EJMO

DOI: 10.14744/ejmo.2024.24486
EJMO 2024;8(3):281–294

Review

The Role of Artificial Intelligence in Diagnosing Malignant Tumors

Shmmon Ahmad,[1] Zafar Khan,[2] Monish Khan,[3] Moh Aijaz,[4] Shivani Thakur,[5] Anjoo Kamboj[6]

[1]Glocal University Pharmacy College, Glocal University Saharanpur India
[2]Department of Research and Development, AIMIL Pharmaceuticals, New Delhi, India
[3]School of Pharmaceutical Sciences, Glocal University Mirzapur Pole, Saharanpur, India
[4]School of Pharmacy, Graphic Era Hill University, Dehradun, Uttarakhand, India
[5]Faculty of Pharmacy, Maharaja Agrasen University, Baddi, Solan, Himachal Pradesh
[6]Chandigarh College of Pharmacy, Landran, Mohali, Punjab, India

Abstract

This paper explores the transformative impact of artificial intelligence (AI) in early tumor diagnosis, emphasizing its role in analyzing health records, medical images, biopsies, and blood tests for improved risk stratification. While screening programs have enhanced survival, challenges remain in patient selection and diagnostic workforces. The review covers diverse AI approaches, including logistic regression, deep learning, and neural networks, applied to various data types in oncology. It discusses the clinical implications, current models in practice, and potential limitations such as ethical concerns and resource demands. We provide an overview of the main artificial intelligence approaches, encompassing historical models like logistic regression, alongside deep learning and neural networks, emphasizing their applications in early diagnosis. We describe the role of AI in tumor detection, prognosis, and treatment administration, and we introduce the application of state-of-the-art large language models in oncology clinics. Our exploration extends to AI applications for omics data types, offering perspectives on their combination for decision-support tools. Concurrently, we evaluate existing constraints and challenges in applying artificial intelligence to precision oncology. The overall aim is to showcase AI's promise in revolutionizing tumor diagnosis while acknowledging and addressing associated challenges, thereby advancing patient care.

Keywords: Artificial intelligence, early tumor diagnosis, machine learning, clinical implications, challenges in implementation, malignant tumors

Cite This Article: *Ahmad S, Khan Z, Khan M, Aijaz M, Thakur S, Kamboj A. The Role of Artificial Intelligence in Diagnosing Malignant Tumors. EJMO 2024;8(3):281–294.*

Artificial Intelligence (AI) encompasses the emulation of human intelligence by computers. Within AI, Machine Learning (ML) is a subset focused on training algorithms to predict outcomes based on experience. ML can be categorized into supervised (involving outcome data) or unsupervised (without outcome data) learning, both seeking patterns for predictions like cancer presence, survival rates, or risk groups. In the analysis of unstructured clinical data, particularly in oncology, a commonly employed technique is Natural Language Processing (NLP). NLP converts unstructured free text into a format analyzable by computers, facilitating the automation of resource-intensive tasks.[1-3]

Two distinct artificial intelligence (AI) methodologies can be employed for the diagnostic imaging of malignant tumors.[4] The initial approach entails defining tumor characteristics, such as texture, volume, and shape, using mathematical equations, followed by quantification through computer programs.[5] The second method, known as deep learning, has garnered significant attention in the medical realm. Esteva et al.[6] utilized a deep convolutional neural network to classify skin lesions, achieving diagnostic

Address for correspondence: Shmmon Ahmad, Ph.D. Glocal University Pharmacy College, Glocal University Saharanpur India
Phone: +91 9012694308 **E-mail:** shmmon@theglocaluniversity.in

Submitted Date: March 16, 2024 **Accepted Date:** May 31, 2024 **Available Online Date:** September 10, 2024

accuracy comparable to 21 qualified dermatologists. Deep learning proves to be a robust tool for integration with imaging technologies, aiming to ease the workload of medical professionals.

AI's learning capability and reliability have been demonstrated in contrast to various diagnostic assays for mediastinal malignant tumors.[7] A proposed machine learning model, integrating positron emission tomography with computed tomographic images and using a multilayer perceptron classifier, successfully predicted thymomas' risk levels.[8] Another study associated computed tomography features with pathological tumor characteristics, highlighting the random forest model's high efficiency in diagnosing thymic carcinoma and high-risk thymoma, with a predictive accuracy of 94.73%.[9] An additional AI model was developed for predicting pathological subtypes of prevascular mediastinal tumors (PMTs), showing sensitivities of 52.9%, 74.2%, and 92.8% for identifying lymphoma, thymoma, and thymic carcinoma, respectively. These instances underscore the potential of machine learning algorithms in conjunction with conventional imaging methods to significantly improve detection efficiency and accuracy, and alleviate diagnostic burdens.[10,11]

AI is employed in personalized treatment planning by utilizing predictive modeling. Through the analysis of extensive patient datasets, AI algorithms can identify patterns and predict a patient's likely response to various treatments. Additionally, AI contributes to personalized treatment by conducting image analysis, where algorithms examine medical images such as CT or MRI scans to identify specific features indicative of particular conditions. This aids healthcare providers in earlier and more accurate diagnoses, ultimately leading to more effective treatment outcomes.[12]

In the realm of medical science known as radiology, which involves using radiation to produce medical images like X-rays, CT scans, ultrasound, and MRI images for detecting deformities and tumors, AI algorithms play a crucial role. They can automatically identify intricate anomalous patterns in image data, offering supportive diagnoses for patients. According to the American Department of Radiology, the adoption of AI in radiology experienced a gradual increase from zero to 30% between 2015 and 2020, indicating a slow but consistent growth.[13]

AI Techniques and Their Advanced Tumor Identification

nnU-Net for Brain Tumor Segmentation

Brain tumor segmentation, a challenging task in medical imaging, is vital for accurate diagnosis and treatment planning. Recent advances in the BraTS challenge show a trend favoring deep neural networks, particularly encoder-decoder architectures with skip connections. Architectural improvements like residual connections and attention mechanisms enhance performance. Training schemes address challenges such as class imbalance using specialized loss functions like Dice loss and focal loss. Optimizing regions of interest, considering the partially overlapping whole tumor, tumor core, and enhancing tumor, improves segmentation. Methods specialized for brain tumor segmentation led to the development of nnU-Net, a general-purpose segmentation method. nnU-Net, with automated pipeline configuration, outperforms on 23 tested datasets, making it effective for diverse biomedical imaging. Investigating nnU-Net's suitability for brain tumor segmentation, it serves as both a baseline algorithm and a versatile framework for model development, showcasing its prowess in biomedical image segmentation.[14]

RAAGR2-Net: A Brain Tumor Segmentation Network Using Parallel Processing of Multiple Spatial Frames

RAAGR2-Net is a novel brain tumor segmentation network utilizing parallel processing of multiple spatial frames in MRI. Employing four modalities—T1, T1c, T2, and FLAIR—offers unique tumor characteristics. While contemporary techniques excel regionally, simultaneous evaluation across all MRI regions remains a challenge. The proposed encoder-decoder architecture, RAAGR2-Net, addresses this by incorporating N4 bias field correction, z-score normalization, and 0 to 1 resampling in data pre-processing. It introduces a Residual Spatial Pyramid Pooling (RASPP) module, leveraging dilated convolution for location information retention. An Attention Gate (AG) module efficiently emphasizes and restores segmented outputs. RAAGR2-Net demonstrates efficacy on BraTS benchmarks, providing accurate brain tumor segmentation while overcoming the drawbacks of current techniques.[15]

Brain Tumor Segmentation with Deep Convolutional Symmetric Neural Network

Gliomas, prevalent primary brain tumors with high mortality, are commonly treated with surgery, and MRI is crucial for assessing and monitoring treatment success. Accurate segmentation from MRI is vital for clinical diagnostics, but the sheer volume of data necessitates efficient automatic segmentation. Despite numerous Deep Convolutional Neural Network (DCNN)-based methods enhancing image feature extraction, they often overlook prior medical knowledge, particularly the left-right asymmetry common in brain tumors. To address this, we propose the Deep Convolutional Symmetric Neural Network (DCSNN), extending DCNNs with symmetric masks in various layers. Validated on the BRATS 2015 database, our method achieves a competitive Dice Similarity Coefficient (DSC) of 0.852, with segmentation taking only 10.8 seconds per case. While not the top performer in the BRATS 2015 challenge, our method outperforms recent DCNN-based approaches, uniquely combining symmetry prior knowledge into brain tumor segmentation. In summary, our novel DCSNN introduces

symmetry considerations to enhance brain tumor segmentation using deep convolutional neural networks.[16]

Investigating Brain Tumor Segmentation and Detection Techniques

Early detection of brain tumors is crucial for effective treatment planning. Digital image processing plays a pivotal role in medical image analysis, particularly in segmenting abnormal brain tissues from normal ones. Past research has proposed semi and fully automatic methods for brain tumor detection and segmentation, with this article focusing on consolidating various segmentation techniques explored by researchers. The simplicity and degree of human supervision determine the clinical acceptance of a segmentation technique. Brain tumors, characterized by uncontrollable cell growth, pose a common and devastating problem. Manual detection by radiologists is prone to inaccuracies, necessitating automation for accurate identification. Image processing is vital for brain tumor segmentation, separating normal and abnormal tissues. This review emphasizes future developments in medical image processing, specifically timely brain tumor detection for proper diagnosis. Existing techniques lack precision in distinguishing normal and abnormal segmented regions, prompting the ongoing pursuit of advanced automated methods for improved outcomes compared to current approaches.[17]

Bu-Net: Brain Tumor Segmentation Using Modified U-Net Architecture

Semantic segmentation of brain tumors is crucial for effective treatment, prompting recent research efforts to enhance neural network-based architectures. Addressing the challenging nature of brain tumor segmentation, this paper introduces BU-Net, a 2D image segmentation method modifying the U-Net architecture with Residual Extended Skip (RES) and Wide Context (WC) blocks. These additions aim to diversify features, expanding the valid receptive field for improved segmentation performance. BU-Net's evaluation on BraTS2017 Challenge datasets for tumor core, whole tumor, and enhancing core segmentation demonstrated superiority over existing techniques, showcasing its potential contribution to bioinformatics and medical research.[18] Brain tumor segmentation poses challenges in MRI images, driving the need for AI models. BU-Net, a proposed model, introduces novel encoder-decoder architecture modifications—RES and WC blocks—focusing on contextual features. The increased valid receptive field through RES improves overall performance. BU-Net outperforms baseline U-Net and other segmentation models on BraTS datasets, contributing to precise brain lesion segmentation. Acknowledging the 2D U-Net's limitations in information loss compared to 3D U-Net, future exploration aims to leverage 3D-based networks for enhanced segmentation performance.[18]

BrainSeg-Net: Brain Tumor MR Image Segmentation via Enhanced Encoder-Decoder Network

Efficiently segmenting MR brain tumor images is crucial for accurate diagnosis, driving recent advancements in neural network applications for improved sub-region segmentation. The complexity arises from small-scale tumor regions, challenging even advanced neural networks due to their size and varied area occupancy. The proposed BrainSeg-Net tackles this issue by incorporating the Feature Enhancer (FE) block, extracting and sharing middle-level features to enhance performance. Additionally, a custom-designed loss function addresses class imbalance. Evaluation on BraTS datasets reveals significant improvements in segmentation for Enhancing Core (EC), Whole Tumor (WT), and Tumor Core (TC) compared to existing techniques.[19] MR brain tumor image segmentation remains complex, with neural network models proposed for semantic segmentation showing room for improvement. BrainSeg-Net addresses the challenge of small-scale tumor segmentation by integrating the FE block, preserving vital location and spatial information. This approach enhances the effective receptive field, contributing to improved accuracy. Evaluations on benchmark databases demonstrate BrainSeg-Net's superior performance compared to existing state-of-the-art techniques and baseline U-Net architecture. Plans involve refining this model further and exploring 3D-based architectures for enhanced segmentation performance, aiming to positively impact human lives.[19]

BrainSeg-Net: Brain Tumor MR Image Segmentation via Enhanced Encoder-Decoder Network

Addressing the challenge of diverse brain images, this study proposes an automatic brain tumor segmentation framework. Utilizing various MRI sequences enhances segmentation accuracy, particularly in areas with fuzzy borders. The framework optimizes a Convolutional Neural Network (CNN) through an Improved Chimp Optimization Algorithm (IChOA) for precise segmentation. The CNN's weight and bias values are fine-tuned, and feature selection is carried out using a Support Vector Machine (SVM) classifier.[19] The novel framework builds upon an enhanced CNN model, emphasizing hyperparameter optimization. A significant contribution lies in eliminating uninformative image parts through pre-processing, promoting data balance, and mitigating overfitting. Post-pre-processing, 17 features are extracted from the remaining objects, enhancing the depth of the segmentation process.[19]

Brain Tumor Segmentation Based on Optimized Convolutional Neural Network and Improved Chimp Optimization Algorithm

In the pursuit of reliable brain tumor segmentation, this study leverages Magnetic Resonance Imaging (MRI) sequences (T1, Flair, T1ce, T2, etc.) for diverse tumor identification. Proposing an automatic segmentation framework, it optimizes a Convolutional Neural Network (CNN) using an Improved Chimp Optimization Algorithm (IChOA). IChOA adjusts CNN weights and biases, normalizes input images, and employs Support Vector Machine (SVM) for feature selection. The enhanced CNN classifies objects, achieving precise brain tumor segmentation. Notably, the framework contributes by removing uninformative image parts through pre-processing, fostering data balance, and mitigating overfitting.[20]

A Novel Framework for Brain Tumor Segmentation Using Neuro Trypetidae Fruit Fly-Based U-Net

The study addresses challenges in medical image processing, particularly in brain images, aiming to improve disease forecasting precision in complex MRI scans. Introducing the innovative Trypetidae fruit fly-based U-Net (TFFbU) system with enhanced fruit fly fitness, the model achieves optimal outcomes. Trained on standard datasets, TFFbU eliminates training errors and accurately detects and segments tumors. Evaluated in MATLAB, TFFbU showcases robustness and effectiveness through metrics like accuracy, recall, precision, Dice, and Jaccard. In brain tumor segmentation, the FFbU model enhances fruit fly fitness, resulting in impressive metrics, including 98.5% Jaccard, 99.1% Dice, 99.8% accuracy, and 99.8% specificity, with a rapid 12-second segmentation process. Compared to other models, FFbU exhibits increased accuracy and reduced execution time, hinting at the potential for superior results with the integration of a hybrid deep learning mechanism and a heuristic mechanism, including a segmentation error detection mechanism.[21]

Malignant Tumor

A malignant tumor is cancerous. These tumors arise from uncontrollably growing cells (Fig. 1). If the disease's cells keep multiplying and spreading, it may become fatal. Malignant tumors have the ability to metastasize, or spread rapidly to other areas of the body. However, not all cancerous tumors grow quickly; some can grow considerably more slowly over time. The cancer cells that spread to other organs are indistinguishable from the original cells, but they are metastasizing. For example, cancer cells from lung cancer that metastasize to the liver are still lung cancer cells.[22,23]

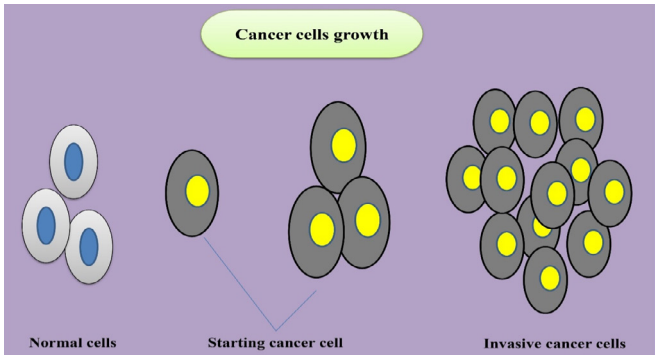

Figure 1. Cancer cells growth.

Different cell types give rise to different kinds of malignant tumors. Examples include:

Carcinoma

Tumors originating from epithelial cells, which are located in the skin and the lining of organs, can manifest in various organs such as the stomach, prostate, pancreas, lung, liver, colon, and breast. These carcinomas, a common type of cancer, primarily arise from renal pelvis epithelial cells, maintaining a urothelial appearance. Although they usually present as solid sheets invading the pelvis, peripelvic tissue, and kidney parenchyma, occasional squamous differentiation may occur. Carcinoma cells typically exhibit pleomorphic to anaplastic characteristics, with numerous mitoses and the presence of necrotic and hemorrhagic areas in larger carcinomas. Some carcinomas may display predominantly spindle-shaped tumor cells, resembling poorly differentiated sarcoma. Distinguishing invasive urothelial carcinomas from tubule carcinomas is crucial.[24–28]

Sarcoma

Sarcoma, a form of cancer, impacts the body's connective tissues, including bones, muscles, cartilage, blood vessels, and tendons. The two primary types are soft tissue sarcoma, prevalent in muscles or blood vessels, and bone sarcoma, which forms in bones (Fig. 2). Symptoms, such as pain and lumps, may vary depending on the type. Soft tissue sarcomas affect tissues supporting or surrounding the body's systems, while bone sarcoma, also known as osteosarcoma, specifically originates in the bone. These sarcomas can emerge in various tissues like fat, muscle, blood vessels, skin, cartilage, tendons, and ligaments.[29,30]

Rare in adults, sarcoma constitutes approximately 1% of adult cancers, according to the American Society of Clinical Oncology (ASCO). It is more prevalent in children, accounting for about 15% of childhood cancers. Sarcomas develop

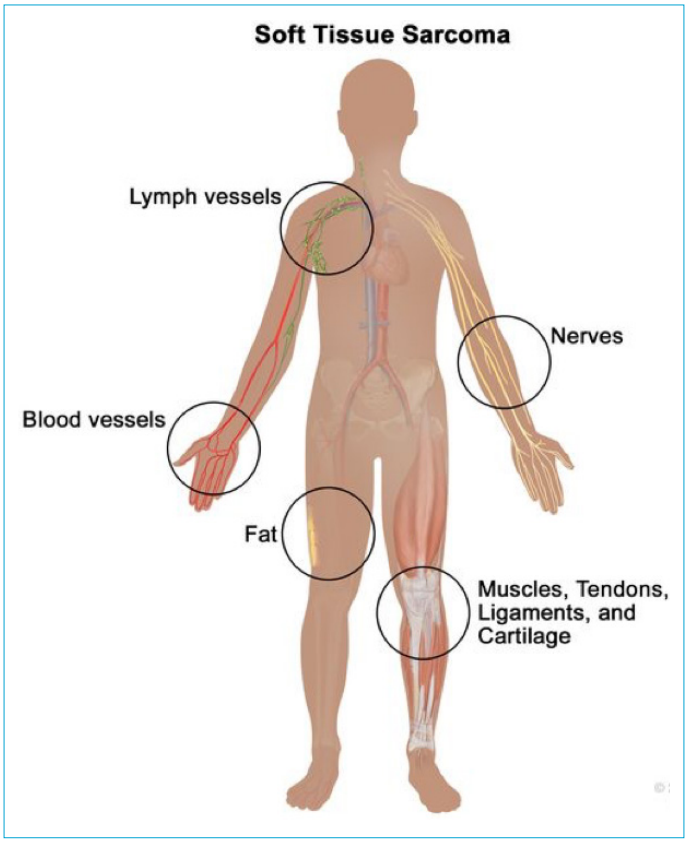

Figure 2. Soft tissue sarcoma develops in the body's soft tissues, encompassing muscles, tendons, ligaments, cartilage, fat, blood vessels, lymph vessels, nerves, and the tissues surrounding joints.[30]

in connective tissues like nerves, cartilage, bones, and fat, arising from cells outside the bone marrow and generally exhibiting malignancy.[31,32]

Germ Cell Tumor

Advancements in neuroimaging have significantly enhanced the precision of Germ Cell Tumor (GCT) diagnosis. When clinical and radiographic studies indicate the likelihood of GCT, immediate serum tumor marker assessment is recommended. If safely feasible, a lumbar puncture for cerebrospinal fluid (CSF) sampling, including tumor markers and cytology, should be performed. In cases of obstructive hydrocephalus, an endoscopic third ventriculostomy (ETV) is advocated for ventricular exploration, simultaneous tumor biopsy, and CSF marker collection. Shunting is considered only if ETV fails, with cautious strategies like externalized shunt placement until completion of chemotherapy cycles. Biopsy becomes crucial for differentiating pure germinomas, which may not express significant β-human chorionic gonadotropin levels, from other tumor types. Treatment decisions based on serum/CSF markers and clinical and radiographic findings, in the absence of histological confirmation, are increasingly accepted. The authors raise the prospect of future tissue requirements for genetic expression profiling but stress its current role for research purposes only. The debate over cytoreductive surgery in pure germinoma patients emphasizes the need for caution, as current data supports chemotherapy or radiation therapy as primary treatments. The authors are commended for navigating the complex medical literature to shed light on the understanding and treatment of these challenging tumors.[33–35]

Blastoma

Blastomas primarily affect children during fetal development or growth. These cancers arise from precursor cells, undifferentiated cells capable of becoming any body cell type, making them more prevalent in children with higher precursor cell counts. Blastomas, such as hepatoblastoma, medulloblastoma, nephroblastoma, neuroblastoma, and pleuropulmonary blastoma, originate in various tissues. While hepatoblastoma commonly manifests in the liver, neuroblastoma typically begins in nerve tissue near the abdomen.

The causes of blastoma are believed to be genetic rather than environmental. Specific genetic features may predispose individuals to certain blastomas, such as hepatoblastoma in children with Aicardi syndrome. Symptoms vary depending on the type but may include abdominal swelling, pain, weight loss, and more. Treatment approaches, similar to those for adult cancers, depend on tumor size, with surgical removal offering a cure for small tumors.

Wilms tumor or nephroblastoma, affecting the kidneys, generally appears as a single tumor, with a high survival rate in children. Medulloblastoma, a malignant brain tumor, primarily forms in the cerebellum, and while treatments are effective, long-term side effects may occur. Neuroblastoma, originating in nerve tissue, is the most common cancer in infants under 1 year. Pleuropulmonary blastoma, found in the chest, particularly the lungs, is rare and typically occurs in children under 5 years.

Other less common blastomas include chondroblastoma, gonadoblastoma, hemangioblastoma, lipoblastoma, medullomyoblastoma, osteoblastoma, pancreatoblastoma, pineoblastoma, retinoblastoma, and sialoblastoma. Gliomas, affecting the brain, include glioblastomas in adults. Diagnosis involves various tests such as blood tests, biopsies, scans, and radioisotope scans tailored to the individual's age, symptoms, and suspected blastoma type.[36,37]

Meningiomas

Meningiomas are primary central nervous system (CNS) tumors originating in the brain or spinal cord and are the most

prevalent type among primary brain tumors. These tumors are categorized into three grades based on various factors, including tumor characteristics, location, and genetic findings. Grade 1 meningiomas are low grade, exhibiting slow growth, while Grade 2 atypical meningiomas are mid-grade with a higher likelihood of recurrence. Grade 3 anaplastic meningiomas are malignant and fast-growing.[38]

Diagnosis involves the removal of tumor tissue for neuropathological review. Molecular testing aids in identifying subtypes associated with location and disease characteristics. On MRI, Grade 2 and 3 meningiomas typically appear as enhancing masses on the brain's outer lining, which may or may not brighten with contrast, and can potentially invade brain tissue.

The causes of atypical and anaplastic meningiomas are not precisely known, but genetic changes are implicated in cancer development. Exposure to radiation, particularly in childhood, is a recognized risk factor, and individuals with neurofibromatosis type 2 have an elevated risk. Meningiomas form along the dura mater, the outermost layer covering the brain and spinal cord, arising from meningeal cells and commonly occurring along the brain's surface.[39]

These meningiomas can spread through cerebrospinal fluid, with Grade 2 meningiomas potentially invading surrounding tissue, including nearby bone, while Grade 3 meningiomas, characterized by irregular cells, may invade the brain or spread to other organs. Symptoms vary depending on tumor location and may include vision changes, loss of hearing or smell, confusion, seizures, and morning headaches. Overall, meningioma diagnosis and treatment involve a comprehensive understanding of the tumor's grade, subtype, and associated symptoms for effective management.[40]

The TNM Staging System for Tumors

The cancer staging system known as TNM (tumor-node-metastasis) was formulated by Pierre Denoix from 1943 to 1952. Widely embraced globally, this classification system is recognized as the primary method for assessing cancer risk and has become the universally acknowledged standard for staging in all types of solid tumors.[41]

The most popular cancer staging system is the TNM system. The TNM system is the primary method used by the majority of hospitals and medical facilities to report cancer cases. Unless your type of cancer has a different staging system, you will probably find a description of your cancer using this staging system in your pathology report. Blood cancers and tumors in the brain and spinal cord are two examples of cancers with various staging systems.[42–44]

Within the TNM framework, the size and scope of the primary tumor are indicated by the T. Typically, the primary tumor refers to the main tumor (Fig. 3).

The number of cancerous lymph nodes in the vicinity is indicated by the N.

Whether or not cancer has spread is indicated by the M. This indicates that the cancer has progressed to other body parts from the original tumor. There will be numbers following each letter in the TNM system description of your cancer that provide additional information about it, such as T1N0MX or T3N1M0. The meaning of the letters and numbers is explained below.

Primary Tumor (T)

- **TX:** It is impossible to measure the main tumor.
- **T0:** No main tumor is detected.

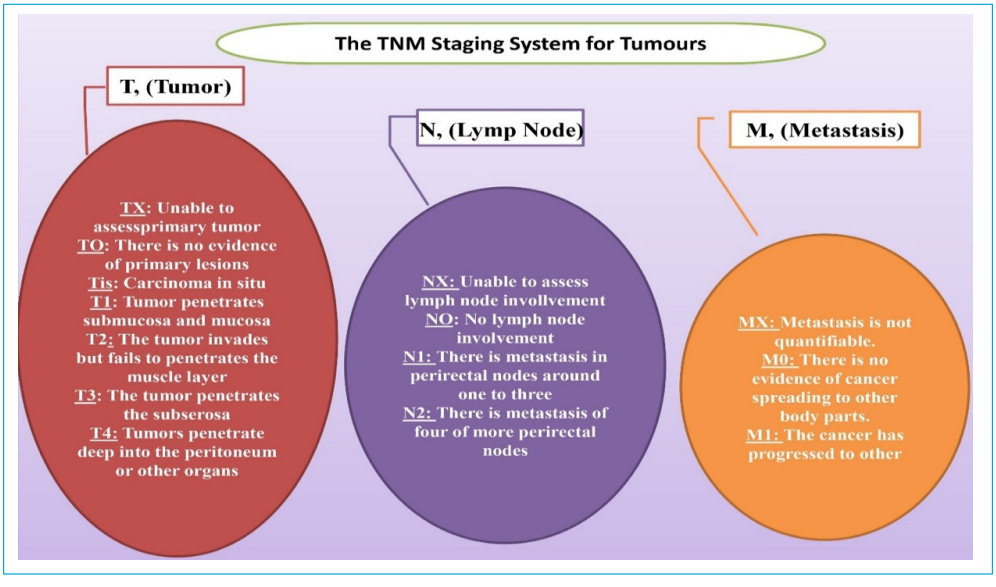

Figure 3. The TNM staging system for tumors.

- **T1, T2, T3, T4:** Relates to the primary tumor's dimensions and/or scope. The tumor's size or the extent to which it has spread into neighboring tissues is indicated by the number following the T. To give more information, T can be further divided into T3a and T3b.[45,46]

Localized Lymph Nodes (N)

- **NX:** Cancer in adjacent lymph nodes is too small to quantify.
- **N0:** There is no cancer in the surrounding lymph nodes.
- **N1, N2, N3:** Describes the quantity and distribution of cancerous lymph nodes. The higher the number after the N, the more lymph nodes are affected by cancer.[47,48]

Distant Metastasis (M)

- **MX:** Metastasis is not quantifiable.
- **M0:** There is no evidence of cancer spreading to other parts of the body.
- **M1:** The cancer has progressed to other parts of the body.

Other Ways to Describe Stage: The TNM system provides a detailed description of cancer. However, TNM combinations are categorized into five less specific stages for many cancers.

Current Stages:

- **Stage 0:** There are abnormal cells, but they haven't permeated the surrounding tissue. Also known as CIS, or carcinoma in situ. Though it may develop into cancer, CIS is not cancer.[49,50]
- **Stage I, Stage II, and Stage III** (may also be written as Stage 1, Stage 2, and Stage 3): There is cancer. The larger the cancer tumor and the more it has invaded neighboring tissues, the higher the number.[51–53]
- **Stage IV** (may also be written as Stage 4): The cancer has progressed to distant regions of the body. The cancer is more advanced the higher the number. After the first number, letters and numbers are frequently used to provide more details about the cancer. For example, there are three subtypes of Stage 2 prostate cancer: 2A, 2B, and 2C.[50,51]

A different staging system classifies cancer into five primary categories and is applied to all forms of the disease. Cancer registries use this staging system more frequently than physicians do. However, you might still hear one of the following descriptions of your cancer from your physician or nurse.[54,55]

- **In situ:** Although abnormal cells exist, they have not spread to adjacent tissue.
- **Localized:** There is no indication that cancer has spread beyond its initial site.
- **Regional:** Cancer has spread to nearby lymph nodes, tissues, or organs.
- **Distant:** Cancer has spread to distant regions of the body.
- **Unknown:** Insufficient data exists to determine the stage.

Artificial Intelligence Methods in Medical Imaging

The surge in powerful machine learning and the increasing availability of clinical data has elevated artificial intelligence (AI) in medicine. Algorithms now play a vital role in clinical care, enhancing image reconstruction, cancer detection, and individual risk prediction for treatment decisions. Entry into clinical care depends on technological feasibility, workflow integration, and immediate benefits. Research is advancing the integration of imaging data with genomics, linking large-scale observations with biological understanding. AI's impact on imaging and precision medicine stems from collaborative new technology development. Deep learning, a potent form of AI, is being investigated in various applications within medical imaging. Despite its promises, users must be cautious about potential biases and pitfalls. Grand challenges focus on advancing AI applications, emphasizing benchmark test sets and open-science principles. The goal is to transition AI from competition to research benefits for improved patient care.[56,57]

Machine Learning Algorithms Based on Predefined Engineered Features

Traditional artificial intelligence (AI) approaches involve machine learning algorithms anchored in predefined engineered features. These methods heavily depend on algorithms with explicit parameters derived from expert knowledge. The engineered features are meticulously designed to measure specific radiographic traits, including the three-dimensional tumor shape, intratumoral texture, and pixel intensity distribution (histogram). Following a selection process, only the most relevant features are utilized. Statistical machine learning models, such as support vector machines and random forests, are subsequently employed to identify potential biomarkers extracted from imaging data.[58] Correlation between deep learning algorithms, machine learning algorithms, and artificial intelligence is represented in Figure 4.

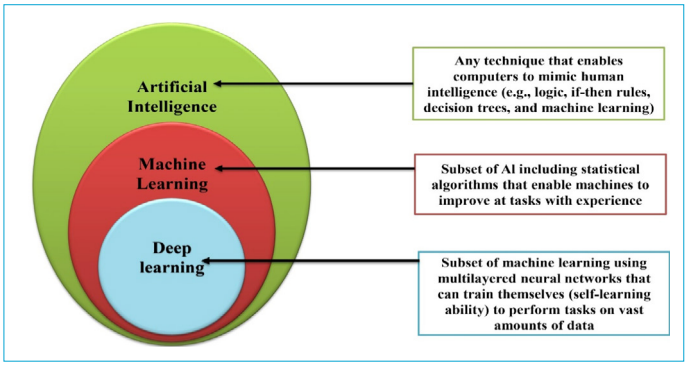

Figure 4. Artificial intelligence and its sub-divisions.[64]

Deep Learning Algorithms

Recent progress in AI research has led to the emergence of novel non-deterministic deep learning algorithms. The fundamental techniques of deep learning have been present for many years, but only recently has there been an adequate supply of data and computational power. These algorithms, devoid of explicit feature predefinition or selection, acquire knowledge directly by traversing the data space, endowing them with enhanced problem-solving capabilities. While diverse deep learning architectures have been investigated for various tasks, convolutional neural networks (CNNs) currently stand out as the most prevalent typologies in medical imaging (Figs. 4, 5).[59–63]

Clinical Application Areas of Artificial Intelligence

Radiology-Based Diagnostics Cover Various Areas

Thoracic Imaging: Lung cancer, a prevalent and life-threatening tumor, benefits from screening for pulmonary nodules, where early detection can be life-saving. Artificial intelligence (AI) plays a role in automatically identifying and classifying these nodules as benign or malignant.[4]

Abdominal and Pelvic Imaging: The expanding use of medical imaging, particularly computed tomography (CT) and magnetic resonance imaging (MRI), leads to more incidental findings like liver lesions. AI proves valuable in characterizing these lesions, distinguishing between benign and malignant cases, and prioritizing follow-up evaluations.[4,66]

Colonoscopy: Detection and classification of colonic polyps are crucial for preventing colorectal cancer. AI-based tools contribute to early detection and consistent monitoring, recognizing the potential risk even when polyps are initially benign.[67]

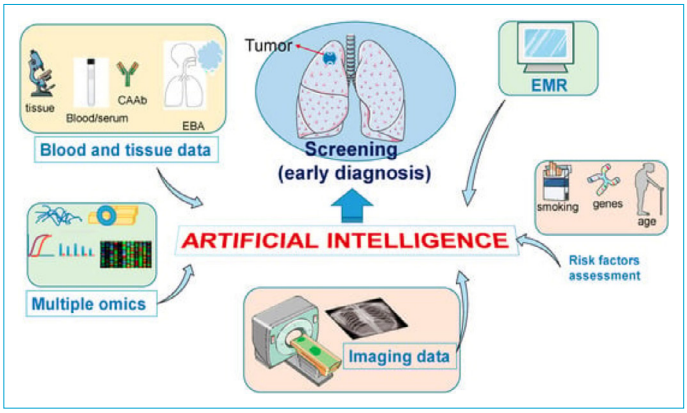

Figure 5. The utility of AI tools interpreting medical images has been demonstrated in several settings and in several diseases, including lung cancer.[65]

Mammography: Screening mammography, challenging for expert interpretation, benefits from AI assistance in identifying and characterizing microcalcifications, aiding in accurate analysis.[4]

Brain Imaging: AI's diagnostic predictions find application in brain imaging, where abnormal tissue growth may indicate benign or malignant tumors, primary or metastatic.[68]

Radiation Oncology: AI automation in radiation treatment planning involves tumor segmentation for dose optimization. Additionally, AI assesses treatment response over time, enhancing the accuracy and speed of evaluating the success of radiation therapy.[4,69,70] In the below-mentioned table, the performance metrics of AI models are discussed (Table 1).

Non-Radiology-Based Applications Encompass

AI's Efficacy in Dermatology: Skin cancer diagnosis traditionally relies on visually inspecting suspicious areas by trained dermatologists. Given the diverse sizes, shades, and textures of skin lesions, interpretation is challenging. Deep learning algorithms, with their substantial learning capacity, excel in handling this variability and detecting characteristics that extend beyond human consideration.[70]

In dermatopathology, AI, particularly machine learning, is integral for automated analysis. Machine learning encompasses algorithms and instructions that enable computers to learn and execute tasks autonomously. These methods, whether supervised or unsupervised, depend on available data for learning. Reinforcement learning enhances data analysis by allowing the system to learn from both the environment and input data. Neural networks, especially deep learning and convolutional neural networks (CNN), are widely used. Deep learning employs multilayered neural networks for increased sensitivity and specificity. CNN, specifically effective in dermatopathological image analysis, disintegrates images into pixels and utilizes layers like convolutional, pooling, and fully connected for extraction, classification, and accurate output. A subtype, region-based CNN, excels in identifying specific objects within images, such as lesion locations.[72]

AI's Efficacy in Pathology: Accurate cancer diagnosis from biopsy samples requires quantifying digital whole-slide images, a task complicated by variations in imaging hardware, slide preparation, magnification, and staining techniques. Traditional AI methods often demand extensive tuning to address these challenges, whereas more robust AI excels in mitosis detection, histologic primitive segmentation (nuclei, tubules, and epithelium), event counting, and tissue characterization and classification.[73–75]

Table 1. Performance metrics of AI models and radiologists[71]

	Accuracy	Sensitivity	Specificity	AUC	Positive predictive rate	Negative predictive rate	F1 score
AI models							
Radiomics	0.61	0.32	0.76	0.66	0.4	0.68	0.35
Deep learning (DL)	0.73	0.21	1	0.89	1	0.71	0.35
Clinical	0.73	0.53	0.84	0.82	0.63	0.78	0.57
Radiomics+DL	0.71	0.37	0.89	0.82	0.64	0.73	0.47
Radiomics+DL +clinical	0.82	0.68	0.89	0.83	0.77	0.85	0.72
Radiologists without AI assistance							
Radiologist 1	0.63	0.58	0.65	0.61	0.46	0.75	0.51
Radiologist 2	0.64	0.58	0.68	0.63	0.48	0.76	0.52
Radiologist 3	0.7	0.84	0.62	0.73	0.53	0.88	0.65
		Krippendorff's alpha	0.4757				
Radiologist 4	0.86	0.68	0.95	0.82	0.87	0.85	0.77
Radiologist 5	0.79	0.95	0.7	0.83	0.62	0.96	0.75
		Krippendorff's alpha	0.4806				
Radiologists with AI assistance							
Radiologist 1	0.77	0.74	0.78	0.76	0.64	0.85	0.68
Radiologist 2	0.8	0.89	0.76	0.83	0.65	0.93	0.76
Radiologist 3	0.86	0.84	0.86	0.85	0.76	0.91	0.8
		Krippendorff's alpha	0.6333				
Radiologist 4	0.88	0.79	0.92	0.85	0.83	0.89	0.81
Radiologist 5	0.82	0.84	0.81	0.83	0.7	0.91	0.76
		Krippendorff's alpha	0.7331				

In recent years, there has been significant growth in novel AI applications in pathology, presenting opportunities to enhance diagnostic processes, minimize errors, improve reproducibility, and offer prognostic insights. Despite this progress, the integration of AI tools into clinical practice faces challenges related to interpretability, validation, regulation, generalizability, and cost. To address these issues, a careful approach involving standardized usage recommendations and alignment with existing information systems is essential. As the demand for personalized cancer care rises, AI applications could be effectively implemented alongside human pathologists in a multimodal approach that incorporates proteomics, genomics, and AI-based multiplexed biomarker quantifications. This comprehensive strategy aims to tailor tumor precision therapy for individual patients. By supporting the reporting system, expediting reporting time, and objectively assessing morpho-biological features, AI technology can contribute to more efficient pathology practices. Additionally, AI-aided reporting allows pathologists to concentrate on complex cases, meeting the escalating workload demands.[76]

Harnessing Sequencing Technologies for Comprehensive Genomic Insights: The increasing abundance of sequencing data in DNA and RNA presents opportunities for advancing cancer diagnosis and care. AI-driven tools proficiently identify and extract crucial features, establishing associations between somatic point mutations and various cancer types.[77] These tools also anticipate the repercussions of mutations on the sequence specificities of RNA-binding and DNA-binding proteins.[78] Applying Cancer RNA-Seq for Transcriptome Analysis proves invaluable in unraveling gene expression changes within tumors. Whether applied to coding regions or the entire cancer transcriptome, this sequencing method enables the detection of strand-specific information, a pivotal aspect of gene regulation. The inclusive nature of cancer transcriptome sequencing, encompassing both coding and noncoding RNA, provides strand orientation, offering a holistic understanding of expression Dynamics (Table 2).[79–83]

Conclusion

In conclusion, the early detection of tumors through artificial intelligence (AI) enhances treatment prospects. AI, particularly the subfield of deep learning (DL), has significantly impacted cancer management by automating feature extraction and analyzing extensive medical data. Despite AI's rapid progress, its application in addressing malignant tumors faces challenges and uncertainties, with uneven distribution across cancer types and insufficient attention to

Table 2. Artificial intelligence applied in different types of cancer treatment by global scientists

Authors	Type of Cancer	No of Patients in Study	Country/ Region	Study Population	Methods	Results	References
Kuo et al.	Prostate Cancer	100	Taiwan	Hospital	Fuzzy Neural Network	Improved Interpretability and Forecasting	[84]
Delen et al.	Breast Cancer	433272	USA	SEER	ANN and DT	Accuracy: DT (93.6%), ANN	[85]
Lu, et al.	Breast Cancer	82707	USA	SEER	Dynamic Gradient Boosting Machine with GA	Accuracy Improved (28%)	[86]
Vasudevan et al.	Glioblastoma	215	India	TCGA	Neural Network	Accuracy: DT (89.2%)	[87]
Tian et al.	Bladder Cancer	115	China	Hospital	Statistical Analysis	NEDD8: Poor Prognosis Found	[88]
Hasnain et al.	Bladder Cancer	3503	USA	Hospital	KNN, RF, etc	Sensitivity& Specificity (>70%)	[89]
Qian et al.	Nasopharyngeal Carcinoma	3269	China	Hospital	Large Scale, Big Data Intelligence Platform	m EBV DNA: a Robust Biomarker for NPC Prognosis	[90]
Biglarian et al.	Gastric Cancer	436	Iran	Hospital	Cox Proportional Hazard, ANN	TP (83.1%)	[91]
Zhu et al.	Gastric Cancer	289	China	Hospital	ANN	TP: ANN (85.3%)	[92]
Bottaci et al.	Colorectal Cancer	334	UK	Hospital	Six Neural Networks	Accuracy (>80%), mean Sensitivity (60%), mean Specificity (88%)	[93]
Bychkov et al.	Colorectal Cancer	641	Finland	Hospital	LSTM, Naïve Bayes, SVM	Hazard Ratio (2.3); CI (95%,1.79–3.03), AUC (0.69)	[94]
Chang et al.	Oral Cancer	156	Malaysia	MOCDTB	Hybrid model of ReliefF-GA-ANFIS	Accuracy (93.81%), AUC (0.9)	[95]
Lynch et al.	Lung Cancer	10442	USA	SEER	GBM, SVM	RMSE (32,15.05) for GBM, SVM	[96]
Sepehri et al.	Lung Cancer	101	France	Hospital	SVM with RFE and RF	Accuracy (71%, 59%)	[97]
Lu et al.	Ovarian Cancer	364	UK	Hospital	Unsupervised Hierarchical Clustering	RPV: A Novel Prognostic Signature Discovered	[98]
Acharya et al.	Ovarian Cancer	469	Singapore & Malaysia	TCGA	Improved SVM	Accuracy (81.8%), ROC(0.922)	[99]

malignancies. Challenges persist in various fields, including medicine, such as a lack of standardization, technological immaturity, high costs, ethical controversies, and inadequate supervision.

It is crucial to recognize that while AI cannot be a universal solution for all tumors or replace human intelligence entirely, its gradual application in the diagnosis, treatment, and prognosis assessment of malignant tumors is yielding notable improvements. The expectation is for an increasing number of AI-involved tasks in the medical field, contributing to enhanced generalization, accuracy, and stability for the benefit of humanity.

Future Perspectives

The future of AI in diagnosing malignant tumors holds promise for heightened accuracy in early detection, leveraging the historical evolution of medical imaging from X-rays to advanced techniques like CT, MRI, and PET. Recent improvements in imaging hardware enable nuanced tissue distinctions, challenging for traditional AI and the human eye. Open-source deep learning platforms facilitate extensive experimentation with raw acquisition data, addressing challenges of signal-noise differentiation. Overcoming obstacles, AI integration into healthcare is imminent, particularly in oncology, enhancing knowledge of tumors and refining therapy decisions. Smartphone applications with risk assessment tools promise immediate cancer risk estimates, encouraging timely intervention and healthier behaviors. Algorithms aiding physicians in referrals optimize resource allocation in primary care, while the integration of ChatGPT transforms colorectal surgery by providing personalized information and predicting outcomes in neuro-oncology. As technology advances, AI and ML secure the future of medical sciences, notably in cancer diagnosis and treatment, offering faster guidance maps and boosting confidence in refining traditional methods.

Disclosures

Acknowledgments: We received a lot of help from several people to complete this review. I would want to thank everyone who helped with this review. I extend my gratitude to Glocal University Pharmacy College Saharanpur, School of Pharmacy Graphic Era Hill University, Dehradun, and Chandigarh College of Pharmacy, Landran, Mohali, Punjab who provided us with the required facilities.

Ethics Committee Approval: Not applicable.

Funding Source: No funding was received for this project.

Conflict of Interest: The authors declare no competing interests

Data Availability: All authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials.

Authorship Contributions: Concept – S.A., Z.K.; Design – M.A., Z.K.; Supervision – S.A., S.T.; Materials – M.K., M.A.; Data collection &/or processing – M.K., Z.K.; Analysis and/or interpretation – A.K., S.A.; Literature search – Z.K., M.K.; Writing – S.T., A.K.; Critical review – A.K., S.A.

References

1. Hunter B, Hindocha S, Lee RW. The role of artificial intelligence in early cancer diagnosis. Cancers (Basel) 2022;14:1524.
2. Chen ZH, Lin L, Wu CF, Li CF, Xu RH, Sun Y. Artificial intelligence for assisting cancer diagnosis and treatment in the era of precision medicine. Cancer Commun (Lond) 2021;41:1100–15.
3. Koh DM, Papanikolaou N, Bick U, Illing R, Kahn CE Jr, Kalpathi-Cramer J, et al. Artificial intelligence and machine learning in cancer imaging. Commun Med (Lond).2022;2:133.
4. Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJWL. Artificial intelligence in radiology. Nat Rev Cancer 2018;18:500–10.
5. Castellino RA. Computer aided detection (CAD): An overview. Cancer Imaging 2005;5:17–9.
6. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature 2017;542:115–8.
7. Ozkan E, Orhan K, Soydal C, Kahya Y, Seckin Tunc S, Celik O, et al. Combined clinical and specific positron emission tomography/computed tomography-based radiomic features and machine-learning model in prediction of thymoma risk groups. Nucl Med Commun 2022;43:529–39.
8. Dai H, Huang Y, Xiao G, Lan B, Jiang G, Tian J. Predictive features of thymic carcinoma and high-risk thymomas using random forest analysis. J Comput Assist Tomogr 2020;44:857–64.
9. Lin CY, Yen YT, Huang LT, Chen TY, Liu YS, Tang SY, et al. An MRI-based clinical-perfusion model predicts pathological subtypes of prevascular mediastinal tumors. Diagnostics (Basel) 2022;12:889.
10. Pang J, Xiu W, Ma X. Application of artificial intelligence in the diagnosis, treatment, and prognostic evaluation of mediastinal malignant tumors. J Clin Med 2023;12:2818.
11. Wang D, Zhang Y, Li B, Zhuang Q, Zhang X, Lin D. Histological classification and invasion prediction of thymoma by machine learning-based computed tomography imaging. Contrast Media Mol Imaging 2022;2022:4594757.
12. Open Medscience. Revolutionising medical imaging with AI and Big Data analytics. Available at: https://openmedscience.com/revolutionising-medical-imaging-with-ai-and-big-data-analytics/#:~:text=AI%20algorithms%20can%20detect%20early,function%20and%20diagnose%20heart%20disease. Accessed Aug 16, 2024.
13. Sajid H. AI in radiology: Pros & cons, applications, and 4 examples. Available at: https://www.v7labs.com/blog/ai-in-radiology. Accessed Aug 16, 2024.
14. Isensee F, Jäger PF, Full PM, Vollmuth P, Maier-Hein KH. nnU-Net for brain tumor segmentation. In: Crimi A, Bakas S, editors. Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries. Cham: Springer; 2021. pp. 118–32.
15. Rehman MU, Ryu J, Nizami IF, Chong KT. RAAGR2-Net: A brain tumor segmentation network using parallel processing of multiple spatial frames. Comput Biol Med 2023;152:106426.
16. Chen H, Qin Z, Ding Y, Tian L, Qin Z. Brain tumor segmentation with deep convolutional symmetric neural network. Neurocomput 2020;392:305–13.
17. Lather M, Singh P. Investigating brain tumor segmentation and detection techniques. Proc Comput Sci 2020;167:121–30.
18. Rehman M, Cho S, Kim JH, Chong KT. BU-Net: Brain tumor segmentation using modified U-net architecture. Electronics 2020;9:2203.
19. Rehman MU, Cho S, Kim J, Chong KT. BrainSeg-Net: brain tumor mr image segmentation via enhanced encoder-decoder network. Diagnostics (Basel) 2021;11:169.
20. Ranjbarzadeh R, Zarbakhsh P, Caputo A, Tirkolaee EB, Bendechache M. Brain tumor segmentation based on optimized convolutional neural network and improved chimp optimization algorithm. Comput Biol Med 2024;168:107723.
21. Vinisha A, Boda R. A novel frameworkfor brain tumor segmentation using neuro trypetidae fruit fly-based U-net. Int J Intell Syst Appl Eng 2024;12:783–96.
22. Institute for Quality and Efficiency in Health Care. In brief: How do cancer cells grow and spread? Available at: https://www.ncbi.nlm.nih.gov/books/NBK279410/. Accessed Aug 16, 2024.
23. Cooper GM. The development and causes of cancer. Available at: https://www.ncbi.nlm.nih.gov/books/NBK9963/. Accessed Aug 16, 2024.
24. McDaniel B, Badri T, Steele RB. Basal cell carcinoma. Available at: https://www.ncbi.nlm.nih.gov/books/NBK482439/. Accessed Aug 16, 2024.
25. Cleveland Clinic. Carcinoma. Available at: https://my.clevelandclinic.org/health/diseases/23180-carcinoma. Accessed Aug 16, 2024.
26. Kuhn E, Morbini P, Cancellieri A, Damiani S, Cavazza A, Comin CE. Adenocarcinoma classification: Patterns and prognosis. Pathologica 2018;110:5–11.
27. Basset-Seguin N, Herms F. Update in the management of basal cell carcinoma. Acta Derm Venereol 2020;100:adv00140.
28. Britannica. Carcinoma. Available at: https://www.britannica.com/science/carcinoma. Accessed Aug 16, 2024.

29. Vodanovich DA, M Choong PF. Soft-tissue sarcomas. Indian J Orthop 2018;52:35–44.
30. National Cancer Institute. Soft tissue sarcoma treatment (PDQ®)–patient version. Available at: https://www.cancer.gov/types/soft-tissue-sarcoma/patient/adult-soft-tissue-treatment-pdq. Accessed Aug 16, 2024.
31. Islam MN, Chehal H, Smith MH, Islam S, Bhattacharyya I. Merkel cell carcinoma of the buccal mucosa and lower lip. Head Neck Pathol 2018;12:279–85.
32. Gilbert NF, Cannon CP, Lin PP, Lewis VO. Soft-tissue sarcoma. J Am Acad Orthop Surg 2009;17:40–7.
33. Faouzi S, Ouguellit S, Loriot Y. Stage 1 germ-cell tumour. Bull Cancer 2019;106:887–95. French.
34. Lakpour N, Saliminejad K, Ghods R, Reza Sadeghi M, Pilatz A, Khosravi F, et al. Potential biomarkers for testicular germ cell tumour: Risk assessment, diagnostic, prognostic and monitoring of recurrence. Andrologia 2021;53:e13998.
35. Batool A, Karimi N, Wu XN, Chen SR, Liu YX. Testicular germ cell tumor: A comprehensive review. Cell Mol Life Sci 2019;76:1713–27.
36. Aggarwal P, Sharma SK, Kapila K, Verma K, Agarwal J. Pulmonary blastoma. Indian J Chest Dis Allied Sci 1990;32:59–64.
37. Tsamis I, Chachali SP, Gomatou G, Trontzas I, Mitsogianni M, Syrigos N, et al. Pulmonary blastoma: A comprehensive overview of a rare entity. Adv Respir Med 2021;89:511–9.
38. Alruwaili AA, De Jesus O. Meningioma. Available at: https://www.ncbi.nlm.nih.gov/books/NBK560538/. Accessed Aug 16, 2024.
39. Louis DN, Perry A, Wesseling P, Brat DJ, Cree IA, Figarella-Branger D, et al. The 2021 WHO classification of tumors of the central nervous system: A summary. Neuro Oncol 2021;23:1231–51.
40. Buerki RA, Horbinski CM, Kruser T, Horowitz PM, James CD, Lukas RV. An overview of meningiomas. Future Oncol 2018;14:2161–77.
41. Bera K, Katz I, Madabhushi A. Reimagining T staging through artificial intelligence and machine learning image processing approaches in digital pathology. JCO Clin Cancer Inform 2020;4:1039–50.
42. Rosen RD, Sapra A. TNM classification. In: StatPearls. Treasure Island (FL): StatPearls Publishing; 2024.
43. Feng SH, Yang ST. The new 8th TNM staging system of lung cancer and its potential imaging interpretation pitfalls and limitations with CT image demonstrations. Diagn Interv Radiol 2019;25:270–9.
44. Lu J, Zheng ZF, Wang W, Xie JW, Wang JB, Lin JX, et al. A novel TNM staging system for gastric cancer based on the metroticket paradigm: a comparative study with the AJCC-TNM staging system. Gastric Cancer 2019;22:759–68.
45. Baars A, Buter J, Pinedo HM. Making use of the primary tumour. Bioessays 2003;25:79–86.
46. Brierley J, O'Sullivan B, Asamura H, Byrd D, Huang SH, Lee A, et al. Global consultation on cancer staging: promoting consistent understanding and use. Nat Rev Clin Oncol 2019 ;16:763–71.
47. Karpf M. Lymphadenopathy. Available at: https://www.ncbi.nlm.nih.gov/books/NBK256/. Accessed Aug 16, 2024.
48. Cleveland Clinic. Swollen lymph nodes. Available at: https://my.clevelandclinic.org/health/symptoms/15219-swollen-lymph-nodes. Accessed Aug 16, 2024.
49. Coumans FA, Siesling S, Terstappen LW. Detection of cancer before distant metastasis. BMC Cancer 2013;13:283.
50. PDQ Adult Treatment Editorial Board. Table 5. Definition of distant metastasis (M)a. Available at: https://www.ncbi.nlm.nih.gov/books/NBK65744/table/CDR0000062787__1944/. Accessed Aug 16, 2024.
51. Tan B. Stages of cancer. Available at: https://www.cancercenter.com/stages-of-cancer. Accessed Aug 16, 2024.
52. American Cancer Society. Cancer staging. Available at: https://www.cancer.org/cancer/diagnosis-staging/staging.html. Accessed Aug 16, 2024.
53. Markman M. Stage 4 cancer. Available at: https://www.cancercenter.com/stage-four-cancer. Accessed Aug 16, 2024.
54. Nezis IP, Stravopodis DJ, Papassideri I, Robert-Nicoud M, Margaritis LH. Stage-specific apoptotic patterns during Drosophila oogenesis. Eur J Cell Biol 2000;79:610–20.
55. Nezis IP, Modes V, Mpakou V, Stravopodis DJ, Papassideri IS, Mammali I, et al. Modes of programmed cell death during Ceratitis capitata oogenesis. Tissue Cell 2003;35:113–9.
56. Bohr A, Memarzadeh K. The rise of artificial intelligence in healthcare applications. Artific Intell Healthcare 2020:25–60.
57. Ahuja AS. The impact of artificial intelligence in medicine on the future role of the physician. PeerJ 2019;7:e7702.
58. Linardatos P, Papastefanopoulos V, Kotsiantis S. Explainable AI: A review of machine learning interpretability methods. Entropy 2021;23:18.
59. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature 2015;521:436–44.
60. Miotto R, Wang F, Wang S, Jiang X, Dudley JT. Deep learning for healthcare: Review, opportunities and challenges. Brief Bioinform 2018;19:1236–46.
61. Shen D, Wu G, Suk HI. Deep learning in medical image analysis. Annu Rev Biomed Eng 2017;19:221–48.
62. Shin HC, Roth HR, Gao M, Lu L, Xu Z, Nogues I, et al. Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. IEEE Trans Med. Imag 2016;35:1285–98.
63. Litjens G, Kooi T, Bejnordi BE, Setio AAA, Ciompi F, Ghafoorian M, et al. A survey on deep learning in medical image analysis. Med Image Anal 2017;42:60–88.
64. Busnatu Ș, Niculescu AG, Bolocan A, Petrescu GED, Păduraru DN, Năstasă I, et al. Clinical applications of artificial intelligence- An updated overview. J Clin Med 2022;11:2265.

65. Espinoza JL, Dong LT. Artificial intelligence tools for refining lung cancer screening. J Clin Med 2020;9:3860.
66. Gatti M, Maino C, Tore D, Carisio A, Darvizeh F, Tricarico E, et al. Benign focal liver lesions: The role of magnetic resonance imaging. World J Hepatol 2022;14:923–43.
67. Younghak Shin, Balasingham I. Comparison of hand-craft feature based SVM and CNN based deep learning framework for automatic polyp classification. Annu Int Conf IEEE Eng Med Biol Soc 2017;2017:3277–80.
68. Orringer DA, Pandian B, Niknafs YS, Hollon TC, Boyle J, Lewis S, et al. Rapid intraoperative histology of unprocessed surgical specimens via fibre-laser-based stimulated Raman scattering microscopy. Nat Biomed Eng 2017;1:0027.
69. Jones S, Thompson K, Porter B, Shepherd M, Sapkaroski D, Grimshaw A, et al. Automation and artificial intelligence in radiation therapy treatment planning. J Med Radiat Sci 2024;71:290–8.
70. Masood A, Al-Jumaily AA. Computer aided diagnostic support system for skin cancer: A review of techniques and algorithms. Int J Biomed Imaging 2013;2013:323268.
71. Jartarkar SR, Cockerell CJ, Patil A, Kassir M, Babaei M, Weidenthaler-Barth B, et al. Artificial intelligence in dermatopathology. J Cosmet Dermatol 2023;22:1163–7.
72. Albarqouni S, Baur C, Achilles F, Belagiannis V, Demirci S, Navap N. AggNet: Deep learning from crowds for mitosis detection in breast cancer histology images. IEEE Trans Med Image 2016;35:1313–21.
73. Djuric U, Zadeh G, Aldape K, Diamandis P. Precision histology: How deep learning is poised to revitalize histomorphology for personalized cancer care. NPJ Precis Oncol 2017;1:22.
74. Janowczyk A, Madabhushi A. Deep learning for digital pathology image analysis: A comprehensive tutorial with selected use cases. J Pathol Inform 2016;7:29.
75. Bejnordi BE, Lin J, Glass B, Mullooly M, Gierach GL, Sherman ME, et al. DEEP learning-based assessment of tumor-associated stroma for diagnosing breast cancer in histopathology images. Proc IEEE Int Symp Biomed Imaging 2017;2017:929–32.
76. Shafi S, Parwani AV. Artificial intelligence in diagnostic pathology. Diagn Pathol 2023;18:109.
77. Yuan Y, Shi Y, Li C, Kim J, Cai W, Han Z, et al. DeepGene: An advanced cancer type classifier based on deep learning and somatic point mutations. BMC Bioinformatics 2016;17:476.
78. Alipanahi B, Delong A, Weirauch MT, Frey BJ. Predicting the sequence specificities of DNA- and RNA-binding proteins by deep learning. Nat Biotechnol 2015;33:831–8.
79. Jan YT, Tsai PS, Huang WH, Chou LY, Huang SC, Wang JZ, et al. Machine learning combined with radiomics and deep learning features extracted from CT images: A novel AI model to distinguish benign from malignant ovarian tumors. Insights Imaging 2023;14:68.
80. Illumina. Detecting changes in the cancer transcriptome. Available at: https://sapac.illumina.com/areas-of-interest/cancer/research/sequencing-methods/cancer-rna-seq.html. Accessed Aug 16, 2024.
81. Hrdlickova R, Toloue M, Tian B. RNA-Seq methods for transcriptome analysis. Wiley Interdiscip Rev RNA 2017;8:10.1002/wrna.1364.
82. Casamassimi A, Federico A, Rienzo M, Esposito S, Ciccodicola A. Transcriptome profiling in human diseases: New advances and perspectives. Int J Mol Sci 2017;18:1652.
83. Lang J, Cho WC, Huang T, Wu T, Xu J. Editorial: Applications of RNA-seq in cancer and tumor research. Front Genet 2023;14:1331576.
84. Delen D, Walker G, Kadam A. Predicting breast cancer survivability: A comparison of three data mining methods. Artif Intell Med 2005;34:113–27.
85. Lu H, Wang H, Yoon SW. A dynamic gradient boosting machine using genetic optimizer for practical breast cancer prognosis. Expert Syst Appl 2019;116:340–50.
86. Vasudevan P, Murugesan T. Cancer subtype discovery using prognosis-enhanced neural network classifier in multigenomic data. Technol Cancer Res Treat 2018;17:1533033818790509.
87. Tian DW, Wu ZL, Jiang LM, Gao J, Wu CL, Hu HL. Neural precursor cell expressed, developmentally downregulated 8 promotes tumor progression and predicts poor prognosis of patients with bladder cancer. Cancer Sci 2019;110:458–67.
88. Hasnain Z, Mason J, Gill K, Miranda G, Gill IS, Kuhn P, et al. Machine learning models for predicting post-cystectomy recurrence and survival in bladder cancer patients. PLoS One 2019;14:e0210976.
89. Biglarian A, Hajizadeh E, Kazemnejad A, Zali M. Application of artificial neural network in predicting the survival rate of gastric cancer patients. Iran J Public Health 2011;40:80–6.
90. Zhu L, Luo W, Su M, Wei H, Wei J, Zhang X, et al. Comparison between artificial neural network and Cox regression model in predicting the survival rate of gastric cancer patients. Biomed Rep 2013;1:757–60.
91. Bottaci L, Drew PJ, Hartley JE, Hadfield MB, Farouk R, Lee PW, et al. Artificial neural networks applied to outcome prediction for colorectal cancer patients in separate institutions. Lancet 1997;350:469–72.
92. Lu TP, Kuo KT, Chen CH, Chang MC, Lin HP, Hu YH, et al. Developing a prognostic gene panel of epithelial ovarian cancer patients by a machine learning model. Cancers (Basel) 2019;11:270.
93. Bychkov D, Linder N, Turkki R, Nordling S, Kovanen PE, Verrill C, et al. Deep learning based tissue analysis predicts outcome in colorectal cancer. Sci Rep 2018;8:3395.
94. Chang SW, Kareem SA, Kallarakkal TG, Merican AF, Abraham MT, Zain RB. Feature selection methods for optimizing clinicopathologic input variables in oral cancer prognosis. Asian Pac J Cancer Prev 2011;12:2659–64.

95. Lynch CM, Abdollahi B, Fuqua JD, de Carlo AR, Bartholomai JA, Balgemann RN, et al. Prediction of lung cancer patient survival via supervised machine learning classification techniques. Int J Med Inform 2017;108:1–8.
96. Sepehri S, Upadhaya T, Desseroit MC, Visvikis D, Le Rest CC, Hatt M. Comparison of machine learning algorithms for building prognostic models in non-small cell lung cancer using clinical and radiomics features from 18F-FDG PET/CT images. J Nucl Med 2018;59:328.
97. Acharya U, Akter A, Chowriappa P, Dua S, Raghavendra U, Koh JEW, et al. Use of nonlinear features for automated characterization of suspicious ovarian tumors using ultrasound images in fuzzy forest framework. Int J Fuzzy Syst 2018;20:1385–402.
98. Qian Z, Li Y, Wang Y, Li L, Li R, Wang K, et al. Differentiation of glioblastoma from solitary brain metastases using radiomic machine-learning classifiers. Cancer Lett 2019;451:128–35.
99. Kuo RJ, Huang MH, Cheng WC, Lin CC, Wu YH. Application of a two-stage fuzzy neural network to a prostate cancer prognosis system. Artif Intell Med 2015;63:119–33.