A REVIEW ON THE ROLE OF ARTIFICIAL INTELLIGENCE IN HEALTHCARE TRANSFORMATION

By

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A thesis submitted to the School of Pharmacy in partial fulfillment of the requirements for the degree of
Bachelor of Pharmacy (Hons.)

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Declaration

It is hereby declared that

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2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
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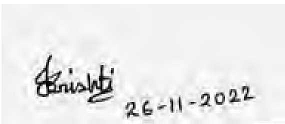

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Approval

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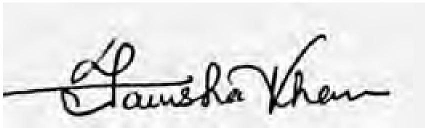

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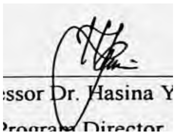

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Ethics Statement

The study does not involve any kind of animal or human trial.

Abstract

Artificial intelligence (AI) is an influential area of computational science which can significantly transform medical practice and healthcare delivery. There are many cases where AI can conduct healthcare tasks better than humans. This review article outlines latest development in the implementation of artificial intelligence in the health sector and different diseases like cancer, cardiac disease, and ophthalmic disease, as well as its challenges and future possible advancements of AI-augmented healthcare systems. The primary application categories are diagnostic and therapeutic recommendations, patient involvement and adherence, and administrative services.

Keywords: Artificial intelligence; machine learning; electronic health records; healthcare transformation

Dedication

I would want to dedicate this project to my family and my supervisor, Tanisha Tabassum Sayka Khan (Lecturer, School of Pharmacy, Brac University), with whom I have had the pleasure of working on this project.

Acknowledgement

Firstly, I am very grateful to my Almighty Allah for rewarding me with patience, self-confidence, and strength, which have been instrumental in completing this project successfully.

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List of Acronyms

AAK1	AP2-associated protein kinase 1.
ACE2	Angiotensin I converting enzyme 2.
AI	Artificial Intelligence
Anti-VEGF	Anti-Vascular Endothelial Growth Factor
AMD	Age-related Macular Degeneration
CAD	computer aided device
CADD	Computer-Aided Drug Discovery
CAM	Convex Analysis of mixtures
CAGR	Compound Annual Growth Rate
CARA	Computer-Assisted Retina Analysis
CASP	Computer-Aided Synthesis Process
CDF	Cumulative Distribution Function
CFP	Color Fundus Photographs
CNN	Convolutional Neural Network
CSP	Crystal Shape Prediction
CT	Computed Tomography
DD	Drug Design
DCE-MRI	Decomposition of contrast-enhanced MRI
DNN	Deep Neural Network

DR	Diabetic Retinopathy;
EMRs	Electronic Medical Records
FP's	False Positives.
GGMRF	Generalized Gaussian Markov random field
H&E	Hematoxylin and Eosin
HER	Electronic health records
HGSOC	High-Grade Serous Ovarian Cancer
HTS	High Throughput Screening
IUI	Intrauterine Insemination
ML	Machine Learning
MRI	Magnetic Resonance Imaging
MACE	Major Adverse Cardiac Events
MDA	Macular Degeneration
MTNR1A	Melatonin receptor 1A.
NICVD	National Institute of Cardiovascular Diseases
NLP	Natural Language Processing
NMF	Non-negative Matrix Factorization
NPDR	Non-Proliferative Diabetic Retinopathy
NR3C1	Nuclear receptor subfamily 3 group C member 1.
NRP1	Neuropilin 1.

NSP14	Non-structural protein 14
OCD	Obsessive-Compulsive Disorder
OCT	Optical Coherence Tomography
PARP1	Poly-ADP-ribose polymerase 1.
PDR	Proliferative Diabetic Retinopathy
PSA	Prostate-specific antigen
QSAR	Quantitative Structure-Activity Relationship
SMILES	Simplified Molecular-Input Line-Entry System
SNCSAE	stacked non-negatively constrained sparse autoencoder
STEMI	ST-elevation Myocardial Infarction
TMPRSS2	Transmembrane serine protease 2.
VS	Virtual screening

Chapter 1

Introduction

1.1 Background

Researchers and health professionals are highly interested in artificial intelligence (AI) in the healthcare sector (Seminara et al., 2021).The subject of research has been conducted in a variety of fields, including data science, business, accounting, and the health professions. (Miller & Brown, 2018). There is substantial evidence that AI algorithms can perform tasks like assessing medical imagery or combining symptoms and biomarkers from electronic medical records (EMRs) with illness identification and diagnosis as well as or better than humans (Bohr &Memar Zadeh, 2020). From different perspectives of research papers, several startup companies are currently using AI-based technologies to provide healthcare solutions and services, the much more advanced Artificial intelligence technology in the healthcare sector is IBM's "Watson for Oncology," which helps doctors by proposing appropriate treatment solutions (Hee Lee & Yoon, 2021). Drug discovery and development is time-consuming as it takes several years and costs several billion dollars. The drug discovery duration can be reduced significantly with the help of machine learning techniques (Manne, 2021). This review paper examines how artificial intelligence (AI) can treat various diseases and perceive this knowledge among everyone. It lowers the cost of creating medicines by allowing convolutional neural networks to find a secure and efficient medication candidate. AI is helpful for both diagnosing and treating cancer, particularly for radiation therapy. Healthcare artificial intelligence can provide users with answers to questions more quickly; create revolutionary treatments and therapies, and coordinated development and operations for patients, payers, staff members (both medical and non-medical), researchers, and doctors.

1.2 Rationale of the Study

In the healthcare system, AI facilitates health service monitoring, patient records evaluation, predictive medicine, diagnosis of diseases, and, eventually, medical decision. If we utilize AI in every healthcare field, we can improve data quality, governance, security, and interoperability for each patient. More broadly, skills as fundamental as digital literacy, genomics foundations, AI and machine learning, critical-thinking abilities, and the creation of a continuous-learning mindset will become main stream for all healthcare professionals. The application of AI is widespread, from insurance processing to maintaining healthcare data security, medical imaging technology, intelligent wearables, and drug development. Therefore, a piece of comprehensive knowledge on AI and its applications will assist healthcare personnel in making more timely and informed operational decisions to provide the best possible treatment for each patient.

1.3 Aim of the Study

Healthcare AI can improve preventative care and quality of life, generate more precise diagnoses and treatment plans, and improve patient outcomes. Artificial intelligence (AI) can assist in predicting and observing the emergence of contagious diseases by analyzing data from the public sector, the healthcare business, and other sources.

1.4 Objectives of the Study

Artificial intelligence is a prominent academic topic, and its applications in the healthcare system are wide. Healthcare organizations gather and evaluate patient health data to dynamically recognize and minimize disease risk, eliminate treatment gaps, and discover more about clinical, hereditary, behavioral, and environmental factors that impact the public. When diagnostic relevant information, test reports, and data from unorganized records are combined, a detailed overview of a patient's health is revealed, providing valuable information for disease diagnosis, prevention, and treatment. In order to identify early disease risks, AI-powered technologies can help assemble, evaluate, and compare a flood of certain pieces of information to population statistics. It also accelerates the electronic approval, submission, and evaluation of clinical documentation for medications that need to be approved. It will keep track of how well patients are taking their medications. Hence, the objectives of this study are-

- To explore AI's role in healthcare transformation.
- To address the concerns that arises when artificial intelligence is applied in healthcare.

Chapter 2

Methodology

Initially, an outline was created and relevant articles were collected by following the outline to conduct the review in a systematic manner. PubMed, Springer, Medline, Scopus, Web of knowledge, and Inspec databases have been used to collect information on the applications of artificial intelligence in healthcare. The primary goal of this review paper was to include all published articles that used AI systems in ophthalmology, cardiology, cancer, smart wearables, and drug screening. Irrelevant and duplicate papers were discarded, and the remaining articles underwent a thorough screening to confirm that they satisfied the requirement of the study.

Chapter 3

Artificial Intelligence

3.1 What is Artificial Intelligence?

Artificial Intelligence (AI) is a term that refers to machine intelligence that simulate human intelligence-assisted processes such as reflection, deep learning, adaptation, interaction, and sensory conceptual understanding (Ng et al., 2021). It has become extremely popular worldwide. Also, it is the restatement of human intelligence in computer system designated to know and understand and resemble human actions (Park et al., 2020). Machine learning could be a branch of computing that refers to circumstances within which machines will learn and analyze within the same approach that humans will and thus assist in problem-solving (Rong et al., 2020). Machine learning (ML) techniques that evaluate structured data such as imaging, genome sequencing, and electronic health records are included in the first group of artificial intelligence (AI) (EHR). Machine learning (ML) algorithms are used in clinical settings to group patients' characteristics or forecast disease outcomes (Darcy et al., 2016). The second group of AI involves natural language processing (NLP) tools, which takes the input data retrieved from patient records journals to supplement and enhance systematic medical data (Murff et al., 2011). The research of how machines and humans interact using natural language, with a focus on the computer's ability to read human language, is known as natural language processing (NLP). Many uses of extensive data analysis in healthcare, such as EMRs (emergency medical records) and the translation of physicians' narratives require it. Data extraction, conversion from unstructured to structured data, and data and document categorization are typical applications. NLP processes are designed to transform document into machine-readable structured information that can then be assessed using machine learning techniques (Jiang et al., 2017). Artificial intelligence in healthcare refers to the use of advanced algorithms to computerize the execution of particular tasks. When researchers, doctors, and scientists enter data into computers, newly developed algorithms can review, comprehend, and even treat complex medical problems. Furthermore, robotic surgeries, web-based medical assistance, organizational process management, diminish dosage error, the identification of clinical trial participants, machine-based image diagnosis, and basic diagnostics are some of the expected inventions with the help of artificial intelligence (Ahuja, 2019).

3.2 How to Build Effective and Trusted AI-augmented Healthcare Systems?

The cognitive strategy employed to manage with the difference between the familiar and the unfamiliar is called trust. Many studies have emphasized the significance of improving AI-based systems and assisting clinicians. But, checking the magnitude and significance of human trust in AI technology necessitates a significant amount of time and effort (Asan et al., 2020). A user's perspective of an AI system's capability is still a significant factor for trust in AI systems, dependent on the level of the algorithms used for generating decisions, input parameters, and quantitative problem description. The degree to which users trust AI significantly impacts how much they rely on it (Lee & See, 2004). Each application may necessitate a customized AI process, depending upon the nature and amount of information available, the amount of variability, the target patient population, and the most useful details in the data and the rationale for healthcare decisions. Several human factors, including prior experiences, client education, consumer preferences, and views of technology, as well as characteristics of AI systems, such as controllability, transparency, model complexity, associated hazards, etc., might affect how much people trust AI. Artificial intelligence would perform a task as anticipated and consistently. Given the shifts in AI consistency brought on by the accessibility of new data, reliability may be particularly problematic in the health care sector (Mcknight et al., 2011).

3.3 Importance of Artificial Intelligence in Healthcare

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AI could make drug discovery more efficient, affordable, and secure. However, AI cannot wholly eradicate every stage of drug development. It can contribute to discovering novel drugs that might make promising medication candidates. It can also help develop new usage for substances that have already been tested (Ibrić et al., 2009). AI helps do repetitive analysis tests, x-rays, and CT scans. The period and data needed to examine cardiology and radiology are intense. For instance, AI can diagnose skin cancer more efficiently than dermatologists (Haenssle et al., 2018). The AI market is rapidly rising, from $200 million in 2015 to $700 million in 2018. Also, it can be predicted to rise to $5 billion (about $15 per person in the US) by 2024. A remarkable 40% yearly growth rate from 2017 to 2024 demonstrates how AI will transform pharmaceutical and related industries in the future (Mouratidis et al., 2018). Pharmaceutical firms can save the expenses of clinical trials, lower the probability that drugs will fail, and save important moments by utilizing computer software and AI-based algorithms. A better environment for drug development and design can also be provided by AI, assuring trouble-free drug development and overall accelerated improvement of pharmaceutical companies (Kalyane et al., 2020). The exemplary implementations of AI in healthcare have been evaluated from various perspectives. In 2018, Forbes predicted that managerial processes, image classification, surgical robots, virtual assistants, and support for clinical decisions would be critical sectors. Several writers discussed AI-related topics in a 2018 study, along with devices connected, dosage-reduced errors, and cyber security (Bohr &Memarzadeh, 2020). According to a 2019 paper by eminent writers, significant topics include robotics-assisted surgery, linked and cognitive devices, focused and precision medicine, and electroceuticals (Singhal& Carlton, 2019). This clinical data is essential for any pharmaceutical company and provides various information. AI is used in clinical trial design and data mining (Wang &Preininger, 2019). Some applications of AI are mentioned in Figure 1.

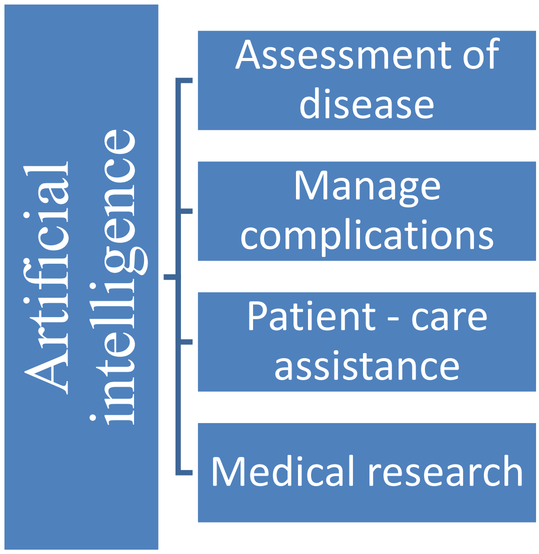


Figure 1: Applications of artificial intelligence in healthcare sector in different segments (adapted from Bohr & Memarzadeh, 2020)

The success rates in the healthcare sectors are visible towards the US Pharmaceutical market analysis. The artificial intelligence market in medicine is predicted to be valued at USD 2.1 billion in 2018 and USD 36.1 billion by 2025, with a CAGR of 50.2 percent between those two years. In 2018, it was expected that machine learning technologies would be a significant portion of the health sector. Among all machine-learning technologies, deep learning is estimated to have the highest share of the global healthcare sector. AI's expansion in the healthcare business is driven by the accessibility of big data and a need to minimize medical expenses (Jiang et al., 2017). Intrauterine insemination (IUI) is a technique of artificial fertilization used to treat infertility. Also, with the support of a three-layer neural network, the AI's efficiency in estimating the success rate of IUI was 71.92%, and the precision and sensitivity reached 76.19% and 66.67%, respectively (Sene et al., 2021).Modern AI innovations like natural learning and machine learning have the potential to implement change such as electronic phenotyping, a method designed to decrease population heterogeneity. Electronic phenotyping can be a difficult task that usually requires advanced and powerful methods for detecting diversity across multiple data types and patient records (Yokoi et al., 2021).

Chapter 4

Relevance of Artificial Intelligence in Healthcare Transformation

The healthcare system is a collection of individuals, organizations, and facilities that work together to deliver medical services to diverse populations (Lin et al., 2019). The objective of a healthcare system is to improve the public's health as effectively as appropriate given a society's resources and attempt to compete for requirements (Davenport & Kalakota, 2019).

AI gives individuals the power to manage their well-being and overall health. Additionally, AI provides health practitioners better understanding of the routines and requirements of the patients they look after, enabling them to provide further feedback, direction, and encouragement for maintaining their health (Bajwa et al., 2021). Artificial Intelligence (AI) is beneficial in healthcare in several different ways, including disease prediction and preliminary diagnosis. It can also be used to improve and optimize hospital operations and improve diagnostic test results and make them quick to attain and simple (Manne & Kantheti, 2021). The healthcare system is anticipated to be among the five most prominent industries, with far more than 50 AI use instances and more than $1 billion in start-up equity, according to McKinsey research (a business journal). (Global Survey: The State of AI in 2021 | McKinsey, n.d.). This case suggests that artificial intelligence is prepared to be a game-changer in healthcare. Artificial neural networks, which are used in clinical decision-making for medical diagnosis, are broadening AI's application in the healthcare sector (Davenport & Kalakota, 2019).When comparing patient care to medical guidelines, unexpected patterns in treatments are discovered, and the efficacy of specific drugs is measured (Rajpurkar et al., 2022). It predicts human health by learning from previous practices for disease prediction (Ahmed and colleagues, 2020). Other examples of artificial intelligence in the healthcare system include early disease diagnosis – detecting morbidity to predict disease. AI uses are managing medical records and data to improve drug delivery and development (Manne & Kantheti, 2021).Strong data management is an important consideration in the medical field. With several achievements, the first phase of revolutionizing algorithms for machine learning has been applied to speed up drug discovery (Bohr & Memarzadeh, 2020). Clinical trial pharmaceutical production can take more than ten years and cost billions of dollars, and it is incredibly time-wasting (Ibri et al., 2009). Algorithms outperform radiologists in detecting malignant tumors and advising researchers on how to build cohorts for expensive clinical trials. However, we believe that it will be many years before AI replaces humans and other treatment processes in broad medical process domains for various reasons (Davenport & Kalakota, 2019). Clinical trial design and data mining are two areas where artificial intelligence has been used. This clinical data is critical for any pharmaceutical company because it provides a wide range of information (F. Wang & Preininger, 2019). Deep learning models are prepared for specialized image identification tasks in laboratories and industries (such as nodule detection on chest computed tomography or hemorrhage on brain magnetic resonance imaging) (Singhal & Carlton, 2019). Additionally, radiologists consult with other medical professionals on disease diagnosis, management, and therapy (for example, by providing local adjuvant therapies). Additionally, it conducts image-guided procedures like vascular stent placement and cancer biopsies (interventional radiology) and defines the performance criteria for imaging evaluations (adapted to the patient's situation)(Park et al., 2020). Therefore, it relates image findings to other medical records and test results and discusses process and outcome (Rajpurkar et al., 2022). Healthcare can benefit enormously from artificial intelligence (AI), providing better and more efficient treatment alternatives. On the other hand, prior research on human-computer interactions has revealed that individuals are reluctant to adopt AI (Adegboro et al., 2022).

Chapter 5

Role of Artificial Intelligence in Diagnosis and Management of Different Diseases

5.1 Diagnosis

Concerning disease diagnostics, the incorporation of artificial intelligence has implications (Menschner et al., 2011). The healthcare industry and patients' general well-being may benefit significantly from using AI to support medical specialists in diagnosing. Adding AI to current technical infrastructure accelerates the selection patient clinical data from various sources specific to the patient's needs and the treatment procedure (Dilsizian & Siegel, 2013). Last year, researchers at Babylon, a significant global software business specializing in e-health, found a novel application for machine learning to diagnose disease. They developed new AI symptom checkers to decrease medication errors in primary healthcare (Richens et al., 2020). AI has assisted medical professionals and altered disease diagnoses, such as early detection of pregnancy complications and leading gynecologists' judgments for the first treatment (De Ramón Fernández et al., 2019Finding and diagnosing COVID-19 is a crucial step in the virus-fighting process. Most current diagnosis screening procedures are non-invasive and include viral, nucleic acid, serological throat swab testing, chest X-ray, and chest CT imaging (Fang et al., 2020; Lu et al., 2020a; Li et al., 2020c; Ozturk et al., 2020; Schwartz, 2020; Zeng et al., 2020). Identification and tracking of infected patients are essential for controlling the pandemic. Thus there is unquestionably a necessity for advancements in this area (Ai et al., 2020; Fang et al., 2020). In the subcategories that follow in figure 2, AI methods for SARS-CoV-2 and COVID-19 evaluation and detection are presented. One of the significant sectors in which artificial intelligence has found use in medicine and healthcare is medical imaging. High-dimension imaging data can find in several modalities like computed tomography (CT), X-ray, and magnetic resonance imaging (MRI). They have information that can use to create AI software. Radiologists can quickly complete these tasks by using imaging data to produce image-derived phenotypes generated through qualitative and quantitative evaluation of structural alterations (Petersen et al., 2017; Suinesiaputra et al., 2018; Mauger et al., 2019; Abdulkareem & Petersen, 2021). The framework's viewpoint, strategy, and performance under certain limitations are all included in system planning. With a firm grasp of the framework's design, the consumer may comprehend its boundaries and restrictions. A visual representation of the disease recognition model using practical machines and deep learning classification techniques is shown in Figure 2. Before the computation takes care of it, real-world information needs ongoing maintenance and pre-preparing (Jo et al., 2019). Artificial intelligence can precisely anticipate an illness in this process (Kumar et al., 2022).

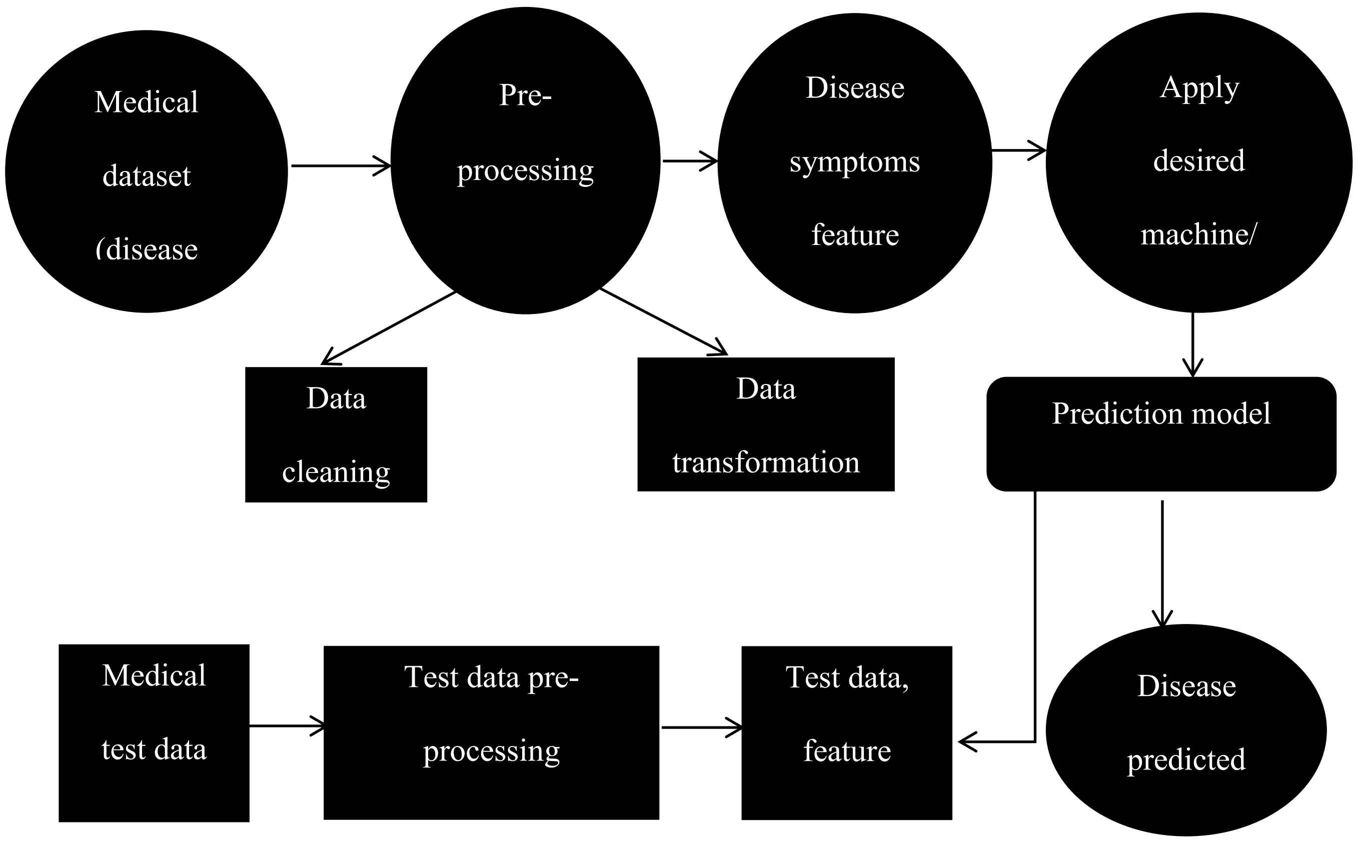


Figure 2: Illustration of disease detection system using artificial intelligence conceptual model (adapted from Kumar et al., 2022)

A set of facts or other experiences can be used to optimize the performance standards using the idea of AI. Learning is only the application of model parameter optimization using training datasets or prior knowledge. Features could either be descriptive—used to draw knowledge from the input data—or predictive—used to make future predictions. Two crucial activities are carried out in machine learning: (1) analyzing the enormous amount of data and model optimization, and (2) testing the model and effectively displaying the solution. This Alzheimer disease detection process is illustrated in the Figure 3.

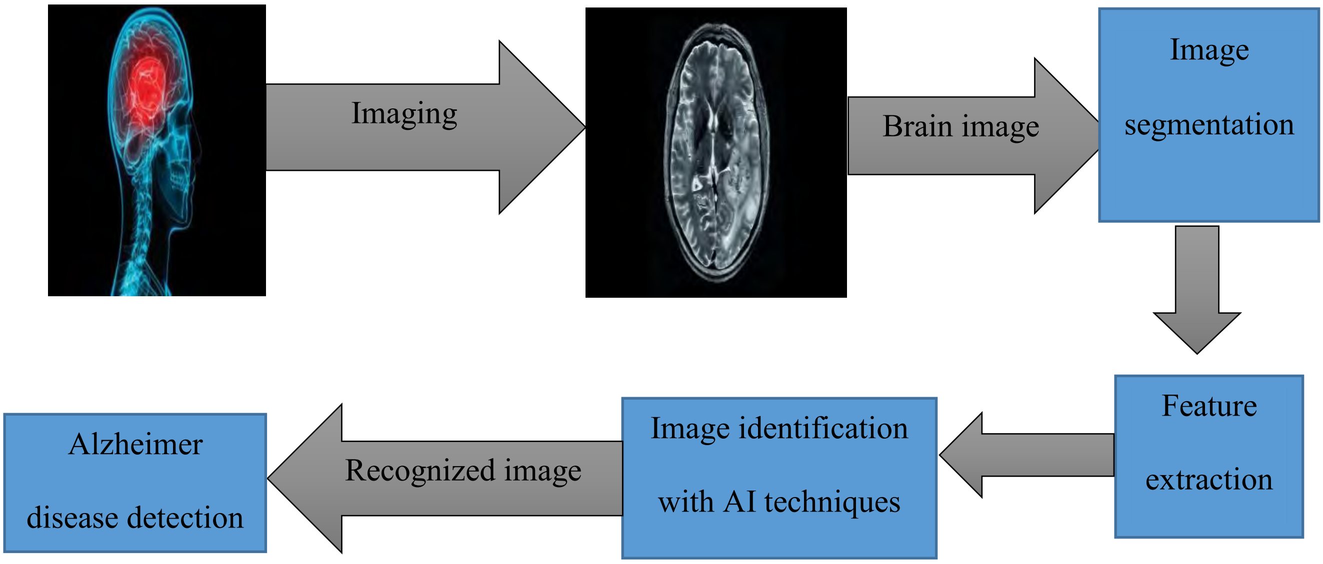


Figure 3: AI techniques for Alzheimer disease detection from brain images (adapted from Subasi, 2020) .

5.2 Cardiology

Cardiovascular disease is currently among the leading causes of death and has become more prevalent recently. Machine learning technology has developed to incorporate the latest direction and analyze cardiac irregularities because treating cardiology patients is expensive. AI is employed to research novel medication treatments and improve the effectiveness of clinicians. Using cardiac-based methods, one may exactly predict the outcome of a COVID-19 patient. The adoption of a machine learning system by researchers to discover COVID-19 patients more likely to experience damage to the heart is recommended. In order to help healthcare workers handle cardiology cases more successfully, this system involves intelligent robotics, cloud-based data, soft analysis, smart monitoring, and other applications. Figure 4 given below, illustrates the various advanced and time-tested methods and software available when dealing with cardiology cases, especially during the most challenging COVID-19 period (Kusunose et al., 2020). From August 2017 to

October 2018, the National Institute of Cardiovascular Diseases (NICVD) in Dhaka conducted a prospective longitudinal observational study. The NICVD is Bangladesh's largest public tertiary care cardiac hospital, treating patients with cardiovascular disorders from all over the country. To discover probable patients who are 18 years old and hospitalized for an ST-elevation myocardial infarction (the gap between the end of ventricular depolarization and the beginning of ventricular repolarization on the ECG) (STEMI),research physicians reviewed NICVD hospital admission records and visited patients admitted to cardiology wards. Artificial intelligence is applied to diagnose STEMI based on ST-segment elevation in the ECG in the hospital records (Akhtar et al., 2021). Only one study from Bangladesh described post-STEMI outcomes as a composite of major adverse cardiac events (MACE) in a rural environment was identified in the literature (Kim et al., 2019). During the COVID-19 pandemic, AI significantly impacted cardiology by understanding and evaluating how the human heart functions. It employs an electronic health record, which makes it easier to spot the crucial indicators of heart disease. AI in cardiology has many advantages, including increased knowledge, patient care, risk reduction, everyday decision-making, heart imaging, surgical precision, and creative teaching and learning techniques. The main applications of this technology include cardiovascular anatomy evaluation, cardiac MRI ventricle segmentation, identification of arrhythmias, assessment of heart imaging, hypertension, oxygen saturation, heart rate checking, awareness of heart attacks, recording digital heart data, analysis of blood rate of flow, precise system information, and medicines for COVID-19 patients (Haleem et al., 2021a). Artificial intelligence tools and strategies in the treatment of cardiology have been shown in Figure 4.

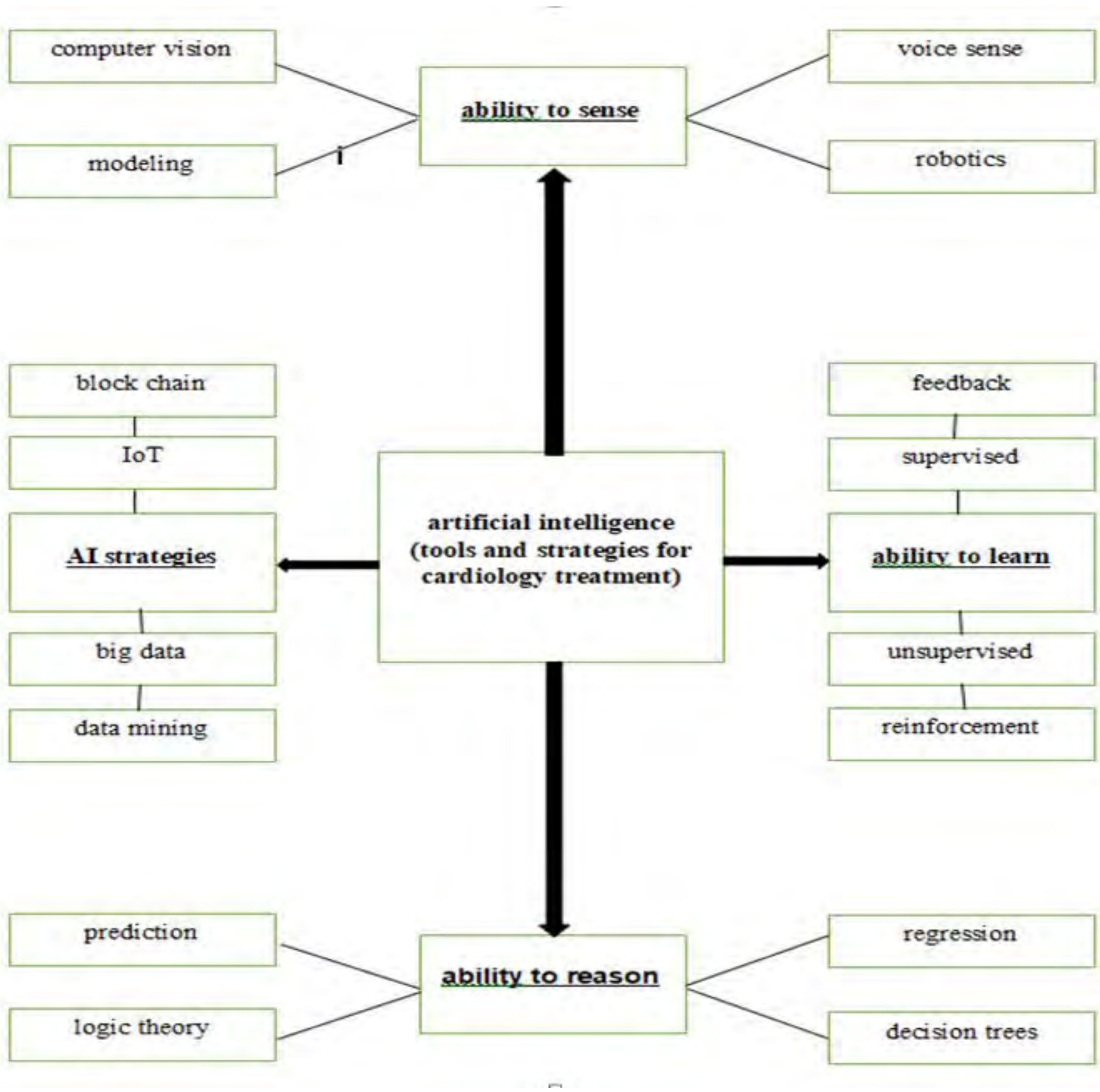


Figure 4: Artificial intelligence tools and strategies dealing with cardiology cases (adapted from Haleem et al., 2021a)

The comprehensive clinical process is covered by the six artificial intelligence (AI) in cardiac imaging sectors (Figure 5) that are covered in this particular issue. They include the capture and segmentation of cardiac images, form and motion estimations, image-based cardiac diagnosis, imaging-genetics research, and image-based cardiac diagnostics, along with AI's legal and ethical implications (Lekadir et al., 2020).

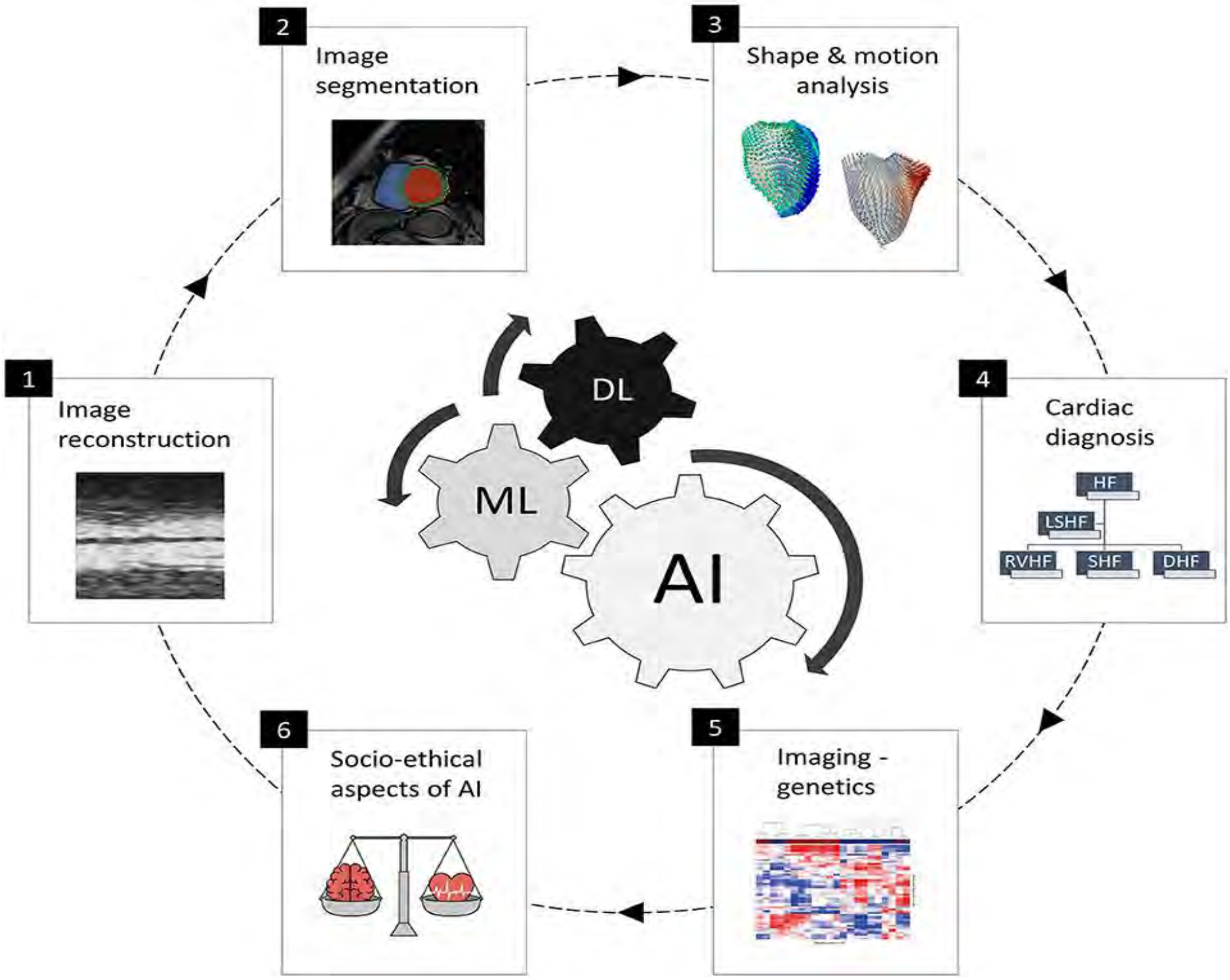


Figure 5: The six domains of artificial intelligence in cardiac imaging by machine learning and deep learning (adapted from Lekadir et al., 2020).

5.3 Ophthalmology

According to recent research articles, nearly 85-90 percent of diseases like DR (Diabetic retinopathy), MDA (macular degeneration), glaucoma, and cataracts can be cured by using artificial intelligence (Moura et al., 2017; Al-Fadhili et al., 2017). AI-assisted automatic detection and diagnosis of common eye illnesses may considerably improve the function of clinicians in the hospital. Even outside the clinic, artificial intelligence (AI) platforms concentrate on giving patients more healthy alternatives and minimizing obstacles to eye care in places where an ophthalmologist is not readily available (Khalid et al., 2018). Modern ophthalmology depends heavily on imaging for diagnosis and record-keeping and vast quantities of visual data derived from color fundus photographs (CFP). CFP was scanned from optical coherence tomography (OCT), OCT angiography, corneal topography, and other diagnostic procedures (Schmidt-Erfurth et al., 2018). Multimodal imaging technology lets doctors see significant structures and provides valuable data for decision-making in everyday practice (Jahangir & Khan, 2021). If effective data treatment techniques are unavailable, this vast volume of data may be difficult to compute this enormous volume of data accurately. In addition to being the focus of numerous AI algorithms in OCT, clinicians have long utilized glaucomatous alterations to the optic nerve head to identify at-risk patients. For instance, they created a method to detect neuronal and connective tissues by digitally staining OCT pictures of the optic nerve head. This digital staining enables automated assessment of glaucoma-related optic nerve parameters. For 40 healthy and 60 glaucomatous eyes, their system could stain six tissue layers (RNFL, retinal pigment epithelium, all other retinal layers, choroid, peripapillary sclera, and the lamina cribrosa), with the results demonstrating a dice coefficient of 0.84, the sensitivity being 92%, specificity being 99.9%, and accuracy being 94% (Kapoor et al., 2019). Ophthalmic modalities in AI diagnosis with image features and their application have been mentioned in Table 1. However, accessibility provides a robust environment to integrate AI with ophthalmology and evaluate massive amounts of data to develop data-driven deep learning (DL) algorithms (Stagg et al., 2021). The development of new arteries in the retina's macular region is decreased by anti-vascular endothelial growth factor (anti-VEGF) therapy because it prevents vascular endothelial proliferation. Patients may be able to save money by using machine learning to anticipate the need for anti-VEGF injections for AMD (age-related macular degeneration) (Shetty et al., 2021).

Table 1: The ophthalmic imaging modalities during diagnosis by AI (adapted from Lu et al., 2018)

Imaging modalities	Image features	Applications
Fundus image	Show a magnified and subtle view of the surface of the retina	Retinal diseases diagnose
Optical coherence tomography	Show micrometer-resolution, cross-sectional images of the retina	Retinal diseases diagnose
Ocular ultrasound B-scan	Show a rough cross-sectional view of the eye and the orbit	Evaluate the condition of lens, vitreous, retina, and tumor
Slit-lamp image	Provides a stereoscopic magnified view of the anterior segment in detail	Anterior segment diseases diagnose
Visual field	Show the size and shape of field-of-view	To find disorders of the visual signal processing system that includes the retina, optic nerve, and brain

5.4 Cancer

AI is altering the current environment in precision oncology to merge the substantial quantity of data obtained from multi-omics analyses with recent developments in high-performance computation and ground-breaking deep-learning algorithms (Bhinder et al., 2021). Advanced technologies for cancer detection, screening, diagnosis, and categorization, the characterization of cancer genomics, the assessment of the tumor microenvironment, the evaluation of biomarkers for predictions and prognostic purposes, and approaches for follow-up and drug discovery are just a few of the expanding applications of AI (Kann et al., 2021).Recent years have seen a tremendous advancement in artificial intelligence technology, which is now being used throughout society, including the medical profession. AI-enabled medical equipment is increasingly used in healthcare situations. Notably, AI is expected to play a big part in effectively completing the current worldwide trend of precision medicine. The history of AI and the state of medical AI today will be discussed in this study, emphasizing cancer. We also go over the situation of AI drug discovery in oncology today. Cancer radiology represents the highest proportion of authorized AI devices in the oncology-related sector (54.9%). Pathology (19.7%), radiation oncology (8.5%), gastroenterology (8.5%), clinical oncology (7.0%), and gynecology 1 (1.4%) are the fields that come after it. The bulk of these devices were designed to be applied to a broad spectrum of solid malignancies (cancer in general, 33.8%) in order to explore the various tumor forms. The specific tumor that counts for the largest number of AI devices is breast cancer (31.0%), followed by lung and prostate cancer (8.5% each), colorectal cancer (7.0%), brain tumors (2.8%) and others (6 types, 1.4% each) (Hamamoto et al., 2020). Clinical cancer research has shown some success with AI, particularly Deep Learning, associated with the expanding diversity of current biomedical data. AI-based techniques are widely used in several areas of cancer clinical research to increase accuracy and effectiveness (Varghese et al., 2019).They include the application of AI for biomedical literature utility, genetic analysis, medication discovery, and cancer image recognition. Clinical research on several types of cancer has benefited from using AI. Artificial intelligence (AI) has been effectively employed in radiology to assist the radiologist in defining disease by introducing increasing computer capabilities and algorithms.AI has recently used various well-established imaging techniques to produce positive screening and therapy outcomes for several cancer types. To categorize each region as a tumor or not, for instance, a CNN classifier employing multiparametric MRI (mpMRI) was developed. Highly trained and qualified radiologists segmented each tumor in the 140 individuals with locally advanced rectal cancer whose MRI scans were used in their research (Trebeschi et al., 2017). The probability maps that were produced have an extraordinarily high AUC of 0.99.The decomposition of contrast-enhanced MRI (DCE-MRI) from heterogeneous tissues was used to diagnose breast cancer subtypes using a wholly automated convex analysis of mixtures (CAM) technique. The potential for cancer recurrence has also been identified and detected using AI (S. Wang et al., 2019). In order to identify the predictive indicators of high-grade serous ovarian cancer (HGSOC), they trained a DL network on 8917 CT images from the feature learning cohort .After that, a DL-Cox proportional hazard (Cox-PH) model was generated to anticipate each patient's 3-year and personal recurrence likelihood. Predicting outcomes related to cancer, such as survival, life expectancy, progression, and tumor-drug sensitivity, is another practical application of AI. Numerous computational methods have demonstrated that mammography is frequently the primary imaging test method for detecting breast cancer (Li et al., 2018). An enhanced DL method was created in one study to find papillary thyroid carcinoma in ultrasound pictures. In a different study, histological slides, such as pictures stained with hematoxylin and eosin (H&E), were also utilized to categorize multiclass breast cancer (Shao et al., 2022).Early identification of cancer has become a new topic of various forms of cancer classification and detection employing machine aid, which has demonstrated the capacity to lessen limitations caused by the manual method. This study includes sections on state-of-the-art methods, analyses, and comparisons of benchmark datasets for identifying brain tumors, breast cancer, lung cancer, liver tumors, leukemia, and skin lesions from the perspectives of F-measure, sensitivity, specificity, accuracy, and precision. Figure 6 provides the study's visual representation (Saba, 2020).

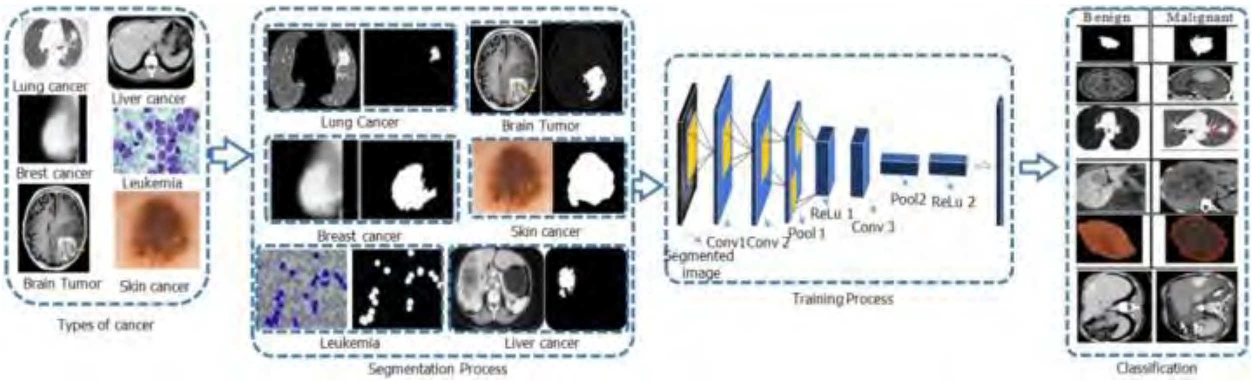
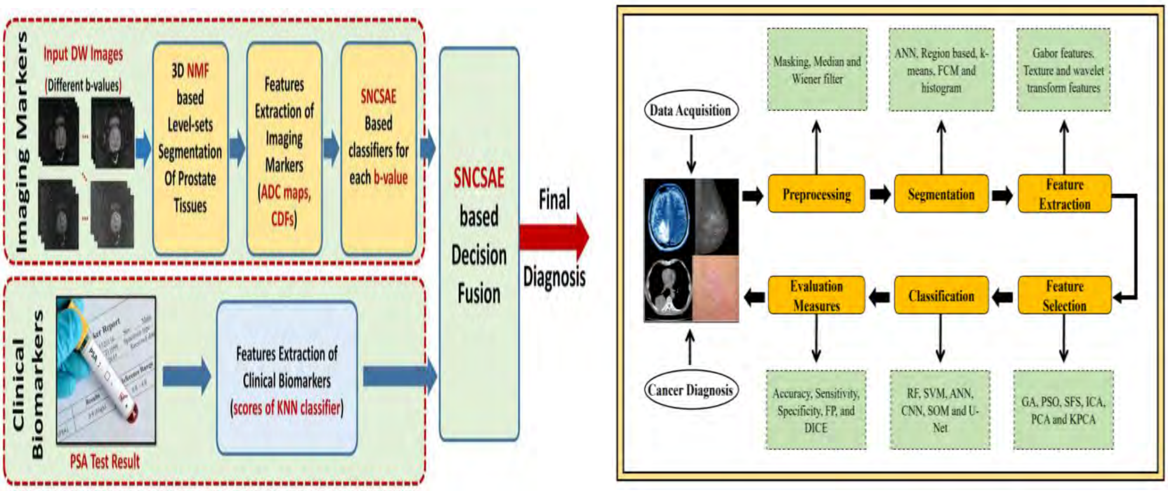


Figure 6: Machine assisted system for early cancer detection with segmentation and training process in different segments of the body (adapted from Saba, 2020).

Figure 7(a) and (b) summarizes the fundamental system processing operations. The computer aided device (CAD) system starts by employing a level set-based model to delineate the prostate region. A nondeterministic speed factor employs non-negative matrix factorization in this paradigm (NMF). However, it regulates how the level set grows. The probabilistic shape, the spatial voxel interactions, and the DW-MRI intensity information are all combined by the NMF. According to the average Hausdorff distance and the Dice similarity coefficient, the segmentation model's segmentation accuracy is 5.72 mm and 86.89 percent, respectively. In our earlier work, we compare this segmentation model to other segmentation models and provide additional details about it. Then, generalized Gaussian Markov random field (GGMRF) model-smoothed, intensity-based DW-MRI features, such as ADCs, are retrieved, normalized, and globally characterized using the cumulative distribution function (CDF).The PSA screening results are merged with the DW-MRI properties for increased diagnostic accuracy. The input prostate volume is then utilized to predict whether the diagnosis of the input prostate volume is benign or malignant using a stacked non-negatively constrained sparse auto encoder (SNCSAE). It incorporates a two-stage classification method employing CDFs of the expected ADCs and PSA-based probabilities (Ali et al., 2021).



(a) (b)

Figure 7: A flowchart of a standard CAD system created by AI for diagnosing multi-organ with cancer (adapted from Ali et al., 2021).

Figure 8 illustrates a design description of the research methodology. The first step in the proposed methodology is to get microscopic images of blood samples. Later, because deep neural networks need more data for training and better performance, data augmentation techniques were developed to solve the issue of limited data. Last but not least, a squeeze and excitation learning strategy based on deep convolutional neural network (CNN) architecture was suggested for identifying leukemia from microscopic images of blood samples (Bukhari et al., 2022). The following methodology subsections provide in-depth explanations of each phase.

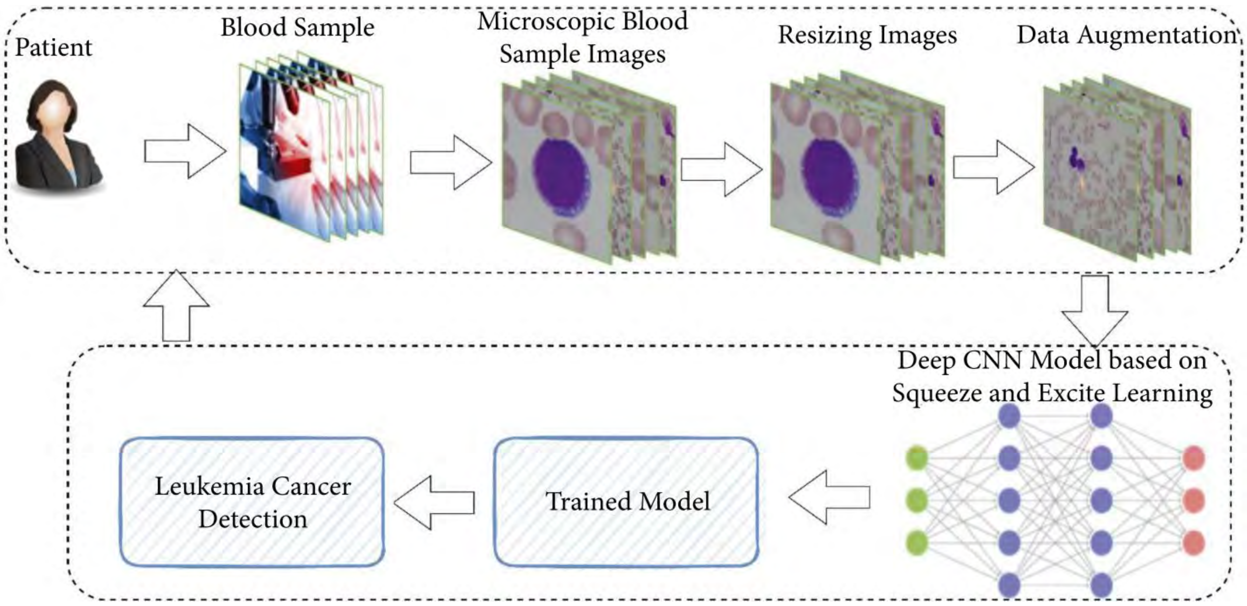


Figure 8: Leukemia detection process by using a deep learning framework from blood sample (adapted from Bukhari et al., 2022).

5.5 Diabetic Retinopathy

The most extensively studied subject of artificial intelligence (AI) applications for blind people and other optical illnesses is diabetic retinopathy (DR). Users can employ standard fundus photographs for early screening thanks to the ability of NN (neural network) models to recognize images. The author was the first to investigate DL model applications for DR detection (Gulshan et al., 2016). Diabetic retinopathy must be immediately diagnosed and treated to reduce the unnecessary visual loss caused by diabetes worldwide (Wong & Bressler, 2016). The high prevalence of diabetes patients and the limited human resources available for eye care globally make screening expensive (Bellemo et al., 2019). Automated AI algorithms research for diabetic retinopathy has demonstrated robust diagnostic performance and cost-effectiveness. Several countries like the USA, Singapore, Thailand, and India experienced these advantages of using artificial intelligence (Gulshan et al., 2016).The Food and Drug Administration-approved AI algorithm "IDX-DR," which achieved 87%

sensitivity and 90% specificity for diagnosing so much diabetic retinopathy, was implemented by the Centers for Medicare & Medicaid Services to authorize Medicare reimbursement.(Shetty et al., 2021). Most of the AI-based DR diagnostic systems today are based on false positives. FP's two-dimensional capabilities are limited because it can only recognize DME by identifying hard exudates in the posterior pole. Thus, even though they cover DME, AI systems based on FP may overlook situations. OCT has a greater rate of DME identification than FP. There are two ways of DR screening, and AI is now utilized at the point of care to decide which patients to send.

Fully automatic mode: This mode is utilized at screening locations without a trustworthy evaluator for the retinal images. The outcomes of AI seem to be what informed the referral. Patients with a referable DR and ungradable photographs should be referred to an ophthalmologist. An ophthalmologist should evaluate all referable images and at least 10% of non-referable images afterward.

Assistive (augmented intelligence) mode: This method is applied in locations where an ophthalmologist or trustworthy examiner is present. The clinician presented the AI algorithm's findings, and depending on his clinical assessment, he either acknowledged the AI grade or altered it.

The diagnostic facility in Mohakhali, icddr, had previously launched the market-leading FLAIR technology-based computer-assisted retina analysis (CARA) artificial intelligence platform on the first Tuesday of the previous month. CARA is a teleophthalmology method that integrates currently available tools (hardware and software) and procedures at the point of treatment and comprises image input, image improvement, automated pre-screening, and professional grading. CARA is conveniently available online and works with all well-known fundus camera brands, image formats, and electronic medical records. It is an inexpensive tool for assessing lots of patients. According to icddr, b, it has acquired regulatory approval from Health Canada, the US Food and Drug Administration (FDA), the European Union, and others. One of the most severe effects of diabetes is diabetic retinopathy, which, if undiagnosed and untreated, frequently results in lifelong blindness. The International Diabetes Federation (IDF) estimates that Bangladesh has 5.9 million diagnosed diabetics and an additional 3.9 million people with undiagnosed diabetes. About 1.8 million people, or 27% of all people with diabetes, have diabetic retinopathy. Furthermore, the IDF predicts that by 2025, Bangladesh will be one of ten countries with many people with diabetes (13.7 million) (Icddr,b - Press Releases, 2019). The AI implementation in diabetic retinopathy screening enables automated diagnosis and subsequent clinical decisions. As indicated in Figure 9, the AI system might suggest recommending the patient to the eye clinic for simply a reference diagnosis of diabetic retinopathy. The heatmap makes an effort to illustrate how each image pixel or region contributed to the final categorization to help researchers and physicians understand how the AI model arrived at its conclusion. The "black box" is revealed via heatmaps, illustrating the regions where the AI system focuses on providing a supportive environment between physicians and patients (Lim et al., 2020).

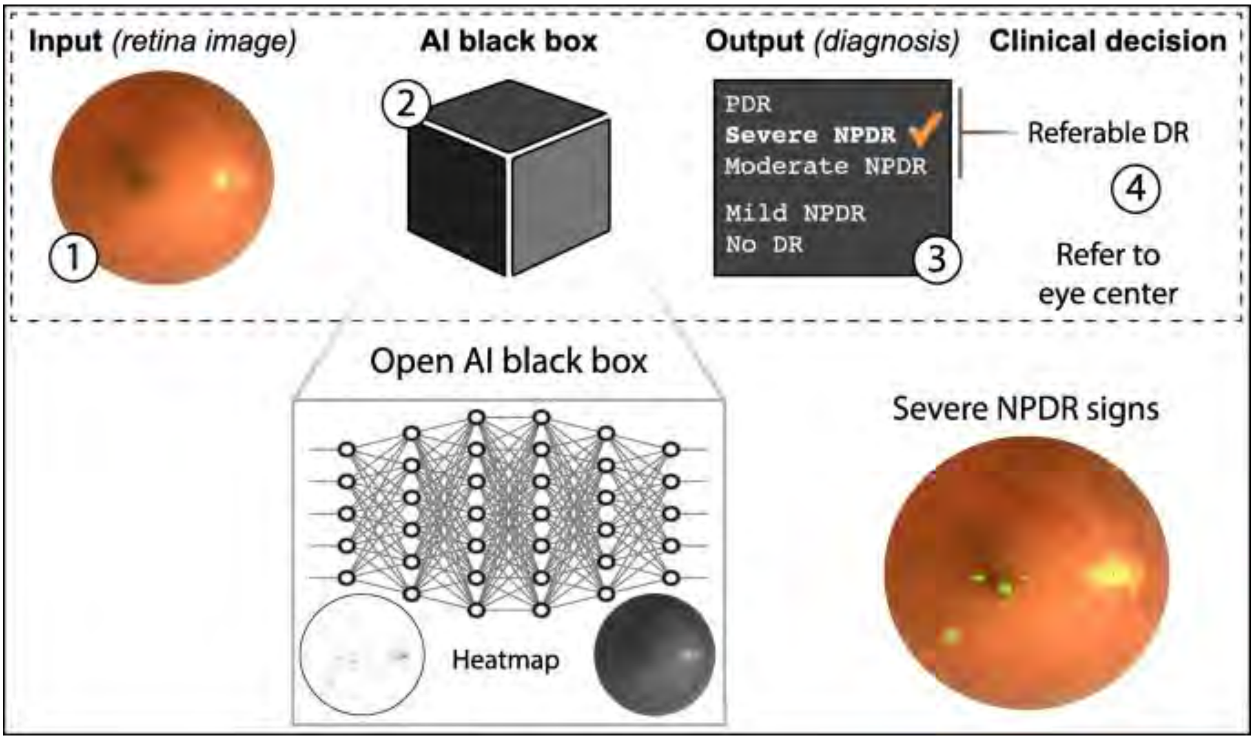


Figure 9: Schematic representation of diabetic retinopathy diagnosis using AI (adapted from Lim et al., 2020)

Abbreviations: DR: diabetic retinopathy; NPDR: non-proliferative diabetic retinopathy; PDR: proliferative diabetic retinopathy.

The deep neural network's output is a vector indicating the input image's category (five stages of DR). The AI software predicts the DR stage based on the output vector values from the heat map described (Figure 10).

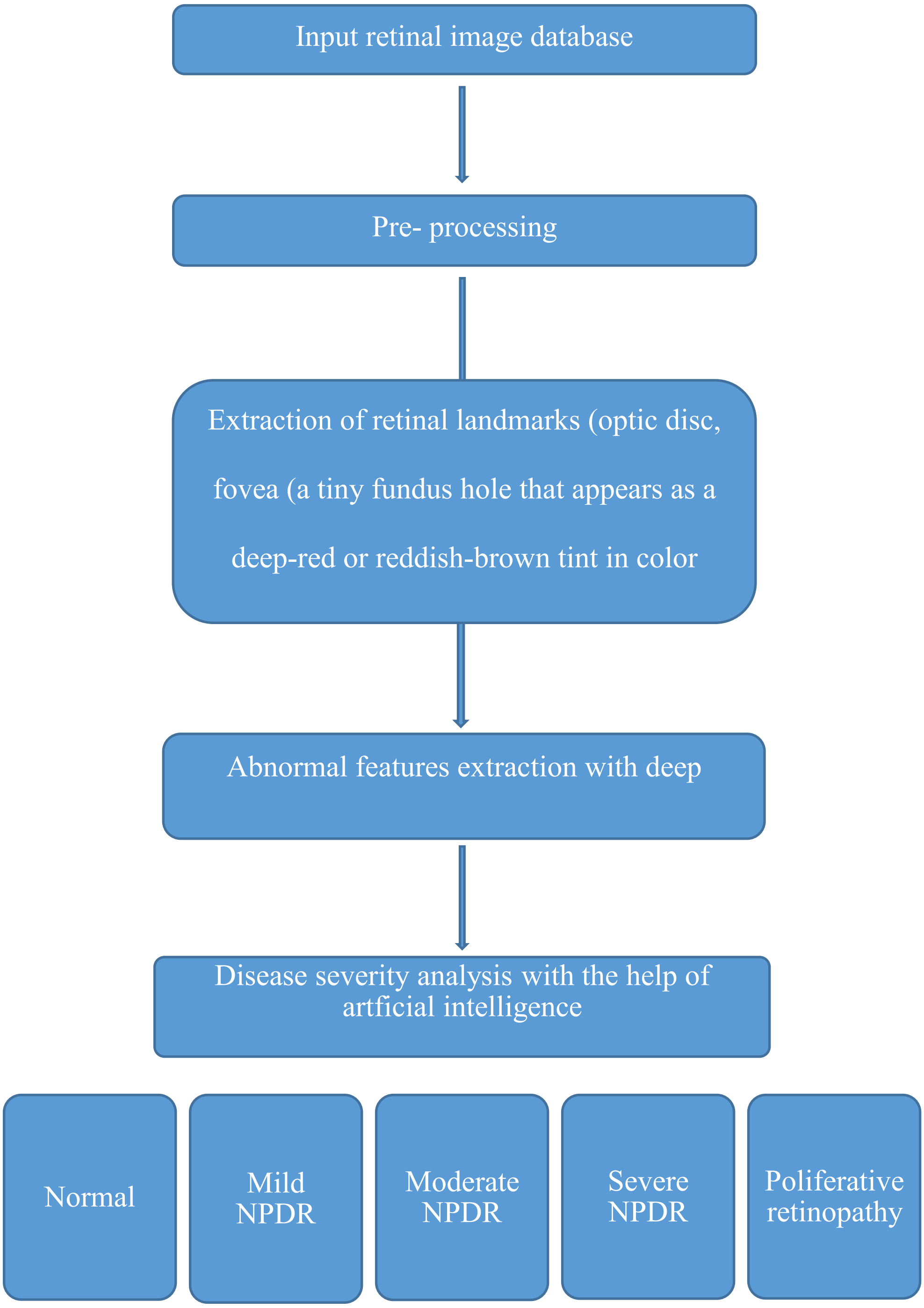


Figure 10: The workflow of a deep learning system in detecting the heat map produced by AI on various DR severity levels with the help of several vector (adapted from Ting et al., 2019)

5.6 Otolaryngology

The innovation and clinical application of AI technologies involve otorhinolaryngologists. As a result, gathering accurate data on patients and illnesses is crucial for developing AI technology (Bur et al., 2019).The automatic waveform classification of acoustic sound properties and the automatic recognition of auditory brainstem response wave forms are the first applications of machine learning, a branch of artificial intelligence, in otorhinolaryngology. In order to help clinicians perform more precise diagnoses for the ear using digital otoscopy, Aaron C. Moberly, MD, an assistant professor of otolaryngology-head and artificial neck disc replacement surgery in the famous Medical Center in Columbus. Also, their colleagues established software called "Auto-Scope" using AI. Fifty-four papers on AI-related subjects in otolaryngology were detected (Qi & Zhang, 2020).Furthermore, the number of articles published on artificial intelligence has increased significantly, with more than half of the current literature appearing in the last two years. Twenty-one (38.1%) and 37.0% of the publications were about neurotology and head and neck oncology, respectively. Applying machine learning algorithms to image data increases the detection and total elimination of head and neck cancers. Using white light and narrow-band imaging, Mascharak and colleagues at Stanford University created a machine-learning system to visually identify oropharyngeal cancers in the oropharynx (Crowson et al., 2020).This method was created to improve the early diagnosis of oropharyngeal cancers by creating an automated detection system. In order to detect nodal metastasis and extranodal extensions on preoperative CT scan images from patients with neck and head cancer, the author trained a neural network. The area under the patient operating curve for the six authors from the departments of otolaryngology and head and neck surgery was 0.91, indicating high accuracy (Kann et al., 2018).Some other authors used a categorization algorithm. This technique separates cancer from healthy oral mucosa with a sensitivity of 89% and an accuracy of 91%

using hyperspectral imaging data from marginal tumor tissue. Machine learning may enhance the early identification of oropharyngeal carcinomas through faster and more accurate cancer and healthy tissue segmentation. It may even be applied to improve intraoperative tumor margin evaluation. The 19 publications from the identified neurotology journals included various subjects, such as vestibular rehabilitation and audiology. In several papers, machine learning algorithms were applied to determine hearing results. The ability of machine learning algorithms to forecast audiologic outcomes in patients with sudden sensorineural hearing loss was examined by Bing and colleagues. The accuracy of the prediction of audiometric recovery by the authors was 77.58% using a cohort of 1220 patients and 149 factors(Bing et al., 2018).The author then used machine learning to assess the results of auditory and speech perception in young children who have undergone cochlear implantation by using preoperative neuroanatomic data and other clinical characteristics. In a recently published paper, a set of CT scans from 239 individuals with chronic rhinosinusitis was analyzed to classify osteomata complicated occlusion using neural networks. The authors' system, mediated by Google, categorized the osteomata complex as "open" or "closed" with 85% accuracy. AI has indeed established a presence in research throughout all specialized fields of otolaryngology, despite the field's relative youth. Ontological imaging with AI is encouraging, demonstrating the technology's potential to automate some imaging processes in a healthcare environment with rising requirements and workload (Chawdhary & Shoman, 2021).Different maps are incorporated into the artificial intelligence (AI) methodologies used for voice-based analysis in otolaryngology employing audiovisual spectrograms. This method of otolaryngology disease identification produces results in outputs shown in Figure 11.

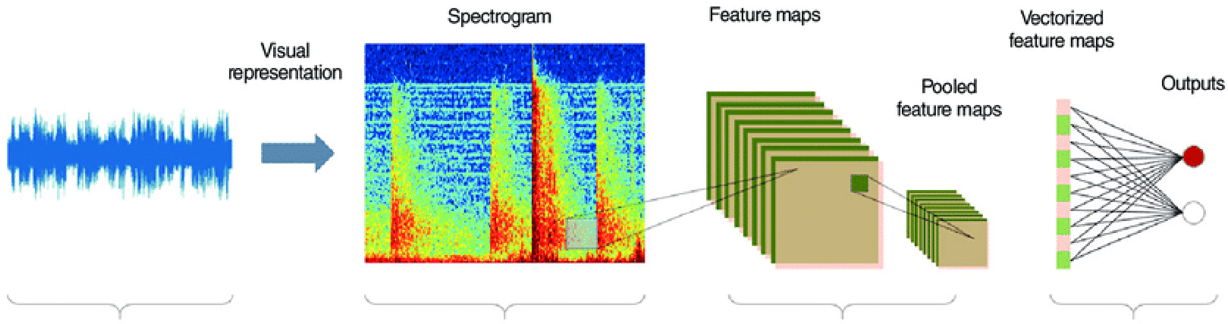


Figure 11: Otolaryngology disease identification produces results in outputs through spectrogram (Tama et al., 2020).

Figure 12 demonstrates how AI can be used to assist otolaryngology procedures. Clinical interactions, including as office visits, imaging studies, operations, and pathology, generate a lot of data that can be utilized to create machine learning algorithms that assist clinical decisions.

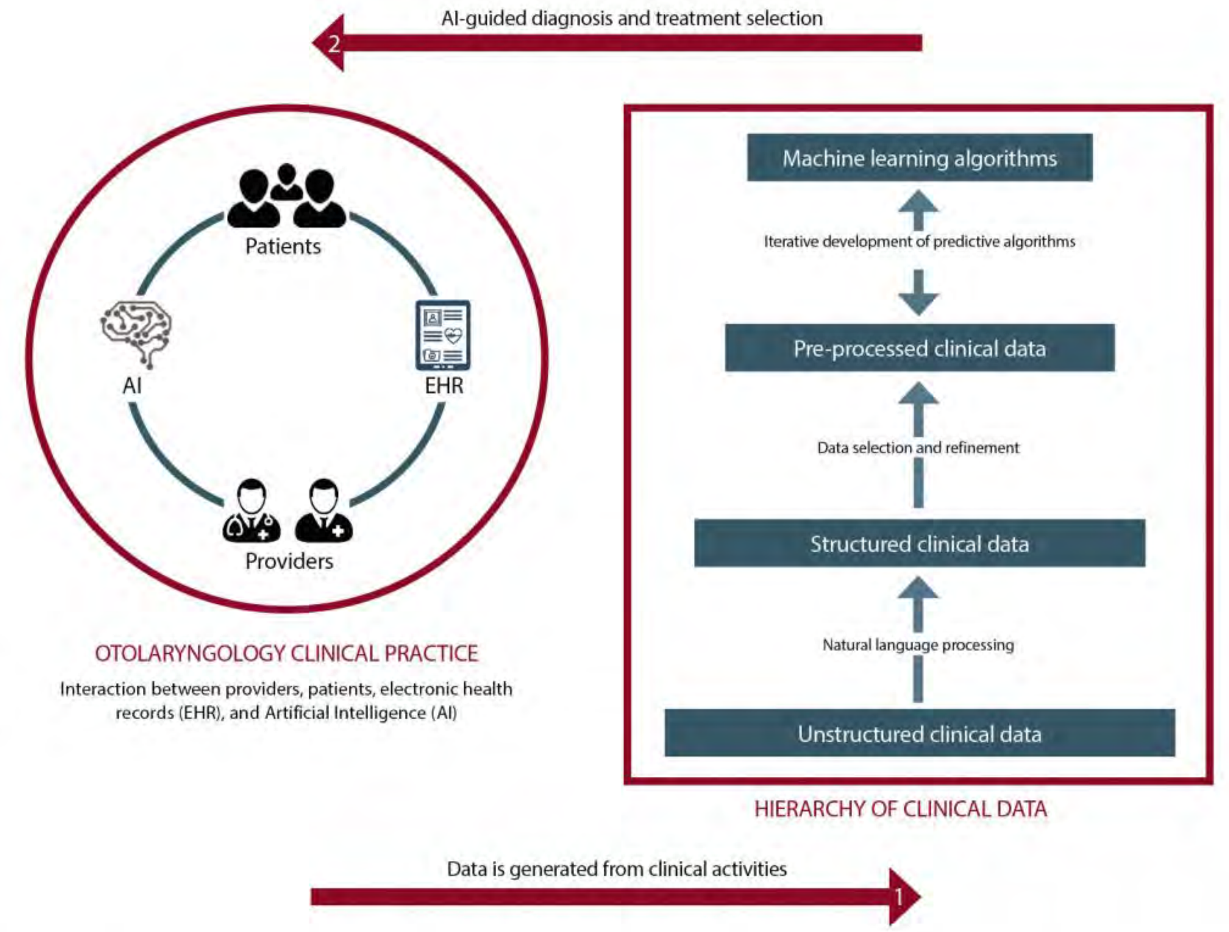


Figure 12: Otolaryngology data from clinical practice and AI guided diagnosis and treatment selection (adapted from Formeister et al., 2020)**.**

Chapter 6

Role of Artificial Intelligence in Drug Development

6.1 Drug Design

Traditional drug discovery takes years and involves massive financial expenditure. Being late in the benefits of reaching or treating the public increases the cost of pharmaceuticals and treatment costs. It also restricts innovation and research to a small number of extensive participants in the business (Ostern et al., 2021). However, AI is altering that. The world's first medicine for obsessive-compulsive disorder (OCD), code-named DSP-1181, was revealed on January 30, 2020. Exscientia, a British startup, worked with Sumitomo Dainippon Pharma, a Japanese pharmaceutical company, to accomplish this. The researchers claim that the algorithm used to identify the drug, a process that took just one year instead of several, can be applied to discover new drugs.AI is beneficial in figuring out how different pharmaceuticals interact when taken concurrently or as part of the same treatment plan, in addition to helping researchers identify novel drugs. It aids in analyzing and simulating the numerous permutations and combinations of drug-drug interaction consequences. To encourage additional research and development, some governmental institutions, including the NHS in the UK, are establishing specialized AI labs for healthcare. Every player in the ecosystem benefits from accelerating the discovery process (Sinha & Al Huraimel, 2020).In the world of essential information, deep learning technology has demonstrated outstanding application potential in drug design. This method, which has won international drug design competitions, is utilized by numerous drug research teams worldwide. Merck Sharp &Dohme Ltd. (MSD) organized a Kaggle competition in 2012 to assess how well data science could increase the predictive accuracy of the quantitative structure-activity relationship (QSAR) method.In order to create a quantitative mapping relationship between chemical structure or physicochemical characteristics and their biological functions, the quantitative structure-activity relationship (QSAR) employs mathematical techniques (Esposito et al., 2004).Virtual screening (VS), a powerful computational drug discovery technique, is illustrated in Figure 13 and is used to make tiny active compounds that bind to therapeutic targets (usually proteins).In the early stages of therapeutic research, this procedure can remove compounds with the wrong structures, and it also serves as a productive way to discover new hits (Lavecchia& Giovanni, 2013).The Drug Design (DD) protocol is compatible with any popular docking program. During our DD campaigns, we integrated billion-size (1B+) chemical libraries vs. a variety of targets using the docking suites FRED, Glide, Autodock-GPU, QuickVina, and ICM. The setup and management of DD against a generic target protein are described in this technique. Despite the preparation stages for proteins, ligands, and docking grids being illustrated using specialized software, they are all easily transferable to other software and computer-aided drug discovery (CADD) packages (Gentile et al., 2022).Drug repositioning, commonly referred to as drug repurposing, is a way to obtain fresh evidence from already approved medications. Drug recycling for new indications can also reduce the need for new drug development. However, because of the apparent accessibility and well-known safety of licensed pharmaceuticals, it can reduce drug safety issues effectively (Novac, 2013). De novo drug design creates novel chemical entities with estimated activity for the target of interest using a molecular technique and evaluation computer (Kerstjens& De Winter, 2022).

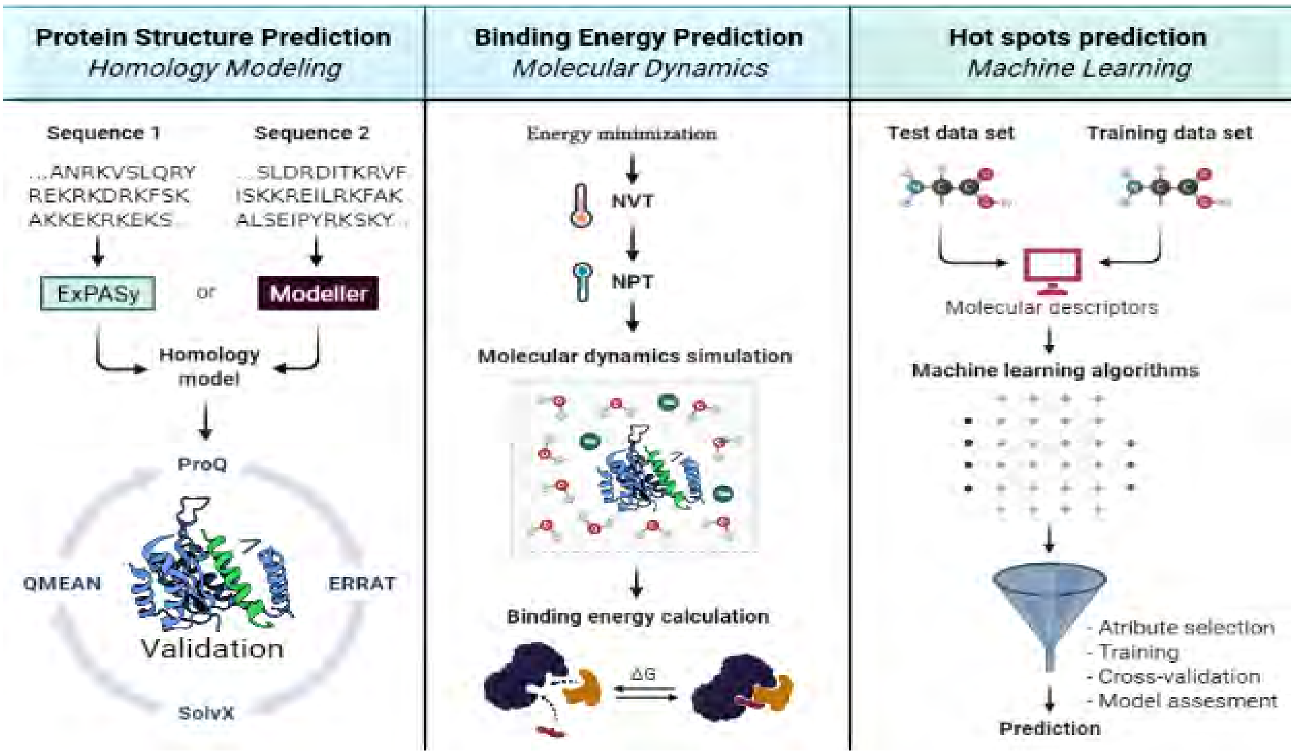


Figure 13: Drug design process by using different predictions and dynamics of machine learning process (adapted from Kerstjens & De Winter, 2022).

6.2 Chemical Synthesis

A guideline strategy for designing retrosynthesis is computer-aided synthesis (CASP). Specifying the chemical synthesis factors that synthesized management software may require is essential. Various human involvement in automated platforms and synthesis planning tools have combined. Even though the industry is still developing the application of CASP for fully automated synthesis planning, these early accomplishments show the tools' value in a DMTA cycle. The various roles that artificial intelligence can engage in medicinal chemistry synthesis will be described in more detail from this perspective. These roles included all that figure 15(A) shows can incorporate into a medicinal chemistry workflow, are already integrated with some pharmaceutical companies, and need additional development to complete even more challenging tasks. In Figure 14, we emphasize the three critical roles of computer-aided synthesis planning (CASP) in retrosynthetic planning, condition prescription, and forward-reaction prediction (Coley et al., 2019). Consequently, there are three main computer-aided synthesis planning jobs. Retro synthesis can be split into minor challenges solved by gradually producing retrosynthetic recommendations. Additionally, the single step can be used continuously to identify complete multistep pathways. The chemical synthesis process makes it compelling; suggestions must include response conditions that will result in a positive forward reaction. The proposed synthetic processes are validated using reaction prediction, which predicts the potential products given a set of starting components and conditions. The inclusion of AI-based CASP tools into the medicinal chemistry process can be visualized in various ways, and it is growing. As mentioned in the introduction, we will divide the use cases into multistep route planning, forward-reaction prediction, and condition recommendation. These tools are not intended to suggest transformations that a skilled chemist cannot recognize. Major breakthroughs will be accomplished because more scientists accept using CASP to minimize their workload and machine learning models for synthesizing planning (Choudhary et al., 2021). Automated retrosynthesis, synthesis, and optimization are the various stages. Figure 14 represents a process for integrating automated retrosynthesis, a synthesis robot, and reaction optimization. The target synthesis obtained by the retrosynthetic module can change into synthesis code that can be executed on a robotic platform. Using the robot's response, the optimization module can enhance the entire series. Figure 15 lists several prospects for the use of AI approaches in drug discovery.

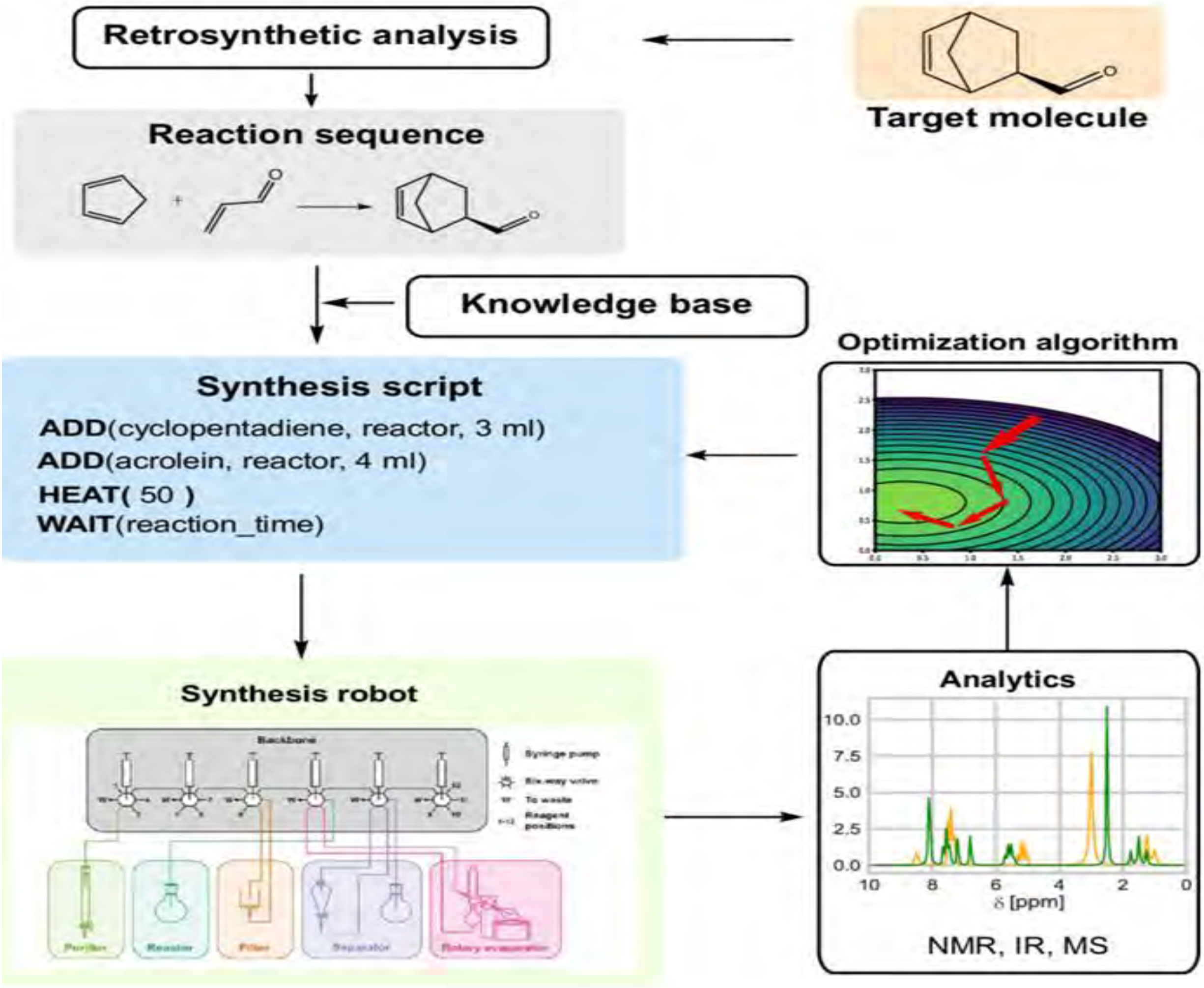


Figure 14: A workflow for combining automated retrosynthesis, a synthesis robot, and reaction optimization (adapted from Gromski et al., 2020).

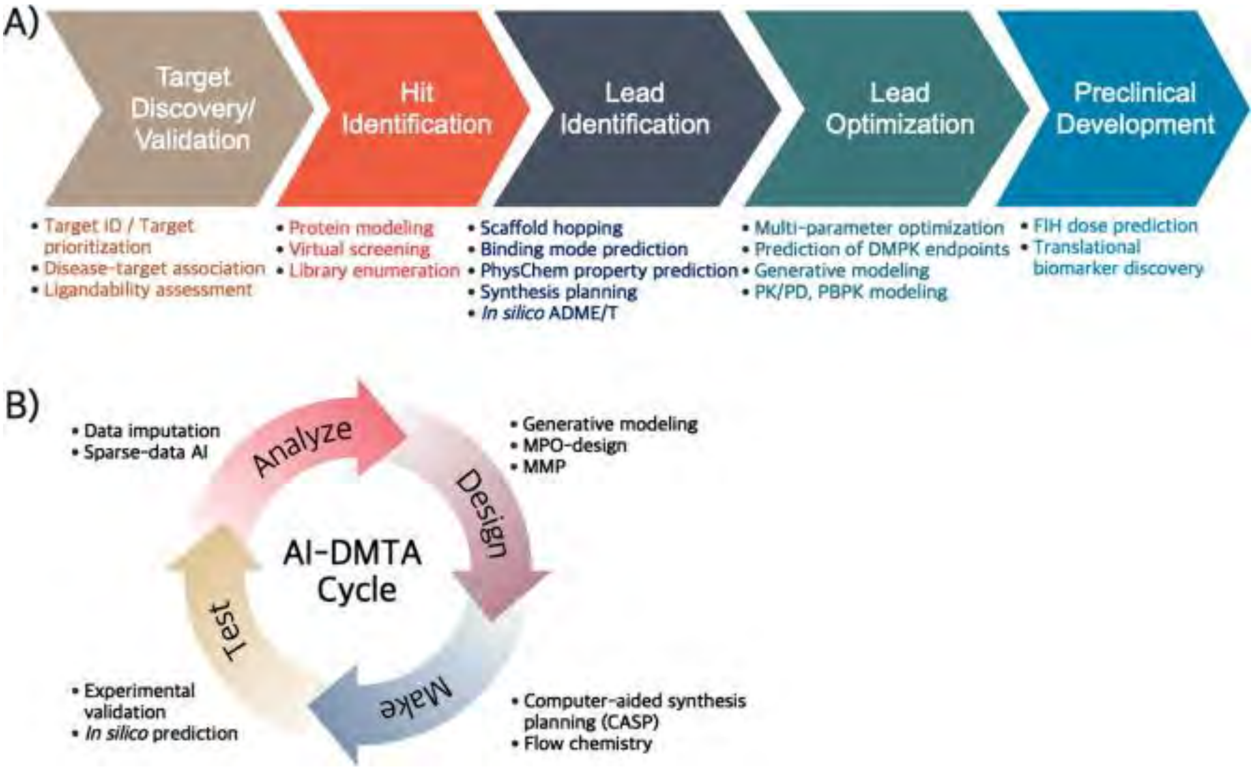


Figure 15: Possibilities for using AI approaches in the drug discovery process. (A) A schematic illustration of the preclinical drug development process highlights potential AI applications in various stages of the process. (B) An example of an AI-driven design-build-test-analyze cycle highlights ways to use AI to make the DMTA cycle more effective (Vijayan et al., 2022).

6.3 Drug Screening

A drug's discovery and development can take over ten years and cost an average of US$2.8 billion. Nevertheless, Phase II clinical trials and regulatory approval are unsuccessful for nine out of 10 medicinal compounds. Based on synthesis feasibility, algorithms like Nearest-Neighbour classifiers, RF, extreme learning machines, SVMs, and deep neural networks (DNNs) are employed for virtual screening (VS), which also can predict in vivo activity and toxicity. A platform for the identification of treatments for conditions like immuno-oncology and cardiovascular disorders has been created by several biopharmaceutical corporations working with IT firms, including Bayer, Roche, and Pfizer.AI Prediction of Secondary Drug Screening Based on Physical Property. The selection of drug candidates that exhibit various desired features, particularly concerning bioavailability, bioactivity, and toxicity, is crucial in drug design. When developing a new medicine, physical properties like melting point and partition coefficient (logP) should be accounted for because they substantially impact a drug's bioavailability. While the melting point indicates how quickly a medication dissolves in an aqueous medium, the logP, a measurement of the relative solubility between oil and water, assesses cellular drug absorption.Examples include potential energy measurements (ab initio calculations), a molecular fingerprint, a simplified molecular-input line-entry system (SMILES) string, and molecular graphing with different atom or bond weights. Molecular models that can be used in an AI drug design algorithm include molecular fragments or bonds, Coulomb matrices, atomic coordinates in 3D, the electron density surrounding the molecule, or combinations of these (Chan et al., 2019). The chemical collections from the primary and secondary assays for the drug screening illustrates in Figure 16.

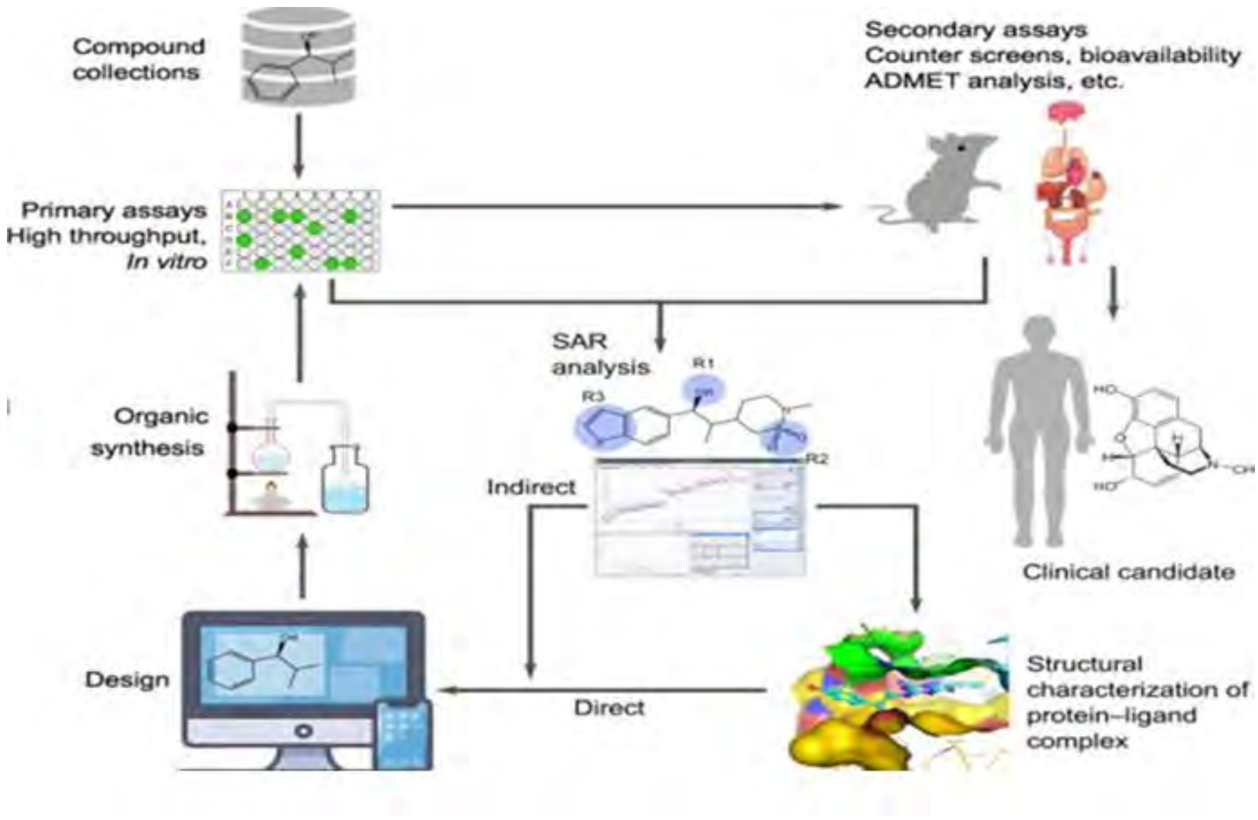


Figure 16: Drug screening and drug discovery by artificial intelligence with different steps (adapted from Chan et al., 2019).

6.4 Polypharmacology

Drug promiscuity, also known as polypharmacology, is the capacity of small compounds to interact simultaneously with several protein targets. Understanding the polypharmacology of potential drug molecules is essential for drug discovery to increase their efficacy and safety and find new therapeutic applications for currently used medications. The technology for predicting drug crystal form is divided into two types: that which uses molecular mechanics to predict crystal form and that which uses quantum mechanics. The Material Studio program's Polymorph module serves as the primary representation of the molecular mechanics-based software. It consists of several algorithms designed to recognize minimal-energy polymorphs. For instance, if the molecular structure is already known, AI can utilize the Polymorph module to compute the least lattice energy and find all potential energy crystal configurations and molecule organization principles. Cluster analysis and energy arrangement determine the most likely crystal shape. This approach can be attained by looking at a drug's molecular makeup or correlating it with experimental data from X-ray diffraction. The evolutionary crystallography software package, often known as the universal crystal structure prediction software, is the primary example of quantum mechanics-based software (universal structure predictor: evolutionary Xtallography). It can determine crystal structures at both the atomic and molecular levels. The stable and metastable structures of therapeutic molecular crystals can only be predicted using molecular structures. They may also quickly simulate and explore stable compositions and architectures based on unit cell characteristics, fixed unit cell shapes, and unit cell volumes discovered through experimentation. Crystal structure and crystal shape prediction are both possible (CSP). Ten international research organizations held six worldwide crystal structure projections in 1999, 2001, 2004, 2007, 2010, and 2015. The accuracy of the prediction approach is evaluated using the coherence between numerous known but unpublished crystal structures and the predicted ones. The fourth time saw the appearance of computer software with a perfect forecasting success rate. The use of AI to predict crystal shape is explained in more detail in the following section (Heng et al., 2021). In addition to the efforts described above, numerous initiatives are being taken to introduce innovative concepts in the field, to address the challenges in drug polypharmacology and rational multi-targeting molecular design (Sirois et al., 2021).

Deep learning and artificial intelligence approaches have been shown to significantly improve polypharmacology predictions. In particular, AI can take advantage of large complex data generated from HTS and multi-omics technologies and learn the patterns that are difficult to find using any other approaches. A general workflow of using AI techniques for polypharmacology predictions is summarized in Figure 17 (Awale & Reymond, 2019).

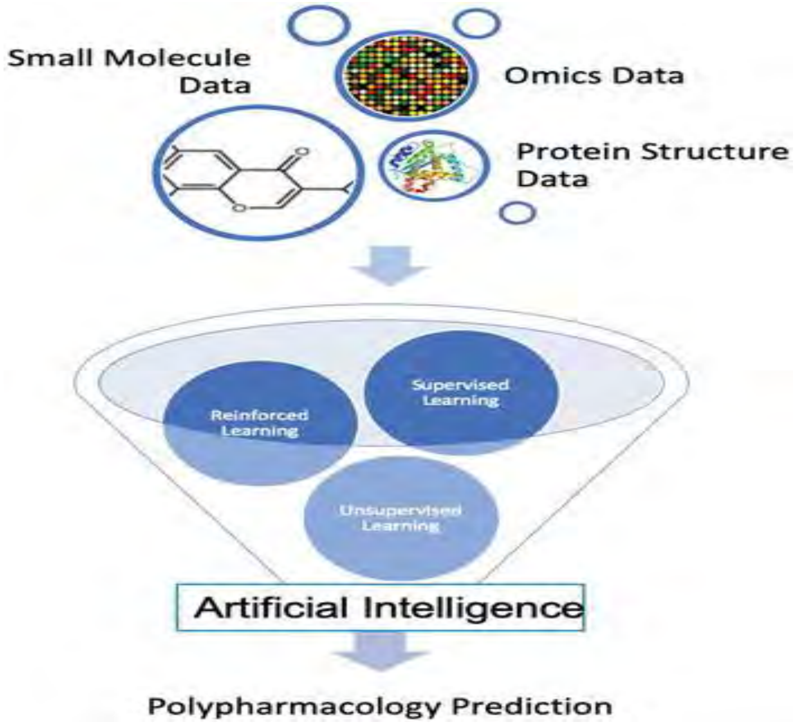


Figure 17: Web-based AI tools for polypharmacology prediction (adapted from Awale & Reymond, 2019).

6.5 Drug Repurposing

Utilizing current medications to treat novel and difficult-to-treat disorders, such as COVID-19, is known as drug repurposing or repositioning. The possibility of shortened development cycles and lower total costs has made drug repurposing a potential strategy. A potent remedy for developing disorders like COVID-19 is the medication repurposing technique (Zeng et al., 2020). Yet, without foreknowledge of the complete drug-target network, the development of promising and affordable approaches for the effective treatment of complex diseases is challenging. Although AI-based drug repurposing is in the developmental stage, several examples have shown encouraging results, including baricitinib identified by Benevolent AI, dexamethasone predicted by CoV-KGE, and melatonin from network medicine-based findings (Figure 18).The failure rate of medication repurposing between preclinical investigations and clinical trials for COVID-19 can be decreased by implementing efficient and reliable in vitro and in vivo models. Clinical trial success rates may increase using tailored medication or genotype-informed drug repurposing. Figure 18 depicts the experiment-based approach, also known as activity-based repositioning, which uses experimental tests to investigate novel pharmacological applications for original drugs. It employs cell-based and protein-target-based screens in disease models without knowledge of target protein structural details. Experimental repositioning techniques include the target evaluation matrix, cell assay technique, animal model method, and clinical framework (Roy et al., 2021).In comparison, *in silico* repositioning provides analytical biology, bioinformatics, and cheminformatics techniques to perform the virtual screening of enormous drug chemical libraries in public databases. This method relies on the chemical interactions between drug compounds and protein targets to identify molecules that may be bioactive. Although experimental studies are helpful in determining therapeutic efficacy, they can be time-consuming and produce very modest results. For this reason, computational methodologies have improved this approach by delving deeper into drug executions. It can assess the interaction of ligand(s) with respective target proteins, predict novel signaling pathways, and enable rapid development in less time at lower costs, which is essential for the current pandemic (COVID-19) situation (Naasani, 2021). AI medication repurposing algorithms provide a quick and affordable technique to find novel therapy alternatives for developing diseases (Zhou et al., 2020).

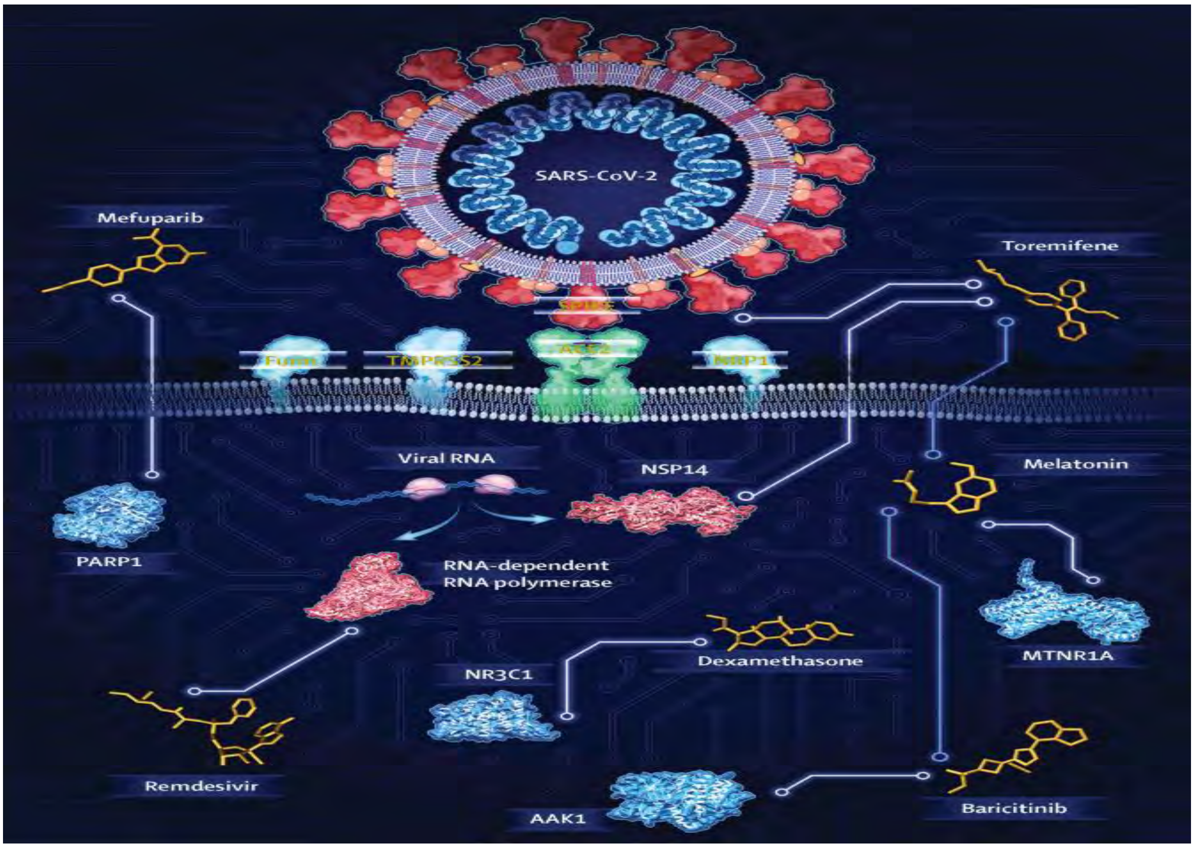


Figure 18: Overview of AI-assisted drug repurposing for COVID-19 (adapted from Zhou et al., 2020).

Abbreviation: PARP1=poly-ADP-ribose polymerase 1. NR3C1=nuclear receptor subfamily 3 group C member 1. AAK1=AP2-associated protein kinase 1. MTNR1A=melatonin receptor 1A. TMPRSS2=transmembrane serine protease 2. ACE2=angiotensin I converting enzyme 2. NRP1=neuropilin 1. NSP14=non-structural protein 14.

Chapter 7

Role of Artificial Intelligence in Smart Wearable Technology

The earlier physiological data examination techniques took place in hospitals. Patient monitoring, status evaluations, and recommendations are necessary for managing chronic diseases. The systematic collection of individual physical and health data has been greatly improved by autonomous wearable, software tools, and mobile apps. Wearable technology can record patient health data everywhere (Nguyen et al., 2021). AI can help improve healthcare delivery efficiency at the same time. AI will revolutionize the healthcare sector; it will bring together the skills of medical professionals, licensed pharmacists, and others to offer complete ongoing, and a scientific management approach is established through effective management of chronically ill patients.

Additionally, it encourages the healthy growth condition, postpones the progression of the disease, and lowers the prevalence of impairment (Jabarulla& Lee, 2021). Machine learning enables the smart medical area to evaluate massive amounts of health data to construct complicated, nonlinear correlations between our bodies and diseases that are hard to define in the form of an equation, leading to outcomes with higher accuracy (Krittanawong et al., 2022). Deep learning, wearables, and blockchain technology integration will boost the effectiveness of controlling chronic diseases by increasing efficiency, automation, data security, and privacy. The hypothetical technical process shown in (Figure 20) illustrates how AI and blockchain may gather data from wearable devices, analyze it, and upload it to a stable cloud platform or a specific data management structure unit to continuously enhance the appropriate algorithm model. The research's prime objective is to address the significant issues and difficulties associated with treating and preventing chronic diseases.

Wearable technology can gather patient data, which can then be securely shared with healthcare organizations using block chain privacy protection and trustworthy data tracing. Using AI technology, medical institutions can manage much information on chronic diseases. Wearable technology ensures many wearable sensors' wireless synchronous calculation speed, providing vital technical support for healthy digital twins. An adaptive procedure will complete the comprehensive computation of blood glucose, blood pressure, heart rate, blood oxygen content, temperature, respiration, and posture. Additionally, it will successfully handle the multi-point detect health's general calculation problems (Xie and others, 2021). Blockchain-based data processing is being integrated into the healthcare system by artificial intelligence for usage by academic researchers, university medical students, hospital employees, and government clinicians (figure 20). This review article discusses the most recent developments in AI's application to chronic diseases, including cancer, cardiac disease, and ophthalmic disease, along with its limitations and potential future developments in AI-augmented healthcare systems. These things are described in Figure 19 (Vyas et al., 2022).

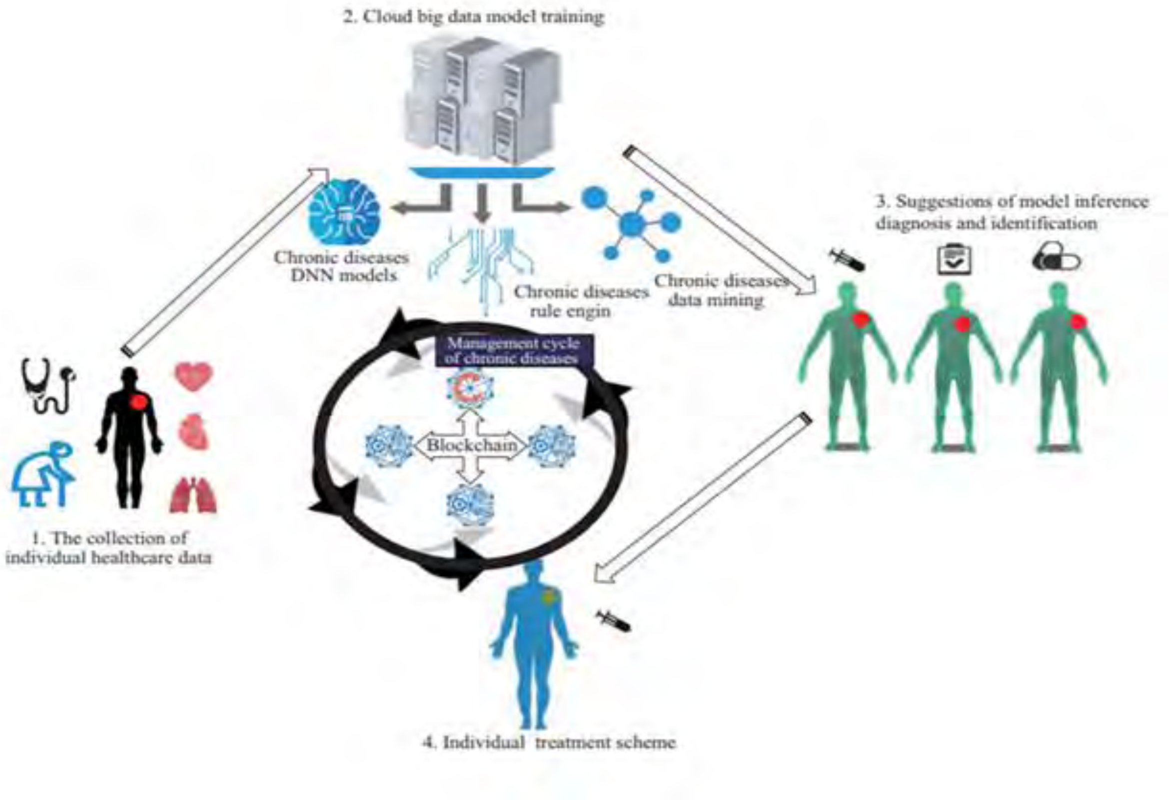


Figure 19: The technical method of managing chronic diseases is centered on the block chain and AI-based disease detection (adapted from Xie et al., 2021)

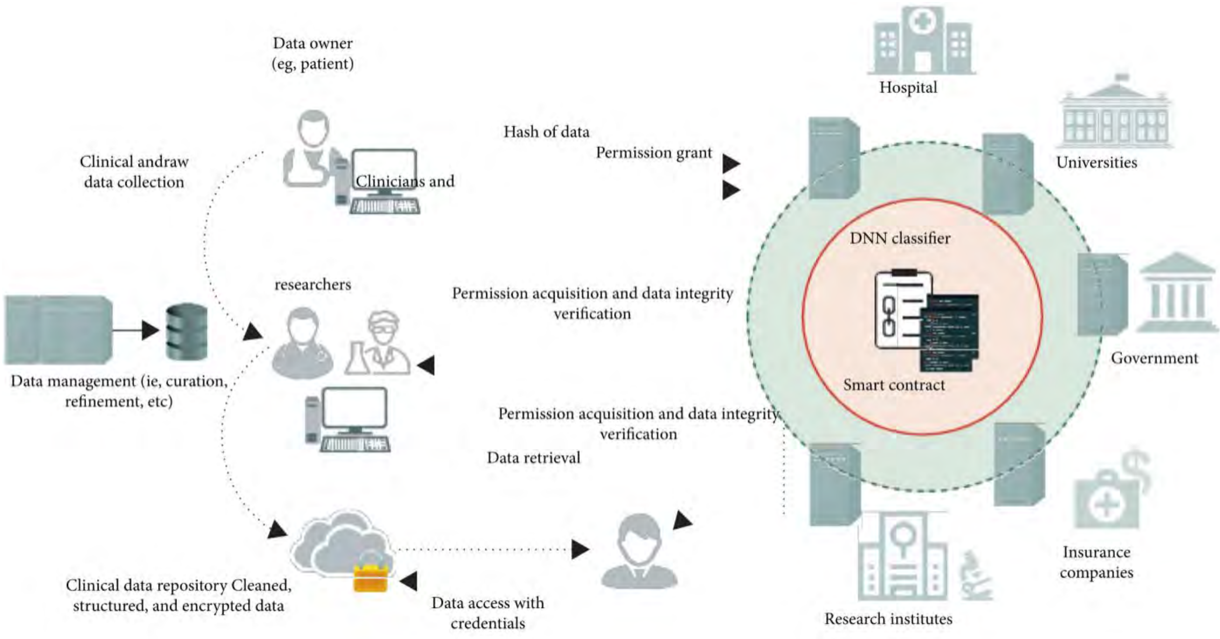


Figure 20: Blockchain-based data processing in the healthcare system. Artificial intelligence in the healthcare system launches block chain –based data management which is being used by academic researchers, medical students from universities, hospital staff members and government clinicians (adapted from Sharma et al., 2022).

Chapter 8 Challenges and Future Prospects

8.1 Challenges

Despite the remarkable accuracy of AI-based models in many ocular illnesses, there are still several clinical and technological barriers to their usage in actual clinical practice. These challenges could appear at different points in both scientific and clinical settings. Many research has employed relatively homogeneous populations of training sets; retinal pictures for AI practice and testing frequently come under many criteria, including field width, a field of perspective, picture magnification, image quality, and the ethnicity of participants. Retinal images are routinely categorized by field width, the field of perspective, picture magnification, image quality, and participant ethnicity for AI training and testing.(Gargeya&Leng, 2017; Mayro et al., 2019).If the disease is rare, it cannot be accessible. Second, AI cannot retain a condition detached from our technique because the computer detects a structure or function mechanically. There will only be a few distinct qualities and varieties (Nguyen et al., 2015). Most importantly, it might result in a mistake. The author discussed the process of neural networks incorrectly classifying data. Even when AI can perform a task well, human involvement must still be involved. In a study with 415 participants, the subjects were instructed to picture undergoing a physical examination and receiving prescription recommendations from a physician or an AI system.Participants valued the AI system less than a doctor, even after it understood their recommended course of therapy and recommended it. This study supports earlier research indicating that users prefer human doctors and shows that people are reluctant to trust AI, even if it performs at a level comparable to a human doctor (Asan et al., 2020). Due to the challenge of explaining AI-generated models and the fact that many doctors are unaware of the essential workings of algorithms, doctors now encounter new ethical concerns (SFR-IA Group, 2018). The development of AI has been delayed by the inherent challenges of machine learning, the flaws in ethics and law, and society's lack of acceptance. Based on available data, AI programs are developed to learn and make inferences. Disparity relied on by biased data sources is the most prevalent ethical problem (L. Jiang et al., 2021).Before being hired, healthcare professionals must pass strict tests, and while working, they are obligated to adhere to several norms of behavior. There are currently no worldwide uniform laws or regulations governing the use of AI in medicine to standardize the conduct of practitioners (Bernstam et al., 2022). AI crime (a new and dangerous crime in the health sector) could happen if criminals use AI (Kayaalp, 2018).Racism and inequality are risks in healthcare AI. AI systems can collect biases from the data they are given and learn from it. If the data represents underlying flaws and disparities in the healthcare system, even if AI systems are trained on reliable, representative data, there may be problems (Shaheen, 2021). The most obvious risk is that occasionally inaccurate AI systems can cause patient harm or other problems with healthcare. A patient could suffer harm if an AI system prescribes the incorrect medication and fails to identify a tumor on a radiological exam. Also, it decides to provide one patient a medical bed over another based on an inaccurate prediction of which patient will gain more weight (Shaheen, 2021).AI may also endanger privacy by accurately predicting patient personal information without ever acquiring that information itself (Marwan et al., 2018). Particularly if the AI system's findings are shared with outside parties like banks or life insurance companies, patients may consider this as an invasion of their privacy (van der Schaar et al., 2020).The "black box" issue is one frequent critique of AI systems. Deep learning algorithms frequently challenge to explain their predictions in precise detail (Davenport & Kalakota, 2019).

8.2 Future Prospects

In this context, the critical purpose of artificial intelligence is to forecast how future drug molecules will interact with the proteins of human cells and, in turn, how well the drug will work. AI can also explore illness mechanisms, find biomarkers, and study them. For instance, in 2020, AI technology allowed for the analysis of the action of thousands of medications in connection to their capacity to obstruct an enzyme that the SARS-CoV-2 virus needs to proliferate in human cells (Laptev et al., 2021).In the future, AI may help with controlling medical issues, avoiding diseases, and keeping an eye on the likelihood of disease spread (Banka et al., 2018). In the future, even when an AI system is connected to a physical medium, AI robots, AI hospitals, and AI cloud doctors in the cyber-physical space will gain legal personalities and be acknowledged as participants in cyber-physical relations in the digital world. Future legal recognition of artificial intelligence (AI) beings that can conduct digital activities and make judgments (both with and without physical representation in the actual world) includes AI robots, AI hospitals, and AI cloud doctors (Laptev et al., 2021).Online consultations will increase as telehealth becomes more widely accepted. This healthcare can help prevent disease outbreaks and meet the medical requirements of more people worldwide. AI experts must keep secure compatibility in mind while the institutionalization and integration of digital health are now being discussed (Varoquaux & Cheplygina, 2022). The ultimate goal of artificial intelligence is to create machines with general intelligence similar to humans, and these machines will be able to engage in complex thought and reasoning, much like people. Though it is feared that such machines would replace humanity, the direction of AI is moving toward computers with general intelligence to handle a variety of tasks as well as possible (Kaushal et al., 2020).

Chapter 9 Conclusion

Artificial intelligence in healthcare, specifically in health service management, is essential to make medical judgments, especially predictive analyses, in diagnosing and treating patients. The challenges include facilitating early acceptance, long-term implementation in the health system, failing to take the user's perspective, and using technology necessary for AI adoption in the public health sector but not being exploited to its full potential. Among the ethical concerns facing clinical uses of AI include safety, efficacy, privacy, information and permission, the freedom to decide, "the right to try," costs, and access.

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