WORLD JOURNAL OF PHARMACEUTICAL RESEARCH

SJIF Impact Factor 8.084

Volume 12, Issue 1, 452-465. Review Article ISSN 2277– 7105

A REVIEW ON THE ROLE OF ARTIFICIAL INTELLIGENCE IN THE TREATMENT AND DIAGNOSIS OF EARLY STAGE OF CANCER

Dr. Mohd. Wasiullah[1], Piyush Yadav*[2], Prakash Dubey[3] and Vinay Kumar Deepak[4]

[1]Principal, Dept. of Pharmacy, Prasad Institute of Technology, Jaunpur (222001) U.P, India.

[2]Principal, Dept. of Pharmacy, Prasad Polytechnic, Jaunpur (222001) U.P, India.

[3]Dept. of Pharmacy, Prasad Institute of Technology, Jaunpur (222001) U.P, India.

[4]Assistant Professor, Dept. of Pharmacy, Prasad Institute of Technology, Jaunpur (222001) U.P, India.

Article Received on 15 November 2022,
Revised on 04 Dec. 2022,
Accepted on 25 Dec. 2022
DOI: 10.20959/wjpr20231-26670

***Corresponding Author**
Piyush Yadav
Principal, Dept. of Pharmacy, Prasad Polytechnic, Jaunpur (222001) U.P, India.

ABSTRACT

Today, artificial intelligence (AI) and machine learning are proving to have a variety of applications in many fields, including medicine. Cancer is one of the most common non-communicable diseases in modern times, causing many deaths worldwide. Attempts to increase cancer mortality and morbidity are ongoing studies. The integration of artificial intelligence in cancer research is being actively pursued with very promising results. It is a key factor that plays an important role in improving cancer prognosis, including early detection and accurate diagnosis using various imaging and molecular techniques. Using artificial intelligence as a tool in these areas showed the potential for detection and diagnosis with higher accuracy. This is just one of the many uses of AI in cancer research. The current review aims to delve into the literature and enumerate the applications of artificial intelligence in various common cancer types.

KEYWORDS: Artificial intelligence; Machine learning; Breast cancer; Prostate cancer; CNS tumor.

INTRODUCTION

Computers play an increasingly important role not only in our daily life, but also in medical and related fields. Their advent has greatly improved the functioning of hospitals and introduced better methods of diagnosis and treatment. We are now at the door of another revolution. Artificial intelligence (AI) is defined as the ability of a system to correctly interpret data from external sources, learn from it, use this knowledge to perform specific tasks, and achieve goals through flexible adaptation.[1] This kind of behavior, which is very similar to how the human mind works, can find wide application in diagnostics. Cancer is a heterogeneous group of diseases with often aggressive courses and poor cure rates. They affect most parts of the body, especially those with clusters of intensively dividing cells (glands, skin). The key to effective treatment is early diagnosis of lesions, often hampered by the presence of nonspecific symptoms.[2] The purpose of this study is to describe the application of artificial intelligence in the diagnosis of cancer, especially breast, prostate, skin and colon cancer. We discuss the potential use of AI for cancer diagnosis and its efficacy compared to conventional clinical diagnosis.

Concept of Development of Artificial Intelligence in Research

Research and development of theories, methods, techniques, and application systems for simulation, extension, and expansion of human intelligence. Essentially, AI is a branch of computer science. Researchers are trying to understand the nature of intelligence and design new intelligent machines that can react in ways similar to human intelligence. Research in this area includes robotics, speech recognition, image recognition, and natural language processing. Apply scientific advances and engineering developments to medicine and promote the development of medical technology. AI technology has played an important role in building fast, accurate and intelligent medical systems in the medical field.

Based on the rapid development of computer technology, the image level and quality of medical imaging equipment have improved steadily in recent years.[3] His four main directions for future medical development are “individualized, precision, minimally invasive, and remote.” With the help of computer technology, these directions have become more and more clear.[4] Adopting AI technology in the field of medical image recognition is a goal with great potential benefits for both patients and doctors. Using AI to analyse medical images can significantly reduce costs and improve efficiency. However, practical application of medical image processing requires the system to be flexible enough to adapt to the actual characteristics of the processed images.[5] Recently, the development of AI has entered a new era. AI is starting to evolve rapidly in professional applications. Many applications are impractical, but very likely in the next 10 to 15 years.[6]

Laboratory medicine is an important branch of modern medicine. Approximately 70% of the information needed to make clinical decisions comes from laboratory tests. The main purpose of such tests is sample recognition and interpretation. However, image recognition and decision-making systems using AI techniques will play an important role in this field, even undermining existing technologies. AI applications in the pre-analytical phase are primarily focused on sample collection and transfer, and identification of ineligible samples. These applications include blood collection robots, sample transfer robots, automated sample delivery, and automated identification of ineligible samples.[7] At the analysis stage, image recognition is the most popular technique as it helps solve the problem of morphological interpretation of examination objects such as bone marrow sections, blood smears, urine sediments, fluorescent sections and bacterial colonies. Deep learning allows computers to classify red blood cells based on cell morphology. AI plays a more important role in the post-analysis phase. Machine learning techniques can perform intelligent report validation and validation, generate reports on key values, and even analyse historical data for multiple test items to find test tube labelling errors. AI technology can also contribute to the transition from test reports to diagnostic reports. AI technology, by multiparameter data mining, related to fibrillation of peripheral blood can predict risk of acute myocardial infarction, which can not be obtain by single test item.[8,9]

Machine Learning

The replication of human intelligence by AI with the utilization of data-driven algorithms that have been instructed and self-train through experience and data analysis is generally defined as machine learning (ML).[10] After been programmed, ML can find recurrent patterns in large amount of appropriately engineered data and progressively learn and independently improve performance accuracy without human intervention. The ML algorithms are generally classified in supervised learning (the most frequent one, which utilizes classified data), unsupervised learning (where algorithms can independently identify patterns in data without previous classification), semi-supervised learning (can use a combination of both labelled and unlabelled data) and reinforcement learning (uses estimated errors as proportional rewards or penalties to teach algorithms).[10,11] Deep learning (DL) is a class of ML techniques that has the ability to directly process raw data and perform detection or classification tasks automatically without the need for human intervention. The sets of algorithms utilized by DL are generally artificial neural networks (ANNs) constituted by several layers that elaborate inputs with weights, biases (or thresholds) and deliver an output. ML models, combined with large amounts of qualitative and quantitative information derived from medical imaging (radiomics) and clinical data, can support physicians in the evidence-based decision-making process.[11]

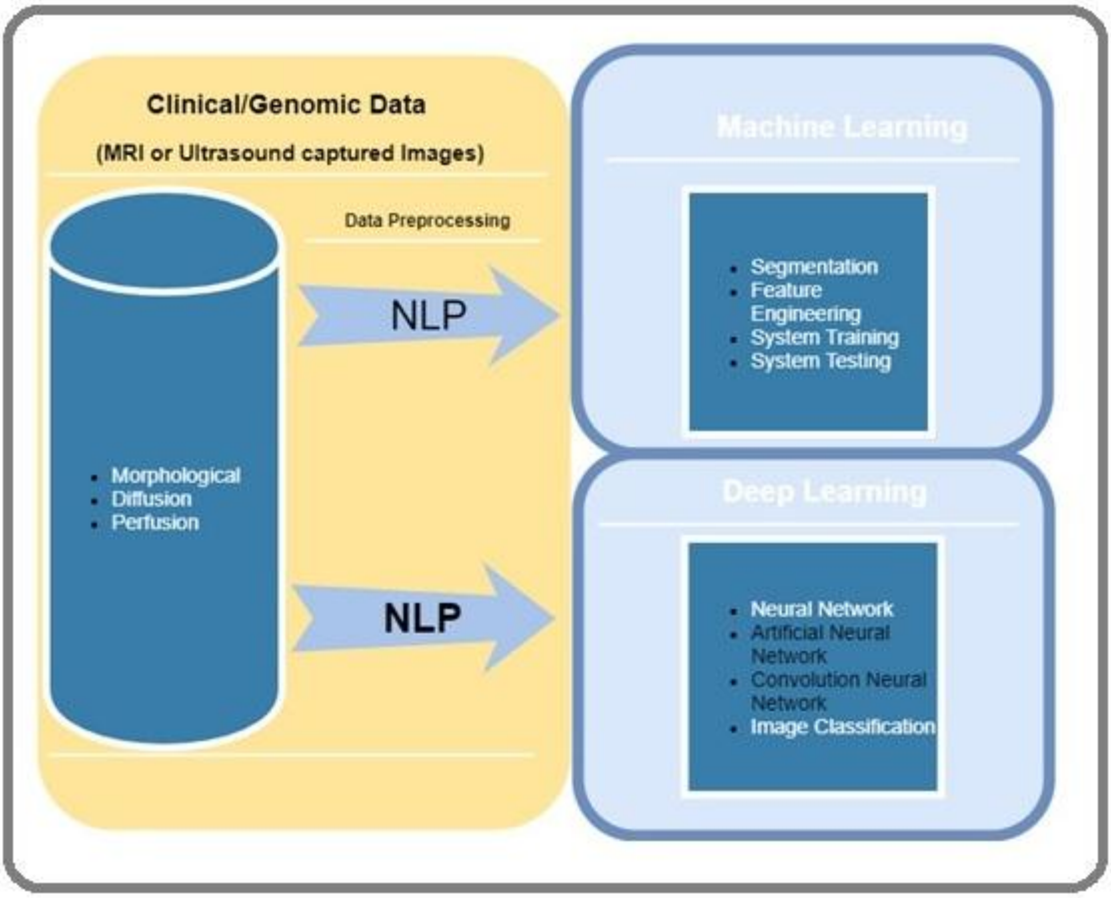

Figure 1: Radiomic Workflow for Machine Learning & Deep Learning Approach for Biomedical Imaging.

AI IMAGE IN DETECTION OF CANCER

An AI-based deep learning algorithm was implemented to identify complex patterns in medical and clinical images. They translate images and attempt to complement clinical decisions, enabling meaningful decisions that are most difficult for humans to make. to an integrated indication system. This includes his X-ray images studied in pathology, genomics, and a collection of electronic health reports and social networks. Examination of cross-sectional X-ray images reconstructed by MRI and CT scans is always a challenge when it comes to recognizing complex patterns. It is possible to train computers efficiently to produce results that can be produced quickly. ML can be implemented on MRI datasets or digitally acquired images. Figure 2 shows the phases of cancer detection for image processing. Low-level transformation methods are used to implement image classification, represent the initial stages of image analysis such as segmentation and registration, are formulated mathematically using statistical and biomechanical modeling, it aims to solve computer vision-based image processing. Computer-aided detection (CADe) is a term used for detection related to the detection of objects in X-ray images. CADe has been used as a companion assistant in detecting occult cancers in low-volume CT screening cases,[12] and with very high sensitivity during detection he discriminates brain tumor progression in MRI image.[13]

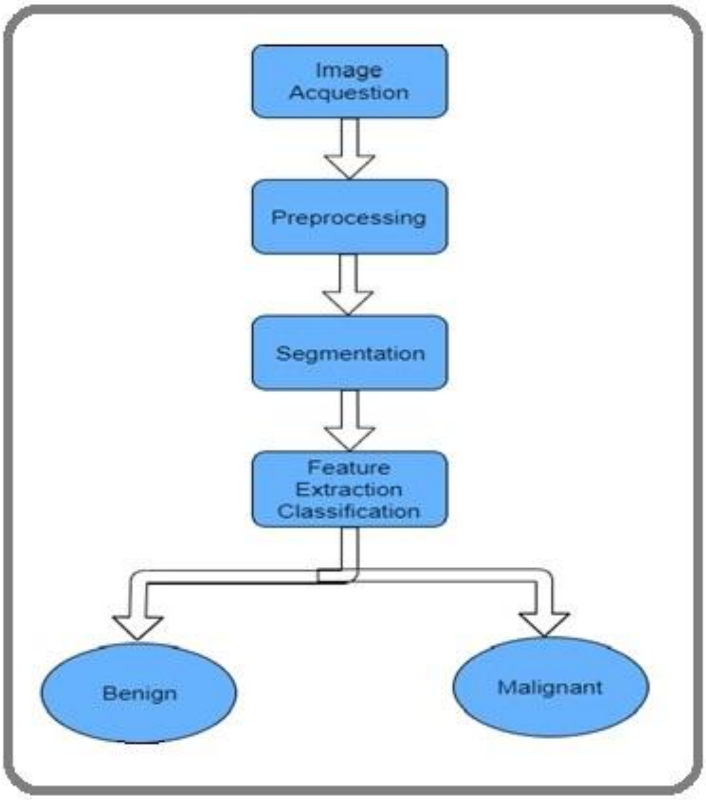

Fig: Cancer Detection Stages by Image Processing Methodology.

BREAST CANCER

Breast cancer is the second most common cancer in the world and the second leading cause of death in women.[14] Early signs of breast cancer are usually invisible and easily missed, so screening methods such as mammograms and ultrasounds should be performed regularly. There is no doubt that image-based diagnosis has some limitations, including: B. Presence of image noise, poor sharpness, poor contrast, and radiologist performance, such as visual perception ability and experience.[15] Perhaps AI will help diagnose breast cancer, making it more accurate and faster. Comparing the diagnostic capabilities of lesions by radiologists and AI, we observed that the AI system showed better diagnostic results than the human reader. This study evaluated maximum intensity projection (MIP) lesions on dynamic contrast-enhanced (DCE) breast magnetic resonance imaging (MRI). The AI system used Retina Net to calculate the likelihood of malignancy, and the radiologist's task was to classify lesions as benign or malignant. Thirteen normal, 20 benign, and 52 malignant cases were classified. AI achieved the highest values for sensitivity, specificity, and area under the receiver operating characteristic curve (AUC), which were 0.926, 0.828, and 0.925, respectively. This compares to human readers without AI (0.847, 0.841, and 0.884) and human readers with AI (0.889, 0.823, and 0.899).[16] AI systems are useful not only for MRI evaluation, but also for ultrasound image classification. Quan Xia's study compared the classification of breast lesions for each breast mass assessed by physicians and AI in the system recommended by the American Radiological Society (BI-RADS). The AI had a sensitivity of 95.8%, a specificity of 93.8% and an accuracy of 89.6%, while senior physicians achieved lower values of 79.2%, 81.3% and 60.5% respectively (Junior: 75.0%, 68.8%, 43.8%).%). The sensitivity was 100%, the specificity was 93.8%, and the accuracy was 93.8%, so the best effect was achieved with the help of AI in the work of senior physicians. His AI in this study diagnoses lesions better than physicians and improves the quality of breast cancer ultrasound diagnosis by physicians.[17]

PROSTRATE CANCER

The clinical variability of prostate cancer in terms of tumor size (from very small to highly destructive tumors), high recurrence rates and mortality that varies from patient to patient poses many challenges. ML-based supervised techniques is often applied to imaging modalities. Uncover suspicious lesions, including US imaging, to provide overall biological advantage in cancer research. Deep learning-based prostate cancer applications are beneficial for treatment and generating high-performance outcomes.

Multiparametric Magnetic Resonance Imaging (mpMRI) can display soft tissue contrast to identify suspicious prostate lesions and provide insight into tissue characteristics. Investigations show that mpMRI is a promising imaging technique for prostate cancer due to its potential to discover lesions and provide surgical features. AI model-based prostate tumor identification and classification has provided flexibility as CADe and CAD systems.[18] In conjunction with PI-RADS, the CAD system could potentially improve the feasibility and treatment accuracy of his mpMRI.[19] Initial in his mpMRI-based CADx system targeting supervised learning models]. Work added feature extraction and trivial classification. The report states that feature extraction plays an important role in improving the system's results, depending on the CAD. CNN added that the work has been fully scaled up and reports of excellent performance in prostate cancer detection and treatment have been submitted.

Another feature of the CNN algorithm such as B. The addition of mpMRI images adds automatic windowing for better classification and normalization of MRI images.[19]

SKIN CANCER

The development of artificial intelligence-based diagnostic methods has become a trend in the diagnosis of melanoma and skin cancer. According to the Skin Cancer Foundation, the global incidence of skin cancer is increasing every year.[20] Incidence rates vary widely around the world, being highest in Australia (37 cases per 100,000) and lowest in South Central Asia (0.2 per 100,000).[21] The gold standard for diagnosis of melanoma and skin cancer is histopathological evaluation. Convolutional Neural Networks (CNNs) are examples of the use of AI in diagnosing melanoma and skin cancer. CNNs have been monitored and trained to analyse visual aspects of skin lesions such as: B. Diameter, shape, color, pattern, etc. CNNs require guidance from validated diagnostics for each image they learn during the training phase. Therefore, the main problem in using it effectively is creating a reliable record of the highest quality images. The first study comparing CNN and dermatologist performance was by Esteva et al. Released. 2017.[22] Dermatologists had an average sensitivity of 86.6%. At this sensitivity, the physician's specificity (71.3%) was significantly lower than that of his CNN (82.5%). Other comparative studies by Haenssle,[23] Tschandl[24] showed that her CNN specificity of results was not comparable or inferior to that of dermatologists. Tschandl proved that CNN can classify both pigmented and non-pigmented skin lesions as accurately as dermatologists. In lesions of basal skin cancer or Bowen's disease, CNN outperformed the doctor (the doctor's diagnosis of basal skin cancer was correct 51% of the time, while CNN's diagnosis was 85% of the time).[24] probabilistically correct). Population diversity can be the biggest barrier to the use of large-scale CNNs. The sensitivity of CNN drops from 91% to 85.5% when using results from one hospital and comparing them with results from another hospital with a different population.[25] Melanoma skin lesions can look different in different populations, complicating the CNN training process. Satisfactory sensitivity results obtained from imaging skin lesions in one patient group may not be easily transferable to another group.[26] Rajpara Study 117 showed that traditional dermatoscopy and artificial intelligence are equally good at diagnosing melanoma lesions. Sensitivity of artificial intelligence surpasses that of dermatoscopy.[27]

APPLICATION OF AI IN LUNG CANCER

Biomedical imaging and ML have opened up new dimensions in research. Early detection of lung cancer is always important. ML has added new features and capabilities to improve lung cancer diagnosis and track treatment response. Various models have been developed to propagate the early stages of detection and allow AI to significantly classify pulmonary nodules into her two classes (benign or malignant).[28-29] The National Lung Screening Trial (NLST) showed her 20% lung cancer mortality in men and women of all ages masked by using low-dose CT (LDCT) for screening.[30] To date, there is no authenticated and validated approach for classifying nodes as malicious or benign. Classical biostatistics and ML methodologies have been implemented to account for various obstacles in lung cancer screening. ML has demonstrated multiple methods and novel techniques to detect biomarkers to minimize false positive imaging results and more accurately classify benign and malignant nodules.[31] Most of the trapped lung nodules are found unexpectedly and cause problems for cancer patients. In a recent study, four quantitatively evaluated semantic features such as minor axis radius, contour, concavity and texture were considered in the ML model to classify benign or malignant nodules in lung cancer screening. This model classified the nodes with 74.3% accuracy.[27] Image-based biomarkers can be stored in her radiographs and incorporated into the underlying pathophysiology of the tumor. Clinical and biomedical implementations rely on size-based measurements to provide reasonable estimates of prognostic factors such as survival and recurrence rates. An AI method is being studied that uses predefined algorithms and deep learning (a process called radiomics) to quantify the phenotypic characteristics of his radiographs based on the presence of specific mutations.[32-33]

APPLICATION OF AI IN CNS TUMOR

The occurrence of CNS tumors exhibits a large spectrum in the field of pathology and may be more diverse than any other tumor in the human body. This wide range of diagnoses requires highly unique and accurate assessment of imaging modalities. One of the most important biomarkers for determining the prognosis of CNS tumors is isocitrate dehydrogenase (IDH). Changes in the presence of IDH mutations can be effectively detected using machine learning techniques, including deep CNNs trained on conventional MR images.[34-35] Technically similar studies have already been done in other brain tumors. The study results showed that an algorithm trained to extract radiomic features from conventional MRI can generate predictive models for pituitary adenoma and pediatric brain tumor subtypes. Various challenges arise when differentiating between different tumor types. One of the major challenges in diagnosing CNS tumors is to distinguish between primary CNS lymphomas and glioblastomas based on similarities in imaging phenotypes. Results show that the radiomics model uses image texture-based features to emphasize differences between glioblastoma and primary CNS lymphoma.[34-36] Interestingly, a similar diagnostic dilemma often arises when evaluating histopathological sections of these two different disease processes.[37] Recent studies have implemented AI in brain tumors and focused on efficiently classifying biological and histopathological subclasses of brain tumors.[37-38] AI-based systems that require new models to accurately classify tumors must test datasets and train corresponding large sets of data. Thereby, AI can help improve the accuracy of discrimination between multiple tumors to provide better quality treatment.[39] Treatment of tumors is determined by precise classification of tumor subclass. MR imaging is very helpful in defining CNS tumors. These tumors exhibit different classes of contrast enhancement, which may be associated with hemorrhage, peritumoral edema, or blurred boundaries with adjacent bone, blood vessels, fat, or surgical packing material. I have. It is hoped that automated identification of CNS tumors will lead to the development of powerful density-based algorithms to describe tumors and associate them with the microenvironment that plays an important role.[40]

CONCLUSION

Artificial intelligence will greatly remodel studies on the early detection of many forms of cancer, and consequently will improve clinical practice in general. Artificial intelligence offers excellent opportunities for the automation of tasks through the detection of complex patterns. In this respect, research is crucial to facilitate the interdisciplinary incorporation of such techniques, and improvements in this field may open the door to further studies in the future. Many commercial solutions for automated cancer detection are becoming available, and we are likely to see increasing adoption in the coming years. Artificial intelligence plays an increasingly important role in medical diagnostics. Algorithms are improving year by year, and the range of AI applications is expanding. One of the most important applications of this technology is cancer diagnosis. Algorithms are most commonly used to detect cancerous changes in X-rays or other standardized samples. This process is preceded by algorithm training, under the supervision of 118 specialists, where large amounts of data are presented to the AI to display amazing patient results. In this article, we analyzed the diagnostic efficacy of artificial intelligence in some of the most common types of cancer. The research results are very promising and demonstrate the high effectiveness of AI. For breast cancer diagnosis, the high accuracy of AI has been demonstrated in both her MRI and ultrasound analyses of lesions, especially when the analyses were corroborated by expert opinion. Further research is needed to use artificial intelligence to advance medical diagnostics, including improving existing algorithms and creating new ones. Additionally, many ethical issues related to the use of AI in patient diagnosis and treatment and social standardization of the use of computer data analysis in treatment need to be resolved. However, these efforts have the potential to significantly improve the diagnosis and treatment of cancer patients.

REFERENCES

1. Kaplan A, Haenlein M. Siri, Siri in my Hand, who's the Fairest in the Land? On the Interpretations, Illustrations and Implications of Artificial Intelligence. Business Horizons, 2019; 62(1): 15-25.
2. Hausman DM. What Is Cancer. Perspect Biol Med, 2019; 62(4): 778-784.
3. Liao CW, Fuh LJ, Shen YW, Huang HL, Kuo CW, Tsai MT, Hsu JT. Self-assembled micro-computed tomography for dental education. *PLoS One,* 2018; 13: e0209698. [PMC free article] [PubMed] [Google Scholar].
4. Timp S, Varela C, Karssemeijer N. Computer-aided diagnosis with temporal analysis to improve radiologists' interpretation of mammographic mass lesions. *IEEE Trans Inf Technol Biomed,* 2010; 14: 803–808. [PubMed] [Google Scholar]
5. Odle T. The AI era: the role of medical imaging and radiation therapy professionals. *Radiol Technol,* 2020; 91: 391–400. [PubMed] [Google Scholar]
6. Caobelli F. Artificial intelligence in medical imaging: game over for radiologists? *Eur J Radiol,* 2020; 126: 108940. [PubMed] [Google Scholar]
7. Naugler C, Church DL. Automation and artificial intelligence in the clinical laboratory. *Crit Rev Clin Lab Sci,* 2019; 56: 98–110. [PubMed] [Google Scholar]
8. Sun Y, Liu Y, Wang G, Zhang H. Deep learning for plant identification in natural environment. Comput Intell Neurosci, 2017; 2017: 7361042. [PMC free article] [PubMed] [Google Scholar]
9. Gruson D, Helleputte T, Rousseau P, Gruson D. Data science, artificial intelligence, and machine learning: opportunities for laboratory medicine and the value of positive regulation. *Clin Biochem,* 2019; 69: 1–7. [PubMed] [Google Scholar]
10. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med, 2019; **25**: 44–56. [PubMed] [Google Scholar]

11. Gillies RJ, Kinahan PE, Hricak H. Radiomics: Images Are More than Pictures, They Are Data. Radiology, 2016; **278**: 563–577. [PMC free article] [PubMed] [Google Scholar]
12. Liang M, Tang W, Xu DM, Jirapatnakul AC, Reeves AP, Henschke CI, Yankelevitz D. Low-Dose CT Screening for Lung Cancer: Computer-aided Detection of Missed Lung Cancers. Radiology, 2016 Oct; 281(1): 279-288. https: //doi. org/10.1148/radiol.2016150063
13. Ambrosini RD, Wang P, O'Dell WG. Computer-aided detection of metastatic brain tumors using automated three-dimensional template matching. Journal of Magnetic Resonance Imaging, 2009 Dec 20; 31(1): 85-93. https: //doi. org/10.1002/jmri.22009.
14. Ferlay J, Soerjomataram I, Dikshit R, Eser S, Mathers C, Rebelo M, Parkin DM, Forman D, Bray F. Cancer incidence and mortality worldwide: sources, methods and major patterns in GLOBOCAN 2012. Int J Cancer, 2015; 136(5): E359-86.
15. Giger ML. Computer-aided diagnosis in radiology. Acad Radiol, 2002; 9(1): 1-3.
16. Adachi M, Fujioka T, Mori M, Kubota K, Kikuchi Y, Xiaotong W, Oyama J, Kimura K, Oda G, Nakagawa T, Uetake H, Tateishi U. Detection and Diagnosis of Breast Cancer Using Artificial Intelligence Based assessment of Maximum Intensity Projection Dynamic Contrast-Enhanced Magnetic Resonance Images. Diagnostics (Basel), 2020; 10(5): E330.
17. Differential diagnosis of breast cancer assisted by S-Detect artificial intelligence system [Internet]. [cited 2021 Sep 1]. Available from: https: //www.aimspress.com/article/10.3934/mbe.2021184.
18. Castellino RA. Computer aided detection (CAD): an overview. Cancer Imaging, 2005; 5(1): 17-19. https: //doi. org/10.1102/1470-7330.2005.0018
19. Wang S, Burtt K, Turkbey B, Choyke P, Summers RM. Computer Aided-Diagnosis of Prostate Cancer on Multiparametric MRI: A Technical Review of Current Research. BioMed Research International, 2014; 2014: 1-11. https: //doi.org/10.1155/2014/789561.
20. S. C. Foundation, "Skin Cancer Facts and Statistics," Online, Jan. 2017. [Internet]. [cited 2021 Sep 31]. Available from: https: //www.skincancer.org/skin-cancer-information/skin-cancer-facts/
21. Ali Z, Yousaf N, Larkin J. Melanoma epidemiology, biology and prognosis. EJC Suppl, 2013; 11(2): 81-91.
22. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, Thrun S. Dermatologistlevel classification of skin cancer with deep neural networks. Nature, 2017; 542(7639): 115-118.

23. Haenssle HA, Fink C, Schneiderbauer R, Toberer F, Buhl T, Blum A, Kalloo A, Hassen ABH, Thomas L, Enk A, Uhlmann L, Reader SL-IAL-IIG, Alt C, Arenbergerova M, Bakos R, Baltzer A, Bertlich I, Blum A, Bokor-Billmann T, Bowling J, Braghiroli N, Braun R, Buder-Bakhaya K, Buhl T, Cabo H, Cabrijan L, Cevic N, Classen A, Deltgen D, Fink C, Georgieva I, Hakim-Meibodi LE, Hanner S, Hartmann F, Hartmann J, Haus G, Hoxha E, Karls R, Koga H, Kreusch J, Lallas A, Majenka P, Marghoob A, Massone C, 121 Mekokishvili L, Mestel D, Meyer V, Neuberger A, Nielsen K, Oliviero M, Pampena R, Paoli J, Pawlik E, Rao B, Rendon A, Russo T, Sadek A, Samhaber K, Schneiderbauer R, Schweizer A, Toberer F, Trennheuser L, Vlahova L, Wald A, Winkler J, Wölbing P, Zalaudek I. Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists. Ann Oncol, 2018; 29(8): 1836-1842.
24. Tschandl P, Rosendahl C, Akay BN, Argenziano G, Blum A, Braun RP, Cabo H, Gourhant JY, Kreusch J, Lallas A, Lapins J, Marghoob A, Menzies S, Neuber NM, Paoli J, Rabinovitz HS, Rinner C, Scope A, Soyer HP, Sinz C, Thomas L, Zalaudek I, Kittler H. Expert-Level Diagnosis of Nonpigmented Skin Cancer by Combined Convolutional Neural Networks. JAMA Dermatol, 2019; 155(1): 58-65.
25. Schadendorf D, van Akkooi ACJ, Berking C, Griewank KG, Gutzmer R, Hauschild A, Stang A, Roesch A, Ugurel S. Melanoma. Lancet, 2018; 392(10151): 971-984.
26. Tschandl P. Artificial intelligence for melanoma diagnosis. Ital J Dermatol Venerol, 2021 Jun; 156(3): 289-299.
27. Rajpara SM, Botello AP, Townend J, Ormerod AD. Systematic review of dermoscopy and digital dermoscopy/ artificial intelligence for the diagnosis of melanoma. Br J Dermatol, 2009; 161(3): 591-60.
28. Hawkins S, Wang H, Liu Y, Garcia A, Stringfield O, Krewer H, Li Q, Cherezov D, Gatenby RA, Balagurunathan Y, Goldgof D, Schabath MB, Hall L, Gillies RJ. Predicting Malignant Nodules from Screening CT Scans. Journal of Thoracic Oncology, 2016 Dec; 11(12): 2120-2128. https: // doi.org/10.1016/j.jtho.2016.07.002
29. Liu Y, Balagurunathan Y, Atwater T, Antic S, Li Q, Walker RC, Smith GT, Massion PP, Schabath MB, Gillies RJ. Radiological Image Traits Predictive of Cancer Status in Pulmonary Nodules. Clinical Cancer Research, 2016 09 23; 23(6): 1442-1449. https: //doi.org/10.1158/1078-0432. ccr-15-3102
30. Ciompi F, Chung K, van Riel SJ, Setio AAA, Gerke PK, Jacobs C, Scholten ET, Schaefer-Prokop C, Wille MMW, Marchianò A, Pastorino U, Prokop M, van Ginneken

B. Towards automatic pulmonary nodule management in lung cancer screening with deep learning. Scientific Reports, 2017; 04 19; 7(1). https: //doi.org/10.1038/srep46479

31. Reduced Lung-Cancer Mortality with Low-Dose Computed Tomographic Screening. New England Journal of Medicine, 2011 08 04; 365(5): 395-409. https: //doi.org/10.1056/ nejmoa1102873
32. Scholtz J, Lu MT, Hedgire S, Meyersohn NM, Oliveira GR, Prabhakar AM, Gupta R, Kalra MK, Shepard JO, Hoffmann U, Ghoshhajra BB. Incidental pulmonary nodules in emergent coronary CT angiography for suspected acute coronary syndrome: Impact of revised 2017 Fleischner Society Guidelines. Journal of Cardiovascular Computed Tomography, 2018 01; 12(1): 28-33. https: //doi.org/10.1016/j. jcct.2017.11.005
33. Tunali I, Stringfield O, Guvenis A, Wang H, Liu Y, Balagurunathan Y, Lambin P, Gillies RJ, Schabath MB. Radial gradient and radial deviation radiomic features from pre-surgical CT scans are associated with survival among lung adenocarcinoma patients. Oncotarget, 2017 Oct 06; 8(56): 96013-96026. https: //doi.org/10.18632/ oncotarget.21629
34. Li Q, Kim J, Balagurunathan Y, Qi J, Liu Y, Latifi K, Moros EG, Schabath MB, Ye Z, Gillies RJ, Dilling TJ. CT imaging features associated with recurrence in nonsmall cell lung cancer patients after stereotactic body radiotherapy. Radiation Oncology, 2017 09 25; 12(1). https: // doi.org/10.1186/s13014-017-0892-y.
35. Chang K, Bai HX, Zhou H, Su C, Bi WL, Agbodza E, Kavouridis VK, Senders JT, Boaro A, Beers A, Zhang B, Capellini A, Liao W, Shen Q, Li X, Xiao B, Cryan J, Ramkissoon S, Ramkissoon L, Ligon K, Wen PY, Bindra RS, Woo J, Arnaout O, Gerstner ER, Zhang PJ, Rosen BR, Yang L, Huang RY, Kalpathy-Cramer J. Residual Convolutional Neural Network for the Determination of IDH Status in Low- and High-Grade Gliomas from MR Imaging. Clinical Cancer Research, 2017 Nov 22; 24(5): 1073-1081. https: //doi. org/10.1158/1078-0432.ccr-17-2236
36. Zhang B, Chang K, Ramkissoon S, Tanguturi S, Bi WL, Reardon DA, Ligon KL, Alexander BM, Wen PY, Huang RY. Multimodal MRI features predict isocitrate dehydrogenase genotype in high-grade gliomas. Neuro-Oncology, 2016 06 26; 19(1): 109-117. https: //doi.org/10.1093/neuonc/now121.
37. Kang D, Park JE, Kim Y, Kim JH, Oh JY, Kim J, Kim Y, Kim ST, Kim HS. Diffusion radiomics as a diagnostic model for atypical manifestation of primary central nervous system lymphoma: development and multicenter external validation. Neuro-Oncology, 2018 02 09; 20(9): 1251-1261. https: //doi. org/10.1093/neuonc/noy021

38. Kunimatsu A, Kunimatsu N, Kamiya K, Watadani T, Mori H, Abe O. Comparison between Glioblastoma and Primary Central Nervous System Lymphoma Using MR Imagebased Texture Analysis. Magnetic Resonance in Medical Sciences, 2018; 17(1): 50-57. https: //doi.org/10.2463/mrms. mp.2017-0044
39. Coroller TP, Grossmann P, Hou Y, Rios Velazquez E, Leijenaar RT, Hermann G, Lambin P, Haibe-Kains B, Mak RH, Aerts HJ. CT-based radiomic signature predicts distant metastasis in lung adenocarcinoma. Radiotherapy and Oncology, 2015 03; 114(3): 345-350. https: //doi. org/10.1016/j.radonc.2015.02.015
40. Xu Y, Jia Z, Wang L, Ai Y, Zhang F, Lai M, Chang EI. Large scale tissue histopathology image classification, segmentation, and visualization via deep convolutional activation features. BMC Bioinformatics, 2017 05 26; 18(1). https: //doi.org/10.1186/s12859-017-1685-x.