, patient-specific treatment, and constant patient monitoring. It also discusses challenges these technologies face, such as privacy issues, ethics, and technology growth limitations. It stresses that these challenges require a multi-disciplinary approach to solving. The chapter goes beyond the theoretical aspect of these advances by describing detailed case examples in the area of oncology and chronic illness management. The market size of Quantum Computing in the Healthcare Global market is forecasted to be around USD 1,897.5 Million by 2032 from USD 85 million in 2023, with a Compound Annual Growth Rate (CAGR) of 42% within the forecast period from 2023 to 2033 [4]. Healthcare practitioners are able to model complicated molecular interactions at the atomic level through quantum computing. The healthcare industry in particular, avails expansion from this advanced technology to a great extent. This method can also provide very fast DNA sequencing, which creates the prospects for developing the concept of personalized medicine [5]. The creation of new treatments and medicines can be displayed in a more detailed analysis in Fig. (1).

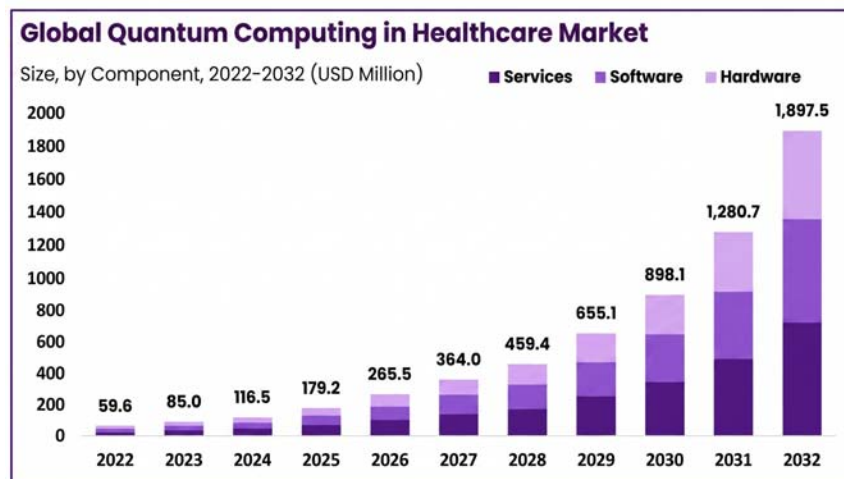


Fig. (1). Global quantum computing in healthcare market from 2022 to 2032 [47].

This technology is based on the principles of quantum and superposition. Just like any normal computer, quantum computers incorporate the use of qubits rather than bits. Quantum computing is yet to scale, but it has the potential for reimaging

industries, from drug discovery and molecular modeling to clinical trial design and medical imaging [6 - 8]. Other domains of application of Quantum machine learning algorithms are in fields such as the treatment of patients, recognizing patterns of patients, and understanding the existing and upcoming health risks and challenges of the populations. Some of the major challenges of understanding and applying quantum computing technology are not only that the technology is still in its developmental stage, but also that quantum computers currently remain very expensive, and there is a relative lack of familiarity with the prospects of quantum computing among biomedical researchers. There is ongoing research on developing a hybrid of current and quantum computing models that will be useful in the healthcare sector [9 - 11].

The intelligence of IoT devices aids in vigilant patient characterization and assists healthcare professionals in modifying therapies and implementing regular interventions [12]. The results of quantum computing algorithms can become a breakthrough in solving critical tasks in healthcare, such as the prognosis of the disease's course, the development of new drug delivery systems, and improving general health [13]. This can improve the efficacy of health care devices to a very large extent. Finally, the chapter stresses the need for interdisciplinary efforts to leverage such technologies to the maximum positive impact on the sphere of healthcare [14]. An effective, accurate, and patient-oriented ecosystem of the healthcare system can be formed with a conglomeration of the QC, ML, and IoT together, which can prove to be a boon in the medical systems. Such a combination has the possibility of helping boost the delivery of healthcare and bring in an exciting new phase of medical breakthroughs [15].

BACKGROUND AND RELATED WORK

Healthcare is one of the most topical and growing areas where concepts of Quantum Computing, Machine Learning, and the Internet of Things are under development. The potential links between these technologies have been explored in the literature, with researchers highlighting the need for interdisciplinary collaboration to overcome the challenges of data privacy [16], ethical considerations, and technical scalability. Studies also show that IoT is the key driver for monitoring an individual's health [17] by having interconnected devices, whereby the need for constant checkups and effective delivery of health care services is facilitated [18, 19]. Sensing in healthcare, ubiquitous connectivity, and cloud structure have evolved greatly in healthcare data capture, analysis, and utilization, resulting in the improvement of proactive and personalized healthcare services provision [20].

CHAPTER 12

Revolutionizing Medical Imaging and Healthcare: The Power of Edge Computing

Akash Saxena¹, Konda Hari Krishna², Mayur Bhojar³, Kawerinder Singh Sidhu^{4,*}, Gowri A.⁵ and Sanjeevkumar Angadi⁶

¹ Department of CSE, Compucom Institute of Technology and Management, Jaipur, India

² Department of CSE, School of Computing, Mohan Babu University, Tirupati, Andhra Pradesh, India

³ Department of CSE, Jagdambha College of Engineering and Technology, Yavatmal, India

⁴ Department of Management, Uttarakhand Institute of Management, Uttarakhand University, Dehradun, Uttarakhand, India

⁵ Department of Information Technology, Hindusthan College of Arts & Science, Coimbatore, India

⁶ Department of CSE, PCET'S & NMVPM'S Nutan College of Engineering and Research, Talegaon Dabhade, Maharashtra, India

Abstract: Medical professionals and radiologists are finding it more and more challenging to evaluate and classify medical images as a result of the rapid advancement of medical imaging equipment over the past ten years. The wealth of knowledge contained in medical photographs greatly aids in diagnosis, planning surgeries, education, and research. Our work aimed to apply neural networks (ML), and advanced learning techniques have been used for healthcare image analysis; MRI evaluation (MRI) is the focus of this study. Convolution Neural Networks (CNNs) and Generative Adversarial Networks (GANs), two types of deep neural networks, have demonstrated exceptional performance in processing massive amounts of imaging data and supporting patient care, diagnosis, and treatment planning.

This paper highlights the potential of DNNs to improve diagnostic accuracy in several organs, such as the brain, lung, and chest, and focuses on their advancements in various imaging tasks, such as categorization, differentiation, authorization, and recognition. All facets of human existence have been impacted by the novel coronavirus illness outbreak, which has taken millions of lives. Additionally, it is evident that the COVID DL approach may obtain the highest classification accuracy when used on a CT image with an equal number of COVID-19 patients, lung tumour patients, and normal individuals. Additionally, we provide examples of how DL approaches could be used in the search for new drugs or vaccines to fight the coronavirus. For this reason, developments like synthetic data acquisition and transfer learning helped to lessen

* Corresponding author Kawerinder Singh Sidhu: Department of Management, Uttarakhand Institute of Management, Uttarakhand University, Dehradun, Uttarakhand, India; E-mail: kssidhu0410@gmail.com

these issues and enhance model performance with sparse data. The report ends with a discussion of upcoming research that focuses on the models' improved interpretability and the integration of pictures and clinical information.

Keywords: COVID-19, Deep learning, Diagnosis technologies, Multimodal imaging.

INTRODUCTION

Since medical imaging offers vital evidence about a patient's state, it is critical for therapy planning. It may find use in the domains of research and education. Businesses, academic institutions, and the general public are among the many sectors that are significantly more captivated by the recent boom of advancements in machine learning. All guidelines have undergone studies, and in an effort to find a solution, Deep Learning (DL) and computational imaging on medical images have been thoroughly examined. Numerous research articles have been written with similar objectives. Since the techniques discussed are drawn from a range of peer-reviewed papers, they help to build a thorough set of recommendations for the intellectual community and even the regulatory bodies entrusted with fighting the pandemic. Recent advancements in DNNs have transformed medical imaging by enabling the analysis of complex and sizable datasets and offering capabilities beyond those of clinical diagnostic aids. DNNs are more accurate and dependable than human radiologists in diagnosing conditions like cancer, heart disease, and neurological disorders, compared to traditional image processing techniques [1]. These systems also exhibit self-renewal properties and can identify complex patterns in medical imaging data. The DNN model helped achieve better registration performance compared to other existing methods. The pandemic of new coronavirus illness (COVID-19) and the following containment measures have generated a worldwide health pandemic touching all aspects of human life.

In the beginning, when just a few people were affected, it did not symbolize attacks of this enormous scope because a significant proportion of cases were settled on their own. Examples of deep learning's applications in the healthcare sector include one-dimensional bio signal analysis, seizure and cardiac arrest prediction, computer-assisted detection and diagnosis to improve clinical decision making, algorithmic modelling, Drug target identification for therapy selection, increased operational efficiency, stratified care delivery, and electronic health record analysis. To successfully integrate DNNs into clinical practice, further scholarly work is necessary to address problems with data availability, model interpretability, and ethical considerations.

Since a sizable percentage of cases were resolved on their own, it did not initially represent attacks of this massive extent when just a small number of people were impacted. Univariate bio signal processing, predictive modelling for seizure and cardiac emergency, computerized disease detection and diagnosis to enhance clinical decision making, algorithmic modelling, drug target identification for therapy selection, improved operational efficiency, stratified care delivery, and electronic health record analysis are a few examples of deep learning's uses in the healthcare industry [2]. Additional research work is required to overcome obstacles in data availability, model ability, and responsible AI practices in order to properly integrate DNNs into clinical practice.

Since the techniques discussed are drawn from a range of peer-reviewed papers, they help to build a thorough set of recommendations for the intellectual and even the regulatory bodies entrusted with fighting the pandemic. Prior research has used supervised data-driven modelling techniques (manually crafted features) to classify and segment brain tumours. These feature-engineering techniques employ the traditional machine learning methodology. Rather, they develop a task-oriented algorithm that learns about the subject by employing a hierarchy of increasingly complex skills. The fact that the pandemic has progressed to the point where contemporary treatment services are overloaded must be acknowledged. Emergency departments and critical care units have become overcrowded to handle the constantly increasing number of patients.

Healthcare providers and patients' support networks are forced to make snap decisions in these circumstances based on scant information. Because DNNs offer particular advantages in terms of pattern identification in medical pictures, they are one of the main ways that AI is being used in medical applications [3]. Using the limited information base and resources at hand, the goal is to prevent such abrupt impairments and diagnosis infection as soon as possible. The conventional nose-throat-swab Reverse Transcription Polymerase Chain Reaction (RT-PCR) test is time-consuming and has low sensitivity. Due to a lack of pertinent mathematical models, researchers are faced with the challenging task of learning physics principles from scratch.

in situations when the underlying assumptions of the model are violated, its goal is to adjust to the data (think noise). More study is needed to make DL successful in managing COVID-19, even though a number of studies have been published regarding its applicability in this context. Now regarded as a state-of-the-art method for medical image analysis, DL has been effectively applied in a number of contexts. One common use of Deep Neural Networks (DNNs) is the analysis of brain pictures. The research claims that DNNs handle the majority of picture analyses.

Integrating Blockchain and Machine Learning for Secure Health Data Management and Advanced Disease Diagnosis in Healthcare

Komil Kumar¹, Konda Hari Krishna², Bharti³, Kawerinder Singh Sidhu^{3,*}, Sanjeevkumar Angadi⁴ and Manoj Kumar Singh⁵

¹ School of Education & Humanities, Jigyasa University, Dehradun, Uttarakhand, India

² Dept. of CSE, School of Computing, Mohan Babu University, Tirupati, Andhra Pradesh, India

³ Uttaranchal Institute of Management, Uttaranchal University, Dehradun, Uttarakhand, India

⁴ PCET'S & NMVPM'S Nutan College of Engineering and Research, Talegaon Dabhade, Maharashtra, India

⁵ Computer Science & Engineering, IMS Engineering College, Ghaziabad, Uttar Pradesh, India

Abstract: This article explains how efforts to forecast the frequency of infectious diseases have significantly increased as a result of the availability of statistical data for analysis. These models increase the accuracy of diagnoses, reduce the likelihood of human error, and facilitate preventative healthcare measures. Large volumes of patient data, including imaging, medical histories, diagnostic results, and lifestyle factors, are analyzed using these algorithms, which include both supervised and unsupervised approaches.

Healthcare practitioners can spot trends and improve their diagnostic and illness risk forecasts by utilizing machine learning models like decision trees, support vector machines, artificial neural networks, and clustering approaches like K-means. Because machine learning is still crucial for preventing disease and developing treatment plans, advances in artificial intelligence are propelling a shift towards data-driven, effective, and patient-focused healthcare systems.

Keywords: Blockchain technology, Clustering, Healthcare analytics, Machine learning, Secure health data management, Support vector machines.

INTRODUCTION

Machine learning has emerged as a revolutionary technique in the healthcare industry, particularly in the fields of diagnostics and disease prediction. By using

* Corresponding author Kawerinder Singh Sidhu: Uttaranchal Institute of Management, Uttaranchal University, Dehradun, Uttarakhand, India; E-mail: kssidhu0410@gmail.com

vast amounts of medical data, Machine Learning (ML) systems are able to recognize patterns, classify diseases, and produce amazingly accurate forecasts regarding health outcomes [1]. Conventional diagnostic techniques frequently depend on human judgment, which is vulnerable to subjectivity and temporal limitations.

Humans today face a variety of challenges due to environmental conditions and personal lifestyle choices. Many people are still ignorant of the fact that these common health issues might result in more serious complications. In order to provide quicker and more accurate diagnoses, machine learning models—such as deep learning, decision trees, support vector machines, and ensemble approaches—analyze complex medical data, including genomic data, medical imaging, and electronic health records. Healthcare practitioners may spot ailments early, optimize treatment methods, and lessen the overall strain on healthcare systems thanks to these predictive algorithms. More effective, data-driven, and individualized healthcare solutions are being made possible by the growing integration of machine learning into medical decision-making.

Medical datasets have been subjected to analysis through machine learning algorithms since their early development. Currently, machine learning provides several critical technologies for insightful data analysis. The digital revolution has facilitated the collection and storage of data in a more accessible and cost-effective way, especially in recent years. Extensive information systems are employed to gather and share data, and contemporary hospitals are equipped with advanced monitoring and data collection instruments. Significant progress has been made in medical diagnostics for niche, specialized issues, and machine learning technology is now highly effective for assessing medical data [2]. Standard diagnostic tests and the knowledge of medical professionals are frequently used in the traditional approach to healthcare diagnosis. Despite their great success, these approaches have drawbacks, such as the subjectivity of diagnosis, the challenge of managing huge datasets, and the inability to identify subtle, early-stage illnesses. By utilizing enormous volumes of patient data, machine learning overcomes these obstacles and offers insights that can enhance the precision of diagnoses, forecast the course of diseases, and support decision-making processes that result in better patient outcomes. In medical imaging, pictures from CT scans, MRIs, and X-rays are analyzed using methods like convolutional neural networks. Important characteristics, including aberrant growths or lesions, that may be suggestive of illnesses like cancer, TB, or brain abnormalities, are automatically extracted from medical images by CNNs. In addition to increasing image analysis speed and accuracy, this method assists radiologists by highlighting potentially troublesome regions in photos, which

lowers human error. Deep learning has enormous potential to increase diagnostic precision, especially in the early stages of illness.

Precise diagnosis information is frequently found in medical records from specialty hospitals or their departments. Patient data, including the accurate diagnosis, must be entered into a software application in order to apply a learning algorithm. In theory, medical diagnostic information can be automatically extracted from case descriptions that have already been resolved, despite the fact that this may appear oversimplified. The resulting classifier can be used to teach students or non-specialist doctors how to diagnose specific medical diseases, or it can assist clinicians in diagnosing new cases, thereby increasing the speed, accuracy, and reliability of diagnoses.

LITERATURE SURVEY

Ahsan and Siddique's (2022) thorough analysis of 1,216 research publications highlighted important works and significant figures in the field of machine learning applications. Furthermore, a 2023 article in *The Open Public Health Journal* examined machine learning's application in clinical analysis, highlighting its use in precise disease identification and image analysis. This study demonstrated how machine learning algorithms improve medical picture interpretation, leading to increased diagnostic precision [3].

Predictive analytics was the subject of a review in 2023 that examined machine learning's use in disease detection. It highlighted current developments in this field and emphasized the crucial role that machine learning prediction models play in the healthcare industry. Additionally, a 2023 paper that examined the current status of AI in clinical practice and talked about its possible uses and effects on healthcare was published in *BMC Medical Education*. According to the paper, improved diagnostic tools and individualized treatment plans are two ways that AI and ML are transforming patient care.

In 2023, Tajidini and Kheiri conducted a thorough investigation designed to identify a number of illnesses, including diabetes, liver disease, dengue fever, heart disease, and hepatitis. The variety of machine learning methods and algorithms used to examine these circumstances, as well as the ensuing decision-making procedures, was highlighted in the evaluation.

Abdollahi *et al.*'s 2021 study investigated healthcare classification algorithms and suggested an ensemble learning approach that uses neural networks and is tailored for chronic diseases. The outcomes showed how effective state-of-the-art machine learning techniques are in treating long-term conditions, with remarkable accuracy in diagnosing conditions like diabetes, cancer, and heart disease [4]. The

Smart Solutions: IoT and Wearable Devices Transforming Patient Health Monitoring

Rupika Nanda^{1,*} and Neha Sah¹

¹ School of Fashion Design, Lovely Professional University, Phagwara, India

Abstract: Over the years, there have been continuous efforts to integrate digital capabilities into clothing. The Internet of Things (IoT) is a network of connected devices that exchange data and communicate with one another to offer more functionality. Wearable technology might provide innovative solutions to problems in the medical industry. Health and illness prevention are the goals of certain wearable technology applications, such as weight management and physical activity tracking. Basically, wearable technology is used to monitor patients' health conditions. With increasing advancements in the IoT sector, wearable devices are becoming more sophisticated as they include features like heart monitoring, emotions, physical activity, temperature, pulse rate, and BP. This study highlights the impact of wearable technology on patient health monitoring and tracking, chronic life-threatening diseases, and real-time monitoring of patients. By facilitating early health issue detection and enabling healthcare providers to give immediate treatment through real-time data collection and analysis, wearables lower the rate of hospital re-admissions. However, it can be challenging for patients and healthcare providers to access, store, integrate, and securely share health records. Patients have the power to send their medical records to healthcare professionals privately, and healthcare professionals can access their information worldwide and maintain the patient's medical background on the basis of the information sent by the patients. In terms of sensor systems, data processing, and artificial intelligence, wearables add therapeutic value as a result of technological advancement. This study is beneficial for researchers, healthcare professionals, and policymakers as it offers a comprehensive overview of wearable technology and its impact on patient health monitoring and research outcomes.

Keywords: Evolution, Health monitoring, Sustainable health care solutions, Internet of Things (IoT), Wearable health technology.

* Corresponding author Rupika Nanda: School of Fashion Design, Lovely Professional University, Phagwara, India; Email: lovirupi999@gmail.com

INTRODUCTION

Health Monitoring is an Essential Part for Patients

In recent years, public health systems have faced growing challenges related to chronic diseases. With rising healthcare costs, increasing health complications, and the threat of infectious diseases such as COVID-19, there is a strong push to adopt remote health monitoring devices, especially for the elderly and individuals with disabilities. Technology plays a critical role in this shift, enabling automation and smarter systems across various sectors, particularly in intelligent and remote healthcare settings [1, 2].

The integration of wearable technology, big data, Artificial Intelligence (AI), and the Internet of Things (IoT) is rapidly transforming the way we live and communicate. However, traditional wearable technologies often fall short in reliably capturing comprehensive health information. As highlighted by Blue Stream Consultancy, “Smart healthcare is defined by the technology that leads to better diagnostic tools, better patient treatment, and devices that improve the quality of life for anyone and everyone” [3].

Among the fastest-growing technological advancements, IoT and wearable technologies are being increasingly used in diverse domains ranging from smart homes and industrial applications to automobiles and, most significantly, healthcare. These innovations make it possible to collect, transmit, and analyze health data in real time, enhancing patient care.

The desire to live longer and healthier lives is becoming more pronounced, especially as global demographics shift. Due to declining birth rates in many regions, the aging population is growing. It is projected that by 2050, there will be approximately 1.6 billion individuals aged 65 and above worldwide. This demographic shift will place immense pressure on healthcare systems, particularly for managing age-related conditions such as strokes, dementia, and heart disease. As a result, wearable health devices are being designed not only for the elderly but also for broader age groups, incorporating tools like actuators, GPS devices, mobile platforms, and a wide range of sensors [4].

IoT facilitates the seamless transmission of health information by connecting medical devices, sensors, and healthcare systems through the internet. This enables healthcare providers to manage chronic conditions more efficiently, monitor patients remotely, and respond promptly to emergencies. By encouraging preventive care, improving operational efficiency, and lowering healthcare costs, IoT integration is redefining how healthcare is delivered [5].

Remote health monitoring is especially beneficial for non-critical patients, allowing them to be observed from the comfort of their homes. This reduces the strain on hospital resources while improving healthcare access for individuals in rural or underserved areas. Wearable technology, in particular, has revolutionized real-time patient monitoring by tracking key health indicators such as heart rate, blood pressure, and respiratory rate.

One of the major advantages of wearable health monitoring is its continuity. These devices can detect early signs of health problems by analyzing changes in vital signs over time. This proactive approach enables timely interventions. Moreover, healthcare professionals can monitor patients remotely and receive real-time updates without being physically present. This is especially useful for individuals recovering from surgery, those with chronic illnesses, or patients requiring continuous support.

Remote health monitoring improves accessibility and enhances patient outcomes. The data generated by wearables supports personalized treatment plans. By analyzing a patient's daily activity and physiological responses, healthcare providers can tailor therapies to suit individual needs. This level of customization leads to more effective management of chronic health conditions and promotes a higher quality of life [6].

This chapter explores the transformative role of wearable technologies and the Internet of Things in healthcare. It delves into the advantages, challenges, and emerging opportunities that these technologies bring, while also reflecting on their potential to shape the future of healthcare delivery.

EVOLUTION AND TECHNOLOGICAL ADVANCEMENTS IN PATIENT MONITORING SYSTEMS

Health is widely recognized as a fundamental human need, defined not merely by the absence of illness, but as a state of complete physical, mental, and social well-being. However, achieving this ideal remains a challenge in many parts of the world. Global healthcare systems continue to face numerous obstacles, including inadequate infrastructure, a severe shortage of medical professionals, and glaring disparities between urban and rural healthcare access [7]. These challenges became even more evident during the COVID-19 pandemic, when already strained systems struggled to cope with surging demands.

In rapidly developing regions, the strain on healthcare systems can hinder economic progress. For example, in China, while rapid expansion has spurred growth in the healthcare sector, the pandemic also exposed vulnerabilities that negatively impacted the economy. In such contexts, remote health monitoring

Technological Innovations in IoT for Healthcare Applications, Medical Imaging, and AI-Driven Predictive Analysis

Priyanka Gupta¹, Ramandeep Sandhu^{1,*} and Harpreet Kaur Channi²

¹ School of Computer Science & Engineering, Lovely Professional University, Phagwara, Punjab, India

² Department of Electrical Engineering, Guru Nanak Dev Engineering College, Ludhiana, Punjab, India

Abstract: Everywhere in the world, the death rate is rising in direct proportion to illness and accidents. Despite everyday advances in technology, there are still many areas where there remains a gap. Lack of proper support and solutions for human society is particularly evident in healthcare units. Significant technological advancements have been made throughout the last few decades and are being used in various sectors of the economy, academia, and healthcare. Advanced examination and diagnosis remain challenging for studies that can benefit medical professionals and the general public. In this chapter, the authors focus on brain tumor detection and classification using deep learning. The proposed work aims to explore the potential of deep learning models, such as namely convolutional neural networks, to improve the accuracy and speed of brain tumor diagnosis. By incorporating deep learning techniques into support systems for clinical decisions and using natural language processing tools, healthcare professionals can obtain valuable data and decision support, ultimately enhancing the quality, efficiency, and availability of healthcare delivery. In this chapter, the proposed methodology will examine feature extraction, data pre-processing, and the detection and categorization of brain tumors using data from training and testing using medical imaging, such as MRI scans, as input.

Keywords: Brain tumor detection, Brain tumor, Classification, Convolutional Neural Network (CNN), Deep learning, Healthcare.

INTRODUCTION

Early diagnosis and accurate classification of brain tumors are enormous challenges for the medical field, and these challenges directly affect patient

* Corresponding author Ramandeep Sandhu: School of Computer Science & Engineering, Lovely Professional University, Phagwara, Punjab, India; Email: ramandeepsandhu887@gmail.com

survival rates and treatment outcomes. Since brain tumors are a broad category of neoplasms with a wide variety of prognoses and treatment approaches, accurately identifying them is essential for efficient medical intervention. Magnetic Resonance Imaging (MRI) and radiologists' expertise are crucial to the traditional techniques of diagnosing and categorizing brain cancers. However, because tumor appearance and stages vary so much, these techniques can be laborious, prone to human error, and have limitations. Modern developments in AI, particularly in Deep Learning (DL) techniques, have automated medical picture processing and improved its accuracy. [1]. A subfield of machine learning called "deep learning" creates hierarchical input representations by layering neural networks. Because of this, it excels at difficult tasks like picture identification and categorization. Brain tumor identification and classification using cutting-edge deep learning techniques has become a groundbreaking method that has the potential to greatly enhance both diagnostic procedures and patient outcomes. This research explores the use of sophisticated deep learning algorithms for brain cancer diagnosis and multi-classification, utilizing the latest developments in neural networks using convolution (CNNs), learning through transfer, and ensemble learning models. Fig. (1), as shown below, represents various stages involved in the detection of brain tumors with ML and DL techniques [2].

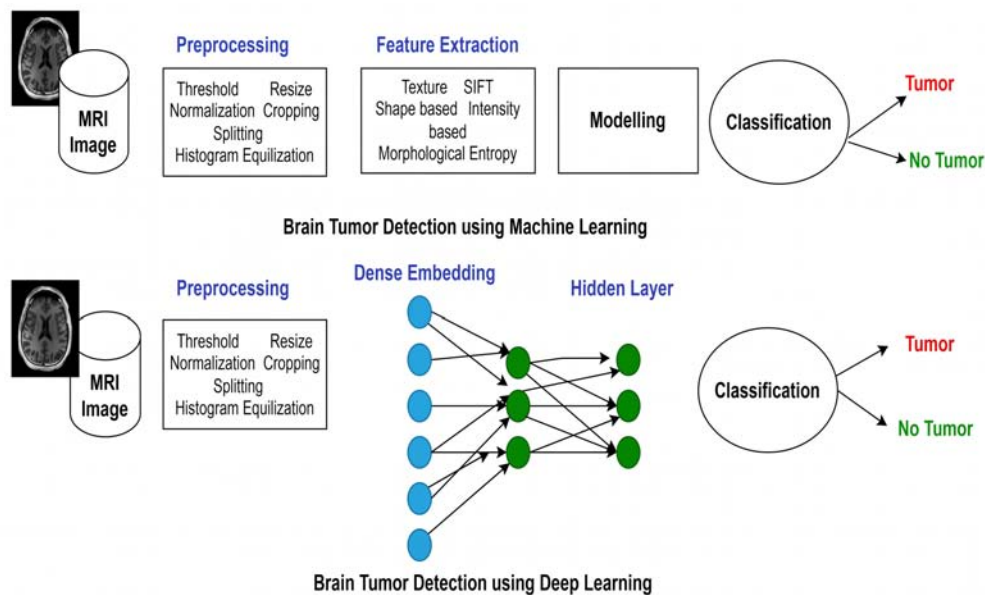


Fig. (1). Distinction in machine learning and deep learning.

In the chapter, the work provides a thorough grasp of the practical implications as well as difficulties in clinical settings of these models, as well as pushing the

boundaries of medical image processing by methodically assessing their performance on brain MRI datasets. Health care platforms that engage patients, resources, and agencies and make medical records conveniently accessible through devices like wearables devices, smartphones, and tablets, as well as the Internet of Things (also known as IoT), are referred to as smart healthcare.

Intelligent medical treatment involves many different stakeholders, such as clinicians, hospitals, research organizations, and workers [3]. The framework is adaptable and addresses a broad range of subjects, such as medical research, patient choice, assessment and evaluation of healthcare administration, and illness detection and prevention. [4]. Artificial Intelligence (AI), Machine Learning (ML) techniques within the framework of deep neural networks (DL), and Wireless Local Area Network (WLAN) technologies have transformed smart health care to guarantee patient and stakeholder satisfaction. [5]. With the advent of 5G technology and above 5G wireless technology, high computation performance, large data volumes, support for numerous terminal units, and other features, these technologies have made it possible for the medical sector to handle multiple healthcare signals from a single user [4, 5].

Brain Tumor Detection

Although many diseases have been conquered in recent years thanks to advancements in biomedicine and human intelligence, cancer continues to affect people because of its unpredictable nature. This illness continues to be a serious concern for humanity. Brain tumor malignancy is among the most life-threatening and urgent illnesses. A separate study of cancer symptoms indicates that the disease is similar in adults and youngsters. [6]. The number of new primary brain tumor cases recorded in 2018 was over 80,000 [3]: Meningiomas accounted for 26.5% (21,200) of the cases, followed by gliomas at 26.3% (29,320) and pituitary tumors at roughly 16.2% (13,210). The remaining instances were lymphomas, malignant, and medulloblastoma brain tumors. The main causes of this type of illness are morbidity and ailments associated with malignancy. The quick and correct identification of this condition is essential for its effective management [7].

A therapy modality's commitment is determined by the tumor's category, pathological type, and stage at the point of inquiry. The brain, which consists of tissues and neural cells that control vital bodily functions, including respiration, sense perception, and muscular function, is the most intricate and important component of the human anatomy. Every cell has certain capabilities [8]. Some of these skills allow the cell to expand properly, while other capabilities cause the cell to cease growing and eventually become abnormal. An amorphous mass of

AI in Drug Discovery: Tailoring Personalized Medicine using Genomic Analysis

Nisha Banerjee^{1,*} and Sreejita Dutta¹

¹ NSHM College of Management and Technology, The Shmunis School of Biomedicine and Cancer Research, Tel Aviv, Israel

Abstract: Just like our fingerprints, we humans are all the same but different, and this difference makes all the difference in all aspects possible. Talking about differences and variation, we can discuss Diseases. Even though we have common diseases, many aspects can be variable, and that is where the problem begins. Due to minuscule differences in our genome makeup, a disease can not only affect differently, but also prognosis, bodily response at the cellular level, or even at the molecular level can also be different. AI algorithms can predict the progression of the disease earlier in the treatment and chances of relapse with greater accuracy, helping doctors to improve patient outcomes. In genomic analysis, convolutional neural networks and recurrent neural networks are deep learning methods, which have proved its performance in genomic sequence analysis and phenotype prediction. Using AI, we can predict what mutation can be self-induced in a pathogen in a pathogenic disease to make it untreatable. After all, every organism is trying to be the fittest in the war of survival, as in the famous Darwinian theory. In the chapter of the following book, we are going to review, revise, analyze, and also foresee the vision that AI can bring to personalized medicine using better genomic analyses and improve the health of the world as a community. This is the part where AI plays an important role to discover full potential of genomic information and enabling personalized healthcare approaches. This chapter also discusses the drawbacks and limitations that will come along as the other side of the coin. Speaking of limitations, this book chapter discusses the ethical considerations and other challenges to be taken care of.

Keywords: Artificial intelligence, Genomic analysis, Healthcare, Machine learning, Precision medicine.

* Corresponding author Nisha Banerjee: NSHM College of Management and Technology, The Shmunis School of Biomedicine and Cancer Research, Tel Aviv, Israel; Email: nishasonali2000@gmail.com

INTRODUCTION

The Critical Role of Drug Discovery in Healthcare

The convergence of Artificial Intelligence (AI) and genomic analysis has propelled the field of Personalized medicine in recent years into new dimensions, with a promising effort to revolutionize healthcare delivery on a global scale by extensively harnessing the power of Machine Learning (ML), deep learning, and other artificial intelligence techniques. Clinicians and researchers can now understand the complex genomic data with unprecedented accuracy and speed. This has helped in unlocking invaluable insight into the mechanisms of the disease, the drug response, and how an individual responds to the Treatment. This chapter mainly explores the different applications of artificial intelligence in genomic analysis and personalized medicine. Further, this chapter highlights genomic data processing and the role of AI algorithms in identifying genetic variations and also predicting the susceptibility of the disease and stratifying the patients based on their molecular profiles. However, there are challenges and limitations when it comes to the actual integration of artificial intelligence and genomics. Ethical considerations such as data privacy concerns, algorithm bias, and the need for robust validation frameworks are a huge scope for future work. Informed consent is required about the actual application of AI in healthcare, and data ownership and equity of access must also be taken care of. This chapter critically analyzes these issues and fosters a deeper understanding of the opportunities and pitfalls associated with AI-powered personalized medicine, and ultimately gives way to responsible innovation and equitable healthcare delivery. The main aim of the paper is to improve patient outcomes and enhance the quality of life for individuals around the globe by exploring case studies and background studies about how AI can help in personalized medicine by studying genomic analysis. Drug discovery is the cornerstone of enhancing human fitness and fighting illnesses. The strength of AI technology to understand state-of-the-art styles and hidden systems has enabled many photo-based detection and diagnostic structures in healthcare to perform as well or better than clinicians, in a few cases. Vaccines, evolved through drug discovery, play an important role in stopping infectious diseases and protecting complete populations. New drugs can be used for preventive measures, together with cholesterol-lowering medicinal drugs that help prevent heart disorders, or antivirals used to prevent the spread of infections. Drug discovery isn't always about locating new medications; it's also about enhancing current ones. In conclusion, drug discovery is a non-stop and vital enterprise in healthcare. It fuels progress in dealing with illnesses, promoting public fitness, and, in the long run, improving the well-being of individuals and societies.

Challenges of Traditional Drug Discovery Methods: Need for AI

Traditional drug discovery methods, even as instrumental in growing many lifestyle-saving medicines, face significant challenges that hinder efficiency and success rates. Here's a breakdown of a few key hurdles. The system from target identity to FDA can take over a decade, with highly related research and improvement changes. Difficulty in correctly modeling human biology in preclinical research, along with the use of animal models, can result in deceptive effects and wasted resources. Traditional strategies for drug layout may be sluggish and rely heavily on intuition and experience. Difficulty in predicting how a drug will have interaction with the complex human frame machine can lead to unexpected outcomes or limited efficacy. Difficulty in figuring out biomarkers to successfully predict which patients will respond best to a particular drug Table 1.

Table 1. Traditional drug discovery vs. AI for drug discovery.

Feature	Traditional Drug Discovery	AI for Drug Discovery
Approach	Trial-and-error, target-based, or serendipitous discovery	Data-driven, analyzes large datasets to identify patterns and potential drug candidates
Speed	Slower, it can take 10-15 years for a new drug to reach the market	Faster, AI can accelerate processes and reduce development time
Cost	Highly expensive, with high failure rates at each stage	Potentially lower cost, reduces the need for extensive physical experimentation
Success Rate	Lower success rate, many potential drugs fail clinical trials	Potentially higher success rate, AI can identify promising candidates with better efficacy predictions
Bias	Reliant on existing knowledge and historical data, it may miss novel solutions.	Can be biased by the data it's trained on, and needs careful data curation.
Explainability	Easier to understand the rationale behind drug selection	Complex models can be difficult to interpret requires explainable AI techniques
Strengths	Well-established methods provide a strong foundation for drug development	Ability to explore vast chemical spaces, identify previously unknown drug candidates
Weaknesses	Time-consuming and expensive, high attrition rate	Reliant on large, high-quality datasets, it requires ongoing development and refinement.

AI excels at analyzing big datasets, figuring out patterns, and making predictions that human researchers might leave out. Clinicians have used genotype information as a guiding principle to help decide the perfect dose of warfarin. The Clinical Pharmacogenetics Implementation Consortium published genotype-based drug guidelines to help clinicians optimize drug therapy with genetic test effects. By combining AI's statistics analysis power with pharmaceutical technology

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Salil Bharany

Dr. Salil Bharany is a proactive assistant professor and researcher with 8+ years of experience in teaching undergraduate and postgraduate courses. His research is focused on wireless sensor networks, energy, IoT, artificial intelligence, cybersecurity, big data analytics, and renewable energy technologies.



Upinder Kaur

Upinder Kaur is an Assistant Professor in the Department of Computer Science and Engineering at Lovely Professional University, Punjab, India. Her research interests include Flying Ad Hoc Networks (FANETs), Unmanned Aerial Vehicle (UAV) communications, wireless and mobile networks, machine learning, deep learning, and intelligent routing protocols. She has published numerous research articles in reputed international journals and conferences. Her current research focuses on the application of artificial intelligence and optimization techniques for next-generation aerial and autonomous networking systems.



Ateeq Ur Rehman

Ateeq Ur Rehman is working as an Assistant Professor at the School of Computing, Gachon University, South Korea. He received his PhD degree from the College of Internet of Things Engineering at Hohai University, China. He received his B.Sc. (Hons.) and M.Sc. degrees, both in Electrical Engineering, from the COMSATS Institute of Information Technology, Lahore, Pakistan, and the Blekinge Institute of Technology, Sweden, in 2009 and 2011, respectively. His Master's thesis was awarded the highest grade according to the ECTS system. He has over 15 years of experience in teaching, research, curriculum development, student advising, and mentoring at both undergraduate and postgraduate levels. His research interests include, but are not limited to, the Internet of Things, social networks, and intelligent systems. He has authored/co-authored more than 200 impact-factor journal papers and many conference papers. So far, he has accumulated more than 5,000 citations, with an h-index of 42 and an i10-index of 124.



Kapil Joshi

Dr. Kapil Joshi is an Associate Professor in the Department of Computer Science & Engineering (CSE) at the Uttaranchal Institute of Technology (UIT), Uttaranchal University, Dehradun, Uttarakhand, India. He completed his Ph.D. in Computer Science & Engineering on the topic "Image Quality Enhancement Using Fusion Techniques" from Uttaranchal University, Dehradun. He has over 10 years of experience spanning industry, academia, and research. His teaching interests include Operating Systems, Database Management Systems, and Machine Learning. His primary research areas encompass Image Processing, Deep Learning, Computer Vision, and Pattern Recognition. Currently, he is pursuing postdoctoral research (remote) at the Singapore Institute of Technology (SIT), Singapore, under international academic supervision, further strengthening his engagement in advanced research and global collaboration. He has published various patents and 500+ research papers in reputed journals (UGC/Scopus), as well as 40+ books with international publishers. Dr. Kapil Joshi has published more than 100 research papers in various international journals.



Keshav Kaushik

Dr. Keshav Kaushik is an Associate Professor at the Center for Cyber Security and Cryptology, Sharda School of Computing Science & Engineering, Sharda University, India. He holds a Ph.D. in Computer Science and Engineering and has around 12 years of full-time academic, research, and teaching experience. His research interests include cybersecurity, digital forensics, IoT and firmware security, AI/ML for cybersecurity, blockchain-enabled trust, cyber-physical systems, UAV/6G security, and quantum/post-quantum security. He has published over 280 research papers, authored or edited 40 books, and holds multiple granted patents and copyrights. He has been listed among the World's Top 2% Scientists by Stanford University/Elsevier for 2024 and 2025.