J. Electrical Systems 20-3 (2024):5114-5125

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Navigating the Depths: A Comprehensive study of Deep Learning and its Advancements in Medical Image Analysis

Abstract: - Medical imaging is the technique of capturing images of internal organs for diagnostic purposes, contributing to the identification and study of diseases. The primary goal of medical image analysis is to enhance the effectiveness of clinical research and treatment options. Deep learning has revolutionized this field, demonstrating remarkable outcomes in tasks such as registration, segmentation, feature extraction, and classification. The increased availability of computational resources and the resurgence of deep convolutional neural networks are key drivers for these advancements. Deep learning techniques excel in uncovering concealed patterns within images, aiding clinicians in achieving precise diagnoses. They have proven to be particularly effective in organ segmentation, cancer detection, disease categorization, and computer-assisted diagnosis. Numerous deep learning approaches have been proposed for various diagnostic purposes in the analysis of medical images. A significant hurdle in integrating deep learning models into the medical domain is the scarcity of training data, primarily attributed to the challenges associated with collecting and accurately labelling data, a task requiring expertise. To address this limitation, transfer learning (TL) has emerged as a valuable strategy, leveraging pre-trained state-of-the-art models to tackle various medical imaging tasks. This comprehensive review highlights the methodologies, including preprocessing, segmentation, feature extraction, and classification, and evaluates the performance of various DL models and also the recent advancements in the deep learning like transfer learning approaches in medical image processing.

Keywords: Deep Learning(DL), Medical Image Analysis, Convolutional Neural Networks(CNN), Transfer Learning(TL)

I. INTRODUCTION

Deep Learning (DL) has successfully tackled several intriguing and hard applications in the past few years, especially those involving non-linearity of datasets. Advances in deep learning techniques have led to a variety of uses and applications in a wide range of fields, including speech recognition, natural language processing (NLP), image processing, and numerical data analysis and prediction. Deep learning does have several limitations, though, including the need for large amounts of labeled training data and costly training procedures (both in terms of time and processing) [1].

Scientists have found transfer learning to be an interesting area of study ever since the Machine Learning (ML) revolution began. Due to the nature of machine learning algorithms, transfer learning—also known as domain adaptation—was centered on homogeneous data sets and how to link them to one another prior to the emergence of deep learning models [2]. Because traditional machine learning models have been primarily developed for linear problems, they are less dependent on the quantity of the dataset and typically need less money to train than deep learning models. Consequently, since transfer learning may overcome the two constraints of large training data and training costs, its application in deep learning is more motivated than ever in the fields of artificial intelligence (AI) and machine learning (ML).

Current deep learning transfer learning techniques seek to minimize the time and expense of the training process as well as the need for large training datasets, which can be challenging to get in some fields, like medical pictures. Furthermore, a pre-trained model with minimal processing power and training time can be used on a low-end edge device such as a mobile[3]. Additionally, because DTL views learning as a continuous process, advancements in this area are paving the way for more complex and intuitive AI systems. Google's Deep Mind Project and

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technological innovations like Progressive Learning are excellent examples of this concept[4]. DTL is now at the forefront of artificial intelligence and machine learning research as a result of all of this.

1.1 DL Techniques

Many DL techniques have been utilized in the field of medical imaging [5], specifically with the prevalence of convolutional neural networks (CNNs)[6]. CNNs are well-suited for image analysis tasks because of their capacity to capture local spatial patterns and automatically learn hierarchical representations from input images [7]. Additional DL techniques utilized in medical imaging encompass recurrent neural networks (RNNs), which excel in processing sequential data, and generative adversarial networks (GANs), which have the ability to produce new samples based on learned data distributions [8]. In assessing the performance of our DL models in medical image diagnosis, several evaluation metrics are commonly employed, including Receiver Operating Characteristic (ROC) curves and confusion matrices, among other techniques [9]. The ROC curve is a visual representation that showcases the diagnostic capability of our DL models as we adjust its discrimination threshold. This highlights the balance between sensitivity (or True Positive Rate) and specificity (1–False Positive Rate), which gives us an indication of how effectively our models differentiate between different classes. Model performance can be compared using the Area under the ROC Curve (AUC), which offers a comprehensive metric. However, confusion matrices offer a concise overview of prediction outcomes in a classification problem. The count of accurate and inaccurate predictions is tallied and categorized for each class. This provides a detailed analysis of the model's performance, including important metrics like precision, recall, and F1-score. These metrics are particularly valuable when working with imbalanced classes.

1.2 Medical Image Analysis Using Deep Learning

The primary objective of medical image analysis is to detect and localize pathological locations within the anatomy, enabling doctors to gain a deeper understanding of the progression of diseases. The analysis of a medical image involves four main phases: (1) preprocessing the image; (2) segmentation; (3) feature extraction; and (4) pattern identification or classification. Preprocessing refers to the act of improving the quality of image data for further analysis or eliminating unwanted distortions from photographs. Segmentation is the process of delineating distinct regions, such as tumors and organs, for further investigation. Feature extraction involves the meticulous selection of relevant information from certain areas of interest (ROIs) to aid in their identification. Classification is used to categories the ROI according to the retrieved features [10].

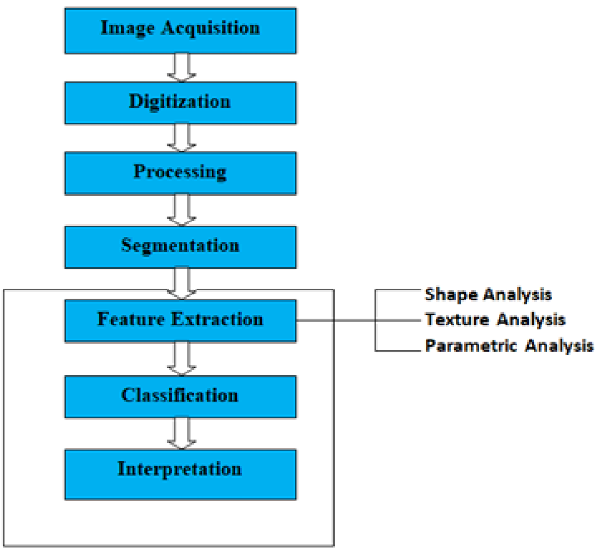

Figure 1Steps of medical image analysis

II. MEDICAL IMAGE ANALYSIS USING DEEP LEARNING

The main objective of medical image analysis is to identify the areas of the body that are impacted by the disease, in order to assist physicians in understanding how the lesions develop over time. The analysis of a medical image is primarily based on four essential steps: image preprocessing, segmentation, feature extraction, and pattern identification or classification[11] . Preprocessing is a crucial step in refining images, eliminating any unwanted distortions or enhancing the image information to facilitate subsequent processing. Segmentation involves the isolation of specific regions, such as tumours and organs, for further examination. Feature extraction is the process of extracting precise details from the regions of interest (ROIs) that aid in their recognition. Using extracted features, classification helps categorize the ROI.

2.1 Convolutional Neural Networks

One supervised deep learning system that can be used to distinguish between different types of data is a CNN. In order to transform picture pixels into features, it first takes pictures as input and then allocates filters to them. This structure is generally composed of three layers: the convolutional layer, the pooling layer, and the fully connected layer. The convolutional layer is the initial layer of a convolutional network. Subsequent convolutional or pooling layers should come after the fully connected layer. The features extracted from the image by the convolutional block can be examined by the network to uncover hidden correlations. Pooling layers, another name for down sampling, is a technique used to reduce the convolved feature size. Based on the features obtained by the preceding layers, fully-connected layers perform classification tasks. Convolutional layers frequently utilize the rectified linear unit (ReLu) function to activate neurons, whereas fully connected layers use a SoftMax activation function or traditional machine learning classifiers (SVM, KNN, etc.) to categorize inputs.

The deep network needs a lot of computing power, even if it can extract information more precisely. In order to classify brain tumours using MRI images, Badža and Barjaktarović [12] constructed a basic CNN model with two convolutional blocks. Using 10-fold cross-validation, the model achieved the greatest accuracy of 95.56% when analysing 3064 MRI images. An effective CNN architecture with a 22.7% error rate was presented by Racha Pudi and Lavanya to classify the colorectal cancer in his to pathological pictures. The model had five convolutional blocks with a drop out layer in each to avoid overfitting [13].

The encoder and decoder are the two components of the deep learning architecture used for picture segmentation. The decoder is responsible for creating the final output, which is often a segmentation mask that contains the shape of the item. The encoder utilizes filters to extract features from the image. A fully convolutional network (FCN) is an encoder-decoder model that functions as completely connected layers by using 1×1 convolutions instead of dense layers [14]. A 3D FCNN-based model for multimodal brain tumour image segmentation was developed by Sun et al. [15] Four paths were available in the encoder to extract multiscale image characteristics. Following that, the decoder received these four fused feature maps. The model segmented the dataset using Dice by performing mental validation on the Brain Tumour Segmentation Challenge dataset 2019 (BraTS2019).

The DSC metrics for the whole, core, and enhanced tumours were 0.89, 0.78, and 0.76, respectively. U-Net, which can learn from a limited amount of annotated medical images, was introduced by Ronneberger et al. in 2015 to address biomedical image segmentation [16] . Using skip connections to connect its four encoder and four decoder blocks, U-Net is a U-shaped encoder-decoder based framework. Dharwadkar and Savvashe created a ventricular segmentation model for cardiac MRI images using U-Net architecture. The current model utilizes only three of the four layers present in the original U-Net [17]. The suggested model received a dice score of 0.91 for the right ventricle segmentation challenge (RVSC) dataset.

In order to separate the left ventricle from cardiac CT angiography, Li et al. developed an 8-layer U-Net. There were eight encoder and eight decoder blocks in the displayed U-Net model. Each encoder and decoder block now contains residual blocks in the form of skip connections, which further increase network efficiency[18] . A DSC of 0:9270±139 was obtained when the model was trained using 1600 CT images from 100 patients. In the U-Net++ design, Li et al. [19] included an attention mechanism between layered encoder-decoder circuits to enhance our understanding of the liver segmentation research area. Using experimental study of the liver tumour segmentation challenge dataset 2017 (LiTS2017), the model obtained a DSC of 98.15%.

By using 3D convolutions to handle 3D MRI images, V-Net expands on U-Net [20]. A V-Net-based framework was created by Guan et al. to distinguish brain tumours from 3D MRI brain images. To reduce irrelevant data and improve segmentation accuracy, the created framework combined the attention guide filter (AG) and squeeze and excite (SE) modules into the V-Net architecture [21]. The model achieved dice metrics of 0.68, 0.85, and 0.70 for the full, core, and improved tumor, respectively, when tested on the BraTS2020 dataset.

Cover up regional Another CNN variation that's utilised for segmenting medical images is CNN. The object identification and segmentation architecture of Mask R-CNN is two-phase. Potential bounding boxes are returned by the first step, which is called the region proposal network (RPN), and each box is used in the second stage to generate the segmentation mask. A hybrid model integrating mask R-CNN and U-Net was presented by Dogan et al. [22] for the purpose of segmenting the pancreas from CT images. The two components of the suggested system were the pancreatic segmentation and detection components. The region proposal network and the mask production network were utilised in pancreatic localization to establish the pancreas portion's bounding boxes. Then, the subregion centred by the rough pancreas region was cut. Ultimately, U-Net was tasked with precisely segmenting the cropped subregion. Across the 82 abdominal CT scans, the two-phase approach's average DSC was 86.15%.

2.2 Improving the Performance of CNN

The CNN model is often used for image classification because it achieves better accuracy with a low error rate. However, it needs large data sets to generalize the hidden correlations found in the learning data. Here, we have discussed two approaches that may optimize the performance of CNN: (1) transfer learning and (2) general adversarial network (GAN).

2.3 Transfer Learning

Transfer learning is a highly efficient approach for training a network when the available dataset is minimal. In this case, the model is first trained using a vast dataset, such as ImageNet, which consists of 1.4 million photos categorized into 1000 groups. Afterwards, the model is utilized for the specific task at hand [23].

The literature on transfer learning is documented in Table 1. The LeNet model has gained popularity in the field of Convolutional Neural Networks (CNNs) due to its straightforward architecture and reduced training time. Deep neural network models utilize the notion of the max pooling layer to extract the most pertinent characteristics from a given region. However, in the field of medical picture analysis, where the quality is inadequate, pixels with lower brightness may contain important information. Therefore, Hazarika et al. [24] incorporated the minimum pooling layer into LeNet for the purpose of classifying Alzheimer's disease (AD). In the improved LeNet, the min-pooling and max-pooling layers were combined, and the resulting layer replaced all max-pooling levels. Based on the experimental analysis of 2000 brain pictures, the initial LeNet model achieved an accuracy of 80% in classifying AD, whereas the modified LeNet model achieved a significantly higher accuracy of 96.64%.

Hosny et al. [25] implemented a refined version of the AlexNet model to classify skin lesions into seven categories using photographs of the skin. The proposed architecture replaces the last three layers with new layers to ensure their suitability for identifying seven types of skin lesions. The settings of these newly added layers were first determined at random and subsequently adjusted during the training process. The model attained an accuracy of 98.70% and a sensitivity of 95.60% after being trained on a dataset of 10,015 pictures. Dulf et., al [26] evaluated and tested five distinct models, namely GoogleNet, AlexNet, VGG16, VGG19, and InceptionV3, to discover the optimal model for classifying the eight kinds of colorectal polyps. The primary factors considered for adopting the network were sensitivity and F1-score. Therefore, InceptionV3 was selected based on its F1-score of 98.14% and sensitivity of 98.13%. In the InceptionV3 model, the 5×5 convolutional layer is substituted with two 3×3 convolutional layers in order to reduce the computing cost.

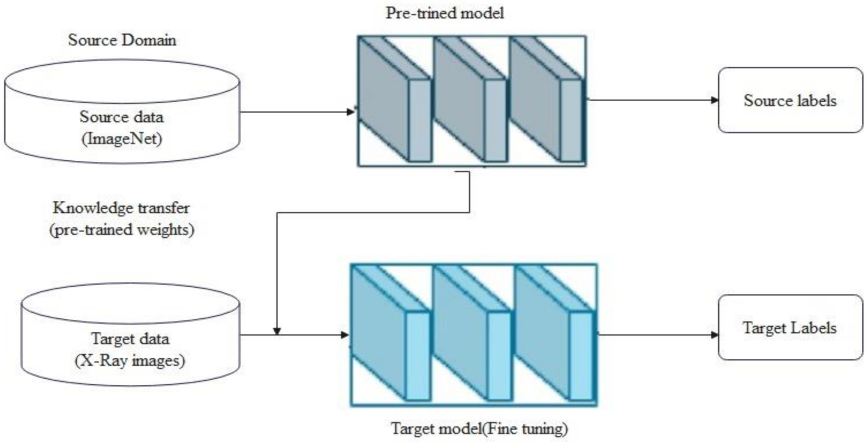

Figure 2Block diagram of transfer learning

Hameed et al. [27] employed an ensemble deep learning approach to classify breast cancer into carcinoma and non-carcinoma categories based on histopathology images. The framework was designed using VGG models, specifically VGG16 and VGG19.VGG19 shares the fundamental design of VGG16 but includes three extra convolutional layers. In addition to the first block, the next four blocks were modified throughout training in order to refine the models. Ultimately, the VGG16 and VGG19 models were combined, resulting in an overall accuracy of 95.29%.

Togacar et.,al. [28] used both VGG16 and AlexNet to extract features from MRI scans, with each model capturing 1000 features, in order to classify brain tumors[29] .The collected features were then assessed to determine which features were the most effective using the recursive feature elimination (RFE) feature selection technique. In the end, the SVM classifier produced 96.77% accuracy using 200 selected characteristics. A ResNet-based SVM for X-ray-based pneumonia identification was presented by Eid and Elawady [29]. The proposed model used a boosting approach to choose the relevant features from chest X-rays, and an SVM classifier to predict pneumonia based on those characteristics. Preferred ResNet was used to obtain features from the X-rays. After being trained on 5,863 X-rays, the model's accuracy was 98.13%.

Xiao et al. segmented the left ventricle from echocardiogram images using a Res2Net-based 3D-UNet.A series of 3×3×3 filters was used in place of Res2Net's basic residual unit to extract 3D features at numerous scales [30]. Lastly, a group of 1 x 1 × 1 filters combined feature maps from every group. The model obtained a DSC of 95.30%, as per an experimental investigation of 1186 lung pictures from the Lung Nodule investigation dataset 2016 (LUNA16). Goyal et al. [31] segmented the kidneys from the MRI images using the mask R-CNN. InceptionResNetV2 was chosen as the CNN network in the suggested study in order to segment the kidneys[32]. Subsequently, post processing procedures such removing any voxels unrelated to the kidney and fill operation were carried out in order to improve the segmentation result. The suggested model was tested using 100 images, and it received a mean dice score of 0.904.

Table 1overview of the existing works of transfer learning models in medical imaging

Reference	**Model**	**Performance measures**	**Findings**	**Modality**	**Accuracy**
[16]	VGG16	Accuracy	Brain tumor classification	MRI	95.71%
[17]	Inception v3	Accuracy	Breast cancer	Histopathology images	83% Accuracy for benign and 89% accuracy

					for malignant
[18]	VGG16	AUC	Breast tumor classification	Mammogram	98.96%
[19]	Alex-net	Accuracy	skin lesions	public dataset, ISIC 2018	95.91%
[20]	VGG19	Accuracy	Thyroid nodule cell classification	Cytology images	93.05%
[21]	ResNet50	Accuracy	Brain tumor classification	MRI	97.2%
[22]	AlexNet	Accuracy	Lung nodule classification	CT and X-ray	99.6%
[23]	ResNet50	Accuracy	Breast tumor classification	Mammogram	85.71%
[24]	ResNet50	Accuracy	Breast tumor classification	Histopathological images	99%
[25]	DenseNet201	Accuracy	Skin lesion classification	Skin images	96.18%
[26]	Google Net	Accuracy	Skin image classification	Skin images	99.29%
[27]	GoogleNet	Accuracy	Thyroid nodule classification	Ultrasound	96.04%
[28]	GoogleNet	Sensitivity	Colorectal polyps classification	Gastrointestinal polyp images	98.44%
[29]	Faster R-CNN+VGG16	Precision	Brain tumor segmentation and classification	MRI	77.60%
[29]	U-Net+InceptionV3	Precision	Breast tumor segmentation and classification	Mammogram	98.87%
[30]	Mask R-CNN+ResNet-50	Accuracy AUC Sensitivity	White blood cells detection and classification	Cytological images	98.87% 98.88% 98.98%

III. EVALUATION METHODS AND AVAILABLE DATASETS

Impressive results have been achieved using deep learning algorithms for medical imaging in a number of tasks, such as picture segmentation, classification, registration, and reconstruction[33]. Appropriate measurements and benchmarks are required in order to assess these strategies' performance[22].

3.1 Metrics for Performance Evaluation

A number of metrics have been put up to assess how well deep learning techniques perform in medical imaging. Surface distance measurements, the Jaccard index, and the dice coefficient are frequently used metrics for image segmentation applications [23]. Metrics including accuracy, precision, recall, and F1 score are frequently employed for image classification tasks [24]. Peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) are often used metrics for image reconstruction tasks [25]. Furthermore, some research has suggested new measures tailored to certain uses, like tumour size quantification in cancer imaging and registration accuracy[26]. It is crucial to remember that no single indicator can accurately represent the effectiveness of a deep learning approach[27]; instead, a variety of metrics should be employed for a thorough assessment[34]. Furthermore, the particular application and clinical significance should guide the choice of measurements[30].

Several deep learning (DL) techniques have been used and their respective performances have been compared in the field of medical imaging[31]. For example, Chong et al.'s noteworthy comparison study[32] investigated the efficacy of recurrent neural networks (RNNs) and convolutional neural networks (CNNs) in lung CT scan tumour detection[35]. Both models produced excellent results[36], according to the study, however CNNs performed better than RNNs[37], with an accuracy rate of 92% as opposed to 89%[38]. Moreover, the CNN model exhibited enhanced sensitivity and specificity[39], highlighting the possible benefits of CNNs in medical imaging tasks. Zeng et al.'s[40] comparison of the efficacy of CNNs and deep belief networks (DBNs) for mammography-based breast cancer detection was another illuminating comparison[41]. Despite the remarkable accuracy rates attained by both models, the DBN showed a better area under the receiver operating characteristic (ROC) curve (AUC), scoring 0.96 against CNN's 0.92. According to this research, DBNs may be able to differentiate between benign and malignant cases in mammograms more accurately than CNNs[42]

The Hausdorff Distance (HD) parameter is a mathematical concept used in the field of computational geometry and image processing to quantify the similarity or dissimilarity between two sets of points or shapes[43]. It measures the maximum distance from any point in one set to the nearest point in the other set, providing a measure of how much one set deviates from the other.

In the context of image analysis or pattern recognition, the Hausdorff Distance is often employed to compare two images or shapes by treating them as sets of points in a multidimensional space[44]. The HD parameter is calculated by finding the maximum distance between a point in one set and its nearest neighbor in the other set, and vice versa.

Key features of the Hausdorff Distance parameter include:

Sensitivity to Global and Local Differences: Unlike some other distance measures, such as the Euclidean distance, which may only capture local differences, the Hausdorff Distance considers both global and local disparities between sets of points or shapes.

Robustness to Outliers: The HD parameter is less sensitive to outliers or isolated points in the data, as it focuses on the maximum distance rather than averaging all distances.

Symmetry: The Hausdorff Distance is symmetric, meaning that the distance from set A to set B is the same as the distance from set B to set A, ensuring consistency in comparisons.

Useful in Shape Matching and Object Recognition: Hausdorff Distance is commonly used in applications such as shape matching, object recognition, and image registration, where it provides a quantitative measure of similarity or dissimilarity between complex structures or patterns.

Computational Complexity: Calculating the Hausdorff Distance between two sets of points can be computationally intensive, especially for large datasets. Efficient algorithms and data structures are often employed to optimize the computational complexity of the calculation.

Overall, the Hausdorff Distance parameter is a valuable tool for quantifying the similarity between sets of points or shapes, making it useful in various fields, including computer vision, medical imaging, and geographical analysis.

3.2 Publicly Available Datasets and Competition

Datasets and contests that are open to the public are essential for the advancement of DL research in medical imaging. For the purpose of comparing various approaches and encouraging researcher collaboration, these resources offer standardized data and assessment processes. For example, the Alzheimer's Disease Neuroimaging Initiative (ADNI) for MRI[45], the Retinal OCT (ORIGA) dataset for OCT, BraTS for Brain Tumor Segmentation and the Cancer Imaging Archive (TCIA) for CT and MRI are among the many publicly accessible datasets for many medical imaging modalities. Furthermore, a number of contests, such the Medical Segmentation Decathlon and the International Symposium on Biomedical Imaging (ISBI) challenge, have been held to benchmark the effectiveness of DL techniques for medical imaging [54]. But for various medical imaging modalities and tasks, the accessibility and calibre of publicly accessible datasets and competitions can differ. Furthermore, the restricted diversity of certain datasets with regard to patient groups and imaging techniques may have an impact on the generalizability of the findings. It is crucial to create norms and regulations for dataset curation and evaluation procedures in order to overcome these problems. For DL research in medical imaging, cooperation between researchers, physicians, and industry partners is necessary to guarantee the quality and accessibility of publically available datasets and competitions.

IV. ETHICAL CONSIDERATIONS FOR USING DL METHODS

The fast advancement and broad application of deep learning techniques in medical imaging in recent years has brought up several ethical issues, including data security and privacy, bias and fairness, explain ability and interpretability, and integration with clinical procedures. Some of these problems are covered in this section along with how they might affect DL in medical imaging in the future3.1. Design Requirements.

4.1 Data Privacy and Security

The necessity to safeguard patient privacy and data security is one of the primary ethical issues with deep learning in medical imaging. Sensitive patient information is contained in medical photographs, and improper use or disclosure of this information could have detrimental effects on patients' privacy and wellbeing. As a result, it's critical to have the right safeguards in place to ensure the availability, confidentiality, and integrity of medical pictures and related data. Encryption, anonymization, and safe data exchange protocols are just a few of the techniques that have been suggested in a number of studies to improve data privacy and security in medical imaging[46]. By using these techniques, you can lessen the chance of data breaches and cyber attacks while still protecting patient privacy.

4.2 Fairness and Bias

The potential for prejudice and injustice is a significant ethical factor to take into account when using DL in medical imaging. Large datasets are used to train deep learning models. However, if the datasets used for training are biased or unrepresentative, the resulting models may reinforce or magnify these biases, producing unfair or erroneous predictions[47]. The problem of bias in medical imaging datasets has been brought to light in a number of research. One such example is the unequal representation of particular demographic groups. Researchers have suggested a number of strategies, including data augmentation, data balancing, and fairness-aware training, to solve these problems. These techniques can lessen bias and increase the DL models' fairness.

4.3 Interpretability and Explainability

Another ethical issue in medical imaging is the black-box nature of DL models, which can make it challenging to comprehend how they create their predictions and to spot possible biases or inaccuracies[48] . Because explainability and interpretability are essential for fostering confidence and trust between patients and healthcare professionals, this lack of transparency and interpretability may restrict the application of DL in clinical settings. Researchers have suggested a number of techniques, including saliency maps, attention mechanisms, and counterfactual explanations, to improve the explainability and interpretability of DL models in order to solve these problems. These techniques can aid in enhancing the DL models' interpretability and transparency and make it easier to incorporate them into clinical procedures.

4.4 Integration with Clinical Workflows

Another crucial factor in the application of DL in medical imaging is its integration with clinical workflows. DL models need to be effectively, dependable, and efficiently incorporated into clinical workflows in order to be therapeutically valuable. This necessitates carefully weighing a number of variables, including the impact on clinical decision-making, the quality and applicability of the forecasts, and the availability and accessibility of data. A number of research have suggested different approaches, including workflow optimization, clinical decision rules, and decision support systems, to incorporate DL into clinical workflows [49]. These techniques can enhance clinical decision-making's efficacy and efficiency while streamlining the application of DL in clinical settings.

V. FUTURE RESEARCH DIRECTIONS

Several crucial areas for future research in the application of DL in medical imaging lie ahead. The following items are included: (1) Creating more resilient and precise deep learning models capable of accommodating fluctuations in data quality and heterogeneity. (2) Improving the comprehensibility and clarity of deep learning models to promote their incorporation into healthcare workflows. (3) Tackling ethical concerns, including safeguarding data privacy and security, ensuring impartiality and fairness, and adhering to regulatory requirements. (4) Exploring the feasibility of employing Deep Learning (DL) in conjunction with additional modalities, such as genomics, proteomics, and metabolomics, to enhance the precision and specificity of medical imaging diagnosis. (5) Investigating the application of deep learning in personalized medicine, wherein models can be trained using patient-specific data to offer customized therapy suggestions. (6) Establishing techniques to guarantee the resilience and applicability of deep learning models across diverse demographics and clinical environments. (7) Exploring the feasibility of employing deep learning to fully automate the complete medical imaging process, encompassing image capture, analysis, and interpretation.

To summarize, DL approaches have demonstrated significant potential in the domain of medical imaging, offering a diverse array of applications and possible advantages for patient care. Nevertheless, its utilization also gives rise to significant ethical concerns, including those related to data privacy and security, bias and fairness, as well as explainability and interpretability. To fully harness the potential of DL in medical imaging and ensure fair distribution of its advantages, it is crucial to address these difficulties. Subsequent investigations should prioritize the advancement of more resilient and precise models, augmenting their comprehensibility and clarity, and investigating novel applications and scenarios for deep learning in medical imaging. Furthermore, it is crucial to engage in collaboration with healthcare professionals, patients, and other stakeholders to guarantee that the creation and implementation of DL models in medical imaging are in accordance with their requirements and preferences. This encompasses engaging patients in the development and assessment of deep learning models and guaranteeing that the advantages of these models are available to everyone, irrespective of their socioeconomic situation, color, or ethnicity. Furthermore, it is imperative to build regulatory frameworks to guarantee that DL models adhere to ethical and quality standards, and that their utilization is both transparent and accountable. This entails formulating protocols for safeguarding data privacy and security, addressing issues of bias and fairness, and ensuring comprehensibility and interpretability. Additionally, it involves setting benchmarks for validating models and evaluating their performance. DL has the capacity to completely improve the realm of medical imaging and revolutionize the methods by which we identify and cure diseases. Nevertheless, the achievement of its objectives will be contingent upon effectively resolving the ethical and technical obstacles associated with its use, as well as fostering a cooperative and patient-centric attitude towards its creation and execution. Through ongoing research and innovation, Deep Learning (DL) is positioned to make a substantial impact on the progress of healthcare and enhance the well-being of patients globally.

One of the deadliest and most public types in cancer is brain tumors it causes both young people and adults. One of the major causes for the increase in mortality rate is late diagnosis and high cost of devices used for brain tumor examination. Most of the existing approaches have used ML algorithms but they possess certain issues like less accuracy, high loss and high computational complexity to solve problems. Further research is essential to improve the analysis of brain tumors using advanced deep learning approaches, hybrid deep transfer learning models and fine tuned deep learning models.

The Hausdorff Distance (HD) serves as a prevalent metric for assessing the effectiveness of medical image segmentation techniques. Despite its widespread use, current segmentation methods do not directly target the reduction of HD. While certain convolutional neural networks (CNNs) have been employed to address HD reduction directly, there remains a necessity to implement fully convolutional neural networks (FCNs) for this purpose.

VI. CONCLUSION

State-of-the-art deep learning techniques have transformed the field of medical image analysis, providing unparalleled precision and speed in the detection of diseases and evaluation of patient health. CNNs have become a fundamental tool in this field, showcasing impressive abilities in tasks like image segmentation, classification, and detection. Transfer learning is an important strategy for enhancing CNN performance, allowing models to benefit from knowledge gained from extensive datasets and pre-trained architectures. The use of evaluation methods and publicly available datasets is crucial for advancing research and comparing the performance of deep learning models. Nevertheless, when implementing deep learning methods in medical settings, it is crucial to prioritize ethical considerations such as data privacy, fairness, bias, interpretability, and integration with clinical workflows. Future research directions in medical image analysis are expected to prioritize addressing challenges related to interpretability, explain ability, and robustness in deep learning models. Additionally, there will be a focus on seamlessly integrating AI technologies into clinical workflows. In general, advanced deep learning approaches have the potential to greatly transform medical image analysis. Further research is essential to improve the medical image analysis using advanced deep learning approaches, hybrid deep transfer learning models and fine tuned deep learning models.

References

[1] M. Iman, H. R. Arabnia, and R. M. Branchinst, “Pathways to Artificial General Intelligence: A Brief Overview of Developments and Ethical Issues via Artificial Intelligence, Machine Learning, Deep Learning, and Data Science BT - Advances in Artificial Intelligence and Applied Cognitive Computing,” 2021, pp. 73–87.

[2] F. Zhuang et al., “A comprehensive survey on transfer learning,” Proc. IEEE, vol. 109, no. 1, pp. 43–76, 2020.

[3] S. Voghoei, N. H. Tonekaboni, J. G. Wallace, and H. R. Arabnia, “Deep learning at the edge,” in 2018 International Conference on Computational Science and Computational Intelligence (CSCI), 2018, pp. 895–901.

[4] N. M. Curran, J. Sun, and J.-W. Hong, “Anthropomorphizing AlphaGo: a content analysis of the framing of Google DeepMind’s AlphaGo in the Chinese and American press,” AI Soc., vol. 35, no. 3, pp. 727–735, 2020.

[5] M. Ghaderzadeh and F. Asadi, “Deep learning in the detection and diagnosis of COVID-19 using radiology modalities: a systematic review,” J. Healthc. Eng., vol. 2021, no. 1, p. 6677314, 2021.

[6] V. Sangeetha and K. J. Prasad, “Syntheses of novel derivatives of 2-acetylfuro [2, 3-] carbazoles, benzo [1, 2-b]-1, 4-thiazepino [2, 3-] carbazoles and 1-acetyloxycarbazole-2-carbaldehydes,” 2006.

[7] S. Islam, A. Dash, A. Seum, A. H. Raj, T. Hossain, and F. M. Shah, “Exploring video captioning techniques: A comprehensive survey on deep learning methods,” SN Comput. Sci., vol. 2, no. 2, pp. 1–28, 2021.

[8] A. Radford, L. Metz, and S. Chintala, “Unsupervised representation learning with deep convolutional generative adversarial networks,” arXiv Prepr. arXiv1511.06434, 2015.

[9] N. Ayache, “Medical Imaging in the Age of Artificial Intelligence,” Healthc. Artif. Intell., pp. 89–91, 2020.

[10] B. Sistaninejhad, H. Rasi, and P. Nayeri, “A review paper about deep learning for medical image analysis,” Comput. Math. Methods Med., vol. 2023, no. 1, p. 7091301, 2023.

[11] C. M. Kuzmiak, Ed., “Breast Imaging.” IntechOpen, Rijeka, 2018, doi: 10.5772/66022.

[12] M. M. Badža and M. C. Barjaktarović, “Classification of brain tumors from mri images using a convolutional neural network,” Appl. Sci., vol. 10, no. 6, 2020, doi: 10.3390/app10061999.

[13] V. Rachapudi and G. Lavanya Devi, “Improved convolutional neural network based histopathological image classification,” Evol. Intell., vol. 14, no. 3, pp. 1337–1343, 2021.

[14] J. Long, E. Shelhamer, and T. Darrell, “Fully convolutional networks for semantic segmentation,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 3431–3440.

[15] J. Sun, Y. Peng, Y. Guo, and D. Li, “Segmentation of the multimodal brain tumor image used the multi-pathway architecture method based on 3D FCN,” Neurocomputing, vol. 423, pp. 34–45, 2021.

[16] V. K. Waghmare and M. H. Kolekar, “Brain Tumor Classification Using Deep Learning BT - Internet of Things for Healthcare Technologies,” C. Chakraborty, A. Banerjee, M. H. Kolekar, L. Garg, and B. Chakraborty, Eds. Singapore: Springer Singapore, 2021, pp. 155–175.

[17] J. Chang, J. Yu, T. Han, H. Chang, and E. Park, “A method for classifying medical images using transfer learning: A pilot study on histopathology of breast cancer,” in 2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom), 2017, pp. 1–4, doi: 10.1109/HealthCom.2017.8210843.

[18] A. Saber, M. Sakr, O. M. Abo-Seida, A. Keshk, and H. Chen, “A Novel Deep-Learning Model for Automatic Detection and Classification of Breast Cancer Using the Transfer-Learning Technique,” IEEE Access, vol. 9, pp. 71194–71209, 2021, doi: 10.1109/ACCESS.2021.3079204.

[19] K. M. Hosny, M. A. Kassem, and M. M. Fouad, “Classification of Skin Lesions into Seven Classes Using Transfer Learning with AlexNet,” J. Digit. Imaging, vol. 33, no. 5, pp. 1325–1334, 2020, doi: 10.1007/s10278-020-00371-9.

[20] A. B. Bakht, S. Javed, R. Dina, H. Almarzouqi, A. Khandoker, and N. Werghi, “Thyroid Nodule Cell Classification in Cytology Images Using Transfer Learning Approach BT - Proceedings of the 12th International Conference on Soft Computing and Pattern Recognition (SoCPaR 2020),” 2021, pp. 539–549.

[21] A. Çinar and M. Yildirim, “Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture,” Med. Hypotheses, vol. 139, no. February, p. 109684, 2020, doi: 10.1016/j.mehy.2020.109684.

[22] C. J. Lin and Y. C. Li, “Lung nodule classification using taguchi-based convolutional neural networks for computer tomography images,” Electron., vol. 9, no. 7, pp. 1–9, 2020, doi: 10.3390/electronics9071066.

[23] A. S. A. Rahman, S. B. Belhaouari, A. Bouzerdoum, H. Baali, T. Alam, and A. M. Eldaraa, “Breast Mass Tumor Classification using Deep Learning,” in 2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT), 2020, pp. 271–276, doi: 10.1109/ICIoT48696.2020.9089535.

[24] Q. A. Al-Haija and A. Adebanjo, “Breast Cancer Diagnosis in Histopathological Images Using ResNet-50 Convolutional Neural Network,” in 2020 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS), 2020, pp. 1–7, doi: 10.1109/IEMTRONICS51293.2020.9216455.

[25] K. Thurnhofer-Hemsi and E. Domínguez, “A Convolutional Neural Network Framework for Accurate Skin Cancer Detection,” Neural Process. Lett., vol. 53, no. 5, pp. 3073–3093, 2021, doi: 10.1007/s11063-020-10364-y.

[26] K. M. Hosny, M. A. Kassem, and M. M. Foaud, “Skin melanoma classification using ROI and data augmentation with deep convolutional neural networks,” Multimed. Tools Appl., vol. 79, no. 33, pp. 24029–24055, 2020, doi: 10.1007/s11042-020-09067-2.

[27] W. Chen et al., “A New Classification Method in Ultrasound Images of Benign and Malignant Thyroid Nodules Based on Transfer Learning and Deep Convolutional Neural Network,” Complexity, vol. 2021, p. 6296811, 2021, doi: 10.1155/2021/6296811.

[28] E. H. Dulf, M. Bledea, T. Mocan, and L. Mocan, “Automatic detection of colorectal polyps using transfer learning,” Sensors, vol. 21, no. 17, 2021, doi: 10.3390/s21175704.

[29] Y. Bhanothu, A. Kamalakannan, and G. Rajamanickam, “Detection and Classification of Brain Tumor in MRI Images using Deep Convolutional Network,” in 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), 2020, pp. 248–252, doi: 10.1109/ICACCS48705.2020.9074375.

[30] W. M. Salama and M. H. Aly, “Deep learning in mammography images segmentation and classification: Automated CNN approach,” Alexandria Eng. J., vol. 60, no. 5, pp. 4701–4709, 2021, doi: https://doi.org/10.1016/j.aej.2021.03.048.

[31] A. ul Haq et al., “MCNN: a multi-level CNN model for the classification of brain tumors in IoT-healthcare system,” J. Ambient Intell. Humaniz. Comput., vol. 14, no. 5, pp. 4695–4706, 2023, doi: 10.1007/s12652-022-04373-z.

[32] M. Aamir et al., “A deep learning approach for brain tumor classification using MRI images,” Comput. Electr. Eng., vol. 101, p. 108105, 2022, doi: https://doi.org/10.1016/j.compeleceng.2022.108105.

[33] A. B. Bakht, S. Javed, R. Dina, H. Almarzouqi, A. Khandoker, and N. Werghi, “Thyroid nodule cell classification in cytology images using transfer learning approach,” in Proceedings of the 12th International Conference on Soft Computing and Pattern Recognition (SoCPaR 2020) 12, 2021, pp. 539–549.

[34] Y. Bhanothu, A. Kamalakannan, and G. Rajamanickam, “Detection and Classification of Brain Tumor in MRI Images using Deep Convolutional Network,” 2020 6th Int. Conf. Adv. Comput. Commun. Syst. ICACCS 2020, no. March, pp. 248–252, 2020, doi: 10.1109/ICACCS48705.2020.9074375.

[35] E. Gibson et al., “Automatic multi-organ segmentation on abdominal CT with dense V-networks,” IEEE Trans. Med. Imaging, vol. 37, no. 8, pp. 1822–1834, 2018.

[36] J. M. Valverde et al., “Transfer learning in magnetic resonance brain imaging: A systematic review,” J. imaging, vol. 7, no. 4, p. 66, 2021.

[37] Y. Wu et al., “Recent advances of deep learning for computational histopathology: principles and applications,” Cancers (Basel)., vol. 14, no. 5, p. 1199, 2022.

[38] A. Nogales, A. J. Garcia-Tejedor, D. Monge, J. S. Vara, and C. Anton, “A survey of deep learning models in medical therapeutic areas,” Artif. Intell. Med., vol. 112, p. 102020, 2021.

[39] C. Su, T. A. O. Tu, P. Han, P. Lakshminarayanan, and T. McNUTT, “Deep learning approaches for anomalies detection of bladder CT contours in prostate cancer patients,” J. Mech. Med. Biol., vol. 22, no. 08, p. 2240033, 2022.

[40] N. Zeng, H. Li, and Y. Peng, “A new deep belief network-based multi-task learning for diagnosis of Alzheimer’s disease,” Neural Comput. Appl., vol. 35, no. 16, pp. 11599–11610, 2023.

[41] C. R. Jack Jr et al., “The Alzheimer’s disease neuroimaging initiative (ADNI): MRI methods,” J. Magn. Reson. Imaging An Off. J. Int. Soc. Magn. Reson. Med., vol. 27, no. 4, pp. 685–691, 2008.

[42] F. Isensee, P. F. Jäger, S. A. A. Kohl, J. Petersen, and K. H. Maier-Hein, “Automated design of deep learning methods for biomedical image segmentation,” arXiv Prepr. arXiv1904.08128, 2019.

[43] P. Rajpurkar et al., “Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning,” arXiv Prepr. arXiv1711.05225, 2017.

[44] Z. Obermeyer, B. Powers, C. Vogeli, and S. Mullainathan, “Dissecting racial bias in an algorithm used to manage the health of populations,” Science (80-.)., vol. 366, no. 6464, pp. 447–453, 2019.

[45] G. Chartrand et al., “Deep learning: a primer for radiologists,” Radiographics, vol. 37, no. 7, pp. 2113–2131, 2017.

[46] D. Demner-Fushman, W. W. Chapman, and C. J. McDonald, “What can natural language processing do for clinical decision support?,” J. Biomed. Inform., vol. 42, no. 5, pp. 760–772, 2009.

[47] D. Shen, G. Wu, and H.-I. Suk, “Deep learning in medical image analysis,” Annu. Rev. Biomed. Eng., vol. 19, no. 1, pp. 221–248, 2017.

[48] R. Yousef, G. Gupta, N. Yousef, and M. Khari, “A holistic overview of deep learning approach in medical imaging,” Multimed. Syst., vol. 28, no. 3, pp. 881–914, 2022.

[49] S. K. Zhou et al., “A review of deep learning in medical imaging: Imaging traits, technology trends, case studies with progress highlights, and future promises,” Proc. IEEE, vol. 109, no. 5, pp. 820–838, 2021.