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Unveiling the Complexity of Medical Imaging through Deep Learning Approaches

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ABSTRACT Recent advancements in deep learning, particularly convolutional networks, have rapidly become the preferred methodology for analyzing medical images, facilitating tasks like disease segmentation, classification, and pattern quantification. Central to these advancements is the capacity to leverage hierarchical feature representations acquired solely from data. This comprehensive review meticulously examines a variety of deep learning techniques applied across diverse healthcare domains, delving into the intricate realm of medical imaging to unveil concealed patterns through strategic deep learning methodologies. Encompassing a range of diseases, including Alzheimer's, breast cancer, brain tumors, glaucoma, heart murmurs, retinal microaneurysms, colorectal liver metastases, and more, the analysis emphasizes contributions succinctly summarized in a tabular form.The table provides an overview of various deep learning approaches applied to different diseases, incorporating methodologies, datasets, and outcomes for each condition.Notably, performance metrics such as accuracy, specificity, sensitivity, and other crucial measures underscore the achieved results. Specifically, an in-depth discussion is conducted on the Convolutional Neural Network (CNN) owing to its widespread adoption as a paramount tool in computer vision tasks. Moreover, an exhaustive exploration encompasses deep learning classification approaches, procedural aspects of medical image processing, as well as a thorough examination of key features and characteristics. At the end, we delve into a range of research challenges and put forth potential avenues for future improvements in the field.

KEYWORDS
Deep learning
Complexity
CNN
Medical image analysis
Pattern recognition
Segmentation

INTRODUCTION

Deep learning (DL) stands as an advanced form of machine learning (ML), centred on the utilization of artificial neural networks (ANNs) for the analysis and prediction of data.The inception of deep learning dates back to 1943, when Warren McCulloch and Walter Pitts formulated a computational framework inspired by the neural networks within the human brain (Wang and Raj 2017). These DL models draw inspiration from the intricate communication observed among biological neurons within the brain, serving as a structural framework to understand information. Furthermore, similar to their biological counterparts, DL models comprise multiple layers of artificial neurons,including an initial input layer, a conclusive output layer, and a varying number of intermediate processing layers positioned between them.These intermediary layers, collectively referred to as hidden layers,play a pivotal role in extracting crucial features from the input images and recognizing intricate patterns.In each layer, artificial neurons activate upon receiving impulses from neighboring neurons in subsequent layers,leveraging multiple processing levels within the deep architecture (LeCun *et al.* 2015).In essence, each layer within a deep architecture holds a specific algorithm that employs a designated activation function.The amalgamation of these algorithms constructs complex and generalized machines, endowed with remarkable capabilities to address a diverse range of medical image-related challenges (Saba *et al.* 2020).

Over the past few decades,DL has risen to prominence as an incredibly powerful technology.This is primarily due to its remarkable ability to handle and make sense of enormous amounts of data (Islam and Zhang 2018).These algorithms have demonstrated superior capabilities in learning and categorizing

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across various domains.For instance, they excel in transfer learning, where insights gained from one task are applied to solve another (Tan *et al.* 2018). They've also been instrumental in speech recognition,enabling computers to understand and interpret human speech effectively Chen and Mak (2015).In the domain of recognizing handwritten digits, these models play a pivotal role in identifying characters and symbols accurately (Alwzwazy *et al.* 2016).Furthermore, DL has made significant strides in disease detection, contributing to the early and precise identification of various medical conditions Pereira *et al.* (2016). It has also been instrumental in disease segmentation, allowing for the precise delineation of affected areas within medical images (Trajanovski *et al.* 2020). The field of computational medicine (see Figure 1) has also benefited greatly from DL's capabilities (Islam and Zhang 2018). Consequently,deep learning has become a revolutionary technology that has the ability to completely revolutionise a wide range of industries. Its exceptional ability to process information and undertake intricate tasks with unparalleled proficiency marks it as a technology with immense possibilities for reshaping diverse industries.

In the field of diagnosing medical conditions using historical radiological screening methods,the process is time-intensive, subjecting patients to prolonged waiting times spanning from hours to weeks for test outcomes.Moreover,discrepancies in outcomes among labs may arise due to reliance on individual proficiencies. To address these issues, the medical field has turned to the application of deep learning algorithms. These algorithms have been leveraged to diagnose diverse conditions, including cancer(Albarqouni *et al.* 2016), tongue tumor(Trajanovski *et al.* 2020), Alzheimer's disease(Islam and Zhang 2018), glaucoma(Yang *et al.* 2021),brain tumor(Pereira *et al.* 2016; Muhammad *et al.* 2020; Dong *et al.* 2017; Abiwinanda *et al.* 2019; Rasool and Bhat 2023), and other life-threatening diseases with increased accuracy and speed. These models highlight irregularities in medical imagery, which primarily include X-rays, MRI scans, CT scans, and similar types of medical images (Arif *et al.* 2022; Meena and Roy 2022; Albarqouni *et al.* 2016). Furthermore, these sophisticated algorithms have proven to be immensely valuable in expediting the assessment of medical images and mitigating the time-consuming nature of conventional scans. They excel in precision, as they adeptly extract intricate features from medical images (Pereira *et al.* 2016). This capability enables them to undertake a variety of tasks, including medical image classification (see Figure 6), object detection, pattern recognition, and various other tasks within computer vision. Table 1 highlights the key features, merits and demerits of different deep learning architectures. Meanwhile, in Table 2, the proficient effectiveness of deep learning across various healthcare tasks is highlighted.

This paper examines a broad range of diseases and presents a comprehensive analysis of the methodologies employed,using deep learning in the field of healthcare. The primary focus of this analysis centers on the tasks of disease detection, segmentation, and classification.Encompassing a wide spectrum of health-related ailments, this comprehensive review delves deeply into the substantial advancements achieved, with special attention given to convolutional neural networks (CNNs) in the context of medical imaging. The findings of this research underscore the transformative potential of deep learning within the healthcare sector. One of the most notable impacts is observed in the enhancement of diagnostic capabilities and the interpretation of medical data. The paper effectively demonstrates how deep learning techniques have the capacity to revolutionize healthcare practices, particularly by improving the accuracy and efficacy of disease detection and diagnosis processes.

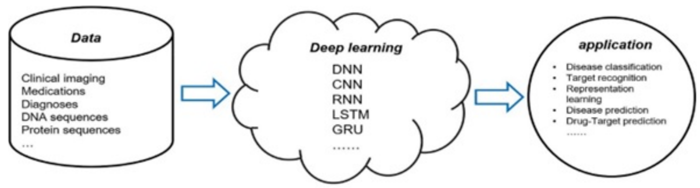

Figure 1 Deep learning applications in computational medicine (Yang *et al.* 2021)

CONVOLUTIONAL NEURAL NETWORK

Deep architectural models encompass various neural networks, with one prominent example being the feed-forward artificial neural network known as the Convolutional Neural Network(CNN).The CNN comprises an input layer, an output layer, and numerous hidden layers, making it a highly acclaimed and potent algorithm within the domain of computer vision.Among the diverse range of deep learning algorithms, the CNN stands out. In the subsequent discussion,the functions and significance of each layer within the CNN framework will be thoroughly elucidated.

Convolution Layer

The Convolutional Neural Network (CNN) serves as the central neural network architecture in the field of Deep Learning,specifically designed for computer vision tasks. This network stands out for its exclusive use of convolutional layers, each comprised of multiple filters with arbitrary weights. These layers extract information and discern patterns from input data via convolutional operations.The core principle of convolutional operations involves the meticulous computation of dot products between the filters and discrete regions of input images,which are referred to as "receptive fields". The filters systematically traverse the input images,scanning from the rightmost edge to the left and descending from the topmost to the bottom. This meticulously orchestrated process yields intricate feature maps while simultaneously reducing the complexity of the network through a process of weight diminishment. This weight reduction proves particularly advantageous during training, as it aids in effectively training the network even when working with limited datasets. For better understanding, the visual depiction of the convolution operation is shown in Figure 2.

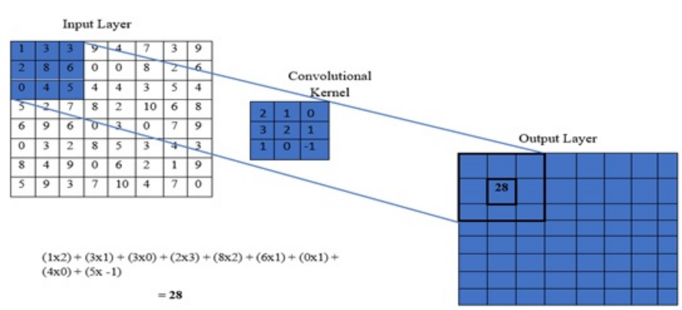

Figure 2 Convolution Operation

Weight Sharing

Within convolutional neural networks (CNNs), weights are not allocated to individual pairs of neurons in adjacent layers.Instead, each weight operates across the entirety of the input array, spanning every pixel. This obviates the need for procuring supplementary weights for every neuron, resulting in a substantial reduction in both training time and associated expenses. The acquisition of a singular set of weights for all inputs streamlines the training process, yielding significant efficiency gains.

Sparse Connectivity

The sparse connectivity nature of CNNs leads to each neuron having a restricted number of connections to other neurons.As a result, the abundance of weights and connections required in a fully-connected layer characterized by dense connectivity (as depicted in Figure 4) is noticeably reduced as illustrated in Figure 3. Storing these weights in memory does not consume a substantial amount of space due to this configuration.This specific characteristic makes the approach highly memory efficient.

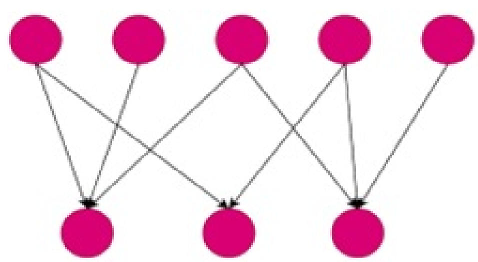

Figure 3 Sparse Connectivity

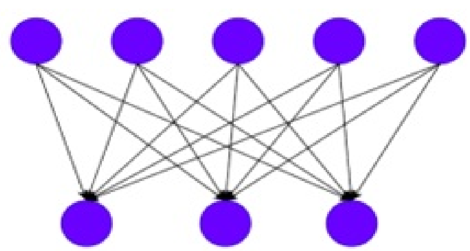

Figure 4 Dense Connectivity

Pooling Operation

Pooling layers receive convoluted feature maps as input,typically positioned between convolutional layers within a neural network architecture. This pivotal layer functions by combining neuron clusters from the preceding layer with those of the subsequent layer. This process enables the selective extraction of crucial information from input images, while concurrently discarding extraneous or irrelevant features. A range of pooling techniques exists, encompassing global average pooling (GAP), global maximum pooling, minimum pooling, maximum pooling, and average pooling (Alzubaidi *et al.* 2021). Among these varied techniques, the preeminent and widely adopted techniques include maximum pooling, minimum pooling, and Global Average pooling. The illustration of these techniques is visually depicted in Figure 5.

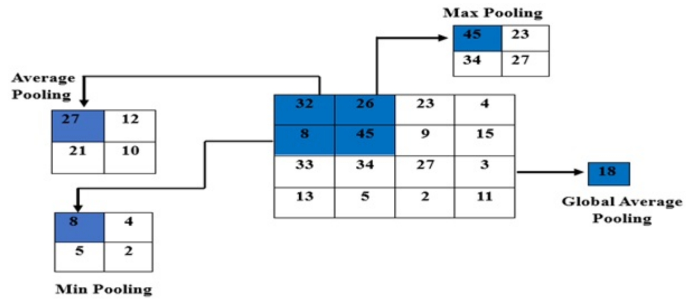

Figure 5 Visual Depiction of Pooling Operations

Fully Connected Layer

After subjecting the input images to a sequence of convolutional and pooling layers, the features extracted as a result then undergo a flattening process.Following this,these features are introduced into the fully connected layer (FCL), which generates probabilities corresponding to each label and thus predicts the final output. The subsequent step involves the utilization of a loss function to compare the outcomes produced by the fully connected layer with the original data (Liu *et al.* 2023). The objective here is to reduce this loss function, thereby enhancing the efficiency of the network. In cases where the actual outcome deviates from the anticipated result, the loss function comes into play, adjusting the elements within the matrix to diminish errors. This iterative process persists until the model's performance reaches a plateau.As the loss function's value decreases, the overall performance of the model improves,and conversely, an increase in the loss value corresponds to a decrease in performance.However, given the substantial number of parameters intrinsic to the fully connected layer, a potential issue of overfitting arises. To counteract this concern, a strategy known as the dropout approach (Albarqouni *et al.* 2016) is usually employed.This approach involves randomly deactivating specific neurons during the training process, effectively preventing intricate co-adaptations of data that could potentially lead to overfitting and thus maintaining the generalization ability of the model.

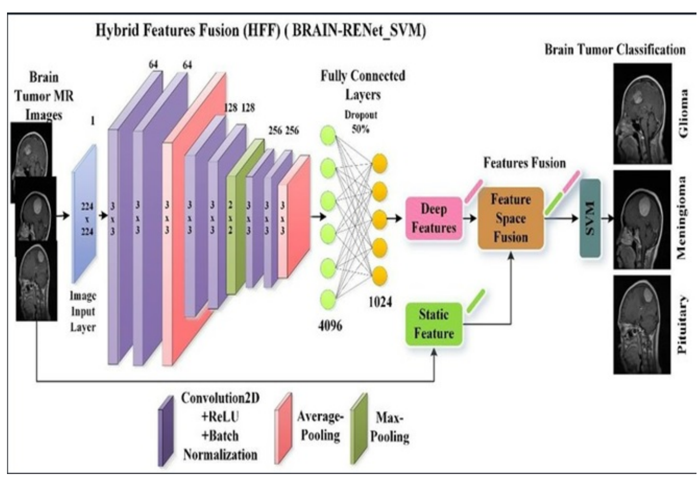

Figure 6 BRAIN-RENet deep CNN for Brain Tumor (Zahoor *et al.* 2022)

CLASSIFICATION OF DEEP LEARNING APPROACHES

The three categories of deep learning techniques are supervised,unsupervised, and semi-supervised.

Supervised Learning

Supervised learning stands as a robust methodology that relies on labeled data to establish a relationship between a set of input variables (denoted as 'x') and their corresponding output variables (denoted as 'y'). This method harnesses the power of this established relationship to predict outcomes for entirely new and unseen data instances. Throughout the process of learning,models are trained to produce the intended outcomes by utilizing a dependable training dataset composed of both input instances and their corresponding outputs (Gulshan *et al.* 2016; Rajpurkar *et al.* 2018). This contributes to the algorithm's long-term development.

To ascertain the efficacy of these trained models, a crutial tool comes into play –the loss function.This function quantifies the disparity between the model's predictions and the actual outputs, providing a metric for the model's performance. The algorithm then undertakes a dynamic self-improvement process, iteratively adjusting its internal parameters until the discrepancy between predictions and actual outcomes is effectively minimized.This iterative refinement process captures the essence of supervised learning, results in models that possess the capability to generate predictions of remarkably high accuracy.

When working with image data, deep learning employs supervised learning techniques such as convolutional neural networks (CNNs)(Pereira *et al.* 2016; Vorontsov *et al.* 2019), artificial neural networks(ANNs), recurrent neural networks (RNNs) (Lipton *et al.* 2015), and deep neural networks (DNNs)(Chen and Mak 2015). In healthcare, supervised learning empowers predictions and diagnoses. Notably in medical imaging, like X-rays, CNNs excel, recognizing patterns and improving diagnostics. This synergy advances healthcare, enhancing precision, prognostics, and patient outcomes.One advantage of deep supervised learning is its ability to produce outputs based on prior knowledge and expertise.However, a drawback of this approach is its heavy reliance on properly labeled data. If the data is not appropriately labeled, the algorithms may fail to generate accurate results. Additionally, training the algorithms with irrelevant input features can lead to inaccurate outcomes.

Unsupervised Learning

This method standardizes the learning procedure by removing the necessity for labels, making it applicable even when labeled data is absent. In this context, the algorithm uncovers essential features necessary for detecting patterns within the input data that were previously unnoticed (Miotto *et al.* 2016). Various sophisticated deep learning techniques, including autoencoders, restricted Boltzmann machines,and Generative Adversarial Networks(GANs),have demonstrated impressive performance in tasks involving nonlinear dimensionality reduction and classification(Esteban *et al.* 2017; Du *et al.* 2017). Furthermore,the utilization of recurrent neural networks in unsupervised learning across diverse applications, incorporating methods like Gated Linear Units and extended shortterm memory networks, has yielded promising results. In the field of healthcare,this strategy holds great potential due to the complexities associated with processing vast medical data.Unsupervised learning, circumventing the need for manual labeling, extracts patterns directly from the data.This aids in diagnosis, trend recognition,and adaptation to evolving medical knowledge, ultimately enhancing patient care. One of the primary advantages of unsupervised learning lies in its ability to efficiently reduce data dimensions without heavy reliance on manual labeling—an often time-consuming and expertise demanding task. Instead, unsupervised learning gleans insights directly from the data and categorizes it without explicit labels.This learning approach progressively improves its results as it computes outcomes, sharing certain resemblances with elements of human intelligence.

Semi-Supervised Learning

Semi-supervised learning occupies a significant position that bridges the gap between supervised and unsupervised learning methodologies. It presents a valuable technique for analyzing datasets that are partially labeled, yet predominantly unlabeled, which finds relevance in the medical domain as well (Liu *et al.* 2020). In the domain of deep learning, the utilization of techniques such as Generative Adversarial Networks (GANs) and Recurrent Neural Networks has proven effective for semi-supervised learning in the medical field as well(Saba *et al.* 2020).Especially within the context of medical applications like DNA segment analysis, where human involvement remains crucial due to the complexity of longer sequences, the development and deployment of semi-supervised approaches have garnered notable attention. A key advantage of this approach lies in its capacity to enhance algorithmic efficiency and generalizability, a boon particularly valuable when working with a limited number of labeled examples alongside a substantial volume of unlabeled data.However, it's worth noting that a potential limitation of this method is the risk of making erroneous decisions if insignificant input features find their way into the training data.

MEDICAL IMAGE PROCESSING STEPS

Pre-Processing

The preprocessing of medical images constitutes a foundational step that plays a crucial role in improving the quality and reliability of diagnostic and analytical procedures.This initial stage involves a series of essential steps aimed at optimizing raw medical image data for subsequent analysis. The process begins with image acquisition, where modalities such as X-rays, MRIs, CT scans, and ultrasounds capture anatomical or physiological information. However, these images often contain noise, artifacts, and inconsistencies.Various preprocessing techniques including noise reduction, image intensity normalization, and artifact removal, are implemented to address challenges related to image quality and variability (Abiwinanda *et al.* 2019). Specifically, intensity normalization is applied to standardize pixel values across images, ensuring uniform measurements and facilitating more reliable analysis in the medical domain.Subsequently, image registration, which is an another preprocessing step, aligns multiple images from different modalities or time points,facilitating accurate comparisons and overlays. This systematic process enhances image quality, ultimately contributing to improved diagnostic accuracy. Consequently, it aids healthcare professionals, researchers, and computer algorithms in conducting more effective analyses.

Segmentation

Image segmentation serves as a pivotal technique used to divide images into distinct regions based on similar characteristics, including grey level, texture, color, luminosity, and contrast Sharma and Aggarwal (2010). In healthcare sector,specifically in medical image segmentation, the goals encompass the analysis of the skeletal system, identification of the region of interest, assessment of tumor growth, and measurement of tissue volume, among other objectives.The field of artificial intelligence (AI) has produced methodologies for automated segmentation, broadly categorized into three primary approaches: supervised, unsupervised, and semi-supervised methodologies.

Classification

For image classification,particularly in the medical domain, CNN-based deep neural networks are commonly utilized. CNNs prove to be effective in extracting features, facilitating the efficient categorization of medical images without the need for intricate and costly feature engineering.In the context of classifying patches depicting lung ailments, a tailored CNN with a shallow ConvLayer was introduced by (Li *et al.* 2014). This approach has demonstrated effectiveness. Additionally, separate studies emphasize the notable improvements in accuracy and sensitivity achieved by employing a CNN-based algorithm on extensive chest X-ray film datasets (Sharma and Aggarwal 2010).

Post-processing

The primary aim of postprocessing in medical imaging is to standardize and enhance the visual representation of images, thereby enabling more accurate diagnostic analysis. Post-processing techniques serve a multitude of purposes, encompassing image enhancement, restoration, analysis, and compression. One such method, Connected-Component Labeling, frequently employed in computer vision, aids in the analysis and segmentation of images by considering pixel interactions. This approach enables the identification of interconnected regions within the image, effectively grouping similar pixels together (Mimboro *et al.* 2021). Consequently, pixels belonging to the same component are linked and display comparable intensity values. This process proves instrumental in eliminating unwanted pixels or noise that may be present in the image due to various factors, including the imaging process itself.

MEDICAL IMAGERY WITH STATE-OF-THE-ART DEEP LEARNING

Medical imagery has undergone a profound transformation through the integration of state-of-the-art deep learning techniques. This convergence has brought about a revolution in diagnostic accuracy and treatment planning by enabling the automated detection of subtle patterns and anomalies within medical images. Utilizing advanced neural networks such as convolutional neural networks (CNNs) and their variants like U-Net, ResNet, and other novel architectures, these technologies excel in identifying intricate details in X-rays, MRIs, CT scans, and more.This fusion of medical expertise and deep learning capabilities stands as a cornerstone in modern healthcare, providing clinicians with powerful tools to make faster and more informed decisions, ultimately leading to improved patient care.

(Ahuja *et al.* 2022) introduced Darknet models for brain tumor classification.The method automates identification,localization, and segmentation of tumor from the TIW-CE MRI dataset. To address overfitting, the training dataset was augmented through geometrical methods and 2-level wavelet decomposition. Darknet models pretrained for brain tumor classification were adopted, along with a 2D superpixel segmentation approach for segmentation. Impressive results were achieved, with training accuracy reaching 0.99 and validation accuracy at 0.98.Notably, the proposed approach demonstrated superior performance compared to state-of-the-art techniques when evaluated on the T1W-CE MRI dataset.

(Sreng *et al.* 2020) introduced an automated two-phase system for glaucoma screening using deep learning.In the initial phase, the authors employed the DeepLabv3+ architecture to accurately segment the optic disc region.Subsequently,they leveraged pretrained deep convolutional neural networks for precise glaucoma classification.The authors meticulously assessed their methodologies using five distinct datasets,encompassing a total of 2787 retinal images.The results of their study showcased that the most effective approach for optic disc segmentation entailed a fusion of the DeepLabv3+ and MobileNet architectures. In terms of glaucoma classification, the combination of techniques outperformed conventional methods across various datasets,including Rim-one, Origa, Drishti-gs1, and Acrima.Impressively, the achieved Area Under Curve (AUC) scores were as follows: 100 percent for rim-one, 0.99 for acrima, 0.91 for drishti-gs1, and 0.92 for origa.The system's performance closely paralleled that of Cuhkmed, the leading team in the refuge challenge, on the refuge dataset. Specifically,they achieved an accuracy of 0.95 percent.

(Zhu *et al.* 2021) introduced a dual-attention multi-instance deep neural network designed for the early detection of Alzheimer's disease and its preliminary stages. This network comprises three key components. Firstly, they employ spatially focused patch-nets with attention to enhance the features of aberrantly altered micro-structures within the cerebral cortex. This enhancement enables the extraction of distinct characteristics within each sMRI patch. To ensure equitable input from all patches and to generate a comprehensive weighted representation of the entire brain structure,they adopt an attention based multi-instance learning pooling technique. Lastly,the authors employ a global classifier endowed with attentional awareness.This classifier is tasked with learning additional pivotal features and categorizing data related to Alzheimer's disease. The proposed model's efficacy is evaluated using initial sMRI images obtained from 1689 individuals in two distinct datasets. The experimental outcomes underscore the superiority of their approach compared to other state-of-the-art techniques. Their method excels in accurately identifying specific affected areas and achieving improved classification performance. This is characterized by better generalizability and overall accuracy.

(Saba *et al.* 2020) proposed a new approach for identifying tumors utilized the grab-cut method to accurately distinguish the symptoms of real lesions. Deep learning and manually created features were retrieved from the segmented images and subsequently optimized using entropy. A serial fusion approach was employed to combine the optimized features into a unified feature vector, enabling the identification of gliomas or normal images.To assess the efficiency of the suggested approach, specific benchmark datasets from 2015 to 2017 were employed. Ultimately, various classifiers were applied to ascertain whether the images were indicative of normalcy or disease. Notably, the proposed method yielded the most favorable testing outcomes on the BRATS 2015 dataset, achieving a Dice Similarity Coefficient(DSC) of 0.9636 and an accuracy of 0.9878.

(Feng *et al.* 2019) introduced an innovative deep learning architecture, aimed at detecting Alzheimer's disease. The proposed methodology amalgamated a fully layered bidirectional long short-term memory (FSBi-LSTM) with a three-dimensional Convolutional Neural Network(3D CNN). Initially, the researchers extracted prominent characteristics from MRI and PET scan images.To augment the model's performance, they employed the FSBi-LSTM technique to process latent information extracted from the deeper feature maps. To substantiate their approach, they conducted experiments employing data from the Alzheimer's Disease Brain Imaging Initiative dataset. The findings exhibited mean accuracies of 0.86, 0.94, and 0.65 for discerning progressive mild cognitive impairment from normal control, distinguishing Alzheimer's disease from normal control, and identifying stable mild cognitive impairment from normal control, respectively.

(Albarqouni *et al.* 2016) introduced AggNet,a sophisticated deep learning system aimed at the identification of mitosis in histology images related to breast cancer. Leveraging advanced deep learning techniques, the researchers devised a strategy for achieving precise labeling by harnessing the power of crowd-sourced mass annotation within the domain of biomedicine.Their innovative approach encompassed the integration of deep learning principles into the very fabric of data collection, constituting an integral facet of the learning process. This unique methodology incorporated an additional layer of crowdsourcing, further enhancing the efficacy of their multiscale Convolutional Neural Network (CNN). To facilitate comprehensive training and robust evaluation, the researchers harnessed the complete AMIDA13 dataset. The outcomes of their investigation yielded invaluable insights into the potency of deep CNN learning when coupled with mass annotations.The study's findings underscored the pivotal role played by data aggregation in the amalgamation process, emphasizing its profound significance in the realm of deep learning for biomedical image analysis.

(Liu *et al.* 2018) suggested a novel deep learning approach for analyzing breast cancer tissue microarrays.Their method aims to predict the H-Score autonomously. To achieve this objective, they leveraged the H-Score dataset for experimentation, drawing inspiration from the H-Score asassessment routinely performed by medical professionals.In the H-Score assessment procedure, various factors such as the total cell count,the quantity of tumor-associated cells, and the categorization of cells based on the intensity of positive marks are evaluated. The authors employed a single fully convolutional network (FCN) to extract nucleus areas from both tumor and healthy tissues. Additionally, they utilized an extra FCN to specifically isolate the nuclei area pertaining to the tumor cells.To further enhance their approach, the authors designed a multi-column convolutional neural network(CNN). This CNN utilizes the outputs from the initial FCNs, as well as the image containing details about stain intensities,as its input. The CNN functions as an advanced decision-making system,directly generating the H-Score for the original tissue microarray image source.

(Lian *et al.* 2018) presented a hierarchical fully convolutional network (H-FCN) aimed at automating the identification of specific local patches and regions within brain structural MRI (sMRI) scans.The primary objective was the identification of Alzheimer's disease. The H-FCN model effectively facilitated the acquisition and fusion of multi-scale feature representations, enabling the construction of hierarchical classification frameworks. To gauge the efficacy of their proposed methodology, comprehensive testing was conducted on a diverse cohort sourced from two distinct datasets: ADNI-1 and ADNI-2. The results underscored the effectiveness of the H-FCN approach,showcasing its proficiency in pinpointing localized degenerative patterns and diagnosing cerebral disorders.

(Wu *et al.* 2019) introduced a novel approach that utilizes deep convolutional neural networks for breast cancer scans classification. The authors employed a patch-level framework with a large capacity, enabling the network to learn from pixel-level labels effectively. Additionally, they incorporated a two-stage design and training process that allowed the network to learn from large breast-level labels, specifically optimized for high-resolution healthcare images in terms of breadth and width. To pretrain the network, they utilized BI-RADS classification screening, a similar task with labels that are more susceptible to noise. Among various options,the authors combined multiple input viewpoints optimally. The training and evaluation of the proposed model involved over 200,000 tests. For model validation, a reader study was conducted, involving fourteen readers who examined 720 diagnostic mammograms. The results demonstrated that, when provided with the same information,the model's reliability was comparable to that of expert radiologists. However, the authors acknowledged the need for additional clinical validation due to the relatively limited test set used in their experiments, despite the encouraging findings.The proposed network achieved successful prediction of breast cancer presence, with an AUC (Area Under the Curve) value of 0.895.

(Liu *et al.* 2021) introduced a novel three-dimensional technique known as the Context-Aware Network (CANet) for segmenting gliomas. Their approach involved a combination of deep supervised learning and graph convolution contexts within a hybrid feature extractor.To enhance the segmentation process by capturing pertinent features, the authors employed simple feature fusion methods, such as element-wise summation, synergizing with conditional random fields. Furthermore,the authors integrated a context-guided attention-CRF's mean-field estimate as a convolutional procedure into the segmentation network, enabling holistic end-to-end training. The effectiveness of their method was assessed using the BRATS 2017-2019 datasets, showcasing CANet's supremacy in various evaluation measures. In their future work, the authors intend to merge the proposed network with new training strategies to further enhance its efficacy.

(Sarraf and Tofighi 2016) introduced a Convolutional Neural Network(CNN) as a technique to differentiate between brain scans of people with Alzheimer's disease and those of healthy individuals. They employed CNN and LeNet-5 models to effectively differentiate functional MRI scans of Alzheimer's patients from those of normal individuals. The study utilized the ADNI dataset for both training and testing, achieving an impressive accuracy of 0.96.This research suggests that the most effective approach for distinguishing patient information from healthy data obtained from fMRI scans involves harnessing the shift and scale invariant characteristics provided by CNNs, in conjunction with deep learning classification.

(Zeineldin *et al.* 2020) introduced the DeepSeg framework, which serves as a completely automated approach designed for the detection and delineation of brain tumors using FLAIR MRI data.The DeepSeg architecture proposed by the authors is modular, emphasizing the connection between encoding and decoding through two interconnected core components.Spatial data retrieval is achieved through the utilization of convolutional neural networks (CNNs) in the encoder part. The decoder component takes the generated semantic map, aggregates it, and produces the full-resolution likelihood map.The authors utilize different CNN architectures, including dense convolutional networks, residual neural networks, and NAS-Net.These architectures are based upon a modified U-Net design. The proposed architectures are

Table 1 Key Features and Characteristics of Deep Learning Models

Model Architecture	Short Description	Key Features
Recurrent Neural Network	• An artificial neural network called a recurrent neural network (RNN) is one type of such network that utilizes sequential input or time series input. • Any length of input may be analyzed by RNN. • Extensively employed in natural language processing and speech recognition.	Merit: An RNN's internal memory allows it to retain previous input. Demerits: Recurrent neural network's computation is slow. It has problems like Vanishing Gradient or Exploding Gradient.
Deep Auto-Encoder	• The essential use of an autoencoder includes illness detection, denoising of images, and compression of images. • It is a method of unsupervised learning. • In an autoencoder neural network, the amount of units in the output layer matches that of the input layer.	Merit: The widely used autoencoder achieves a high success rate in many fields and reduces the complexity of the network by lowering the dataset dimensions. Demerit: Their rate of learning is very sluggish.
Deep Boltzmann Machine	• The deep Boltzmann machine is a powerful and effective computational tool for compressing any distribution. • It is an unsupervised deep learning model. • Each node between levels of the network is connected to every other node.	Merit: Top-down feedback is integrated for strong conclusions on indefinite basics. Demerit: For big datasets, parameter optimization is time-consuming.
Deep Belief Network	• Deep Belief Network (DBN) is particularly strong in its classification. • The same neural network methodology used in DBN can be applied to various applications and data formats. • It supports both unsupervised as well as supervised learning.	Merits: • In addition to voice recognition, Deep Belief Networks can be used for picture recognition, capturing motion data, and more. • They are a computationally effective variant of feedforward neural networks. • Directly increasing the probability of results. Demerits: • To outperform alternative methods, DBN needs a lot of data. • Due to its complex data models, DBN is expensive to train, often requiring multiple machines. • DBN is challenging for people with less experience.

Deep Neural Network	• A Deep Neural Network (DNN) is an artificial neural network that includes additional layers of neurons between its input and output layers. • DNNs are extremely scalable, allowing them to address problems of any scale. • DNNs are frequently employed to extract high-level abstract features because they perform better than conventional models. • They have more than two hidden layers.	Merit: Recognizes appropriate characteristics instantly without human assistance. Demerits: • Computation of DNNs is quite resource-intensive. • Necessitates a lot of memory and processing power. • Enormous amounts of data and training are needed to achieve desired goals.
Generative Adversarial Networks	• The generation network and the discriminator are the two artificial neural networks which make up a Generative Adversarial Network. In which the generator serves as convolutional neural network. while as, discriminator serves as deconvolutional neural network.	Merit GANs can produce synthetic data that matches the distribution of real data. Demerit: To achieve effective results, GANs frequently require plenty of training data.
Convolutional Neural Networks	• Convolutional neural networks are created using the behavior of neurons of the human brain. • Convolutional neural networks are constructed from several building blocks, including layers of convolution, layers of pooling, and fully connected layers.	Merit: Using a backpropagation algorithm, convolutional neural networks are designed to acquire a spatial hierarchy of characteristic patterns automatically and adaptively. Demerits: • The CNN cannot function without a significant quantity of data related to training. • Because of MaxPooling operations, CNNs often run substantially slower.

evaluated using the 2019 BraTS competition dataset for brain tumor segmentation.The obtained segmentation results show Dice and Hausdorff distance values ranging from 0.81 to 0.84 percent and 9.8 to 19.7, respectively.

Costanzo *et al.* (2023) introduced a prompt and precise machine learning technique for microwave-based medical imaging in cancer identification.Authors utilized an innovative architecture that combines U-Net and ResNet-18, leveraging ResNet-18's residual connections and pre-trained weights.This fusion yields highly accurate segmentations at a reduced computational cost. The study employed a dataset of 1500 breast images containing randomly situated tumors. For each proposed network, they generated training and validation samples. The authors conducted comprehensive quantitative assessments using diverse breast models, including instances of abnormal lesions, to validate their machine learning approach's efficacy. To demonstrate the deep neural network-based inversion and segmentation strategy's performance in breast imaging,the authors presented three numerical scenarios. The evaluation metrics encompassed Percentage Reconstruction Relative Error, Root Mean Square Error, and the Coefficient of Determination.The study covered sixty distinct images separate from the training set, considering both noise free images and those with added Gaussian noise. Moreover, the study featured a meticulous comparison of computational costs and image reconstruction precision.The results of numerical tests conducted in both noisy and noise-free environments demonstrated the proposed method's effectiveness in reconstructing the distribution of dielectric properties for breast imaging.Proposed method exhibited exceptional capability in detecting abnormal scatterers, such as tumors.

Tang *et al.* (2020) introduced a new method that utilizes deep learning to examine pre-operative multimodal MRI brain data in individuals with glioblastoma. Their approach focuses on extracting tumor genotype related features and their seamless integration into the prediction of Overall Survival.To evaluate the effectiveness of their approach, the authors utilized a dataset comprising brain MRI scans from 120 glioblastoma patients, along with up to four different genotypic/molecular indicators.When compared to other cutting-edge approaches, suggested method exhibited the highest accuracy in forecasting overall survival.

Awotunde *et al.* (2022) introduced an advanced approach to fuzzy elephant herding optimization (EFEHO). This technique, referred to as EFEHO-OTSU, was specifically developed to enhance OTSU segmentation. Its primary goal was to achieve precise identification of optimal segmentation. Following this, authors implemented a dual-attention multi-instance deep neural network for the purpose of Alzheimer's disease detection,including its early stage characterized as moderate cognitive decline. The evaluation was conducted using the ADNI AIBL datasets, resulting in a remarkable accuracy score of 0.942, the highest among all achieved within the ADNI dataset.

Shubham *et al.* (2023) introduced a deep learning-driven approach to identify glomeruli within pictures of human kidney tissue. The segmentation architecture utilized was U-Net, with EfficientNet B4 serving as the underlying backbone.Training and evaluation utilized the HuBMAP dataset, which comprises eight training sets and five public test sets. The optimization algorithm employed was Adam.The training was conducted over four K-folds, with each fold undergoing a 100 epoch process.Within each epoch,300 iterations were performed, and a batch size of six patches was utilized.The selected loss function was binary cross-entropy. Importantly, the training dataset included eleven newly frozen as well as nine Formalin-fixed Paraffin-Embedded

Table 2 Evaluation of Deep Learning Techniques in Healthcare Applications

Author	Purpose	Approach	Dataset	Results
(Dominguez-Morales *et al.* 2017)	Detection and Classification of Cardiac murmurs	CNN employing Neuromorphic Hearing Sensors	Sonogram Images	Accuracy:0.97, Specificity:0.95, Sensitivity:0.93, PhysioNet score: 0.9416
(Dai *et al.* 2018)	Detection of retinal microaneurysms	Multiple-Sieve CNN	DIARETDB1 Dataset	Precision: 0.99 and Recall: 0.87, Accuracy:0.96, F1 score:0.934
(Fu *et al.* 2018)	Ocular Disc and Cup Segmentation from Fundus Images	Deep learning-based M-Net	ORIGA dataset and Singapore Chinese Eye Study (SCES) dataset	ORIGA Dataset:CDR: 0.80, RDAR: 0.79 SCES Dataset:CDR:0.83, RDAR:0.82
(Ahuja *et al.* 2022)	Brain tumors segmentation and classification	DarkNet-53 models, 2d-superpixel segmentation approachs	TIW-CE MRI Dataset	Accuracy:98.54, Area under curve:0.99, Average Dice Index:0.94±2.6
(Saba *et al.* 2020)	Identify gliomas or normal images	Grab cut method	BRATS 2015,2016,2017 datasets	BRATS2015:0.99(DSC), BRATS2016:1.00(DSC), BRATS2017:0.99(DSC)
(Vorontsov *et al.* 2019)	Colorectal Liver Metastases	Convolutional Network	Training and Validation: LiTS challenge dataset,Testing:26 CT images.	Total per-lesion DSC:0.14-0.68
(Shen *et al.* 2020)	Diagnosis of Breast Cancer	Deep Learning and fuzzy learning	INbreast Dataset, Private Dataset.	Accuracy:0.82. Average Recall:0.78,Average Specificity:0.78, Average Precision:0.84,Average F1-score:0.79
(Pereira *et al.* 2016)	Brain Tumor Segmentation	Convolutional Neural Network	BRATS2013,BRATS2015	BRATS2013:WT:0.88, CT:0.83,ET:0.77, BRATS2015:WT:0.78, CT:0.65, ET:0.75.
(Costanzo *et al.* 2023)	Cancer Detection	UNet and ResNet Models	Breast Imaging Dataset	In noise-free settings, U-Net 1, U-Net 2, and U-Net 3 achieved mean IoU scores of 0.995, 0.996, and 0.994, respectively.
(Chen *et al.* 2021)	Diagnosis of Breast Cancer	3D CNN	Breast-CEUS Dataset	Sensitivity:0.97, Accuracy: 0.86
(Sreng *et al.* 2020)	Identifying glaucoma through optic disc segmentation in retinal images	Combination of DeepLabv3+ and MobileNet for optic disc segmentation and deep CNN for glaucoma classification	ACRIMA, DRISHTI-GS1, RIM-ONE, REFUGE and ORIGA.	Accuracy: 0.99(ACRIMA), 0.86(DRISHTI-GS1),0.95(RIM-ONE),0.97(ORIGA).
(Shubham *et al.* 2023)	Detection of glomeruli within human kidney tissue	UNet for segmentation with EfficientNetB4 as its backbone	HuBMAP Dataset	Accuracy: 0.99, and Dice Coefficient:0.90.

(Bhattacharjee *et al.* 2023)	Segmentation of Pulmonary Nodules	ResiU-Net	Dataset of lung cancer CT scans from National Center for Cancer Diseases (IQ-OTH/NCCD)	F score of 97.44, an intersection over union score of 95.02, a dice score of 94.87, a binary cross-entropy loss of 0.34, along with a combined dice coefficient and binary focal loss of 0.7585.
(Zhao *et al.* 2023)	Segmentation and classification of kidney masses	3D U-Net and ResNet	Utilized an institutional CT image dataset for training and evaluated on the kidney tumor segmentation (KiTS21) Challenge Dataset	Achieved a 0.99 DSC for bilateral kidney boundary segmentation, alongside 0.86 accuracy for <5 mm masses and 0.91 accuracy for 5 mm masses
(Li *et al.* 2023)	Transcranial Brain Hemorrhage Detection	Residual attention U-Net	Employed a simulation approach to construct training datasets, utilized images generated through conventional imaging algorithms as network input.	Employed two synthetic samples: the first showcased enhanced visibility of a 10-mm hemorrhage spot, while the second accurately reconstructed a barely visible 5-mm hemorrhage spot using the trained network.
(Zhu *et al.* 2023)	Predicting the survival time of glioblastoma multiforme patients using non-invasive methods	Modified 3D-UNet	BraTS2018,BraTS2019, BraTS2020	DSC of BraTS2018-0.83(WT),0.75(CT),0.66(ET), BraTS2019-0.79(WT), 0.72(CT),0.75(ET),Brats2020-0.83(WT),0.72(CT),0.69(ET).
(Rajput *et al.* 2023)	Survival prediction for brain tumor patients using interpretable ML	3D-UNet	BraTS2020	Survival Prediction accuracy-0.55, MSE-79826.24, medianSE-14148.89, SpearmanR-0.711

(FFPE) PAS kidney images. These images featured histological stains designed to enhance resolution and precision during model training. The proposed method attained an impressive accuracy level of 0.99, along with a Dice coefficient measuring 0.9060.

Rajput *et al.* (2023) introduced an end-to-end AI approach to forecast survival days (SD) in glioblastoma multiforme(GBM) brain tumor patients. Proposed method employs MRI-derived features and patient data, encompassing shape, location, and radiomics aspects.Feature selection involves recursive elimination, permutation importance, and correlation analysis, revealing 29 key features, notably age, location, and radiomics parameters,influencing SD prognosis. The model's predictions are corroborated through post-hoc interpretability techniques, confirming alignment with established medical knowledge and showcasing a 33 percent SD prediction enhancement over prior methods.

Zhao *et al.* (2023) presented an innovative deep learning method that enables the complete automation of segmenting and categorizing renal masses in CT images. Their method employs a two-step process involving a cascade architecture that combines a 3D U- Net and ResNet. This combination effectively achieves precise segmentation and classification of focal renal lesions. Initially,they employ a 3D U-Net-driven technique to define kidney boundaries within CT images, creating a region of interest for identifying renal masses. Subsequently, an ensemble learning model utilizing the 3D U-Net detects and segments these masses,followed by classification using a ResNet algorithm. The algorithm demonstrated impressive performance with a high Dice similarity coefficient (DSC) for delineating bilateral kidney boundaries and renal masses. The effectiveness of this proposed technique was confirmed through assessment with an independent validation dataset and the Kidney Tumor Segmentation (KiTS21) challenge dataset. The outcomes underscore the method's potential to precisely localize and categorize renal masses.

Bhattacharjee *et al.* (2023) put forward an innovative segmentation framework that refines dual skip connections.The novel framework combines a pre-trained Residual Neural Network(ResNet) 152 with the U-Net architecture, resulting in what they term ResiU-Net. Their research encompassed the comparison of nine different pretrained and fine-tuned encoder backbones. These included ResNet18, ResNet 34, ResNet 50, ResNet 101, ResNet 152, SEResNet18,ResNext 101, SE-ResNet34, and ResNext 50. The findings indicated that the proposed ResiU-Net approach outperformed the alternatives. For Training and evaluation, authors utilized the HuBMAP dataset, which comprises eight training sets and five public test sets. The optimization algorithm employed was Adam. The suggested approach attains a Fscore of 97.44, an intersection over union score of 95.02, a dice score of 94.87 percent, a binary cross-entropy loss of 0.34, and a combined dice coefficient and binary focal loss of 0.7585. The ResiU-Net proposed in this study surpasses existing methods, yielding superior evaluation metrics. The model's training duration was 43 minutes, underscoring its rapid yet precise segmentation capability

Li *et al.* (2023) introduced an innovative deep learning approach designed to detect transcranial brain hemorrhages and address other transcranial brain imaging needs. Proposed methodology employs an attention-guided mechanism to emphasize important features as they pass through skip connections. The researchers conducted two separate ex-vivo experiments using artificially created samples to generate testing data.In the first image, they notably improved image contrast and significantly reduced artifacts, leading to a clear distinction of the hemorrhage spot.Proposed approach also accurately reconstructed the spot's boundaries, size, and shape. In the second sample, a hemorrhage spot with a diameter of 5 millimeters was hardly discernible using the delay-and-sum (DAS) approach. Nevertheless, the proposed method achieved a high level of accuracy in detecting the aforementioned spot.

Zhu *et al.* (2023) introduced a novel approach for the non-invasive prediction of overall survival time in patients with glioblastoma multiforme. The proposed approach is based on utilizing multimodal MRI radiomics.The methodology involves segmenting distinct tumor subregions, namely the Whole Tumor (WT), Enhancing Tumor (ET), and Core Tumor (CT), for comprehensive assessment. The model's performance was truly remarkable, as evidenced by the evaluation metrics.Notably, the specificity index of 0.999 underscores its remarkable accuracy in effectively identifying normal tissue regions.To validate its effectiveness, the proposed model underwent evaluation on three significant datasets: BraTS2020, BraTS2019, and BraTS2018. The validation subsets within these datasets consisted of 125 cases for BraTS2020 and BraTS2019, and 66 cases for BraTS2018, respectively. Across all three datasets,the model consistently demonstrated outstanding performance, reinforcing its reliability and applicability.While the proposed model excelled at accurately segmenting the subregions of brain tumors,however some fine details along the edges were slightly blurred due to the absence of distinct features.

Table 2 compiles the summarized outcomes of diverse deep learning techniques within the healthcare domain.

CRITICAL OBSERVATIONS

Deep learning technology, as highlighted by authors such as (Rajkomar *et al.* 2018) and (Esteva *et al.* 2017), has made significant contributions to the healthcare sector and has demonstrated remarkable effectiveness in medical image analysis. Pioneering research conducted by (Rajpurkar *et al.* 2018) and (Gulshan *et al.* 2016) showcases the accuracy of deep learning in detecting diseases, including cancer and brain tumors. Convolutional Neural Networks (CNNs), studied by researchers including (Lipton *et al.* 2015) and (Shin *et al.* 2016), have played a key role in improving medical image classification.The benefits of deep learning in healthcare, such as faster evaluation and handling large datasets, have been emphasized by authors such as (Miotto *et al.* 2016). However, challenges related to data quality, interpretability, and biases, as discussed by (Cheplygina *et al.* 2019), necessitate ongoing research and collaboration to fully leverage deep learning's potential in healthcare.

CONCLUSION

Recent advancements in deep learning have introduced novel perspectives for the analysis of medical images, revolutionizing the identification of disease patterns within these images. This paper presents a comprehensive review and synthesis of cutting-edge deep learning applications in medical image analysis, with a primary focus on disease detection, segmentation, and classification. We elucidate the strengths and limitations of these approaches, the utilized datasets, assessment metrics, methodologies, with a particular emphasis on convolutional neural networks (CNNs) as a prominent deep learning application for computer vision tasks. Additionally,we underscore deep learning-based classification techniques, encompassing supervised, unsupervised, and semi-supervised methods, as well as their integration into medical image processing procedures. Despite the remarkable efficiency achieved by deep learning techniques across diverse medical applications, there remains an evident scope for enhancement due to inherent challenges linked to healthcare data. These challenges and outline potential future directions are discussed as under:

Enhanced Accuracy and Early Detection

Deep learning algorithms possess the capacity to enhance the accuracy of disease detection and diagnosis (Zheng *et al.* 2020). Future developments may focus on refining existing models and creating new ones that are even more adept at identifying subtle patterns in medical images,leading to earlier and more accurate diagnoses.

Multi-Modal Fusion

Combining information from various medical imaging modalities (such as MRI, CT, PET, Ultrasound, etc.) can offer a more holistic perspective of a patient's state. This approach enhances diagnostic accuracy by assessing various health facets (Zhang *et al.* 2021). Future research might focus on developing optimized deep learning techniques that effectively integrate and analyze data from multiple modalities for improved diagnostic accuracy.

Interpretable and Explainable Models

Deep learning models often operate as black boxes, complicating the comprehension of their predictions (Rajput *et al.* 2023). In medical settings, interpretability is paramount for fostering trust and elucidating decision-making processes to clinicians. The path ahead involves designing models that offer clear insights into their decision logic.Incorporating attention mechanisms, feature visualization, and saliency mapping can provide visibility into what the model focuses on during analysis.Integrating medical knowledge into model architectures and utilizing explainable AI techniques like rule-based systems or gradient-based explanations can further enhance interpretability. As the field progresses, these efforts will promote greater trust in AI-driven medical diagnostics and treatment planning.

Data Augmentation and Synthesis

Since medical datasets are often limited, techniques that effectively generate synthetic medical images could play a crucial role in training more robust deep learning models and addressing data scarcit (Mumuni and Mumuni 2022). Addressing limited medical datasets involves refining Generative Adversarial Networks and transferring pre-trained models for improved synthetic image generation. Domain adaptation, semi-supervised, and active learning strategies optimize data use,while collaborative sharing expands resources. Multi-modal integration and tailored image augmentation further enrich datasets. Embracing these approaches and interdisciplinary collaboration can effectively tackle data augmentation challenges, revolutionizing healthcare diagnostics through advanced machine learning solutions.

Knowledge Transfer and Few-shot Learning

Developing deep learning models with the ability to transfer knowledge across different medical domains or learn from only a few examples is a significant challenge (Li *et al.* 2019). This challenge becomes crucial in scenarios involving rare diseases or situations where there is limited available data for training. The future direction in addressing this challenge involves the advancement of cross-domain adaptation techniques and few-shot learning methods.Domain adaptation techniques can facilitate the effective generalization of models trained in one medical domain to another.

Class Imbalance

In the field of deep learning for medical image analysis, class imbalance presents a significant challenge (Johnson and Khoshgoftaar 2019). This issue is particularly apparent in datasets like BraTS for brain tumor segmentation.To overcome this, the future trajectory involves innovative data augmentation, strategic re-sampling methods, and advanced algorithms. These endeavors hold the potential to bolster accuracy and clinical utility, ensuring robust diagnostics and well-informed healthcare decisions.

Lack of Standardization in Medical Imaging

The variability in resolutions, orientations, and acquisition protocols of medical imaging modalities like MRI and CT poses a challenge in ensuring consistent preprocessing and analysis of diverse datasets (Cobo *et al.* 2023). To address this, the future direction involves devising standardized protocols for data acquisition and preprocessing, defining uniform imaging practices and resolution standards, as well as exploring advanced techniques beyond normalization and registration to enhance the reliability and accuracy of deep learning-based medical image analysis.

Small Anomalies Detection

Detecting subtle anomalies or abnormalities that could signal a disease poses a difficulty, particularly when these irregularities are small and blend with healthy tissues.To overcome the hurdle of identifying tiny anomalies within medical images (Pang *et al.* 2021), the future lies in refining algorithms for improved sensitivity.Embracing multi-modal analysis and leveraging contextual cues can enhance the ability to spot minute irregularities.Integrating deep generative models and leveraging self-supervised learning strategies can empower the system to recognize intricate patterns.By relentlessly pursuing these avenues, the field aims to bolster the accuracy of medical image analysis and pave the way for more effective disease detection.

Data Privacy and Security

Medical data,being sensitive and governed by privacy regulations, presents a substantial challenge in devising methods that balance patient data protection with effective analysis (Ramzan *et al.* 2022). The future entails the development of privacy-preserving techniques that enable meaningful analysis while upholding confidentiality. Differential privacy, federated learning, and homomorphic encryption are promising avenues. Additionally, exploring decentralized data sharing models and blockchain-based solutions can enhance security.By integrating these strategies, the field aims to achieve a harmonious equilibrium between robust data analysis and stringent privacy considerations, ensuring trust and compliance in healthcare applications.

Longer Training Time

A significant challenge in medical imaging's deep learning is extended model training due to complex structures (Ahmad *et al.* 2020). To optimize training, researchers explore transfer learning, leveraging pretrained models and hardware advancements like GPUs. Additionally, model compression techniques and generative adversarial networks for data augmentation show promise. This convergence of strategies holds potential for curtailing training time, expediting model development and real world deployment.

Limited Annotation and Ground Truth

Obtaining accurate annotations and ground truth labels for medical images can pose a considerable difficulty due to the need for expert clinicians and time-consuming manual labeling, especially for complex structures and rare conditions (Zhang *et al.* 2020). Future direction involves exploring semi-supervised learning techniques, which leverage a smaller set of fully labeled data alongside a larger pool of unlabeled data. Additionally, weakly supervised learning approaches, where models are trained with less detailed annotations like image-level labels, hold potential. These methods aim to alleviate the burden of meticulous manual annotation while maintaining high accuracy, thus optimizing the use of expert resources and enhancing the efficiency of medical image analysis.

Availability of data and material

Not applicable.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

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