Journal of AI

Volume: 8, **Issue No:** 1, January-December 2024, **Pages:** 107-137

Artificial Intelligence in Cancer: A SWOT Analysis

Gülşah Torkay[1,2], Nouran Fadlallah[3], Ahmet Karagöz[4], Mesut Canlı[5], Ezgi Saydam[6], Ayşenur Mete[7], Furkan Kızılışık[8], Hakan Darici[9], Yusuf Yeşil[10]

[1] Yildiz Technical University, Institute of Science, Türkiye **Email**: gulsah.torkay@istinye.edu.tr **Orcid**: 0000-0002-6803-494X
[2] Stem Cell and Tissue Engineering R&D Center, Istinye University, 34010, Istanbul, Turkey
[3] Istanbul Bilgi University, Türkiye **Email**: nouran.fadlallah@gmail.com **Orcid**: 0000-0003-0951-2128
[4] Bogazici University, Türkiye. **Email**: krgz.ahmet@hotmail.com **Orcid**: 0000-0001-9527-6912
[5] Istanbul University, İstanbul Faculty of Medicine, Türkiye. **Email**: mesut.canli@istanbul.edu.tr **Orcid**: 0000-0003-2686-7801
[6] Gebze Technical University, Türkiye. **Email**: ezgisaydam12@gmail.com **Orcid**: 0000-0001-5483-7111
[7] Karabuk University, Türkiye. **Email**: aysemette10@gmail.com **Orcid**: 0000-0002-8999-7454
[8] Biruni University, Türkiye. **Email**: furkan.kizilisik@gmail.com **Orcid**: 0000-0003-0750-3754
[9] Istinye University, Türkiye. **Email**: hdarici@istinye.edu.tr **Orcid**: 0000-0001-9393-554X
[10] Istanbul University, İstanbul Faculty of Medicine, Türkiye. **Email**: dryesilyusuf@gmail.com **Orcid**: 0000-0001-5932-5617

Corresponding author: *gulsah.torkay@istinye.edu.tr*

Received: 01.05.2024 *Accepted: 07.09.2024* *Online: 19.09.2024* *Published: 31.12.2024*

Review Article

Abstract

Cancer, a collection of maladies that has undergone extensive examination over centuries, remains a formidable challenge. Despite the array of available pharmacological and therapeutic interventions, the intricate molecular dynamics and heterogeneity of cancer continue to challenge the scientific community. Artificial Intelligence (AI) emerges as a promising avenue, offering the potential for expedited, precise diagnostics devoid of human expertise. Additionally, AI facilitates the tailoring of patient-specific therapeutic strategies targeting various facets of cancer, spanning macroscopic to microscopic levels. Nonetheless, it is imperative to scrutinize the potential benefits and limitations of AI technologies in this context. This review undertakes a comprehensive Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis of AI's application in cancer. An extensive compilation of AI applications encompasses predictive modeling, diagnostic capabilities, prognostic assessments, and personalized therapeutic modalities, spanning genomic analyses to individualized treatment regimens. The synthesis of evidence suggests that the advantages of AI outweigh its drawbacks; nevertheless, obstacles to its widespread integration persist.

Keywords: *Artificial intelligence, cancer, deep learning, machine learning, precision oncology, SWOT analysis*

Cite this paper (APA)

Torkay, G., Fadlallah, N., Karagöz, A., Canlı, M., Saydam, E., Mete, A., Kızılışık, F., Darici, H., Yeşil, Y. (2024). Artificial Intelligence in Cancer: A SWOT Analysis. Journal of AI. 8(1), 107-137. Doi: 10.61969/jai.1469589

1. INTRODUCTION

Since Alan Turing's seminal inquiry into the capabilities of machines to exhibit intelligence (Turing and Haugeland, 1950), substantial progress has been made in domains such as computational biology and evolutionary algorithms (Yang, 2012). Turing's question spurred scientific endeavors, leading to the development of advanced artificial intelligence (AI) algorithms that now find application across diverse industries, including healthcare (Bohr and Memarzadeh, 2020).

In the 1980s, rudimentary, rule-based AI systems emerged, albeit with limited computational prowess, rendering them inadequate for addressing the complex challenges encountered in healthcare, such as disease diagnosis, decision-making, and image processing (Davenport and Kalakota, 2019). Notably, computer vision, a branch of AI facilitating the extraction of meaningful insights from visual data like digital images, relies on Deep Learning (DL) and Convolutional Neural Networks (CNNs), subfields within the broader domain of machine learning (ML), demanding substantial data volumes. Herein, image processing research assumes significance within the healthcare sector.

ML, a subset of AI, enables software to acquire knowledge autonomously through exposure to representative data, yielding predictive capabilities that can be refined through iterative practice. ML classifications encompass supervised, unsupervised, and reinforcement learning (RL). Supervised learning delves into establishing correlations between input features and desired outcomes, effectively addressing classification and regression challenges. Unsupervised learning is geared towards uncovering patterns, clustering data, discovering rules, and facilitating information extraction from data without prior guidance (Sarker, 2021). In contrast, RL centers on decision-making strategies that maximize cumulative rewards, successfully applied in domains like robotics, autonomous vehicles, and strategic games. Concurrently, DL, a facet of ML, employs multi-layered artificial neural networks (ANNs) to tackle problems spanning object recognition, speech analysis, and natural language processing (NLP). It is essential to recognize the interrelatedness of these technologies, as depicted in Figure 1.

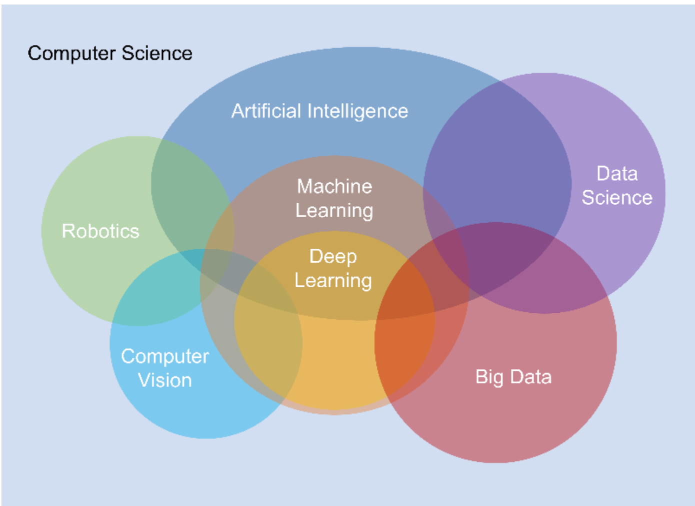

Figure 1: Current approaches and interdisciplinary interactions in computer science.

Over the past decade, AI has permeated diverse industrial domains, with research and development efforts promptly extending into healthcare, owing to the potential advantages of AI in medical practice. AI has, thus far, applied every facet of medical processes, ranging from disease prediction to treatment to hospital administration (Jiang et al., 2017). A noteworthy area of medical integration for AI is in the domain of oncology.

Cancer, a spectrum of diseases with historical origins, has challenged researchers for centuries, characterized by unregulated cell proliferation and the loss of cellular control mechanisms. Its classification into various distinct types and subtypes underscores the complexity of treatment, necessitating individualized therapeutic strategies dictated by factors such as cancer type, stage, molecular phenotype, and patient profile.

Dysregulation in the mechanisms governing physiological events, including cell proliferation, growth, apoptosis, and deoxyribonucleic acid (DNA) repair can catalyze the transformation of normal cells into cancerous ones. Genetic and epigenetic changes play pivotal roles in tumor initiation and progression, contributing to metastasis, drug resistance, autocrine signaling, and the initiation of vascular networks. Consequently, AI algorithms find utility in predicting cancer prognosis at the molecular level (Kourou et al., 2014). The intricate landscape of cancer genomics research, characterized by epigenetic alterations, variations in mutations, signaling pathway aberrations, and the consequent tumor subgroup diversity, can be effectively navigated using big data, statistical methods, and AI, as evidenced by recent literature (Catto et al., 2010; Dlamini et al., 2020; Khalifa et al., 2020; Zhang et al., 2020; Zhao et al., 2020).

Cancer development is influenced by genetic and environmental factors, including smoking, viral infections, obesity, sun exposure, alcohol consumption, chemical agents, and DNA damage (Parsa, 2012). Commonly diagnosed cancers include lung, breast, and colorectal, with leading causes of cancer-related mortality being lung, liver, and stomach cancers (Ferlay et al., 2019). Given the substantial patient population and mortality rates associated with cancer, there is a pronounced need for AI-based models that span the entire spectrum of cancer care, from prevention to treatment.

In the realm of cancer diagnostics, methods and devices such as immunohistochemistry (IHC), frozen section analysis in pathology, polymerase chain reaction (PCR), DNA microarrays, computer tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET) play pivotal roles (Goyal et al., 2006). However, the selection of specific diagnostic methods depends on the type of cancer, each demonstrating varying levels of sensitivity and specificity. For instance, breast cancer diagnosis may suffice with manual examination and mammography, while colon cancer may necessitate colonoscopy and biopsy.

Cancer treatment predominantly involves surgery and radiotherapy, with surgery aimed at tumor removal, while radiotherapy employs ionizing radiation to target specific areas and induce cell damage through DNA disruption (Keam et al., 2020). Chemotherapy, though generally not targeted to a specific location of the body, remains a gold standard for cancer treatment for inhibiting cancer cell proliferation (DeVita and Chu, 2008).

Despite the unique developmental processes and molecular intricacies inherent to each cancer type, the fundamental principles underlying the disease remain consistent. Hanahan and Weinberg's definition and subsequent revisions of the hallmarks of cancer, elucidating molecular and biochemical processes (Hanahan and Weinberg, 2000; Hanahan and Weinberg, 2011), continue to guide our understanding. In January 2022, Hanahan expanded on these hallmarks, introducing "New Dimensions" (Hanahan, 2022). Figure 2 provides a reinterpretation, encapsulating the transition from the traditional "10 hallmarks of cancer" to the "10 hallmarks of AI in cancer" as a summary.

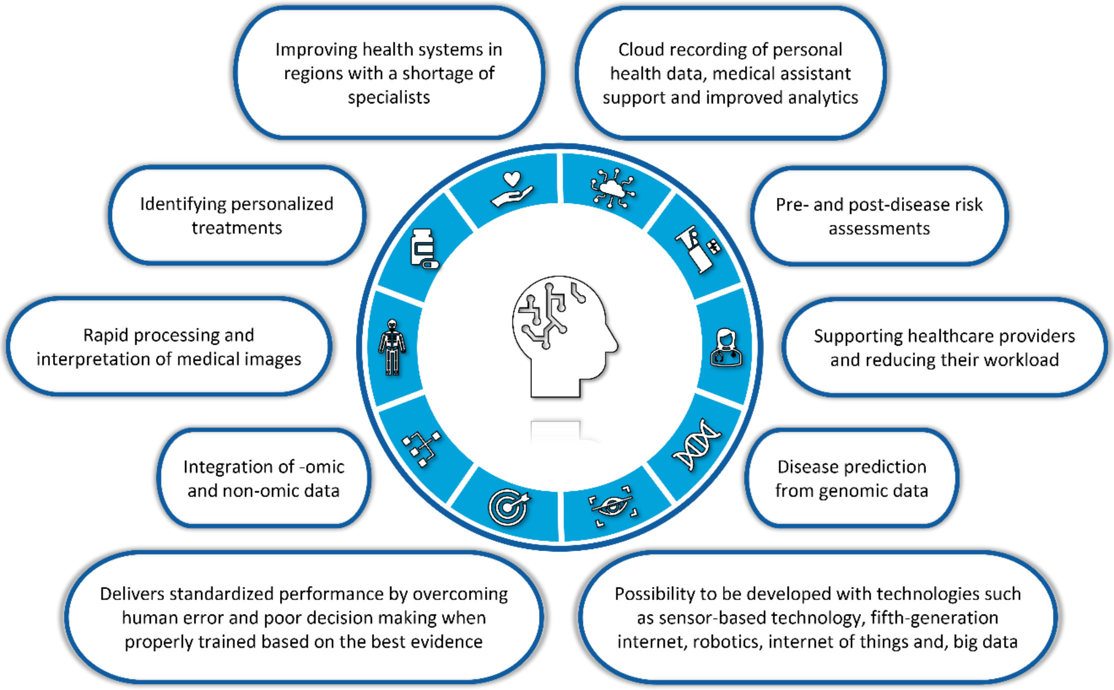

Figure 2: Areas where AI can aid cancer research.

CNNs are designed to emulate the human brain's mechanisms for object recognition, with ANNs serving as their foundational building blocks (Lindsay, 2021). In the human brain, each neuron encodes specific information collectively contributing to the comprehension of distinctive features within an image. To illustrate, consider a CNN model tasked with recognizing 'cats' and 'dogs' in images. This model comprises interconnected layers that interact sequentially. The initial layer serves as the input layer, receiving images of cats and dogs. During training, these images are labeled as either 'cat' or 'dog.' Subsequent layers are responsible for identifying specific features in the images. For instance, one neuron might specialize in identifying triangular ears, while another focuses on tail shape or whiskers. Further layers delve into finer details, aptly termed hidden layers, as the precise characteristics sought by individual neurons remain opaque to developers. With each image passing through these layers, a score is assigned based on the similarity between various aspects of the image and the neuron's feature. At the output layer, the model aggregates these scores to determine the image's category. Throughout the training process, these scores are compared to the provided labels, and mathematical formulas compute a loss function, allowing for the recalibration of each neuron's contribution (referred to as weights) to the image's overall score. This iterative process continues until training concludes, usually when the validation error is no longer decreasing (O'Shea and Nash, 2015). Subsequently, during model usage, images traverse the same layers and neurons, with the score calculated based on their similarity to each neuron's feature, but no further alterations are made to the model. In a similar vein, for a CNN model designed to identify brain tumors in MRI scans, each neuron can scrutinize specific features associated with tumor shapes or cerebral anomalies. The model aggregates scores for every small detail within the MRI, enabling it to accurately detect even minute irregularities and distinguish tumors from other abnormalities (Ranjbarzadeh et al., 2021). Figure 3 provides a simplified and schematic representation of an artificial neuron and a neuron in the human brain's structure.

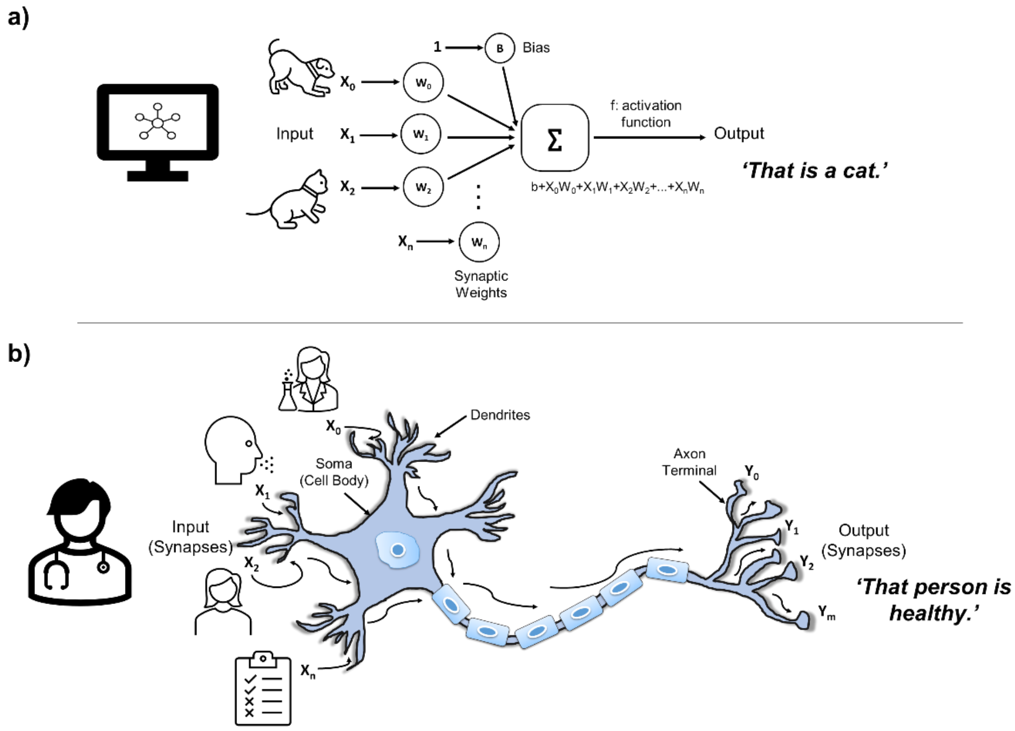

Figure 3: The similarity between an artificial neuron and a neuron. A neuron in a biological nervous system is a processing element in ANNs. Dendrites correspond to the summation function, while the cell body corresponds to the activation function. Biological synapses, that is, intercellular connection areas, correspond to weights in ANNs. Axons are the output region. Learning for an ANN can be expressed as updating the weight coefficients between synapses and dendrites. a) In an ANN, each of the input values (x_i) is multiplied by the weights (w_i), and the bias value (B) is added to the obtained information. The output value is acquired by applying the activation function (f) to the result. b) In the human brain, the learning process produces new axons by stimulating axons or changing the strength of existing axons. A doctor interprets data based on life experience and decides whether a person is healthy or not.

2. AI IN CANCER AND MEDICINE

The paradigm of evidence-based medicine revolves around the formulation of therapeutic judgments rooted in prior knowledge and accumulated experience. While traditional statistical methodologies leverage various mathematical techniques to discern these patterns, AI introduces approaches for uncovering intricate correlations that resist easy translation into mathematical equations. Neural networks, akin to the human brain, encode data through a vast interconnection of neurons, enabling ML systems to approach complex problems with a semblance of clinical acumen. Additionally, these systems can assimilate knowledge from each new case they encounter and amass exposure to a greater number of examples in a brief span than a human physician can accumulate in a lifetime (Buch et al., 2018). This holds true for clinical processes in oncology, where AI augments existing methods with enhanced sophistication. Nonetheless, it remains uncertain whether complex algorithms trained on extensive data sets consistently yield more precise predictions than human clinicians. Key requisites include the accuracy of labels and the cleanliness of data. Figure 4 delineates the conventional methods employed in the overarching disease process alongside the potential contributions of AI.

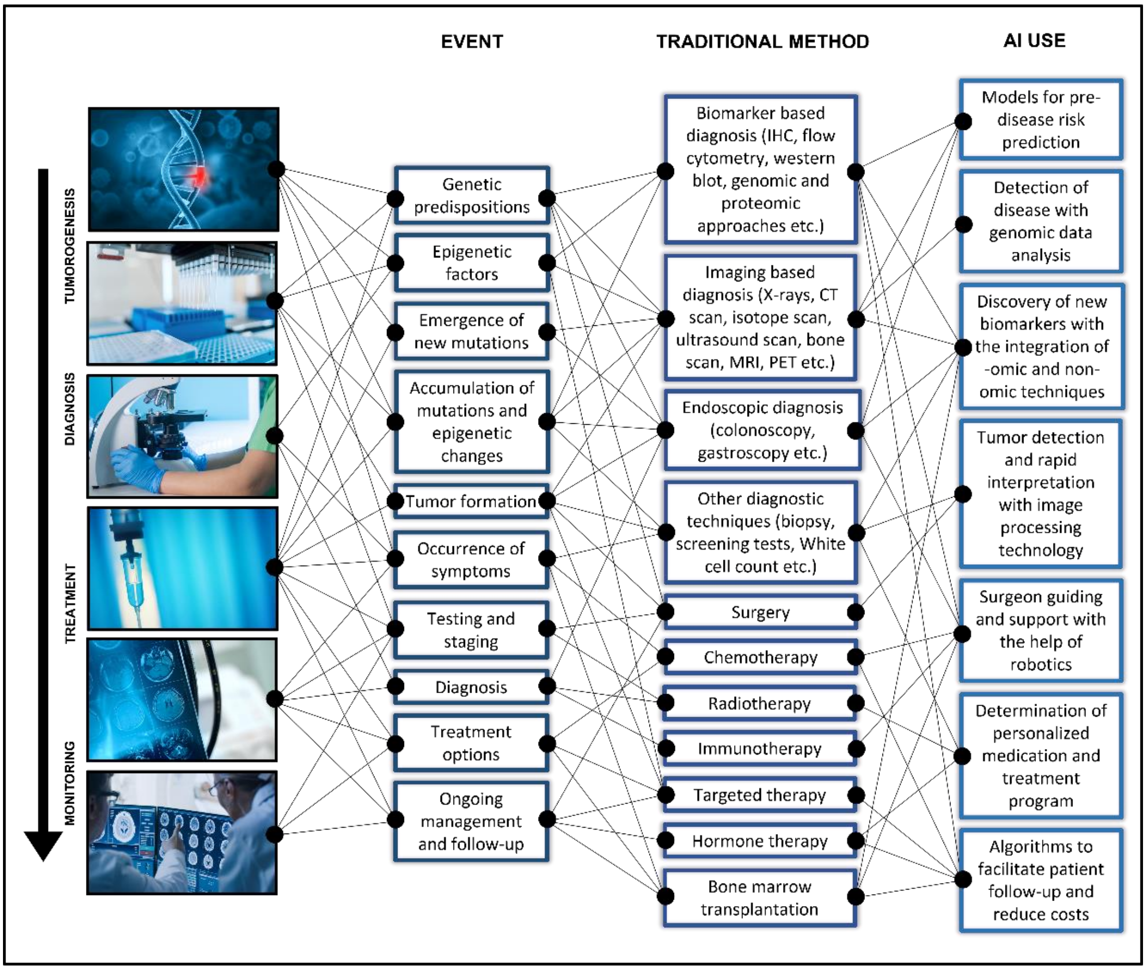

Figure 4: The diagram of the events that occur in the cancer process, the traditional methods used in this process, and possible AI approaches (Neural connections are added for visual purposes alone; they have no meaning.).

2.1 Personalized Medicine

AI assumes a pivotal role in the advancement of personalized medicine, predicated on its capacity for in-depth data analysis, thereby elucidating targeted objectives and intervention strategies. The realization of AI's potential in personalized medicine hinges not only on the refinement of pertinent assays but also on the effective storage, collection, accessibility, and subsequent integration of data (Schork, 2019). Digital health records, interconnected for diagnostic and treatment decision-making, serve as reservoirs for AI, which leverages patient data to discern optimal treatment plans and tailored therapeutic solutions (Amisha et al., 2019). The substantial cost involved in drug development, estimated at approximately $2.6 billion, with a high attrition rate between trial phases and regulatory approvals, underscores the pressing need for more efficient methodologies (Fleming, 2018).

Various machine intelligence methodologies have been harnessed to guide resource-intensive traditional experiments. ML tools have emerged, capable of swiftly and cost-effectively identifying potential bioactive molecules from vast pools of candidate compounds, exemplified by quantitative structure-activity relationship (QSAR) modeling. However, the advent of the 'big' data era in drug discovery has precipitated a transformation in ML approaches, ushering in the era of DL, which offers enhanced efficacy and potency in handling extensive datasets (Zhang et al., 2017). In a bid to streamline costly and time-consuming conventional experiments, multiple machine intelligence technologies have been employed. Notable among these is QSAR modeling, a ML technique adept at identifying physiologically active molecules from among millions of candidate compounds, thus promising cost-effective pre-clinical cost reduction and risk mitigation through virtual screening, activity scoring, and diverse drug design strategies. Beyond the prediction of molecular attributes, DL methodologies are enlisted for the generation of tailored molecules, further catalyzing AI's role in drug design (Zhong et al., 2018). ANNs such as deep neural networks (DNNs) and repetitive networks, particularly in the realm of drug discovery, assume a prominent role, underscoring AI's potency. The synergy of synthesis planning and facile synthesis avenues has become a reality, heralding the prospect of computer-aided drug discovery in the near future (Hessler and Baringhaus, 2018).

2.2 Diagnosis

AI diagnostic systems assume paramount significance for several compelling reasons. Given the global shortage of highly skilled specialists such as radiologists, the quest for rapid and dependable solutions has become imperative. AI systems, unlike their human counterparts, possess the capacity to analyze vast datasets within remarkably short timeframes, while consistently upholding high levels of accuracy and precision. Their prowess in comprehending extensive datasets enables the discernment of intricate relationships and the identification of subtle details that often elude human perception. Predominantly, AI's application in clinical diagnosis is exemplified through image analysis, a domain where AI algorithms, particularly CNNs, have outshone radiologists in terms of swiftness and accuracy.

There are many examples where AI is used in cancer diagnosis. For instance, in a study conducted at Stanford Academic Medical Center, while radiologists took an average of 240 minutes to label 420 images, the AI model under investigation labeled the same dataset in a mere 1.5 minutes (Rajpurkar et al., 2018). Su and colleagues (2020) created a DL model for the diagnosis of hydronephrosis from ultrasound images. Yadav and Jadhav (2019) used CNN networks to diagnose multiple lung diseases from X-ray images. Coudray and colleagues (2018) created a classification and segmentation model for lung cancer histopathology. Bien and colleagues (2018) developed a diagnostic model for knee MRIs.

AI's remarkable precision and reliability stem from its immunity to fatigue and distractions, attributes inherently human. Furthermore, AI exhibits a capacity for rapid adaptation, facilitating the diagnosis of novel diseases within a relatively short time frame (Davenport and Kalakota, 2019). This adaptability is exemplified by the prolific generation of scientific publications and AI models dedicated to the diagnosis of the novel coronavirus (COVID-19) within a month of its declaration as a pandemic. For instance, Chen and colleagues (2020) swiftly developed a CNN model capable of diagnosing COVID-19 on CT scans with a high degree of accuracy a mere few months after the initial case was reported.

In the realm of medical applications, AI engineers undertake the training of CNNs using a vast repository of medical images, meticulously annotated by domain specialists. Medical image processing predominantly serves two core functions: diagnosis classification and segmentation. In the classification paradigm, the AI model endeavors to categorize the input image into predefined classes. These classes may assume a binary form, as exemplified in the diagnosis of COVID-19, where classes are defined as "healthy" or "not healthy" (Islam et al., 2020). Alternatively, multiple classes may be employed, encompassing categories like "healthy," "COVID," or "pneumonia" (Jin et al., 2020). Conversely, segmentation models are tasked with delineating and annotating affected regions within the image, akin to the discerning eye of a radiologist, surpassing the sole provision of class labels. A quintessential instance is the diagnosis of COVID-19 through the precise delineation of afflicted areas (Yan et al., 2020). The quintessential segmentation DL algorithm is Unet, expressly designed for the nuanced demands of medical data (Ronneberger et al., 2015). By meticulously orchestrating the CNNs in a specific sequence, these models attain highly accurate segmentation of regions of interest (ROIs), with the training data being enriched with medical images annotated by seasoned professionals, explicitly highlighting ROIs.

Both classification and segmentation techniques undergo an initial training phase on extensive datasets, followed by testing on novel data samples constituting approximately one-third of the training dataset's size. The test dataset serves as the crucible for evaluating the model's accuracy, generalizability, precision, and other pivotal metrics. In medical applications, an additional crucial step precedes the model's deployment, involving the validation of the newly tested data by domain specialists, commonly referred to as establishing the "ground truth." This ground truth can be ascertained through primarily two approaches. The first entails a panel of experts validating the model's outputs, typically employing a consensus voting mechanism. The second approach involves validation by subjecting the samples to another, typically superior test and comparing the outcomes. For instance, in the context of X-ray image classification, the model's results may be corroborated by performing a concurrent CT scan. Following the validation step, the model's performance is comprehensively re-evaluated, thereby determining its suitability as a bona fide AI model or necessitating further optimization.

2.3 Decision Making

Decision-making constitutes a pivotal aspect of human existence, essential for navigating diverse situations. In the context of healthcare, clinical decision-making (CDM) emerges as a cornerstone of healthcare providers' responsibilities, wielding a direct influence on the diagnosis, prognosis, formulation of treatment plans, and post-treatment care. The complexity of the CDM process encompasses various modes, spanning from intuitive and heuristic to analytical and evidence-based (Gigerenzer and Kurzenhaeuser, 2005; Nalliah, 2016). While technological advancements in the healthcare industry have significantly enhanced global well-being, a knowledge gap persists concerning the identification of optimal methods or approaches tailored to specific patient conditions and temporal dynamics. However, there is still a lack of knowledge about finding the best method or approach in specific conditions and times for each patient.

The ascendancy of AI has been unfolding over decades, catalyzed by the proliferation of potent hardware and the deluge of data. A watershed moment occurred in the latter half of the 1990s when IBM's Deep Blue triumphed over world chess champion Garry Kasparov. This victory heralded a rapid acceleration in AI's evolution, with particular strides achieved in the domain of DL and the concurrent escalation of computing power. These advancements empowered AI researchers to grapple with copious datasets and tackle profoundly intricate problems, with some AI applications attaining nearly perfect accuracy in select cases (Odusami et al., 2021). Nonetheless, the opacity inherent in AI decision-making, coupled with the substantial costs associated with false negatives and false positives, has prompted a shift in focus. Rather than replacing human specialists with AI systems for definitive decision-making, the primary objective has transitioned towards the development of Clinical Decision Support Systems (CDSSs). These systems aim to enhance the accuracy and reliability of healthcare providers' decisions, mitigating the risks associated with erroneous judgments (Wijnhoven, 2021).

2.4 Treatment

AI has found application in the analysis of diverse data types, including documents, sensory information, and medical images, with the overarching aim of augmenting the accuracy of CDM. Notably, NLP emerged as an initial foray in healthcare, focusing on knowledge extraction from repositories like the Electronic Health Record (EHR) system, encompassing patient treatment records, laboratory reports, diagnoses, and medical visits (Demmer-Fushman et al., 2009). Various applications of NLP have been devised, spanning disease-treatment classification (Reddy and Baskar, 2018), influenza detection (Ye et al., 2017), prediction models for asymptomatic populations (Hong et al., 2017), and the creation of decision support systems (DSS) (Gatt et al., 2009). While a diverse array of ML algorithms underpin NLP applications, DNNs have particularly excelled in discerning intricate word relationships. Recurrent Neural Networks (RNNs), a subtype of DL, have gained prominence for processing time-series data, exemplified by their utility in handling electroencephalogram (EEG) signals and data from wearable garments. RNN architectures, endowed with robust problem-solving capabilities, hold promise for the development of CDSSs, owing to their aptitude for tackling complex issues. Various RNN applications have been elucidated (Ilbay et al., 2011; Choi et al., 2017; Bhavya and Pillai, 2019; Snorovikhina and Zaytsev, 2020).

Furthermore, the domain of medical image processing stands as a prevalent and influential domain for AI deployment in diagnostic decision-making and the selection of treatment strategies. CNNs stand as the predominant models in this arena, adept at tasks ranging from anomaly detection and classification to segmentation. While medical image processing exists as a distinct field from CDSS, it exerts a direct impact on the decision-making process by furnishing healthcare professionals with supplementary insights and knowledge essential for diagnosis and treatment planning.

3. SWOT ANALYSIS

It is apparent that AI embodies numerous advantageous characteristics, yet it remains an imperfect disruptive technology. While the allure of its attributes such as speed, accuracy, reliability, repeatability, and accessibility are undeniable, challenges persist in the form of data standardization issues, applicability complexities, and hardware dependencies that remain unresolved. The scientific community's accumulation of open-source data has been facilitated by researchers' enthusiastic engagement in the field and the rapid expansion of AI and ML studies in recent years. The escalating processing power, which not only adheres to but often surpasses Moore's Law, empowers users to analyze vast datasets with greater ease (Shalf, 2020). This progression reverberates in the realm of medicine, where AI serves as a means to bridge the gap created by the scarcity of human specialists and their inherent limitations. However, as AI increasingly assumes a pivotal role, questions regarding the allocation of responsibility for the outputs, data security, and ethical concerns come to the fore. Consequently, it becomes imperative to adopt a balanced perspective, acknowledging both the benefits and potential challenges. In this review, we have undertaken a comprehensive exploration of AI in a general context, elucidating its prospects in healthcare, with a specific focus on its strengths, weaknesses, opportunities, and threats—a succinct SWOT analysis—pertaining to AI in medicine, particularly within the domain of cancer research.

3.1 Strengths

The insufficiency of human resources in terms of both capacity and time to conduct intricate analyses has prompted the adoption of AI and ML as alternative tools to supplant human labor as much as possible. When summarizing the strengths inherent to AI, it is evident that it offers remarkable attributes, including speed, precision, reproducibility, accessibility, and the capacity to discern relationships among concepts. Furthermore, AI possesses additional advantages, such as its independence from remuneration, its capability to operate around the clock without the need for breaks, its immunity to emotional fluctuations, and its capacity to autonomously generate standardized responses.

3.1.1 Speed

One of the paramount strengths of AI resides in its capacity to swiftly analyze vast quantities of data, a quality of particular significance in the realm of healthcare, and notably, in the context of diagnosis, as acknowledged by the Food and Drug Administration (FDA). In the domain of medical imaging diagnosis, AI's speed is particularly compelling when addressing intricate tasks, such as the precise pixel-by-pixel segmentation of medical images to identify potential tumor regions. The time required by radiologists to perform a comparable task is substantially greater (Zhang et al., 2021). Consequently, AI, when employed within healthcare facilities, can expedite the medical imaging analysis process, serving either as a decision support tool for diagnosis or by offering potential ROIs for expert examination.

In the analysis of genetic sequences from biopsy samples, AI-driven models, particularly those based on DL, demonstrate their efficacy in reducing interpretation time, as exemplified by the work of Karim et al. (2021). Another noteworthy application involves the use of AI to aid pathologists in diagnosis, wherein pathology slides can be digitized through slide scanners and subjected to AI algorithms for preliminary assessments, thus expediting the diagnostic process (Komura and Ishikawa, 2018). These algorithms can either streamline the diagnostic process by presenting ROIs or trigger the initiation of pertinent tests before the samples are scrutinized by expert pathologists (Bera et al., 2019).

Early diagnosis in the initial stages of cancer treatment is of paramount importance, affording patients ample time for intervention. Sun and colleagues (2019) have developed a model incorporating a DNN based on genetic variations for 12 types of cancer, facilitating the assessment of cancer risk before a formal diagnosis, thereby expediting treatment.

Drug discovery, characterized by its complexity, stands as another domain where AI's efficacy surpasses human capabilities in terms of speed. AI-facilitated in silico studies have the potential to identify drug molecule targets objectively and evidentially on a large scale. This approach holds promise for significantly abbreviating protracted drug development processes, primarily by streamlining operations and minimizing resource utilization (Workman et al., 2019). However, it is worth noting that this field remains a work in progress (Bender and Cortés-Ciriano, 2021).

In the field of biomedicine, Ko and colleagues (2018) conducted a study that assessed the performance of supervised ML in the analysis of cross-sectional clinical data for multicolor flow cytometry, an essential prognostic factor for measuring minimal residual disease which is an important prognostic factor and aimed to avoid the disadvantages of manual interpretation. Their developed algorithm achieved a remarkable accuracy of nearly 90% within a mere 7 seconds, a stark contrast to the 20 minutes required for human manual interpretation.

3.1.2 Accuracy

The concept of accuracy, which denotes the precision of a measurement system, holds paramount significance within the field of medical science. Recent AI models consistently exhibit levels of accuracy that are on par with human capabilities (Kheradpisheh et al., 2016). However, AI's precision in discerning minute details confers upon it a substantial advantage, as it meticulously analyzes data at the pixel and digit level. This enables AI models to achieve a sensitivity that surpasses human capabilities. An illustrative example in the domain of disease diagnosis involves a recent study proposing a model that outperforms 72% of general practitioners on written test cases (Richens et al., 2020).

Beyond accuracy, the performance of AI models in cancer research must be evaluated using a range of metrics tailored to the specific problem at hand, such as sensitivity, specificity, and other metrics used in classification, segmentation, and object detection tasks (Goyal et al., 2020). For instance, in breast cancer screening, sensitivity measures the model's ability to correctly identify true cancer cases, ensuring that no malignancies are missed, while specificity ensures that healthy tissues are not incorrectly flagged as cancerous. This balance is crucial in clinical settings to minimize both false positives and false negatives. Moreover, in the context of MRI-based brain tumor segmentation, metrics like the Dice coefficient and Intersection over Union (IoU) assess how closely the AI-generated segmentations align with actual tumor boundaries (Güvenç et al, 2023). Such metrics are vital in guiding precise surgical interventions. Similarly, in object detection tasks, such as identifying lung nodules in CT scans, the ROC curve and AUC score are often employed to evaluate the model's performance across different threshold settings, which is particularly important for early-stage lung cancer detection (Srivastava et al., 2023). These diverse evaluation metrics provide a comprehensive understanding of an AI model's strengths and weaknesses, enhancing its applicability in different aspects of cancer research.

Two critical facets of accuracy are sensitivity and specificity in the context of diagnosis. As part of cancer, sensitivity represents the ratio of correctly identifying cancer samples from the total number of cancer cases within the patient pool. Specificity pertains to the accuracy of diagnosing cancer cases selected from the entire patient sample. To facilitate a deeper comprehension of these concepts, Figure 5 can be taken into consideration.

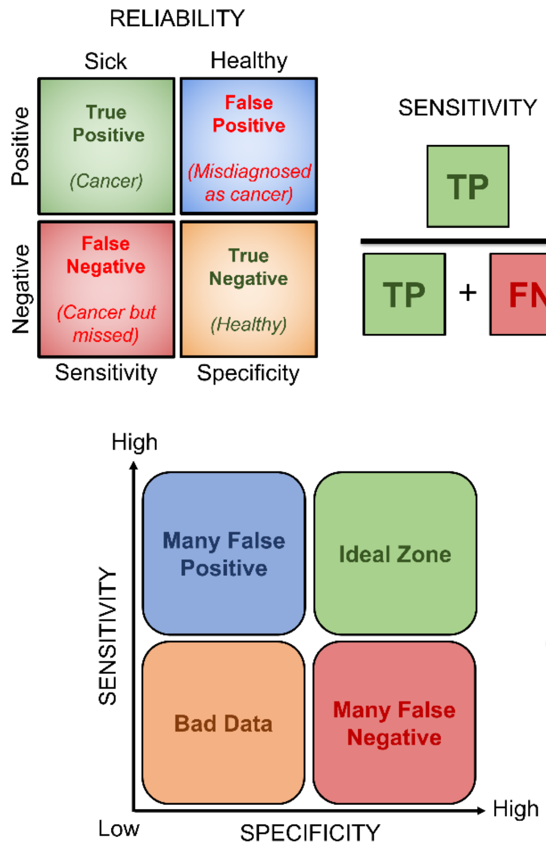

Figure 5: Statistical reliability standards encompass key attributes, namely accuracy, precision, specificity, and sensitivity. While these concepts are distinct, they are often evaluated in conjunction. Precision pertains to the reliability of a method when it yields consistent results upon repeated analyses using the same samples. Such consistency indicates that the results can be replicated reliably. Specificity, on the other hand, measures a test's ability to correctly identify and exclude samples that lack a particular characteristic. A highly specific test minimizes the occurrence of false-positive results. Sensitivity, conversely, gauges a test's effectiveness in correctly identifying samples possessing a specific characteristic. A test with high sensitivity minimizes the occurrence of false-negative results. The overarching concept of accuracy, which can be perceived as an evaluation encompassing all these attributes, essentially assesses whether a method can measure what it is intended to measure accurately and reliably.

Clinicians heavily rely on their knowledge and experience in diagnosing patients, which is acquired gradually over time. Consequently, newly graduated clinicians may lack the years of experience that their more seasoned colleagues possess. Furthermore, not all physicians encounter the same diversity of cases throughout their careers. For instance, physicians practicing in smaller locations may have limited exposure to a variety of patient cases. This situation can be likened to an AI model trained with insufficient data. A study conducted by Liang and colleagues (2019) grouped physicians by their level of experience and compared their performance with an AI system. The findings revealed that the AI-based model outperformed the two groups of less experienced physicians but exhibited lower accuracy than the three groups of senior physicians, with an average accuracy score of 88.5%. These results suggest that AI models may assist young physicians in diagnosis but may not perform as proficiently as experienced physicians (Liang et al., 2019). Additionally, aside from a lack of experience, human errors stemming from physical and psychological conditions can also lead to diagnostic inaccuracies.

Prognosis holds a critical role in cancer treatment, and the accuracy of prognosis predictions must be reliable. To achieve more accurate results, the development of AI models that comprehensively analyze the data commonly used in prognosis is imperative. In clinical settings, prognosis relies on genetic tests and histological images, but predictions based on these tests can remain subjective. DL models that integrate histological and genomic data can offer a more objective perspective on prognosis. Although models combining histological and genomic data yield more accurate results than clinicians, further refinement is needed to enhance objectivity. For instance, in a study by Mobadersany and colleagues (2018), experts were still required to identify ROIs on slides, indicating that human expertise remains essential in AI training. While algorithms can be developed to automate the selection of ROI regions, this process still necessitates expert input, underscoring the ongoing need for time to mature these processes.

As an illustration, computer-aided systems can assist in detecting polyps and adenomas during colonoscopy procedures. In a study by Liu and colleagues (2020), patients were randomized for colonoscopy, and a DL-based computer-assisted system was used in one of the groups. The study observed significant increases in the detection rate of adenomas, the average number of adenomas, the number of small adenomas, and the number of proliferative polyps compared to the control group (Liu et al., 2020). Such systems can offer decision support to endoscopists in challenging circumstances. Nevertheless, further randomized controlled studies and extensive datasets are required to bolster reliability.

3.1.3 Repeatability and Accessibility

AI models, even though trained on specific datasets, exhibit a remarkable ability to perform effectively on data beyond their initial training scope. Transfer learning (TrLe) techniques are employed to extend the utility of AI models trained for specific applications to different domains (Kim et al., 2020). For instance, an object detection model initially trained on common objects can be further trained on medical images, delivering high accuracy since the primary training data focus on extracting general features rather than domain-specific nuances. This versatility contributes to the repeatability and reproducibility aspects of AI models, as they can consistently perform with accuracy over multiple uses and can serve as building blocks for more complex models. An example of this is demonstrated by Namikawa and colleagues (2020), who efficiently classified gastric cancers and ulcers using their AI-based diagnostic system. In their study, they developed and re-validated algorithms previously obtained in another study, resulting in a model with improved specificity (Namikawa et al., 2020). This showcases how previously generated algorithms can be adapted and enhanced using new datasets.

Moreover, AI's inherent accessibility is of paramount importance in the realm of healthcare, especially for reaching remote areas where skilled clinicians may be scarce or unavailable. Additionally, ANNs possess online learning capabilities, allowing them to autonomously learn and adapt continuously. As previously mentioned, computers are immune to human limitations like stress, fatigue, hunger, or institutional pressures. This makes AI more reliable in hazardous environments and during times of crisis.

3.1.4 Learning Relationships

AI possesses a remarkable advantage that sets it apart from other technologies: its ability to approximate nonlinear relationships and unveil even the subtlest connections within vast datasets. Leveraging its talents in pattern association, classification, and sample clustering, AI aids in understanding the intricate biological causation required for various applications. As a result, new studies are conducted continuously to train AI through the development of novel models. One noteworthy model in this regard is TrLe, which mitigates data scarcity challenges by utilizing a pre-trained model in a related problem context (Hutchinson et al., 2017).

Unlike humans, AI demonstrates the capacity to meticulously analyze extensive datasets, enabling it to perform tasks such as clustering, classification, and the discovery of new patterns. This capability empowers the resolution of complex medical problems, including medical imaging analysis, prognosis, and drug discovery. Furthermore, AI can uncover novel relations between symptoms, diseases, or drugs, as it doesn't rely on understanding causation to reveal these connections, a feature distinct from medical professionals. This opens up new possibilities for expediting our comprehension of current and future diseases.

The complex and variable molecular and genetic mechanisms underlying cancer present one of the most challenging aspects of cancer treatment. These intricate and variable systems are pivotal for personalized treatment, drug development, and generate vast datasets that defy analysis through classical methods. To address this challenge, cutting-edge sequencing technologies and AI are employed for data analysis (Fountzilas and Tsimberidou, 2018). Additionally, predicting the prognosis of highly heterogeneous cancers like hepatocellular carcinoma (HCC) can be exceptionally challenging. While various molecular subtypes of HCC have been identified through multi-omic studies, some exhibit similar survival outcomes. Consequently, identifying HCC subtypes sensitive to survival and evaluating multi-omic data are crucial for prognosis prediction and treatment planning. Chaudhary and colleagues (2018) harnessed DL computing frameworks to address these challenges using multi-omic HCC data. Using ribonucleic acid (RNA) sequencing, micro-RNA (miRNA) sequencing, and methylation data from The Cancer Genome Atlas (TCGA), their study resulted in the identification of two optimal subgroups with distinct survival outcomes (Chaudhary et al., 2018). In their review of the roles of AI in prostate cancer, Goldenberg and colleagues (2019) demonstrated that AI not only enhances image processing-mediated diagnosis but also supports researchers and clinicians in various aspects, ranging from molecular biology and genetics to robotic surgery, thereby improving disease prognosis and saving valuable time for patients.

Leveraging computational biology for prognostic evaluations can significantly expedite the process for both patients and clinicians. Recent advancements in algorithms enable the swift and highly accurate synthesis of data that may be challenging to integrate and interpret or time-consuming to analyze. For instance, Daemen and colleagues (2008) integrated microarray and proteomic analyses with computational biology techniques using samples from rectal cancer patients at different stages of treatment. Their models achieved a remarkable sensitivity of 96% in predicting treatment responses (Daemen et al., 2008). Evaluating multiple types of data simultaneously is a key strategy to enhance predictive power. Genomic, proteomic, metabolomic data, histopathological samples, clinical outcomes, and even patient questionnaires can be synthesized to develop diverse prognostic scores. To achieve this, we can leverage the latest advancements in molecular biology techniques and AI.

In summary, AI's strengths collectively contribute to bridging gaps in human efforts to achieve accurate and unbiased healthcare. AI-driven DSSs aim to mitigate all facets of human error, accelerate expert decision-making, and enhance the overall quality of healthcare.

3.2 Weaknesses

AI, while boasting numerous strengths, also exhibits certain weaknesses and areas that necessitate improvement. One prevalent issue is the system's incapacity to scrutinize its own functioning and the possibility of failing to learn effectively. This predicament can be addressed through adjustments to the datasets and models employed. Although machines possess extensive storage capacity and formidable processing capabilities, they lack human-like cognitive faculties entirely. AI networks excel at detecting minuscule anomalies in images, often imperceptible to humans. However, they struggle to establish cause-and-effect relationships with these anomalies, which presents a formidable challenge, particularly in the context of medical images (Shvetsova et al., 2021). Furthermore, AI models, crafted with highly specific data for particular purposes, prove susceptible to even minor alterations, rendering replicability challenging under varying conditions. Disparate learning methods, datasets, ROIs, and even different software developers can all influence outcomes. Therefore, method standardization holds significant importance. Moreover, certain domains, such as healthcare, may encounter difficulties in acquiring data, and AI consistently relies on hardware for data processing. Lastly, the substantial energy consumption associated with large-scale AI models has undeniable implications for global warming, posing a threat to human health.

3.2.1 Causality

To address the weaknesses of DL and traditional ML, it's crucial to delve into the concept of causality. In the real world, humans inherently strive to discern cause-and-effect relationships between events because comprehending the underlying reasons empowers them to make decisions that can shape a better future. ML algorithms excel at identifying patterns and correlations between inputs and outputs, and they are adept at predicting outcomes. However, this capacity is not synonymous with understanding causation. Recent research emphasizes the necessity for AI systems to construct causal models that facilitate explanation and comprehension (Lake et al., 2017).

ML algorithms do not possess an intrinsic understanding of genuine causal relationships or how inputs and outputs are intrinsically linked; instead, they tend to memorize the relationship between inputs and outputs, which can lead to overfitting (Ying, 2019). Overfitting occurs when an analysis is tailored too closely to a specific dataset, rendering it less adaptable to new, unseen data. Causality can aid ML in mitigating overfitting while enhancing accuracy and interpretability. It does so by mitigating the adverse impacts of selection bias, interobserver variability, and other factors on accuracy, and by facilitating a genuine comprehension of the data's significance. Outputs should be comprehensible and interpretable not only to programmers but also to other researchers (Azuaje, 2019).

However, a significant challenge arises in the form of the "black box" problem, which stems from the non-transparency of the information processing systems used by AI to solve problems. This opacity hampers researchers' ability to precisely understand why a particular output is generated. Engineers are actively working on solutions to this problem, advocating for the use of more interpretable models (Rudin, 2019). For instance, studies involving AI and the cancer genome are burgeoning, yet scientists remain essential for interpreting the outcomes produced by these models (Liu et al., 2018).

3.2.2 Reproducibility

In ML, the process of training algorithms and fine-tuning hyperparameters is crucial to achieving optimal results. Equally important is the ability to consistently obtain the same outcomes when using identical data, algorithms, and hyperparameters, which is referred to as reproducibility. Reproducible AI algorithms play a pivotal role in enhancing the comprehensibility, interpretability, accuracy, and dependability of the workflow (Cutillo et al., 2020).

The term "reproducibility" gained prominence following a 2016 study conducted by Baker, which revealed that over half of scientists struggled to replicate their own experiments, and seven out of ten encountered difficulties when trying to reproduce experiments conducted by other researchers (Baker, 2016). Achieving reproducibility in AI is indeed challenging because it hinges on factors such as training data, the selection or generation of features, algorithmic procedures, hardware, and software configurations, and is influenced by variations between laboratories and population diversity. For instance, the Watson for Oncology system, which was initially trained in the United States, exhibited slight inconsistencies when applied to different cases and evaluated by various experts in India. However, these disparities might also be attributed to differences in treatment approaches between countries and variations in demographics (Somashekhar et al., 2018).

3.2.3 Data Availability (Annotations & Privacy Restrictions)

DL algorithms often demand large volumes of data during the training process, yet the biomedical field frequently encounters limitations in terms of the quantity of available data (Huang et al., 2020). While there are some publicly available anonymized datasets for research purposes, these datasets are often insufficient in size to achieve the high levels of accuracy and precision required for applications in the healthcare industry. Moreover, there are various other sources of medical data, such as electronic health records, experimental data, physiological monitoring data, and medical imaging data, which are stored in secure databases (Hulsen et al., 2019). Accessing such data is hindered by strict regulations and privacy concerns surrounding medical data, making it challenging to obtain the necessary datasets for training ML algorithms in healthcare. To address these data limitations, researchers have explored alternative approaches such as TrLe and leveraging different portions of the same pathological sections in ML education. Additionally, the use of synthetic images generated through Generative Adversarial Networks (GANs) has been investigated as a means to augment training datasets (Iqbal and Ali, 2018). Some studies have shown that even experts have difficulty distinguishing between real and artificial images (Abdelhalim et al., 2021).

Beyond data availability, data annotation presents another significant challenge in the medical field. Annotating medical data, such as segmenting tumors in medical images, requires the expertise of professionals, often experienced radiologists. Finding professionals with the available time for annotation work can be a substantial challenge. Efforts to increase data standardization and facilitate access to clean data are essential but remain ongoing processes. Converting examples into numerical values and selecting appropriate methods for data preprocessing and activation functions are also critical aspects that rely on the programmer's experience. Moreover, the lack of highly accurate reference datasets, which include meticulously characterized tumors and detailed clinical annotations, is a significant concern. Furthermore, collecting extensive personal health data raises security and privacy concerns, making it susceptible to potential security breaches (Rigaki and Garcia, 2020). Blockchain applications have been explored as a potential solution to enhance data security (Saldanha et al., 2022).

In summary, the challenges in data science, particularly in the context of medical data, are more prominent than the lack of AI capabilities. Addressing issues related to data quantity, quality, standardization, annotation, and security is crucial for advancing AI applications in healthcare.

3.2.4 Applicability

The applicability of AI models in healthcare often faces challenges due to a gap between AI engineers and the healthcare system. While AI models may hold theoretical promise in medical applications, they may not align with the practical processes and quality metrics of the healthcare system (He et al., 2019). For instance, historically, computer scientists have aimed to achieve automatic diagnosis or CDSS for medical purposes since the 1960s (Miller, 1994). However, AI models typically lack an understanding of causality and rely on observed data relationships, which contrasts with the diagnostic process in healthcare. In medical diagnosis, the emphasis is on comprehending the biological causal relationships between symptoms and diseases rather than merely identifying correlations in data. Consequently, computer science shifted its focus to computer-aided diagnosis systems, where AI models serve as decision assistants rather than decision-makers. This shift aligns more closely with practical healthcare applications.

Additionally, evaluation metrics and quality assurance criteria differ significantly between engineering and medical sciences. While an AI model that is 100 times faster than traditional methods but has an 80% accuracy rate may seem like a significant advancement in engineering contexts, medical applications demand a different standard. In clinical settings, achieving a 99% accuracy rate with low precision is not acceptable. The medical field prioritizes precision and reliability over raw speed. Moreover, the testing and quality assurance process for AI in medicine is more complex because even minor malfunctions can have critical consequences. AI models in medicine require periodic testing and ongoing performance monitoring to ensure that they consistently meet the required standards over time. Unfortunately, not all AI models have robust methods for conducting stability analyses, which further complicates quality assurance efforts.

3.2.5 Hardware Dependence

ML algorithms require powerful hardware at various stages, including data storage, data preprocessing, training, and deployment. The training of ML models, especially those dealing with large datasets or complex tasks like image processing, demands substantial storage capacity and efficient processors, such as graphics processing units (GPUs) and tensor processing units (TPUs) (Jawandhiya, 2018). These specialized hardware components are capable of handling the intense computational workloads required during training.

The ability to perform parallel processing is another critical factor in ML performance, and it depends on the processors' ability to run in parallel. For example, DL models, particularly ANNs, distribute memory across network connections and weight values. The information processed by the network is encoded in the connections and weights of neurons, and individual links or neurons do not carry meaningful information on their own. Therefore, determining the appropriate number of neurons and layers in a neural network can impact the computational load. Adding extra layers increases the computational time required for training and inference.

In practice, many ML applications are deployed to cloud services due to their advantages in terms of hardware availability, cost efficiency, and scalability. However, there are challenges related to deploying ML models in the medical domain. Medical data processing and storage in the cloud can be subject to regulatory restrictions and privacy concerns. Additionally, real-time applications may not use cloud services because of data transfer delays, as immediate response times are crucial in such scenarios. These considerations underscore the importance of selecting the right hardware and deployment strategies for specific ML applications, particularly in healthcare settings where data privacy and real-time decision-making are paramount.

3.3 Opportunities

The burgeoning success of AI algorithms in recent decades can be attributed to the confluence of advancements in hardware technology and the opportunities afforded to AI researchers. These opportunities are underscored by notable progress in data generation, scientific publications, and financial investments within the domains of both cancer research and AI. AI, having benefited significantly from these favorable conditions, has now matured to offer invaluable contributions to healthcare professionals and cancer patients alike.

Within ANNs, information is not confined to conventional files or databases but is rather distributed and retained throughout the network via intricate connections. This unique attribute ensures a robust fault tolerance mechanism, where meaningful information remains intact even in the event of cell malfunction. Moreover, ANNs obviate the need for distinct mathematical models, distinguishing them from traditional programming paradigms. In essence, the distinctive programming logic of ANNs mitigates conventional challenges, ushering in novel prospects for AI in healthcare and beyond.

3.3.1 Amount of Produced Data

The exigent demand for vast datasets to effectively train AI networks is now being met, driven by an unprecedented surge in data production. This surge is catalyzed by several factors, including the widespread adoption of technology-driven devices, ubiquitous internet connectivity enabling data sharing among individuals and devices, and the proliferation of capacious data storage repositories such as cloud services. Notably, the medical domain has witnessed an extraordinary expansion in data generation, chiefly due to the pervasive digitization of medical instruments, resulting in an unparalleled proliferation in the quantity and caliber of data. Concurrently, research institutions have played a pivotal role in augmenting this data deluge. For instance, the repositories of gene sequencing data and the cumulative knowledge amassed in drug discovery endeavors have reached unprecedented levels. Consequently, the burgeoning volumes of healthcare-related data represent golden opportunities for AI researchers to craft increasingly sophisticated neural networks.

3.3.2 Number of Publications in AI and Cancer

The landscape of AI research has been evolving over several years, but it is within the past two decades that ML in healthcare has witnessed a remarkable surge in momentum (as depicted in Figure 6). Following the proven success of its AI, the number of people working in this field has also increased (Tran et al., 2019), and the increase rate of publications is 45.15% from 2014 to 2019 (Guo et al., 2020). This upswing in activity has been underpinned by a confluence of factors, including the burgeoning volumes of digitized data generated worldwide and the availability of formidable computational hardware capable of processing these data troves. Furthermore, the practice of openly disseminating the outcomes of AI research has significantly contributed to this growth, as it allows subsequent researchers to build upon the foundational work of their peers rather than reinventing the wheel. This collaborative and information-sharing ethos has emerged as a substantial boon, particularly in the field of healthcare. The domain of oncology, notably, has been a focal point for researchers over the years, with knowledge in this sphere accumulating incrementally. The diminishing costs associated with technologies like next-generation sequencing have facilitated the acquisition of data, including genomic data, with increased ease, making it more accessible for reuse and further research endeavors.

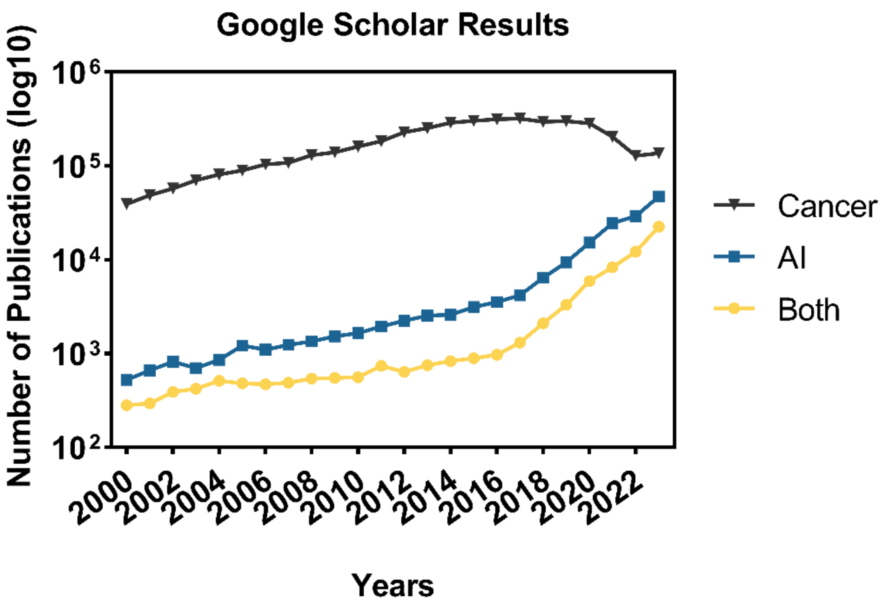

Figure 6: The trend in cancer and AI-related publications since 2000, as revealed by a Google Scholar search conducted in May 2024, indicates a consistent and gradual increase in research activities in the field of cancer up until the year 2013. Notably, there has been a concurrent increase in publications that encompass both AI and cancer, a trend that has gained substantial momentum, particularly after the year 2015. For ease of visualization, the number of articles is presented in a logarithmic base.

3.3.3 Number of Organizations and Money Spent on Cancer Research and AI

Cancer, often referred to as the second leading cause of death after cardiovascular diseases in contemporary times, is a disease with a documented history dating back to as early as the 400s BC. It continues to be a focal point of extensive research efforts and represents a significant segment of the pharmaceutical industry.

Recent data indicates that The American Cancer Society, for instance, has made substantial investments, amounting to nearly $5 billion, in cancer research since its inception in 1946. Governments and scientific research institutions worldwide annually allocate substantial funding and resources for cancer research and clinical investigations. Despite the persistent challenges in completely eradicating this disease, the wealth of data and research possibilities in this field offer a ray of hope for cancer patients and their families. Concurrently, AI and ML technologies have garnered increasing attention from researchers and investors alike in recent years. Numerous grants and funding opportunities are being awarded across various sectors to advance these technologies. When the realms of cancer research and AI converge, a highly compelling and vital research domain emerges, holding immense promise for the future of cancer diagnosis, treatment, and care.

3.3.4 Available Computation Power

Since the inception of computers, there has been a consistent and impressive surge in processing power. Advancements in semiconductor technology, coupled with increased processor efficiency, have rendered computers thousands of times faster than their early counterparts. Furthermore, the advent of graphics processors has significantly bolstered computers' parallel processing capabilities, while the cost of computers and servers has simultaneously plummeted. The availability of cloud service providers has further streamlined access to essential hardware for operations demanding substantial processing power. This shift, away from multi-million-dollar investments in infrastructure, towards efficient pay-as-you-go models, has revolutionized computing. These developments empower computers with the capability to process vast datasets, a task that far exceeds the capacity of the human brain. Consequently, clinicians, despite their extensive knowledge and experience, cannot consistently guarantee the precision of their diagnoses when dealing with such immense data volumes (Huang et al., 2020).

In this context, AI models and ML technologies emerge as pivotal tools for achieving accurate disease diagnosis and prognosis. For instance, while prognosis reliant on genomic and histological analyses by clinical experts may retain subjectivity, Mobadersany and colleagues (2018) have achieved more objective prognosis outcomes through their DL approaches. These DL methods adeptly integrate histological and genomic data, ushering in a new era of precision in prognosis (Mobadersany et al., 2018).

3.3.5 Early Diagnosis

Early diagnosis constitutes a pivotal determinant for favorable treatment outcomes in various types of cancer. Typically, patients seek medical attention only when severe symptoms manifest, resulting in missed opportunities for early detection. AI technology offers the potential to identify cancer risk before the disease's clinical onset, affording ample time for intervention. A prospective paradigm could involve routine non-invasive screenings, followed by AI-driven analyses. Eisner and colleagues (2013), for instance, devised a metabolic profiling approach to construct an ML predictor utilizing relatively straightforward samples such as urine. This innovation allows the prediction of patients who may or may not require a colonoscopy, an invasive diagnostic method for colorectal cancer precursor polyps. While their clinical research yielded specificity and sensitivity rates nearing 60%, this study hints at the possibility of clinicians deploying a preliminary DSS, providing a faster and less burdensome alternative to fecal-based testing prior to colonoscopy (Eisner et al., 2013).

In a retrospective study, Liu and colleagues (2005) conducted a comprehensive analysis of complex protein profiles extracted from serum samples obtained from individuals with astrocytoma, benign brain tumors, and healthy subjects. Employing AI-driven protein fingerprinting techniques, their models were trained to discern potential biomarkers capable of distinguishing glioma patients from healthy individuals and distinguishing astrocytoma from benign brain tumors. The outcomes of their endeavors demonstrated sensitivities and specificities exceeding 85%, underscoring the vital role AI can play in the identification of disease biomarkers, particularly when early and straightforward diagnoses are essential (Liu et al., 2005).

The scope of AI's contributions to early cancer diagnosis extends across various stages of the disease. Genomic studies strive to unveil cancer risk before its clinical manifestation, while medical imaging and image processing techniques aim to pinpoint cancer's location, size, stage, and grade from its incipient stages. A hallmark feature of AI is its remarkable speed and precision when applied to tasks it has learned, rendering it invaluable not only for early diagnosis but also for addressing challenges encountered during treatment, such as drug resistance and metastasis, in the domain of precision oncology. Notably, next-generation sequencing (NGS) techniques play a prominent role in this context (Dlamini et al., 2020). AI's utility extends beyond clinical and patient settings to encompass pre-clinical investigations, *in vitro* studies, and *in vivo* research, lending crucial support to basic science researchers as they explore novel diagnostic and treatment avenues.

3.3.6 Reducing Work Loads of Healthcare Providers

The COVID-19 pandemic has underscored the immense burden faced by healthcare professionals, highlighting the potential for AI to alleviate their workload in the future. AI holds promise in streamlining various healthcare processes, including the reduction of documentation tasks for clinicians. Additionally, AI-driven tools, particularly those incorporating virtual reality (VR) and augmented reality (AR), such as case simulations, can enhance the education of young physicians in clinical diagnosis and decision-making. However, it's important to acknowledge that significant advancements are still required in this domain (Baniasadi et al., 2020).

In the field of medical imaging and preparations, AI-driven scanning can facilitate the selection of specific ROIs, potentially reducing the time needed for examination. Pathologists and physicians can optimize their time by focusing on regions flagged as high-risk by AI or on patients identified as high-risk. Moreover, looking ahead, robotic systems have the potential to revolutionize surgical procedures by minimizing invasiveness and assuming responsibility for routine tasks, thereby reducing surgeons' workloads. Nevertheless, it's essential to recognize that Robot-assisted Surgery (RAS) applications entail intricate procedures necessitating seamless human-robot interaction, multitasking capabilities, preparedness, and rapid responses to diverse stimuli and unforeseen scenarios (Shafiei et al., 2020).

The shortage of specialists for specific cancer types and the time constraints preventing specialists from staying current with the ever-expanding body of knowledge pose significant limitations in cancer treatment. CDSSs address this challenge by leveraging computational reasoning approaches to evaluate the mounting volume of information, providing critical support to clinicians in oncology treatment (Somashekhar et al., 2018). An exemplary CDSS is IBM's Watson for Oncology system, which acquires knowledge by comprehensively reviewing the literature, protocols, and patient charts, and learning from test cases and experts at institutions like the Memorial Sloan Kettering Cancer Center. Remarkably, this system has demonstrated high consistency in providing breast cancer treatment recommendations for diverse patients beyond its original training context. AI-driven CDSSs hold considerable potential for enhancing cancer treatment, particularly in regions facing shortages of specialized expertise.

3.4 Threats / Risks

The integration of clinical expertise with AI capabilities remains a challenge, as clinicians typically possess limited knowledge of AI, while data scientists and engineers may lack clinical insights. Overcoming these barriers necessitates the establishment of multidisciplinary collaboration frameworks. Moreover, the field of AI grapples with significant legal constraints, particularly concerning health data, as governments impose increasingly stringent regulations. Researchers bear substantial legal responsibilities in this context. Furthermore, as previously mentioned, the vulnerability of health data to potential cyberattacks poses a major threat. Beyond legal responsibilities, the allocation of liability for potential consequences arising from AI applications is a contentious issue that requires careful consideration.

3.4.1 Legal Restrictions

A paramount challenge hindering the advancement of AI systems in medical applications pertains to the realm of laws and regulations. Data sharing, a pivotal factor for accelerating research and enhancing accuracy, is currently constrained by ethical and financial considerations (Fountzilas and Tsimberidou, 2018). Concerns about the implications of new technologies, particularly those related to medical data, have given rise to apprehensions among social scientists. Varying regulations already exist across countries regarding the use of medical data (Essén et al., 2018). In the United States, federal laws delineate health data in the Privacy Rule established under the Health Insurance Portability and Accountability Act (HIPAA). The Privacy Rule stipulates that only specific entities, such as physicians and healthcare providers, may handle health data under tightly defined circumstances. Conversely, European Union laws encompass health data within their broader data privacy regulations (Price and Cohen, 2019). With the growing integration of AI in healthcare settings, it is plausible that additional laws and restrictions will be enacted governing the collection, annotation, training, and utilization of data. The extent to which these laws may constrain the open AI community's ability to develop medical systems remains to be determined, as these decisions are influenced by myriad factors, including AI systems' performance within the healthcare landscape, as well as social and political considerations (Renda, 2019). At present, openly accessible medical data are anonymized through the removal of at least patient names and identification information. However, this anonymization approach is imperfect, as there are techniques for re-identifying anonymized data. Consequently, there is a pressing need to identify more robust methods for safeguarding patient privacy without impeding the utilization of medical data for AI systems. The utilization of secure personal health data marketplaces employing blockchain technologies, which have garnered increased attention in recent years, offers a potential solution. Such marketplaces can both mitigate regulatory challenges and facilitate developers' access to the requisite data set.

3.4.2 Ethics and Legal Responsibility

Since the inception of AI, there has been a persistent curiosity regarding its capacity to address ethical questions and adhere to an ethical framework. A prominent example of this conundrum is the ethical dilemmas posed by autonomous vehicles, where decisions might involve choosing between jeopardizing the lives of passengers or pedestrians. In the field of medical applications, ethical concerns encompass several key aspects: obtaining informed consent from patients for the use of AI-based models in their healthcare, ensuring the safety and transparency of AI models, addressing issues of fairness and bias in AI models, and safeguarding data privacy (Gerke et al., 2020).

Additionally, the question of responsibility, both ethical and legal, looms large when it comes to deploying AI models. Determining who is accountable for mistakes made by or resulting from AI, and how to establish legal liability, remains a pivotal issue that can hinder the adoption of AI technologies in various institutions. In medical contexts, the significance of this question varies; for instance, the responsibility associated with a DSS is considerably different from that of a surgical robot. However, even in the case of highly advanced AI-based models employed in critical applications, a similar chain of responsibility can be applied, drawing parallels with established norms in other automated domains such as aviation. This chain typically entails the user of the model, followed by the manufacturer, and ultimately the parent company. This approach is grounded in the understanding that, despite their sophistication, AI technologies remain contingent on human trainers and operators who impart their acquired intelligence.

Nevertheless, ethical considerations are intrinsic to any undertaking involving humans or living entities, encompassing research, treatment, surgical interventions, and beyond. As such, the solicitation of consent forms from patients and/or their relatives is a customary practice. It is reasonable to extend a similar principle to AI. Algorithms that learn from human decisions, or more precisely, are trained by humans, inevitably inherit human fallibility. Therefore, it is imperative that AI systems undergo continuous scrutiny by experts to verify their proper functioning. Instances of overdiagnosis, underdiagnosis, or misdiagnosis underscore the potential risks, as patient lives may hang in the balance. Consequently, the question arises whether AI can ever entirely supplant human experts, a prospect that, for the foreseeable future, remains a distant possibility.

3.4.3 Data Dependence

AI fundamentally operates on data and its performance, accuracy, precision, and speed are intricately tied to data quality. It relies on a constant influx of new data to refine its capabilities. Learning in AI occurs through exposure to examples, and these examples must comprehensively represent the problem domain. When AI models trained on specific types of data encounter different data types or data presented in a dissimilar manner, achieving the desired level of accuracy becomes challenging. This challenge is particularly evident in radiomics studies where medical images yield tens of thousands of features. The selection of input features for training an AI network is crucial, as varying feature combinations can significantly impact model accuracy, even when derived from the same set of images.

Moreover, AI models tend to be highly specialized and are typically proficient only in the tasks they were trained for. Consequently, the dependence on data is a limiting aspect of AI. Although various models have been developed to address this limitation, the maturity required for extensive healthcare applications has not yet been attained. For instance, attempting to predict drug sensitivity or intolerance based solely on gene expression profiles or specific gene mutations may prove inadequate. In precision oncology, a comprehensive prognosis necessitates consideration of a patient's genomic and demographic attributes, alongside -omic profiles like epigenomics, proteomics, and metabolomics, along with non-omic data such as histopathology. AI can play a pivotal role in integrating and standardizing these diverse data sources, offering invaluable support to clinicians, and aiding in more accurate treatment decisions.

However, the integration and standardization of such multifaceted data pose formidable challenges. Researchers are actively engaged in addressing these issues, with precision oncology emerging as a prominent application area for AI. Nevertheless, it is essential to acknowledge that AI has a substantial distance to cover in overcoming these obstacles, and traditional methods continue to serve as the gold standard in oncology. The complexities of pre-processing and integrating data, coupled with the need to grasp the phenotypic status of patients, underscore the extensive journey ahead for AI in the field of oncology (Patel et al., 2020).

4. TAKE-HOME POINTS

As a conclusion to this paper, Figure 7 summarizes the SWOT analysis of AI in cancer (and many other medical fields).

Figure 7: SWOT analysis of the use of AI in cancer.

- Cancer, comprising numerous diverse types, remains a formidable challenge due to the elusive causes and absence of definitive treatments. This complexity renders the entire journey from diagnosis to treatment an arduous task for both healthcare practitioners and patients.
- In recent years, AI has made its presence felt in the healthcare sector, promising transformative impacts across various medical processes, encompassing diagnostics, decision-making, personalized therapy, and treatment.
- The heterogeneity of cancer types, each characterized by distinct genetic and epigenetic traits, further complicates the treatment landscape, underscoring the imperative for personalized approaches tailored to individual cases.
- In this challenging landscape, the fusion of big data and AI offers newfound hope to both patients and clinicians grappling with the intricacies of cancer diagnosis and treatment. Precision oncology, in particular, leverages AI to assimilate and process extensive datasets emanating from multi-omics analyses.
- AI's remarkable strengths include its speed, capacity for high-precision training, repeatability, accessibility, and proficiency in deciphering intricate data relationships that often confound human comprehension.
- However, certain unresolved weaknesses persist, such as the lack of causal understanding, insatiable data requirements, obstacles to accessing healthcare data, ethical and legal quandaries, issues regarding applicability, hardware prerequisites, and the intricate problem of explainability epitomized by the black box conundrum.
- Notwithstanding these challenges, AI offers manifold opportunities. The burgeoning volume of data generation, the availability of open-source code, escalating AI-related funding, and expanding programming capabilities augur a promising future. AI has the potential to enhance early diagnosis rates, elevate treatment success probabilities, and alleviate the burdens on healthcare professionals through automated processes.

- Key impediments to the extensive implementation of AI in healthcare encompass legal responsibilities, regulatory constraints, and ethical dilemmas.
- To usher in an era of more widespread AI utilization in cancer care, enhancing data accessibility and integrity, along with securing healthcare data to requisite levels, stands as a paramount imperative.
- Healthcare professionals grapple with substantial workloads, a challenge thrown into stark relief during events like the COVID-19 pandemic. While AI applications cannot fully supplant human expertise at present, they can significantly augment healthcare delivery. Ongoing research and technological advancements hold promise for the field of oncology.
- Anticipations point to a future where AI becomes an increasingly ubiquitous presence in the healthcare sector, further revolutionizing the landscape and enhancing patient care.

ACKNOWLEDGEMENTS

Gülşah Torkay would like to acknowledge the financial support from the Scientific and Technological Research Council of Turkey (TUBITAK) 2210-A General Domestic Graduate Scholarship Program and 2211-E National PhD Scholarship Program for Former Undergraduate and MSc/MA Scholars (App No: 1649B022101483 and App No: 1649B032304943).

FUNDING

There is no funding for this study.

AUTHORS` CONTRIBUTIONS

All authors contributed to the manuscript and read and approved the final version of this paper.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

DATA AVAILABILITY

There is no raw data associated with this review article.

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