Artificial Intelligence in Early Detection of Cancer

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***Abstract*—Cancer is still one of the world's top causes of death, and improving survival rates and treatment outcomes depends on early detection. Artificial intelligence (AI) has advanced so quickly in recent years that it has revolutionized cancer diagnosis by improving accuracy, speed, and accessibility. With an emphasis on its uses in clinical decision support, genetics, and medical imaging, this research investigates the role of AI in early cancer diagnosis. A number of AI methods, such as convolutional neural networks (CNNs), deep learning (DL), and machine learning (ML), have shown exceptional accuracy in detecting malignant tumours on imaging modalities like CT, MRI, and mammography. Personalized risk assessment, increased diagnostic efficiency, and a notable decrease in false-positive and false-negative rates have all been made possible by AI-assisted technologies. Adema's, combination genomics multinomial intelligence artificial Brinda compression integral biological tumoral, toque permit oftener concipient's predictive medicinal de precision. Despite these limitations, AI holds immense promise for revolutionizing oncology by enabling earlier and more accurate cancer detection, optimizing treatment strategies, and ultimately improving patient outcomes. Continued interdisciplinary collaboration, regulatory oversight, and ethical governance will be essential to fully realize AI's potential in cancer care.**

***Index Terms*—Artificial Intelligence, Cancer Detection, Deep Learning, Early Diagnosis, Genomics, Machine Learning, Medical Imaging, Precision Medicine**

I. INTRODUCTION

Due to deficient computing infrastructure and algorithms, interest in AI has moved between periods of optimism and disappointment since the late 1950s (1). However, the growth of algorithms for deep learning, big data, and appropriate computing infrastructure has sparked a renewed interest in technologies related to AI and boosted their use in a variety of industries. (2). Early cancer detection and artificial intelligence (AI) are two quickly developing topics with a lot in common. According to UK national registry data, there seems to be a significant relationship among cancer stage & I-year cancer mortality, with some subtypes showing progressively worse outcomes as each stage progresses. (3). With a high incidence and fatality rate, cancer is a major global public health concern (4). The GLOBOCAN 2020 database indicates that there have been about 10.3 million deaths and 19.3 million new cases reported each year (5). Cancer prevention and treatment are still challenging (6). Cancer continues to be the second most common cause of mortality in the US, behind heart disease. 1.9 million new instances of cancer, or roughly 5370 cases per day, and 609,820 cancer-related fatalities, or roughly 1670 deaths per day, are predicted for the United States in 2023. (7). The goal of the quickly developing discipline of artificial intelligence (AI) in computer science is to build machines that are capable of doing tasks that normally require human intelligence. Among the methods that comprise artificial intelligence (AI) are machine learning (ML), deep learning (DL), and natural language processing (NLP). Large Language Models (LLMs) are a kind of artificial intelligence system that comprehends, compresses, creates, and forecasts new text-based material using extraordinarily large data sets and deep learning techniques (8). From the first rule-based systems to the present day of machine learning and deep learning algorithms, artificial intelligence has seen tremendous change over time (9).

II. CASE STUDY

Table 1: - An outline of the characteristics of studies on the application of artificial intelligence (AI) to the diagnosis of breast cancer.

Purpose Or Aim	Design Of The Study	Information for AI development or evaluation	Count of subjects or pictures	Subjects 'mean or median age	References
To assess how well a commercially available AI system performs on its own versus how well radiologists diagnose BC & on DM	Retrospective databases of images	DM tests gathered from earlier reader studies	2652DMs	Various Ranges	10
Using ROI (region of interest), describe and evaluate a CAD system.	Retrospective (image databases)	DDSM	600 DM from 150 women's	NR	11
To recognize and classify mammography lesions, use a CAD system based on deep CNSs.	Retrospective (image databases)	DDSM	2949 Mammogram	NR	12
To develop a model that uses CNN to differentiate between mass and non-mass breast areas based on symmetry in dense and non-dense breasts separately, as well as a model to distinguish between dense and non-dense breasts on mammography.	Retrospective	DDSM	2482 Images	NR	13
To develop a CNN-based CAD method to ascertain whether BC is apparent on the radiography	Retrospective	DDSM	10,480 images from 2620 women	NR	14
To assess a system that uses a completely complex-value relaxation neural network (FCRN) to recognize benign, malignant, and normal lesions in digital mammography pictures in order to increase classification accuracy.	Retrospective	DDSM	322 Images (no. of subjects NR)	NR	15
to create a CAD system that uses a Swarm Optimization Neural Network to identify microcalcification clusters in digital mammograms.	Looking back	DDSM	322 Images From 161 Subjects	NR	16
Reducing false positives in mammography breast cancer screening by using computer-aided detection with a support vector machine (SVM) based method.	Looking back	A BC Screening database	10,064 images from 1539 subjects	NR	17

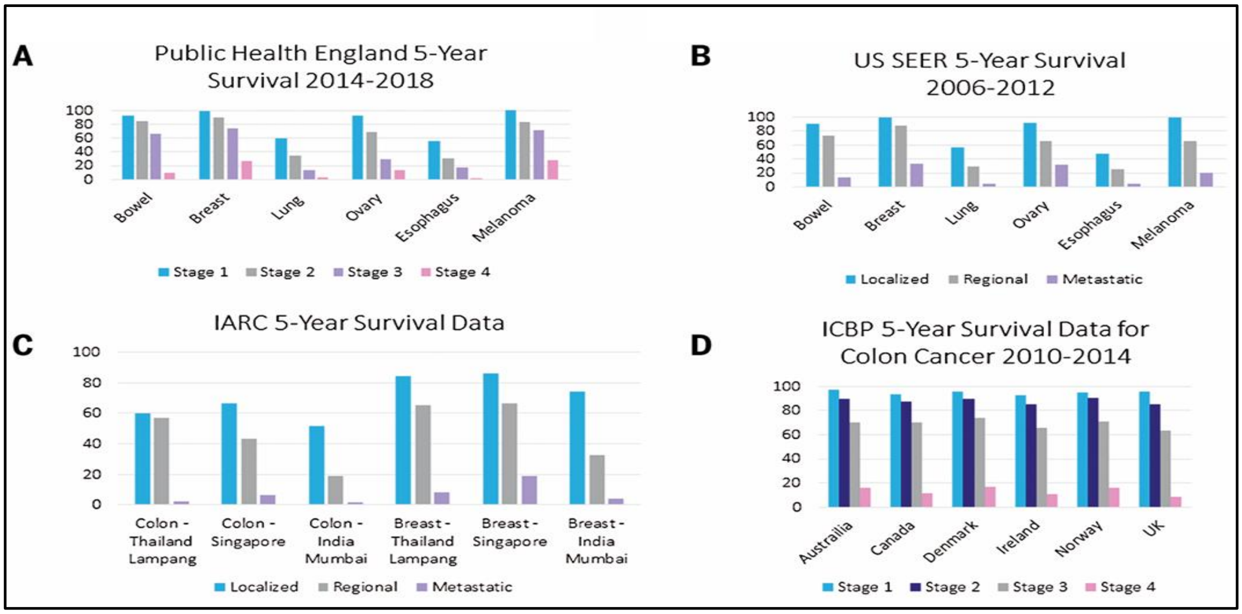

Fig. 1. Early cancer detection increases patient survival.

III. A SUMMARY OF ARTIFICIAL INTELLIGENCE IN CANCER

3.1. Definitions & Model Architectures: -

Computers that imitate human intelligence are referred to as artificial intelligence (AI) (Figure 1). The act of teaching computer systems to make predictions based on experience is known as machine learning (ML), a subfield of artificial intelligence. Generally speaking, there are two types of machine learning: supervised (where the computer is permitted to view the outcome data) and unsupervised (no Computers that imitate human intelligence are referred to as artificial intelligence (AI) (Figure 1). Teaching computer systems to make predictions based on experience is known as machine learning (ML), a subfield of artificial intelligence. ML can be broadly divided into two categories: supervised (the computer is given access to the outcome data) and unsupervised (no outcome data are provided). Both methods search for data patterns that enable outcome predictions, such as risk groups, survival rates, or the existence or absence of cancer. Natural language processing (NLP) is a widely used method in the study of cancer and more generally when examining unstructured clinical data (18). NLP enables the automation of resource-intensive processes by converting unstructured free-text into a format that can be analysed by a computer. learning (outcome data are given). Both approaches look for patterns in the data to predict outcomes like risk groups, survival rates, or the presence or absence of cancer. Natural language processing (NLP) is frequently used in the study of cancer and more generally for the analysis of unstructured clinical data (SAMPLE NO2). The entire application of AI in medical diagnosis is still in its infancy. However, more information is becoming available regarding the use of AI in the diagnosis of numerous illnesses, including cancer. In order to diagnose breast cancer, researchers in the UK combined a sizable dataset of mammograms with artificial intelligence .This study found that when an AI system was used to analyze mammograms, the absolute decrease in false positives and false negatives was 5.7% and 9.4%, respectively (19).

3.2 Data Types: Electronic Healthcare Records

Numerous new healthcare data modalities can be analysed using AI. The recent global expansion of electronic health record (EHR) infrastructures has made it possible to store and access large amounts of clinical data (20). Other digital databases contain pathway data and outcome measurements. For example, user-uploaded performance data is used by the Digital Cancer Waiting Times Database to improve assessments of cancer referral networks (21).

3.3. Data Types: Radiology

Imaging investigations have also benefited from the switch from radiographic film to digital images in

Patient Archive and Communication Systems (PACS). Quantitative techniques for analyzing radiological images, such as CT, nuclear medicine, MRI, and ultrasound scans, are referred to as radiomics. It can be classified into two categories: deep learning and classic machine learning. For traditional machine learning methods, highlighted areas of interest (ROIs) are used to extract textural features. These characteristics are typically associated with readouts of heterogeneity, intensity, and size and form. Models for prognostication or classification are trained using these features. In the context of early cancer diagnosis, this entails categorizing unclear nodules or cysts as benign or malignant. A radiomics method has been used in numerous studies to correctly diagnose lung nodules in this way (22). As was previously mentioned, CNNs provide the basis of DL-based medical imaging classification. For example, breast cancer has been successfully diagnosed using the 2019 Efficient Net designs (AUC 0.95) (23).

3.4. Data Types: Digital Pathology

"Digital pathology," or the creation and analysis of digital images from scanned pathology slides, is another important field of AI research pertaining to early diagnosis. According to a 2018 UK survey, 60% of institutions possessed digital pathology scanners, and this percentage is predicted to increase worldwide (24). The experience of Shuffler and associates with 288,903 digital slides over a three-year period shows how effective this technology is in streamlining diagnostic procedures and enabling extensive research data sharing (25). According to the Path LAKE digital pathology center of excellence, the COVID-19 pandemic has brought attention to a number of advantages of digital working, including enhanced worker resilience, time savings, outsourcing, and simple access to professional supervision training (26). CNNs have been used extensively for automated whole-slide analysis in cancer identification; among other tumour subtypes, high diagnostic accuracy has been noted, and a role model reported by Coudray et al. identified lung cancer with an AUC of 0.97. multiple models have been created to automatically assess grades and stages, and CNNs are able to subtype tumors by identifying multiple targetable receptors and genetic characteristics. Applications such as Paige-AI may provide clinically accessible methods for automated analysis, such as prostate biopsies based on a CNN model (27). There have also been some fascinating developments in predictive biomarker analysis. Machine learning algorithms have discovered predictive indications from peripheral blood samples and tumor biopsy data, including whole-genome profile evaluations (28).

3.5. Data Types: Multi-Omics Data

Because tumour biology is so complicated, models that just use one type of data may overlook crucial predictive information derived from the interaction of interdependent biological systems. There is a push to incorporate data from several models, including clinical, transcriptomic, metabolomic, genomic, and radiomic components, in order to enhance diagnosis accuracy and better characterize the tumor landscape. To help with model development and the identification of correlations between data modalities, a number of sizable datasets are available, such as "Linked Omics," which has multi-omics data for 11,158 patients across 32 cancer types (29). Multi-omics data, such as single-nucleotide polymorphism (SNP) mutations (like TARDBP), gene methylation (like 64-MMP), and transcriptome abnormalities (like miRNA-21), are known to predict the development of meningiomas, using central nervous system (CNS) malignancies as an example (30). These findings demonstrate how applying machine learning approaches to multi-omics data might uncover previously undiscovered aspects of tumor biology, which could have important consequences for prognosis and diagnosis. Unsupervised clustering techniques revealed previously unreported genetic variation in this population, leading to the identification of three unique patient groupings. These subgroups differed in key histological features (microvascular proliferation and necrosis), genetic features (mutations in cell-cycle genes), and clinical features (age). The scientists identified three GBM subtypes with differently increased genes associated with vesicle-mediated transport and synaptic activity (31).

IV. THE PROMISE OF AI IN CANCER DETECTION

One of the most common diseases in the world, cancer affects a lot of people. However, the development of artificial intelligence (AI) has opened up new possibilities for early detection and improved patient outcomes. The World Health Organization has introduced another important priority as, One of its main objectives is to raise the proportion of early-stage cancer diagnoses, and with the aid of AI technologies in healthcare, this indicator has improved to a new level (32).

4.1 Types of AI Used in Cancer Detection: -

AI is made up of several techniques, such as ML and DL, which have been applied to the battle against cancer diagnosis. Any data pattern can be automatically processed by an ML algorithm, which bases its decision on past performance. These algorithms can be monitored in situations when the results are provided or unsupervised in cases where outcome data is unavailable. The AI in cancer detection is shown in Figure 1 (33).

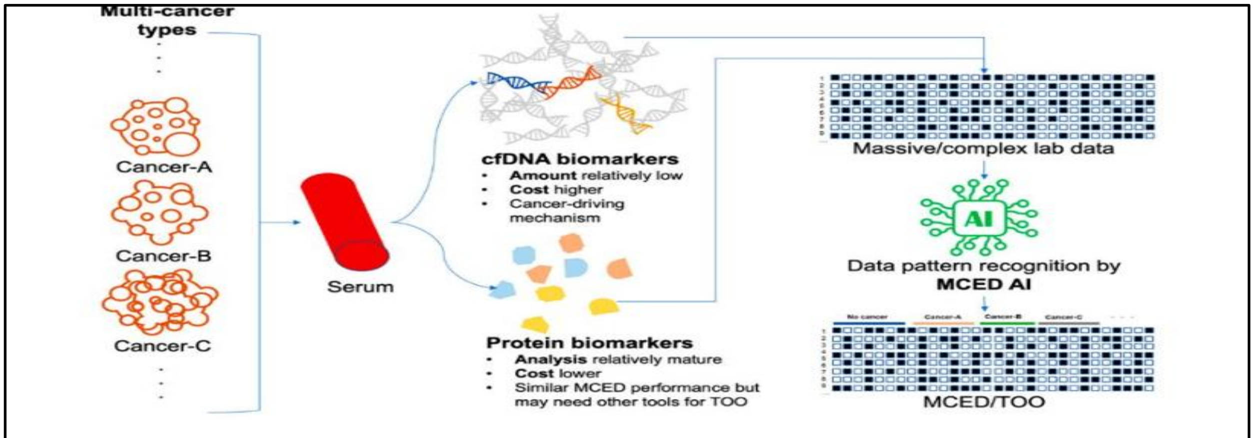

Figure 1: AI in Cancer Detection

A branch of machine learning called deep learning makes use of interconnected structures that mimic the structure of the human brain (34). Convolutional neural networks (CNNs) and other deep learning architectures have revolutionized computer vision research by enabling the use of colour images as input data. CNNs have proven to be remarkably effective in identifying cancer; some models have an AUC of 0.97 for lung cancer diagnosis (35).

4.2 Benefits of AI-Assisted Cancer Screening: -

AI-assisted cancer screening offers several significant advantages: -

(A) Improved Accuracy: AI systems can analyse a lot of multi-modal data to identify some weak signals that observers might miss. By reducing false-positive diagnoses, this skill could improve attend ability of diagnosticians (36).

(B) Faster Analysis: While traditional procedures may take days, AI-based diagnosis may be done almost instantly because it only takes minutes to scan tissue samples and only a second to analyse them (37).

(C) Better Triage: By identifying high-risk cases, it is possible to prioritize the most critical ones and add the most hazardous ones to the list of radiologists' cases (38).

(D)Personalized Risk Assessment: AI can either use routine clinical data from patients to enrol them in particular screening programs that may identify the disease early in people who are at high risk for it (39).

(E)Decreased Needless Procedures: As a result, when a cancer diagnosis is negative, AI-based solutions can spare patients from undergoing numerous follow-up biopsies, relieving their stress and saving the healthcare system money (40).

(F)Expanded Access: By using AI technologies, cancer imaging can be accurately and quickly diagnosed in areas with a shortage of specialists, such as rural and low-income areas (41).

4.3 Current Limitations of AI Cancer Detection: -

Despite its promise, AI in Cancer detection is still in its early stages and faces several challenges: -

(1) The "Black Box" Problem: AI decision-making procedures present difficulties because medical professionals are unable to comprehend or evaluate the AI systems' decision-making processes (42).

(2) Possibility of Bias: Some people think that these algorithms may integrate outside variables, which would prevent them from recommending themselves to populations who might experience discrimination in their medical care or exams (43).

(3) Hallucinations: Similar to other cutting-edge technologies, medical artificial intelligence has an

issue with the algorithms that use the data producing false or entirely fabricated news (44).

(4) Need for Validation: As with any diagnostic or therapeutic technology, there is frequently anticipation that AI optimization of a particular medical task will soon prove to be successful and feasible for clinical usage. Nevertheless, the initial therapeutic AI tools frequently still desperately need significant prospective validation studies to show how effective and secure their use in the clinic is (45).

AI's role in cancer detection is expected to grow over time as scientists strive to overcome these constraints. The ultimate goal is to identify individuals at reasonably manageable cancer stages in order to reduce morbidity and death and reverse the diseases' progression. AI appears to be an intriguing tool in this field, but it shouldn't be seen as a direct replacement for a human physician who makes cancer treatment plans and diagnoses patients (46).

V. AI-POWERED MEDICAL IMAGING FOR CANCER

Artificial Intelligence (AI) has significantly improved medical imaging, particularly for cancer diagnosis. The majority of aspects of oncology, such as diagnosis, treatment, and the discovery of novel anticancer medications, can be altered by this technology (47).

5.1 Convolutional Neural Networks for Image Analysis: -

Convolutional Neural Networks (CNNs) may be a cutting-edge cancer imaging technique, according to recent research. Since these deep learning architectures learn directly from the images as densitometry scans, they are perfect for the analysis (48). CNNs have been utilized to diagnose cancer using certain of with strong performance metrics, like the AUC of 0. CT was utilized in four studies to diagnose lung cancer; chest CT was used in 97% of the investigations. Figure 2: AI-Powered Medical Imaging for Cancer (49).

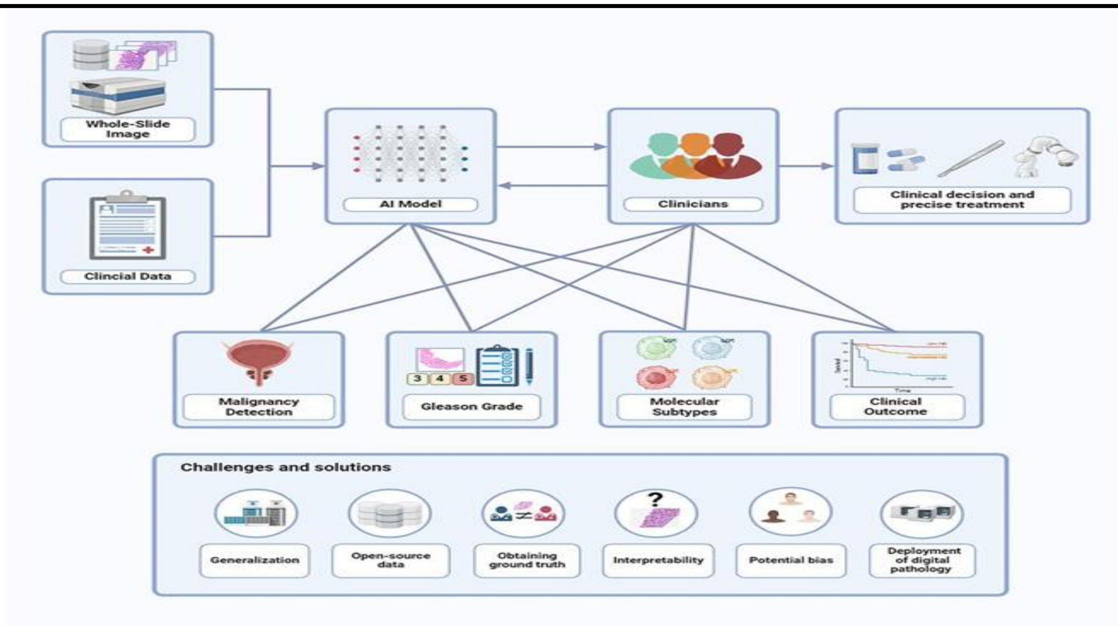

Figure 2: AI-Powered Medical Imaging for Cancer

5.2 Key Imaging Modalities Enhanced by AI: -

AI has improved a number of imaging techniques used to diagnose and detect cancer: -

{1}. Computed Tomography (CT): In order to improve the efficacy of lung cancer screening techniques, deep learning models to separate pulmonary nodules in CT scans have also been established (50).

{2}. Mammography: To reduce false positive cases and improve early identification of breast illnesses, deep learning has been used to detect breast lesions in mammograms (51).

{3}. Magnetic Resonance Imaging (MRI): The review also noted that artificial intelligence techniques can reliably identify the main brain malignancies, including cerebral metastases, high-grade gliomas, and low-grade gliomas (52).

The diagnosis and characterisation of cancer have generally improved with the aid of AI integration in such imaging techniques. For example, when radiologists were requested to employ deep learning models for both pulmonary nodule identification and management, their effectiveness grew as the amount of time spent reading declined (53).

VI. CASE STUDIES OF AI IMAGING SUCCESS

Several case studies highlight the success of AI in cancer imaging: -
(1). Lung Cancer Detection: AI systems that can classify, quantify, and even forecast malignancy have made it possible to automatically detect pulmonary nodules. According to reports, these technologies are remarkably reliable in identifying precancerous expansion (54).
(2). Brain Tumour Classification: Gliomas, meningiomas, pituitary adenomas, and other brain tumor forms can be correctly identified and classified by AI models (55).
(3). Breast Cancer Screening: Mammograms and DBT pictures are currently analysed using deep learning models, which have demonstrated good efficacy in identifying and categorizing breast abnormalities (56).
(4). Treatment Response Prediction: Radiomics and machine learning have been used to predict the prognosis of numerous cancer treatments, such as radiation therapy for nasopharyngeal carcinoma and neoadjuvant chemotherapy for non-small cell lung cancer (57).

VII. LEVERAGING AI AND GENETICS FOR EARLY DETECTION

AI and genetics have been used to provide improved techniques for estimating cancer in its early stages. Together, these initiatives have the potential to significantly improve how medical professionals identify patients' cancer risks and consequently advance effective methods of intervention (Won die & Lulie, 2024) (58).

7.1 AI Analysis of Genomic Data: -

Genomic algorithms based on artificial intelligence have shown promise in identifying gene mutations and malfunctioning proteins that may contribute to the development of cancer. These algorithms are able to identify non-linear or even multi-stage interactions. This is difficult to identify with the traditional method; For example, genome-wide association studies (GWAS) have proven successful in discovering genetic variants that interact to increase the risk of cancer (59). However, gathering, analysing, and using patient genetic data is the main obstacle to using AI in genetic analysis. While scientists continue to struggle with these issues, artificial intelligence is being used to create a method of extracting valuable information from the genetic data and so aid in cancer early diagnosis (60).

7.2 Integrating Imaging and Genetic Biomarkers: -

Genetic biomarkers and computer image analysis technology appear to work well together to increase the accuracy of cancer detection. In addition to genetic biomarkers, new studies have demonstrated the benefits of medical picture analysis for disease prognosis and diagnosis (61).
For example, a study that takes into account four different kinds of picture features in addition to genetic and demographic data received a high Area Under the Curve (AUC) of 0.949 in testing data. Figure 3's combination of data sources illustrates how AI may be used to integrate the different details to improve the cancer risk assessment (62).

7.3 Personalized Cancer Risk Assessment: -

The shift in cancer screening recommendations from age-dependent to risk-dependent is primarily due to artificial intelligence. In order to produce more accurate findings, these created AI systems can use a wide range of data on the patient's history, imaging results, and gene profile. Short-term cancer risk assessments (63). Healthcare organizations are working to improve cancer screening and prevention in the future by using genetics and artificial intelligence for early cancer detection. This integration will make it feasible to improve patients' conditions and, thus, reduce the need for additional medical care, costs associated with the detection and treatment of advanced cancer (64).

VIII.. IMPROVING AI PERFORMANCE AND ACCURACY

Researchers are focusing on ways to enhance the current AI models since AI has shown great promise as a cancer detection tool. These advancements are intended to address issues such as biases, the need for reliable future predictions, and inadequate data or contextual information. In this manner, the use of novel techniques reveals significant opportunities for the use of artificial neural networks in cancer diagnostics (Yimer & Tuwani, 2024) (65).

8.1 Continuous Model Updating and Refinement: -

The accuracy of Artificial Intelligence models in cancer detection makes ongoing observation & sporadic updating desirable. Thus, this strategy helps to lessen the detrimental effects of drift on resource allocation and care decisions. Researchers advise paying particular attention to data preprocessing, mistake correction, and data standardization that would enhance AI's functionality (66).

8.2 Key considerations for continuous model improvement include:

(1). Expanding the training data set by adding pictures of every potential variation, such as different skin tones, ages, body types, etc (67).

(2). Samples are taken at different angles, under varied lighting circumstances, and with different equipment to improve the model's generalization in order to overcome the aforementioned problems (68).

(3). If image acquisition technology changes, models can be updated with photos from new technologies by retraining (69).

The aforementioned tactics aid researchers in creating suitable and long-lasting techniques for improving AI models to suit actual clinical practice scenarios. As AI applications for cancer detection advance, it will be crucial to improve patient quality and fulfil the objectives of precision medicine (70).

IX.. IMPLICATIONS FOR HEALTHCARE

It is becoming more and more clear that it is not a matter of "if" but "when" Artificial Intelligence shall be introduced into standard clinical care given the ease with which many nations have access to infrastructure capable of running Machine software, the rapidity of AI investment, the speed at which AI-based applications can be created, and the myriads of opportunities AI offers for the medical field (71). Current healthcare delivery models will undoubtedly be transformed by the clinical use of AI models; in fact, their application will go beyond clinical settings (72). By addressing the shortcomings of traditional rules-based clinical decision support systems, AI can enhance diagnostic and decision support (73). There are also increasingly becoming opportunities to test, treat, and assist with au tomate triage. AI-enabled health services could be delivered to patients' homes through smart device integration, facilitated by the Internet of Things and fast Wi-Fi, democratizing healthcare (74).

X. ARTIFICIAL INTELLIGENCE ASSISTANCE IN DIAGNOSTICS

10.1 Accuracy of Diagnosis: **-**

Effective disease diagnosis continues to be a global challenge despite all of the scientific advancements. The intricacy of the different disease mechanisms and underlying symptoms always makes the creation of early diagnostic tools challenging. AI has the potential to transform diagnosis, among other facets of healthcare. Data is used as an input resource in machine learning (ML), a branch of artificial intelligence. Although it can overcome some of the difficulties and complexity of diagnosis, its accuracy is primarily dependent on the quantity and quality of the input data (75). In conclusion, machine learning (ML) can facilitate decision-making, workflow management, and timely and economical task automation. Convolutional Neural Networks (CNN) and data mining techniques are also used in deep learning to assist find patterns in data. These are quite useful for finding important patterns in large datasets for medical diagnosis. These techniques are very useful in healthcare systems for identifying, forecasting, or categorizing diseases (76). Furthermore, an AI using CNN properly recognized cases of melanoma and recommended treatment options when compared to dermatologists, according to a study that employed deep learning to detect skin cancer (77). The random forest approach fared better than the others, correctly diagnosing appendicitis in 83.75% of patients with an accuracy of 84.11%, sensitivity of 81.08%, and specificity of 81.01%. Additionally, a study was conducted using a dataset of 625 cases to predict the need for appendix surgery and identify acute appendicitis early using various machine learning techniques. Medical professionals are more equipped to diagnose and treat appendicitis thanks to the updated approach. The scientists also propose that similar methods may be used to identify disorders like COVID-19 using photographs or blood samples, or even to evaluate photos of individuals with appendicitis (78).

XI. CHALLENGES IN EARLY CANCER DETECTION

11.1 Challenge 1: Knowing the biology of early cancer: -

The unique set of abnormal traits that define cancer, such as potentially lethal invasion and metastasis as well as ongoing cellular evolution and diversification, are caused by substantial changes in a cell's genome or epigenome. Early, negligible dysregulation of molecular and cellular phenotypes gives way to malignant transformation in cancer (79). Fast, aggressive tumours that grow in between screening visits may not be detected by annual screening (80). Active surveillance, on the other hand, can track slow-growing tumors that are changing into malignant ones over a period of years and screen for susceptible populations. Some cancers have a clear progression from a precancerous stage to malignancy, such as polyps prior to colon cancer. However, not all precursors will turn into cancer, and not all cancers will have a major effect (81). However, it is becoming more and more clear that immune cells or their metabolites may be useful for early detection (82).

11.2 Challenge 2: Calculating the chance of getting cancer

A complete understanding of individual cancer is necessary to determine who should be tested, how to do it, when to do it, and how to interpret the data. Not everyone will benefit equally from early detection techniques. Therefore, it is essential to identify people who are more likely to develop cancer and to customize an early detection strategy for them in order to optimize the advantages of early detection and limit the dangers (due to overdiagnosis and treatment).
(83).

11.2.1 Screening at-risk populations: -

The ideal cancer screening procedure would be non-invasive or minimally invasive, inexpensive, and offer little false positives or negatives to reduce risk and optimize screening's advantages. A number of currently available screening tests, such as mammography for breast cancer, reduce overall or cancer-specific mortality (84),
the cervical cancer Pap smear (85) For colorectal cancer, a colonoscopy (86), & low-dosage computed to myography (CT) (87). For carcinoma of the lung. Despite their effectiveness, these technologies are not always inexpensive, extremely sensitive, or minimally intrusive specific and constructive. Furthermore, not all of the at-risk groups are reached by these testing. For instance, as of 2019, less than 5% of eligible individuals in the US had undergone a lung cancer screening (88).

11.3 Challenge 3: Identifying and verifying biomarkers for cancer detection: -

One of the biggest challenges in ordinary human biology is locating the little signal of the early tumors. Two crucial A diagnostic test's sensitivity and specificity are markers. Sensitivity is the ability of a test to correctly identify individuals who have the condition being tested for (the true positive rate); a test with a higher sensitivity will miss fewer cases, or false negatives. The ability of a test to correctly identify persons who do not have the condition (the true negative rate) is known as its specificity; a test with high specificity does not yield a positive result in the absence of the condition (i.e., does not cause false positives) (89).

11.3.1 Challenges in biomarker validation: -

Although several biomarkers have been proposed for early cancer diagnosis, few have been validated in large-scale experiments. For example, elevated levels of prostate-specific antigen (PSA) in the blood could be a diagnostic tool for early prostate cancer diagnosis (90). However, PSA varies greatly between individuals and within individuals as they age (or develop other non-malignant prostate disorders). This could lead to overdiagnosis, unnecessary diagnostic testing (like invasive biopsy, which carries risk), and overtreatment of insignificant illness (which could have detrimental effects without improving survival) (91). When examined out of context, highly specialized biomarkers can exhibit dichotomy even if they are confirmed. For example, KRAS mutations are strongly associated with the progression of colorectal cancer (92), Nonetheless, many pancreatic tumors with mutations in KRAS are not malignant (93).

11.4 Challenge 4: Creating precise early detection technology

One major difficulty is creating technologies with the specificity to reduce false positives and the sensitivity to identify the earliest tumors (94). The accuracy of early cancer detection has increased with the development of contemporary technologies. Finding recently developed solid tumors that are likely to have not spread and are treatable is one goal of early detection (95). This typically indicates before repression and before the formation of tumor microenvironments that promote increased angiogenesis. of immunity against tumors (96).

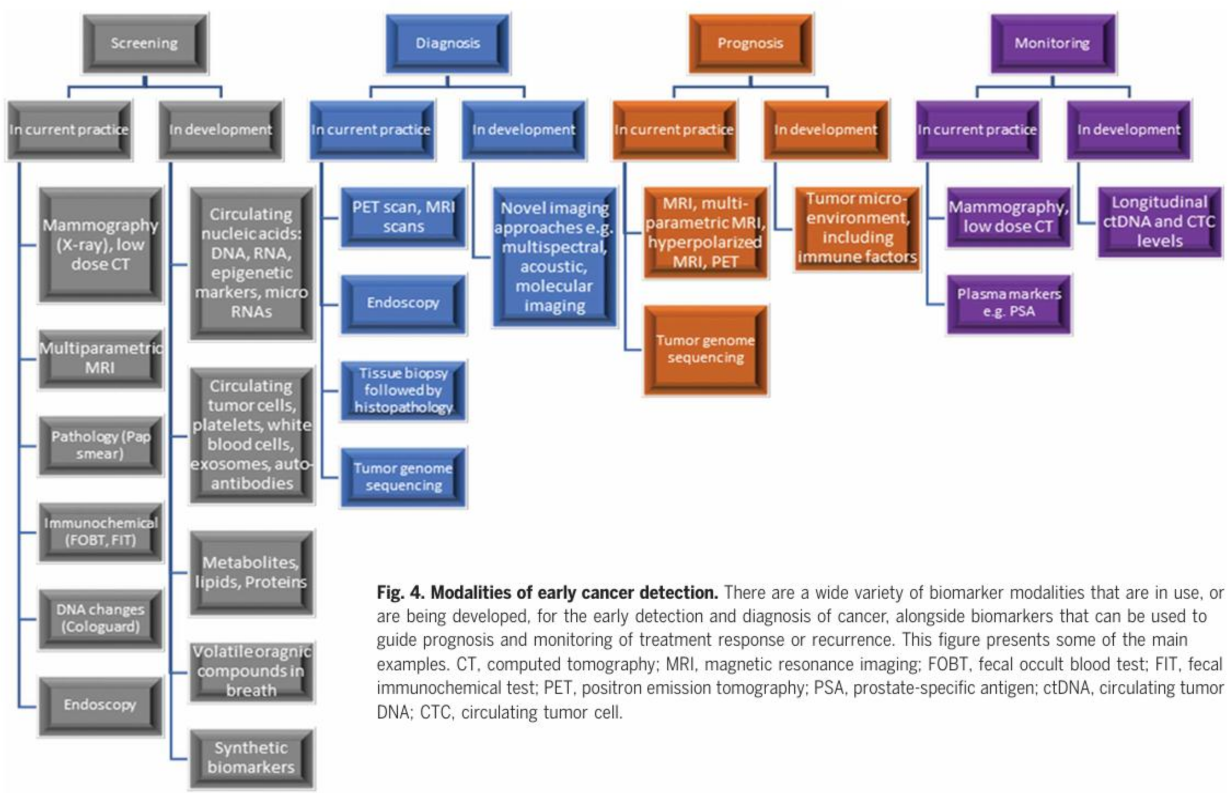

Fig. 4. Modalities of early cancer detection. There are a wide variety of biomarker modalities that are in use, or are being developed, for the early detection and diagnosis of cancer, alongside biomarkers that can be used to guide prognosis and monitoring of treatment response or recurrence. This figure presents some of the main examples. CT, computed tomography; MRI, magnetic resonance imaging; FOBT, fecal occult blood test; FIT, fecal immunochemical test; PET, positron emission tomography; PSA, prostate-specific antigen; ctDNA, circulating tumor DNA; CTC, circulating tumor cell.

XII. AI SUPPORT FOR THERAPY

Clinical decision assistance and precision medicine: -
Precision medicine, formerly referred to as personalized medicine or tailored therapy, is a technique that tailors medical care to each patient based on their unique characteristics, such as biomarkers, environment, lifestyle, and genetics (97). This tailored approach aims to improve patient outcomes by providing more effective, efficient, and safe focused interventions. AI is now a helpful tool for human progress optimum treatment, offering the capacity to predict outcomes, assess complex datasets, and improve therapeutic strategies (98). Personalized care is one cutting-edge field that demonstrates the possibilities of precision medicine on a large scale (99).

It is now widely acknowledged that AI has the ability to assist physicians in making treatment decisions, particularly in predicting the reaction (100). Huang et al. conducted a study in which they trained a support machine learning model using patient gene expression data. successfully forecasted the chemotherapeutic response (101). In a different study, Sheu et al. sought to forecast how people would react to various antidepressant classes by utilizing electronic health records (EHRs) of AI and 17,556 patients(102).

XIII. CONCLUSION

The application of AI to the detection and treatment of cancer fundamentally changes the area. Because it can improve medical imaging as a tool, assess genetic data, and offer customization in risk variables, it promises to greatly aid in early diagnosis and improve patients' quality of life. AI and professional production are revolutionizing cancer diagnosis and treatment by opening up new possibilities for early cancer identification and personalized treatment plans. However, prejudice, data privacy, and regulatory compliance are some of the issues that need serious consideration in order to promote the appropriate use of these technologies. AI has the potential to completely transform cancer prevention, diagnosis, and treatment in clinical settings, and its position in cancer care will only expand in the future. As AI develops in the future, its application is anticipated to grow in the near future in both clinical practice and cancer research, which could serve as a means of guaranteeing the provision of high-quality healthcare worldwide. It is necessary to keep working on the ethical concerns, human supervision, and patient trust in order to maximize such potential. When appropriately integrated with technologies built on intricate AI systems and ethics, the AI potentially significantly improve the lives of millions of cancer patients worldwide by contributing to the fight against the illness.

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