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METHODOLOGY

A Systematic Review of Real-Time Deep Learning Methods for Image-Based Cancer Diagnostics

Harini Sriraman, Saleena Badarudeen, Saransh Vats, Prakash Balasubramanian

School of Computer Science and Engineering, Vellore Institute of Technology, Chennai, 600127, India

Correspondence: Prakash Balasubramanian, School of Computer Science Engineering, Vellore Institute of Technology, Chennai, Tamil Nadu, India, Tel +91-044-39931228, Fax +91-044-39932555, Email Prakash.bala@vit.ac.in

Abstract: Deep Learning (DL) drives academics to create models for cancer diagnosis using medical image processing because of its innate ability to recognize difficult-to-detect patterns in complex, noisy, and massive data. The use of deep learning algorithms for real-time cancer diagnosis is explored in depth in this work. Real-time medical diagnosis determines the illness or condition that accounts for a patient's symptoms and outward physical manifestations within a predetermined time frame. With a waiting period of anywhere between 5 days and 30 days, there are currently several ways, including screening tests, biopsies, and other prospective methods, that can assist in discovering a problem, particularly cancer. This article conducts a thorough literature review to understand how DL affects the length of this waiting period. In addition, the accuracy and turnaround time of different imaging modalities is evaluated with DL-based cancer diagnosis. Convolutional neural networks are critical for real-time cancer diagnosis, with models achieving up to 99.3% accuracy. The effectiveness and cost of the infrastructure required for real-time image-based medical diagnostics are evaluated. According to the report, generalization problems, data variability, and explainable DL are some of the most significant barriers to using DL in clinical trials. Making DL applicable for cancer diagnosis will be made possible by explainable DL.

Keywords: artificial intelligence, AI, machine learning, DL, CNN, healthcare, real-time diagnosis, classification, image processing, elastography, feedforward neural network

Introduction

Applications across a wide range of industries, including healthcare, climate change,[1] agriculture,[2] etc. are being revolutionized by DL. Computers can perform tasks like picture categorization, object identification, and landmark location better than trained human operators. Experts agree that Machine Learning (ML) is a revolutionary technology with the potential to revolutionize how imaging data are interpreted. However, the application of such potent technologies to medical imaging is still in its infancy. Medical imaging will facilitate finding therapies suited to each person's needs and assist with the limited medical competence accessible in developing countries.

In a professional context, there are two ways to detect cancer: through a biopsy, the findings known in a few days, or invasive surgery. Without invasive testing, AI can identify cancer in minutes. In[3] and,[4] wireless capsule endoscopy is used to obtain medical images. Convolutional neural network (CNN) are the foundation of the majority of AI-based methods for cancer detection.[5]

Several neural network models are being developed and employed to attain the best outcomes in medical diagnostics due to the increased innovation in DL. Specifically, the most common models used are GoogleNet, ResNet50, AlexNet, SegNet, VGG, Inception, and Xception.

The paper begins with a brief introduction to AI. It emphasizes current developments in DL research that have practical applications for or could have future implications for cancer research. Cancer research was chosen because it offers the most significant potential for DL for medical image processing. With this narrative literature review,

• This paper aims to increase public knowledge of DL's existing contributions to cancer research and its potential. Readers in various professions unfamiliar with such technology's technical details will find this interesting.

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• In this work, DL approaches were exclusively evaluated. DL techniques are being considered since, in recent times, DL has proven to be more suitable for image categorization. Further, it was explored to perform image-based cancer diagnosis, and the emphasis is mainly on deep-learning techniques.

• From this paper, the readers will clearly understand the best image modality for a particular type of cancer diagnosis, its pros and cons, and the recent clinical trials carried out.

• Applicability of different pre-trained models for various cancer diagnoses, that too in real-time is verified and highlighted.

• This paper also highlights the Expected accuracy of existing methods and possible improvements for the existing techniques.

Methods

The protocols used to find, collect, and evaluate the state of the art being studied are described in this section. The potential for real-time cancer detection analysis was looked at first, followed by the efficacy and accuracy of several models used in cancer detection. The PRISMA diagram for the systematic review conduction is shown in Figure 1.

Search Strategy

The following supplementary queries were also considered.

• Which approach was used?
• Which models were used in the approach?
• Is the approach able to generate real-time results?
• If a real-time analysis is impossible, why is it not possible?
• What was the accuracy of the models involved?

For this systematic review, the search criteria defined for the selection of articles are as follows:

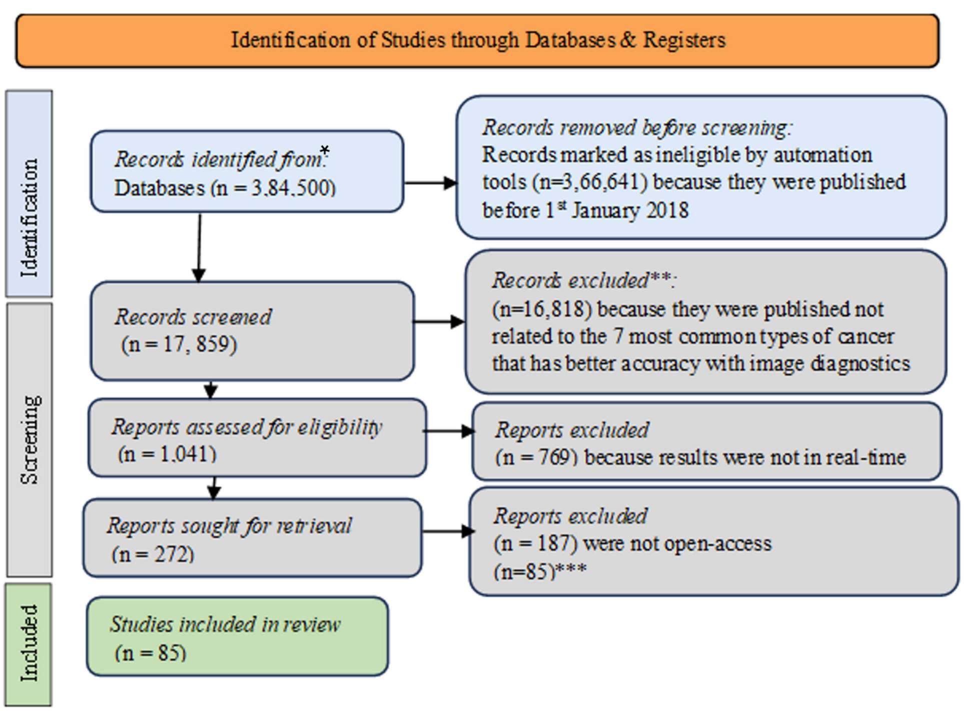

Figure 1 PRISM flow diagram of the systematic review conducted.
Notes: *Records were identified from PubMed and Google Scholar. **Records included only if they mentioned all or one of the most common types of cancer (top 6). ***Most common imaging techniques alone were considered. Example, CT, MRI, X-RAY, Mammography.

- Domain
  - Cancer Detection
  - Real-Time Cancer Detection
  - Secure Transmission of Medical Data

- Metrics
  - Possibility of real-time analysis and detection
  - Accuracy of models
  - Categorization
  - Target organs covered

- Techniques Used
  - DL and its types

- Time of Research and Publication
  - Articles published in 2018 or later

DL Models

Based on the above observations, this paper shall study the techniques and infrastructure used in 22 of 25 cited references where real-time cancer detection was possible. DL includes techniques like CNNs, Long Short Term Memory Networks (LSTMs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), Radial Basis Function Networks (RBFNs), Self-Organizing Maps (SOMs) and Deep Belief Networks (DBNs) and their use based on[3] is comprehensively given in Table 1. Table 2 summarizes the CNN techniques used for cancer diagnosis with images as input.

Imaging Modalities in Cancer Diagnosis

Radiological imaging is one of the most often utilized image modalities for cancer diagnosis. As per,[35] in cancer disease, when the tumor is apparent in radiological imaging, a body tissue of 1 cm^3 in size will include approximately 1 billion cancer cells. Detection at this point would be too late because phenotypic alterations might already be underway. Early molecular cancer identification is crucial for effective treatment.[36] This is where molecular-level nuclear imaging is superior. To perform early diagnosis, ascertain the stage of the disease, comprehend fundamental pathological processes, predict the course of the disease, and administer customized medication, nuclear imaging takes non-invasive photographs of the pathophysiologic state and provides information on specific molecular changes. In Table 3, Imaging modalities for different types of cancer are highlighted based on[37–42] and.[42–48]

Table 1 Suitability of DL Techniques for Cancer Detection

Technique	Suitable for Cancer Detection using Images?	Real-Time?
LSTM	No. Image data input not suitable	Yes
CNN	Yes, especially with images	Yes
SOM	No. Clusters of nodes are used but individual nodes use CNN	Yes
DBN	No. Ideal for image generation only	Yes

Table 2 Convolution Neural Network Models for Cancer Detection

Organ(s) Targeted	Underlying Technique	Remarks	Real-Time?	Accuracy	Reference
Barrett's Esophagus	CNN	Camera inside Esophagus, Global prediction (classification), Dense prediction for segmentation	Possible	89.9% Classified as EAC if prediction > 90%	[6]
Pancreas	Invasive Exome Analysis	PancSeq protocol: (Invasive), DNA Sequencing, Exome Analysis, Mutational Signature Analysis of WES data, RNA sequencing. Mutation calling uses the MuTect algorithm	Not possible. Real-time DNA Sequencing and exome analysis are possible. However, in the biopsy, some pieces of tissues may need processing of 29–39 days.	>90%	[7]
Colon:	CNN	CNN based on SegNet Colonoscopy sequentially warped into a binary image 1: Polyp 0: No polyp	Possible	Sensitivity 94.38% Specificity 95.92%	[8]
Prostate gland	Shear Wave Elastography	Ultrasound, Vibration elastography, Acoustic radiation force, Shear wave elastography	Possible	Sensitivity varies from 65 to 85% Specificity varies from 33 to 82%	[9]
Colon:	CNN	AI-doscopist The exact source code requires a license to use. Regression-based CNN structure, ResNet50, YOLOv2	Possible Results are generated on-site, instead of the patient having to wait 2 weeks.	Polyp-based Sensitivity: 96.875% Specificity: 92.9%	[10]
Oesophagus	CNN	CAD systems CNN for classification; results on the heat map. Yellow -> high probability of cancerous lesion, blue -> non-cancerous lesion	Possible	Image datasets – 98.04% sensitivity, 95.03% specificity	[11]
Liver	CNN	Image Fusion Techniques DL models include CNN, Convolutional Sparse Representations, Stack Autoencoders, Image Fusion Indicators Data shortage could be a problem. A proposed solution is to augment the data using techniques like GAN	Possible	US Modal + CT/MRI: 98.7% (only 1.3% of inconspicuous lesions). Combining PET and MRI can boost liver cancer diagnosis rates from 94.4% to 100%	[12]

(*Continued*)

Table 2 (Continued).

Organ(s) Targeted	Underlying Technique	Remarks	Real-Time?	Accuracy	Reference
Barrett's oesophagus	CNN	CNN model using feature extraction and classification, YOLOv2 dataset used	Possible	Dysplasia detection: 95.414% accuracy (437 of 458 true predictions from given confusion matrix)	[13]
Upper gastrointestinal tract	CNN	Reduction of blind spot rate during EGD in the diagnosis of upper gastrointestinal lesions. Image categorization was the primary technique.	Possible	In actual EGD videos, WISENSE accurately detected blind areas with a 90.4% accuracy rate.	[14]
Thyroid	Ultrasound + Shear Wave Elastography	96 individuals with 97 thyroid nodules who had pathology results underwent conventional B-mode ultrasonography, 2D SWE, and 3D SWE.	Possible	With a sensitivity of 0.881, NPV of 0.788, an accuracy of 0.804 (80.4%), and Youden's index of 0.57, B-mode ultrasound plus 2D SWE produced the best results.	[15]
Gastrointestinal Tract	CNN	On the Kvasir dataset, benchmark CNN models including GoogleNet, ResNet50, and AlexNet were pre-trained.	Possible	AUC was 99.98%, sensitivity was 96.8%, specificity was 99.20, and accuracy was 97% for AlexNet.	[16]
Colon	CNN	Mask-RCNN with ResNet50 and ResNet101 backbones,	Possible	Segmentation results of 66.07% IOU on the ETIS-LARIB dataset, 69.04% IOU on the CVC-Colon dataset	[17,18]
Prostate Gland	RTSE + CETRUS	CETRUS (Ultrasound), Real-Time Strain Elastography	Possible	Sensitivity: 92.1% Accuracy: 86.2% Negative Predictive Value: 84.6%	[19]
Gastrointestinal Tract	CNN	Five CNN models were trained: VGG, ResNet, MobileNet, Inception-v3, and Xception. Training on Google Colab; Keras was used for neural networks	Possible	Accuracies are as follows: VGG: 98.3% ResNet: 92.3% MobileNet: 97.6% Inception-v3: 90% Xception: 98.2%	[20]
Lower Gastrointestinal Tract	FFNN	FFNN is based on hybrid features of GoogleNet, LBP, GLCM, and FCH	Possible	Accuracy: 99.3% Precision: 99.2% Sensitivity: 99% Specificity: 100% AUC: 99.87%	[21]

(*Continued*)

Table 2 (Continued).

Organ(s) Targeted	Underlying Technique	Remarks	Real-Time?	Accuracy	Reference
Gastrointestinal Tract	CNN	Training using the VGG-19 CNN dataset, Logistic Regression and Ensemble of extracted features were best for validation.	Possible	83% accuracy, F1 score of 0.821	[22]
Gastrointestinal Tract	CNN	VGG-16, ResNet-18, and DenseNet-201 combined for an ensemble of deep features as a singular feature vector, Feature extraction based on SVD for optimization	Possible	Accuracy: 97%	[23]
Breast	MRI/ Ultrasound CNN + Augmented reality + optical 3D sensor	MRI for detecting the lesion and creating a tumor model, Optotrak system for 3D location of the lesion	Possible	The error values of the three-dimensional views were 0.75, 0.99, and 0.80 respectively	[24]
Breast	CNN	The model were created by fusing the Tensorflow and Keras Python libraries, and the Curated Breast Imaging Subset of the DDSM Digital Database for Screening Mammography (CBISDDSM) was used in this work	Possible	The final models, "model 1" and "model 2", respectively, attained AUCs of 0.785 and 0.774.	[25]
Knee	CNN	MRI of the knee 3D deep neural network model for ACL injuries.	Possible	ROC-AUC values of 0.983 0.006, and 0.983 are obtained with standard knee dataset	[26]
Lung	CNN	Two CNN architectures are used for testing. Named VGG and ResNet. More precisely VGG16 and ResNet50. And is trained on Automatic Cancer Detection and Classification in Whole slide Lung Histopathology (ACDC@LUNGHP) dataset.	Possible	ResNet has higher accuracy when the ImageNet dataset is used (75.2% vs 70.5% for Top-1 accuracy and 93% vs 91.2% for Top-5 accuracy). Results showed that CNN can be used for lung cancer detection but efforts are required to increase classification accuracy.	[27]

(*Continued*)

Table 2 (Continued).

Organ(s) Targeted	Underlying Technique	Remarks	Real-Time?	Accuracy	Reference
Skin	CNN	Human Against Machine (HAM) 10000 dataset is used for the classification of skin cancer. VGG16, VGG19, and a Deep CNN model are implemented, trained, and evaluated.	Possible	The DCNN has given superior results compared to VGG16 and VGG19. Having training accuracy of 99 (VGG16: 98 and VGG19: 96), testing accuracy of 99 (VGG16: 96 and VGG19: 94), training loss of 0.03 (VGG16: 0.12 and VGG19: 0.19) and testing loss of 0.02 (VGG16: 0.16 and VGG19: 0.20).	[28]
Skin	CNN	Human Against Machine with 10000 training images (HAM1000) dataset is used. Different CNN architectures along with a few standard ways for comparison are used.	Possible	Better results were obtained using CNN trained and testing accuracy was 83.11% with precision 0.81 and recall 0.80. Fscore obtained was 0.82.	[29,30]
Breast	ROI-based DL for CAD and multi-fractal dimension, feature fusion	Applying ROI-based DL on digital mammogram images to extract relevant features	Possible	The area under the curve will be a problematic issue in diagnosis. But with multi-fractal dimension approach and feature fusion, this can be handled better.	[31,32]
Breast	Transfer Learning	Modified Xception Model helps achieve better results	Possible	Accuracy: 99% Precision: 99.003% Recall: 98.995% Sensitivity: 98.55% Specificity: 99.14%	[33,34]

Table 3 Various Image Modalities and Cancer Affected Organs

Cancer affected organs	Suitability of Image Modality
Breast	***Popular Image Modalities***: Digital Breast Tomosynthesis (DBT); Mammography (MMG); MRI; Dedicated CT; positron emission mammography; Dynamic contrast-enhanced MRI; ultrasound imaging; ***Suitability:*** MMG has the highest accuracy of 87.3%
Ophthalmology	***Popular Image Modalities***: Optical coherence tomography (OCT); Retinal Fundus Photographs (RFP) ***Suitability***: RFP has the best accuracy of nearly 100%

(*Continued*)

Table 3 (Continued).

Cancer affected organs	Suitability of Image Modality
Respiratory	***Popular Image Modalities***: CT scans, chest X-rays (CXR) ***Suitability***: CT has the highest accuracy of 88.7%
Ovary	**Popular Image Modalities**: Optical Imaging; CT; MRI **Suitability**: Optical has the highest accuracy of 86%
Leukemia	**Popular Image Modalities**: Fluorodeoxyglucose with Positron Emission Tomography (FDG-PET); MRI; Positron emission tomography-computed tomography (PET-CT) Scans; Ultrasound Imaging **Suitability**: Even though it is extremely difficult to detect leukemia, MRI is the most suitable
GI tract	**Popular Image Modalities**: Ultrasound (US); CT; MRI Imaging; PET **Suitability**: FDG Pet with 90% accuracy
Gliomas	**Popular Image Modalities**: Computed Tomography, MRI, Hyperstereoscopy Image, MR Spectroscopy **Suitability**: 98% accuracy for classification is achieved using MR images

Image Pre-Processing

Images can be gathered after an imaging modality is selected for a specific disease type. It might be impossible to extract the information required for medical analytics for illness diagnosis from the image data in its raw format. Pre-processing for the photos must be done in stages. Image pre-processing methods for cancer illness identification are highlighted in this subsection. Pre-processing includes a five-step procedure: background removal, identification of the bounding box, enlarging the bounding box, normalizing image intensity, and image resizing. Table 4 shows the pre-processing techniques used for various types of cancer.[49–55]

Immunotherapy and DL Models

The field of immunotherapy is becoming more and more popular for treating cancer. There are numerous immunotherapy strategies available,[56,57] and it is necessary to determine which therapy is best for each individual patient. For accurate therapy, these identifications should also be made in real-time with diagnostics. DL methods like those in[58,59] are applied to increase the precision. The use of ML and DL methods as an immunotherapy modality is covered in full in.[59]

Challenges

With the prevalent use of image processing for medical diagnosis, the following challenges are encountered for real-time use.

- To ensure that image processing aids in real-time medical diagnosis, scalable algorithms and cutting-edge parallelization approaches must be created. With the development of scalable algorithms and more advanced parallelization approaches in recent years, a sustainable ecosystem for image-based medical diagnostics is still required. Every tool and method for accessing everywhere should be present in this ecosystem. This might be disseminated in a cloud setting.

Table 4 Pre-Processing Techniques for Various Types of Cancer

Cancer Type	Image Pre-Processing Techniques used
Breast Cancer	Mean filter or average filter; Median filter, Wiener filter; Adaptive median filter. The adaptive Median Filter is the one that provides the best accuracy. • Maximum accuracy with Pre-processing: 95.42% • Maximum accuracy with Pre-processing: 98.34%
Lung Cancer	Enhancement; Noise/background removal; contrast optimization • Maximum accuracy with Pre-processing: 92% • Maximum accuracy with Pre-processing: 86%
Skin Cancer	CHC-Otsu algorithm; Otsu Thresholding. In addition to showing improvement in accuracy, these techniques also reduced the execution time. • Maximum accuracy with Pre-processing: 93.3% • Maximum accuracy with Pre-processing: 92.1%
GI Tract Cancer	Augmentation approaches; Gaussian noise; salt and pepper noise; Poisson noise removal • Maximum accuracy with Pre-processing: 93.3% • Maximum accuracy with Pre-processing: 92.1%
Gliomas	The maximum accuracy achieved for detecting cancerous brain tumors is 98%.

• Real-time image processing for medical diagnostics requires a High-Performance Computing (HPC) environment like a GPU, TPU, or FPGA. Additionally, a computerized process and analog microscopes for examination necessitate significant infrastructure investments. Global attention must be paid to the availability of this infrastructure in rural areas, emerging countries, and underdeveloped countries for these technologies to be used worldwide. Rural places with limited equipment and experience, particularly those with imbalanced medical expertise, will profit from these developments.

• Due to network capacity limitations, transmitting breast cancer pathology images will be complex. Moreover, there is no guarantee that highly qualified cancer specialists at big city hospitals will always be accessible for online diagnosis. Making an automated version that is on par with human expertise in making informed decisions is necessary.

• Even though the cloud environment is faster, edge devices in the health care centers could become a bottleneck. Edge devices must have faster processing power. When possible, computations should be performed entirely on edge devices, with the least amount of data being uploaded or downloaded to or from the cloud.

Discussions

This section highlights the essential findings in the current work made during the literature survey to provide a real-time medical diagnosis of diseases like cancer.

Computer-assisted diagnosis (CAD) is used to help diagnose early esophageal squamous cell carcinomas (ESCCs) and precancerous lesions in real-time are done in.[12,60–73] It is crucial to find cancer early. However, endoscopic examination quality control and the general need for skilled endoscopists are significant issues on a global scale. For automating to enable a CAD system to function as “a second observer” during an endoscopic examination and help non-experts diagnose cancer and reduce missed diagnoses, high-performance DL models are required. In theory, there are proofs for high-performance deep-learning models that can detect cancer in an automated manner. In the real-time diagnosis of cancer and spinal illnesses, execution speed is just as crucial as accuracy. In,[74] Rapid findings are available from the IdyllaTM EGFR Mutation Test three hours after the request. This study sought to evaluate the results of the IdyllaTM EGFR Mutation Test in comparison to those from the most recent standardized testing.

Possibility of Real-Time Analysis and Detection

Millions of AI/DL models for cancer and spinal illness detection were never used in clinical settings.[75–83] This is due to several factors. One is that, until recently, there needed to be more relevant regulatory agency instruction regarding the procedures required for regulatory approval. This has recently begun to alter. One significant and occasionally under-appreciated impediment to the application of AI in healthcare settings is the unavailability of user-friendly software. With many advancements in DL models for exascale computing in the cloud, it becomes a reality to have real-time medical diagnostics in remote and rural areas in the absence of experts and costly equipment.

The first step in applying DL in clinical practice is digitization. While pathology has been reluctant to adopt digitization, radiography has already undergone this change. Since more than 20 years ago, there have been tools for digitizing pathology samples, but advancements have needed to be faster. The speed of digital images has significantly increased recently, and cloud storage is now widely available. An additional innovation is required to make this technology more user-friendly, affordable, and accessible in environments with limited resources.

One of the main problems in medicine is communication. Pathologists currently dictate reports entered into electronic health records and distributed to clinicians. "How AI will function in this communication system" is unclear. Furthermore, it is unclear how the doctor would receive the AI reports and what they will contain. Finally, it is unclear how the clinician will apply this knowledge to the patient's clinical management. DL experts will need to address some of these problems collaboratively with pathologists and physicians.

Accuracy of Models in Real-Time

When data to train AI models is more easily accessible, one imagines that DL models predicting response to medicines will develop and perform well enough to be integrated into clinical. In the long run, DL models may be used to create precise medication based on the distinct profiles of each patient. DL models can be used to find individualized strategies for lowering risky behaviors (such as smoking and binge eating) that increase a person's likelihood of acquiring cancer. DL models, which will soon be a standard toolset for comprehending extensive experimental results, can be used to understand gene expression and genetic programs in cancer diagnosis and treatment. With high accuracy, it can be used to model the response to cancer treatment and create therapeutics. Large datasets and DL models will increase our understanding of cancer biology and cancer immunology, which will ultimately help us identify the pattern and correlation of different features in images for cancer diagnosis.

Clinical Trials, DL, and Roadblocks for Computer-Aided Cancer Diagnosis

DL in cancer diagnosis aspires to eventually automate an activity currently performed by humans with improved speed or accuracy. A comparison is needed between human decisions or another "ground truth" set of diagnoses or classifications to determine the effectiveness of a DL model. This section explains the current literature analysis for any work on the clinical usage of a deep-learning cancer diagnosis. A supervised mode of DL is used in all the clinical applications discussed here. In,[84] Coudray et al developed a model to detect lung cancer with an accuracy of 97%. Here the model was tested in a clinical workflow with tile-based slide images. When the same model was used for the whole slide image, the accuracy dropped to 83%. In,[85] local gene expression was done using histopathology images from 23 breast cancer patients. ST-Net was used to do the modeling and achieved better accuracy. In[86] and,[87] DL based model for treating gut cancer was proposed and analyzed for its clinical efficiency. In,[66] intraoperative cancer diagnosis based on a DL model is proposed with an accuracy of 94.6%. Many CNN models are increasingly being used in clinical trials for aiding cancer diagnosis using medical image diagnostics. Even though complete automation of cancer diagnosis using DL in the clinical workflow is not possible currently, many clinical trials use DL capabilities to understand the statistics better and make better decisions.

Explainable DL: Road Ahead for DL in Clinical Cancer Diagnosis

Studying the biological patterns or processes revealed by DL could increase our knowledge and contribute to the medical community's trust in such systems. DL clinical applications currently suffer from scalability and customizability difficulties. Explainable DL models[88–91] can ensure doctors that the DL system is performing as expected. To comply with health regulatory norms, this is necessary. Patients may also utilize it to understand how their diagnosis and treatment are being carried out and if they feel the need to contest the results. The clinical study in[92] explains that using an explainable DL model in lung cancer diagnosis achieved more than 98% accuracy. A detailed review of explainable DL for medical diagnosis is done in.[93] In,[94,95] comprehensive frameworks for cancer diagnosis using pre-trained CNN models are proposed. These models have better computationally cost and accuracy.

Regulatory-Approved DL for Clinical Cancer Diagnosis

The discipline of radiology is a trailblazer for regulatory-approved devices/techniques available in the market. This is likely because DL technology intensely loves imaging, and radiology is an image-intensive field. Regulatory-approved devices are increasingly available, with many developed countries adopting Software as a Medical Device (SaMD). As explained in this paper, autonomous cancer diagnostics is possible through imaging techniques, and many of these devices are already regulatory-approved. ML/DL-based SaMD are strongly tied to each nation's industrial and cultural histories; a development concentrated on each nation's advantages can result in increased global competitiveness. Additionally, considering each nation's advantages and building a framework for more operational improvements are necessary to maximize DL's healthcare possibilities.

Future Directions

The automated real-time diagnosis of medical conditions will increase by deploying new DL techniques across scientific research, inquiry, and healthcare support. The data and computational resources available will determine the growth rate and application scope. Further, DL-driven efforts will be made in these areas, for example, to guide and plan the use of radiation and systemic therapy and to forecast cancer patients' reactions using multimodal data dynamically. The hope and enthusiasm around AI will continue to be fueled by such initiatives. However, clinical translation will not advance until a rigorous statistical foundation, regulatory infrastructure, and standards for benchmarking to ensure quality control and validation. The first will be DL tools that focus on workflow efficiencies.

Conclusions

The main objective of this systematic review was "Can DL models automate medical diagnosis (particularly for cancer illnesses) in real-time?" It was found that automated cancer diagnosis is only possible with a high-performance DL model, high-performance infrastructure, and sophisticated governance mechanism.[96] The literature was examined to find DL models that can conduct precise medical diagnoses utilizing photos without a specialist's assistance. High-performance DL models with this kind of potential have been found.[97,98] The next step is to confirm that these models can be used in a way that allows for real-time outcomes. These kinds of high-performance DL models have been discovered. The next stage is to verify that these models can be applied in a fashion that allows for real-time results. Real-time results depend on the model's efficiency and the availability of high-performance infrastructure. The high-performance infrastructure includes

- advanced input devices (AR/VR-based radiography instruments),
- high-performance processing units (GPU, TPU, and FPGA), and
- a high-speed communication medium with incredibly swift edge devices.

Even though such high-performance infrastructure is only accessible in far-off places, it is via widespread use that a sustainable digital healthcare system will be created. A sophisticated governance framework, protocols for utilizing high-performance DL models and high-performance infrastructure must all be designed. This last criterion is still a work in progress. Society can only have a fully automated, real-time-delivering DL model if all three conditions are met.

For DL to be practically used in cancer diagnosis, the biological relevance of explainability must be thoroughly studied. Explainability will help receive regulatory approval and make DL a diagnostic tool. Medical imaging comprises cross-validating clinically significant regions discovered by DL against pathology analysis. The best guess method of DL will not be sufficient for clinical usage in diagnosing cancer. Probabilistic DL to quantify prediction uncertainty will be crucial in aiding DL to be a better diagnostic tool.

Disclosure

The authors declare no conflicts of interest in this work.

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