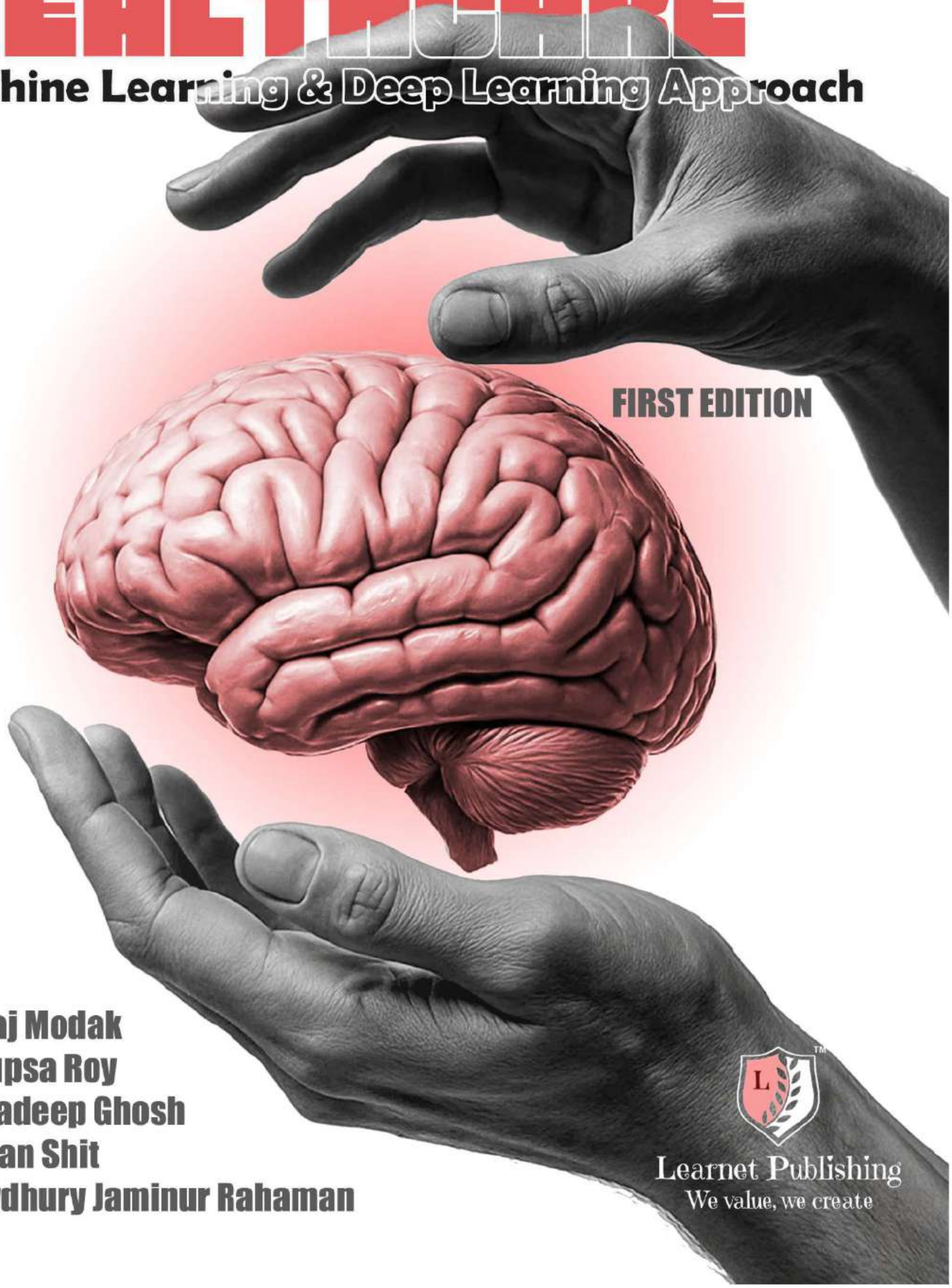
Emerging Trends on

COMPUTATIONAL INTELLIGENCE IN HEALTHCARE

Machine Learning & Deep Learning Approach



FIRST EDITION

Debraj Modak
Dr. Rupsa Roy
Subhadeep Ghosh
Anirban Shit
Chowdhury Jaminur Rahaman

Learnet Publishing
We value, we create

Emerging Trends on Computational Intelligence in Healthcare: Machine Learning & Deep Learning Approach

Debraj Modak

Dr. Rupsa Roy

Subhadeep Ghosh

Anirban Shit

Chowdhury Jaminur Rahaman

Department of Electronics and Communication Engineering

Abacus Institute of Engineering and Management

India

First Edition
2026

Learnet Publishing
Kolkata

ISBN No.: 978-81-685619-5-3

Published by

Learnet Publishing

19/B, Kali Kumar Majumder Road

Post Office – Santoshpur Avenue

Police Station – Survey Park

Kolkata – 700075

West Bengal, India

Price

MRP: INR 499 (Digital Copy)

Contact Information

Email IDs: learnetpublishing@gmail.com / info@learnetpub.co.in

Mobile No.: +91-9836423405

Websites

www.learnetpub.co.in

www.jctmg.in

Originality, Responsibility and Disclaimer

This book is dedicated to our families, whose unwavering support, encouragement, and patience have been the cornerstone of our academic and professional journeys.

We also dedicate this work to all educators, researchers, and healthcare professionals who continuously strive to advance knowledge and improve human well-being through innovation and dedication.

Finally, this book is devoted to the pursuit of knowledge and the vision of a future where artificial intelligence and machine learning contribute meaningfully to accessible, efficient, and equitable healthcare for all.

Preface

The rapid development of artificial intelligence has transformed significantly in the healthcare domain. The convergence of Machine Learning (ML), Deep Learning (DL), and healthcare data analytics has opened up innovative ideas for improving diagnosis, treatment, and patient outcomes.

This book, ***Emerging Trends on Computational Intelligence in Healthcare: Machine Learning & Deep Learning Approach,*** is written to provide a complete understanding of how AI technologies work within the healthcare ecosystem. It links the gap between theoretical perceptions and practical implementations, offering insights into both foundational techniques and advanced methodologies.

The content is structured to guide readers progressively, beginning with the fundamentals of healthcare data incorporated into ML, and advancing toward deep learning applications, emerging technologies, and real-world deployment challenges. Special emphasis has been placed on ethical considerations, regulatory aspects, and future research directions, ensuring a holistic perspective on the subject.

This book is intended for students, researchers, academicians, and professionals in the fields of Artificial Intelligence (AI), Data Science (DS), and healthcare. It is assumed that this work will provide an insightful resource for research and contribute to this fast-growing emerging field.

Writing this book has been a deeply enriching experience, and we sincerely hope it inspires further exploration and novelty in AI-enabled healthcare solutions.

Acknowledgement

We would like to express our heartfelt gratitude to everyone who has supported and contributed to the completion of this book.

At the outset, we extend our deepest appreciation to our mentors, teachers for their invaluable guidance, encouragement, and academic support. Their insights and expertise have significantly contributed to the development of the ideas presented in this work.

We are also thankful to our colleagues and peers for their constructive feedback, thoughtful discussions, and continuous motivation, which have significantly enhanced the quality and depth of this book.

We extend our deepest gratitude to our families for their continuous support, patience, and understanding throughout the writing of this book. Their encouragement has always been a source of inspiration.

Finally, we acknowledge the contributions of the global research community in the fields of artificial intelligence-based healthcare, whose pioneering work has inspired and informed this book.

This work would not have been possible without the unwavering support and encouragement of all these individuals.

Table of Contents

CHAPTER 1

INTRODUCTION TO HEALTHCARE DATA ANALYTICS AND ARTIFICIAL INTELLIGENCE

1.1 Evolution of Healthcare Data Systems

Healthcare data systems have evolved significantly over the past few decades, transforming how medical information is collected, stored, and utilised. Initially, healthcare institutions relied heavily on paper-based records, in which patient information, such as medical history, prescriptions, laboratory outcomes, and clinical notes, was manually documented. Although this system enabled physicians to track patient care, it often led to inefficiencies, data duplication, and difficulties retrieving or sharing information across departments. With advancements in information technology, healthcare organisations gradually transitioned to Electronic Health Records (EHRs) and Electronic Medical Records (EMRs). These AI systems enable healthcare providers to store patient information electronically, facilitating access, updating, and sharing of medical records. EHR systems improved clinical decision-making by enabling physicians to quickly review patient histories, laboratory results, imaging reports, and treatment plans. Additionally, digital records helped reduce medical errors and improved the coordination of care among healthcare professionals.

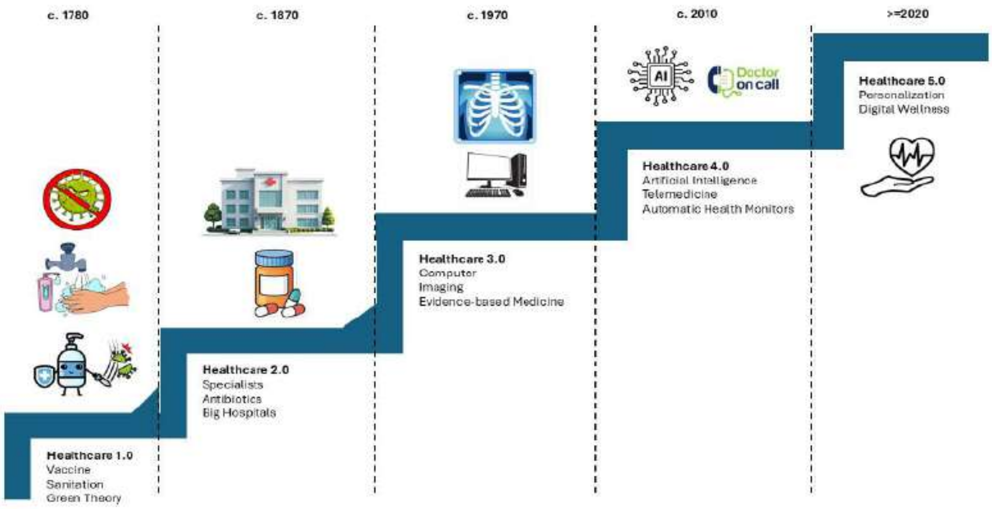


Figure 1.1: Evaluation of Healthcare Systems

The integration of health information systems (HIS) further enhanced the management of healthcare data. These systems connect different departments within hospitals, including laboratories, pharmacies, radiology units, and administrative services. As a result, patient data can be efficiently interchanged across several platforms, aiding faster diagnoses and more efficient treatment planning.

Nowadays, the evolution of healthcare data systems has been driven by developing technologies such as Big Data Analytics, Cloud Computing, and Machine Learning. Cloud-based systems allow healthcare professionals to securely store and access large amounts of patient data from remote locations. Big data technologies enable the study of massive healthcare datasets to detect patterns, predict disease outbreaks, and support population health management. Furthermore, wearable devices, along with Internet of Things (IoT) technologies, now generate real-time patient data, facilitating real-time monitoring of vital signs and early identification of health issues. Overall, the evolution of healthcare data systems has greatly improved data accessibility, interoperability, and healthcare delivery, data-driven medical practices.

1.2 Types of Healthcare Data

Healthcare systems create large amounts of data from numerous sources, including hospitals, laboratories, wearable devices, and research institutions. These data sources acts as a critical role in modern healthcare analysis, medical research, and clinical decision-making. Healthcare data is typically categorised into several types based on its origin and purpose. The major types include Electronic Health Records (EHR), genomic dataset, medical imaging data, wearable device data, and clinical trial data.

1.2.1 Electronic Health Records (EHR)

Electronic Health Records (EHRs) are electronic versions of patients' health histories, systematically maintained by healthcare professionals. These medical data records contain comprehensive information about a patient's medical status, demographic details, diagnoses, medications, allergies, immunisation records, treatment schedules, laboratory outcomes, and physician notes. Unlike conventional paper-based histories, EHR systems enable medical professionals to store, retrieve, and share patient data electronically.

During clinical research studies, the clinical trial information estimates the safety and effectiveness of novel medical treatments, medical devices, and drugs. Clinical data are a vital part of the clinical research procedure and are observed before new treatments are approved for widespread use.

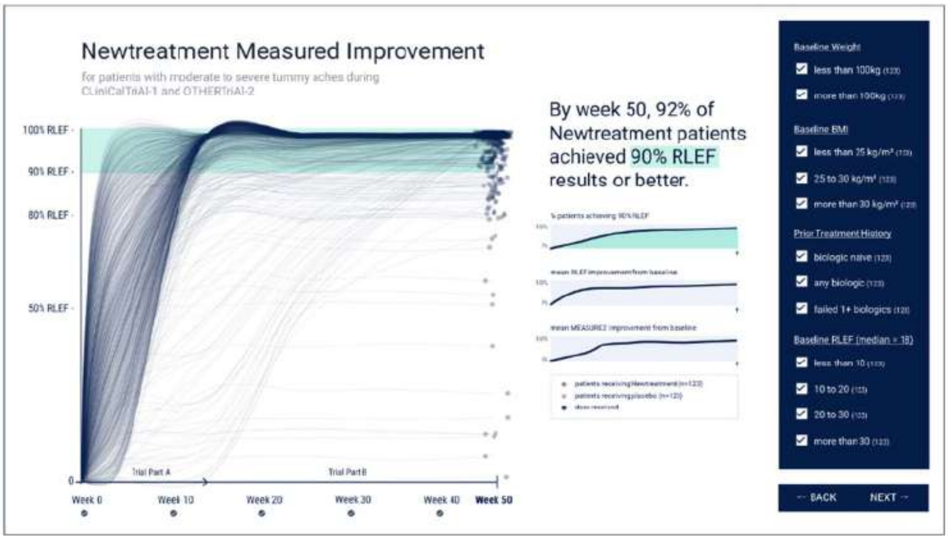


Figure 1.6: Visualisation of Clinical Trial Data [4]

Usually, Clinical trials are carried out in several phases, each intended to address precise research questions. Early segments focus on assessing treatment safety, whereas later segments evaluate efficacy and long-term consequences in more patient populations.

The clinical trial data rely on evidence-based medicine. Most of the researchers apply statistical methods incorporated into the machine learning techniques for analysing clinical and statistical-based trial datasets. These analysis results provide the regulatory authorities with the information to determine whether to approve a medication or medical device for public use.

1.3 Challenges in Healthcare Data Analytics

Deriving valuable perceptions from large amounts of healthcare data analytics holds great potential to revolutionise clinical research, disease analysis, and treatment for patients. Since medical data is sensitive and complicated, healthcare data can be difficult to obtain. Healthcare datasets are commonly gathered from various sources, i.e. labs, wearable technology, hospitals, and research studies. This can result in problems with data privacy, heterogeneity, and quality. To overcome these, precise analytics, trustworthy machine learning models, and efficient healthcare decisions are incorporated into this model.

1.4 Role of Artificial Intelligence in Healthcare

AI has transformative emerging technology in the healthcare segment, enabling advanced data analysis, improved diagnostic accuracy, and more efficient drug delivery. AI technologies, including ML, DL, and NLP, are progressively being combined into healthcare systems to analyse large, complex medical datasets. These technologies help healthcare professionals recognize patterns, detect disease consequences, and support clinical decision-making. The integration of AI into healthcare has significantly improved the processing of large volumes of clinical data produced by EHR, genomic sequencing, medical imaging systems, wearable devices, and clinical trials. Among the various applications in healthcare, CDSS, predictive healthcare analytics, and personalised medicine are among the most impactful.

1.4.1 Clinical Decision Support Systems

Clinical Decision Support Systems (CDSS) are computer-based systems considered to assist medical personnel in making informed clinical based decisions. These systems utilize artificial intelligence techniques to analyse patient health data and provide references that support diagnosis, treatment planning, and patient management. CDSS systems typically integrate data from multiple healthcare sources such as EHR, laboratory reports, imaging results, and clinical guidelines. By analysing this information, the system can generate alerts, reminders, and recommendations to support medical persons in making evidence-based decisions. CDSS can notify doctors about probable drug communications, abnormal laboratory results, or early warning signs of critical conditions. ML algorithms are commonly applied in CDSS to recognize patterns in patient data and support diagnostic processes. For instance, AI models can analyse imaging data to detect tumours or identify early signs of diseases i.e. pneumonia or diabetic retinopathy.

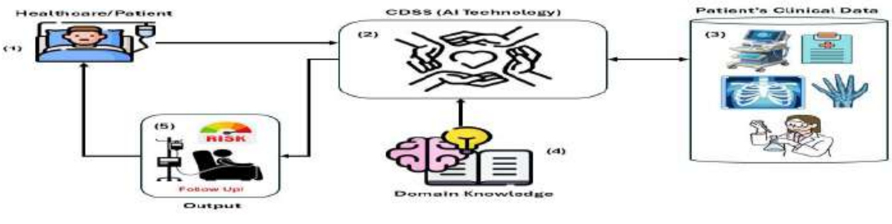


Figure 1.7: Architectural Diagram of a CDSS. **(1)** User provides information; **(2)** CDSS in Artificial Intelligence (AI) techniques for analysing data **(3)** Patient's clinical data contains numerous types of patient record **(4)** Domain knowledge in CDSS **(5)** CDSS output.

CHAPTER 2

MACHINE LEARNING TECHNIQUES FOR HEALTHCARE DATA

2.1 Fundamentals of Machine Learning

Machine Learning (ML) is mainly a subfield of artificial intelligence. It is about making algorithms that find patterns in data and make predictions on their own. In recent years, machine learning has become progressively significant in many fields, particularly in healthcare. Here, large volumes of medical data are generated through wearable technology, genomic sequencing, medical imaging systems, electronic health records, and clinical trials.

Computers can learn from experience, which is the main idea of machine learning. This learning process consists of training some algorithms using historical data so that they can develop patterns and generate predictions when we give new data to that model. Machine Learning contains several stages, such as data collection, preprocessing of data, feature extraction, model training, evaluation of model, and deployment. Each of these stages performs a crucial role that ensures the generation of correct and dependable outcomes.

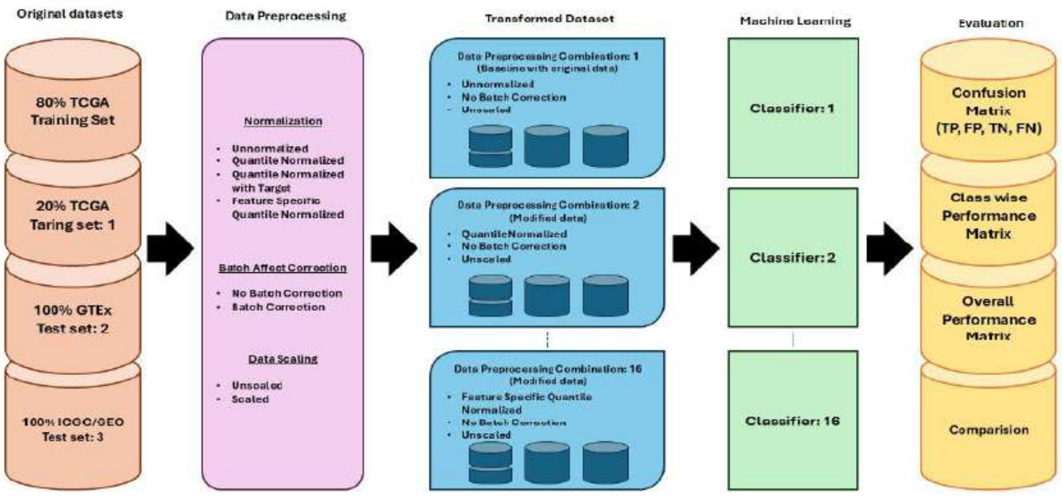


Figure 2.1: Fundamentals of Machine Learning

systems. Machine learning technologies have the potential to improve patient outcomes, improve treatment options, and improve diagnostic capabilities. Machine learning is going to be an essential part of healthcare systems in the future as healthcare data increases.

2.2 Data Preprocessing in Healthcare

One of the significant steps in the pipeline of healthcare data analytics in Machine Learning is data preprocessing. It has been noticed that healthcare data is generally complex in nature. These datasets are usually gathered from a variety of sources, including wearable technology, medical imaging equipment, lab information, electronic health records, patient monitoring equipment, etc.

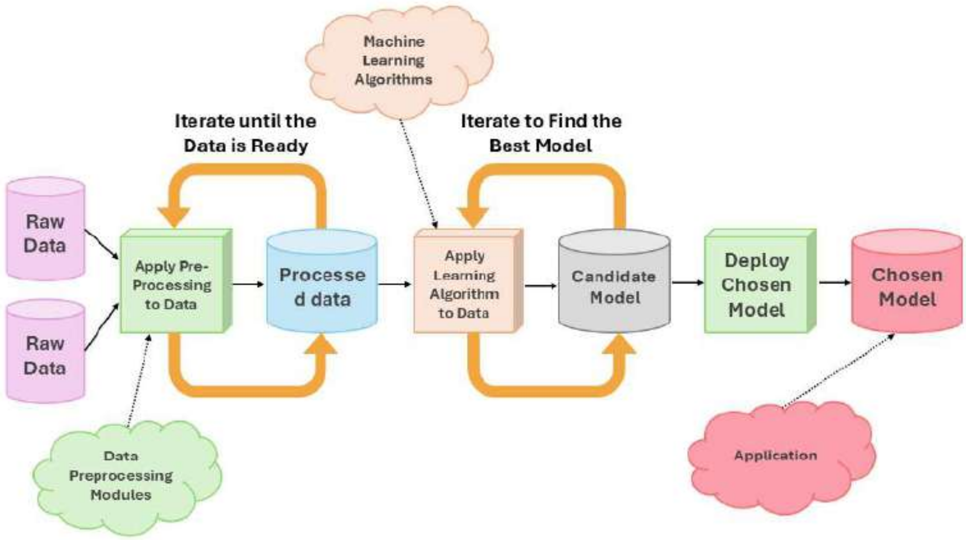


Figure 2.4: Roadmap of Data Pre-processing

One of the most significant steps in the ML-based healthcare data analytics process is data pretreatment. In most cases, the data in the healthcare domain tends to be diversified and complicated. In addition, the data in the healthcare domain tends to be sourced from various places, including wearable devices, medical imaging devices, lab devices, electronic health records, and monitoring devices. In most cases, raw healthcare data tends to contain inconsistencies, missing information, redundant data, and "noisy" data because of the diversification and scalability of the data sources.

value is also known as the mean. The median is also used for imputing missing values in numerical variables. If there are any outliers present in the dataset, the median is often preferred over the average for imputing missing values in numerical variables. For imputing missing values in categorical variables, the most frequent value in the dataset is used. This is also known as the mode. For handling missing values in healthcare analytics, other imputation techniques are also used. One such technique is KNN imputation. This technique is also known as K-nearest neighbours' imputation. In KNN imputation, missing values are imputed by considering the values in similar data points.

Another sophisticated technique is regression imputation, which relies on predicting the missing data using regression models. This technique is where the prediction of the missing data is done using the available data to create a prediction model of the missing variable using related variables.

Another effective method for handling missing data is using indicator variables. The indicator variables represent the presence or absence of the data. Using indicator variables, machine learning algorithms can be trained on patterns that include missing data. For example, if there is more missing data for tests in certain patients, then using machine learning algorithms, the missing data could be used in making predictions.

In conclusion, dealing with missing values is an important step in healthcare data preprocessing that affects machine learning models. Various techniques, including deletion techniques, statistical techniques, machine learning techniques, and indicator variables, can be used to deal with missing values. However, the choice of which technique to use depends on the type of data set being used. When missing data is properly handled in healthcare data sets, it is possible to have accurate predictions from machine learning models.

2.3 Supervised Learning Methods

One of the most commonly used machine learning techniques is supervised learning, especially in healthcare-related applications. In supervised learning, machine learning algorithms are trained on input data and associated outputs. The algorithms are trained to understand the relationship between input variables and the expected output. This helps in making accurate predictions for given input data. Supervised learning is widely used in classification and regression problems. Supervised learning is commonly used in healthcare analytics for disease diagnosis, risk assessment, and treatment outcome predictions. For instance, in healthcare-hyperparameters, which include the regularization parameter and kernel-specific hyperparameters. The selection of the most suitable kernel function can be a challenging task.

Furthermore, SVM models may not be as interpretable as some of these simple machine learning algorithms. Interpretability is a significant factor in healthcare analytics problems, as in some cases, clinicians may need to understand how predictions are being made by these models. Though SVM is a highly accurate machine learning algorithm, interpreting how predictions are being made by these models may sometimes prove difficult.

To measure the performance of SVM models, a number of performance metrics can be used. These metrics include accuracy, precision, recall, F1 score, and ROC AUC score. These metrics can be used to measure how effectively a machine learning model is able to differentiate between different classes and make predictions accordingly.

Recently, Support Vector Machine has been combined with various machine learning techniques in order to enhance the performance of these models in terms of predictions. These hybrid machine learning models can be used in advanced healthcare analytics problems.

In conclusion, Support Vector Machines are a class of strong supervised learning algorithms that promise robust predictive performance, especially when working with complex datasets. The ability to create optimal decision boundaries and work with nonlinear relationships makes Support Vector Machines a valuable tool in healthcare analytics and diagnosis. Although Support Vector Machines require careful tuning of parameters and can be computationally expensive, they remain an important tool in disease classification, image processing, genomic research, and decision support systems. As more data emerges in the field of healthcare, Support Vector Machines will remain an important tool in facilitating data-driven research and diagnosis.

2.4 Unsupervised Learning Methods

Unsupervised learning is one of the methods applied in machine learning, where the algorithm processes the data sets. Unsupervised learning is also used to recognize hidden patterns, structures, or relationships within the datasets. This is applicable when the data sets lack labelled data. It is one of the methods applied in healthcare analytics to process complex data sets, leading to valuable insights.

CHAPTER 3

DEEP LEARNING APPROACHES IN HEALTHCARE ANALYTICS

3.1 Essentials of Deep Learning

A specialised division of machine learning is Deep Learning, which focuses on using artificial neural networks with multiple layers to learn complex forms from large datasets. It has become one of the most powerful technologies in artificial intelligence and is widely applied in fields such as healthcare, computer vision, natural language processing, robotics, and speech recognition. Deep learning models are capable of automatically extracting meaningful representations from raw data, allowing them to perform complex tasks that were previously difficult for traditional machine learning algorithms.

The structure and operation of the human brain serve as inspiration for the deep learning concept. In the human brain, billions of neurons are interconnected with each other to process information and make decisions. Similar to this idea, artificial neural networks are made up of neurons, those are interconnected computational units. These neurons are arranged into layers that work together to develop input data and generate predictions or decisions.

Three primary layers: **input layer**, **hidden layers and output layer** make up a standard deep learning model. The input layer receives raw data from the dataset. This dataset provides numerical values, images, audio signals, or text, based on the provided application. The input data is mathematically transformed by the hidden layers, which also extract key properties that aid in the model's comprehension of underlying patterns. The output layer generates the classification result or final calculation.

The existence of several hidden layers in the neural network refers to being "deep" in deep learning. These layers allow the prototypical to study hierarchical data representations. As an example, at the time of medical image analysis, simple features such as edges and textures can be detected by the first layers, while deeper layers recognize intricate forms such as tumours, organs, or abnormalities. Deep learning models can perform complex tasks with proper accuracy using this hierarchical learning capability.

The **activation function** is a major part of Deep Learning models. Instigation functions present nonlinearity in the neural network, enabling the formation to learn critical relationships

The high computational cost of deep learning models presents another difficulty. High-performance CPUs and graphics processing units (GPUs) are among the computing resources needed for deep neural network training. Deep learning applications may become costly and resource-rigorous as a result.

Another vital problem in healthcare applications is structural interpretability. Because of the challenging internal decision-making procedures of deep learning models, which is difficult to understand, they are continuously mentioned as "black-box" schemes. Before utilizing predictions in clinical settings to make medical choices, healthcare practitioners need formulations that are pure and reasonable.

Researchers are actively exploring emerging technologies such as "Explainable Artificial Intelligence" (XAI) to address this challenge. These procedures aim to deliver insights into how deep learning models make decisions, making them more trustworthy for healthcare submissions. In conclusion, deep learning represents a significant advantage in artificial intelligence and machine learning. By using multi-layer neural networks with the capability of learning complicated patterns from large datasets, deep learning models have altered many fields, especially healthcare. Their capability to analyse medical metaphors, process huge healthcare datasets, and support clinical decision-making makes them valuable tools for improving patient outcomes. As computational power and data accessibility remain to increase, deep learning techniques are predictable to act an even more vital role in the upcoming healthcare analytics and medical research world.

3.2 Neural Network Architecture

The structural layout and model of an artificial neural network, including the placement of neurons, layers, and connections that process incoming data and provide outcomes, is referred to as neural network architecture. It develops the network's information flow and how the formation extracts patterns from the data. The configuration of the human brain, where interrelated neurons pass signals to carry out intricate activities like recognition, learning, and decision-making, serves as an inspiration for neural networks.

A typical neural network consists of three main types of layers: the **input layer**, **hidden layers**, and the **output layer**. The input layer receives raw data from the dataset, where each neuron represents a specific feature of the input. This information is then passed to one or more hidden layers, where computations are performed to identify patterns and relationships within the data.

3.3 Deep Learning for Medical Imaging

Deep learning has significantly transformed the field of medical imagery by allowing automated analysis and clarification of complex medical images. Medical specialists must carefully review the huge volumes of visual data provided by medical imaging technologies, like computed tomography (CT), magnetic resonance imaging (MRI), ultrasonography, and X-rays. One kind of deep learning model, Convolutional Neural Networks (CNNs), has established remarkable effectiveness in evaluating these images and assisting medical practitioners in more precisely and effectively diagnosing illnesses.

Deep learning models are often employed in healthcare-related tasks such as diagnostic support, picture segmentation, and illness detection. Deep learning representations, for example, can observe brain tumours in MRI images, lung diseases in chest X-ray images, and diabetic retinopathy in eye images. Deep learning models can increase the efficiency of image analysis by radiologists and minimize diagnostic errors.

Despite these drawbacks, deep learning models play a significant role in the development of medical imaging in modern healthcare systems due to their contribution to diagnostic accuracy in clinical decisions.

3.3.1 Disease Detection from X-ray and MRI

Because it allows medical professionals to observe the inside structure of the human body and identify a variety of disorders, it is essential to modern medicine. Two of the most popular medical imaging methods are magnetic resonance imaging and X-ray imaging. These methods allow medical professionals to produce intricate images of bones, organs, and bodily tissues in order to identify anomalies and track illnesses. Automatic disease detection based on X-ray and MRI images has become a major area of research in medical image analysis due to rapid advancements in artificial intelligence technology, particularly deep learning technology.

One of the earliest and most commonly used medical imaging techniques is X-ray imaging. It is used to create images of internal body parts, particularly bones and thick body tissues, using electromagnetic waves. X-ray images are commonly used to detect overlapping images, noise, and low contrast.

Diseases such as lung tumours, pneumonia, TB, and bone fractures. X-ray images are commonly used as a principal diagnostic tool in clinics and hospitals, as they are fairly quick cancer cells are present in the body. Deep learning models can be used to classify these images and help in the detection of cancer.

However, there are many challenges that need to be addressed. The availability of big datasets is one of the issues with using AI-based tumour classification systems. Large datasets are necessary for deep learning models to function successfully. However, creating these large datasets can be costly. The other challenge facing AI-based tumour classification systems is the lack of interpretability of deep learning models. Deep learning models, in most cases, can be considered black box models. This means that the decision-making process of these models can never be understood. This can be a major challenge, especially in the medical field, because it is important to know the decision-making process of a model before one can start relying on it.

The ethical and regulatory issues surrounding AI-based tumour classification systems play an important role in the application of these models. The ethical issues, in this case, include patient data privacy and security. These two issues must be considered before AI-based models can be applied in the medical field. The other ethical issue in this case is the validation of AI-based models. The validation of these models must be considered before one can start relying on them.

Thus, in conclusion, the classification of tumours is a vital aspect in the diagnosis and treatment of cancer nowadays. Machine learning and deep learning technologies have enabled the development of machines capable of analysing images and assisting in the diagnosis of cancer through machine learning algorithms, which are helpful in classifying tumours in medical images such as MRI, CT scans, and mammograms using technologies such as CNNs. Even though there are certain issues with machine learning, further research in this field will help improve the diagnosis of cancer in the future.

3.4 Natural Language Processing in Healthcare

A subfield of artificial intelligence called Natural Language Processing (NLP) focuses on how computers process natural languages. Great volumes of unstructured medical texts produced in hospitals and other healthcare facilities are processed in great part by NLP. In general, medical records contain useful information in the form of clinical notes, discharge summaries, radiology reports, and doctors' observations. Most of these reports are written in natural languages, which cannot be easily analysed by data processing techniques. NLP helps in the

CHAPTER 4

ADVANCED AI TECHNIQUES FOR HEALTHCARE DATA ANALYTICS

Advanced AI methods are significantly transforming the study of healthcare data. Through this approach, the system became faster, more intelligent, and more insightful. The AI technologies, such as Deep Learning (DL), Natural Language Processing (NLP), and Reinforcement Learning, enable computers to analyse the large quantities of medical data, i.e. from patient records to patients' scans or diagnosis reports, with significant productivity.

Deep learning models can enable the detection of subtle patterns in medical images that may be overlooked by naked eye, but AI can easily detect. After detection, it can assist the doctor in diagnosing the disease accurately. Natural Language Processing methods transform the unstructured clinical notes into structured data, which makes it easier to access & utilise patient data very efficiently. The previous data of the patient was analysed by the new AI model, named Predictive Analytics, which can easily forecast & identify health diseases. This approach is incorporated into the transfer learning, which was trained on a large dataset and adapted quickly for precise diagnoses, better treatment and expert outcomes in medical tasks.

4.1 Reinforcement Learning in Healthcare

Presently, modern AI is focused on the medical sector and enables training on optimal decision-making approaches through interaction-based policy, named as Reinforcement Learning (RL). Unlike conventional ML methods that depend on labelled datasets, reinforcement learning is based on a trial-and-error policy. In this framework, the healthcare staff take actions or receive rewards for positive feedback and penalties for negative feedback. By optimizing cumulative incentives, the healthcare staff gradually improves their own mindset and decisions over time. Reinforcement learning is suitable for dynamic, complex, and sequential decision-making contexts in the healthcare sector through diagnostic experience. Healthcare systems encompass a widespread range of decision-making, sequential, time-dependent processes. long-term care planning, medicine modification, and real-time monitoring are necessary for serious disease treatment. Each medical smart decision made by a healthcare professional can affect the short-term and long-term effects on health management. It offers a structural outline to optimise significant decisions on patient health and diagnosis efficiently.

adaptive, and personalized decisions. The capacity of reinforcement learning to deal with sequential decision-making processes and achieve optimal results in the long run makes it highly applicable for use in various healthcare areas. Thus, reinforcement learning can contribute to personalizing treatment plans, managing chronic diseases, providing recommendations for clinicians, and optimizing operations in hospitals and clinics. Despite the issues concerning data, safety, interpretability, and generalization faced when applying reinforcement learning in healthcare, researchers continue making efforts to overcome these challenges.

4.2 Explainable Artificial Intelligence (XAI) in Medical Systems

Explainable Artificial Intelligence (XAI) is an essential factor when incorporating artificial intelligence in healthcare operations. As the application of artificial intelligence models, especially DL algorithms, becomes widespread in disease diagnosis, medical image interpretation, clinical decision support, and risk prediction among other applications, the demand for interpretability increases considerably. Although these models tend to have high accuracy rates, they are described as "black box" models due to their opaque nature, in which humans cannot understand their reasoning. In a field such as healthcare in which decisions may affect patients' lives, it raises some concerns in terms of interpretability. XAI ensures that the model becomes explainable and understandable.

The decision-making process of healthcare practitioners is strongly dependent on evidence-based reasoning. In case of receiving predictions or recommendations from an AI-based system, the practitioner needs to know what rationale stands behind it. For instance, if an AI system predicts the possibility of occurrence of a particular disease for a specific patient, the practitioner should learn which criteria were used for generating this result. Otherwise, there is a risk that the prediction itself would be perceived sceptically, reducing its use in the decision-making process.

The main objective behind Explainable AI (XAI) in the healthcare sector is to foster trust between humans and machines. Trust is one of the critical factors that drive the implementation of AI applications within the clinical setting. In cases where doctors fail to comprehend the mechanism behind a particular prediction, there are high chances that they will shy away from trusting such systems. Explainable AI acts as an interface that enables medical experts to assess the reasoning behind certain decisions made by AI models.

represents a complex system that requires the implementation of changes gradually. XAI tools need to be developed so that they could easily integrate with current EHR systems.

The current progress in XAI development solves most of these problems. Hybrid algorithms that integrate the interpretability and high efficiency of their parts are created in order to provide both high performance and explainability of the system. Human-machine cooperation is key to achieving the goals of XAI. Instead of competing with humans in decision-making, artificial intelligence acts as a tool that supports human activities. XAI contributes to such cooperation because it allows for gaining insights that can be combined with human knowledge. With the help of XAI, it should be easier for AI to be implemented safely and efficiently. Furthermore, explainable AI can aid the implementation process by resolving issues related to trust and interpretation.

4.3 Multimodal Learning with Healthcare Data

Multimodal learning has become a popular approach in artificial intelligence, especially in healthcare, considering that medical data comes in various formats and forms. There is a huge volume of medical data in different modalities, which include imaging, clinical texts, electronic health records (EHRs), genomics, sensors, and lab test results. The diagnosis might rely on information from different modes such as information from imaging modalities like X-rays or MRIs, as well as clinical text that is provided by the physician, lab results, and genetics.

The core principle of multimodal learning is the synergy between various types of data. The use of more than one modality allows for the discovery of associations that cannot be found when examining just one type of data. A multimodal learning system usually comprises different modules, such as data pre-processing, feature extraction, modality fusion, and decision making. Data pre-processing is performed for each individual modality, and it may include normalization and resizing in the case of medical imaging and tokenization and cleansing in the case of clinical text. Convolutional neural networks (CNNs) have been widely adopted to extract features from image data, while NLP models are popular choices for textual data.

Multimodal learning has many applications in the field of medicine. The most important application of multimodal learning is in the field of disease diagnosis. It is possible for multimodal learning to have higher levels of accuracy than unimodal learning when diagnosing compromising the degree of accuracy, which helps the researcher recognize the correct pattern. Therefore, the decision is going to be even more precise.

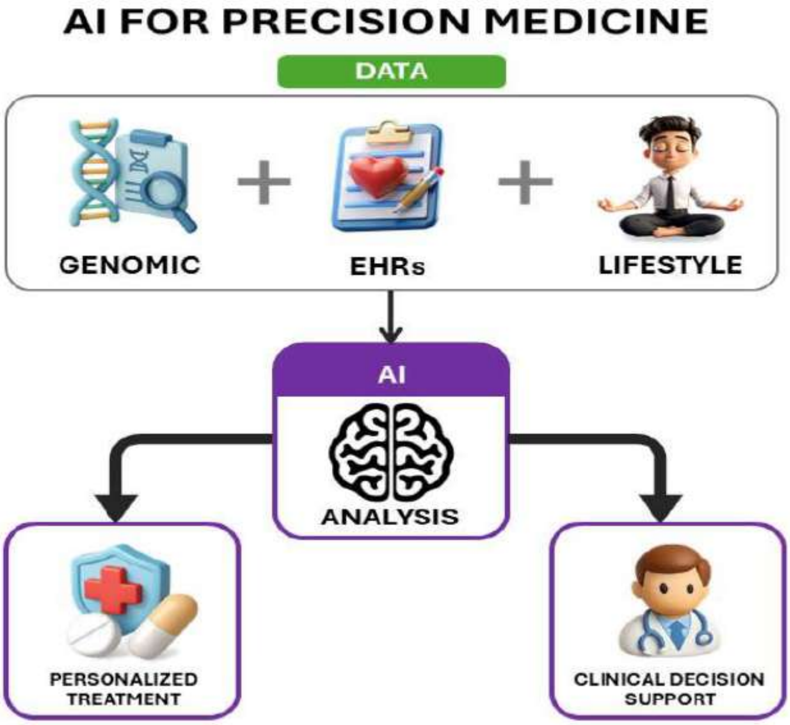


Figure 4.5: AI for Precision Medicine

The prospects of AI in discovering new drugs and advancing precision medicine look very promising indeed. With advances in computing technology, an increased amount of available data, and the rise of ML algorithms, AI tools will only become more efficient. Finally, AI will have its application in the development of new kinds of medicines, including immunotherapeutic and genetic medicines.

4.5 Integration of AI with Internet of Medical Things (IoMT)

The integration of AI and IoMT represents one of the innovations in the modern healthcare systems. IoMT is characterized as a networked environment that involves medical devices and applications, which provide health-related information via the internet. Such devices include fitness trackers, smartwatches, remote monitoring solutions, implantable devices, and even hospital-based devices like smart beds, infusion pumps, and others. In combination with AI technologies, these devices become more intelligent and have the potential to analyse

CHAPTER 5

FUTURE DIRECTIONS AND PRACTICAL IMPLEMENTATION

The rapid developments in artificial intelligence in the healthcare industry have crafted openings to boost patient role care, operational competence, and medical exploration. With the factor progress of artificial intelligence technologies, the forthcoming of artificial intelligence in healthcare will occupy the improvement of more faithful scalable, and available artificial intelligence technologies. The growing trends in artificial intelligence contain reasonable artificial intelligence, fused erudition, buff figuring, and multimodal learning, which will impact the development of the next edifice of artificial intelligence technologies in healthcare. The bearing of artificial intelligence in healthcare indicates the integration of artificial intelligence technologies with existing healthcare common sense. It is sizable to confirm that artificial intelligence technologies in healthcare not only basis precise results but are also stark ethical, and easy to employment. It is vital to educate healthcare contributors about artificial intelligence technologies and persuade certainty in artificial intelligence.

The imminent of artificial intelligence in healthcare will incorporate the proposal of unconventional artificial intelligence technologies to real-world healthcare infrastructure, which will require opportunities for more bespoke, analytical, and pre-emptive patient care. The application of artificial intelligence in healthcare, which applications on modernization and application, has the theoretical to reform the healthcare industry to make it more efficient, patient-centred, and data-obsessed.

5.1 Implementation of AI Systems in Hospitals

The functioning of artificial intelligence (AI) techniques in hospitals set apart a transformative period in the way healthcare obligations are provided, participated, and raised. Over the earlier period, hospitals have regularly transitioned from disused, skill-driven empirical techniques about data-single-prepared executive-making conditions. This passage has been fuelled by the extending skill of electronic health information (EHRs), novelties in computational energy and the urgent progression of ML and DL techniques. However, the effectual operation of AI systems in hospital locations is not merely a technical endeavour; it is a composite, multidisciplinary development that entails settlement between medical roadmaps, high-tech infrastructure, governing images, and human factors.

supervised trials are universally supervised to rate the viability and efficiency of AI systems in real-actual hospital locations.

Implementing AI systems in hospitals necessitates robust computational resources, including high-performance servers, cloud computing platforms, and secure data storage solutions. The choice between on-premises and cloud-based deployment depends on factors such as cost, scalability, data security, and regulatory compliance. AI methods and executive situation both influence how well systems work. AI also has reduced and breaks in plotting or cooperation can diminish victory in healthcare controlling. Poor command, deficiency of self-self-control, and scepticism in AI can produce difficulties. Hence, hospitals must licence in educating and examining to help personnel use AI tools efficiently. Defence and confidentiality considerations are prevalent in the attention of AI approaches in hospitals. Distinct conventional software system, AI shows can lose precision over time due to amendments in data, proven practices, or enduring groups. This is called simulation drift, so repeated monitoring and rehabilitation are required. Hospices should hound routine, analyse faults, and keep learned virtual reality to keep them true and reliable.

Monetary considerations also modify AI use in hospitals. AI can decrease costs over epoch, but the preliminary cost for technology, foundation, and guidance is high. Hospitals would do cost–help examination to examination if AI is commercially practical. They must study return on financing, efficiency gains, and better patient outcomes. Also, payment models and financial incentives can influence how widely AI is accepted. Management and domination are very valuable for AI use. Effective implementation needs effective management, transparent approach, and good supremacy. Hospitals must create AI crews to supervise incident, use, and estimation of AI systems.

5.2 AI-driven Healthcare Decision Support Systems

Artificial intelligence-driven healthcare decision support systems (AI-DSS) represent one of the most impactful applications of AI in modern medicine, fundamentally reshaping how clinical decisions are made, validated, and executed. These systems are designed to assist healthcare professionals by providing evidence-based recommendations, predictive insights, and data-driven guidance that augment human expertise rather than replace it. As healthcare systems become increasingly complex, with growing volumes of patient data and expanding

These applications highlight the versatility of AI-DSS and their ability to improve both clinical outcomes and operational efficiency.

In conclusion, AI-driven healthcare decision support systems represent a significant advancement in the field of medical informatics, offering powerful tools for enhancing clinical decision-making. By integrating diverse data sources, providing diagnostic and predictive insights, and supporting personalized treatment planning, these systems have the potential to improve patient outcomes and optimize healthcare delivery. However, their successful implementation requires careful consideration of technical, ethical, regulatory, and human factors. As research and development continue to advance, AI-driven decision support systems are poised to perform a central role in the future of healthcare, transforming the way decisions are made and care is delivered.

5.3 Future Trends in Healthcare AI

The future of artificial intelligence in healthcare is poised to bring transformative changes that will redefine how medical services are delivered, personalized, and optimized. As technological advancements continue to accelerate, AI is expected to move beyond isolated applications toward fully integrated, intelligent healthcare ecosystems. These future trends are not only driven by improvements in computational power and data availability but also by the growing need for efficient, scalable, and patient-centric healthcare solutions.

One of the most promising trends is the emergence of digital twins in medicine. A digital twin refers to a virtual representation of a patient that integrates real-time physiological data, medical history, genetic information, and lifestyle factors. By simulating the biological processes of an individual, digital twins enable clinicians to predict disease progression, evaluate treatment outcomes, and design highly personalized interventions. This approach has the potential to shift healthcare from reactive treatment to proactive and preventive care. For instance, clinicians could test multiple treatment strategies on a patient's digital twin before applying them, thereby reducing risks and improving outcomes.

5.3.1 Digital Twins in medication

The perception of digital twins in medicine represents single of the majority transformative and progressive developments in the function of artificial intellect within healthcare. A digital twin can be understood as a dynamic, virtual symbol of a physical individual—in this case, a human

5.4 Conclusion and Research Opportunities

The integration of artificial intelligence into healthcare systems represents one of the most profound technological transformations in modern medicine. Throughout this chapter, the discussion has explored the implementation, deployment, decision support capabilities, real-world challenges, and future directions of AI in healthcare. Collectively, these aspects illustrate not only the immense potential of AI technologies but also the complexity involved in translating theoretical advancements into practical, reliable, and ethically sound clinical solutions. As healthcare systems worldwide continue to evolve, AI is positioned to become a central component in delivering efficient, accurate, and personalized care.

The implementation of AI systems in hospitals has demonstrated that technological readiness alone is insufficient for successful adoption. Effective integration requires alignment with clinical workflows, robust data infrastructure, interdisciplinary collaboration, and user acceptance. Similarly, the deployment of ML models in clinical environments has highlighted the importance of validation, monitoring, and adaptability. AI systems must operate reliably in dynamic and heterogeneous settings, where variations in data and clinical practices can significantly influence performance. Such lessons indicate that artificial intelligence in health care cannot be seen as purely a technological problem but as a socio-technological problem. The use of AI in creating healthcare decision support systems (DSS) has become a useful approach to supporting clinical decision-making.

In terms of future research directions, the creation of digital twins, artificial intelligence diagnostics, and other forms of an autonomous healthcare system can be considered important landmarks in the development of healthcare AI technology. Such progress should help advance healthcare beyond reactive medicine and bring it into the era of proactive diagnosis and treatment.

Another key issue to address remains that of model interpretability and explainability. Although significant advancements have been made in this domain with the development of different methods aimed at making AI more explainable, it remains vital for future research to develop interpretable models that could generate clinically relevant and actionable insights. To this end, the development of models with embedded interpretability as well as models that would be based on and consistent with the process of clinical reasoning needs to be a priority.

Debraj Modak received his B.Tech in ECE from MAKAUT in 2009 and M.Tech in Digital Communication and Networking from SRM University in 2011. Since 2011, he has served as an Assistant Professor in the Department of ECE at the Abacus Institute of Engineering and Management, Hooghly. He has published 20 research papers in several reputed journals, national & international conferences, and book chapters, in the areas of Networking, THz BG, photosensors, Nano-electronics, semiconductor devices, AI, ML and biomedical engineering. Mr. Modak received the Best Paper Award at the DRDO SPACE IEEE Conference in 2025. He was also honoured with the Best Faculty and Best Research Credential Award from the JIS Group consecutively from 2022 to 2024.

Dr. Rupsa Roy, is an academician and researcher in the field of Electronics and Communication Engineering. She currently works as an Assistant Professor of ECE Department, Abacus Institute of Engineering and Management, MAKAUT, W.B. After doing B. Tech from FIEM, MAKAUT, W.B (in 2015) and M. Tech from KIIT, Bhubaneswar (in 2018), she received her PhD Degree (ECE) from Sikkim Manipal Institute of Technology, Sikkim in 2024 with a research project, which was funded by TMA-Pi. She has published eight International Journals indexed by Scopus, SCI, WOS and UGC approved journals and eleven Conference Papers in IEEE and Springer in the field of Electronics and Communication Engineering.

Subhadeep Ghosh received his B. Tech degree in ECE from JIS College of Engineering, Kalyani, in 2016 and his M. Tech in Mobile Communication and Networking Technology from JIS College of Engineering, Kalyani, in 2022. Currently, he serves as an Assistant Professor in the Department of ECE at the Abacus Institute of Engineering and Management, Mogra. He has published multiple research papers and book chapters, participated in national and international conferences, primarily focused on Networking, AI/ML domains like healthcare and agriculture.

Anirban Shit received his Diploma in ECE from TPI, Hooghly, in 2019, B. Tech in ECE from AIEM, Hooghly, in 2022, and his M. Tech in ECE from Guru Nanak Institute of Technology in 2025. Currently, he serves as an Assistant Professor in the Department of ECE at the Abacus Institute of Engineering and Management, Mogra. He has published several papers in many reputed journals. His research focused on VLSI, Biomedical engineering, AI and ML in various domains such as Healthcare, Agriculture, etc.

Chowdhury Jaminur Rahaman received his Diploma in ETCE from M.B.C. Institute of Engineering & Technology, Bardhaman in 2018 and B.Tech degree in ECE from Greater Kolkata College of Engineering and Management, Kolkata, in 2024. Currently, he serves as a Technical Assistant in the Department of ECE at the Abacus Institute of Engineering and Management, Mogra. He has published several book chapters in some reputed articles. His research activities are primarily focused on Artificial Intelligence and Machine Learning in various domains such as Healthcare, Agriculture, etc.

Published by:

LEARNET PUBLISHING
19/b, Kali Kumar Majumder Road,
P.O.-Santoshpur Avenue, P.S.- Survey Park,
Kolkata-700075, West Bengal
Email: learnetpublishing@gmail.com
Website: www.learnrtpub.co.in
www.jctmg.in

ISBN 978-81-685619-5-3
9 788168 561953